Forecasting International Regional Arrivals in Canada

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ABSTRACT

Considerable research has been done on comparative research models for forecasting tourist arrivals nationally. However, hardly any published study has tested regional international arrival forecasting accuracy. This study focuses upon forecasting arrival to the main regions of entry to Canada, using quarterly international arrival flows into the provinces of Canada from 2000Q1 to 2007Q4. Forecasts are run using the Basic Structural Time Series model (BSM) and the Causal Time Varying Parameter model (TVP) on quarterly data with an ex ante forecasting period 2006Q1 to 2007Q4. Assuming the forecasting process can firstly be shown to operate using time series methods, a further step would be to develop a theoretical model of suitable regional determinant variables for extending the forecasting process into a causal modelling framework.

The aim of this study is to determine whether accurate international regional forecasts can be derived; also to assess whether time-series or regression based models derive the most accurate forecasts; and further develop the theory of demand forecasting for regional tourism demand forecasting.

Forecasts are made for twelve provinces of Canada regionally and for the whole of Canada nationally in order to test whether accurate international regional forecasts can be derived relative to national arrival forecast. To determine the most accurate forecast, accuracy of the arrival forecasts of each model is measured for each region using the mean absolute percentage error (MAPE) and the root mean square error (RMSE), and compared against the bench mark of a simple naïve model.

These forecasts will provide interesting regional forecasts for the first time in Canada and allow for an assessment of the potential use of regional forecasting.

DECLARATION

"I, Vu Thi Thuy Mui (Emma), declare that the Master by Research thesis entitled Forecasting International Regional Arrivals in Canada is no more than 60,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work".

Signature: Date:

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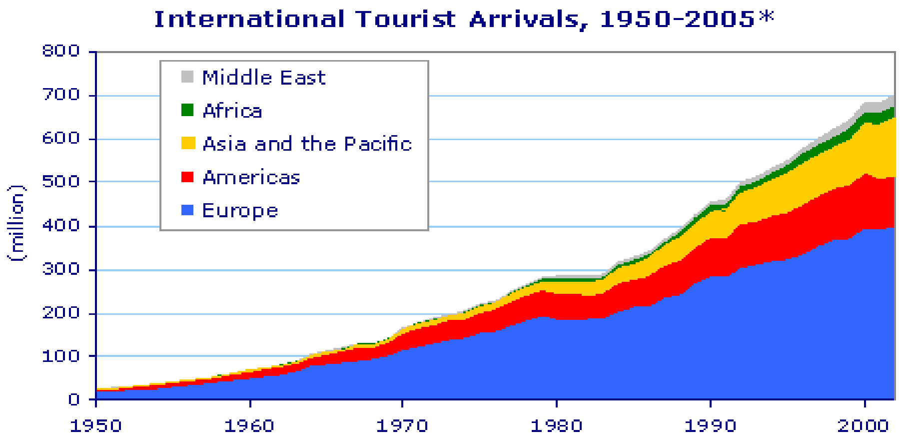
CHAPTER ONE

INTRODUCTION

1.1 OVERVIEW

Over many decades, tourism was an activity symbolizing status merely for the rich; today it has rapidly become a common need for the mass majority. This rapid development also leads to impressive growth in international travel, and international tourism has become one of the fastest growing economic sectors in the world. According to the United Nations World Tourism Organisation (www.unwto.org 2009), from 1950 to 2005, the number of international tourist arrivals shows an evolution from a mere 25 million to 806 million arrivals, corresponding to an average annual growth rate of 6.5% as shown in Figure 1:

Figure 1: World International Tourist Arrivals from 1950 to 2005



Source: World Tourism Organisation

International tourist arrivals reached 924 million in 2008, and generated US$ 856 billion in 2007, or 30% of the world's exports of services (UNWTO), a remarkable economic phenomena of the past one hundred years.

Owing to the important contributions of the tourism sector to an economy, the future of the whole set of tourism industry sectors requires planning. Therefore, in making decisions involving the future, accurate forecasts are needed for the planning process. The importance of tourism demand forecasting is emphasised by Song and Turner (2006, p89) with the following reasons:

"First, tourism demand is the foundation on which all tourism-related business decisions ultimately rest. Companies such as airlines, tour operators, hotels, cruise ship lines, and recreation facility providers are interested in the demand for their products by tourists. The success of many businesses depends largely or totally on the state of tourism demand, and ultimate management failure is quite often due to the failure to meet market demand. Because of the key role of demand as a determinant of business profitability, estimates of expected future demand constitute a very important element in all planning activities. It is clear that accurate forecasts of tourism demand are essential for efficient planning by tourism-related businesses, particularly given the perishable nature of the tourism product. Second, tourism investment, especially investment in destination infrastructures, such as airports, highways and rail links, requires long-term financial commitments and the sunk costs can be very high if the investment projects fail to fulfill their design capacities. Therefore, the prediction of long-term demand for tourism-related infrastructure often forms an important part of project appraisal. Third, government macroeconomic policies largely depend on the relative importance of individual sectors within a destination. Hence, accurate forecasts of demand in the tourism sector of the economy will help destination governments in formulating and implementing appropriate medium to long term tourism strategies."

Tourism forecasting has been an important component in tourism research and different approaches have been used to generate forecasts of tourism demand. Considerable research has been done on comparative research models for forecasting tourist arrivals nationally. Twenty years ago there were only a handful of academic journals that published tourism-related research. Now there are more than 70 journals that serve a thriving research community covering more than 3000 tertiary institutions across five continents (Song and Li, 2008). However, very few published studies have tested regional international arrival forecasting accuracy and none for Canada. Increasing international tourism arrival volumes have affected regions within countries that now compete among themselves to increase returns from tourism. Forecasting of international regional tourist arrivals has become a more pressing issue as the total volume of travel increases (Vu and Turner 2005).

Sub-national forecasts based upon regional data are extremely important for assessing regional development trends, and potential international tourism growth and decline locations within a national economy. Moreover, forecasting of international tourist regional arrivals within countries has become a more pressing issue as the total volume of travel increases. Regional tourism growth may lead to changing consumption patterns and greater demand for imported goods (Bryden 1973), while tourism can import economic change such as inflation, resettlement and a widening of the divide between rich and poor at the domestic level. Variable regional growth is an area of study in itself. Most commonly the tourism literature focuses upon economic impacts (Bryden 1973; Archer and Fletcher 1990; Eadington and Redman 1991; Briassoulis 1991; Gray 1982; Burns and Holden 1995). Regional impacts can vary from the earning of foreign exchange and boosting local taxation to include employment creation (Witt et al. 2004), education opportunities, cultural impact (positive and negative), infrastructure improvements, communications development and investment and environmental change (Budouski 1976; Hall and Page 1999). Social impacts (Dann and Cohen 1991; Dogen 1989; Pearce 1989) refer to the affects tourism has on collective and individual value systems, behaviour patterns, and quality of life and community structures.

In research conducted by Vu and Turner (2005), it was found that more accurate regional forecasts can be derived than international arrivals forecasts in the case of Thailand, and that a comparison of domestic and international regional arrivals forecasts is very useful in examining potential future tourism-based regional growth accuracy. This research forecasts international regional arrivals to the main regions of entry to Canada, using international arrivals data, over the period 2000Q1 to 2007Q4. Canada was chosen as the country of study mainly due to the availability of reliable tourism data, and also because it is a popular travel destination for business and leisure. It is also a developed economy and quite different in character to the earlier work completed in Thailand, and in particular as a developed economy potentially able to provide economic causal data, so that causal modeling may be possible for the first time in a regional economic setting. A general overview of Canada and how it is affected by the global spread of tourism is given below.

1.2 TOURISM IN CANADA

Canada is the second largest country in the world, smaller only to Russia, but has a very small population of 31 million people compared with its geographic size of 3.9 million square miles. Canada is divided into 10 provinces (Alberta, British Columbia, New Brunswick, Newfoundland, Nova Scotia, Ontario, Prince Edward Island, Quebec and Saskachewan) and 3 territories (Northwest Territories, Yukon Territory and Nunavut). Of the three territories, Nunavut recently became Canada's third territory on the first of April,

1999. Nunavut is comprised of a mainland and many islands in the Arctic Ocean with the land and water are frozen most of the year. People come to this remote region of Nunavut mainly to see the wildlife, therefore tourist flows to Nunavut are very low in numbers, and for this reason tourism forecasting for Nunavut is not included in this research.

During the mid- to late 19th century, waves of immigrants arrived from Europe, attracted by the opportunity of a new and better life in Canada. Asian immigrants from China, Japan and India settled mainly in the western provinces during this time. Over the last fifty years, people from all over the globe have sought a better life or refuge in Canada, fleeing civil wars, political unrest and natural disasters. Today, Canada is home to immigrants from more than 240 countries.

As tourism is a profound social force in modern society and the largest economic activity in the global economy, it is also one of the fastest growing economic sectors in Canada. According to the World Tourism Organization (UNWTO), Canada is one of the top ten countries in the world in terms of tourist arrivals, tourist receipts and tourist spending. Until 2000, the tourism industry experienced steady growth in international travel. The horrors of terrorist attacks in the USA on September 11, 2001, war in Afghanistan, Canada's non-commitment policy on the 2003 war in Iraq, an outbreak of Severe Acute Respiratory Syndrome (SARS) in Toronto and publicity on the potential spreading of Mad Cow disease, caused considerable declines in tourist arrivals to Canada in 2002 and 2003.

In 2005, international tourism continued the tremendous recovery that began in 2004, when arrivals grew by 10.7 percent. Worldwide travel reached 808 million in 2005, an increase of

5.5 percent—the largest annual increase in more than 25 years. Almost all regions shared in this rebound, with Asia-Pacific experiencing growth of 7.4 percent, the Middle East 6.9 percent, the Americas 5.8 percent and Europe 4.3 percent. In January 2006, the World Tourism Organization (WTO), World Tourism Barometer, reported that events and developments such as natural disasters and acts of terrorism do not appear to be deterring global international tourism; rather they have caused temporary shifts in travel patterns.

As events in the past few years have shown, the tourism industry in Canada and around the world can be strongly affected by shock events; therefore the need for accurate planning is the central objective for sustainable tourism.

1.3 OBJECTIVE OF THE RESEARCH

This study is a further attempt to examine and test regional based forecasting accuracy for regional (sub-national) areas. The search is also intended to compare different forecasting methods by testing them on quarterly time series of visitor arrivals to the ten provinces and two territories of Canada. Model estimation is carried out using international arrivals data, over the forecast period 2000Q1 to 2005Q4, with ex ante forecasts for 2006 and 2007. The models compared in this thesis are: the basic structural time series model (BSM) and the Time Varying Parameter (TVP) models. The accuracy of the models will be measured using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), and compared against the benchmark of a simple naïve model.

More specifically, the aim is to:

- Determine whether accurate international regional forecasts can be derived relative to national arrival forecasts in the case of Canada.

- Assess whether time-series or regression based models derive the most accurate forecasts. Specifically, which of the latest forecasting models, BSM or TVP, forecasts more accurately regional international tourist arrivals to Canada.

- Further develop the theory of demand forecasting for regional tourism demand forecasting.

This analysis methodology as stated in point 2 above is the first study to incorporate econometric modelling techniques to forecast regional international tourist arrivals.

1.4 OUTLINE OF THE THESIS

This thesis contains four chapters beginning with the introduction, which presents a discussion of the contribution of tourism to the world economy, and an explanation of the need for regional based forecasting. The remainder of Chapter One is a short overview of Canada, and how the tourism industry in Canada is affected by the process of global tourism change. The reason why Canada is chosen for this study is also given. Finally, the chapter outlines the objectives of the research.

Chapter Two reviews the relevant literature on tourism demand forecasting and the application of quantitative forecasting models to tourism arrival forecasting.

Chapter Three discusses the choice of the forecasting models used for this research - namely the basic structural time series model and the time varying parameter model - and the methodology used to empirically test these models.

Chapter Four discusses the forecasting performance evaluation, and presents the results of the forecasting performance comparison. The most accurate forecasting model is identified, and the key findings gathered from the empirical results are discussed. Conclusions from the comparative analysis are given and to the overall thesis objectives. Finally, there is discussion on the limitations of the study, and implications for future research are stated.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

Along with the global growth of tourism, academic interest in tourism has also increased. The academic study of demand modelling and forecasting, has resulted in a widespread literature from the late 1970's. These publications vary immensely in scope, modelling and forecasting techniques, data types, and objectives. The major literature review articles that attempt to summarise this literature are Crouch, 1994; Witt and Witt, 1995; Lim, 1997a, 1997b, 1999; Li et al., 2005 and Song and Li, 2008.

For empirical investigations it can be difficult to find exacting measures for the determinants of tourism demand due to lack of data availability. Consequently, some research is based on time-series modelling that does not require determinant (causal) measures. In many cases as discussed below these techniques are highly accurate. The other major alternative, econometric modelling, attempts to use determinant variables to explain arrivals volume changes and predict ahead in time. The variables used in empirical studies of tourism demand functions and the problems associated with these measures are addressed below (refer to Song and Witt 2000, Song and Turner 2006) and further discussed in Chapter Three (Methodology).

2.2 TYPE OF DEPENDENT VARIABLE

Expenditure in international tourism demand is measured in terms of the number of tourist visits from an origin country to a destination country, or in terms of tourist expenditure (spending) by visitors from the origin country to the destination country. The number of tourist nights spent by residents of the origin, in the destination, is an alternative tourism demand measure. Length of stay is not used alone in current literature because it can be reflected as part of expenditure. The forecasting of receipts (Turner and Witt 2009) is also not common because receipt data derived from tourism is a difficult set of data to accurately obtain and tends to be spending in the destination country, rather than a correct reflection of total monetary transfer including moneys spent in the source country on airfares and pre-travel payments for accommodations car hire and entertainment. Because tourism is not a recognised economic sector in national accounts, efforts are being made to develop satellite tourism accounts that may then allow for more accurate receipts forecasts in the future (Spurr, 2006).

International tourism demand data are collected in various ways. Tourist arrivals data is most commonly recorded by frontier counts (inbound) through immigration records, and less reliably as registrations at accommodation establishments (inbound) or sample surveys (inbound and outbound). One problem with frontier counts is that in certain cases a substantial transit traffic element may be present. More significant difficulties arise with accommodation establishment records which exclude tourists staying with friends or relatives, or in other forms of unregistered accommodation. Sample surveys may be applied at points of entry/exit to returning residents or departing non-residents, or household surveys may be carried out (outbound), but in both cases the sample size is often relatively small and the time of collection intermittent. International tourist expenditure data are usually collected by the bank reporting method or sample surveys. The former method is based on the registration by authorised banks and agencies of the buying and selling of foreign currencies by travellers. There are many problems associated with this method of data collection such as identifying a transaction as a tourism transaction, the non-reporting of relevant transactions and the unreliability of its use for measuring receipts from specific origin countries (the geographic breakdown relates to the denomination of the currency and not the generating country). Sample surveys provide more reliable data on tourist expenditures, but as with visit data the sample size is often relatively small and collection intermittent.

2.3 TYPE OF INDEPENDENT VARIABLES

The possible explanatory variables used as determinants of tourism demand include the following (Morley 1991, 1996; Witt and Witt 1992; Frechtling 1996; Lim 1999; Song and Witt 2000; Song and Turner 2006):

- **Population**

Population can be used as an explanatory variable because it is expected that the level of inbound tourists into the destination country depends upon the population of the tourist origin countries. However, the main argument for not having population as a separate variable is that it may cause multicollinearity problems. Population can also act as a spurious independent variable for time change reflecting tourism growth rates that are common over time, but not caused by population change. Additionally, for some destinations the populations used are slow to change, and do not reflect faster volume changes in tourist arrivals and departures.

- **Income**

Income is an important explanatory variable in nearly all forecasting demand studies because it is a direct determinant of the capacity of individuals within a given market to afford travel. The appropriate income variable is personal disposable income or private consumption expenditure in the origin country (in constant price terms), and is expected to have a positive influence on tourism demand.

- **Own price**

Own price consists of two components: the cost of travel to the destination, and the cost of living for the tourist in the destination – and these are expected to have negative influences on demand.

Travel costs could be air fares/ferry fares between the origin and destination or petrol cost (based on the distance travelled) for surface travel. Turner and Witt (2001) considered travel to New Zealand from four origin countries and showed that airfare often has a statistically significant impact on the demand for tourism for holiday and VFR purposes, but not for business purposes.

The cost of living in a country is measured by the consumer price index (CPI) and it is usually taken as a reasonable proxy for the cost of living for the tourist in the destination.

The bundle of goods and services bought by residents of a country differs from that bought by inbound tourists to that country, and this is a weakness in using the CPI. Also the destination price variable should be adjusted by the exchange rate between the origin and destination currencies. Exchange rates are sometimes used separately to represent tourists' costs of living. However, the use of the exchange rate alone in the demand functions can be very misleading because even though the exchange rate in a destination may become more favourable, this could be counterbalanced by a relatively high inflation rate. Martin and Witt (1987) have shown that the exchange rate-adjusted relative CPI is a good approximation to the real tourist price index.

- **Substitute price**

The price of substitutes may be important determinants of demand in causal models as Gray (1966, p.86) indicated: '…there is a high elasticity of tourism demand substitution among countries so that higher than expected prices in one country may result in a change of destination rather than a decision to forgo overseas travel'. So both the tourist travel costs and tourist living costs at the destination are likely to cause substitution possibilities, thereby influencing the demand for tourism to a destination. Although attention has been paid to the notion of substitute travel costs in the literature, they do not often feature in tourism demand functions.

- **Marketing expenditure**

In attempting to persuade potential tourists to visit the country, national tourist organisations engage in sales-promotion activities such as media advertising and public relations. Therefore, promotional expenditure is expected to play a role in determining the level of international tourism demand. However, much of the tourism-related marketing activity is likely to have little impact on the demand for tourism to that destination, because marketing activities including general travel and tour operator advertising are not specific to a particular destination. Empirical studies that have included some forms of a marketing variable in their tourism demand models include Witt and Martin (1987a) and Crouch et al. (1992).

- **Trade Openness**

Trade Openness has been shown to have a positive impact on tourist arrivals. It draws out the relationship between trade and tourism, in that people come to a country for trade, and possibly return for a holiday.

- **Lagged dependent variable**

A lagged dependent variable can be included in the tourism demand function to bring in the effect of habit persistence – a visitor would tend to return to a particular destination in future if the visitor likes the place; there is less uncertainty associated with touring that destination again as compared to travelling to a new and foreign environment. Constraints on supply are also a second justification for the inclusion of a lagged dependent variable in tourism demand functions. These constraints may be shortages of hotel accommodation, passenger transportation capacity and trained staff.

- **Dummy variables**

These are included in the international tourism demand functions to allow for the effect of 'one-off' events. When an event occurs, these variables take the value of 1 and 0 otherwise.

Events such as September 11, 2001 in New York; October 12, 2002 in Bali and the worldwide financial crisis at the start of 2009 are likely to reduce the level of international tourism. But events such as hosting the Olympic Games or a tennis tournament are likely to stimulate international tourism. Dummy variables can also be used to accommodate the effects of seasonality (Chadee and Mieczkowski 1987) when quarterly data are used in tourism model estimation.

2.4 FORECASTING MODELS

Forecasting models can be classified in many ways such as long term or short term, micro or macro. In this research, tourism demand modelling and forecasting methods are broadly divided into two categories: qualitative and quantitative methods. Qualitative forecasting techniques are generally more subjective than their quantitative counterparts. Qualitative methods include the Delphi technique, and sales force opinions that are 'artistic in nature' and not able to be generalized. In their study, Song and Turner (2006) also concluded that the majority of the published studies use quantitative methods to forecast tourism demand. Quantitative forecasting methods use historical data in order to estimate the behavior of a variable of interest into the future. Since the objective of this research is to use quantitative methodology, the literature review focuses upon relevant quantitative research.

The quantitative forecasting literature is dominated by two sub-categories of methods: non-causal time-series models and causal econometric approaches. Each method has different strengths and weaknesses. The causal models require the need to identify and forecast independent variables in the defined model in order to forecast arrivals. This represents a significant challenge as the incorrect prediction of these independent variables will result in an incorrect forecast. On the other hand, the non-causal time-series methods only require historical observations of a variable; therefore they are less costly in data collection and model estimation. However, such methods provide no direct indication of the cause of arrival variations over time.

In the following discussion, the review of quantitative models is divided into the two main sections – non-causal time-serries approaches and causal econometric approaches.

2.4.1 Non-causal time-series methods

A time-series refers to observations on a variable that occur in a time sequence. Most time-series are stochastic in that the future is only partly determined by past values. However, most time-series forecasting models predict future values solely on the basis of the past values of the time series (Morley 1993; Frechling 1996; Makridakis et al. 1998). However, it is also the case that the components of a time series measured as trend, cycle, seasonal and error terms may also measure changes in underlying causal determinants such as business cycles, GDP growth, disposable income growth and seasonal variation. Consequently, particular attention is paid to exploring the historic trends and patterns (such as seasonality) of the time series involved, and to predict the future of this series based on the trends and patterns identified in the model.

Time-series analysis enables a model to be developed to extrapolate the trend, cycle and seasonal patterns of the historical data in order to predict the future values of the data. Various time-series methods use the components of trend, cycle and seasonal change to varying degrees. Time series models can be ranked from simple models measuring only trend (such as the moving average model); through to more complex methods capable of measuring trend and seasonality (such as several of the exponential smoothing models); through to complex models that measure all components and allow for stochastic change (such as the Box Jenkins ARIMA and the basic structural models). The different types of time-series models are described next.

2.4.1a Naïve

The simple Naïve method simply states that the current period's actual value is the next period's forecast. Due to its simplicity, not involving any mathematical modelling or using any sophisticated computer software, this forecasting method can be used as a benchmark to compare the accuracy of other forecasting methods. Naïve I and Naïve II are two additional versions of the naïve method. Naïve I uses seasonally adjusted data and Naïve II uses raw data:

Naïve I	***Naïve II***
$F_t = A_{t-1}$	

where,

F_t = Forecasting value at time *t*,

A_t = Observed value at time *t*.

In a number of previous studies (Martin and Witt, 1989; Witt and Witt, 1992; Witt *et al.*, 1994) this simple forecasting method was shown to be more accurate than other models such as the exponential smoothing, structural time series and the Box- Jenkins approach.

On the other hand, other studies have indicated that the Naïve models are the least accurate (Turner et al., 1997; Kulendran and Shan, 2002).

2.4.1b Moving average

Moving average techniques calculate an average of actual data from a specified number of prior periods *n* to obtain a forecast for the next period. Mathematically,

$$F_t = (A_{t-1} + A_{t-2} + ... + A_{t-n})/n \quad ,$$

where,

F = forecast value,

A = actual value,

n = number of averaging periods.

The moving average model was indicated as the most popular technique for short term forecasting (less than one year ahead) in a questionnaire survey by Martin and Witt in 1988.

2.4.1c Exponential Smoothing

All exponential smoothing methods also average out the data but in an exponential manner. Whereas in Moving Averages the past observations are weighted equally, Exponential Smoothing assigns exponentially decreasing weights as the observations get older. That is, recent observations are given relatively more weight in forecasting than the older observations. The main difference among the various exponential smoothing methods is the way they treat the trend and the seasonality. These techniques commonly include simple exponential smoothing and Holt-Winters' exponential smoothing methods.

Simple exponential smoothing assumes no trend and is appropriate for stationary and non-seasonal time series with no structural change:

$$F_t = \alpha A_t + (1-\alpha) F_{t-1} \quad ,$$

where:

F_t = forecast value of period t,

α = smoothing constant between 0 and 1,

A_t = actual value of period t,

F_{t-1} = forecast value of period t-1.

Holt-Winters' exponential smoothing method is an extension of simple exponential smoothing to be applied for tourism arrival forecasting where seasonal effects are present in a tourist arrival data series. The Holt-Winters method has three updating equations (Makridakis et al. 1998) giving more weight to recent observations and less weight to observations further in the past:

$$L_t = \alpha(A_t / S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1}) \quad ,$$

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1} \quad ,$$

$$S_t = \gamma(A_t / L_t) + (1 - \gamma)S_{t-s} \quad ,$$

where,

L_t = level of the series of constant between 0 and 1,

A = level smoothing constant between 0 and 1,

A_t = actual value of period t,

s = number of seasonal periods in a year,

T_t = trend of the series of period t,

B = trend smoothing constant between 0 and 1,

S_t = seasonal component of period t,

Γ = seasonal smoothing constant between 0 and 1 .

A thorough investigation of the application of various exponential smoothing models has been made by Lim and McAleer (2001). Since most tourism arrival series display both trend and seasonality the Holt-Winters model is more likely to be used for forecasting tourism series (Turner, Kulendran and Pergat 1995).

2.4.1d Autoregressive Model

A common approach for modelling univariate time series is the autoregressive (AR) model. It is simply a linear regression of the current value of the series against one or more prior values of the series:

$$y_t = \delta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + ... + \theta_p y_{t-p} + \varepsilon_t ,$$

where:

δ = constant term,

θ = unknown parameter to be estimated,

$\boldsymbol{\varepsilon}$ = uncorrelated random error with zero mean and constant variance.

All these models above have appeared frequently in post-2000 studies (Song and Li, 2008), but usually they are used as benchmarks for forecasting accuracy evaluation.

2.4.1e Box-Jenkins Approach

The Autoregressive Integrated Moving Average (ARIMA) model was developed by George Box and Gwilym Jenkins (Box and Jenkins, 1976). The Box-Jenkins model is the result of combining two models: autoregressive (AR) and moving average (MA). The model assumes that the time series is stationary, Box and Jenkins recommend differencing non-stationary series one or more times to achieve stationarity. This process produces an ARIMA model with the 'I' standing for 'Integrated', and is represented by ARIMA (*p,d,q*):

$$F_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - ... - \theta_q \varepsilon_{t-q} ,$$

where:

p = order of autoregression,

d = order of integration,

q = order of moving average,

F_t = forecast value for period t,

ϕ_x = x^{th} autoregression parameter,

$\boldsymbol{\varepsilon_t}$ = the error term at time t,

θ_x = x^{th} moving average parameter.

An extension of ARIMA is the mixed seasonal ARIMA (SARIMA) where seasonality in the data is accommodated using seasonal differences, and it has a general form of ARIMA $(p,d,q)(P,D,Q)^s$ where s is the seasonal order and can be expressed as:

$$\phi_p(B)\Theta_p(B^s)\,\nabla_d\nabla_s{}^D F_t = \Theta_Q\,\phi_q(B)\,(B^s)\varepsilon_t\,,$$

where,

$\phi_p(B)$ = nonseasonal AR operator,

$\phi_q(B)$ = nonseasonal MA operator,

$\Theta_p(B^s)$ = seasonal AR operator,

$\Theta_Q(B^s)$ = seasonal MA operator,

B = backship operator,

A^d = nonseasonal d^{th} differencing,

$A_s{}^D$ = seasonal D^{th} differencing at s number of lags,

F_t = Forecast value for period t,

s = 12 months,

p = order of nonseasonal AR process,

P = order of seasonal AR process,

q = order of nonseasonal MA process,

Q = order of seasonal MA process.

Different versions of the ARIMA models have been applied in tourism studies that utilise different time-series forecasting techniques. Depending on the frequency of the time series, either simple ARMA or ARIMA (SARIMA) models could be used with the latter gaining an increasing popularity over the last few years, as seasonality has recently been recognised as a dominant feature of tourism, with decision makers also very interested in the seasonal variation in tourism demand (Makridakis and Hibon, 1997; Turner, Kulendran and Fernando, 1997; Chu, 1998b; Preeze and Witt, 2003; Gonzalez and Moral, 1995; Kulendran anh King, 1997; Kulendran and Shan, 2002; Turner and Witt, 2001b; Kulendran and Wong, 2005; Louvieris, 2002).

In regard to the forecasting performance of the SARIMA models, empirical studies over many years have presented contradictory evidence. For example, Cho (2001) states that the ARIMA and the adjusted ARIMA models outperformed the exponential smoothing time-series model and concludes that the ARIMA models are suitable for forecasting the fluctuating series of visitor arrivals. Goh and Law (2002) state that the SARIMA models outperformed seven commonly used time-series models including Naive I and II, moving average 3 and 12 month, and exponential smoothing (simple, Holt and Winter); while the ARIMA model's performance was above the average of all forecasting models considered. However, Smeral and Wuger (2005) suggest that the ARIMA or SARIMA models could not even outperform the Naive I model. The majority of studies in the tourism literature suggest the SARIMA method as an accurate model overall, provided that the data requirements are adequately met. It is also evident from the diverse range of publications in corporate modelling published over the past twenty years, that different models produce more or less accurate forecasts with different tourism arrivals series in different places and at different times. No conclusion is evident that any one technique is superior. However, the levels of forecast accuracy have been measured and are now quite high as indicated in the more recent post 2000 publications using advanced models (Song and Witt 2000; Song and Turner 2006; Song, Witt and Li 2009).

2.4.1f Neural Models

Neural Models can be classified as time-series models but like structural models (discussed below). They can include determinant variables. The development of Neural models is relatively recent, in particular with their application to tourism studies. Palmer et al. (2005) provides an overall description of their application to tourism while Kon and Turner (2004) provide a literature review as well as a detailed example application. Law (2000) states that Neural networks contain processing units ("nodes") and the connection between these nodes have weight that can be adjusted in a learning process. The Neural network maps any series and non-linear function (Cybenko, 1989). Neural models are particularly useful in mapping imperfect data (Burger et al., 2001; Law and Au, 1999; Fernando, 2005).

Neural models lack a systematic procedure for model building and a reliable model involves selecting a large number of parameters experimentally through trial and error. This process is sometimes referred to as data mining. However, this term has several definitions that can sometimes suggest a random process of analysis, that is not reflective of either the Neural modelling process, or the Box Jenkins process. The particular process followed in any one analysis can vary greatly to another study so that the comparison of accuracy is made more difficult when neural models are compared (in regard to accuracy) with other methodologies. However, neural models can achieve high levels of accuracy (Turner et al., 1995).

