

Identifying and Predicting Turning Points in Australian Inbound Tourism Demand Growth

By
Emmanuel Damian Fernando
BBus, MBA, MCIM, MACS

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**School of Economics and Finance
Faculty of Business and Law
Victoria University
Melbourne, Australia**

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Abstract

This study identifies the importance of forecasting turning points in tourism demand. Recognising the limitations of the current linear models in use, and the lack of adequate research in turning point prediction in tourism, the objective of this study is to forecast turning points in tourism demand accurately by applying non-linear models such as Logit, Probit and Markov Switching and the Leading Indicator approach.

The specific aim of this study is to forecast turning points in Australian inbound tourism demand growth caused by ‘economic factors’ within both the tourism-generating country and destination country (Australia). This objective of this study is achieved by establishing that Logit and Probit models can be used effectively in turning point forecasting of tourism demand.

To identify turning points in tourism demand growth, the parametric Markov switching model and the non-parametric Bry and Boschan method are used. To forecast turning points, three leading indicators and many economic variables are used together with the non-linear Logit and Probit models, and the non-parametric Bry and Boschan method. Of the economic variables used, this study identifies ‘price of tourism’ as significant in causing turning points in Australian tourism demand growth.

The time period of the study’s data is from 1975 Quarter 1 to 2007 Quarter 4, with four major tourism-generating countries to Australia, the USA, New Zealand, the UK and Japan being selected for the study.

Introducing non-linear models to the tourism economics literature, to identify and forecast turning points, together with the higher accuracy of the results of this study, are important contributions to turning point forecasting in tourism economics. As previous tourism studies have not used non-linear methods in turning point forecasting, this research is an important first step with immense research potential.

Declaration

“I, Emmanuel Damian Fernando, declare that the PhD thesis entitled *Identifying and Predicting Turning Points in Australian Inbound Tourism Demand Growth* is no more than 100,000 words in length, exclusive of tables, figures, appendices and references. 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 1

Introduction

1.1 Introduction

Tourism is seen as one of the significant engines of economic growth. As a result, it has become an important economic activity for developed and developing countries. The contribution of tourism to the global and national economies, in terms of national output, employment opportunities, foreign exchange earnings and exports, is significant. According to the World Travel and Tourism Council (WTTC), in 2007 the travel and tourism sector contributed 3.6% (US\$1,754.5 billion) of the world's Gross Domestic Product (GDP) and generated 234.3 million jobs (9% of total world employment). According to the Australian Bureau of Statistics (ABS) and Australian Tourism Satellite accounts, in 2006/07 tourism contributed A\$38.9 billion to Australia's GDP and A\$22.4 billion to export income. Further, the tourism sector has generated 482,800 employment opportunities, which is 4.7% of total employed persons during 2006/2007. Due to the continued growth of global tourism, and the economic importance of the tourism sector, there is a need to analyse and forecast tourism demand, because monitoring changes in demand is important in order to invest, plan and to develop an appropriate management strategy for governments and the tourism sector.

Tourism forecasting is an attempt to anticipate the future, and in many business endeavours its value lies in enabling operators to minimize losses due to disparities between demand and supply. Because of the importance of tourism in the worldwide economy and its perishable nature, accurate forecasting plays an important role in tourism planning and development.

National and international travel organisations, governments and tourism academics are currently putting considerable effort into generating accurate tourism forecasting models. The World Tourism Organization, the Australian Tourism Forecasting

Council, Tourism Australia and the Bureau of Tourism Research, are some of the organisations involved in producing tourism forecasts for the use of governments and the tourism sector.

Broadly categorised, most of the above organisations and academic researchers are mainly forecasting the number of tourist arrivals, and use common quantitative forecasting methods including time series models such as autoregressive and moving average methods, and econometric techniques including regression. These forecasting methods are often linear and they are often good at forecasting arrival numbers. The objective of this study is not to forecast the number of tourist arrivals but to forecast turning points in tourism demand growth.

1.2 The Research Problem

Inbound tourism demand growth goes through expansion and contraction periods, and these demand fluctuations are associated with increasing and decreasing demand. These demand fluctuations create turning points in tourism demand. The point where demand changes from contraction to expansion is referred to as a trough or upturn and the point where demand changes from expansion to contraction is referred to as a peak or downturn.

Tourism demand turning points can occur for a number of reasons, including changes in economic, social or political factors in the tourist origin or destination country, unexpected crises (terrorism, natural disaster, a widely spreading epidemic) and expected events (Olympics, Commonwealth Games). Irrespective of the reason, during expansion, resources are in high demand, while in contraction resources are in low demand. Monitoring such changes in demand (turning points) is important in order to invest, plan and to develop an appropriate management strategy to avoid financial and other risks. In order to pursue such a process the Australian Government and the tourism sector need an early prediction of turning points and the economic factors that contribute to generating turning points in tourism demand.

If the government and the various industries of the tourism sector, including airlines, tour operators, hotels and food suppliers, have prior knowledge of the beginning and

ending of turning points in tourism demand, they can benefit through more proactive resource allocation, investment and planning. In this context, an accurate forecasting of turning points is needed.

More specifically, accurate turning point prediction in tourism demand will assist policy makers, planners in public agencies, tourism business managers and tourism markets in the following three ways:

1. Tourism suppliers are interested in the demand for their products. Accurate forecasts of future turning points in tourism demand are crucial in all planning activities, as suppliers want to avoid the financial cost of excess capacity or the opportunity cost of unfilled demand.
2. At the macro-economic level, forecasting turning points in demand is important for investment in destination infrastructure, such as airports and highways, which require long-term commitments from public finances.
3. Government macro-economic policies depend largely on the relative importance of individual sectors within the economy. The accurate forecast of turning points in tourism demand will help governments in formulating and implementing effective medium and long-term development strategies in the tourism sector.

Currently, research into the forecasting of directional changes (positive or negative) in annual tourism demand generated by economic factors is focused upon the use of econometric and time series models (Witt and Witt (1989), Witt and Witt (1991) and Witt et al. (2003)). These studies suggest that econometric models outperform time series models in terms of directional change forecasting and that econometric models are capable of producing forecasts around turning points (Witt and Witt (1989)).

However, the problem associated with the limited past studies in tourism economics is that they use linear econometric and linear time series models in order to predict the turning points for demand growth, when the series are fundamentally non-linear. These models, and current research, have been unsuccessful in predicting turning

points in tourism growth, most likely because tourism demand growth is both volatile and non-linear.

Even in regard to macroeconomic cycles, Burns and Mitchell (1946) have pointed out non-linearity as a main concern when predicting turning points in economic cycles. Non-linearity refers to the fact that the behaviour of the series describing the cycle depends on the phase in which it evolves (contraction and expansion). The question is how to predict these movements accurately.

Current research also stresses the importance of forecasting turning points in tourism demand (Witt and Witt (1991) and Witt et al. (2003)). The Australian Government Tourism White Paper (2004) has emphasised the importance of forecasting in the tourism sector (www.tourismaustralia.com.au). More recently, Song and Li (2008) conducted a comprehensive analysis of past tourism forecasting studies, and highlighted the importance of turning point forecasting and the lack of research in this area.

Recognising both the importance of investment and planning needs of government and the tourism sector, and the inability of current linear econometric and time series methods to forecast turning points, it is evident that there is a need to develop more appropriate non-linear methods to predict turning points.