2.4.1g Structural Time Series Models

The structural time series models (BSM) (Engle, 1978; Nerlove et al., 1979; Kitagawa, 1981; Harvey, 1989) are based on a decomposition of the time series into four components which are normally recognizable visually in a time plot of the series. These components include a stochastic trend, a periodic cycle, a seasonal component, and an irregular component assumed with zero mean, and serially uncorrelated. Unlike the earlier time-series models, structural models are more advanced because they allow for stochastic change. Therefore, structural time series models offer clear interpretations through the decomposition into components (Kendall and Ord, 1990), and this is a major attraction of time series forecasting generally. The BSM model is given as:

$$\textit{observed series} = \textit{trend} + \textit{cycle} + \textit{seasonal} + \textit{irregular}\ .$$

This time series model can be developed into a multivariate structural time series model (STSM) now more commonly referred to as Causal Structural Modelling (CSM) by including explanatory variables (CSM will be discussed further in the next section ***Causal econometric methods***). The multivariate CSM is as follows:

$$Y_t = \mu_t + \gamma_t + \psi_t + \lambda_1 x_1 + \lambda_2 x_2 + \ldots + \lambda_k x_k + \varepsilon_t \quad ,$$

$t = 1,2,..., T$,

where:

Y_t = number of tourist visits in period t,

μ_t = trend component,

γ_t = seasonal component,

ψ_t = cyclical component,

$x_{1,}$ x_2, ... x_k are explanatory variables,

$\lambda_{1,}$ λ_2, ... λ_k are unknown parameters,

ε_t = irregular component.

When the linear combination of explanatory variables is removed from the equation, the multivariate CSM collapses to the BSM:

$$Y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t ,$$

$$t = 1,2,..., T .$$

The BSM was introduced by Harvey and Todd (1983) and further developed after the development of the STAMP (2006) software, with non-stationary being handled directly, without the need for explicit differencing operations. It has been argued that differencing (used in Box Jenkins modelling) can lead to problems with over differencing. Statistically, the treatment of the BSM can be performed by casting it into the state space form (SSF) so that the Kalman filter can be used to evaluate the likelihood function (Kalman, 1960; Kalman and Bucy, 1961; Meinhold and Singpurwalla, 1983).

The ARIMA and BSM models are advanced time-series forecasting techniques and have shown favourable forecasting performance in the tourism context. Most focus is on the use of the Box-Jenkins ARIMA model which developed earlier in the 1970's (Turner, Kulendran and Pergat, 1995; Song and Li, 2008). On the other hand, although used in previous research (Gonzalez and Moral, 1995; 1996; Chan, Hui and Yuen, 1999), the BSM is less well-known than ARIMA modelling (Greenidge, 2001; Turner and Witt, 2001a; Goh and Law 2002). However, BSM has been shown to be a highly accurate forecasting model (Gonzalez and Moral, 1995; Turner and Witt, 2001a).

2.4.2 Causal econometric methods

In econometric forecasting, the forecast variable is specifically related to a set of independent determinant variables. Future values of the independent variables are most commonly obtained by using either forecasts by economic agencies such as the World Bank or by using time series methods. The determinants of tourism demand depend on the purpose of the visit. Tourism visits can take place for various reasons (Song and Turner, 2006): holidays, business trips, visits to friends and relatives (VFR) and for other reasons such as pilgrimages, sports, conferences, health and so on. However, because the majority of tourist visits take place for holiday reasons, the emphasis in empirical research in tourism demand modelling has been on holiday tourism. The main difference between the holiday series compared to the business travel series is that business travel is less seasonal (Turner, Kulendran and Pergat 1995).

There are two broad categories of econometric models that have been applied in tourism demand modelling and forecasting: single-equation and multi-equation regression models.

2.4.2a Single-equation econometric models

The specified models in studies published between the 1960s and early 1990s are in static form with very limited diagnostic statistics being reported. Static regression models suffer from a number of problems including structural instability, forecasting failure and spurious regression relationships (Song and Turner 2006). In the mid-1990s, dynamic specifications such as the autoregressive distributed lag model (ADLM), and error correction model (ECM) began to appear in the tourism literature. Syriopoulos (1995), Kulendran (1996), Kulendran and King (1997), Seddighi and Shearing (1997), Kim and Song (1998) and Vogt and Wittayakorn (1998) were the first authors to apply recent advances in econometrics, such as cointegration and error correction techniques, to tourism forecasting. Applications of modern econometric techniques to tourism demand modelling and forecasting over the last few years include Morley (2000), Song et al. (2000, 2003a,b,c), Kulendran and Witt (2001, 2003a,b), Lim and Mc Aleer (2001, 2002), Webber (2001) and Dritsakis (2004).

The introduction of advanced time-series techniques into the causal regression framework has been another emerging trend of tourism demand research. That is the advantages of both methodologies are combined. An example of this trend is the structural time series model with explanatory variables (CSM) (as discussed earlier), which expands the basic structural model without explanatory variables (BSM). The CSM incorporates stochastic and seasonal components into the classical econometric model, and they are specified in the state space form (SSF) and estimated by the Kalman filter algorithms (Kalman 1960). However, the coefficients of the explanatory variables are still treated as fixed parameters in the CSM. Applications of CSM in tourism demand studies include Gonzales and Moral (1995, 1996), Greenidge (2001), Kulendran and Witt (2001, 2003a) and Turner and Witt (2001b). In conclusion, Turner and Witt (2001b) suggest that there is no evidence of forecast accuracy improvement by including explanatory variables in the BSM.

By using a causal structural time-series model to forecast tourism demand a stochastic trend is allowed (Gonzales and Moral 1995), and because the variables are transformed to logarithms with estimated fixed parameters on the causal variables, their demand elasticity is constant. As an alternative to the CSM, the time varying parameter (TVP) model allows such parameters to change over time, and so is more adaptable in dealing with structural change in econometric models (Engle and Watson, 1987). It has been shown that changes in demand elasticities can be best simulated by TVP models (Song and Witt, 2000; Song and Wong, 2003).

All of the above models are grouped within the single-equation approach, and the explanatory variables included in the models should be exogenous. On the other hand, the vector autoregression (VAR) treats all variables as endogenous, and each variable is specified as a linear relationship of the others. Sims (1980) stated that many of the restrictions imposed on the parameters in the structural equations were 'incredible' relative to the data-generating process; therefore it is better to use models that do not depend on the imposition of incorrect prior information. Hence, Sims developed a vector autoregressive (VAR) model in which all the variables are treated as endogenous except the intercept, determinate time trend and dummies. The VAR model is a system estimation technique which has been used widely in macroeconomic modelling and forecasting, but relatively little effort has been made in using this method to forecast tourism demand. The VAR model can be found in Shan and Wilson (2001), Witt et al. (2003, 2004), Song and Witt (2006) and Wong et al. (2006).

2.4.2b Multi-equation regression econometric models

The other deficiency of the single-equation approach noted by Eadington and Redman (1991) are that such approaches are incapable of analysing the interdependence of budget allocations to different consumer goods/services. In addition, they cannot be used to test either the symmetry or the adding-up hypotheses associated with demand theory. There are a number of system approaches available dating back to the system initiated by Stone (1954) to overcome these limitations. By including a group of equations (one for each consumer good) in the system and estimating them simultaneously, this approach permits the examination of how consumers choose bundles of goods in order to maximise their preference or utility within budget constraints. The almost ideal demand system (AIDS) model developed by Deaton and Muellbauer (1980) has been the most commonly used method for analysing consumer behaviour. But the application of this approach to tourism demand studies is still relatively rare. By the end of the last century there had been only five applications of this approach: Fujii, Khaled and Mark (1985), O'Hagan and Harrison (1984), White (1985), Syriopoulos and Sinclair (1993) and Papatheodorou (1999). During the period 2000-2006, there are eleven studies that have employed various versions of AIDS for tourism demand modelling and forecasting for example, Song and Li (2008), Durbarry and Sinclair (2003), Li et al. (2004), De Mello and Fortuna (2005) and Li et al. (2006).

2.5 RECENT DEVELOPMENTS IN ECONOMETRIC MODELLING AND FORECASTING

Most of the published econometric studies on tourism demand forecasting before the 1990s, and some recent studies, are classical regressions with ordinary least squares (OLS) as the main estimation procedure, and are based on the traditional specific-to-general modelling approach (Gilbert 1986; Witt and Witt 1995). This approach starts by constructing a simple model that is consistent with demand theory (Thomas 1997, p. 362), which is then estimated using ordinary least squares and tested for statistical significance. The estimated model is expected to have a high R^2, and the coefficients are expected to be both 'correctly' signed and statistically significant according to the t-statistics of the coefficients (usually at the 5% level). It is also expected that the estimated residuals of the demand model should be normally distributed with zero mean and constant variance, that is, they do not exhibit any problems of autocorrelation and heteroskedasticity. If the estimated model is unsatisfactory, it is re-specified after introducing new explanatory variables, using a different functional form, or selecting a different estimation method. This procedure is repeated until the final model is both statistically and theoretically acceptable. Although this model starts with a relatively simple specification, the final model maybe very complex in terms of the number of variables, the functional form and/or the estimation method.

This modelling approach has been criticized for its excessive data mining (Hendry 1995), as different researchers may obtain different model specifications using the same data set, and therefore could end up with totally different model specifications. Another problem associated with this approach is that the past studies tended to ignore diagnostic checking (Witt and Witt 1995). These tests include the tests for integration orders (unit roots) of the data used in the demand models, heteroscedasticity, non-normality, inappropriate functional form, and structural instability. In addition, the data used in estimating tourism demand models based on the specific-to-general approach are mainly time series, and most of them, such as tourist expenditure, tourist arrivals, income, tourist living costs and transport prices are non-stationary (Song and Turner 2006). Results of statistical tests based on such regression models with non-stationary variables are often unreliable and can be misleading, and tourism demand models with non-stationary variables tend to cause the estimated residuals to be autocorrelated, and this invalidates OLS. Seminal works in the tourism forecasting literature using the specific-to-general modelling approach include, Uysal and Crompton (1985), Witt and Martin (1987a), Martin and Witt (1988), Crouch (1992), Witt and Witt (1992), and Sheldon (1993).

In contrast to the specific-to-general approach, one of the recent advances in econometrics, general-to-specific approach to modelling, overcomes the problems associated with the traditional modelling procedure discussed above. The general-to-specific modelling approach was first suggested by Hendry and von Ungern-Sternberg (1981), and later theorised by Eagle and Granger (1987) and Hendry (1995). Tourism researchers have introduced this methodology to forecast tourism demand since the mid-1990s (Song and Turner, 2006). The first published study on tourism forecasting using this methodology was Syriopoulos (1995) followed by Kulendran and King (1997), Kim and Song (1998), Song et al. (2000), Song and Witt (2000), Kulendran and Witt (2001), Song and Witt (2000) and Song et al. (2003a).

Tourism demand models with non-stationary variables can cause problems for tourism demand analysis. Analysts tend to obtain a high R^2 and significant t statistics for the regression coefficients if the variables in the demand model have a common deterministic trend, but this does not necessarily mean that these variables are actually related, that is, the regression may be spurious. The cointegration technique developed by Eagle and Granger

(1987), coupled with the error correction mechanism, has proved to be a useful tool for solving the problem of spurious correlation. According to Eagle and Granger (1987), if a pair of non-stationary economic variables x_t and y_t belong to the same economic system, such as tourism demand and income, there should be an attractor or cointegration relationship that prevents these two time series from drifting away from each other; that is, there exists a force of equilibrium that keeps the two variables, x_t and y_t, moving together in the long run.

The general-to-specific modelling allows both the long-run equilibrium (cointegration) and short-run dynamic (error correction) relationships to be analysed in the same framework. Therefore, the estimated models can provide useful information for both long and short-term policy making. Eagle and Granger (1987) state that cointegrated variables can always be transformed into an ECM and vice versa. This bi-directional transformation is often called the 'Grange Representation Theorem' and implies that there is some adjustment process that prevents economic variables from drifting too far away from their long-run equilibrium time path. The cointegration and error correction approach to modelling has now become a standard research methodology in applied econometrics and forecasting.

One of the criticisms of the general-to-specific modelling approach is the complexity of the model selection process (Song and Turner 2006). The general-to-specific modelling approach starts with a general autoregressive distributed lag model (ADLM) containing a range of variables suggested by economic theory. This general dynamic model encompasses a number of specific models (simple autoregressive, static, growth rate, leading indicator, partial adjustment, finite distributed lag, dead start, and error correction) and is reduced to these models by imposing certain restrictions on the parameters in the model. To examine whether the final models are statistically acceptable or not, various diagnostic tests, such as those for autocorrelation, heteroskedasticity, functional form and structural instability, are carried out. Thomas (1993) has pointed out that the final model should ideally satisfy these various criteria: be consistent with economic theory, data coherency, parsimony, encompassing, parameter constancy and erogeneity. However, due to various reasons, such as data limitations, errors in variables and insufficient knowledge of the demand system, this can be difficult.

Econometric techniques have advanced significantly during the past two decades. These new developments have also played an important role in the understanding of tourist behaviour and their demand for tourism products/services. Li et al. (2005) reviewed 84 studies on tourism demand analysis published since the 1990s and found that a majority of these studies used modern econometric methods. Compared with the studies between the 1960s and 1980s, more advanced econometric techniques, such as the cointegration/error correction, vector autoregressive, time varying parameter, almost ideal demand systems models and structural models, have been applied to tourism demand studies in the 1990s and early 2000s. Although tourism forecasting has achieved much progress in terms of the use of modern modelling methodologies, Witt and Song (2001) and Song and Witt (2003) note that the forecasting accuracy of individual forecasting methods varies across origin-destination pairs and over different forecasting horizons. Therefore, it is very difficult to obtain a single model that consistently outperforms all models in all situations. Given that tourism planners and business decision-makers attach high importance to the accuracy of forecasting, it is crucial for researchers to explore the best techniques for tourism demand forecasting. Because no single forecasting method has been found to outperform others in all situations (Li, Song and Witt 2005; Song and Li 2008), a new direction in tourism forecasting research has been to combine the forecasts produced by individual models, using various combination techniques. A number of studies suggest that combination techniques can outperform the best constituent single individual forecast. Chong and Hendry (1986), Fair and Shiller (1990) and Shen et al. (2008) have shown that composite forecasts, if combined properly, are superior in terms of lack of bias and accuracy to the original forecasts generated by each of the individual models. But this conclusion is not supported by studies such as Koning et al. (2005), Hibon and Evgeniou (2005) and Song et al. (2009). Turner and Witt (2003) point out that forecast combination is not a straightforward process and should include non-quantitative methods such as expert opinion.

Additionally, the focus of all research is upon forecasting accuracy comparisons. That is selecting forecasting methods that are likely to generate the lowest error magnitudes (Witt and Witt 1992, 1995). Forecasting accuracy is usually measured in unit-free terms, such as mean absolute percentage error (MAPE) or root mean square error (RMSE), when examining various time series. The first major study that examined tourism forecasting accuracy was published by Martin and Witt (1989a) and a study by Kulendran and Witt (2001) shows that simple time-series models and the no-change naive model tend to outperform more sophisticated econometric models. On the other hand, Kim and Song (1998), Song et al. (2000) and Li (2004) found that econometric models are superior to univariate time series models. Kulendran and King (1997) compared the forecasting performance of an error correction model (ECM), autoregressive (AR) model, autoregressive integrated moving average (ARIMA), a basic structural model, and a regression-based time series model. Their results demonstrate that the ECM performs poorly compared with the time-series model. These conflicting results suggest that more research still needs to be done in evaluating forecasting performance in tourism between modern econometric techniques and traditional time-series models in order to reach some agreement in this area (Song and Turner 2006). Issues such as whether or not more modern time-series methods (Neural models and BSM) will continue to outperform more modern econometric methods, and whether more modern econometric methods (despite greater theoretical rigour) are actually capable of producing more accurate (statistically significantly better) forecasts over the older econometric methods in a post-sample forecast analysis are still unclear. It has not been found that econometric models are superior to time-series models in terms of forecasting accuracy, and the conclusion normally depends on the type of econometric and time-series models included in the comparison.

2.6 CRITERION FOR SELECTING THE FORECASTING MODEL

Accurate forecasts of tourist demand can assist a government to reduce risk and uncertainty with policy decisions and help the private sector with decisions relating to sizing, location selection, and operations. As such accurate forecasts can be a preliminary step to policy formulation. Various attributes can be considered when choosing from among those techniques such as accuracy of the forecasts generated, ease of use of the forecasting technique, cost of producing the forecasts, and the speed with which the forecast can be produced (Chu 2009). Above all, accuracy is the most important characteristic of a forecast (Archer, 1987) and is the most frequently used criterion for selecting the best forecasting model (Burger et al., 2001; Lim and McAleer, 2002; Li et al., 2005).

To determine forecasting accuracy, measures used in the tourism forecasting literature include Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Root Mean Square Percentage Error (RMSPE) and Theil's U statistic (Martin and Witt, 1989b; Witt and Witt, 1992; Li et al., 2005). As Song and Turner (2006) summarised in their research: the predominant measure is MAPE, which is used 127 times in 155 individual comparisons (Li, 2004); the next most popular measures are RMSE and RMSPE, used 91 and 83 times in the 155 comparisons.

In this study, the MAPE and RMSE are employed for measuring accuracy and selecting the most appropriate forecasting model for tourism demand.

2.7 CONCLUSION

The large volume of literature in the field of tourism forecasting is almost universally focused on international arrivals and departures between nation states. The reason for the focus has been the supply of data. Until recently tourism arrival series have only been available on a country to country basis mostly from official immigration records except for some survey data conducted irregularly within states, and primarily aimed at measuring domestic tourism.

More recently, over the past two to three years some countries have begun to release regional data. That is, data measuring the international (and sometimes the domestic) travel into sub-regions of a country. The regions used are most commonly states (provinces) that form the major political governing regions within countries. However, sometimes the data is more detailed, including city regions (Thailand) or local areas (Mexico) (Turner and Witt, 2009).

The reason why this data is becoming available is the demand within regions of countries to examine their share of the international and domestic trade generated by tourism. The huge growth worldwide in tourism is now well understood to be economically highly significant.

Moreover, international tourism has the potential to directly involve regional areas in international trade and the direct benefits of export trade from the region.

There is very little research on this phenomenon in tourism. An early study was conducted by Turner and Witt (2002) on large-scale forecasts for provinces in China for total international arrivals. These forecasts use an ARIMA model. More recently in 2006, Vu and Turner (2006) conducted another time series based study in Thailand for nine cities and provinces that receive most international arrivals. In this study the forecast accuracy was compared between ARIMA and BSM models. The BSM model outperformed ARIMA for international arrivals. However, the ARIMA method was accurate for domestic arrivals. Both studies used accommodation data for the regional forecasts, but in the Vu and Turner study the regional accuracy was compared with forecasts for international arrivals into Thailand as a whole using border immigration data. The conclusion was that the regional accommodation forecasts of tourism arrivals (both domestic and international) are at least as accurate as the forecasts using cross-border immigration data. Both of these studies suggest that further work is needed to develop regional forecasting and suggest using data from other countries.

CHAPTER THREE

METHODOLOGY

Chapter Two has described various variables and models used in previous research together with the advantages and limitations of each of the variable and model choices. This chapter provides more detail on the variables, data and models used for this study and a discussion and interpretation of the results is given in Chapter Four.

Among the advanced methods, two of the most successful forecasting models from each of the main approaches (time series and econometric modelling), the basic structural time series model (BSM) and the time varying parameter model (TVP) are chosen for application and comparison because they provide well established reliable results in previous research (Kulendran, 1996; Song and Witt, 2000, 2003; Turner and Witt, 2001a; Vu and Turner, 2006). Although researchers still struggle with deciding which model is the best to use in tourism forecasting (Song and Li, 2008), a model that produces the least error is most commonly identified. It should also be noted at this point, that the comparative forecasting results are not meant to be conclusive in term of model choice, but rather to illustrate the potential of regional based forecasting.

In terms of model choice the most sophisticated time-series models are the Box Jenkins ARIMA and the BSM. The BSM model is more recent in development and allows for stochastic variation in the model parameters. The most sophisticated econometric models are the Error Correction Model (ECM), Causal Structural Model (CSM) and Time Varying Parameter model (TVP). Of these models – the CSM is a direct extension of BSM and more limited in terms of its published comparative accuracy. The CSM along with the ECM has static parameter development for the determinant variables. However, the TVP allows the parameters of the model to vary through time. Both the BSM and TVP models use the Kalman Filter to analyse the data, and are therefore similar in their technical development, and provide a relevant model comparison. There is no current literature providing such a comparison.

Song and Witt (2000) explain the demand for tourism as a function of its determinants as follows:

$$Q_{ij} = f(P_i , P_s ,Y_j , T_j ,A_{ij} , \varepsilon_{ij}) \quad ,$$

where:

Q_{ij} = quantity of tourism product demanded in destination ***i*** by tourists from country *j*,

P_i = price of tourism for destination *I*,

P_s = price of tourism for substitute destinations,

Y_j = level of income in country of origin *j*,

T_j = consumer tastes in country of origin *j*,

A_{ij} = advertising expenditure on tourism by destination ***i*** in country of origin *j*,

ε_{cd} = disturbance term that captures other factors which may influence Q_{ij}.

This demand function is fundamental in past research on tourism analysis (Gonzalez and Moral, 1995; Kuledran and Witt, 2003a; Song et al., 2003a; Vu and Turner, 2006). This study also uses this demand function as the starting point for developing regional tourism demand models. However, in this study, the quantity of tourism demand is explained by factors other then what is contained in the original function. An attempt is made to extend this function by incorporating other explanatory variables which could potentially affect regional tourism demand, to adopt the existing variables to a regional context and test for new independent measures that may be relevant in a regional context. There is no specific reason to assume that the factors causing international travel between nations are the same ones that determine travel to regions within nations. However, it is reasonable to expect that economic determinant variables are most likely to explain international travel.

3.1 VARIABLES USED

3.1.1 Demand (Dependent) variable

In this study, the number of international tourist arrivals serves as the dependent variable for measuring travel demand for Canada from the five most important origin countries. Quarterly data of inbound tourist regional arrivals into Canada are used to generate *ex anti* forecasts and the sample data is from 2000Q1 to 2007Q4. The data were obtained from the Canadian Tourism Board and supplied by the Pacific Asia Travel Association (PATA). The top five inbound source markets to Canada (2007) are: USA, United Kingdom, France, Japan and Germany. In 2007 these top five arrival countries accounted for 92.2 % of the whole world total arrivals (refer to Table 3.1).

Table 3.1 International Tourist Arrivals to Canada by the Top Five Countries (2000-2007)

	France	Germany	Japan	UK	USA	Total top 5	Whole World
2000	622,100	670,500	902,900	1,352,400	46,534,600	50,082,500	54,054,258
2001	511,300	499,800	652,200	1,085,100	45,548,736	48,297,136	51,619,436
2002	420,500	426,800	671,000	1,027,500	43,714,900	46,260,700	49,499,800
2003	359,380	370,100	319,700	969,400	37,758,800	39,777,380	42,388,360
2004	425,000	446,300	560,200	1,111,000	37,033,100	39,575,600	42,835,600
2005	446,600	459,400	578,100	1,211,100	33,755,836	36,451,036	39,772,736
2006	448,400	433,700	499,000	1,166,900	30,954,725	33,502,725	37,487,645
2007	459,446	433,225	439,217	1,204,325	27,642,800	30,179,013	33,560,921
Total	**3,692,726**	**3,739,825**	**4,622,317**	**9,127,725**	**302,943,497**	**324,126,090**	**351,218,756**

Source: Canadian Tourism Board, supplied by the Pacific Asia Travel Association (PATA).

3.1.2 Explanatory (Independent) variables

The proper selection of the demand determinants is the first problem met in the analysis of international tourism arrivals in terms of data reliability and availability. Economic theory does give clues as to the selection of appropriate indicators.

The following will discuss each of the explanatory variables finally chosen in this study, including those variables expected to relate more specifically to the regional context:

- ***Income***

This variable has been included in all previous tourism forecasting studies as it is one of the most significant explanatory variables in economic demand theory. The income variable used in this study is personal income per capita for source countries. The expected sign of the income coefficient is positive, whereby increases in income will lead to increases in tourist flow. The Personal Income per capita variable is calculated as the source country Gross National Income (GNI) divided by the Population (P) of that country:

GNI figures of source countries are published in the OECD Quarterly National Accounts Volume 2009/3. The source country population (P) which is available only on an annual basis is from OECD Stat. (http://stats.oecd.org).

- ***Own Price***

Another variable that could have an important role in determining the demand for international tourism is own price. According to current theory, this variable should contain two components: the cost of living for tourists at the destination and the travel cost to the destination. However, in more recent studies it has not attracted as much attention as before, and has been omitted in many studies due to difficulties in obtaining data (Li et al., 2005). Tourist prices are represented as costs of living in Canada by the tourists from the five source markets and is defined as the ratio of the Regional Consumer Price Index (CPI) in Canada, to the CPI in the origin country, and then multiplied by the exchange rate between Canada and the source country currencies, in order to convert the destination price from destination currency into source currency:

It is expected that an increase in price will cause a decline in tourist flows. However, an increase in the exchange rate of Canadian dollars per source country currency units would result in more tourists visiting Canada from that origin country.

CPI figures are obtained from the Econ Database (2005=100) and Exchange Rates between Canada and the source countries are from the Bank of Canada.

- ***Gross Domestic Product (GDP)***

GDP is another variable that has also been shown to be an important determinant in previous research. The Real GDP variable in the source country represents economic activity and is chosen because it is expected that an increase in GDP will result in an increase in tourist flows from that source country. GDP figures of source countries are published in the OECD Quarterly National Accounts Volume 2009/3.

- ***Unemployment***

The unemployment level in the source country may more immediately reflect the state of economic activity. It might be expected that an increase in unemployment will result in a decrease in travel. However, many travelers are using a luxury good that may be independent of the level of unemployment. This variable has been largely untested in recent research. The unemployment rates of source countries are obtained from the Econ Database.

- ***Trade Openness (TO)***

Trade Openness (TO) is measured as:

This variable has been successfully used in past research and draws out the relationships between trade and tourism. The Export and Import figures are obtained from Statistics Canada. It is expected that increased trade between the source markets and regions (provinces) in Canada will lead to increased tourism, potentially business travel.

- ***Household Consumption Expenditure***

The Household Consumption Expenditure of source countries are obtained from the Econ Database. Change in the level of household consumption may reflect immediate changes in the proportion of households to spend on travel product. An increased in expenditure may positively relate to an increased in travel volume. Turner and Witt (2001) successfully used the more specific variable of new car registrations.

Other variables can also be used to measure non-economic aspects of travel. However, there is no theory currently available to define these possible variables and essentially a common sense data measuring approach is all that is available. From all the data available at a regional level in Canada the following variables are selected:

- ***Provincial Business Bankruptcies***

The number of Business Bankruptcies in each of the 12 provinces of Canada may reflect upon the level of business travel. However, the use of this variable is not tested in the current literature. It is hypothesized that as the number of Business Bankruptcies increase, a decrease in tourist flows will follow. Data for this variable is obtained from Statistic Canada. This variable has not been used in other research to forecast tourist arrivals.

- ***Retail Trade***

It is expected that the cash flow of retail trade in each province might be related to the number of tourists that travel to that province. Retail trade is a requirement for tourists, and expanding retail trade will provide infrastructure and services that attract tourism. This variable was successfully used in one study by Turner and Witt (2001a) for country to country international travel whereby retail trade volume is indicative of expenditure in retail trade services that in turn provides an infrastructure that is attractive to many tourists. Apart from expenditure on accommodation, travel cost, food and beverage tourists next highest expenditure is on shopping or retail trade (Turner and Witt, 2009). Although there is also a tendency for tourism to cause retail trade this is insignificant relative to local trade volume, whilst local trade volume will potentially measure the infrastructure development required to satisfy tourism demand. Retail figures are obtained from Statistic Canada.

- ***Receipts of Food Services***

It might be expected that international tourists would be significant users of restaurant and food service providers in regional areas because of the relatively high expenditure in the travel budget on food services. The volume of food service trade is dominated by the local population in the regional area and although tourists add to this expenditure their trade volume is relatively small. Consequently, an increase in food service demand might be expected to relate to an increase in tourist arrivals. The total Receipts of Food Services figures are obtained from Statistics Canada.

All the monetary figures are in Canadian dollars (where it is applicable).

3.2 FORECASTING MODELS USED

3.2.1 The Basic Structural Model

The basic structural time series model introduced by Harvey and Todd (1983) deals with univariate time varying data with trend and seasonal components. The model decomposes the data into its components and uses the Kalman filter in evaluating the function. Since the components of a time series are often not fixed but stochastic in nature, for the time series $\mathbf{y_t}$ the basic structural model is formulated as follows:

$$Y_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t \ ,$$

where:

Y_t = number of tourist visits in period t,

μ_t = stochastic trend component,

γ_t = seasonal component,

ψ_t = trend component,

ε_t = irregular component.

The trend component changes from the previous period by the amount of the slope β_{t-1} such that:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + a_{1t} \ ,$$

where β the slope, is also stochastic and changes from period ***t*** to ***t-1*** as follows:

$$\beta_t = \beta_{t-1} + a_{2t} \quad .$$

The seasonal component $\boldsymbol{\pi}$ is additive and totals to zero over ***s*** seasons in the year as follows:

The parameters a_t, a_{1t}, a_{2t} and w_t are all stochastic, independent, white noise error terms with expected values of zero.

There is also an optional cyclical component comprising a damping factor p in the range $0<p<1$, the frequency in radians λ in the range $0 \le \lambda \le 1$ and two mutually uncorrelated disturbance k with zero mean and a common variance. There may be two additional cycles of the same form incorporated into the model.

A first-order auto regressive (AR(1)) process is also available. The auto-regressive component acts as a limiting case on the stochastic cycle when λ is equal to ϕ or $\boldsymbol{\pi}$**.**

Harvey (1990) defined a goodness of fit criterion $\boldsymbol{R_s}$ for the time series to test the fit of the BSM model when the data is seasonal with trend. The corresponding coefficient of determination has been defined by measuring the fit against a random walk plus drift and fixed seasonal:

$$R_s^2 = 1-(PP)(PEV)/(SSDSM) \quad ,$$

where:

PEV = prediction error variance,

PP = prediction period,

SSDSM = sum of squares of the differences between the seasonal mean and the first differences Δy_t .

The computed R_s can take negative values, therefore positive R_s values are a requirement for model adequacy.

Heteroskedascity in the data is tested, using the χ^2 statistic for:

H_0: Constant error variance,

H_a: Error variance not constant.

The independence of the error term is tested, using the Q statistic which follows a χ^2 distribution for:

H_0: Independent error terms,

H_a: Error terms are not independent.

The variances of the level, slope, seasonal and irregular components are compared using the q-ratio which is the ratio of the variance of each component to the largest variance of the four components. The component with the largest variance will have a q-ratio of unity.

Components with no variance will have a q-ratio of zero, indicating absence of that component in the data.

The cycle is tested by comparison of the amplitude of the cycle with the level of the trend. This gives an indication of its relative importance. When the cycle is deterministic, but stationary, a joint significance X^2 test which is the same as the seasonal test is also reported.

In this study the BSM forecasts will be obtained using the STAMP 6.0 software.

3.2.2 The Time Varying Parameter (TVP)

The application of the TVP method to tourism demand forecasting has found popularity among tourism researchers only in recent years; these studies include Song and Wong, 2003; Witt *et al.* ,2003; Song *et al.* 2003a; Li *et al.* 2005; Li *et al.* ,2006 and Shen *et al.*, 2008. Traditionally, econometric models of tourism demand are usually based on the search for structural stability and a belief that the future will be similar to the past by assuming that the coefficients of the model are constant over time. However, with changes in expectations and tastes by tourists in the process of making decisions the coefficients can vary systematically over time. To overcome the limitations of the traditional fixed-parameter models, the TVP model has been developed, based on the Kalman (1960) filter technique which relaxes the restriction on the parameter constancy and takes account of the possibility of parameter changes over time, and in this way may improve forecasting accuracy.

According to the general to specific approach, if a dependent variable is determined by k explanatory variables, the data generating process (DGP) may be written as an autoregressive distributed lag model (ADLM) of the form:

$$y_t = \alpha + \sum_{j=1}^{k} \sum_{i=0}^{p} \beta_{ji} x_{jt-i} + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \quad . \qquad (1)$$

Where p is the lag length, which is determined by the type of data used and normally decided by the Aikake Information Criterion (AIC) and Schwarz-Bayesian Criterion (SBC) statistics; k is the number of explanatory variables and ε_t is the error term, which is assumed to be white noise: normally distributed with zero mean and constant variance σ^2. As quarterly data are used in this study, a lag length of four is adopted.

The TVP model is a special case of the ADLM specification. The TVP approach uses a recursive estimation process in which the more recent information is weighted more heavily than the information obtained in the past. With the restriction $p = 0$ imposed on the coefficients in equation (1), the TVP model is specified in a state space form as follows:

$$y_t = x_t \beta_t + u_t \ , \qquad (2)$$

$$\beta_t = \Phi \, \beta_{t-1} + R_t e_t \quad , \qquad (3)$$

where:

y_t : a vector of tourism demand,

x_t : a row vector of k explanatory variables,

β_t : a column vector of k state variables known as the *state vector*,

Φ : a k k matrix initially assumed to be known,

R_t : a $k \quad g$ matrix,

u_t : a residual with zero mean and constant covariance matrix H_t, and

e_t : a $g \quad 1$ vector of serially uncorrelated residuals with zero mean and constant covariance matrix Q_t .

Equation (2) is the measurement equation or system equation, and equation (3) is called the transition equation or state equation, and the assumptions in both equations are that the initial vector β_0 has a mean of b_0 and a covariance matrix P_0, and the residual terms u_t and e_t are not correlated.

If the components of the matrix Φ equal unity, the transition equation (3) becomes a *random walk:*

$$\beta_t = \beta_{t-1} + R_t e_t \qquad (4)$$

If the transition equation is a random walk, the parameter vector β_t is said to be non-stationary.

Another possible form of the transition equation is:

$$\beta_t = \mu - \Phi(\beta_{t-1} - \mu) + R_t e_t \qquad (5)$$

where μ is the mean of β_t and a stationary process is indicated.

The transition equation is determined by experimentation using the goodness of fit and the predictive power of the model. Once the state space (SS) model is formulated, a convenience algorithm, known as the Kalman Filter (KF), can be used to estimate the SS model (for more detail see Harvey (1987)). The KF produces the optimal estimator using each observation, resulting in the final values to be used for forecasting of *b*, *P* and *y*.

In this study, the TVP forecasts are obtained using the EVIEWS 6.0 software.

3.2.3 The Naïve 1

The Naïve 1 method simply states that the current period's actual is the next period's forecast. This simple forecasting method can be used as a benchmark in comparing with forecasting models. Naïve 1 is calculated using the following equation:

$$F_t = A_{t-1} \ ,$$

where,

F_t = Forecasting value at time *t*,

A_t = Observed value at time *t*.

Additionally, the forecasts when summed from the regional flows are compared on the basis of forecast accuracy with the forecast of the total flow for the whole national flow data. This tests the more general issue of the accuracy of regionally disaggregating tourism time series. It is important to determine whether regional based forecasts can be accurately derived, and apart from the absolute measures of forecast accuracy (such as MAPE and RMSE) this issue is also a relative question. Comparison is also made of the forecast growth rates regionally and nationally, to compare the relative accuracy of the different databases and the different types of data.

3.3 FORECAST PERFORMANCE ASSESSMENT CRITERIA

Forecasting of alternative models are generated using identical tourist arrival time-series. Forecasting performance is measured by the forecast accuracy of a model. As the accuracy of a forecasting model depends on how close the forecast arrival number is to the actual arrival number: the closer the forecast arrival number to the actual arrival number the better the model.

To determine forecasting accuracy of each model, two standard error measurements the root mean square error (RMSE), and the mean absolute percentage error (MAPE) are used. RMSE and MAPE are calculated by the following equations:

where *t* is the time period.

In this research, to compare the accuracy of the alternative models, each model is applied to each data series as follows:

- flow of each of the five source countries to each of the twelve provinces of Canada;

- flow of each of the five source countries to Canada nationally;
- total flow of top five source countries to each of the twelve provinces of Canada; and finally,
- total flow of top five source countries to Canada nationally.

MAPE is used in this study as the main criterion for evaluating forecasting performance of the models developed, and RMSE is used as a secondary indicator of forecasting performance. The MAPE generated for each model is interpreted as: highly accurate forecasts are associated with the model if the MAPE is less than or equal to 10%; good forecasts for MAPE are 10-20%; reasonable forecasting for MAPE is 20-50%; and inaccurate forecasting for MAPE is equal to or greater than 50%. The choice of error percentage ranges is subjective as there is no recognised specific range for error assessment.

CHAPTER FOUR

RESULTS AND CONCLUSION

This study focuses upon forecasting international regional arrivals to the provinces of Canada, using quarterly international arrivals data, over the forecast period 2000Q1 to 2007Q4. The top five source markets to Canada (2007) are: USA, UK, Japan, Germany and France, and these markets are analysed separately and as a total group. These countries comprise 92.2% (2007) of all arrivals to Canada. The Basic Structural Model (BSM), the Time Varying Parameter (TVP) and the Naïve process are the three models used to forecast arrivals to Canada for each origin country (France, Germany, Japan, UK and USA) (refer to Chapter 3). Quarterly data from 2000Q1 to 2005Q4 is used as the sample data and the data from 2006Q1 to 2007Q4 comprises the post sample data used to measure the forecasting performance of the models. Measures of Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are used to measure the difference between the actual and forecast values in the post-estimation period.

For the Naïve no-change model, forecasts are made using the actual last period values. The BSM model is a time-series methodology incorporating structural change in the trend, cycle and seasonal components. The Time Varying Parameter (TVP) model is an econometric model incorporating causal independent variables. The TVP model examines whether the determinants of tourism demand for international regional arrivals to Canada are a function of “Personal Income”, “GDP”, “Unemployment Rate”, “Household Consumption Expenditure”, “Own Price”, “Trade Openness”, “Retail”, “Bankruptcy” and “Receipts of Food Service”. This set of independent variables is constrained by the availability of data and based upon earlier research outlined in Chapter Two.

4.1 FORECAST RESULTS OF NAÏVE, BSM AND TVP MODELS

The following is the summary of the one step ahead forecast output MAPE and RMSE values for the analysis. Note that the province (territory) of Nunavut is not included in the analysis. From the following results it is also evident that it is not possible to derive forecast values for some of the very small volume flows in Newfoundland province and the Northwest Territories.

4.1.1 Forecast Results for the Naïve Methodology (2006-2007)

Tables 4.1.1a shows the forecasting performance of the Naïve model for tourist arrivals from each of the top five source countries (France, Germany, Japan, UK and USA) to each province of Canada.

Table 4.1.1a: Naïve Forecast Results for the Flow from Each of the Top Five Source Countries to Each Province of Canada

NAÏVE	FRANCE		GERMANY		JAPAN		UK		USA		Overall average	
Provinces	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
Alberta	31.14	2347	25.58	4266	18.23	6744	15.94	7969	11.29	32253	20.44	10716
British Columbia	45.48	4076	8.02	3135	11.71	5113	9.49	9004	7.07	88873	16.35	22041
Manitoba	26.61	424	31.33	600	26.38	1756	34.06	2862	8.62	13343	25.40	3797
New Brunswick	46.88	1173	17.77	587	25.21	433	29.42	1720	11.88	47512	26.23	10285
Newfoundland	46.25	587	15.28	300	NA	NA	46.24	942	16.98	4118	31.19	1487
Northwest Territories	NA	NA	26.83	1271	24.39	1370	NA	NA	26.79	1724	26.00	1455
Nova Scotia	46.99	1086	32.30	1756	56.48	659	25.50	3999	18.64	24594	35.98	6419
Ontario	11.71	2988	9.17	2368	17.98	6882	4.13	6805	14.16	559789	11.43	115766
Pr. Edward Isl.	13.98	271	3.66	48	36.37	2408	29.88	1720	26.46	7088	22.07	2307
Quebec	5.24	5393	11.92	2608	43.78	4616	11.24	4221	9.39	68516	16.31	17071
Saskatchewan	28.27	407	19.35	354	41.92	470	36.00	2589	9.84	9344	27.07	2633
Yukon	10.10	529	50.80	3051	31.52	547	31.57	641	14.60	12096	27.72	3373

Note: Where flows are too small to record forecasts “NA” is displayed.

Table 4.1.1b shows the forecasting performance of the Naïve model for tourist arrivals from each of the top five source countries (France, Germany, Japan, UK and USA) to Canada.

Table 4.1.1b: Naïve Forecast Results for Flow from Each of the Top Five Source Countries to Canada

FRANCE		GERMANY		JAPAN		UK		USA		Overall average	
MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
3.47	3782	5.75	8054	13.21	20137	7.16	20174	11.27	795575	8.17	169544

Table 4.1.1c shows the forecasting performance of the Naïve model for tourist arrivals for the total flow of the top five source countries (France, Germany, Japan, UK and USA) to each province of Canada.

Table 4.1.1c: Naïve Forecast Results for the Total Flow from the Top Five Source Countries to Each Province of Canada

NAÏVE	**All top 5**	
Provinces	MAPE	RMSE
Alberta	22.97	66068
British Columbia	5.55	118059
Manitoba	6.94	12666
New Brunswick	11.45	48145
Newfoundland	12.12	3636
Northwest Territories	28.93	10523
Nova Scotia	16.90	28152
Ontario	6.82	561641
Pr. Edward Isl.	24.85	11838
Quebec	7.04	73766
Saskatchewan	10.73	9316
Yukon	16.13	21376

Table 4.1.1d shows the forecasting performance of the Naïve model for tourist arrivals from the total flow of the top five source countries (France, Germany, Japan, UK and USA) to Canada.

Table 4.1.1d: Naïve Forecast Results for the Total Flow from the Top Five Source Countries to Canada

TOTAL OF TOP 5	
MAPE	RMSE
8.17	821506

The results from the Naïve analysis indicate that the aggregated forecast for each country (4.1.1b and 4.1.1d) are surprisingly accurate and all are close to or less than 10% MAPE error. This forecast accuracy is most likely related to the short forecasting horizon of two years, whereby the latest actual arrival number remains relevant into the forecast horizon.

It is also notable that some series, for some provinces, are also accurately forecast by the Naïve process, at least in part. This is most common for the provinces British Columbia, Manitoba, New Brunswick, Ontario, Quebec and Saskatchewan. This accuracy level largely relates to the higher accuracy for the USA forecasts, and may relate to the stability in arrival flows from the USA to Canada which is the largest international source market.

4.1.2 Forecast Results for the BSM Methodology (2006-2007)

The BSM results are in listed in Appendix I. These results are cut back to the minimum possible, but are voluminous because of the large number of individual forecast series, 14 provinces by five countries (70) plus country and national series.

Tables 4.1.2a shows the forecasting performance of the BSM model for tourist arrivals from each of the top five source countries (France, Germany, Japan, UK and USA) to each province of Canada.

Table 4.1.2a: BSM Forecast Results for the Flow from Each of the Top Five Source Countries to Each Province of Canada

BSM	**FRANCE**		**GERMANY**		**JAPAN**		**UK**		**USA**		**Overall average**	
Provinces	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
Alberta	24.32	2150	12.64	2464	24.31	5178	15.73	10207	9.57	31422	17.31	10284
British Columbia	22.36	2893	8.36	2687	16.11	7373	8.01	9741	5.76	103182	12.12	25175
Manitoba	26.28	403	22.22	641	44.24	1886	18.74	1921	5.38	8676	23.37	2705
New Brunswick	36.09	662	49.32	976	39.45	368	27.96	1970	4.86	21732	31.53	5142
Newfoundland	48.57	549	24.86	136	NA	NA	44.48	1261	15.43	2941	33.33	1222
Northwest Territories	NA	NA	39.37	1285	81.92	1801	NA	NA	79.39	5470	66.89	2852
Nova Scotia	48.11	1287	29.80	1823	40.33	593	23.11	3617	16.31	17132	31.53	4891
Ontario	19.34	8189	27.20	10790	19.56	7999	12.90	14058	6.28	252089	17.06	58625
Pr. Edward Isl.	18.66	177	37.32	261	73.37	2631	33.87	620	20.40	11194	36.72	2977
Quebec	12.27	13651	7.11	1962	26.28	3318	10.50	4699	6.88	57554	12.61	16237
Saskatchewan	37.07	410	22.37	770	30.98	288	32.50	2054	9.76	8841	26.54	2473
Yukon	12.73	456	21.45	2734	27.40	510	39.20	802	16.79	19162	23.51	4733

Note: Where flows are too small to record forecasts "NA" is displayed.

Table 4.1.2b shows the forecasting performance of the BSM model for tourist arrivals from the top five source countries (France, Germany, Japan, UK and USA) to Canada.

Table 4.1.2b: BSM Forecast Results for the Flow from Each of the Top Five Source Countries to Canada

FRANCE		**GERMANY**		**JAPAN**		**UK**		**USA**		**Overall average**	
MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
7.57	15518	5.73	9937	9.71	20500	10.33	38949	6.31	432671	7.93	103515

Table 4.1.2c shows the forecasting performance of the BSM model for tourist arrivals from the total flow for the top five source countries (France, Germany, Japan, UK and USA) to each province of Canada.

Table 4.1.2c: BSM Results for the Total Flow from the Top Five Source Countries to Each Province of Canada

BSM	All top 5	
Provinces	MAPE	RMSE
Alberta	8.22	44082
British Columbia	5.75	147247
Manitoba	6.26	12222
New Brunswick	4.42	19620
Newfoundland	18.69	8042
Northwest Territories	25.68	10324
Nova Scotia	19.82	54513
Ontario	3.90	193688
Pr. Edward Isl.	17.81	9673
Quebec	3.32	37235
Saskatchewan	8.54	8938
Yukon	16.13	21376

Table 4.1.2d shows the forecasting performance of the BSM model for tourist arrivals from the total flow of the top five source countries (France, Germany, Japan, UK and USA) to Canada.

Table 4.1.2d: BSM Results for the Total Flow from the Top Five Source Countries to Canada

ALL TOP 5	
MAPE	RMSE
3.62	314949

The results for the BSM analysis are markedly more accurate than the Naïve process. As was found with the Naïve analysis there is higher accuracy for the aggregated flows by whole country as opposed to individual flows by source markets to provinces. This finding is contradictory to the findings in Vu and Turner 2006 where the Thailand analysis found similar accuracy at all levels of aggregation.

As was found in the Naïve analysis some provinces are more accurately forecast than others. In the case of the BSM analysis British Columbia, Manitoba, Newbrunswick, Ontario, Quebec and Saskatchewan are more accurately forecast. This set of provinces is the same as that found in the Naïve analysis.

The USA source market is also the most accurately forecast market in the BSM analysis, as found with the Naïve analysis, presumably for the same reason of stability (higher volume) over time of the arrival flows.

4.1.3 Forecast Results for the TVP Methodology (2006-2007)

All the TVP results are in Appendix II.

For each of the forecast results there are associated table(s) showing the significant explanatory variables for each forecast.

Table 4.1.3a shows the forecasting performance of the TVP model for the flow from each of the top five source countries (France, Germany, Japan, UK and USA) to each province of Canada.

Table 4.1.3a: TVP Forecast Results for the Flow from Each of the Top Five Source Countries to the Provinces of Canada

TVP	**FRANCE**		**GERMANY**		**JAPAN**		**UK**		**USA**		**Overall average**	
Provinces	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
Alberta	35.56	1551	24.40	4965	18.61	3846	10.69	6995	8.24	28053	19.50	9082
British Columbia	98.42	3494	13.63	3765	15.73	7943	7.44	6879	13.45	210322	29.73	46481
Manitoba	37.79	363	49.20	850	65.24	2292	48.55	2217	6.45	10550	41.45	3255
New Brunswick	44.95	849	19.48	592	39.54	180	30.33	1955	11.06	47047	29.07	10125
Newfoundland	43.02	564	107.3	489	N/A	N/A	69.39	968	18.13	3815	59.45	1459
Northwest Territories	N/A	N/A	43.68	608	24.81	2214	N/A	N/A	52.99	4399	40.49	2407
Nova Scotia	43.41	1726	32.22	3424	46.00	858	21.83	3867	18.06	22496	32.30	6474
Ontario	15.08	4778	10.60	4159	12.87	7144	10.28	10521	13.58	656012	12.48	136523
Pr. Edward Isl.	17.00	137	75.17	596	206.7	2536	33.11	1673	15.33	7801	69.46	2549
Quebec	6.66	6414	9.15	1935	39.84	3741	19.84	8166	9.78	87165	17.05	21484
Saskatchewan	46.93	225	36.19	395	29.55	289	43.09	2523	8.72	5576	32.90	1802
Yukon	12.72	87	23.99	1350	22.74	229	107.03	764	14.33	15184	36.16	3523

Note: Where flows are too small to record forecasts "NA" is displayed.

Associated Table 4.1.3aa shows the significant explanatory variable(s) of the forecast for arrivals from France to each province of Canada.

Associated Table 4.1.3aa: Significant Explanatory Variable(s) for the Forecast of Flow from France to Provinces of Canada

FRANCE

Province	Personal Income	GDP	Unemp-loyment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
Alberta				√						1
British Columbia	√			√			√			3
Manitoba	√									1
New Brunswick		√								1
Newfoundland									√	1
Northwest Territories	N/A									
Nova Scotia									√	1
Ontario	√							√		2
Pr. Edward Isl.		√								1
Quebec	√									1
Saskatchewan	√									1
Yukon									√	1
TOTAL COUNT	5	2	0	2	0	0	1	1	3	14

Note: Where flows are too small to record forecasts "NA" is displayed.

Associated Table 4.1.3ab shows the significant explanatory variable(s) of the forecast for arrivals from Germany to each province of Canada.

Associated Table 4.1.3ab: Significant Explanatory Variable(s) for the forecast of flow from Germany to Provinces of Canada

GERMANY

Province	Personal Income	GDP	Unemp-loyment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
Alberta	√									1
British Columbia		√								1
Manitoba				√						1
New Brunswick	√									1
Newfoundland						√				1
Northwest Territories				√						1
Nova Scotia							√		√	2
Ontario						√				1
Pr. Edward Isl.				√	√					2
Quebec									√	1
Saskatchewan							√			1
Yukon									√	1
TOTAL COUNT	2	1	0	3	1	2	2	0	3	14

Associated Table 4.1.3ac shows the significant explanatory variable(s) of the forecast for arrivals from Japan to each province of Canada.

Associated Table 4.1.3ac: Significant Explanatory Variable(s) for the Forecast of Flow from Japan to Provinces of Canada

JAPAN

Province	Personal Income	GDP	Unemp-loyment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
Alberta						√				1
British Columbia				√						1
Manitoba			√							1
New Brunswick							√			1
Newfoundland	N/A									
Northwest Territories	√									1
Nova Scotia								√		1
Ontario	√		√	√						3
Pr. Edward Isl.						√				1
Quebec		√								1
Saskatchewan		√								1
Yukon	√									1
TOTAL COUNT	3	2	2	2	0	2	1	1	0	13

Note: Where flows are too small to record forecasts "NA" is displayed.

Associated Table 4.1.3ad shows the significant explanatory variable(s) of the forecast for arrivals from UK to each province of Canada.

Associated Table 4.1.3ad: Significant Explanatory Variable(s) for the forecast of flow from UK to the Provinces of Canada

UK

Province	Personal Income	GDP	Unemp-loyment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
Alberta		√								1
British Columbia									√	1
Manitoba			√						√	2
New Brunswick	√					√				2
Newfoundland						√				1
Northwest Territories	N/A									
Nova Scotia	√									1
Ontario									√	1
Pr. Edward Isl.	√									1
Quebec						√				1
Saskatchewan			√							1
Yukon					√					1
TOTAL COUNT	3	1	2	0	1	3	0	0	3	13

Note: Where flows are too small to record forecasts "NA" is displayed.

Associated Table 4.1.3ae shows significant explanatory variable(s) of the forecast for arrival from USA to each province of Canada.

Associated Table 4.1.3ae: Significant Explanatory Variable(s) of the Forecast of Flow from USA to Provinces of Canada

USA

Province	Personal Income	GDP	Unemp-loyment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
Alberta	√									1
British Columbia							√			1
Manitoba	√									1
New Brunswick									√	1
Newfoundland	√									1
Northwest Territories	√									1
Nova Scotia	√									1
Ontario	√									1
Pr. Edward Isl.		√								1
Quebec									√	1
Saskatchewan	√									1
Yukon	√						√			2
TOTAL COUNT	8	1	0	0	0	0	2	0	2	13

Table 4.1.3e shows the summary count of each of the significant independent variables as found from TVP model for each province by the top five countries.

Table 4.1.3e: Summary Count of Each of the Significant Independent Variables as Found from the TVP Model for Each Provinces of Canada by the Top Five Countries.

Province	Personal Income	GDP	Unemp-loyment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
Alberta	2	1	0	1	0	1	0	0	0	5
British Columbia	1	1	0	2	0	0	2	0	1	7
Manitoba	2	0	2	1	0	0	0	0	1	6
New Brunswick	2	1	0	0	0	1	1	0	1	6
Newfoundland	1	0	0	0	0	2	0	0	1	4
Northwest Territories	2	0	0	1	0	0	0	0	0	3
Nova Scotia	2	0	0	0	0	0	1	1	2	6
Ontario	3	0	1	1	0	1	0	1	1	8
Pr. Edward Isl.	1	2	0	1	1	1	0	0	0	6
Quebec	1	1	0	0	0	1	0	0	2	5
Saskatchewan	2	1	1	0	0	0	1	0	0	5
Yukon	2	0	0	0	1	0	1	0	2	6
TOTAL COUNT	21	7	4	7	2	7	6	2	11	67

The significant explanatory variables tend to be widespread in terms of the type of variable and the range across the range of provinces. Personal Income is the most common variable and is significant for all source countries and a wide range of provinces. This is consistent with current national tourism forecasting as discussed in the literature review (Chapter Two). Food Services is a variable not currently used in the literature and the second most common significant variable in this analysis. This variable can be considered potentially important for future regional studies. Food Services is not significant for Japan, and this may reflect the different dietary requirements of Japanese travellers who tend to stay in accommodation that specifically caters for their diet. Household Consumption Expenditure, Trade Openness and GDP are all similar measures of economic activity although possibly relating to a wide range of types of tourists. Trade Openness and GDP are often used in national level forecasting. Retail Sales is of some relevance and this has also been used in previous national level forecasting, Own Price is not a common significant variable at the regional level, although it is heavily used at the national level. Unemployment and Bankruptcy have not been widely relevant either.

Tables 4.1.3b shows the forecasting performance of the TVP model for total flow from each of the top five source countries (France, Germany, Japan, UK and USA) to Canada.

Table 4.1.3b: TVP Forecast Results for the Flow from Each of the Top Five Source Countries to Canada

FRANCE		**GERMANY**		**JAPAN**		**UK**		**USA**		**Overall average**	
MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
5.71	8343	7.39	10374	6.31	8669	16.72	62098	17.65	1399968	10.76	297891

Associated Table 4.1.3ba shows the significant explanatory variable(s) of the forecast for arrivals from each of the top five source countries to Canada.

Associated Table 4.1.3ba: Significant Explanatory Variable(s) from Each of the Top Five Countries to Canada

Source Countries	Personal Income	GDP	Unem-ployment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
France	√									1
Germany				√	√					2
Japan				√						1
UK						√				1
USA							√		√	2
TOTAL COUNT	1	0	0	2	1	1	1	0	1	7

Tables 4.1.3c shows the forecasting performance of the TVP model for the total flow from the top five source countries (France, Germany, Japan, UK and USA) to each province of Canada.

Table 4.1.3c: TVP Forecast Results for the Total Flow from the Top Five Source Countries to the Provinces of Canada

TVP	**All top 5**	
Provinces	MAPE	RMSE
Alberta	7.76	29859
British Columbia	16.50	282559
Manitoba	14.81	22436
New Brunswick	11.99	51401
Newfoundland	14.95	3512
Northwest Territories	48.91	4973
Nova Scotia	15.07	26157
Ontario	16.45	796553
Pr. Edward Isl.	17.11	10762
Quebec	8.91	100798
Saskatchewan	28.09	21215
Yukon	18.13	19172

Associated Table 4.1.3ca shows the significant explanatory variable(s) for the forecast for arrivals from the total flow of the top five source countries to each province of Canada.

Associated Table 4.1.3ca: Significant Explanatory Variable(s) for the Total Flow from the Top Five Source Countries to the Provinces of Canada

Province	Personal Income	GDP	Unemp-loyment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
Alberta									√	1
British Columbia							√			1
Manitoba									√	1
New Brunswick		√			√				√	3
Newfoundland	√									1
Northwest Territories	√									1
Nova Scotia		√								1
Ontario	√									1
Pr. Edward Isl.		√								1
Quebec		√								1
Saskatchewan						√				1
Yukon							√			1
TOTAL COUNT	3	4	0	0	1	1	2	0	3	14

In the same way that the significant causal variables differ between source countries the impact at the regional level is widely diverse. On the broad scale these results reflect the findings from Table 4.1.3a a-e as would be expected. But they also reinforce the finding that for each regional market different variables are likely to be significant.

Table 4.1.3d shows the forecasting performance of the TVP model for the total flow from the top five source countries (France, Germany, Japan, UK and USA) to Canada.

Table 4.1.3d: TVP Forecast Result for the Total Flow from the Top Five Source Countries to Canada

ALL TOP 5	
MAPE	RMSE
16.61	1442342

Associated Table 4.1.3da shows significant explanatory variables for the forecast for arrivals from the total flow of the top five source countries to each province of Canada.

Associate Table 4.1.3da: Significant Explanatory Variable(s) for the Total Flow from the Top Five Source Countries to Canada

Source Countries	Personal Income	GDP	Unemp-loyment	Household Consumption Expenditure	Own Price	Trade Openness	Retail	Bank-ruptcy	Food Services	TOTAL COUNT
5 COUNTRIES							√			1
TOTAL COUNT	0	0	0	0	0	0	1	0	0	1

The finding for the whole of Canada is less clear and this is most likely because the selection of variables was not designed to explain arrivals at the national level. The variables are designed for regional flows and variables currently used at the national scale (as discussed in Chapter Two) are more relevant. However, the fact that retail sales was the most significant variable is an interesting finding that further recommends use of this variable.

Interestingly, the TVP analysis is less accurate than both the Naïve and BSM analyses. This result is unexpected in that the TVP model has a significant potential advantage for accuracy by using a set of explanatory variables.

Only the province of Quebec is accurately forecast overall, and as with the Naïve and BSM analyses the USA tends to be more accurately forecast into the provinces.

4.2 MODELS COMPARISON: NAÏVE, BSM AND TVP MODELS

4.2.1 Model Comparison for the forecast performance of the flow from each of the top five source countries to each province of Canada

Table 4.2.1a shows a comparison of the forecast performance of the flow from France to each province of Canada.

Table 4.2.1b shows a comparison of the forecast performance of the flow from Germany to each province of Canada.

Table 4.2.1c shows a comparison of the forecast performance of the flow from Japan to each province of Canada.

Table 4.2.1d shows a comparison of the forecast performance of the flow from UK to each province of Canada.

Table 4.2.1e shows a comparison of the forecast performance of the flow from USA to each province of Canada.