1.3 Objective of the Research

Having identified the importance of the early prediction of turning points in the highly volatile tourism sector and the drawbacks of existing linear methods, the objective of the proposed research is to develop accurate non-linear models to forecast turning points in Australian inbound tourism demand growth. Tourism demand can change due to a number of reasons, but one of the main causes for demand change is the dynamic nature of world economies. Further, the available literature in tourism economics has used economic variables/factors for demand forecasting and has identified both the influence and the importance of economic factors on tourism demand (Turner et al. (1997), Witt and Witt (1991), Song and Witt (2000), Song et al.

(2000), Turner and Witt (2001a) and Dwyer and Forsyth (1997)). Therefore, the specific aim of this study is to forecast turning points in tourism demand that are caused by 'economic factors' in the tourism-originating or destination country.

Identifying significant turning points is a prerequisite for predicting turning points. In tourism economics and other disciplines there is no commonly accepted definition or model to date/identify turning points. In the USA, the NBER chronology (National Bureau of Economic Research) for business cycle dating is available (Bry and Boschan (1971)), but no such process is available for most other countries to date cyclical turning points. Some countries use NBER-style procedures to date turning points based on their own coincident indices (defined by production, sales, employment and income data), (Marianne and Kouparitsas (2005)). The need for accurate dating of cycles continues to play an important role in efforts to determine the causes of contractions and expansions (Boldin (1994)). Therefore, this research places greater emphasis on dating /identifying turning points in tourism demand.

The business world relies heavily on leading indicators to date/identify as well as to predict both turning points and future values of economic variables (Marianne and Kouparitsas (2005)). In tourism economics, there are some applications of leading indicators for forecasting (The Bureau of Tourism Research Australia study (1995), Tourism Council of Australia and American Express Travel Related Service (1998), Turner et al. (1997), Kulendran and Witt (2003) and Rossello-Nadal (2001)). Hence, accurate leading indicators would be useful in identifying, predicting and comparing (with other methods) turning points in Australian inbound tourism demand.

Therefore, this research evaluates the usefulness of a number of economic indicators in forecasting turning points in tourism demand.

In summary, the main objectives of this research are to:

- Identify the most appropriate method to extract the smoothed quarterly tourism demand growth rate for each tourism origin market;

- Investigate different definitions, formulas and models to discover the most suitable method to identify significant turning points (dating) in Australian inbound tourism demand (to establish a chronology of the turning points in tourism demand);
- Construct a composite leading indicator to identify and predict turning points in Australian inbound tourism demand using economic indicators;
- Develop an accurate non-linear model or models to forecast turning points in Australian inbound tourism demand;
- Identify the economic indicators that determine the turning points in Australian inbound tourism demand growth;

It is important to mention, in the context of the business cycle and turning point studies, that there are some other extended study areas including amplitude or the depth of the turning points, span or the duration of the turning points, above the trend and below the trend turns, duration of expansion periods, contraction periods and negative /positive growth. These extended topics will not be examined in this study.

1.4 Tourism

Tourism relates to the leisure and business travel activities of visitors to a particular destination. The World Tourism Organization (WTO) defines tourists as people who travel to, and stay in places outside their usual environment for not more than one consecutive year for leisure, business and other purposes not related to the exercise of an activity remunerated from within the place visited. A tourist could be making a trip between two or more geographic locations, either in their country of residence (domestic travellers) or between countries (international travellers). The WTO classifies three forms of tourism: domestic tourism: comprised of residents of a given country travelling only within that country; inbound tourism: involving non-residents travelling to a given country; and outbound tourism: involving residents travelling to another country.

1.4.1 The Tourism Product

The tourism 'product' is a combination of components including accommodation, transport, entertainment, food and tourist attractions. Characteristics of the tourism product may include: (a) intangibility (b) perishability and (c) non homogeneity. Smith (1994) presented a useful model that describes the tourism product as consisting of five elements: the physical plant, service, hospitality, freedom of choice, and involvement.

1.4.2 The Tourism Sector

In reports, speeches, articles and general publications 'the tourism industry' is common language, but there is an ongoing debate in the literature regarding whether tourism constitutes an industry or a sector in its own right (Norbert (2005), p.9).

Tourism is part of the service sector and can be defined as "...the aggregate of all businesses that directly provides goods and services to facilitate business, pleasure and leisure activities away from the home environment" (Smith (1988)), The Australian Government Committee of Inquiry into Tourism (1987) has described the tourism sector as "not one discrete entity but a collection of inter-industry goods and services which constitute the travel experience".

According to TSA's (Tourism Satellite Accounts) definition, the term 'tourism' is not restricted to leisure activity. It also includes travel for business or other reasons, such as education, provided the destination is outside the person's usual environment (ABS 2009)

Because of the complex range of business activities within tourism, it has been categorised (Middleton (1988)) into the following sectors: (a) carriers and transportation companies, (b) accommodation providers, (c) attractions both 'permanent' (such as sites) and 'temporary' (such as events and festivals), (d) private sector support services, (e) public sector support services and (f) 'middlemen' such as tour wholesalers and travel agents.

1.4.3 International Inbound Tourism

Over the decades, international tourism has experienced continued growth and deepening diversification to become one of the fastest growing economic sectors in the world. Today, the business volume of tourism equals or even surpasses that of oil exports. Tourism has become one of the major players in food products and automobile and international commerce, and represents one of the main revenue earners for governments. This growth in tourism has produced new sources of income for many developing countries, increasing diversification and competition among destinations (WTO).

From 1950 to 2005, international tourism arrivals expanded at an annual rate of 6.5%, growing from 25 million to 806 million travellers. Worldwide arrivals reached 903 million in 2007, representing a 6.6% year on year growth. The year 2007 is the fourth consecutive year of sustained growth for the global tourism industry. Between 2004 and 2007, international tourism grew at an extraordinary above-average rate of 6% a year. By 2020, international arrivals are expected to surpass 1.5 billion people (WTO).

Though consumer confidence indices show an increasing degree of uncertainty due to economic imbalance, in particular rising energy prices, international tourism has a proven record of resilience in similar circumstances in the past, and has been able to cope with various types of shocks, including security threats, geopolitical tensions and natural and man-made crises. Overall, prospects for international tourism remain positive, and the UNWTO expects tourism demand to grow, but at a slower pace in the short-term. International tourism is yet expected to keep growing at a solid pace in the medium-term, broadly in line with UNWTO's Tourism 2020 Vision, which forecasts long-term growth of about 4%.