Table 4.2.1a: Significance Test Comparison of Each Model to the Naïve of the Flow from France to Each Province of Canada

FRANCE	**NAÏVE**	**BSM**	**TVP**
	MAPE %	MAPE %	MAPE %
Alberta			
Mean	31.14	24.32	35.56
Standard Deviation	24.63	14.91	15.22
t-obtained		-0.63	-0.73
p-value		0.54	0.48
British Columbia			
Mean	45.48	22.36	98.42
Standard Deviation	29.39	23.79	31.92
t-obtained		-2.65	-0.11
p-value		0.04	0.91
Manitoba			
Mean	26.61	26.28	37.79
Standard Deviation	30.03	16.55	21.29
t-obtained		-0.04	1.54
p-value		0.97	0.17
New Brunswick			
Mean	46.88	36.09	35.87
Standard Deviation	28.30	28.52	28.31
t-obtained		-0.70	-0.72
p-value		0.50	0.49
Newfoundland			
Mean	46.25	48.57	43.02
Standard Deviation	36.10	27.64	25.62
t-obtained		0.16	-0.22
p-value		0.88	0.83
Northwest Territories	NA	NA	N/A
Nova Scotia			
Mean	46.99	48.11	43.41
Standard Deviation	28.84	35.38	31.19
t-obtained		0.07	-0.22
p-value		0.95	0.83
Ontario			
Mean	11.71	19.34	15.08
Standard Deviation	9.92	13.85	12.27
t-obtained		1.25	0.69
p-value		0.25	0.51
Pr. Edward Isl.			
Mean	13.98	18.66	17.00
Standard Deviation	20.85	10.14	10.42
t-obtained		0.54	0.35
p-value		0.60	0.74
Quebec			
Mean	5.24	12.27	6.66
Standard Deviation	4.22	9.62	7.04
t-obtained		2.18	0.65
p-value		0.07	0.54
Saskatchewan			
Mean	28.27	37.07	46.93
Standard Deviation	19.18	25.03	39.39
t-obtained		0.77	1.19
p-value		0.46	0.26
Yukon			
Mean	10.10	12.73	12.72
Standard Deviation	24.96	19.96	7.40
t-obtained		0.22	0.27
p-value		0.83	0.80
Count of MAPE? 10	Count	Count	Count
	1	0	1
10 < MAPE? 20	Count	Count	Count
	3	4	3

Note: Where flows are too small to record forecasts “NA” is displayed

Table 4.2.1b: Significance Test Comparison of Each Model to the Naïve of the Flow from Germany to Each Province of Canada

GERMANY	**NAÏVE**	**BSM**	**TVP**
	MAPE %	MAPE %	MAPE %
Alberta			
Mean	25.58	12.64	24.40
Standard Deviation	17.51	9.90	8.14
t-obtained		17.51	-0.16
p-value		0.12	0.87
British Columbia			
Mean	8.02	8.36	13.63
Standard Deviation	5.61	5.68	6.60
t-obtained		0.15	1.83
p-value		0.88	0.11
Manitoba			
Mean	31.33	22.22	49.20
Standard Deviation	26.49	26.94	106.88
t-obtained		-0.27	0.45
p-value		0.79	0.66
New Brunswick			
Mean	17.77	49.32	19.48
Standard Deviation	16.58	23.52	13.15
t-obtained		2.85	0.32
p-value		0.02	0.76
Newfoundland			
Mean	15.28	24.86	107.27
Standard Deviation	17.01	13.00	125.67
t-obtained		1.13	2.05
p-value		0.29	0.08
Northwest Territories			
Mean	26.83	39.37	43.68
Standard Deviation	41.57	32.62	24.98
t-obtained		0.58	0.88
p-value		0.58	0.40
Nova Scotia			
Mean	32.30	29.80	32.22
Standard Deviation	16.24	19.64	18.02
t-obtained		-0.48	-0.01
p-value		0.64	0.99
Ontario			
Mean	9.17	27.20	10.60
Standard Deviation	10.84	18.85	9.93
t-obtained		2.29	0.48
p-value		0.06	0.64
Pr. Edward Isl.			
Mean	3.66	37.32	75.17
Standard Deviation	5.54	14.59	82.40
t-obtained		5.88	2.45
p-value		0.00	0.04
Quebec			
Mean	11.92	7.11	9.15
Standard Deviation	9.35	5.03	9.02
t-obtained		-1.71	-1.05
p-value		0.13	0.33
Saskatchewan			
Mean	19.35	22.37	36.19
Standard Deviation	18.31	14.55	45.90
t-obtained		0.34	0.95
p-value		0.74	0.36
Yukon			
Mean	50.80	21.45	23.99
Standard Deviation	26.41	17.85	22.94
t-obtained		-2.49	-2.08
p-value		0.03	0.06
Count of MAPE ? 10	Count	Count	Count
	3	2	1
10 < MAPE ? 20	Count	Count	Count
	4	1	3

Table 4.2.1c: Significance Test Comparison of Each Model to the Naïve of the Flow from Japan to Each Province of Canada

JAPAN	**NAÏVE**	**BSM**	**TVP**
	MAPE %	MAPE %	MAPE %
Alberta			
Mean	18.23	24.31	18.61
Standard Deviation	10.61	13.78	20.91
t-obtained		0.96	0.04
p-value		0.35	0.97
British Columbia			
Mean	11.71	16.11	15.73
Standard Deviation	7.59	16.76	11.97
t-obtained		0.99	1.31
p-value		0.36	0.23
Manitoba			
Mean	26.38	44.24	65.24
Standard Deviation	28.87	28.18	1.70
t-obtained		1.40	2.16
p-value		0.19	0.12
New Brunswick			
Mean	25.21	39.45	39.54
Standard Deviation	32.99	22.46	40.15
t-obtained		0.94	0.76
p-value		0.37	0.46
Newfoundland	NA	NA	N/A
Northwest Territories			
Mean	24.39	81.92	24.81
Standard Deviation	38.84	32.11	30.74
t-obtained		2.95	0.02
p-value		0.01	0.98
Nova Scotia			
Mean	56.48	40.33	46.00
Standard Deviation	19.63	26.37	29.12
t-obtained		-1.11	-0.74
p-value		0.30	0.48
Ontario			
Mean	17.98	19.56	12.87
Standard Deviation	9.67	17.42	8.48
t-obtained		0.27	-1.10
p-value		0.79	0.31
Pr. Edward Isl.			
Mean	36.37	73.37	206.70
Standard Deviation	14.69	35.66	323.64
t-obtained		2.17	1.47
p-value		0.08	0.18
Quebec			
Mean	43.78	26.28	39.84
Standard Deviation	22.66	21.51	46.40
t-obtained		-1.42	-0.21
p-value		0.19	0.84
Saskatchewan			
Mean	41.92	30.98	29.55
Standard Deviation	21.73	21.66	29.91
t-obtained		-0.91	-0.92
p-value		0.38	0.37
Yukon			
Mean	31.52	27.40	22.74
Standard Deviation	37.77	16.89	16.85
t-obtained		-0.32	-0.64
p-value		0.76	0.54
Count of MAPE? 10	Count	Count	Count
	0	0	0
10 < MAPE? 20	Count	Count	Count
	3	2	3

Note: Where flows are too small to record forecasts “NA” is displayed

Table 4.2.1d: Significance Test Comparison of Each Model to the Naïve of the Flow from UK to Each Province of Canada

UK	**NAÏVE**	**BSM**	**TVP**
	MAPE %	MAPE %	MAPE %
Alberta			
Mean	15.94	15.73	10.69
Standard Deviation	15.28	10.62	5.92
t-obtained		-0.04	-1.16
p-value		0.97	0.28
British Columbia			
Mean	9.49	8.01	7.44
Standard Deviation	10.62	8.34	7.44
t-obtained		-0.58	-0.76
p-value		0.58	0.47
Manitoba			
Mean	34.06	18.74	48.55
Standard Deviation	23.44	18.22	65.46
t-obtained		-1.36	0.58
p-value		0.20	0.57
New Brunswick			
Mean	29.42	27.96	30.33
Standard Deviation	24.94	20.29	25.77
t-obtained		-0.12	0.07
p-value		0.91	0.95
Newfoundland			
Mean	46.24	44.48	69.39
Standard Deviation	27.50	32.65	84.80
t-obtained		-0.11	0.72
p-value		0.91	0.49
Northwest Territories	NA	NA	N/A
Nova Scotia			
Mean	25.50	23.11	21.83
Standard Deviation	18.80	20.45	15.06
t-obtained		-0.44	-0.85
p-value		0.67	0.42
Ontario			
Mean	4.13	12.90	10.28
Standard Deviation	3.72	4.89	3.20
t-obtained		3.73	3.32
p-value		0.01	0.01
Pr. Edward Isl.			
Mean	29.88	33.87	33.11
Standard Deviation	23.36	19.20	37.27
t-obtained		0.33	0.20
p-value		0.75	0.85
Quebec			
Mean	11.24	10.50	19.84
Standard Deviation	8.46	8.40	15.39
t-obtained		-0.29	1.40
p-value		0.78	0.20
Saskatchewan			
Mean	36.00	32.50	43.09
Standard Deviation	27.48	19.98	18.10
t-obtained		-0.26	0.55
p-value		0.80	0.60
Yukon			
Mean	31.57	39.20	107.03
Standard Deviation	25.97	14.03	184.02
t-obtained		0.56	1.14
p-value		0.59	0.29
Count of MAPE? 10	Count	Count	Count
	2	1	1
10 < MAPE? 20	Count	Count	Count
	2	4	3

Note: Where flows are too small to record forecasts “NA” is displayed

Table 4.2.1e: Significance Test Comparison of Each Model to the Naïve of the Flow from USA to Each Province of Canada

USA	NAÏVE	BSM	TVP
	MAPE %	MAPE %	MAPE %
Alberta			
Mean	11.29	9.57	8.24
Standard Deviation	8.98	6.36	6.37
t-obtained		-0.72	-0.89
p-value		0.50	0.40
British Columbia			
Mean	7.07	5.76	13.45
Standard Deviation	3.13	2.39	10.64
t-obtained		-0.80	1.89
p-value		0.45	0.10
Manitoba			
Mean	8.62	5.38	6.45
Standard Deviation	6.45	3.89	5.94
t-obtained		-0.97	-1.37
p-value		0.37	0.21
New Brunswick			
Mean	11.88	4.86	11.06
Standard Deviation	5.87	4.36	6.69
t-obtained		-7.35	-0.63
p-value		0.00	0.55
Newfoundland			
Mean	16.98	15.43	18.13
Standard Deviation	15.27	6.32	13.97
t-obtained		-0.34	0.29
p-value		0.75	0.78
Northwest Territories			
Mean	26.79	79.39	52.99
Standard Deviation	18.74	27.91	56.60
t-obtained		4.33	1.23
p-value		0.00	0.25
Nova Scotia			
Mean	18.64	16.31	18.06
Standard Deviation	12.82	12.39	11.35
t-obtained		-0.36	-0.12
p-value		0.73	0.91
Ontario			
Mean	14.16	6.28	13.58
Standard Deviation	5.92	6.52	11.83
t-obtained		-12.26	-0.25
p-value		0.00	0.81
Pr. Edward Isl.			
Mean	26.46	20.40	15.33
Standard Deviation	30.00	13.43	10.23
t-obtained		-0.45	-1.05
p-value		0.67	0.33
Quebec			
Mean	9.39	6.88	9.78
Standard Deviation	4.45	5.50	7.86
t-obtained		-1.98	0.15
p-value		0.09	0.88
Saskatchewan			
Mean	9.84	9.76	8.72
Standard Deviation	9.05	6.68	5.64
t-obtained		-0.03	-0.36
p-value		0.98	0.73
Yukon			
Mean	14.60	16.79	14.33
Standard Deviation	9.46	9.38	17.15
t-obtained		0.50	-0.04
p-value		0.63	0.97
Count of MAPE ? 10	Count	Count	Count
	4	7	4
10 < MAPE ? 20	Count	Count	Count
	6	3	7

4.2.2 Model Comparison for the forecast performance of the flow from each of the top five source countries to Canada

Table 4.2.2a shows a comparison of the forecast performance of the flow from each of the top five source countries to Canada.

Table 4.2.2a: Significance Test Comparison of Each Model to the Naïve of the Flow from Each of the Top Five Countries to Canada

	NAÏVE	BSM	TVP
	MAPE %	MAPE %	MAPE %
FRANCE			
Mean	3.47	7.57	5.71
Standard Deviation	2.93	5.06	4.83
t-obtained		1.63	1.14
p-value		0.15	0.29
GERMANY			
Mean	5.75	5.73	7.39
Standard Deviation	2.95	4.26	5.68
t-obtained		-0.01	0.73
p-value		0.99	0.49
JAPAN			
Mean	13.21	9.71	6.31
Standard Deviation	5.93	8.91	3.82
t-obtained		-1.27	-2.61
p-value		0.24	0.03
UK			
Mean	7.16	10.33	16.72
Standard Deviation	4.30	6.80	13.00
t-obtained		1.10	2.15
p-value		0.31	0.07
USA			
Mean	11.27	6.31	17.65
Standard Deviation	3.76	6.02	10.27
t-obtained		-3.32	2.35
p-value		0.01	0.05
Count of MAPE ≤ 10	Count	Count	Count
	3	4	3
10 < MAPE ≤ 20	Count	Count	Count
	2	1	2

4.2.3 Model Comparison for the forecast performance of the total flow from all top five source countries to each province of Canada

Table 4.2.3a shows a comparison of the forecast performance of the total flow from all of the top five source countries to each province of Canada.

Table 4.2.3a: Significance Test Comparison of Each Model to the Naïve of the Flow from the Total of Top Five Countries to Each Province of Canada

	NAÏVE	BSM	TVP
	MAPE %	MAPE %	MAPE %
Alberta			
Mean	22.97	8.22	7.76
Standard Deviation	8.98	4.64	3.27
t-obtained		-1.08	-1.10
p-value		0.32	0.31
British Columbia			
Mean	5.55	5.75	16.50
Standard Deviation	3.06	2.61	11.66
t-obtained		0.14	2.72
p-value		0.90	0.03
Manitoba			
Mean	6.94	6.26	14.81
Standard Deviation	7.86	4.01	8.90
t-obtained		-0.17	4.86
p-value		0.87	0.00
New Brunswick			
Mean	11.45	4.42	11.99
Standard Deviation	6.16	3.25	6.37
t-obtained		-5.96	0.36
p-value		0.00	0.73
Newfoundland			
Mean	12.12	18.69	14.95
Standard Deviation	10.86	17.16	12.41
t-obtained		1.36	0.85
p-value		0.21	0.43
Northwest Territories			
Mean	28.93	25.68	48.91
Standard Deviation	35.02	29.02	51.88
t-obtained		-0.41	0.88
p-value		0.70	0.39
Nova Scotia			
Mean	16.90	19.82	15.07
Standard Deviation	15.60	15.54	11.40
t-obtained		0.37	-0.23
p-value		0.72	0.82
Ontario			
Mean	6.82	3.90	16.45
Standard Deviation	5.77	5.38	12.53
t-obtained		-8.84	1.58
p-value		0.00	0.16
Pr. Edward Isl.			
Mean	24.85	17.81	17.11
Standard Deviation	17.90	16.00	11.40
t-obtained		-0.72	-1.14
p-value		0.50	0.29
Quebec			
Mean	7.04	3.32	8.91
Standard Deviation	4.11	2.13	8.67
t-obtained		-2.53	1.06
p-value		0.04	0.32
Saskatchewan			
Mean	10.73	8.54	28.09
Standard Deviation	7.67	6.68	16.09
t-obtained		-0.36	2.95
p-value		0.73	0.02
Yukon			
Mean	13.32	16.13	18.13
Standard Deviation	8.88	12.11	19.28
t-obtained		0.70	0.63
p-value		0.50	0.55
Count of MAPE ? 10	Count	Count	Count
	4	7	2
10 < MAPE ? 20	Count	Count	Count
	5	4	8

4.2.4 Model Comparison for the forecast performance of the total flow from all top five source countries to Canada

Table 4.2.4a shows a comparison of the forecast performance of the total flow from all of the top five source countries to Canada.

Table 4.2.4a: Significance Test Comparison of Each Model to the Naïve of the Total Flow from the Top Five Source Countries to Canada

	NAÏVE	BSM	TVP
	MAPE %	MAPE %	MAPE %
ALL TOP 5 TO CANADA			
Mean	8.17	3.62	16.61
Standard Deviation	3.76	4.21	9.68
t-obtained		-6.99	2.12
p-value		0.00	0.07
Count of MAPE ≤ 10	1	1	0

The earlier conclusion drawn from a comparison of the MAPE values indicates that the BSM is the more accurate model followed by the Naïve. Throughout Tables 4.2.1a to e it is evident that the forecasts from the two quantitative models are largely not statistically significant. The t-obtained (calculated) values are heavily influenced by high standard deviations in each forecast comparison. This result is symptomatic of high variability in the arrival series. The regional data for international flows into Canada are highly variable in many cases. From the results in Table 4.2.2a where the source markets are compared it is evident that the USA market is the most stable and this is consistent with the previous discussion comparing the MAPE values. The finding in Table 4.2.4a that the BSM model is statistically superior to the Naïve model is also consistent with the earlier finding that the national level forecasting is more accurate than the regional level analysis overall, and that the BSM model tends to be the more accurate method.

4.3 CONCLUSION

The objective of this research has been to determine whether it is possible to accurately forecast regional tourist arrivals, and if so to move toward developing on understanding of the methodology that would be required to achieve this outcome. From the methodology discussed in Chapter Three it was decided to use two main forecasting models, the Basic Structural time series model and the causal Time-Varying Parameter model, and to compare these models against the benchmark Naïve forecasting process. The data selected is recently available tourist arrival flows into the provinces of Canada from 2000 to 2007. Because of the data limitations in the length of the time series, only two years are used as the post sample testing period, 2006 and 2007.

The results of the analysis are discussed in detail above. Here the conclusions upon the research are based upon a summary of these results.

The accuracy of the forecast is primarily based upon using the mean absolute percentage error (MAPE) statistic. This statistic provides a unit free comparative measure of accuracy that is readily interpretable, and commonly used in the literature. The root mean square error measure is also calculated.

The results from analysis indicate that it is possible to accurately forecast regional tourist arrivals with less than 20% error and in many cases below 10% error. In the short term (two years ahead) the naïve process is relevant as an indicator of future arrivals. However, the time series BSM model is the most accurate model. The TVP model is found to be somewhat less accurate despite the use of a wide range of explanatory variables. It is possible to say that the accuracy of the TVP model may be improved if a more relevant set of causal variables could be found to use in the analysis. However, an exhausting process of searching for causal variables was undertaken, initially based upon current research and expanding out to new variables. There is and would always be a limitation on data availability, and the capacity of any causal model will be constrained by such limitations. It may also be the case that the TVP model might accurately forecast in the medium to long term, but the data set available here does not allow for such a comparison.

The results also indicate that some regions are more capable of accurate forecasting than others. For Canada these regions are British Columbia, Manitoba, New Brunswick, Ontario, Quebec and Saskatchewan. It is likely that it is not co-incidental that these are the regions of highest tourist arrival flows, with the possible exception of Alberta which falls between the better forecast provinces and the others, having some high accuracy outcomes for the larger volume flows. The remaining regions tend to have low arrivals numbers and higher variation. Of the source markets studied it is also evident that the larger volume flows from neighbouring USA are more accurately forecast than the lower volume flows from France, Germany, Japan and the UK.

In comparing the accuracy in the level of aggregation of the data it is generally the case that flows are more accurately forecast at higher levels of aggregation, that is all five source countries into each province rather than each source markets into each region. This again may reflect upon the volume of flow in some cases, as the regional destination of each main source market varies except for the USA. As might intuitively be expected, the higher variability in the regional flows makes accurate forecasting more difficult.

In the TVP analysis the causal variables used to some extent support the use of variables currently found in the literature and used for national level tourist arrivals forecasts. The variables selected in the current literature are economic in nature and this principle was followed in this research with some variables included from national forecasting research. However, this finding is not universal and the regional variables of food service activity, household consumption and retail sales were also relevant. Retail sales extended through from the regional to the national scale as a significant variable. On the other hand, own price which is commonly significant in published national forecasting research was not highly significant at the regional or higher scale level.

In this study it has been found that it is possible to use current methods to accurately forecast regional tourist arrivals, at least in cases where there is a consistent and large flow of international tourists. Although time series modelling was more accurate overall, there is significant value in using causal modelling. Moreover, the independent causal variables to be selected, although similar in some cases to the currently used national variables, do varying at the regional level. The impacts on food service level by international tourists are important and useful as a causal measure as is household consumption and retail sales.

From a practical management perspective the study suggests that the accurate forecasting of regional international tourist arrivals is possible, at least in the short-term. However, it may not be practical for all regions, and may need to be limited to the major tourist destination provinces. Additionally, it is suggested by the study that forecasting by individual source market is more problematical, and it may be necessary to examine total arrival flows, especially if arrival volumes are either low or volatile in number. Nevertheless, regional authorities and regional businesses could in many cases undertake regional forecasting and expect reasonably high levels of accuracy, when using the latest forecasting methods.

Furthermore, given the superiority of the time-series model (BSM) the added expense in formulating deterministic models may not be justified, if the objective is forecasting accurate arrival numbers.

4.4 LIMITATIONS OF THE RESEARCH

The main limitation of this research was the inability to use a larger post sample data period. Medium and long term forecasting accuracy could not be tested and the findings of the research are limited to the short-term. This constraint will slowly be removed as longer arrival series become increasingly available.

Although the forecasting models selected are good examples of modern methodology, there are other methods such as Neural and BSM with interventions, that are potentially important techniques that could also be used.

4.5 FURTHER RESEARCH

The limitations discussed above provide two immediate indications of where future research could be done. There is a need to examine other regional series to compare the usefulness of the independent variables examined here. Although data availability will remain an important constraint, there would be some potential for the identification of non-economic causal variables. For example, the level of previous immigration into regions could be significant. Migrants tend to flow into particular regions of countries and the relative extent of variable immigration may well account for tourism arrivals, of the relatives and friends type. Finally, these findings are the direct measures from quantitative models, and the literature review does suggest that further refinement by expert opinion using a non-quantitative method may be the better way to increase the level of accuracy overall.

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APPENDIX I

APPENDIX TO CHAPTER FOUR

BSM results

BSM RESULTS FOR TOURIST ARRIVALS FROM EACH OF THE TOP FIVE COUNTRIES TO EACH PROVINCE OF CANADA

BSM RESULTS FOR TOURIST ARRIVALS FROM FRANCE TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.2aF1 - 4.1.2aF12

ALBERTA

Table 4.1.2aF1: TVP result for tourist arrivals from France to Alberta

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFrance = Trend + AR(1) + Trigo seasonal

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 4.964664e-005.
Very strong convergence in 18 iterations.
(likelihood cvg 8.348675e-011
gradient cvg 1.04888e-006
parameter cvg 6.353669e-010)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 0.00119152 (-2 LogL = -0.00238304).
Prediction error variance is 0.377164

Summary statistics

	LFrance
Std.Error	0.61414
Normality	1.0848
H(6)	0.048518
r(1)	0.016351
r(10)	-0.028099
DW	1.5262
Q(10, 6)	4.0018
Rs^2	0.47157

Estimated variances of disturbances.

Component	LFrance (q-ratio)
Lvl	0.063599 (0.2530)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.25136 (1.0000)

BRITISH COLUMBIA

Table 4.1.2aF2: BSM result for tourist arrivals from France to British Columbia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFRANCE = Level + AR(1) + Irregular

Estimation report

Model with 4 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.08085712.
Very strong convergence in 9 iterations.
(likelihood cvg 9.184793e-012
gradient cvg 3.963656e-006
parameter cvg 3.135312e-005)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 23).
Log-Likelihood is -1.94057 (-2 LogL = 3.88114).
Prediction error variance is 1.00069

Summary statistics

	LFRANCE
Std.Error	1.0003
Normality	1.9387
H(7)	0.66490
r(1)	0.016444
r(9)	-0.0098125
DW	1.8106
Q(9, 6)	25.875
R^2	0.00000

Estimated variances of disturbances.

Component	LFRANCE (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Ar1	1.0355 (1.0000)

MANITOBA

Table 4.1.2aF3: BSM result for tourist arrivals from France to Manitoba

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFrance = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.3417692.
Very strong convergence in 7 iterations.
(likelihood cvg 2.436344e-015
gradient cvg 7.991829e-007
parameter cvg 3.151069e-012)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 8.20246 (-2 LogL = -16.4049).
Prediction error variance is 0.13308

Summary statistics

	LFrance
Std.Error	0.36480
Normality	1.4483
H(6)	0.62649
r(1)	-0.20850
r(8)	0.046249
DW	2.2427
Q(8, 6)	10.165
Rs^2	0.42847

Estimated variances of disturbances.

Component	LFrance (q-ratio)
Irr	0.087944 (1.0000)
Slp	0.0061051 (0.0694)
Sea	0.00000 (0.0000)

NEW BRUNSWICK

Table 4.1.2aF4: BSM result for tourist arrivals from France to New Brunswick

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFRANCE = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.161843.
Very strong convergence in 14 iterations.
(likelihood cvg 1.60293e-011
gradient cvg 5.167533e-008
parameter cvg 2.701093e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -3.88423 (-2 LogL = 7.76846).
Prediction error variance is 0.470348

Summary statistics

	LFRANCE
Std.Error	0.68582
Normality	0.36349
H(6)	1.2742
r(1)	-0.13991
r(10)	0.084284
DW	2.1239
Q(10, 6)	3.2801
Rs^2	0.63088

Eq 2 : Estimated variances of disturbances.

Component	LFRANCE (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.56049 (1.0000)

NEWFOUNDLAND

Table 4.1.2aF5: BSM result for tourist arrivals from France to Newfoundland

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFrance = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.05810272.
Very strong convergence in 7 iterations.
(likelihood cvg 5.872108e-013
gradient cvg 5.651035e-009
parameter cvg 3.885427e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -1.39447 (-2 LogL = 2.78893).
Prediction error variance is 0.36542

Summary statistics

	LFrance
Std.Error	0.60450
Normality	3.8743
H(6)	3.8138
r(1)	0.013654
r(8)	-0.32242
DW	1.9451
Q(8, 6)	5.4515
Rs^2	0.59659

Estimated variances of disturbances.

Component	LFrance (q-ratio)
Irr	0.41365 (1.0000)
Lvl	0.0068869 (0.0166)
Sea	0.00000 (0.0000)

NORTHWEST TERRITORIES

Table 4.1.2aF6: BSM result for tourist arrivals from France to Northwest Territories

N/A

NOVA SCOTIA

Table 4.1.2aF7: BSM result for tourist arrivals from France to Nova Scotia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFRANCE = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.09030676.
Very strong convergence in 7 iterations.
(likelihood cvg 5.06509e-013
gradient cvg 7.105427e-010
parameter cvg 2.980386e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -2.16736 (-2 LogL = 4.33472).
Prediction error variance is 0.349033

Summary statistics

	LFRANCE
Std.Error	0.59079
Normality	4.5869
H(6)	0.65746
r(1)	-0.52009
r(8)	-0.10938
DW	2.5952
Q(8, 6)	10.962
Rs^2	0.53542

Estimated variances of disturbances.

Component	LFRANCE (q-ratio)
Irr	0.14303 (1.0000)
Slp	0.0086116 (0.0602)
Sea	0.017662 (0.1235)

ONTARIO

Table 4.1.2aF8: BSM result for tourist arrivals from France to Ontario

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFRANCE = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.171835.
Very strong convergence in 23 iterations.
(likelihood cvg 9.577857e-008
gradient cvg 3.853062e-006
parameter cvg 7.068619e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 28.124 (-2 LogL = -56.2481).
Prediction error variance is 0.0215309

Summary statistics

	LFRANCE
Std.Error	0.14673
Normality	0.44402
H(6)	0.76711
r(1)	-0.13911
r(10)	-0.16501
DW	2.0496
Q(10, 6)	10.906
Rs^2	0.51787

Estimated variances of disturbances.

Component	LFRANCE (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00042463 (0.0334)
Sea	0.00000 (0.0000)
Ar1	0.012718 (1.0000)

PRINCE EDWARD ISLAND

Table 4.1.2aF9: BSM result for tourist arrivals from France to Prince Edward Island

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFRANCE = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.5865284.
Very strong convergence in 21 iterations.
(likelihood cvg 3.836473e-012
gradient cvg 3.034462e-007
parameter cvg 4.416314e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 14.0767 (-2 LogL = -28.1534).
Prediction error variance is 0.0718008

Summary statistics

	LFRANCE
Std.Error	0.26796
Normality	11.000
H(6)	0.98075
r(1)	-0.021663
r(10)	-0.078995
DW	2.0323
Q(10, 6)	5.6036
Rs^2	0.57295

Estimated variances of disturbances.

Component	LFRANCE (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.085556 (1.0000)

QUEBEC

Table 4.1.2aF10: BSM result for tourist arrivals from France to Quebec

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFRANCE = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.324108.
Very strong convergence in 30 iterations.
(likelihood cvg 1.541105e-012
gradient cvg 8.77883e-007
parameter cvg 9.39459e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 31.7786 (-2 LogL = -63.5572).
Prediction error variance is 0.0185261

Summary statistics

	LFRANCE
Std.Error	0.13611
Normality	0.97033
H(6)	0.38649
r(1)	0.032638
r(10)	0.046675
DW	1.7201
Q(10, 6)	5.7046
Rs^2	0.012964

Estimated variances of disturbances.

Component	LFRANCE (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00022618 (0.0362)
Sea	0.00058989 (0.0943)
Ar1	0.0062528 (1.0000)

SASKATCHEWAN

Table 4.1.2aF11: BSM result for tourist arrivals from France to Saskatchewan

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFrance = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.04163498.
Very weak convergence in 5 iterations.
(likelihood cvg 0.1502939
gradient cvg 0.005704795
parameter cvg 0.09814322)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -0.99924 (-2 LogL = 1.99848).
Prediction error variance is 0.444453

Summary statistics

	LFrance
Std.Error	0.66667
Normality	0.35797
H(6)	0.67326
r(1)	0.11654
r(8)	0.38392
DW	1.6017
Q(8, 6)	11.518
Rs^2	0.22729

Estimated variances of disturbances.