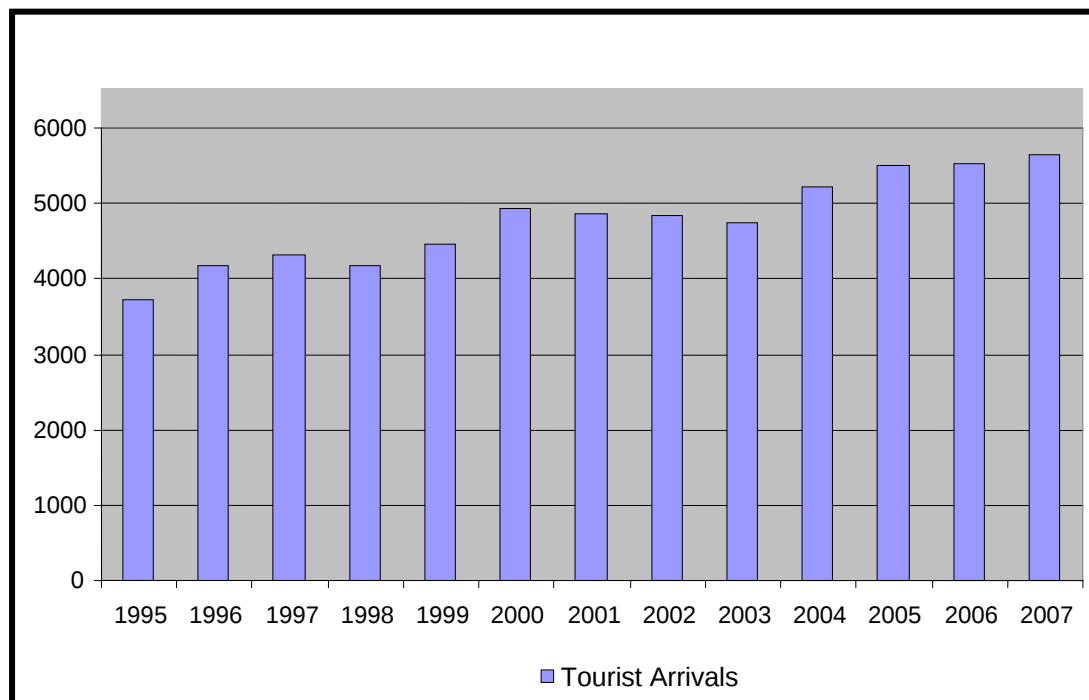
The top ten international inbound tourism destinations in 2007 were France, Spain, the USA, China, Italy, the UK, Germany, Ukraine, Turkey and Mexico listed in decreasing order of number of arrivals. According to the number of tourist arrivals during 2007, the top ten countries share 46% of world inbound tourism, Australia is

ranked 40th in the world destination ranking, and only attracts 0.56% of the international market (WTO).

1.5 Australian Inbound Tourism

Australian Bureau of Statistics (ABS) data reveal that Australia has experienced a steady growth in international visitor arrivals from 1995 to 2007; in 2007, there were over 5.6 million short-term international visitor arrivals to Australia. Figure 1.1 displays arrivals from 1995 to 2007.

Figure 1.1 Australian Inbound Tourist Arrivals 1995-2007 ('000)



Source: <http://www.tourism.australia.com/Research.asp>

In 2001 and 2003 tourist arrivals were comparatively low when the global tourism sector experienced the most severe setbacks from a set of events including the September 11 twin tower attack (2001) and SARS (2003).

In order to gain a better idea about tourism demand fluctuations the tourism demand growth rate provides a clearer picture than arrival numbers, as it shows the direction

and the fluctuation of tourism demand. Table 1.1 presents Australian total tourist arrivals and yearly growth rates from 1982 to 2007.

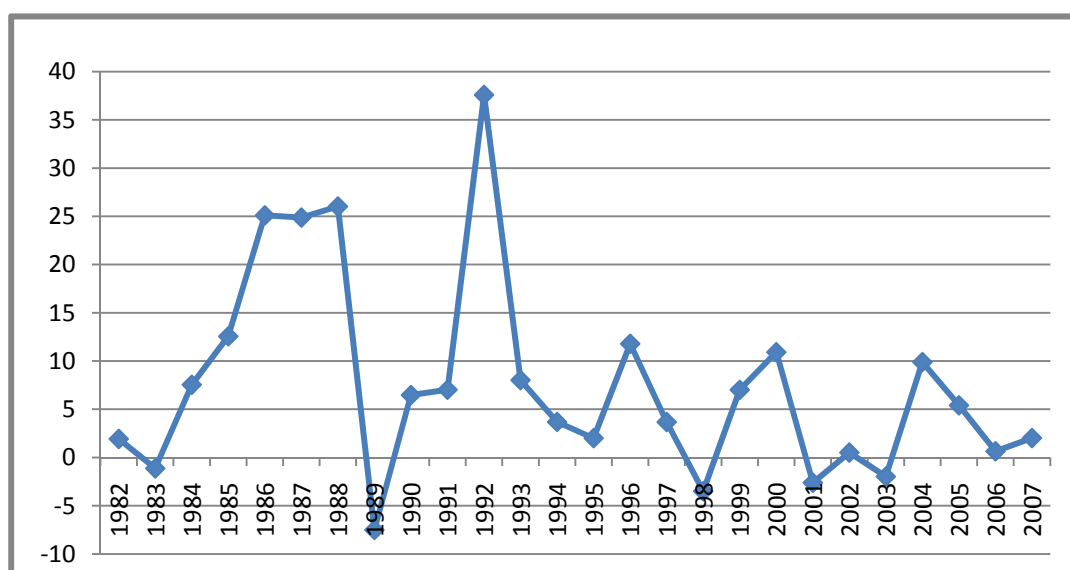
Table 1.1 Total International Visitor Arrivals to Australia from 1982 to 2007

Year	Total Tourist Arrivals	Growth Rate %	Year	Total Tourist Arrivals	Growth Rate %
1982	954700	1.922	1995	3726000	2.004
1983	943900	-1.131	1996	4165000	11.782
1984	1015100	7.543	1997	4318000	3.673
1985	1142600	12.560	1998	4167210	-3.492
1986	1429400	25.101	1999	4459500	7.014
1987	1784900	24.871	2000	4946196	10.914
1988	2249300	26.018	2001	4816800	-2.616
1989	2080300	-7.513	2002	4841400	0.511
1990	2214900	6.470	2003	4745800	-1.975
1991	2370400	7.021	2004	5215100	9.889
1992	3261400	37.589	2005	5497000	5.405
1993	3523000	8.021	2006	5532400	0.644
1994	3652800	3.684	2007	5644100	2.019

Source: <http://www.tourism.australia.com/Research.asp>

Figure 1.2 graphically presents the arrivals growth pattern from Table 1.1

Figure 1.2 Australian Tourist Arrivals Growth from 1982 to 2007



From Table 1.1 and Figure 1.2 it can be seen that Australia has experienced an increase in visitor arrivals over the years. In particular, international visitor numbers commenced a rapid growth in the mid-80s. Between 1975 and 1984, the average growth was 7% per annum. However, Table 1.1 and Figure 1.2 show that in 1985 the growth was 13%, and that international visitor arrivals in Australia grew on average around 25% each year for the three years 1986 to 1988 (see Table 1.1). In 1986 growth was 25.1% and the highest among all OECD countries, which had an average of 3 % (Faulkner and Walmsley (1998)).

Several changes in the mid-80s have been suggested as determinants of the sharp rise in Australia's inbound tourism arrivals during 1984 to 1988. They include the floating of the Australian dollar in 1983 and the devaluation of the Australian dollar through the mid-80s relative to the US dollar, and the trade-weighted index, which made Australian products much cheaper on the world market. Other factors include a strong advertising campaign developed by the Australian Tourist Commission (ATC), sporting events, increased awareness of Australia through films and music, the Expo and the Bicentennial impact on the 1988 increase. In 1989, Australia had a very low growth rate in the aftermath of the increased drawing power of Expo and the Bicentennial of the previous year.

The pilots' strike in 1989, the global contraction in 1990 and 1991 and the gulf war in early 1991 affected the number of tourist arrivals to Australia from the UK, the USA and Japan. After 1992, with economic recovery, travel to Australia gradually increased from the UK, the USA, Japan and New Zealand.

However, growth again dropped in 1998 (-3.5%) due to the Southeast Asian economic crisis, but this decline was countered by an increase in Western travellers in 1999 (7%). In 2000, there was a high growth of 10.9% leveraged by the Sydney Olympics.

From 2001, annual tourism visitor arrivals experienced a negative growth; in 2001 (-2.61%) in 2002 (0.51%), and in 2003 (-1.97%), as an immediate effect of the September 11 attack followed by the Iraq war, SARS and the deterioration of price competitiveness in the Australian tourism sector, due to the introduction of the GST.