Component	LFrance (q-ratio)
Irr	0.32921 (1.0000)
Slp	0.00047668 (0.0014)
Sea	0.0055730 (0.0169)

YUKON

Table 4.1.2aF12: BSM result for tourist arrivals from France to Yukon

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LFrance = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.2524673.
Very strong convergence in 23 iterations.
(likelihood cvg 1.099373e-015
gradient cvg 1.363576e-007
parameter cvg 1.395998e-009)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 6.05922 (-2 LogL = -12.1184).
Prediction error variance is 0.242838

Summary statistics

	LFrance
Std.Error	0.49279
Normality	1.1468
H(6)	0.57341
r(1)	0.12413
r(9)	0.12604
DW	1.4455
Q(9, 6)	5.8442
Rs^2	0.41956

Estimated variances of disturbances.

Component	LFrance (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.034415 (1.0000)
Slp	0.00040019 (0.0116)
Sea	0.021671 (0.6297)

BSM RESULTS FOR TOURIST ARRIVALS FROM GERMANY TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.2aG1 - 4.1.2aG12

ALBERTA

Table 4.1.2aG1: BSM result for tourist arrivals from Germany to Alberta

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGermany = Trend + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.7100762.
Strong convergence in 9 iterations.
(likelihood cvg 3.014601e-005
gradient cvg 2.185518e-006
parameter cvg 4.331551e-005)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 17.0418 (-2 LogL = -34.0837).
Prediction error variance is 0.0785676

Summary statistics

	LGermany
Std.Error	0.28030
Normality	9.2144
H(6)	2.1871
r(1)	-0.049451
r(9)	-0.12978
DW	1.6420
Q(9, 6)	2.9171
Rs^2	-0.094094

Estimated variances of disturbances.

Component	LGermany (q-ratio)
Irr	0.0049677 (0.0904)
Lvl	0.054978 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.00083033 (0.0151)

BRITISH COLUMBIA

Table 4.1.2aG2: BSM result for tourist arrivals from Germany to British Columbia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGERMANY = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report
Model with 5 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.7871819.
Very strong convergence in 20 iterations.
(likelihood cvg 6.950618e-012
gradient cvg 6.782908e-008
parameter cvg 7.849454e-006)

Diagnostic summary report.
Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 18.8924 (-2 LogL = -37.7847).
Prediction error variance is 0.0627734

Summary statistics

	LGERMANY
Std.Error	0.25055
Normality	3.4745
H(6)	0.29369
r(1)	-0.22151
r(10)	0.20625
DW	2.0641
Q(10, 6)	5.0816
Rs^2	0.24632

Eq 1 : Estimated variances of disturbances.

Component	LGERMANY (q-ratio)
Irr	0.028942 (1.0000)
Slp	0.00012936 (0.0045)
Sea	0.00049107 (0.0170)
Ar1	0.014909 (0.5151)

MANITOBA

Table 4.1.3aG3: TVP result for tourist arrivals from Germany to Manitoba

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGermany = Level + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.08239909.
Very strong convergence in 7 iterations.
(likelihood cvg 3.536854e-015
gradient cvg 1.346964e-007
parameter cvg 2.679929e-008)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 20).
Log-Likelihood is -1.97758 (-2 LogL = 3.95516).
Prediction error variance is 0.451446

Summary statistics

	LGermany
Std.Error	0.67190
Normality	8.6355
H(6)	3.1115
r(1)	-0.057500
r(8)	-0.14980
DW	1.7869
Q(8, 6)	2.9273
Rs^2	0.39765

Eq 5 : Estimated variances of disturbances.

Component	LGermany (q-ratio)
Irr	0.58643 (1.0000)
Lvl	0.019700 (0.0336)
Sea	0.00000 (0.0000)

NEW BRUNSWICK

Table 4.1.2aG4: BSM result for tourist arrivals from Germany to New Brunswick

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGERMANY = Level + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.181536.
Very strong convergence in 20 iterations.
(likelihood cvg 1.784882e-010
gradient cvg 3.620687e-007
parameter cvg 8.936493e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 20).
Log-Likelihood is -4.35686 (-2 LogL = 8.71373).
Prediction error variance is 0.809592

Summary statistics

	LGERMANY
Std.Error	0.89977
Normality	2.4765
H(6)	0.61394
r(1)	-0.15051
r(10)	0.072041
DW	1.9970
Q(10, 6)	4.6255
Rs^2	0.60698

Estimated variances of disturbances.

Component	LGERMANY (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.018708 (0.0242)
Sea	0.00000 (0.0000)
Ar1	0.77264 (1.0000)

NEWFOUNDLAND

Table 4.1.3aG5: TVP result for tourist arrivals from Germany to Newfoundland

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGermany = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.2293015.
Very strong convergence in 81 iterations.
(likelihood cvg 5.542522e-011
gradient cvg 1.174717e-006
parameter cvg 4.699706e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -5.50324 (-2 LogL = 11.0065).
Prediction error variance is 0.646515

Summary statistics

	LGermany
Std.Error	0.80406
Normality	1.7788
H(6)	1.5762
r(1)	0.0047863
r(10)	0.28509
DW	1.4450
Q(10, 6)	10.401
Rs^2	0.35479

Estimated variances of disturbances.

Component	LGermany (q-ratio)
Irr	0.029726 (0.0498)
Lvl	0.00000 (0.0000)
Sea	0.0057894 (0.0097)
Ar1	0.59742 (1.0000)

NORTHWEST TERRITORIES

Table 4.1.3aG6: TVP result for tourist arrivals from Germany to Northwest Territory

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGermany = Level + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.1132979.
Very strong convergence in 25 iterations.
(likelihood cvg 1.347383e-015
gradient cvg 4.965292e-007
parameter cvg 1.075836e-010)

Diagnostic summary report.
Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 20).
Log-Likelihood is 2.71915 (-2 LogL = -5.4383).
Prediction error variance is 0.453755

Summary statistics

	LGermany
Std.Error	0.67361
Normality	3.2010
H(6)	1.2950
r(1)	0.0038667
r(10)	-0.12788
DW	1.6480
Q(10, 6)	4.5824
Rs^2	0.31097

Estimated variances of disturbances.

Component	LGermany (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Sea	0.014088 (0.0434)
Ar1	0.32455 (1.0000)

NOVA SCOTIA

Table 4.1.2aG7: BSM result for tourist arrivals from Germany to Nova Scotia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGERMANY = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.1732984.
Very strong convergence in 5 iterations.
(likelihood cvg 4.474774e-011
gradient cvg 3.841372e-009
parameter cvg 7.925531e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -4.15916 (-2 LogL = 8.31832).
Prediction error variance is 0.572029

Summary statistics

	LGERMANY
Std.Error	0.75633
Normality	4.4182
H(6)	0.75479
r(1)	-0.093170
r(8)	-0.066081
DW	2.0452
Q(8, 6)	4.4027
Rs^2	0.42567

Estimated variances of disturbances.

Component	LGERMANY (q-ratio)
Irr	0.54031 (1.0000)
Slp	0.0013927 (0.0026)
Sea	0.00000 (0.0000)

ONTARIO

Table 4.1.3aG8: TVP result for tourist arrivals from Germany to Ontario

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGERMANY = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.9800537.
Very strong convergence in 6 iterations.
(likelihood cvg 9.334425e-014
gradient cvg 2.531308e-009
parameter cvg 6.737939e-009)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 23.5213 (-2 LogL = -47.0426).
Prediction error variance is 0.0214758

Summary statistics

	LGERMANY
Std.Error	0.14655
Normality	1.4328
H(6)	1.0361
r(1)	0.25213
r(8)	0.060316
DW	1.3822
Q(8, 6)	6.6164
Rs^2	0.023119

Estimated variances of disturbances.

Component	LGERMANY (q-ratio)
Irr	0.014206 (1.0000)
Slp	0.00098090 (0.0690)
Sea	0.00000 (0.0000)

PRINCE EDWARD ISLAND

Table 4.1.2aG9: BSM result for tourist arrivals from Germany to Prince Edward Island

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGERMANY = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.1380328.
Very strong convergence in 7 iterations.
(likelihood cvg 2.4029e-013
gradient cvg 1.467021e-008
parameter cvg 4.732578e-012)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 3.31279 (-2 LogL = -6.62558).
Prediction error variance is 0.180825

Summary statistics

	LGERMANY
Std.Error	0.42524
Normality	6.7907
H(6)	0.20121
r(1)	-0.063954
r(8)	-0.097192
DW	2.0364
Q(8, 6)	2.0577
Rs^2	0.79060

Estimated variances of disturbances.

Component	LGERMANY (q-ratio)
Irr	0.10878 (1.0000)
Lvl	0.0020813 (0.0191)
Sea	0.014160 (0.1302)

QUEBEC

Table 4.1.2aG10: BSM result for tourist arrivals from Germany to Quebec

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGERMANY = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.814534.
Strong convergence in 26 iterations.
(likelihood cvg 1.387799e-007
gradient cvg 9.1903e-006
parameter cvg 0.0005512069)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 19.5488 (-2 LogL = -39.0976).
Prediction error variance is 0.0660732

Summary statistics

	LGERMANY
Std.Error	0.25705
Normality	0.85381
H(6)	0.28686
r(1)	-0.029553
r(10)	-0.010390
DW	1.6949
Q(10, 6)	4.9949
Rs^2	0.12126

Estimated variances of disturbances.

Component	LGERMANY (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00010341 (0.0058)
Sea	0.0037205 (0.2098)
Ar1	0.017736 (1.0000)

SASKATCHEWAN

Table 4.1.2G11: BSM result for tourist arrivals from Germany to Saskatchewan

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGermany = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.04518583.
No estimation done.

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -1.08446 (-2 LogL = 2.16892).
Prediction error variance is 0.261118

Summary statistics

	LGermany
Std.Error	0.51100
Normality	12.721
H(6)	0.83958
r(1)	-0.034565
r(8)	-0.41456
DW	2.0217
Q(8, 6)	12.453
Rs^2	0.45760

Estimated variances of disturbances.

Component	LGermany (q-ratio)
Irr	0.36946 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)

YUKON

Table 4.1.2aG12: BSM result for tourist arrivals from Germany to Yukon

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGermany = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.0234464.
Very strong convergence in 18 iterations.
(likelihood cvg 2.487435e-012
gradient cvg 2.331468e-009
parameter cvg 1.255553e-012)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 0.562714 (-2 LogL = -1.12543).
Prediction error variance is 0.306827

Summary statistics

	LGermany
Std.Error	0.55392
Normality	1.1247
H(6)	0.65961
r(1)	-0.11210
r(10)	-0.14237
DW	2.0762
Q(10, 6)	7.2686
Rs^2	0.44617

Estimated variances of disturbances.

Component	LGermany (q-ratio)
Irr	0.28904 (1.0000)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.060961 (0.2109)

BSM RESULTS FOR TOURIST ARRIVALS FROM JAPAN TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.2aJ1 - 4.1.2aJ12

ALBERTA

Table 4.1.2aJ1: BSM result for tourist arrivals from Japan to Alberta

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJapan = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.2123881.
Very strong convergence in 14 iterations.
(likelihood cvg 2.109349e-006
gradient cvg 1.371043e-005
parameter cvg 7.088106e-005)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 5.09731 (-2 LogL = -10.1946).
Prediction error variance is 0.193376

Summary statistics

	LJapan
Std.Error	0.43975
Normality	5.0227
H(6)	6.2901
r(1)	0.052702
r(10)	-0.10248
DW	1.8220
Q(10, 6)	14.298
Rs^2	0.32286

Eq 7 : Estimated variances of disturbances.

Component	LJapan (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.23041 (1.0000)

BRITISH COLUMBIA

Table 4.1.2aJ2: BSM result for tourist arrivals from Japan to British Columbia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJAPAN = Trend + Trigo seasonal + Interv + Irregular

Estimation report
Model with 4 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.5673459.
No estimation done.

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 13.6163 (-2 LogL = -27.2326).
Prediction error variance is 0.0967097

Summary statistics

	LJAPAN
Std.Error	0.31098
Normality	8.8129
H(6)	0.20269
r(1)	0.063952
r(9)	-0.067876
DW	1.8354
Q(9, 6)	11.696
Rs^2	-0.38867

Estimated variances of disturbances.

Component	LJAPAN (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.091021 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)

MANITOBA

Table 4.1.2aJ3: BSM result for tourist arrivals from Japan to Manitoba

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJapan = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 4 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.610572.
Very strong convergence in 2 iterations.
(likelihood cvg 4.720392e-013
gradient cvg 8.597937e-008
parameter cvg 1.078066e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -14.6537 (-2 LogL = 29.3075).
Prediction error variance is 1.36677

Summary statistics

	LJapan
Std.Error	1.1691
Normality	0.36760
H(6)	0.66110
r(1)	-0.20946
r(9)	-0.15159
DW	2.1830
Q(9, 6)	6.6241
Rs^2	0.68293

Eq 13 : Estimated variances of disturbances.

Component	LJapan (q-ratio)
Irr	2.5780 (1.0000)
Lvl	4.0430e-006 (0.0000)
Slp	2.8147e-008 (0.0000)
Sea	2.4757e-008 (0.0000)

NEW BRUNSWICK

Table 4.1.2aJ4: BSM result for tourist arrivals from Japan to New Brunswick

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJAPAN = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.5092058.
Very strong convergence in 47 iterations.
(likelihood cvg 1.851949e-012
gradient cvg 4.047873e-008
parameter cvg 7.686066e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -12.2209 (-2 LogL = 24.4419).
Prediction error variance is 1.16011

Summary statistics

	LJAPAN
Std.Error	1.0771
Normality	0.095255
H(6)	2.4647
r(1)	-0.050698
r(10)	-0.075034
DW	2.0260
Q(10, 6)	13.559
Rs^2	0.48278

Estimated variances of disturbances.

Component	LJAPAN (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	1.3823 (1.0000)

NEWFOUNDLAND

Table 4.1.2aJ5: BSM result for tourist arrivals from Japan to Newfoundland

N/A

NORTHWEST TERRITORIES

Table 4.1.2aJ6: BSM result for tourist arrivals from Japan to Northwest Territories

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJapan = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -1.062795.
Very strong convergence in 6 iterations.
(likelihood cvg 1.007437e-012
gradient cvg 5.995204e-010
parameter cvg 1.843126e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -25.5071 (-2 LogL = 51.0141).
Prediction error variance is 5.96892

Summary statistics

	LJapan
Std.Error	2.4431
Normality	4.1779
H(6)	1.5791
r(1)	-0.25587
r(8)	0.046767
DW	2.4480
Q(8, 6)	4.2761
Rs^2	0.61452

Estimated variances of disturbances.

Component	LJapan (q-ratio)
Irr	3.7401 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.35301 (0.0944)

NOVA SCOTIA

Table 4.1.2aJ7: BSM result for tourist arrivals from Japan to Nova Scotia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJAPAN = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.0309627.
No estimation done.

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -0.743105 (-2 LogL = 1.48621).
Prediction error variance is 0.234396

Summary statistics

	LJAPAN
Std.Error	0.48414
Normality	2.4323
H(6)	0.95762
r(1)	-0.16666
r(8)	0.011012
DW	2.2934
Q(8, 6)	4.7739
Rs^2	0.73634

Estimated variances of disturbances.

Component	LJAPAN (q-ratio)
Irr	0.35376 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)

ONTARIO

Table 4.1.2aJ8: BSM result for tourist arrivals from Japan to Ontario

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJAPAN = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.2749454.
Very strong convergence in 11 iterations.
(likelihood cvg 2.123148e-011
gradient cvg 5.941359e-007
parameter cvg 7.80439e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 6.59869 (-2 LogL = -13.1974).
Prediction error variance is 0.197134

Summary statistics

	LJAPAN
Std.Error	0.44400
Normality	10.175
H(6)	0.87241
r(1)	0.062693
r(10)	0.047065
DW	1.7243
Q(10, 6)	9.7141
Rs^2	0.10480

Estimated variances of disturbances.

Component	LJAPAN (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00045692 (0.0024)
Sea	0.00000 (0.0000)
Ar1	0.19436 (1.0000)

PRINCE EDWARD ISLAND

Table 4.1.2aJ9: BSM result for tourist arrivals from Japan to Prince Edward Island

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJAPAN = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 6 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.3120403.
Very strong convergence in 19 iterations.
(likelihood cvg 3.203682e-011
gradient cvg 1.762646e-007
parameter cvg 5.549034e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 7.48897 (-2 LogL = -14.9779).
Prediction error variance is 0.164802

Summary statistics

	LJAPAN
Std.Error	0.40596
Normality	2.5510
H(6)	3.8502
r(1)	0.034077
r(11)	-0.16420
DW	1.8871
Q(11, 6)	10.882
Rs^2	0.28584

Estimated variances of disturbances.

Component	LJAPAN (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Slp	0.00000 (0.0000)
Sea	0.00055236 (0.0032)
Ar1	0.17168 (1.0000)

QUEBEC

Table 4.1.2aJ10: BSM result for tourist arrivals from Japan to Quebec

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJAPAN = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.1145332.
No estimation done.

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 2.7488 (-2 LogL = -5.49759).
Prediction error variance is 0.145164

Summary statistics

	LJAPAN
Std.Error	0.38100
Normality	3.2796
H(6)	0.68335
r(1)	0.22808
r(8)	0.064115
DW	1.3981
Q(8, 6)	8.3711
Rs^2	0.40506

Estimated variances of disturbances.

Component	LJAPAN (q-ratio)
Irr	0.21909 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)

SASKATCHEWAN

Table 4.1.2aJ11: BSM result for tourist arrivals from Japan to Saskatchewan

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJapan = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.01312837.
Very strong convergence in 6 iterations.
(likelihood cvg 4.519034e-014
gradient cvg 3.146594e-007
parameter cvg 4.756776e-008)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 0.315081 (-2 LogL = -0.630162).
Prediction error variance is 0.291465

Summary statistics

	LJapan
Std.Error	0.53987
Normality	8.1892
H(6)	1.9193
r(1)	-0.10769
r(8)	-0.090202
DW	2.1760
Q(8, 6)	6.2117
Rs^2	0.69957

Estimated variances of disturbances.

Component	LJapan (q-ratio)
Irr	0.28182 (1.0000)
Lvl	0.033771 (0.1198)
Sea	0.00000 (0.0000)

YUKON

Table 4.1.2aJ12: BSM result for tourist arrivals from Japan to Yukon

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LJapan = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.04407249.
Very strong convergence in 17 iterations.
(likelihood cvg 9.438693e-013
gradient cvg 8.615331e-009
parameter cvg 3.921549e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -1.05774 (-2 LogL = 2.11548).
Prediction error variance is 0.355662

Summary statistics

	LJapan
Std.Error	0.59637
Normality	3.4013
H(6)	0.35372
r(1)	0.10967
r(10)	-0.059038
DW	1.6236
Q(10, 6)	6.0818
Rs^2	0.53088

Estimated variances of disturbances.

Component	LJapan (q-ratio)
Irr	0.34662 (1.0000)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.067268 (0.1941)

BSM RESULTS FOR TOURIST ARRIVALS FROM UK TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.2aUK1 - 4.1.2aUK12

ALBERTA

Table 4.1.2aUK1: BSM result for tourist arrivals from UK to Alberta

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 6 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.1429795.
Very strong convergence in 3 iterations.
(likelihood cvg 6.806848e-009
gradient cvg 4.34255e-005
parameter cvg 1.423377e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 3.43151 (-2 LogL = -6.86301).
Prediction error variance is 0.227225

Summary statistics

	LUK
Std.Error	0.47668
Normality	6.2454
H(6)	0.11111
r(1)	0.029869
r(11)	-0.0039312
DW	1.3033
Q(11, 6)	9.9528
Rs^2	0.49238

Eq 5 : Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.25237 (1.0000)
Lvl	5.9205e-005 (0.0002)
Slp	4.4877e-007 (0.0000)
Sea	2.9867e-006 (0.0000)
Ar1	0.012558 (0.0498)

BRITISH COLUMBIA

Table 4.1.2aUK2: BSM result for tourist arrivals from UK to British Columbia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.080508.
Very strong convergence in 28 iterations.
(likelihood cvg 5.240256e-014
gradient cvg 3.95517e-008
parameter cvg 1.37904e-008)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 25.9322 (-2 LogL = -51.8644).
Prediction error variance is 0.0274716

Summary statistics

	LUK
Std.Error	0.16575
Normality	32.299
H(6)	0.079073
r(1)	-0.23713
r(10)	0.13941
DW	2.1124
Q(10, 6)	7.4004
Rs^2	0.026695

Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.0027385 (0.1549)
Lvl	0.0039552 (0.2237)
Sea	0.00010636 (0.0060)
Ar1	0.017684 (1.0000)

MANITOBA

Table 4.1.2aUK3: BSM result for tourist arrivals from UK to Manitoba

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Level + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.3638568.
Very strong convergence in 9 iterations.
(likelihood cvg 2.379985e-013
gradient cvg 1.976197e-009
parameter cvg 2.466667e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 20).
Log-Likelihood is 8.73256 (-2 LogL = -17.4651).
Prediction error variance is 0.125056

Summary statistics

	LUK
Std.Error	0.35363
Normality	4.9089
H(6)	0.43553
r(1)	-0.27026
r(8)	-0.079423
DW	2.2916
Q(8, 6)	6.1844
Rs^2	0.48357

Eq 20 : Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.14606 (1.0000)
Lvl	0.0039474 (0.0270)
Sea	0.00000 (0.0000)

NEW BRUNSWICK

Table 4.1.2aUK4: BSM result for tourist arrivals from UK to New Brunswick

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.3902395.
Very weak convergence in 6 iterations.
(likelihood cvg 1.364477e-005
gradient cvg 0.00157755
parameter cvg 0.000509382)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -9.36575 (-2 LogL = 18.7315).
Prediction error variance is 0.854476

Summary statistics

	LUK
Std.Error	0.92438
Normality	4.3871
H(6)	1.6610
r(1)	-0.10803
r(10)	0.060296
DW	1.7842
Q(10, 6)	4.3188
Rs^2	0.50063

Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.90724 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.10123 (0.1116)

NEWFOUNDLAND

Table 4.1.2aUK5: BSM result for tourist arrivals from UK to Newfoundland

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 6 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.1429795.
Very strong convergence in 3 iterations.
(likelihood cvg 6.806848e-009
gradient cvg 4.34255e-005
parameter cvg 1.423377e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 3.43151 (-2 LogL = -6.86301).
Prediction error variance is 0.227225

Summary statistics

	LUK
Std.Error	0.47668
Normality	6.2454
H(6)	0.11111
r(1)	0.029869
r(11)	-0.0039312
DW	1.3033
Q(11, 6)	9.9528
Rs^2	0.49238

Eq 5 : Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.25237 (1.0000)
Lvl	5.9205e-005 (0.0002)
Slp	4.4877e-007 (0.0000)
Sea	2.9867e-006 (0.0000)
Ar1	0.012558 (0.0498)

NORTHWEST TERRITORIES

Table 4.1.2aUK6: BSM result for tourist arrivals from UK to Northwest Territories

N/A

NOVA SCOTIA

Table 4.1.2aUK7: BSM result for tourist arrivals from UK to Nova Scotia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.5087601.
No estimation done.

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 12.2102 (-2 LogL = -24.4205).
Prediction error variance is 0.0747993

Summary statistics

	LUK
Std.Error	0.27349
Normality	1.0115
H(6)	0.16314
r(1)	0.068195
r(8)	0.071985
DW	1.5816
Q(8, 6)	3.0391
Rs^2	0.64141

Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.094076 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)

ONTARIO

Table 4.1.2aUK8: BSM result for tourist arrivals from UK to Ontario

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.67365.
Very strong convergence in 44 iterations.
(likelihood cvg 7.164227e-015
gradient cvg 3.555933e-007
parameter cvg 2.510568e-009)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 40.1676 (-2 LogL = -80.3352).
Prediction error variance is 0.00613365

Summary statistics

	LUK
Std.Error	0.078318
Normality	4.4282
H(6)	0.43621
r(1)	0.15669
r(10)	0.026434
DW	1.6453
Q(10, 6)	8.2489
Rs^2	-0.043537

Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00017769 (0.0278)
Sea	0.00000 (0.0000)
Ar1	0.0063879 (1.0000)

PRINCE EDWARD ISLAND

Table 4.1.2aUK9: BSM result for tourist arrivals from UK to Prince Edward Island

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.2820577.
Very strong convergence in 7 iterations.
(likelihood cvg 9.4391e-012
gradient cvg 1.479927e-008
parameter cvg 6.61464e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 6.76938 (-2 LogL = -13.5388).
Prediction error variance is 0.156442

Summary statistics

	LUK
Std.Error	0.39553
Normality	1.9836
H(6)	0.98835
r(1)	0.12431
r(8)	-0.28005
DW	1.6390
Q(8, 6)	14.381
Rs^2	0.37165

Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.15658 (1.0000)
Lvl	0.00000 (0.0000)
Sea	0.0017355 (0.0111)

QUEBEC

Table 4.1.2aUK10: BSM result for tourist arrivals from UK to Quebec

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.7046332.
Very strong convergence in 6 iterations.
(likelihood cvg 6.302417e-015
gradient cvg 3.330669e-010
parameter cvg 9.366538e-008)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 16.9112 (-2 LogL = -33.8224).
Prediction error variance is 0.053014

Summary statistics

	LUK
Std.Error	0.23025
Normality	4.5768
H(6)	0.48309
r(1)	-0.24485
r(8)	0.14817
DW	1.9895
Q(8, 6)	5.0236
Rs^2	0.17805

Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.013419 (0.6049)
Lvl	0.022183 (1.0000)
Sea	0.0010153 (0.0458)

SASKATCHEWAN

Table 4.1.2aUK11: BSM result for tourist arrivals from UK to Saskatchewan

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.1535327.
Very strong convergence in 6 iterations.
(likelihood cvg 3.610709e-012
gradient cvg 8.579248e-009
parameter cvg 1.663502e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 3.68479 (-2 LogL = -7.36957).
Prediction error variance is 0.224572

Summary statistics

	LUK
Std.Error	0.47389
Normality	2.8393
H(6)	2.9521
r(1)	0.042534
r(8)	0.34218
DW	1.4736
Q(8, 6)	10.425
Rs^2	0.28918

Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.21760 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.0030737 (0.0141)

YUKON

Table 4.1.2aUK12: BSM result for tourist arrivals from UK to Yukon

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUK = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -0.306122.
Very strong convergence in 5 iterations.
(likelihood cvg 9.68338e-014
gradient cvg 4.08007e-010
parameter cvg 7.251213e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -7.34693 (-2 LogL = 14.6939).
Prediction error variance is 0.86495

Summary statistics

	LUK
Std.Error	0.93003
Normality	1.0910
H(6)	1.8226
r(1)	-0.23203
r(8)	-0.15097
DW	2.2926
Q(8, 6)	9.0894
Rs^2	0.43149

Estimated variances of disturbances.