From 2004 to 2007, Australian inbound tourism growth increased more slowly, as a result of the continuing Iraq and Afghanistan war, uncertainties in most of the global economies resulting in reluctance to travel, soaring fuel prices together with higher airfares, the strong Australian dollar and global inflation.

Though Australian inbound tourism experienced ups and downs, during 1982 to 2007 the international tourism sector grew significantly, overall by 400%. This growth is almost three times higher than the growth in global tourism (at 140%) for the same period.

1.5.1 Source Countries of Inbound Tourism to Australia

Having analysed the ups and downs of inbound tourism growth, this section will look at the main source countries that generate tourists to Australia and shifts in demand over the past 13 years in these markets.

Table 1.2 Top Ten Tourist-Originating Countries to Australia from 1995 to 2007 ('000)

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
New Zealand	538	672	686	709	729	817	815	790	839	1033	1098	1075	1138
UK	348	368	411	468	528	580	617	643	673	676	708	734	688
Japan	783	813	814	751	707	721	674	715	628	710	685	650	573
USA	305	317	330	374	417	488	446	434	422	433	446	456	459
Singapore	202	223	239	247	267	286	296	287	253	251	265	253	263
S.Korea	168	228	234	67	109	157	176	190	207	212	250	260	253
China	43	54	66	77	93	120	158	190	176	251	285	308	357
Malaysia	108	134	144	112	140	152	149	159	156	167	165	150	159
Germany	124	125	129	127	145	143	148	135	138	141	146	148	151
Hong Kong	132	153	152	143	140	154	154	151	129	137	159	154	147
Top 10 Total	2751	3087	3205	3075	3275	3618	3633	3694	3621	4011	4207	4188	4188
% of Top 10	73.8	74.1	74.2	73.8	73.4	73.4	74.8	76.3	76.3	76.9	76.53	75.7	74.2

Source: Tourism Research Australia (2007), *International Visitors in Australia*

<http://www.tourism.australia.com/Research.asp>

The main visitor source countries, in decreasing order of total arrivals to Australia for the years 1995 to 2007, are shown in Table 1.2. In terms of arrivals, in year 2007 the top ten markets account for 74.2% of all arrivals to Australia. New Zealand is the number one source of international visitors to Australia contributing 20.1% to total arrivals in 2007. After New Zealand, the United Kingdom, Japan and the United States are the top tourist-generating countries to Australia. Of these countries, New Zealand and the United Kingdom have the highest average annual growth of 111.2% and 97.7 %, respectively, in 2007 compared to 1995, while the Japanese market has been in steady decline (26.81% decline in 2007 compared to 1995) and the United States has been slow but consistent (50 % average annual growth compared to 1995).

While some traditional markets declined, an important shift is the strong growth of Asian tourism to Australia. The inbound tourism figures show a rapid increase in tourist arrivals from China, South Korea, Singapore, Hong Kong, Malaysia, Indonesia and Taiwan. Some of the important drivers for this growth relate to the Chinese ADS scheme (Approved Destination Status) and the lifting of Taiwan's travel restrictions in 1979 and South Korea's in 1989.

The most significant shift is the high growth in visitor numbers from the Chinese market, which has grown by 730.2% in 2007 compared to 1995. Due to the enormous size of the Chinese population, this market has huge potential for the Australian inbound tourism sector. The other important and emerging market is South Korea with 50% growth from 1995, while Singapore, Malaysia, Germany and Hong Kong have been growing slowly but consistently since 1995.

1.5.2 Top Four Tourist-Originating Countries

As discussed earlier, the major tourist-generating countries for Australia are New Zealand, Japan, the USA and the UK. Table 1.3 and Figure 1.3 show that these four countries have been consistently responsible for more than 50% of the total Australian inbound tourism arrivals market. In 2007 the contribution of these four countries was 50.63%. According to the 2007 tourist arrivals statistics (Table 1.3), New Zealand accounted for 20.1% of total tourist arrivals, the UK 12.18%, Japan 10.15%, and the

USA 8.13%. Table 1.3 displays the consistent contribution of these four countries from 1995 to 2007, and Figure 1.3 displays the arrivals patterns of the four countries.

Table 1.3 Arrivals from Top Four Tourist-Originating Countries from 1995 to 2007 ('000)

YEAR	TOTAL TOURIST ARRIVALS ('000)	FROM TOP 4 COUNTRIES ('000)	% OF TOP 4 COUNTRIES
1995	3726	1971	52.90
1996	4165	2167	52.03
1997	4318	2238	51.83
1998	4167	2300	55.20
1999	4459	2380	53.38
2000	4931	2606	52.85
2001	4856	2550	52.51
2002	4839	2581	53.34
2003	4745	2561	53.97
2004	5215	2851	54.67
2005	5497	2937	53.43
2006	5532	2917	52.73
2007	5644	2858	50.63

Source: <http://www.tourism.australia.com/Research.asp>

Figure 1.3 Top Four Countries' Tourist Arrivals from 1995 to 2007 ('000)

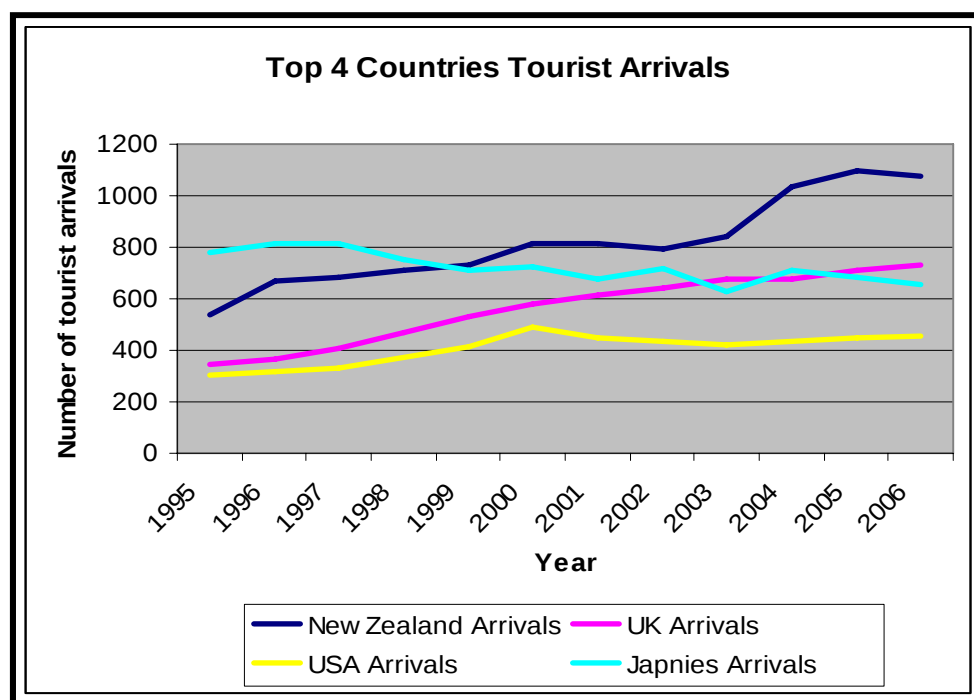


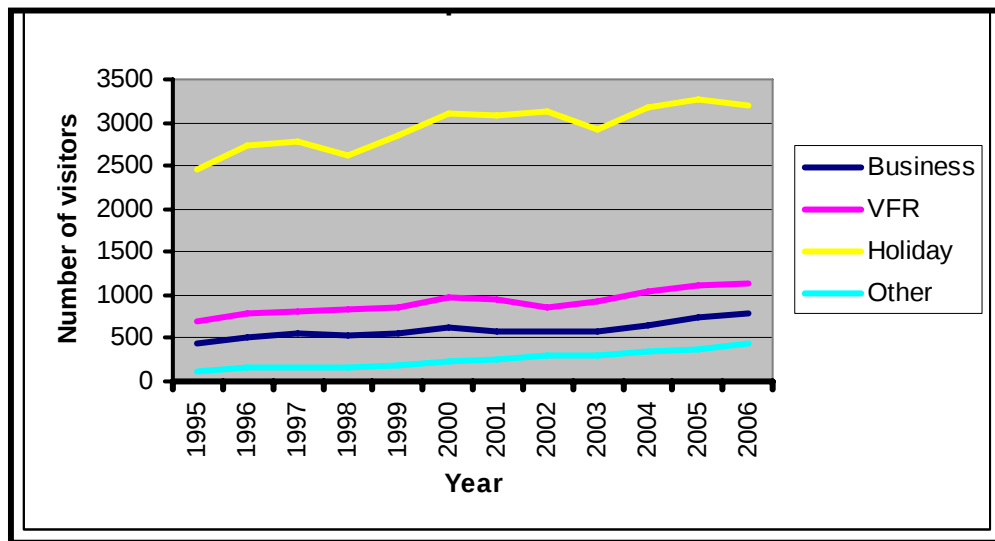
Table 1.2 and the Figure 1.3 indicate that out of the four major countries, New Zealand has become the leading inbound tourist market for Australia. From 1995 to 1999 Japan had the lead and was the major inbound market for Australia.

It is worth mentioning the significant growth in tourist arrivals to Australia from Japan during 1980 to 1998, with growth of 48% in 1987 and 63.4% in 1988 (these periods are not shown in the above table and the figure). This growth was mainly due to the Japanese Government's 'Ten Million Program' designed to boost travel abroad in order to reduce Japan's balance of payment surplus. This program was aimed at doubling the amount of Japanese overseas travel from the 1986 level of 5.5 million to 10 million by the end of 1991, with an increase in Japanese workers' annual leave entitlements providing a substantial medium to long-term impact on Japanese outbound travel. After 2000 Japanese arrivals declined due to Japan's severe economic recession in 1997-1998 (brought about by reduced business investment, decreased private consumption and financial problems in the banking sector and real estate market) resulting in a negative growth of 1.5 % in 1998 and again in 2001 when the IT bubble collapsed.

The continuing slow Japanese economy caused further decline in Japanese tourist arrivals to Australia in 2003 and the UK became the second highest tourist-generating country to Australia, pushing Japan to third place. The USA has consistently been in fourth place in tourist arrivals numbers over the past fifteen years. The important aspects of these main four markets has been the decline in Japanese growth, the higher growth in the UK helping to offset the Japanese decline and the maintenance of a 50% contribution from these four countries to total arrivals to Australia.

1.5.3 Purpose and the Destinations of Australian Inbound Tourists

The Australian Bureau of Statistics (ABS) categorises international visitor arrivals to Australia into five categories based on the purpose of visit including: holiday (HOL), visiting friends and relatives (VFR), business (BUS), education (EDU) and other (OTH). Figure 1.4 shows visitors by purpose of visit from 1995 to 2007.

Figure 1.4 Purpose of Visit ('000)

Source: <http://www.tourism.australia.com/Research.asp>

Figure 1.4 indicates that holiday visitors play a major role with regard to inbound tourism numbers. This figure also shows that compared to business travellers and VFR, holiday traveller demand fluctuates more. The VFR and business traveller markets are relatively stable with marginal increases over the period.

The following table (Table 1.4) shows the relative volume of tourist arrivals to each state in Australia (in 2007). According to Table 1.4, the three most popular states are: New South Wales followed by Queensland and Victoria comprising nearly 80% of Australian inbound tourism. For all four purposes of visit (Business, VFR, Holiday and Other) New South Wales attracts the highest number of tourists, Queensland is the second favourite for holiday tourists while Victoria is second highest for business travellers. In 2007, international visitor expenditure in Australia was A\$16.3 billion. New South Wales received most of this expenditure (A\$6 billion), followed by Queensland (A\$3.9 billion) and Victoria (A\$3.3 billion).

Table 1.4**Arrivals to Each State in 2007 (%)**

STATE/TERRITORY	% TOTAL
<i>New South Wales</i>	37.6
<i>Victoria</i>	18.4
<i>Queensland</i>	21.5
<i>South Australia</i>	4.5
<i>Western Australia</i>	11.7
<i>Tasmania</i>	1.5
<i>Northern Territory</i>	2.9
<i>Australian Capital Territory</i>	1.8
Australia	100.0

Source: <http://www.tourism.australia.com/Research.asp>

1.5.4 Inbound Visitor Nights

The following table (Table 1.5) displays the top ten markets by nights spent in Australia, and the average length of stay. The top ten markets by nights spent in Australia are the same as the top ten countries by the number of arrivals, but the order of the countries differs. This is mainly due to travellers from New Zealand and Japan being more likely to visit Australia for a shorter period of time. In 2007 the highest number of nights spent in Australia was from the UK market (13% of total visitor nights) while Singapore and Malaysia spent the lowest. The top ten markets account for 67% of total visitor nights spent in Australia.

Table 1.5**Top Ten Markets by Nights Spent and the Average Length of Stay**

Country	% OF INBOUND VISITOR NIGHTS (2007)	AVERAGE LENGTH OF STAY (DAYS)			
		2004	2005	2006	2007
Korea	7%	28	34	44	47
China	9%	44	41	48	44
Germany	4%	43	38	49	46
Malaysia	3%	32	32	37	37
UK	13%	38	33	34	33
Hong Kong	3%	30	23	29	32
USA	6%	23	21	24	23
Singapore	3%	17	22	24	22
Japan	7%	17	16	18	21
New Zealand	9%	13	15	14	13

Source: <http://www.tourism.australia.com/Research.asp>

Table 1.5 also indicates the average length of stay in Australia by the top ten markets. The average length of a visit to Australia is 30 days with Korean, Chinese, German and Malaysian visitors staying much longer than this while USA, Japan, Singapore and New Zealand tourists stay only a short period. It is worth mentioning here that the above-average lengths of stay are largely due to international students being included in the figures as tourists.

1.5.5 Total Inbound Economic Value (TIEV)

Table 1.6 Inbound Economic Value for Australian Economy

TOTAL INBOUND ECONOMIC VALUE (\$ MN)				
Country	2004	2005	2006	2007
UK	3,588	3,301	3,243	3,708
New Zealand	1,697	1,960	2,030	2,139
USA	1,975	1,886	1,924	1,958
Japan	2,034	1,983	2,064	1,696
China	1,176	1,552	1,470	1,809
Korea	842	880	1,022	1,300
Singapore	721	679	772	914
Germany	810	750	740	802
Malaysia	629	599	600	697
Canada	432	508	567	620
Top 10 Economic Value	13,904	14,098	14,432	15,643
Total Economic Value	19,592	19,560	20,349	22,350