Component	LUK (q-ratio)
Irr	0.42337 (1.0000)
Lvl	0.053521 (0.1264)
Sea	0.040200 (0.0950)

BSM RESULTS FOR TOURIST ARRIVALS FROM USA TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.2aUSA1 - 4.1.2aUSA12

ALBERTA

Table 4.1.2aUSA1: BSM result for tourist arrivals from USA to Alberta

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 6 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.62288.
Very strong convergence in 15 iterations.
(likelihood cvg 3.859456e-012
gradient cvg 2.038394e-005
parameter cvg 1.096134e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 38.9491 (-2 LogL = -77.8982).
Prediction error variance is 0.0052936

Summary statistics

	LUSA
Std.Error	0.072757
Normality	1.7300
H(6)	2.4606
r(1)	-0.030439
r(11)	0.0072768
DW	1.8282
Q(11, 6)	8.2061
Rs^2	0.50131

Eq 8 : Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	5.7009e-006 (0.0009)
Lvl	0.00000 (0.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0063017 (1.0000)

BRITISH COLUMBIA

Table 4.1.2aUSA2: BSM result for tourist arrivals from USA to British Columbia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report
Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 2.140936.
Strong convergence in 24 iterations.
(likelihood cvg 3.536413e-011
gradient cvg 2.202105e-006
parameter cvg 2.830677e-005)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 51.3825 (-2 LogL = -102.765).
Prediction error variance is 0.00147181

Summary statistics

	LUSA
Std.Error	0.038364
Normality	1.1169
H(6)	0.51744
r(1)	0.098726
r(10)	-0.044113
DW	1.6542
Q(10, 6)	6.8894
Rs^2	0.35053

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0017536 (1.0000)

MANITOBA

Table 4.1.2aUSA3: BSM result for tourist arrivals from USA to Manitoba

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.871318.
Strong convergence in 100 iterations.
(likelihood cvg 8.065348e-010
gradient cvg 2.992347e-007
parameter cvg 0.0003911519)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 44.9116 (-2 LogL = -89.8232).
Prediction error variance is 0.00436858

Summary statistics

	LUSA
Std.Error	0.066095
Normality	0.49534
H(6)	2.8993
r(1)	-0.050435
r(10)	0.017764
DW	1.8564
Q(10, 6)	7.3302
Rs^2	0.012014

Eq 3 : Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.0021797 (1.0000)
Sea	0.00014308 (0.0656)
Ar1	7.6924e-007 (0.0004)

NEW BRUNSWICK

Table 4.1.2aUSA4: BSM result for tourist arrivals from USA to New Brunswick

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 6 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 2.56917.
Weak convergence in 100 iterations.
(likelihood cvg 4.052133e-009
gradient cvg 1.154296e-005
parameter cvg 7.377724e-005)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 61.6601 (-2 LogL = -123.32).
Prediction error variance is 0.000641652

Summary statistics

	LUSA
Std.Error	0.025331
Normality	0.24570
H(6)	0.31974
r(1)	-0.12554
r(11)	0.0030855
DW	1.8970
Q(11, 6)	8.8719
Rs^2	0.17712

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	1.8531e-005 (0.0437)
Lvl	1.4371e-007 (0.0003)
Slp	1.3147e-005 (0.0310)
Sea	0.00000 (0.0000)
Ar1	0.00042366 (1.0000)

NEWFOUNDLAND

Table 4.1.2aUSA5: BSM result for tourist arrivals from USA to Newfoundland

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.9827994.
Very weak convergence in 17 iterations.
(likelihood cvg 0.0003979417
gradient cvg 0.0007853723
parameter cvg 2.685881)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 23.5872 (-2 LogL = -47.1744).
Prediction error variance is 0.0435029

Summary statistics

	LUSA
Std.Error	0.20857
Normality	5.8787
H(6)	0.63075
r(1)	-0.0072369
r(10)	-0.12095
DW	1.8891
Q(10, 6)	6.8789
Rs^2	0.22693

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.00054744 (0.0378)
Slp	0.00014322 (0.0099)
Sea	0.0017864 (0.1232)
Ar1	0.014497 (1.0000)

NORTHWEST TERRITORIES

Table 4.1.2aUSA6: TVP result for tourist arrivals from USA to Northwest Territories

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is -1.103313.
Very strong convergence in 7 iterations.
(likelihood cvg 1.408769e-015
gradient cvg 7.993606e-010
parameter cvg 4.014524e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is -26.4795 (-2 LogL = 52.959).
Prediction error variance is 5.93245

Summary statistics

	LUSA
Std.Error	2.4357
Normality	1.4873
H(6)	1.2224
r(1)	-0.12224
r(8)	0.13554
DW	1.9786
Q(8, 6)	11.940
Rs^2	0.52450

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	6.6950 (1.0000)
Slp	0.00066799 (0.0001)
Sea	0.00000 (0.0000)

NOVA SCOTIA

Table 4.1.2aUSA6: BSM result for tourist arrivals from USA to Nova Scotia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.952504.
Very strong convergence in 15 iterations.
(likelihood cvg 1.706204e-011
gradient cvg 2.937772e-006
parameter cvg 6.3551e-008)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 22.8601 (-2 LogL = -45.7202).
Prediction error variance is 0.0147839

Summary statistics

	LUSA
Std.Error	0.12159
Normality	0.76357
H(6)	1.3619
r(1)	-0.032153
r(8)	-0.15923
DW	1.8586
Q(8, 6)	7.3170
Rs^2	0.62340

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.0029122 (1.0000)
Slp	0.00000 (0.0000)
Sea	0.0029107 (0.9995)

ONTARIO

Table 4.1.2aUSA8: BSM result for tourist arrivals from USA to Ontario

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.833278.
Very strong convergence in 21 iterations.
(likelihood cvg 2.781859e-012
gradient cvg 6.456835e-007
parameter cvg 3.967423e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 43.9987 (-2 LogL = -87.9973).
Prediction error variance is 0.00319703

Summary statistics

	LUSA
Std.Error	0.056542
Normality	3.1431
H(6)	0.14692
r(1)	0.089029
r(10)	-0.041883
DW	1.7011
Q(10, 6)	7.6494
Rs^2	0.36152

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0038092 (1.0000)

PRINCE EDWARD ISLAND

Table 4.1.2aUSA9: BSM result for tourist arrivals from USA to Prince Edward Island

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.6814166.
Very strong convergence in 93 iterations.
(likelihood cvg 1.082009e-012
gradient cvg 7.328083e-007
parameter cvg 3.24191e-009)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 16.354 (-2 LogL = -32.708).
Prediction error variance is 0.0571939

Summary statistics

	LUSA
Std.Error	0.23915
Normality	0.14938
H(6)	1.4715
r(1)	-0.094037
r(10)	0.079728
DW	2.0136
Q(10, 6)	17.382
Rs^2	0.48808

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.0099689 (0.1714)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.058176 (1.0000)

QUEBEC

Table 4.1.2aUSA10: BSM result for tourist arrivals from USA to Quebec

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 2.017611.
Very strong convergence in 7 iterations.
(likelihood cvg 2.201064e-015
gradient cvg 2.495781e-008
parameter cvg 2.16445e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 48.4227 (-2 LogL = -96.8453).
Prediction error variance is 0.00240528

Summary statistics

	LUSA
Std.Error	0.049044
Normality	3.7446
H(6)	0.63204
r(1)	-0.013403
r(10)	0.0056368
DW	1.8639
Q(10, 6)	10.089
Rs^2	0.015993

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.00036088 (0.1597)
Lvl	0.0022596 (1.0000)
Sea	0.00000 (0.0000)
Ar1	0.00000 (0.0000)

SASKATCHEWAN

Table 4.1.2aUSA11: BSM result for tourist arrivals from USA to Saskatchewan

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.480133.
Strong convergence in 100 iterations.
(likelihood cvg 5.557297e-010
gradient cvg 2.081607e-006
parameter cvg 0.0002036461)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 35.5232 (-2 LogL = -71.0464).
Prediction error variance is 0.0108119

Summary statistics

	LUSA
Std.Error	0.10398
Normality	2.3280
H(6)	1.3291
r(1)	-0.14315
r(10)	0.18091
DW	1.9423
Q(10, 6)	5.3817
Rs^2	0.48734

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.0038841 (1.0000)
Lvl	0.00057335 (0.1476)
Sea	0.00051439 (0.1324)
Ar1	0.00049630 (0.1278)

YUKON

Table 4.1.2aUSA12: BSM result for tourist arrivals from USA to Yukon

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LUSA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.852754.
Very strong convergence in 31 iterations.
(likelihood cvg 3.145949e-013
gradient cvg 2.794801e-007
parameter cvg 8.267016e-011)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 44.4661 (-2 LogL = -88.9322).
Prediction error variance is 0.00399484

Summary statistics

	LUSA
Std.Error	0.063205
Normality	0.77597
H(6)	1.1647
r(1)	-0.11234
r(10)	-0.11058
DW	2.0912
Q(10, 6)	6.2629
Rs^2	0.23613

Estimated variances of disturbances.

Component	LUSA (q-ratio)
Irr	0.0011754 (0.8407)
Slp	0.00000 (0.0000)
Sea	7.3689e-005 (0.0527)
Ar1	0.0013981 (1.0000)

BSM RESULTS FOR TOURIST ARRIVALS FROM EACH OF TOP 5 COUNTRIES TO CANADA

One year ahead

Table 4.1.2bF

Table 4.1.2bG

Table 4.1.2bJ

Table 4.1.2bUK

Table 4.1.2bUSA

FRANCE

Table 4.1.2bF: BSM result for tourist arrivals from France to Canada

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LALL FRANCE = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.335416.
Very strong convergence in 25 iterations.
(likelihood cvg 3.954623e-011
gradient cvg 5.536238e-007
parameter cvg 7.494824e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 32.05 (-2 LogL = -64.0999).
Prediction error variance is 0.017462

Summary statistics

	LALL FRANCE
Std.Error	0.13214
Normality	1.4233
H(6)	0.29617
r(1)	-0.073990
r(10)	-0.053097
DW	1.8280
Q(10, 6)	4.0861
Rs^2	0.081145

Estimated variances of disturbances.

Component	LALL FRANCE (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00021188 (0.0269)
Sea	0.00030408 (0.0385)
Ar1	0.0078892 (1.0000)

GERMANY

Table 4.1.2bG: BSM result for tourist arrivals from Germany to Canada

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LALL GERMANY = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.605957.
Very strong convergence in 71 iterations.
(likelihood cvg 4.38413e-011
gradient cvg 6.307103e-007
parameter cvg 9.379892e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 38.543 (-2 LogL = -77.0859).
Prediction error variance is 0.00927762

Summary statistics

	LALL GERMANY
Std.Error	0.096320
Normality	1.1736
H(6)	0.30487
r(1)	0.086591
r(10)	-0.014519
DW	1.6088
Q(10, 6)	6.0237
Rs^2	0.13938

Estimated variances of disturbances.

Component	LALL GERMANY (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00022708 (0.0682)
Sea	0.00027150 (0.0815)
Ar1	0.0033294 (1.0000)

JAPAN

Table 4.1.2bJ: BSM result for tourist arrivals from Japan to Canada

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LALL JAPAN = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.5294719.
Very weak convergence in 9 iterations.
(likelihood cvg 0.005898936
gradient cvg 0.004079875
parameter cvg 0.4181972)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 12.7073 (-2 LogL = -25.4146).
Prediction error variance is 0.103156

Summary statistics

	LALL JAPAN
Std.Error	0.32118
Normality	6.9046
H(6)	0.33301
r(1)	0.089620
r(10)	-0.050275
DW	1.8104
Q(10, 6)	13.158
Rs^2	0.019521

Estimated variances of disturbances.

Component	LALL JAPAN (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.11268 (1.0000)
Sea	0.00000 (0.0000)
Ar1	0.010450 (0.0927)

UK

Table 4.1.2bUK: BSM result for tourist arrivals from UK to Canada

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LALL UK = Trend + Trigo seasonal + Interv + Irregular

Estimation report

Model with 3 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.349103.
Very strong convergence in 4 iterations.
(likelihood cvg 4.982043e-013
gradient cvg 6.251666e-008
parameter cvg 2.427661e-008)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 32.3785 (-2 LogL = -64.757).
Prediction error variance is 0.0128685

Summary statistics

	LALL UK
Std.Error	0.11344
Normality	1.9300
H(6)	0.21971
r(1)	-0.14430
r(8)	0.11417
DW	1.8708
Q(8, 6)	2.8548
Rs^2	0.12627

Estimated variances of disturbances.

Component	LALL UK (q-ratio)
Irr	0.0053768 (1.0000)
Slp	0.00015275 (0.0284)
Sea	0.00032660 (0.0607)

USA

Table 4.1.2bUSA: BSM result for tourist arrivals from USA to Canada

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LALL USA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.977255.
Very strong convergence in 25 iterations.
(likelihood cvg 4.882778e-013
gradient cvg 4.520184e-006
parameter cvg 3.035918e-009)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 47.4541 (-2 LogL = -94.9083).
Prediction error variance is 0.00222406

Summary statistics

	LALL USA
Std.Error	0.047160
Normality	1.8588
H(6)	0.27900
r(1)	0.054028
r(10)	-0.025350
DW	1.6860
Q(10, 6)	7.3052
Rs^2	0.35341

Estimated variances of disturbances.

Component	LALL USA (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0026499 (1.0000)

BSM RESULTS FOR TOURIST ARRIVALS FROM TOTAL OF TOP 5 COUNTRIES TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.2c1 - 4.1.2c12

ALBERTA

Table 4.1.2c1: BSM result for total tourist arrivals from the total of the top five countries to Alberta

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD ALBERTA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.571753.
Very strong convergence in 19 iterations.
(likelihood cvg 8.864812e-013
gradient cvg 3.556488e-007
parameter cvg 4.292859e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 37.7221 (-2 LogL = -75.4442).
Prediction error variance is 0.00632189

Summary statistics

	LWHOLE WORLD
Std.Error	0.079510
Normality	1.6786
H(6)	1.6604
r(1)	0.0096450
r(10)	-0.18366
DW	1.8669
Q(10, 6)	13.825
Rs^2	0.27035

Estimated variances of disturbances.

Component	LWHOLE WORLD ALBERTA (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0075335 (1.0000)

BRITISH COLUMBIA

Table 4.1.2c2: BSM result for total tourist arrivals from the total of the top five countries to British Columbia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD BRIT COL = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (4 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 2.037895.
Very strong convergence in 19 iterations.
(likelihood cvg 3.46268e-013
gradient cvg 2.994982e-006
parameter cvg 4.337185e-008)

Eq 2 : Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 48.9095 (-2 LogL = -97.819).
Prediction error variance is 0.00192197

Summary statistics

	LWHOLE WORLD
Std.Error	0.043840
Normality	2.6342
H(6)	0.42801
r(1)	0.083935
r(10)	-0.021140
DW	1.8043
Q(10, 6)	10.469
Rs^2	0.32649

Eq 2 : Estimated variances of disturbances.

Component	LWHOLE WORLD BRIT COL (q-ratio)
Irr	0.00000 (0.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0022901 (1.0000)

MANITOBA

Table 4.1.2c3: BSM result for total tourist arrivals from the total of the top five countries to Manitoba

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD MANITOBA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.830546.
Very strong convergence in 33 iterations.
(likelihood cvg 3.200005e-012
gradient cvg 9.255115e-007
parameter cvg 8.606722e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 43.9331 (-2 LogL = -87.8662).
Prediction error variance is 0.00500988

Summary statistics

	LWHOLE WORLD
Std.Error	0.070781
Normality	1.7971
H(6)	3.0472
r(1)	-0.026340
r(10)	0.064941
DW	1.8488
Q(10, 6)	9.1904
Rs^2	0.097326

Eq 1 : Estimated variances of disturbances.

Component	LWHOLE WORLD MANITOBA (q-ratio)
Irr	0.00000 (0.0000)
Slp	2.9021e-005 (0.0133)
Sea	0.00013528 (0.0619)
Ar1	0.0021842 (1.0000)

NEW BRUNSWICK

Table 4.1.2c4: BSM result for total tourist arrivals from the total of the top five countries to New Brunswick

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD NEWBRUNSWICK = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 2.474696.
Very strong convergence in 31 iterations.
(likelihood cvg 3.70389e-013
gradient cvg 4.092267e-006
parameter cvg 2.663911e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 59.3927 (-2 LogL = -118.785).
Prediction error variance is 0.000749455

Summary statistics

	LWHOLE WORLD
Std.Error	0.027376
Normality	0.74332
H(6)	0.39334
r(1)	-0.23277
r(10)	0.14101
DW	1.8980
Q(10, 6)	10.297
Rs^2	0.18587

Estimated variances of disturbances.

Component	LWHOLE WORLD NEWBRUNSWICK (q-ratio)
Irr	1.6161e-008 (0.0000)
Lvl	0.00032138 (0.9163)
Sea	0.00000 (0.0000)
Ar1	0.00035075 (1.0000)

NEWFOUNDLAND

Table 4.1.2c5: BSM result for total tourist arrivals from the total of the top five countries to Newfoundland

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD NEWFOUNDLAND = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.918381.
Very strong convergence in 29 iterations.
(likelihood cvg 4.206943e-014
gradient cvg 1.122713e-007
parameter cvg 1.128449e-006)

Eq 34 : Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 22.0411 (-2 LogL = -44.0823).
Prediction error variance is 0.0525714

Summary statistics

	LWHOLE WORLD
Std.Error	0.22928
Normality	0.64899
H(6)	0.46627
r(1)	-0.10882
r(10)	-0.022181
DW	2.1064
Q(10, 6)	6.1775
Rs^2	0.22618

Eq 34 : Estimated variances of disturbances.

Component	LWHOLE WORLD NEWFOUNDLAND (q-ratio)
Irr	0.0075311 (1.0000)
Slp	0.0022546 (0.2994)
Sea	0.0015942 (0.2117)
Ar1	0.0014559 (0.1933)

NORTHWEST TERRITORIES

Table 4.1.2c6: BSM result for tourist arrivals from the total of the top five countries to Northwest Territories

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD NORTH TERR = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.4634245.
Very strong convergence in 27 iterations.
(likelihood cvg 7.839548e-012
gradient cvg 2.036815e-007
parameter cvg 9.611044e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 11.1222 (-2 LogL = -22.2444).
Prediction error variance is 0.110372

Summary statistics

	LWHOLE WORLD
Std.Error	0.33222
Normality	3.1189
H(6)	0.60807
r(1)	-0.027248
r(10)	-0.058110
DW	1.9592
Q(10, 6)	6.6763
Rs^2	0.45981

Estimated variances of disturbances.

Component	LWHOLE WORLD NORTH TERR (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.0043945 (0.0403)
Sea	0.00000 (0.0000)
Ar1	0.10915 (1.0000)

NOVA SCOTIA

Table 4.1.2c7: BSM result for tourist arrivals from the total of the top five countries to Nova Scotia

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD NOVA = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 6 parameters (5 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.212748.
Very strong convergence in 16 iterations.
(likelihood cvg 6.600471e-013
gradient cvg 2.413247e-006
parameter cvg 2.812978e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 29.106 (-2 LogL = -58.2119).
Prediction error variance is 0.0151185

Summary statistics

	LWHOLE WORLD
Std.Error	0.12296
Normality	1.4964
H(6)	1.7186
r(1)	0.0040018
r(11)	-0.095232
DW	1.8383
Q(11, 6)	16.401
Rs^2	0.42467

Estimated variances of disturbances.

Component	LWHOLE WORLD NOVA (q-ratio)
Irr	0.00000 (0.0000)
Lvl	0.00000 (0.0000)
Slp	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.018013 (1.0000)

ONTARIO

Table 4.1.2c8: BSM result for tourist arrivals from the total of the top five countries to Ontario

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD ONTARIO = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 4 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.817138.
Very strong convergence in 17 iterations.
(likelihood cvg 3.1536e-012
gradient cvg 1.279554e-006
parameter cvg 5.419677e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 43.6113 (-2 LogL = -87.2226).
Prediction error variance is 0.00333916

Summary statistics

	LWHOLE WORLD
Std.Error	0.057785
Normality	3.9771
H(6)	0.21639
r(1)	0.11630
r(9)	-0.10180
DW	1.7257
Q(9, 6)	7.2264
Rs^2	0.35005

Estimated variances of disturbances.

Component	LWHOLE WORLD ONTARIO (q-ratio)
Irr	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0039786 (1.0000)

PRINCE EDWARD ISLAND

Table 4.1.2c9: BSM result for tourist arrivals from the total of the top five countries to Prince Edward Island

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD PR ED ISL = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 0.8649878.
Very strong convergence in 13 iterations.
(likelihood cvg 1.183784e-012
gradient cvg 1.721512e-007
parameter cvg 2.339021e-011)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 20.7597 (-2 LogL = -41.5194).
Prediction error variance is 0.0359206

Summary statistics

	LWHOLE WORLD
Std.Error	0.18953
Normality	1.6025
H(6)	4.4989
r(1)	-0.096617
r(10)	-0.029827
DW	2.0651
Q(10, 6)	10.378
Rs^2	0.49844

Estimated variances of disturbances.

Component	LWHOLE WORLD PR ED ISL (q-ratio)
Irr	0.0020134 (0.0494)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.040786 (1.0000)

QUEBEC

Table 4.1.2c10: BSM result for tourist arrivals from the total of the top five countries to Quebec

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD QUEBEC = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.939901.
Very strong convergence in 8 iterations.
(likelihood cvg 7.214757e-012
gradient cvg 3.291245e-006
parameter cvg 3.532469e-007)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 46.5576 (-2 LogL = -93.1153).
Prediction error variance is 0.00245031

Summary statistics

	LWHOLE WORLD
Std.Error	0.049501
Normality	4.3883
H(6)	0.17687
r(1)	0.014961
r(10)	0.012640
DW	1.8815
Q(10, 6)	6.9141
Rs^2	0.32759

Estimated variances of disturbances.

Component	LWHOLE WORLD QUEBEC (q-ratio)
Irr	2.0721e-007 (0.0001)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0029193 (1.0000)

SASKATCHEWAN

Table 4.1.2c11: BSM result for tourist arrivals from the total of the top five countries to Saskatchewan

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD SASKAT = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (2 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.479292.
Very strong convergence in 20 iterations.
(likelihood cvg 1.735929e-012
gradient cvg 2.867928e-007
parameter cvg 2.093166e-009)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 35.503 (-2 LogL = -71.006).
Prediction error variance is 0.00864733

Summary statistics

	LWHOLE WORLD
Std.Error	0.092991
Normality	2.6675
H(6)	1.3418
r(1)	-0.10067
r(10)	0.093600
DW	1.8888
Q(10, 6)	4.1735
Rs^2	0.54538

Estimated variances of disturbances.

Component	LWHOLE WORLD SASKAT (q-ratio)
Irr	0.0068148 (1.0000)
Lvl	0.00026529 (0.0389)
Sea	0.00000 (0.0000)
Ar1	0.00081540 (0.1197)

YUKON

Table 4.1.2c12: BSM result for tourist arrivals from the total of the top five countries to Yukon

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LWHOLE WORLD YUKON = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (1 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.693243.
Very weak convergence in 6 iterations.
(likelihood cvg 0.0009836013
gradient cvg 0.003105008
parameter cvg 0.2681618)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 40.6378 (-2 LogL = -81.2757).
Prediction error variance is 0.00500075

Summary statistics

	LWHOLE WORLD
Std.Error	0.070716
Normality	6.6609
H(6)	0.19211
r(1)	0.11724
r(10)	0.063620
DW	1.7559
Q(10, 6)	7.8751
Rs^2	0.30373

Estimated variances of disturbances.

Component	LWHOLE WORLD YUKON (q-ratio)
Irr	0.0049581 (1.0000)
Slp	2.9932e-007 (0.0001)
Sea	6.1966e-007 (0.0001)
Ar1	0.00017747 (0.0358)

BSM RESULTS FOR TOURIST ARRIVALS FROM TOTAL OF TOP 5 COUNTRIES
CANADA

One year ahead

Table 4.1.2d

CANADA

Table 4.1.3d: TVP result for tourist arrivals from total of top five countries to Canada

Method of estimation is Maximum likelihood

The present sample is: 2000 (1) to 2005 (4)

LGRAND TOTAL = Trend + AR(1) + Trigo seasonal + Irregular

Estimation report

Model with 5 parameters (3 restrictions).
Parameter estimation sample is 2000. 1 - 2005. 4. (T = 24).
Log-likelihood kernel is 1.963741.
Very strong convergence in 27 iterations.
(likelihood cvg 1.641447e-011
gradient cvg 3.429979e-006
parameter cvg 8.353297e-006)

Diagnostic summary report.

Estimation sample is 2000. 1 - 2005. 4. (T = 24, n = 19).
Log-Likelihood is 47.1298 (-2 LogL = -94.2596).
Prediction error variance is 0.00230278

Summary statistics

	LGRAND TOTAL
Std.Error	0.047987
Normality	2.6197
H(6)	0.27156
r(1)	0.10154
r(10)	-0.058604
DW	1.7610
Q(10, 6)	7.4570
Rs^2	0.35626

Estimated variances of disturbances.

Component	LGRAND TOTAL (q-ratio)
Irr	1.4830e-007 (0.0001)
Lvl	0.00000 (0.0000)
Sea	0.00000 (0.0000)
Ar1	0.0027436 (1.0000)

APPENDIX II

Appendix to Chapter Four

TVP results

TVP RESULTS FOR TOURIST ARRIVALS FROM EACH OF THE TOP FIVE COUNTRIES TO EACH PROVINCE OF CANADA

TVP RESULTS FOR TOURIST ARRIVALS FROM FRANCE TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.3aF1 - 4.1.3aF12

ALBERTA

Table 4.1.3aF1: TVP result for tourist arrivals from France to Alberta

@signal LOG(FALVOL) = sv1*LOG(FHCE) + [var = exp(c(1))]

Sspace: SSFALDE6
Method: Maximum likelihood (Marquardt)
Date: 09/29/10 Time: 21:34
Sample: 1 24
Included observations: 24
Convergence achieved after 16 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.118954	NA	NA	NA
C(2)	-58.63224	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.423482	0.020116	70.76201	0.0000
Log likelihood	-30.94086	Akaike info criterion		2.745071
Parameters	2	Schwarz criterion		2.843242
Diffuse priors	1	Hannan-Quinn criter.		2.771116

Variables description:

FALVOL: volume of tourist arrivals from France to Alberta

FHCE: household consumption expenditure of France

BRITISH COLUMBIA

Table 4.1.3aF2: TVP result for tourist arrivals from France to British Columbia

@signal LOG(FBCVOL) = sv1*LOG(FPERIN) + sv2*LOG(FHCE) + sv3*LOG(BCRET) + [var = exp(c(1))]

Sspace: SSFBCDE2
Method: Maximum likelihood (Marquardt)
Date: 09/29/10 Time: 21:55
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 31 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.861035	NA	NA	NA
C(2)	-24.63177	NA	NA	NA
C(3)	-139.0396	NA	NA	NA
C(4)	-7.045756	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	-19.92111	9.514463	-2.093772	0.0363
SV2	21.37999	11.71991	1.824245	0.0681
SV3	4.035779	1.524199	2.647804	0.0081
Log likelihood	-44.79223	Akaike info criterion		4.066019
Parameters	4	Schwarz criterion		4.262361
Diffuse priors	3	Hannan-Quinn criter.		4.118109

Variables description:

FBCVOL: volume of tourist arrivals from France to British Columbia

FHCE: household consumption expenditure of France

BCRET: retail trade of British Columbia

MANITOBA

Table 4.1.3aF3: TVP result for tourist arrivals from France to Manitoba

@signal LOG(FMAVOL) = sv1*LOG(FPERIN) + [var = exp(c(1))]

Sspace: SSFMADE4
Method: Maximum likelihood (Marquardt)
Date: 09/30/10 Time: 08:44
Sample: 1 24
Included observations: 24
Convergence achieved after 26 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-3.133853	1.544680	-2.028804	0.0425
C(2)	-6.284226	0.605663	-10.37578	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.641669	0.047790	13.42689	0.0000

Log likelihood	-26.12803	Akaike info criterion	2.344003
Parameters	2	Schwarz criterion	2.442174
Diffuse priors	1	Hannan-Quinn criter.	2.370048

Variables description:

FMAVOL: volume of tourist arrivals from France to Manitoba

FPERIN: per capita income of France

NEW BRUNSWICK

Table 4.1.3aF4: TVP result for tourist arrivals from France to New Brunswick

@signal LOG(FNBVOL) = sv1*LOG(FGDP) + [var = exp(c(1))]

Sspace: SSFNBDE3
Method: Maximum likelihood (Marquardt)
Date: 09/30/10 Time: 09:50
Sample: 1 24
Included observations: 24
Convergence achieved after 33 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.564512	0.365419	-1.544836	0.1224
C(2)	-9.296305	5.073503	-1.832325	0.0669
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.101298	0.034836	31.61374	0.0000
Log likelihood	-37.69207	Akaike info criterion		3.307672
Parameters	2	Schwarz criterion		3.405843
Diffuse priors	1	Hannan-Quinn criter.		3.333717

Variables description:

FNBVOL: volume of tourist arrivals from France to New Brunswick

FGDP: GDP of France

NEWFOUNDLAND

Table 4.1.3aF5: TVP result for tourist arrivals from France to Newfoundland

@signal LOG(FNFVOL) = sv1*LOG(NFFOOD) + [var = exp(c(1))]

Sspace: SSFNFDE5
Method: Maximum likelihood (Marquardt)
Date: 09/30/10 Time: 17:13
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 23 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.832663	NA	NA	NA
C(2)	-597.0390	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.504785	0.011429	44.16726	0.0000

Log likelihood	-34.94194	Akaike info criterion	3.078495
Parameters	2	Schwarz criterion	3.176666
Diffuse priors	1	Hannan-Quinn criter.	3.104540

Variables description:

FNFVOL: volume of tourist arrivals from France to Newfoundland

NFFOOD: Total Food Services of Newfoundland

NORTHWEST TERRITORIES

Table 4.1.3aF6: TVP result for tourist arrivals from France to Northwest Territories

N/A

NOVA SCOTIA

Table 4.1.3aF7: TVP result for tourist arrivals from France to Nova Scotia

@signal LOG(FNSVOL) = sv1*LOG(NSFOOD) + [var = exp(c(1))]

Sspace: SSFNSDE7
Method: Maximum likelihood (Marquardt)
Date: 09/30/10 Time: 17:41
Sample: 1 24
Included observations: 24
Convergence achieved after 16 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-36.73561	NA	NA	NA
C(2)	-5.244066	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.514407	0.072655	7.080134	0.0000

Log likelihood	-40.75037	Akaike info criterion	3.562531
Parameters	2	Schwarz criterion	3.660702
Diffuse priors	1	Hannan-Quinn criter.	3.588576

Variables description:

FNSVOL: volume of tourist arrivals from France to Nova Scotia

NSFOOD: Total Food Services of Nova Scotia

ONTARIO

Table 4.1.3aF8: TVP result for tourist arrivals from France to Ontario

@signal LOG(FONVOL) = sv1*LOG(FPERIN) + sv2*LOG(ONBRY) + [var = exp(c(1))]

Sspace: SSFONDE3
Method: Maximum likelihood (Marquardt)
Date: 09/30/10 Time: 18:55
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 42 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-4.547450	0.737210	-6.168455	0.0000
C(2)	-25.81276	41967691	-6.15E-07	1.0000
C(3)	-7.901560	1.472311	-5.366772	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.619769	0.260332	2.380686	0.0173
SV2	0.702495	0.372645	1.885160	0.0594

Log likelihood	-11.18655	Akaike info criterion	1.182213
Parameters	3	Schwarz criterion	1.329470
Diffuse priors	2	Hannan-Quinn criter.	1.221280

Variables description:

FONVOL: volume of tourist arrivals from France to Ontario

FPERIN: France personal income per capita

ONBRY: Ontario number of bankruptcies

PRINCE EDWARD ISLAND

Table 4.1.3aF9: TVP result for tourist arrivals from France to Prince Edward Island

@signal LOG(FPRVOL) = sv1*LOG(FGDP) + [var = exp(c(1))]

Sspace: SSFPRDE3
Method: Maximum likelihood (Marquardt)
Date: 09/30/10 Time: 19:22
Sample: 1 24
Included observations: 24
Convergence achieved after 18 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-2.539534	0.272210	-9.329306	0.0000
C(2)	-11.37200	5.098032	-2.230664	0.0257
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.963540	0.012697	75.88808	0.0000

Log likelihood	-14.95511	Akaike info criterion	1.412926
Parameters	2	Schwarz criterion	1.511097
Diffuse priors	1	Hannan-Quinn criter.	1.438971

Variables description:

FPRVOL: volume of tourist arrivals from France to Prince Edward Island

FGDP: GDP of France

QUEBEC

Table 4.1.3aF10: TVP result for tourist arrivals from France to Quebec

@signal LOG(FQUVOL) = sv1*LOG(FPERIN) + [var = exp(c(1))]