Source: Australian Bureau of Statistics, Tourism Satellite Accounts 2006 – 2007

Total Inbound Economic Value (TIEV) is a measure of the yield for the Australian economy from inbound tourism. It is derived from International Visitor Survey data on total trip spending in all countries visited. The importance of this measure is that it only captures the expenditure flows to the Australian economy. Calculating the total inbound tourism economic value (TIEV) to Australia is not a simple or straightforward exercise, especially when determining exactly how much of a visitor's total trip expenditure flows to the Australian economy. Often, visitors may book and pay for their trip outside Australia. In this context, total trip spending is reduced to allow for the share of spending that does not come to the Australian economy. Table 1.6 displays the TIEV and it has the same top ten countries of tourist arrivals and visitor nights spent in Australia. However, the order of the countries differs. The only major difference is that Canada replaces Hong Kong, in tenth place on the TIEV list. In 2007 international visitors consumed around A\$22.3 billion in Australian goods and services. The United Kingdom remains Australia's largest source market in terms

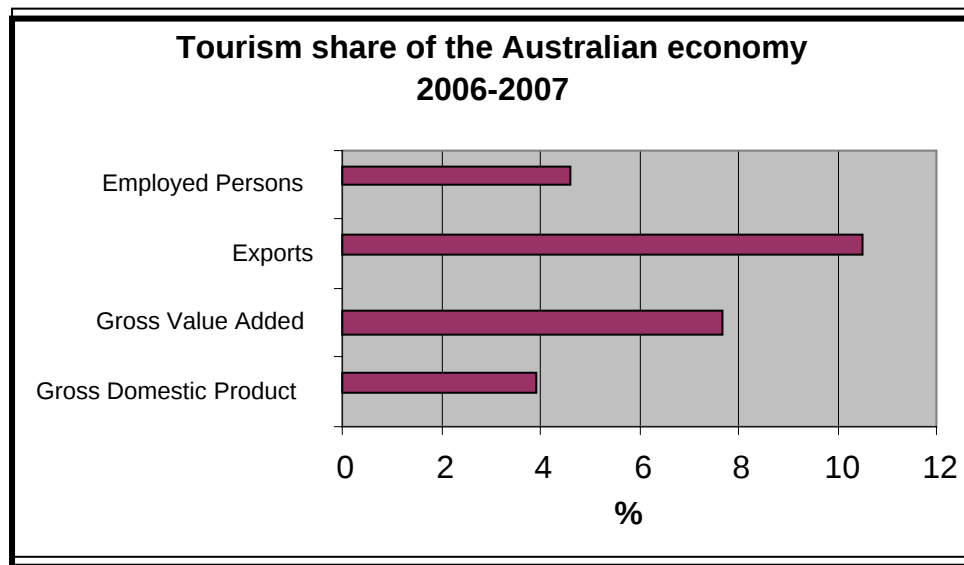
of economic value, worth A\$3.7 billion, followed by New Zealand (A\$2.1 billion), USA (A\$1.9 billion) and China (\$1.8 billion). The top ten TIEV markets account for 70% of all inbound economic value to the Australian economy.

1.6 Economic Importance of Tourism

In October 2000, the Australian Bureau of Statistics (ABS) published the Australian National Accounts: Tourism Satellite Account, 1997-98 (ABS Catalogue No: 5249.0). This is the first ABS attempt to put tourism into a national accounting framework. Unlike other economic activity, tourism is defined by the customer (visitor) rather than as a product. The tourism satellite account (TSA) creates a broad picture of tourism that allows it to be compared to conventional industries like agriculture, manufacturing and retail trade.

Before the development of the TSA there was no accurate method to measure the aggregate contribution of the Australian tourism sector within the overall economy. Thus an important improvement has been achieved in measuring the economic contribution of tourism with the development of the tourism satellite account. These data provide core information on tourism industry yield. Tourism is not an industry in the traditional sense because industries are classified, for statistical purposes, in accordance with the goods and services that they produce, whereas tourism depends on the normal residency of the customer. The Tourism Satellite Account (TSA) partitions industries into tourism and non-tourism activities so that the direct contributions of tourism to the economy can be measured on a consistent basis together with traditional industries. This means that only the value added is measured, where there is a direct economic or physical relationship between the visitor and the producer of a good or service. Similarly, the employment estimates only include employment generated where visitors have a direct relationship with the producer of the good or service.

To examine the contribution of the tourism sector to the Australian economy four major macroeconomic indicators are published by the Australian Bureau of Statistics: Gross Domestic Product (GDP), tourism gross value added (TGVA), employment and Australia's exports.

Figure 1.5 Tourism Share of the Australian Economy

Source: Australian Bureau of Statistics, *Australian National Accounts: Tourism Satellite Account, 5249.0, 2006-07*

1.6.1 Gross Domestic Product (GDP)

Gross Domestic Product (GDP) is the summary measure of the size and value of a national economy. It represents the total value of all goods and services produced in the economy for the year, after deducting the cost of the goods and services used in the process of production, but before deducting allowances for the consumption of fixed capital. In an open economy, GDP consists of five main elements: goods and services produced for consumption (C); goods and services produced for fixed capital formation or investment (I); government expenditure (G); exports of goods and services (X); imports of goods and services (M). The relationship between GDP and its five main components can be defined as $GDP = C + I + G + (X - M)$. Travel and tourism is likely to impact on all aspects of GDP, this impact is precisely calculated by the Australian Tourism Satellite Account (TSA), by calculating the direct contribution of the tourism industry to the Australian economy, by using the demand generated by visitors and the supply of tourism products by domestic producers (ABS 2009).

Tourism GDP measures the total market value of goods and services produced in Australia which are consumed by visitors, less the cost of the inputs used in producing

those goods and services. In 2007, tourism accounted for A\$38.9 billion of total GDP or 3.7% of total GDP. The highest recorded value was in 2000-01 (4.7%). This was largely due to price increases in tourism services resulting from the introduction of the GST and the increased number of visitors associated with the Olympic Games.

1.6.2 Tourism Gross Value Added (TGVA)

Gross value added is the preferred national accounts measure of industry production, as it excludes taxes and subsidies on products. TGVA is measured as the value of the output of tourism products by industries, less the value of the inputs used in producing these tourism products (ABS 2006). Air and water transport, accommodation, cafes, restaurants and takeaway food outlets and other retail trade are the most important tourism industries, together accounting for over 48.5% of tourism gross value added in 2007. Thus, tourism gross value added can be considered as the actual contribution of the tourism sector to the Australian economy. In 2007, the tourism share of total industry gross value added increased by 7.9% to A\$32,306 million, which is the highest growth rate since 1999 (5249.0 - Tourism Satellite Account, 2006-07).

1.6.3 Employment Generation

Tourism is a labour intensive activity overall, employing proportionally more people per dollar of GDP than most other industries (Port Phillip Business 2009), and hence its expansion generates more job opportunities than an equivalent expansion in other sectors of the economy. In a world where traditional industries in the primary and secondary sectors are employing fewer people, new service industries are increasingly viewed as an important source of new jobs. Given the enormous variety of businesses that directly and indirectly facilitate travel, tourism is considered a particularly valuable source of employment. Tourism can generate jobs directly through airlines, travel agents, tour operators, hotels, restaurants, nightclubs, taxis, souvenir sales and indirectly through the supply of goods and services needed by tourism-related activities.

In 2006/2007, the Australian tourism sector generated 482,800 employment opportunities, or 4.7 % of total employed persons. Retail trade generated the most tourism employment. Retail trade, accommodation, cafes and restaurants account for

just over half of the employment generated by tourism. World Travel and Tourism Council describe tourism as one of the world's largest source of employment. In some tourism-dependent economies, such as the Caribbean, as much as 25% of all jobs are associated with tourism (World Travel and Tourism Council).

1.6.4 Exports

According to Mihalic (2002), tourism is a relatively easy way to earn foreign currency, as an invisible tourism export has many advantages over the classic export of goods and services. Exports play an important role in a country's balance of payments. The balance of payments account for a country is a record of transactions during a period of time, between the residents of a country and the rest of the world. Improving the balance of payments is probably the most significant justification used by governments to promote tourism. Since many countries including Australia face balance of payments difficulties due to a deficit in the current account, international tourism receipts are seen as a means to alleviate such a balance of payments problem, because visitor spending brings income to the country, in the same way as exports generate income inflows. In 2006/2007, international visitors consumed A\$22.4 billion worth of goods and services produced by the Australian economy. This represented 10.4% of the total export of goods and services (ABS Catalogue No.5249.0, 2006-07).

Growth in international tourist arrivals benefits activities such as air transport, communications, entertainment, leisure, restaurants and hotels. In the long-run, increased tourism receipts could contribute to higher living standards within Australia. An important feature of the expansion in international tourist arrivals is that it changes the composition of Australia's exports. In the long-run it may, particularly, reduce Australia's reliance on traditional commodity exports in the rural and mining sectors.

While Australia's inbound tourism sector earns foreign exchange through inbound tourism, the number of Australian residents travelling abroad has been increasing over the years. In 2007, 4.7 million Australians travelled overseas and spent A\$26.2 billion on their trips, making Australia the world's 16th biggest spender on outbound travel (Tourism Australia, Market Insights, Tourism Facts 2007).

The benefits discussed above that derive from international tourist arrivals indicate the importance of attracting more tourists to Australia. To bring more international tourists to Australia, Federal and State governments are investing in tourism marketing and tourist-related goods and services. For efficient planning and investment, the government sector, private sector, airlines, hotels and other tourism-related sectors such as restaurants and tour companies, need accurate predictions of turning points in international tourism demand, as represented by tourist arrival numbers.

1.7 Importance of Tourism Economics Within the Spectrum of Tourism

Tourism is one of the biggest sectors in the world economy and its economic contribution and economic importance is extremely high. In this chapter, the importance and the contribution of the tourism sector to the Australian and world economies and the importance of tourism forecasting and turning point forecasting have been identified. As discussed, there has been a phenomenal growth in demand for tourism in the world over the past two decades and a growing interest in tourism research. 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 3,000 tertiary institutions across five continents.

Being an important area of tourism research, Tourism Economics has attracted much attention from both practitioners and academics (Song and Li (2008)). Today governments and policy makers, the airline industry, the hotel industry and other related industries along with academics consider tourism economics as a social science and an instrument for policy-making and planning. Moreover, tourism demand modelling, forecasting and turning point forecasting are considered important fields within 'tourism economics'.

1.8 Structure of the Thesis

The thesis consists of ten chapters:

Chapter 1 introduces the research problem and states the aims and objectives of the research. As the research is designed to predict turning points in Australian inbound tourism demand, the chapter includes an overview of international and Australian inbound tourism, including the structure and the nature of Australian international tourism.

Chapter 2 is a comprehensive review of the literature in tourism forecasting. This chapter looks at the most widely-used tourism forecasting methods such as time series modelling, econometric modelling and leading indicator models.

Chapter 3 discusses the methodologies used in this study, and provides an outline of each method. Further, justification is given for the different methodologies used in this thesis in the light of the literature review.

Chapter 4. In order to predict turning points, identifying true/significant turning points in historical data is a prerequisite (dating). This requires appropriate cyclical patterning and a smoothing method. This chapter discusses different time series data smoothing methods for extracting smoothed quarterly tourism demand growth for each tourism origin market. Finally, this chapter identifies significant turning points using suitable definition/methods in order to establish a chronology of the turning points in tourism demand.

Chapter 5. The objective of this chapter is to introduce/develop a non-linear time series model which can capture the significant turning points in actual tourist arrivals time series data (historical data), and then compare these turning points with the turning points already identified in Chapter 4.

Chapter 6 develops the non-linear econometric models required to identify the significant variables that can create turning points in tourism demand. Finally, turning points are predicted using these econometric models.

Chapter 7 constructs a composite leading indicator to forecast inbound tourism demand turning points. In addition to the constructed leading indicator, it uses some available economic indicators to predict turning points in inbound tourism (OECD Composite Leading Indicator; Business Survey index). This will allow an assessment of the accuracy of the constructed leading indicator to forecast turning points.

Chapter 8. The models/definitions and the non-linear econometric models developed in earlier chapters will be applied to the three leading indicators identified, namely:

1. Constructed composite leading indicator
2. OECD CLI and
3. Business Survey index

These indicators will be evaluated in order to identify the most accurate model and leading indicator to predict turning points for the Australian inbound tourism demand growth rate.

Chapter 9 will compare all the results obtained from Chapter 6 and Chapter 8, and identify the best model/method for each source country of tourist origin.

Chapter 10 summarises the findings of the thesis in order to: (1) conclude upon which smoothing method is best to extract a smoothed growth rate, (2) examine on an accurate model/models to identify/date significant turning points in Australian inbound tourism demand, (3) compare the prediction performance of the constructed composite leading indicator against the other available indicators, (4) Compare the performance of different models/methods to capture turning points in the leading indicators for each tourism origin country, and conclude which methods give an accurate prediction for each country, (5) identify the factors that determine the turning points in Australian inbound tourism demand growth, (6) outline the contribution of the thesis, and (7) discuss the limitations of the research and suggest future directions for research.

Chapter 2

Literature Review

2.1 Introduction

The purpose of this chapter is to review past studies in tourism forecasting. This chapter reviews the various qualitative and quantitative forecasting methods that have been applied to tourism demand forecasting. The first part of this chapter looks at the importance of tourism forecasting, and provides an overview of forecasting methods. The second part briefly reviews qualitative forecasting methods that include surveys, jury of executive opinion and the Delphi method. The third part of this chapter is an in-depth review of quantitative forecasting methods; this section is subdivided into causal and time-series methods. As the objective of this research is to model the forecasting of turning points using quantitative methods, the final section reviews the turning point literature in other disciplines such as finance and macroeconomics.

2.1.1 Tourism Forecasting

Forecasting is an attempt to anticipate the future, where generally a forecast is a statement made today about expectations for tomorrow. Forecasting could be based on speculation, surveyed options, intuition, expert opinion or quantitative analysis of historical patterns. In many business endeavours, its value lies in enabling operators to minimise losses due to disparities between demand and supply. Given the importance of tourism in the worldwide economy and its perishable nature, accurate forecasts of tourism demand play an important role in tourism planning and development.

During the last three decades, there has been a large increase in the number of published studies on tourism demand modelling and forecasting (Lim, (1997); Witt and Witt (1995)). Tourism demand modelling and forecasting is extensively discussed in Song and Li (2008), and there are a number of reviews of empirical research including Li et al. (2005), Song et al. (2000), Song et al.(1999), Lim (1997), Witt (1994), Crouch (1994) Crouch et al. (1992), Crouch and Shaw (1990), Witt (1989a,

1989b), Calantone et al. (1987), Uysal and Crompton (1985), Sheldon and Turgut (1985), Witt and Witt (1995) and Baron (1979).