Sspace: SSFQUDE6
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 09:03
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 18 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-5.074660	0.560093	-9.060388	0.0000
C(2)	-9.027997	0.540615	-16.69948	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.206906	0.013094	92.17264	0.0000

Log likelihood	1.820435	Akaike info criterion	0.014964
Parameters	2	Schwarz criterion	0.113135
Diffuse priors	1	Hannan-Quinn criter.	0.041009

Variables description:

FQUVOL: volume of tourist arrivals from France to Quebec

FPERIN: France personal income per capita

SASKATCHEWAN

Table 4.1.3aF11: TVP result for tourist arrivals from France to Saskatchewan

@signal LOG(FSAVOL) = sv1*LOG(FPERIN) + [var = exp(c(1))]

Sspace: SSFSADE8
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 09:45
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 46 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.189585	0.431044	-2.759775	0.0058
C(2)	-7.601818	1.530138	-4.968059	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.672129	0.040075	16.77190	0.0000

Log likelihood	-33.58117	Akaike info criterion	2.965098
Parameters	2	Schwarz criterion	3.063269
Diffuse priors	1	Hannan-Quinn criter.	2.991143

Variables description:

FSAVOL: volume of tourist arrivals from France to Saskatchewan

FPERIN: France personal income per capita

YUKON

Table 4.1.3aF12: TVP result for tourist arrivals from France to Yukon

@signal LOG(FYUVOL) = sv1*LOG(YUFOOD) + [var = exp(c(1))]

Sspace: SSFYUDE5
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 10:18
Sample: 1 24
Included observations: 24
Convergence achieved after 26 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.669236	0.365463	-4.567458	0.0000
C(2)	-7.721086	1.343685	-5.746201	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.690012	0.035104	19.65623	0.0000

Log likelihood	-28.94320	Akaike info criterion	2.578600
Parameters	2	Schwarz criterion	2.676771
Diffuse priors	1	Hannan-Quinn criter.	2.604645

Variables description:

FYUVOL: volume of tourist arrivals from France to Yukon

YUFOOD: Yukon total receipts of food services

TVP RESULTS FOR TOURIST ARRIVALS FROM GERMANY TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.3aG1 - 4.1.3aG12

ALBERTA

Table 4.1.3aG1: TVP result for tourist arrivals from Germany to Alberta

@signal LOG(GALVOL) = sv1*LOG(GPERIN) + [var = exp(c(1))]

Sspace: SSGALDE4
Method: Maximum likelihood (Marquardt)
Date: 09/19/10 Time: 15:32
Sample: 1 24
Included observations: 24
Convergence achieved after 31 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-3.739906	0.948354	-3.943577	0.0001
C(2)	-7.855686	0.839433	-9.358325	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.026018	0.024016	42.72164	0.0000
Log likelihood	-12.53844	Akaike info criterion		1.211536
Parameters	2	Schwarz criterion		1.309708
Diffuse priors	1	Hannan-Quinn criter.		1.237581

Variables description:

GALVOL: volume of tourist arrivals from Germany to Alberta

GPERIN: Germany personal income per capita

BRITISH COLUMBIA

Table 4.1.3aG2: TVP result for tourist arrivals from Germany to British Columbia

@signal LOG(GBCVOL) = sv1*LOG(GGDP) + [var = exp(c(1))]

Sspace: SSGBCDE5
Method: Maximum likelihood (Marquardt)
Date: 09/20/10 Time: 14:04
Sample: 1 24
Included observations: 24
Convergence achieved after 19 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-3.298114	0.357907	-9.215016	0.0000
C(2)	-8.302166	0.618355	-13.42621	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.513695	0.024355	62.15248	0.0000

Log likelihood	-10.85787	Akaike info criterion	1.071489
Parameters	2	Schwarz criterion	1.169661
Diffuse priors	1	Hannan-Quinn criter.	1.097534

Variables description:

GBCVOL: volume of tourist arrivals from Germany to British Columbia

GGDP: Germany GDP

MANITOBA

Table 4.1.3aG3: TVP result for tourist arrivals from Germany to Manitoba

@signal LOG(GMAVOL) = sv1*LOG(GHCE) + [var = exp(c(1))]

Sspace: SSGMADE7
Method: Maximum likelihood (Marquardt)
Date: 09/20/10 Time: 17:17
Sample: 1 24
Included observations: 24
Convergence achieved after 36 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.794663	0.695360	-2.580912	0.0099
C(2)	-6.727185	1.305717	-5.152101	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.208590	0.054442	22.19959	0.0000
Log likelihood	-27.80649	Akaike info criterion		2.483874
Parameters	2	Schwarz criterion		2.582046
Diffuse priors	1	Hannan-Quinn criter.		2.509919

Variables description:

GMAVOL: volume of tourist arrivals from Germany to Manitoba

GHCE: Germany household consumption expenditure

NEW BRUNSWICK

Table 4.1.3aG4: TVP result for tourist arrivals from Germany to New Brunswick

@signal LOG(GNBVOL) = sv1*LOG(GPERIN) + [var = exp(c(1))]

Sspace: SSGNBDE6
Method: Maximum likelihood (Marquardt)
Date: 09/22/10 Time: 20:41
Sample: 1 24
Included observations: 24
Convergence achieved after 31 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.493835	0.443391	-3.369113	0.0008
C(2)	-8.163748	1.428323	-5.715619	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.830977	0.031958	26.00248	0.0000

Log likelihood	-29.61054	Akaike info criterion	2.634212
Parameters	2	Schwarz criterion	2.732383
Diffuse priors	1	Hannan-Quinn criter.	2.660257

Variables description:

GNBVOL: volume of tourist arrivals from Germany to New Brunswick

GPERIN: Germany personal income per capita

NEWFOUNDLAND

Table 4.1.3aG5: TVP result for tourist arrivals from Germany to Newfoundland

@signal LOG(GNFVOL) = sv1*LOG(GNFTO) + [var = exp(c(1))]

Sspace: SSGNFDE5
Method: Maximum likelihood (Marquardt)
Date: 09/22/10   Time: 21:11
Sample: 1 24
Included observations: 24
Convergence achieved after 29 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.363463	0.684810	-1.991010	0.0465
C(2)	-7.516479	1.458719	-5.152794	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	-0.754231	0.040369	-18.68354	0.0000
Log likelihood	-32.34284	Akaike info criterion		2.861904
Parameters	2	Schwarz criterion		2.960075
Diffuse priors	1	Hannan-Quinn criter.		2.887948

Variables description:

GNFVOL: volume of tourist arrivals from Germany to Newfoundland

GNFTO: trade openness (between Germany and Newfoundland)

NORTHWEST TERRITORIES

Table 4.1.3aG6: TVP result for tourist arrivals from Germany to Northwest Territory

@signal LOG(GNWVOL) = sv1*LOG(GHCE) + [var = exp(c(1))]

Sspace: SSGNWDE4
Method: Maximum likelihood (Marquardt)
Date: 09/23/10 Time: 08:59
Sample: 1 24
Included observations: 24
Convergence achieved after 17 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.857319	NA	NA	NA
C(2)	-3532.957	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.966707	0.021579	44.79920	0.0000

Log likelihood	-34.01061	Akaike info criterion	3.000884
Parameters	2	Schwarz criterion	3.099055
Diffuse priors	1	Hannan-Quinn criter.	3.026929

Variables description:

GNWVOL: volume of tourist arrivals from Germany to Northwest Territory

GHCE: Germany household consumption expenditure

NOVA SCOTIA

Table 4.1.3aG7: TVP result for tourist arrivals from Germany to Nova Scotia

@signal LOG(GNSVOL) = sv1*LOG(NSRET) + sv2*LOG(NSFOOD) + [var = exp(c(1))]

Sspace: SSGNSDE2
Method: Maximum likelihood (Marquardt)
Date: 09/23/10 Time: 08:10
Sample: 1 24
Included observations: 24
Convergence achieved after 16 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.308411	NA	NA	NA
C(2)	-45.50855	NA	NA	NA
C(3)	-379.4661	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	-2.765546	1.629688	-1.696979	0.0897
SV2	3.958187	1.919247	2.062365	0.0392
Log likelihood	-46.94846	Akaike info criterion		4.162371
Parameters	3	Schwarz criterion		4.309628
Diffuse priors	2	Hannan-Quinn criter.		4.201439

Variables description:

GNSVOL: volume of tourist arrivals from Germany to Nova Scotia

NSRET: Nova Scotia retail sales

ALFOOD: Alberta total receipts of food services

ONTARIO

Table 4.1.3aG8: TVP result for tourist arrivals from Germany to Ontario

@signal LOG(GONVOL) = sv1*LOG(GONTO) + [var = exp(c(1))]

Sspace: SSGONDE11
Method: Maximum likelihood (Marquardt)
Date: 09/23/10 Time: 11:02
Sample: 1 24
Included observations: 24
Convergence achieved after 46 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-4.105580	0.861401	-4.766165	0.0000
C(2)	-7.031322	0.759362	-9.259517	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	-1.644500	0.034500	-47.66683	0.0000

Log likelihood	-11.12308	Akaike info criterion	1.093590
Parameters	2	Schwarz criterion	1.191761
Diffuse priors	1	Hannan-Quinn criter.	1.119635

Variables description:

GONVOL: volume of tourist arrivals from Germany to Ontario

GONTO: trade openness (between Germany and Ontario)

PRINCE EDWARD ISLAND

Table 4.1.3aG9: TVP result for tourist arrivals from Germany to Prince Edward Island

@signal LOG(GPRVOL) = sv1*LOG(GHCE) + sv2*LOG(GPROWNP) + [var = exp(c(1))]

Sspace: SSGPRGE2
Method: Maximum likelihood (Marquardt)
Date: 09/23/10 Time: 12:24
Sample: 1 24
Included observations: 24
Convergence achieved after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-49.86941	NA	NA	NA
C(2)	-3.746912	NA	NA	NA
C(3)	-26.59556	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.714750	0.334586	5.124989	0.0000
SV2	-9.909416	5.614414	-1.764996	0.0776

Log likelihood	-45.69098	Akaike info criterion	4.057582
Parameters	3	Schwarz criterion	4.204838
Diffuse priors	2	Hannan-Quinn criter.	4.096649

Variables description:

GONVOL: volume of tourist arrivals from Germany to Prince Edward Island

GHCE: Germany household consumption expenditure

GPROWNP:own price (between Germany to Prince Edward Island)

QUEBEC

Table 4.1.3aG10: TVP result for tourist arrivals from Germany to Quebec

@signal LOG(GQUVOL) = sv1*LOG(QUFOOD) + [var = exp(c(1))]

Sspace: SSGQUDE9
Method: Maximum likelihood (Marquardt)
Date: 09/23/10 Time: 11:28
Sample: 1 24
Included observations: 24
Convergence achieved after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-46.77104	NA	NA	NA
C(2)	-7.892821	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.673961	0.019324	34.87700	0.0000

Log likelihood	-13.79813	Akaike info criterion	1.316511
Parameters	2	Schwarz criterion	1.414682
Diffuse priors	1	Hannan-Quinn criter.	1.342556

Variables description:

GQUVOL: volume of tourist arrivals from Germany to Quebec

QUFOOD: Quebec total receipts of food services

SASKATCHEWAN

Table 4.1.3G11: TVP result for tourist arrivals from Germany to Saskatchewan

@signal LOG(GSAVOL) = sv1*LOG(SARET) + [var = exp(c(1))]

Sspace: SSGSA8
Method: Maximum likelihood (Marquardt)
Date: 09/19/10 Time: 14:47
Sample: 1 24
Included observations: 24
Convergence achieved after 28 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-35.58864	NA	NA	NA
C(2)	-6.070667	NA	NA	NA
	Final State	**Root MSE**	**z-Statistic**	**Prob.**
SV1	0.466239	0.048059	9.701451	0.0000
Log likelihood	-35.12365	Akaike info criterion		3.093637
Parameters	2	Schwarz criterion		3.191808
Diffuse priors	1	Hannan-Quinn criter.		3.119682

Variables description:

GQUVOL: volume of tourist arrivals from Germany to Saskatchewan

SARET: Saskatchewan retail sales

YUKON

Table 4.1.3aG12: TVP result for tourist arrivals from Germany to Yukon

@signal LOG(GYUVOL) = sv1*LOG(YUFOOD) + [var = exp(c(1))]

Sspace: SSGYUDE3
Method: Maximum likelihood (Marquardt)
Date: 09/19/10 Time: 13:36
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 18 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.174769	NA	NA	NA
C(2)	-48.05931	NA	NA	NA
	Final State	**Root MSE**	**z-Statistic**	**Prob.**
SV1	0.879924	0.012109	72.66504	0.0000

Log likelihood	-30.77878	Akaike info criterion	2.731565
Parameters	2	Schwarz criterion	2.829736
Diffuse priors	1	Hannan-Quinn criter.	2.757610

Variables description:

GYUVOL: volume of tourist arrivals from Germany to Yukon

QUFOOD: Yukon total receipts of food services

TVP RESULTS FOR TOURIST ARRIVALS FROM JAPAN TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.3aJ1 - 4.1.3aJ12

ALBERTA

Table 4.1.3aJ1: TVP result for tourist arrivals from Japan to Alberta

@signal LOG(JALVOL) = sv1*LOG(JALTO) + [var = exp(c(1))]

Sspace: SSJALDE7
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 11:53
Sample: 1 24
Included observations: 24
Convergence achieved after 15 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.767311	0.388597	-4.547930	0.0000
C(2)	-7.553889	0.895606	-8.434385	0.0000
	Final State	**Root MSE**	**z-Statistic**	**Prob.**
SV1	-1.063487	0.036015	-29.52929	0.0000

Log likelihood	-28.75368	Akaike info criterion	2.562806
Parameters	2	Schwarz criterion	2.660978
Diffuse priors	1	Hannan-Quinn criter.	2.588851

Variables description:

JALVOL: volume of tourist arrivals from Japan to Alberta

JALTO: trade openness (between Japan and Alberta)

BRITISH COLUMBIA

Table 4.1.3aJ2: TVP result for tourist arrivals from Japan to British Columbia

@signal LOG(JBCVOL) = sv1*LOG(JHCE) + [var = exp(c(1))]

Sspace: SSJBCDE7
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 13:00
Sample: 1 24
Included observations: 24
Convergence achieved after 11 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-33.77471	NA	NA	NA
C(2)	-6.910690	NA	NA	NA
	Final State	**Root MSE**	**z-Statistic**	**Prob.**
SV1	1.369010	0.031576	43.35546	0.0000
Log likelihood	-11.37250	Akaike info criterion		1.114375
Parameters	2	Schwarz criterion		1.212546
Diffuse priors	1	Hannan-Quinn criter.		1.140420

Variables description:

JBCVOL: volume of tourist arrivals from Japan to British Columbia

JHCE: Japan household consumption expenditure

MANITOBA

Table 4.1.3aJ3: TVP result for tourist arrivals from Japan to Manitoba

@signal LOG(JMAVOL) = sv1*LOG(JUNEMP) + [var = exp(c(1))]

Sspace: SSJMADE5
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 14:09
Sample: 1 24
Included observations: 24
Convergence achieved after 14 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.405191	0.410087	-0.988061	0.3231
C(2)	-3.988627	1.603042	-2.488161	0.0128
	Final State	Root MSE	z-Statistic	Prob.
SV1	4.892061	0.290362	16.84815	0.0000

Log likelihood	-39.73284	Akaike info criterion	3.477736
Parameters	2	Schwarz criterion	3.575907
Diffuse priors	1	Hannan-Quinn criter.	3.503781

Variables description:

JMAVOL: volume of tourist arrivals from Japan to Manitoba

GUNEMP: Germany unemployment rate

NEW BRUNSWICK

Table 4.1.3aJ4: TVP result for tourist arrivals from Japan to New Brunswick

@signal LOG(JNBVOL) = sv1*LOG(NBRET) + [var = exp(c(1))]

Sspace: SSJNBDE7
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 17:38
Sample: 1 24
Included observations: 24
Convergence achieved after 12 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-89.22970	NA	NA	NA
C(2)	-5.546159	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.411912	0.062469	6.593832	0.0000

Log likelihood	-40.81876	Akaike info criterion	3.568230
Parameters	2	Schwarz criterion	3.666401
Diffuse priors	1	Hannan-Quinn criter.	3.594275

Variables description:

JNBVOL: volume of tourist arrivals from Japan to New Brunswick

NBRET: New Brunswick retail sales

NEWFOUNDLAND

Table 4.1.3aJ5: TVP result for tourist arrivals from Japan to Newfoundland

N/A

NORTHWEST TERRITORIES

Table 4.1.3aJ6: TVP result for tourist arrivals from Japan to Northwest Territories

@signal LOG(JNWVOL) = sv1*LOG(JPERIN) + [var = exp(c(1))]

Sspace: SSJNWDE2
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 20:29
Sample: 1 24
Included observations: 24
Convergence achieved after 35 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-37.31728	NA	NA	NA
C(2)	-5.388510	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.663198	0.067593	9.811672	0.0000
Log likelihood	-35.60674	Akaike info criterion		3.133895
Parameters	2	Schwarz criterion		3.232066
Diffuse priors	1	Hannan-Quinn criter.		3.159940

Variables description:

JNWVOL: volume of tourist arrivals from Japan to Northwest Territories

JPERIN: Japan personal income per capita

NOVA SCOTIA

Table 4.1.3aJ7: TVP result for tourist arrivals from Japan to Nova Scotia

@signal LOG(JNSVOL) = sv1*LOG(NSBRY) + [var = exp(c(1))]

Sspace: SSJNSDE4
Method: Maximum likelihood (Marquardt)
Date: 10/01/10 Time: 20:48
Sample: 1 24
Included observations: 24
Convergence achieved after 95 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.450871	0.399405	-1.128855	0.2590
C(2)	-6.267333	1.367851	-4.581884	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.708766	0.096477	17.71173	0.0000
Log likelihood	-39.94892	Akaike info criterion		3.495744
Parameters	2	Schwarz criterion		3.593915
Diffuse priors	1	Hannan-Quinn criter.		3.521788

Variables description:

JNSVOL: volume of tourist arrivals from Japan to Nova Scotia

NSBRY: Nova Scotia number of bankruptcies

ONTARIO

Table 4.1.3aJ8: TVP result for tourist arrivals from Japan to Ontario

@signal LOG(JONVOL) = sv1*LOG(JPERIN) + sv2*LOG(JUNEMP) + sv3*LOG(JHCE) + [var = exp(c(1))]

Sspace: SSJONDE4
Method: Maximum likelihood (Marquardt)
Date: 10/02/10 Time: 21:12
Sample: 1 24
Included observations: 24
Convergence achieved after 12 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-83.67538	NA	NA	NA
C(2)	-6.649550	NA	NA	NA
C(3)	-45.27499	NA	NA	NA
C(4)	-134.7262	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	-13.40133	5.474174	-2.448102	0.0144
SV2	-5.887118	2.804507	-2.099163	0.0358
SV3	20.26851	7.253923	2.794145	0.0052

Log likelihood	-30.90845	Akaike info criterion	2.909038
Parameters	4	Schwarz criterion	3.105380
Diffuse priors	3	Hannan-Quinn criter.	2.961128

Variables description:

JONVOL: volume of tourist arrivals from Japan to Ontario

JPERIN: Japan personal income per capita

JUNEMP: Japan unemployment rate

JHCE:Japan household consumption expenditure

PRINCE EDWARD ISLAND

Table 4.1.3aJ9: TVP result for tourist arrivals from Japan to Prince Edward Island

@signal LOG(JPRVOL) = sv1*LOG(JPRTO) + [var = exp(c(1))]

Sspace: SSJPRDE4
Method: Maximum likelihood (Marquardt)
Date: 10/02/10 Time: 21:44
Sample: 1 24
Included observations: 24
Convergence achieved after 7 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-51.80708	NA	NA	NA
C(2)	-5.775440	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	-0.523424	0.055703	-9.396673	0.0000
Log likelihood	-39.03322	Akaike info criterion		3.419435
Parameters	2	Schwarz criterion		3.517606
Diffuse priors	1	Hannan-Quinn criter.		3.445480

Variables description:

JPRVOL: volume of tourist arrivals from Japan to Prince Edward Island

JPRTO: trade openness (between Japan and Prince Edward Island)

QUEBEC

Table 4.1.3aJ10: TVP result for tourist arrivals from Japan to Quebec

@signal LOG(JQUVOL) = sv1*LOG(JGDP) + [var = exp(c(1))]

Sspace: SSJQUDE7
Method: Maximum likelihood (Marquardt)
Date: 10/03/10 Time: 09:32
Sample: 1 24
Included observations: 24
Convergence achieved after 17 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.867731	NA	NA	NA
C(2)	-32493.76	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.064576	0.009198	115.7378	0.0000

Log likelihood	-22.73825	Akaike info criterion	2.061521
Parameters	2	Schwarz criterion	2.159692
Diffuse priors	1	Hannan-Quinn criter.	2.087566

Variables description:

JQUVOL: volume of tourist arrivals from Japan to Quebec

JGDP: Japan GDP

SASKATCHEWAN

Table 4.1.3aJ11: TVP result for tourist arrivals from Japan to Saskatchewan

@signal LOG(JSAVOL) = sv1*LOG(JGDP) + [var = exp(c(1))]

Sspace: SSJSADE6
Method: Maximum likelihood (Marquardt)
Date: 10/03/10 Time: 10:27
Sample: 1 24
Included observations: 24
Convergence achieved after 16 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.673909	NA	NA	NA
C(2)	-1138.704	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.781226	0.016708	46.75626	0.0000

Log likelihood	-36.46724	Akaike info criterion	3.205603
Parameters	2	Schwarz criterion	3.303774
Diffuse priors	1	Hannan-Quinn criter.	3.231648

Variables description:

JSAVOL: volume of tourist arrivals from Japan to Saskatchewan

JGDP: Japan GDP

YUKON

Table 4.1.3aJ12: TVP result for tourist arrivals from Japan to Yukon

@signal LOG(JYUVOL) = sv1*LOG(JPERIN) + [var = exp(c(1))]

Sspace: SSJYUDE6
Method: Maximum likelihood (Marquardt)
Date: 10/03/10 Time: 10:51
Sample: 1 24
Included observations: 24
Convergence achieved after 17 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.954951	0.399022	-2.393231	0.0167
C(2)	-9.549350	3.477110	-2.746347	0.0060
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.606420	0.022948	26.42530	0.0000

Log likelihood	-34.23315	Akaike info criterion	3.019429
Parameters	2	Schwarz criterion	3.117600
Diffuse priors	1	Hannan-Quinn criter.	3.045474

Variables description:

JYUVOL: volume of tourist arrivals from Japan to Yukon

JPERIN: Japan personal income per capita

TVP RESULTS FOR TOURIST ARRIVALS FROM UK TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.3aUK1 - 4.1.3aUK12

ALBERTA

Table 4.1.3aUK1: TVP result for tourist arrivals from UK to Alberta

@signal LOG(UKALVOL) = sv1*LOG(UKGDP) + [var = exp(c(1))]

Sspace: SSUKALDE1
Method: Maximum likelihood (Marquardt)
Date: 09/24/10   Time: 12:42
Sample: 1 24
Included observations: 24
Convergence achieved after 20 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.518311	NA	NA	NA
C(2)	-120.2835	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.663298	0.014813	112.2899	0.0000

Log likelihood	-26.45489	Akaike info criterion	2.371241
Parameters	2	Schwarz criterion	2.469412
Diffuse priors	1	Hannan-Quinn criter.	2.397286

Variables description:

UKALVOL: volume of tourist arrivals from UK to Alberta

UKGDP: UK GDP

BRITISH COLUMBIA

Table 4.1.3aUK2: TVP result for tourist arrivals from UK to British Columbia

@signal LOG(UKBCVOL) = sv1*LOG(BCFOOD) + [var = exp(c(1))]

Sspace: SSUKBCDE6
Method: Maximum likelihood (Marquardt)
Date: 09/24/10 Time: 15:53
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-69.28788	NA	NA	NA
C(2)	-8.811692	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.780722	0.012206	63.96331	0.0000
Log likelihood	-2.917327	Akaike info criterion		0.409777
Parameters	2	Schwarz criterion		0.507948
Diffuse priors	1	Hannan-Quinn criter.		0.435822

Variables description:

UKBCVOL: volume of tourist arrivals from UK to British Columbia

BCFOOD: British Columbia total receipts of food services

MANITOBA

Table 4.1.3aUK3: TVP result for tourist arrivals from UK to Manitoba

@signal LOG(UKMAVOL) = sv1*LOG(UKUNEMP) + sv2*LOG(MAFOOD) + [var = exp(c(1))]

Sspace: SSUKMADE1
Method: Maximum likelihood (Marquardt)
Date: 09/24/10 Time: 16:57
Sample: 1 24
Included observations: 24
Convergence achieved after 47 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-2.287376	0.436867	-5.235861	0.0000
C(2)	-6.311829	42.61145	-0.148125	0.8822
C(3)	-25.31035	1.25E+08	-2.03E-07	1.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	-3.550500	1.746377	-2.033065	0.0420
SV2	1.123246	0.218209	5.147578	0.0000

Log likelihood	-25.56029	Akaike info criterion	2.380024
Parameters	3	Schwarz criterion	2.527281
Diffuse priors	2	Hannan-Quinn criter.	2.419092

Variables description:

UKMAVOL: volume of tourist arrivals from UK to Manitoba

UKUNEMP: UK unemployment rate

MAFOOD: Manitoba total receipts of food services

NEW BRUNSWICK

Table 4.1.3aUK4: TVP result for tourist arrivals from UK to New Brunswick

@signal LOG(UKNBVOL) = sv1*LOG(UKPERIN) + sv2*LOG(UKNBTO) + [var = exp(c(1))]

Sspace: SSUKNBDE1
Method: Maximum likelihood (Marquardt)
Date: 09/24/10 Time: 17:18
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 27 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-1.002314	NA	NA	NA
C(2)	-54.34397	NA	NA	NA
C(3)	-9.743028	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.268419	0.149078	8.508413	0.0000
SV2	0.405825	0.158489	2.560593	0.0104

Log likelihood	-41.51246	Akaike info criterion	3.709371
Parameters	3	Schwarz criterion	3.856628
Diffuse priors	2	Hannan-Quinn criter.	3.748439

Variables description:

UKNBVOL: volume of tourist arrivals from UK to New Brunswick

UKPERIN: UK personal income per capita

UKFTO: trade openness (between UK and New Brunswick)

NEWFOUNDLAND

Table 4.1.3aUK5: TVP result for tourist arrivals from UK to Newfoundland

@signal LOG(UKNFVOL) = sv1*LOG(UKNFTO) + [var = exp(c(1))]

Sspace: SSUKNFDE5
Method: Maximum likelihood (Marquardt)
Date: 09/24/10 Time: 21:17
Sample: 1 24
Included observations: 24
Convergence achieved after 18 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-40.56809	NA	NA	NA
C(2)	-4.310233	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	-0.714910	0.115890	-6.168879	0.0000

Log likelihood	-44.23979	Akaike info criterion	3.853316
Parameters	2	Schwarz criterion	3.951487
Diffuse priors	1	Hannan-Quinn criter.	3.879361

Variables description:

UKNFVOL: volume of tourist arrivals from UK to Newfoundland

UKFTO: trade openness (between UK and New Brunswick)

NORTHWEST TERRITORIES

Table 4.1.3aUK6: TVP result for tourist arrivals from UK to Northwest Territories

N/A

NOVA SCOTIA

Table 4.1.3aUK7: TVP result for tourist arrivals from UK to Nova Scotia

@signal LOG(UKNSVOL) = sv1*LOG(UKPERIN) + [var = exp(c(1))]

Sspace: SSUKNSDE2
Method: Maximum likelihood (Marquardt)
Date: 09/27/10   Time: 11:21
Sample: 1 24
Included observations: 24
Convergence achieved after 10 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-40.09682	NA	NA	NA
C(2)	-5.986865	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.985330	0.050115	19.66134	0.0000

Log likelihood	-25.08240	Akaike info criterion	2.256866
Parameters	2	Schwarz criterion	2.355038
Diffuse priors	1	Hannan-Quinn criter.	2.282911

Variables description:

UKNSVOL: volume of tourist arrivals from UK to Nova Scotia

UKPERIN: UK personal income per capita

ONTARIO

Table 4.1.3aUK8: TVP result for tourist arrivals from UK to Ontario

@signal LOG(UKONVOL) = sv1*LOG(UKONTO) + sv2*LOG(ONFOOD) + [var = exp(c(1))]

Sspace: SSUKONDE5
Method: Maximum likelihood (Marquardt)
Date: 09/27/10 Time: 11:52
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-82.44332	NA	NA	NA
C(2)	-32.26667	NA	NA	NA
C(3)	-10.50654	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.004028	0.128733	0.031287	0.9750
SV2	0.763490	0.049423	15.44807	0.0000
Log likelihood	6.757126	Akaike info criterion		-0.313094
Parameters	3	Schwarz criterion		-0.165837
Diffuse priors	2	Hannan-Quinn criter.		-0.274027

Variables description:

UKONVOL: volume of tourist arrivals from UK to Ontario

ONFOOD: Ontario total receipts of food services

PRINCE EDWARD ISLAND

Table 4.1.3aUK9: TVP result for tourist arrivals from UK to Prince Edward Island

@signal LOG(UKPRVOL) = sv1*LOG(UKPERIN) + [var = exp(c(1))]

Sspace: SSUKPRDE3
Method: Maximum likelihood (Marquardt)
Date: 09/27/10 Time: 13:55
Sample: 1 24
Included observations: 24
Convergence achieved after 11 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-37.51106	NA	NA	NA
C(2)	-5.800713	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.817799	0.055004	14.86809	0.0000
Log likelihood	-27.22321	Akaike info criterion		2.435268
Parameters	2	Schwarz criterion		2.533439
Diffuse priors	1	Hannan-Quinn criter.		2.461313

Variables description:

UKPRVOL: volume of tourist arrivals from UK to Prince Edward Island

UKPERIN: UK personal income per capita

QUEBEC

Table 4.1.3aUK10: TVP result for tourist arrivals from UK to Quebec

@signal LOG(UKQUVOL) = sv1*LOG(UKQUTO) + [var = exp(c(1))]

Sspace: SSUKQUDE4
Method: Maximum likelihood (Marquardt)
Date: 09/27/10 Time: 14:29
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 32 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-3.049493	0.720029	-4.235238	0.0000
C(2)	-6.142956	1.054222	-5.827002	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	-1.743403	0.055396	-31.47166	0.0000
Log likelihood	-20.90362	Akaike info criterion		1.908635
Parameters	2	Schwarz criterion		2.006806
Diffuse priors	1	Hannan-Quinn criter.		1.934680

Variables description:

UKQUVOL: volume of tourist arrivals from UK to Quebec

UKQUTO: trade openness (between UK and Quebec)

SASKATCHEWAN

Table 4.1.3aUK11: TVP result for tourist arrivals from UK to Saskatchewan

@signal LOG(UKSAVOL) = sv1*LOG(UKUNEMP) + [var = exp(c(1))]

Sspace: SSUKSADE5
Method: Maximum likelihood (Marquardt)
Date: 09/27/10 Time: 16:21
Sample: 1 24
Included observations: 24
Convergence achieved after 35 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-2.103976	1.500348	-1.402325	0.1608
C(2)	-2.646619	1.257810	-2.104148	0.0354
	Final State	Root MSE	z-Statistic	Prob.
SV1	4.629519	0.320461	14.44644	0.0000

Log likelihood	-30.13699	Akaike info criterion	2.678083
Parameters	2	Schwarz criterion	2.776254
Diffuse priors	1	Hannan-Quinn criter.	2.704128

Variables description:

UKSAVOL: volume of tourist arrivals from UK to Saskatchewan

UKUNEMP: UK unemployment rate

YUKON

Table 4.1.3aUK12: TVP result for tourist arrivals from UK to Yukon

@signal LOG(UKYUVOL) = sv1*LOG(UKYUOWNP) + [var = exp(c(1))]

Sspace: SSUKYUDE4
Method: Maximum likelihood (Marquardt)
Date: 09/27/10 Time: 19:59
Sample: 1 24
Included observations: 24
Convergence achieved after 27 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.105624	0.556368	-0.189846	0.8494
C(2)	-1.908345	1.472765	-1.295756	0.1951
	Final State	Root MSE	z-Statistic	Prob.
SV1	9.342142	0.753921	12.39141	0.0000

Log likelihood	-43.11777	Akaike info criterion	3.759814
Parameters	2	Schwarz criterion	3.857985
Diffuse priors	1	Hannan-Quinn criter.	3.785859

Variables description:

UKYUVOL: volume of tourist arrivals from UK to Yukon

UKYUOWNP:own price (between UK and Yukon)

TVP RESULTS FOR TOURIST ARRIVALS FROM USA TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.3aUSA1 - 4.1.3aUSA12

ALBERTA

Table 4.1.3aUSA1: TVP result for tourist arrivals from USA to Alberta

@signal LOG(USAALVOL) = sv1*LOG(USAPERIN) + [var = exp(c(1))]

Sspace: SSUSAALDE2
Method: Maximum likelihood (Marquardt)
Date: 09/28/10 Time: 13:51
Sample: 1 24
Included observations: 24
Convergence achieved after 6 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-58.83608	NA	NA	NA
C(2)	-9.024532	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.152985	0.010974	105.0693	0.0000
Log likelihood	6.020589	Akaike info criterion		-0.335049
Parameters	2	Schwarz criterion		-0.236878
Diffuse priors	1	Hannan-Quinn criter.		-0.309004

Variables description:

USAALVOL: volume of tourist arrivals from USA to Alberta

USAPERIN: USA personal income per capita

BRITISH COLUMBIA

Table 4.1.3aUSA2: TVP result for tourist arrivals from USA to British Columbia

@signal LOG(USABCVOL) = sv1*LOG(BCRET) + [var = exp(c(1))]

Sspace: SSUSABCDE9
Method: Maximum likelihood (Marquardt)
Date: 09/28/10 Time: 12:56
Sample: 1 24
Included observations: 24
Convergence achieved after 17 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-51.63922	NA	NA	NA
C(2)	-9.829962	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.865815	0.007336	118.0251	0.0000

Log likelihood	5.734161	Akaike info criterion	-0.311180
Parameters	2	Schwarz criterion	-0.213009
Diffuse priors	1	Hannan-Quinn criter.	-0.285135

Variables description:

USABCVOL: volume of tourist arrivals from USA to British Columbia

BCRET: British Columbia retail sales

MANITOBA

Table 4.1.3aUSA3: TVP result for tourist arrivals from USA to Manitoba

@signal LOG(USAMAVOL) = sv1*LOG(USAPERIN) + [var = exp(c(1))]

Sspace: SSUSAMADE3
Method: Maximum likelihood (Marquardt)
Date: 09/28/10 Time: 14:06
Sample: 1 24
Included observations: 24
Convergence achieved after 21 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-62.40657	NA	NA	NA
C(2)	-9.783751	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.092399	0.007507	145.5110	0.0000

Log likelihood	14.74917	Akaike info criterion	-1.062430
Parameters	2	Schwarz criterion	-0.964259
Diffuse priors	1	Hannan-Quinn criter.	-1.036386

Variables description:

USAMAVOL: volume of tourist arrivals from USA to Manitoba

USAPERIN: USA personal income per capita

NEW BRUNSWICK

Table 4.1.3aUSA4: TVP result for tourist arrivals from USA to New Brunswick

@signal LOG(USANBVOL) = sv1*LOG(NBFOOD) + [var = exp(c(1))]

Sspace: SSUSANBDE5
Method: Maximum likelihood (Marquardt)
Date: 09/28/10 Time: 15:27
Sample: 1 24
Included observations: 24
Convergence achieved after 17 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-51.42565	NA	NA	NA
C(2)	-11.64130	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.058023	0.002966	356.7565	0.0000

Log likelihood	33.18729	Akaike info criterion	-2.598941
Parameters	2	Schwarz criterion	-2.500769
Diffuse priors	1	Hannan-Quinn criter.	-2.572896

Variables description:

USANBVOL: volume of tourist arrivals from USA to New Brunswick

NBFOOD: New Brunswick total receipts of food services

NEWFOUNDLAND

Table 4.1.3aUSA5: TVP result for tourist arrivals from USA to Newfoundland

@signal LOG(USANFVOL) = sv1*LOG(USAPERIN) + [var = exp(c(1))]

Sspace: SSUSANFDE2
Method: Maximum likelihood (Marquardt)
Date: 09/28/10 Time: 16:17
Sample: 1 24
Included observations: 24
Convergence achieved after 10 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-61.30031	NA	NA	NA
C(2)	-7.457167	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.907982	0.024027	37.79031	0.0000

Log likelihood	-12.00445	Akaike info criterion	1.167037
Parameters	2	Schwarz criterion	1.265208
Diffuse priors	1	Hannan-Quinn criter.	1.193082

Variables description:

USANFVOL: volume of tourist arrivals from USA to Newfoundland

USAPERIN: USA personal income per capita

NORTHWEST TERRITORIES

Table 4.1.3aUSA6: TVP result for tourist arrivals from USA to Northwest Territories

@signal LOG(USANWVOL) = sv1*LOG(USAPERIN) + [var = exp(c(1))]

Sspace: SSUSANWDE3
Method: Maximum likelihood (Marquardt)
Date: 09/28/10 Time: 21:08
Sample: 1 24
Included observations: 24
Convergence achieved after 18 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-56.39801	NA	NA	NA
C(2)	-4.684146	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.806149	0.096128	8.386192	0.0000
Log likelihood	-43.89452	Akaike info criterion		3.824544
Parameters	2	Schwarz criterion		3.922715
Diffuse priors	1	Hannan-Quinn criter.		3.850588

Variables description:

USANWVOL: volume of tourist arrivals from USA to Northwest Territories

USAPERIN: USA personal income per capita

NOVA SCOTIA

Table 4.1.3aUSA6: TVP result for tourist arrivals from USA to Nova Scotia

@signal LOG(USANSVOL) = sv1*LOG(USAPERIN) + [var = exp(c(1))]

Sspace: SSUSANSDE2
Method: Maximum likelihood (Marquardt)
Date: 09/28/10 Time: 16:36
Sample: 1 24
Included observations: 24
Convergence achieved after 16 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-62.46866	NA	NA	NA
C(2)	-7.791687	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.069283	0.020326	52.60607	0.0000

Log likelihood	-8.157305	Akaike info criterion	0.846442
Parameters	2	Schwarz criterion	0.944613
Diffuse priors	1	Hannan-Quinn criter.	0.872487

Variables description:

USANSVOL: volume of tourist arrivals from USA to Nova Scotia

USAPERIN: USA personal income per capita

ONTARIO

Table 4.1.3aUSA8: TVP result for tourist arrivals from USA to Ontario

@signal LOG(USAONVOL) = sv1*LOG(USAPERIN) + [var = exp(c(1))]

Sspace: SSUSAONDE4
Method: Maximum likelihood (Marquardt)
Date: 09/29/10 Time: 17:24
Sample: 1 24
Included observations: 24
Convergence achieved after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-60.44839	NA	NA	NA
C(2)	-9.846876	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.417878	0.007274	194.9220	0.0000

Log likelihood	15.47641	Akaike info criterion	-1.123034
Parameters	2	Schwarz criterion	-1.024863
Diffuse priors	1	Hannan-Quinn criter.	-1.096989

Variables description:

USAONVOL: volume of tourist arrivals from USA to Ontario

USAPERIN: USA personal income per capita

PRINCE EDWARD ISLAND

Table 4.1.3aUSA9: TVP result for tourist arrivals from USA to Prince Edward Island

@signal LOG(USAPRVOL) = sv1*LOG(USAGDP) + [var = exp(c(1))]

Sspace: SSUSAPRDE5
Method: Maximum likelihood (Marquardt)
Date: 09/29/10 Time: 17:51
Sample: 1 24
Included observations: 24
Convergence achieved after 10 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-42.48735	NA	NA	NA
C(2)	-6.693605	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.092891	0.035197	31.05094	0.0000
Log likelihood	-17.90686	Akaike info criterion		1.658905
Parameters	2	Schwarz criterion		1.757076
Diffuse priors	1	Hannan-Quinn criter.		1.684950

Variables description:

USAPRVOL: volume of tourist arrivals from USA to Prince Edward Island

USAGDP: USA GDP

QUEBEC

Table 4.1.3aUSA10: TVP result for tourist arrivals from USA to Quebec

@signal LOG(USAQUVOL) = sv1*LOG(QUFOOD) + [var = exp(c(1))]

Sspace: SSUSAQUDE7
Method: Maximum likelihood (Marquardt)
Date: 09/29/10 Time: 19:41
Sample: 1 24
Included observations: 24
Convergence achieved after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-46.06106	NA	NA	NA
C(2)	-11.15084	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.933663	0.003790	246.3564	0.0000

Log likelihood	23.66922	Akaike info criterion	-1.805768
Parameters	2	Schwarz criterion	-1.707597
Diffuse priors	1	Hannan-Quinn criter.	-1.779723

Variables description:

USAQUVOL: volume of tourist arrivals from USA to Quebec

QUFOOD: Quebec total receipts of food services

SASKATCHEWAN

Table 4.1.3aUSA11: TVP result for tourist arrivals from USA to Saskatchewan

@signal LOG(USASAVOL) = sv1*LOG(USAPERIN) + [var = exp(c(1))]

Sspace: SSUSASADE3
Method: Maximum likelihood (Marquardt)
Date: 09/29/10 Time: 20:46
Sample: 1 24
Included observations: 24
Convergence achieved after 10 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-58.74036	NA	NA	NA
C(2)	-8.470561	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.020268	0.014476	70.48120	0.0000
Log likelihood	-0.350502	Akaike info criterion		0.195875
Parameters	2	Schwarz criterion		0.294046
Diffuse priors	1	Hannan-Quinn criter.		0.221920

Variables description:

USASAVOL: volume of tourist arrivals from USA to Saskatchewan

USAPERIN: USA personal income per capita

YUKON

Table 4.1.3aUSA12: TVP result for tourist arrivals from USA to Yukon

@signal LOG(USAYUVOL) = sv1*LOG(USAPERIN) + sv2*LOG(YURET) + [var = exp(c(1))]

Sspace: SSUSAYUDE1
Method: Maximum likelihood (Marquardt)
Date: 09/29/10 Time: 20:54
Sample: 1 24
Included observations: 24
Convergence achieved after 20 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-5.772997	NA	NA	NA
C(2)	-84.38123	NA	NA	NA
C(3)	-12.27711	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.248722	0.108075	11.55423	0.0000
SV2	-0.186330	0.101057	-1.843800	0.0652

Log likelihood	9.486093	Akaike info criterion	-0.540508
Parameters	3	Schwarz criterion	-0.393251
Diffuse priors	2	Hannan-Quinn criter.	-0.501440

Variables description:

USAYUVOL: volume of tourist arrivals from USA to Yukon

USAPERIN: USA personal income per capita

YURET: Yukon retail sales

TVP RESULTS FOR TOURIST ARRIVALS FROM EACH OF TOP 5 COUNTRIES TO CANADA

One year ahead

Table 4.1.3bF

Table 4.1.3bG

Table 4.1.3bJ

Table 4.1.3bUK

Table 4.1.3bUSA

FRANCE

Table 4.1.3bF: TVP result for tourist arrivals from France to Canada

@signal LOG(TFVOL) = sv1*LOG(FPERIN) + [var = exp(c(1))]

Sspace: SSFCDE5
Method: Maximum likelihood (Marquardt)
Date: 10/08/10 Time: 10:28
Sample: 1 24
Included observations: 24
Convergence achieved after 18 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-5.316457	0.602781	-8.819883	0.0000
C(2)	-9.061650	0.475282	-19.06584	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.257702	0.012583	99.95101	0.0000

Log likelihood	3.288952	Akaike info criterion	-0.107413
Parameters	2	Schwarz criterion	-0.009242
Diffuse priors	1	Hannan-Quinn criter.	-0.081368

Variables description:

TFVOL: total volume of tourist arrivals from France to Canada

FPERIN: France personal income per capita

GERMANY

Table 4.1.3bG: TVP result for tourist arrivals from Germany to Canada

@signal LOG(TGVOL) = sv1*LOG(GHCE) + sv2*LOG(GCOWNP) + [var = exp(c(1))]

Sspace: SSGCDE2
Method: Maximum likelihood (Marquardt)
Date: 10/08/10 Time: 10:47
Sample: 1 24
Included observations: 24
Convergence achieved after 14 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-104.9913	NA	NA	NA
C(2)	-7.188049	NA	NA	NA
C(3)	-134.7782	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	2.045365	0.069931	29.24839	0.0000
SV2	-2.651933	1.059299	-2.503480	0.0123

Log likelihood	-7.785958	Akaike info criterion	0.898830
Parameters	3	Schwarz criterion	1.046087
Diffuse priors	2	Hannan-Quinn criter.	0.937897

Variables description:

TGVOL: total volume of tourist arrivals from Germany to Canada

GHCE: Germany household consumption expenditure

GCOWNP: own price (between Germany and Canada)

JAPAN

Table 4.1.3bJ: TVP result for tourist arrivals from Japan to Canada

@signal LOG(TJVOL) = sv1*LOG(JHCE) + [var = exp(c(1))]

Sspace: SSJCDE5
Method: Maximum likelihood (Marquardt)
Date: 10/08/10   Time: 11:25
Sample: 1 24
Included observations: 24
Convergence achieved after 10 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-34.63571	NA	NA	NA
C(2)	-6.541321	NA	NA	NA
	Final State	**Root MSE**	**z-Statistic**	**Prob.**
SV1	1.485380	0.037981	39.10817	0.0000
Log likelihood	-15.62094	Akaike info criterion		1.468412
Parameters	2	Schwarz criterion		1.566583
Diffuse priors	1	Hannan-Quinn criter.		1.494456

Variables description:

TJVOL: total volume of tourist arrivals from Japan to Canada

JHCE: Japan household consumption expenditure

UK

Table 4.1.3bUK: TVP result for tourist arrivals from UK to Canada

@signal LOG(TUKVOL) = sv1*LOG(UKCTO) + [var = exp(c(1))]

Sspace: SSUKCDE4
Method: Maximum likelihood (Marquardt)
Date: 10/08/10 Time: 11:42
Sample: 1 24
Included observations: 24
Convergence achieved after 17 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-3.483348	0.883936	-3.940724	0.0001
C(2)	-6.066897	0.906022	-6.696193	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	-2.531403	0.056728	-44.62369	0.0000
Log likelihood	-16.92415	Akaike info criterion		1.577013
Parameters	2	Schwarz criterion		1.675184
Diffuse priors	1	Hannan-Quinn criter.		1.603057

Variables description:

TUKVOL: total volume of tourist arrivals from UK to Canada

UKCTO: trade openness (between UK and British Canada)

USA

Table 4.1.3bUSA: TVP result for tourist arrivals from USA to Canada

@signal LOG(TUSVOL) = sv1*LOG(CANRET) + sv2*LOG(CANFOOD) + [var = exp(c(1))]

Sspace: SSUSCDE1
Method: Maximum likelihood (Marquardt)
Date: 10/08/10 Time: 11:55
Sample: 1 24
Included observations: 24
Convergence achieved after 11 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-162.0264	NA	NA	NA
C(2)	-11.29009	NA	NA	NA
C(3)	-69.71880	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	-0.172259	0.099419	-1.732651	0.0832
SV2	1.181078	0.113120	10.44090	0.0000

Log likelihood	11.14441	Akaike info criterion	-0.678701
Parameters	3	Schwarz criterion	-0.531444
Diffuse priors	2	Hannan-Quinn criter.	-0.639634

Variables description:

TFVOL: total volume of tourist arrivals from France to Canada

CANRET: Canada retail sales

CANFOOD: Canada total receipts of food services

TVP RESULTS FOR TOURIST ARRIVALS FROM TOTAL OF TOP 5 COUNTRIES TO EACH PROVINCE OF CANADA

One year ahead

Table 4.1.3c1 - 4.1.3c12

ALBERTA

Table 4.1.3c1: TVP result for total tourist arrivals from the total of the top five countries to Alberta

@signal LOG(T5ALVOL) = sv1*LOG(ALFOOD) + [var = exp(c(1))]

Sspace: SST5ALDE3
Method: Maximum likelihood (Marquardt)
Date: 10/03/10 Time: 18:00
Sample: 1 24
Included observations: 24
Convergence achieved after 11 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-83.35175	NA	NA	NA
C(2)	-9.558100	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.902656	0.008404	107.4082	0.0000

Log likelihood	6.158994	Akaike info criterion	-0.346583
Parameters	2	Schwarz criterion	-0.248412
Diffuse priors	1	Hannan-Quinn criter.	-0.320538

Variables description:

T5ALVOL: volume of tourist arrivals from the total of the top five countries to Alberta

ALFOOD: Alberta total receipts of food services

BRITISH COLUMBIA

Table 4.1.3c2: TVP result for total tourist arrivals from the total of the top five countries to British Columbia

@signal LOG(T5BCVOL) = sv1*LOG(BCRET) + [var = exp(c(1))]

Sspace: SST5BCDE7
Method: Maximum likelihood (Marquardt)
Date: 10/03/10 Time: 18:35
Sample: 1 24
Included observations: 24
Convergence achieved after 21 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-5.233692	0.585820	-8.933956	0.0000
C(2)	-11.38689	0.813136	-14.00367	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.874548	0.004661	187.6430	0.0000

Log likelihood	8.402103	Akaike info criterion	-0.533509
Parameters	2	Schwarz criterion	-0.435337
Diffuse priors	1	Hannan-Quinn criter.	-0.507464

Variables description:

T5BCVOL: volume of tourist arrivals from the total of the top five countries to British Columbia

BCRET: British Columbia retail sales

MANITOBA

Table 4.1.3c3: TVP result for total tourist arrivals from the total of the top five countries to Manitoba

@signal LOG(T5MAVOL) = sv1*LOG(MAFOOD) + [var = exp(c(1))]

Sspace: SST5MADE3
Method: Maximum likelihood (Marquardt)
Date: 10/03/10 Time: 19:03
Sample: 1 24
Included observations: 24
Convergence achieved after 16 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-6.285638	0.560018	-11.22399	0.0000
C(2)	-11.42968	0.871849	-13.10969	0.0000
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.948602	0.004241	223.6676	0.0000
Log likelihood	18.53995	Akaike info criterion		-1.378329
Parameters	2	Schwarz criterion		-1.280158
Diffuse priors	1	Hannan-Quinn criter.		-1.352284

Variables description:

T5MAVOL: volume of tourist arrivals from the total of the top five countries to Manitoba

MAFOOD: Manitoba total receipts of food services

NEW BRUNSWICK

Table 4.1.3c4: TVP result for total tourist arrivals from the total of the top five countries to New Brunswick

@signal LOG(T5NBVOL) = sv1*LOG(T5GDP) + sv2*LOG(T5NBOWNP) + sv3*LOG(NBFOOD) + [var = exp(c(1))]

Sspace: SST5NBDE2
Method: Maximum likelihood (Marquardt)
Date: 10/06/10 Time: 10:26
Sample: 1 24
Included observations: 24
Failure to improve Likelihood after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-52.72721	NA	NA	NA
C(2)	-40.93008	NA	NA	NA
C(3)	-13.23670	NA	NA	NA
C(4)	-11.87572	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.765713	0.231760	3.303898	0.0010
SV2	-0.555710	0.255502	-2.174977	0.0296
SV3	0.444838	0.186667	2.383053	0.0172
Log likelihood	20.13152	Akaike info criterion		-1.344293
Parameters	4	Schwarz criterion		-1.147951
Diffuse priors	3	Hannan-Quinn criter.		-1.292204

Variables description:

T5NBVOL: volume of tourist arrivals from the total of the top five countries to New Brunswick

T5GDP: total GDP of the top five countries

NBFOOD: New Brunswick total receipts of food services

NEWFOUNDLAND

Table 4.1.3c5: TVP result for total tourist arrivals from the total of the top five countries to Newfoundland

@signal LOG(T5NFVOL) = sv1*LOG(T5PERIN) + [var = exp(c(1))]

Sspace: SST5NFDE3
Method: Maximum likelihood (Marquardt)
Date: 10/06/10 Time: 12:53
Sample: 1 24
Included observations: 24
Convergence achieved after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-59.24080	NA	NA	NA
C(2)	-7.704594	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.853690	0.021231	40.20976	0.0000

Log likelihood	-11.09149	Akaike info criterion	1.090957
Parameters	2	Schwarz criterion	1.189128
Diffuse priors	1	Hannan-Quinn criter.	1.117002

Variables description:

T5NFVOL: volume of tourist arrivals from the total of the top five countries to Newfoundland

T5PERIN: total personal income per capita of the top five countries

NORTHWEST TERRITORIES

Table 4.1.3c6: TVP result for tourist arrivals from the total of the top five countries to Northwest Territories

@signal LOG(T5NWVOL) = sv1*LOG(T5PERIN) + [var = exp(c(1))]

Sspace: SST5NWDE3
Method: Maximum likelihood (Marquardt)
Date: 10/06/10 Time: 14:02
Sample: 1 24
Included observations: 24
Convergence achieved after 11 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-44.89419	NA	NA	NA
C(2)	-5.626242	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.781445	0.060017	13.02031	0.0000

Log likelihood	-34.99285	Akaike info criterion	3.082738
Parameters	2	Schwarz criterion	3.180909
Diffuse priors	1	Hannan-Quinn criter.	3.108783

Variables description:

T5NWVOL: volume of tourist arrivals from the total of the top five countries to Northwest Territories

T5PERIN: total personal income per capita of the top five countries

NOVA SCOTIA

Table 4.1.3c7: TVP result for tourist arrivals from the total of the top five countries to Nova Scotia

@signal LOG(T5NSVOL) = sv1*LOG(T5GDP) + [var = exp(c(1))]

Sspace: SST5NSDE2
Method: Maximum likelihood (Marquardt)
Date: 10/06/10 Time: 13:31
Sample: 1 24
Included observations: 24
Convergence achieved after 12 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-50.18430	NA	NA	NA
C(2)	-7.956839	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.169734	0.018715	62.50183	0.0000
Log likelihood	-4.404721	Akaike info criterion		0.533727
Parameters	2	Schwarz criterion		0.631898
Diffuse priors	1	Hannan-Quinn criter.		0.559772

Variables description:

USAALVOL: volume of tourist arrivals from the total of the top five countries to Nova Scotia

T5GDP: total GDP of the top five countries

ONTARIO

Table 4.1.3c8: TVP result for tourist arrivals from the total of the top five countries to Ontario

@signal LOG(T5ONVOL) = sv1*LOG(T5PERIN) + [var = exp(c(1))]

Sspace: SST5ONDE6
Method: Maximum likelihood (Marquardt)
Date: 10/06/10 Time: 15:54
Sample: 1 24
Included observations: 24
Convergence achieved after 10 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-55.27489	NA	NA	NA
C(2)	-10.00899	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.315510	0.006708	196.1188	0.0000
Log likelihood	15.40783	Akaike info criterion		-1.117319
Parameters	2	Schwarz criterion		-1.019148
Diffuse priors	1	Hannan-Quinn criter.		-1.091275

Variables description:

T5ONVOL: volume of tourist arrivals from the total of the top five countries to Ontario

T5PERIN: total personal income per capita of the top five countries

PRINCE EDWARD ISLAND

Table 4.1.3c9: TVP result for tourist arrivals from the total of the top five countries to Prince Edward Island

@signal LOG(T5PRVOL) = sv1*LOG(T5GDP) + [var = exp(c(1))]

Sspace: SST5PRDE3
Method: Maximum likelihood (Marquardt)
Date: 10/07/10 Time: 10:42
Sample: 1 24
Included observations: 24
Convergence achieved after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-49.14345	NA	NA	NA
C(2)	-6.961033	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.064862	0.030792	34.58297	0.0000

Log likelihood	-15.85759	Akaike info criterion	1.488132
Parameters	2	Schwarz criterion	1.586303
Diffuse priors	1	Hannan-Quinn criter.	1.514177

Variables description:

T5PRVOL: volume of tourist arrivals from the total of the top five countries to Prince Edward Island

T5GDP: total GDP of the top five countries

QUEBEC

Table 4.1.3c10: TVP result for tourist arrivals from the total of the top five countries to Quebec

@signal LOG(T5QUVOL) = sv1*LOG(T5GDP) + [var = exp(c(1))]

Sspace: SST5QUDE2
Method: Maximum likelihood (Marquardt)
Date: 10/07/10 Time: 11:35
Sample: 1 24
Included observations: 24
Convergence achieved after 11 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-50.48783	NA	NA	NA
C(2)	-10.28687	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	1.376217	0.005838	235.7505	0.0000
Log likelihood	22.39096	Akaike info criterion		-1.699247
Parameters	2	Schwarz criterion		-1.601076
Diffuse priors	1	Hannan-Quinn criter.		-1.673202

Variables description:

T5QUVOL: volume of tourist arrivals the total of the top five countries to Quebec

T5GDP: total GDP of the top five countries

SASKATCHEWAN

Table 4.1.3c11: TVP result for tourist arrivals from the total of the top five countries to Saskatchewan

@signal LOG(T5SAVOL) = sv1*LOG(T5SATO) + [var = exp(c(1))]

Sspace: SST5SADE3
Method: Maximum likelihood (Marquardt)
Date: 10/07/10 Time: 11:49
Sample: 1 24
Included observations: 24
Convergence achieved after 9 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-31.67152	NA	NA	NA
C(2)	-8.159939	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	-1.203075	0.016908	-71.15425	0.0000

Log likelihood	-0.777755	Akaike info criterion	0.231480
Parameters	2	Schwarz criterion	0.329651
Diffuse priors	1	Hannan-Quinn criter.	0.257524

Variables description:

T5SAVOL: volume of tourist arrivals from the total of the top five countries to Saskatchewan

T5SATO: trade openness (between the top five countries to Saskatchewan)

YUKON

Table 4.1.3c12: TVP result for tourist arrivals from the total of the top five countries to Yukon

@signal LOG(T5YUVOL) = sv1*LOG(YURET) + [var = exp(c(1))]

Sspace: SST5YUDE4
Method: Maximum likelihood (Marquardt)
Date: 10/06/10 Time: 14:46
Sample: 1 24
Included observations: 24
Convergence achieved after 23 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-44.92605	NA	NA	NA
C(2)	-8.021681	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.988616	0.018118	54.56489	0.0000
Log likelihood	-6.856145	Akaike info criterion		0.738012
Parameters	2	Schwarz criterion		0.836183
Diffuse priors	1	Hannan-Quinn criter.		0.764057

Variables description:

T5YUVOL: volume of tourist arrivals from the total of the top five countries to Yukon

YURET: Yukon retail sales

TVP RESULTS FOR TOURIST ARRIVALS FROM TOTAL OF TOP 5 COUNTRIES TO CANADA

One year ahead

Table 4.1.3d

CANADA

Table 4.1.3d: TVP result for tourist arrivals from total of top five countries to Canada

@signal LOG(T5CVOL) = sv1*LOG(CANRET) + [var = exp(c(1))]

Sspace: SST5CDE4
Method: Maximum likelihood (Marquardt)
Date: 10/08/10 Time: 12:47
Sample: 1 24
Included observations: 24
Convergence achieved after 11 iterations
WARNING: Singular covariance - coefficients are not unique

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-133.9215	NA	NA	NA
C(2)	-9.555284	NA	NA	NA
	Final State	Root MSE	z-Statistic	Prob.
SV1	0.869233	0.008416	103.2856	0.0000

Log likelihood	-0.218645	Akaike info criterion	0.184887
Parameters	2	Schwarz criterion	0.283058
Diffuse priors	1	Hannan-Quinn criter.	0.210932

Variables description:

T5cVOL: total volume of tourist arrivals from the top five counties to Canada

CANRET: Canada retail sales