2.1.2 Overview of Modelling and Forecasting Methods

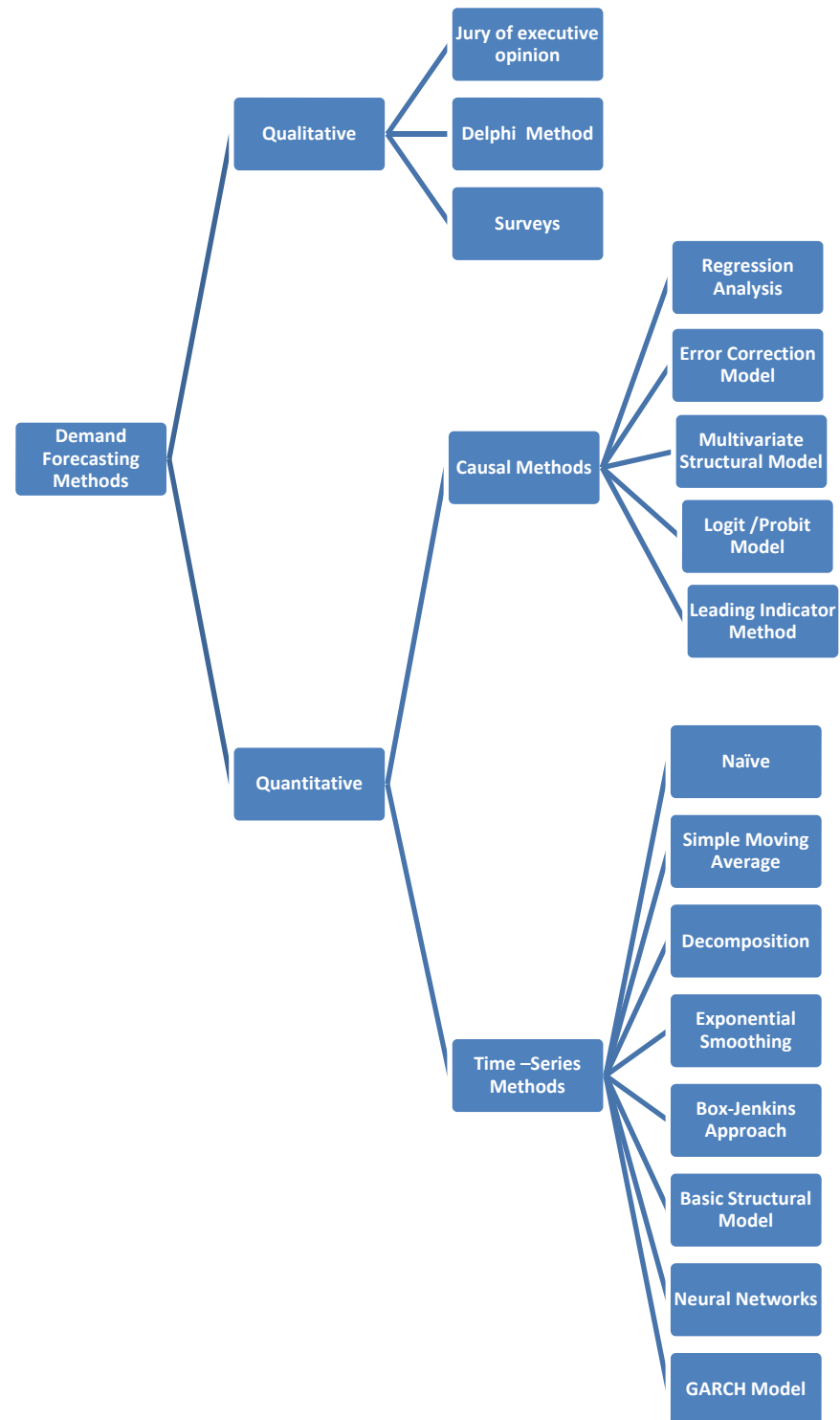
Many methods have been used to forecast tourism demand. These methods often differ in structure and in the data used. Forecasting methods can generally be classified as quantitative or qualitative (Archer (1980), Uysal and Crompton (1985)). Regardless of the type of forecasting method used, the usefulness of any tourism demand model is really determined by the accuracy of the tourism forecasts that it can generate, as measured by comparisons with actual tourism flows (Mahmoud (1984)).

Frechtling (1996, p.19) provides a useful distinction between a forecasting method and a forecasting model, as follows:

“A forecasting method is simply a ‘systematic way of organizing information from the past to infer the occurrence of an event in future. ‘Systematic’ means following a distinct set of procedures in a prescribed sequence”.

“A forecasting model is ‘one expression of a forecasting method’. More specifically a forecasting model is a simplified representation of reality, comprising of a set of relationships, historical information on these relationships, and procedures to project these relationships into the future”.

Figure 2.1 below shows the detailed classification of alternative forecasting methods that are reviewed in this chapter under the quantitative and qualitative headings.

Figure 2.1: Quantitative and Qualitative Forecasting Methods

2.2 Qualitative Tourism Forecasting Methods

Qualitative forecasting methods, also called ‘judgmental methods’ or ‘subjective forecasting’, rely on managerial or expert judgment without using specific models. Therefore, different individuals using the same qualitative method may arrive at widely different forecasts. However, these methods are useful when there is a lack of historical data or when the historical data are not reliable predictors of the future. Though the final forecast may need expert opinion to be part of the forecasting process, there is still a need to develop forecasting methodology.

2.2.1 Jury of executive opinion

In this approach, forecasts are made by a group of executives on the basis of experience, hunches, or facts about the situation. This approach is aimed at generating as much debate and interchange of ideas as possible in order to reach a consensus on the forecast. The advantages of this technique are: (1) simplicity, (2) it does not require much historical data, and (3) the most experienced executives can be brought together to make the forecasts. The disadvantages include: (1) it requires costly executive time, (2) a lack of consistency in the generated forecasts, (3) a ‘bandwagon’ effect where participants are reluctant to state views at odds with a developing consensus, and (4) the most forceful or senior executive’s opinion might carry the most weight, which might lead to a poor forecast.

Moutinho and Witt (1995) adopted a consensus approach permitting full discussion among the experts, in forecasting and ranking the importance of possible future developments in science and technology, having major impacts on tourism development during the period up to 2030. This approach was useful as it supports the clarification of reasoning for proposed developments.

2.2.2 Delphi method

The Delphi method (Brown (1968), Taylor and Judd (1989), Rowe et al. (1991), Moeller and Shafer (1994), Rowe and Wright (1999)), which was developed by the RAND Corporation has been widely applied to tourism forecasting.

The Delphi method is conducted through a sequence of steps. On the first round, each participant of the panel provides a written response to the questions asked. Responses are fed back to the panel, and each participant is then asked to reconsider his or her previous answers and to respond to the questions again. This procedure is repeated for four to six rounds until sufficient convergence is achieved from the collective knowledge of the participants. Thus, the estimates from the panel of experts are treated anonymously (Robinson (1979)). Anonymity eliminates the influence of the supposed greatest authority, as well as the 'bandwagon or herd effect' that is so common in the 'jury of executive opinion' method (Frechtling (1996)). However, the feedback process of the Delphi method is criticized as having a tendency to force convergence towards the group centre, which has sometimes been referred to as 'pool ignorance' (Schroeder (1982)). This method also requires a substantial amount of time from beginning to end, resulting in panel attrition. Seely et al. (1980) highlighted that the most important potential weakness of the Delphi method is not asking pertinent questions, while Taylor and Judd (1989) consider the most important step to be choosing the respondents.

Kaynak and Macaulay (1984) used the Delphi technique to gather data on tourism research, on the future impacts of tourism, and to strengthen a regional database, all of which were intended to form as an effective policy-making tool in solving management and planning problems in the tourism and hospitality industry in Nova Scotia, Canada to the year 2000. The questions were posed to 150 judges, and after two rounds, 44 completed questionnaires were returned.

Liu (1988) used the Delphi forecasting technique to forecast tourism to Hawaii, particularly Oahu, up until the year 2000. Local experts and travel agents were questioned on visitor arrivals and percentage of domestic arrivals to Hawaii, market share, visitor to-resident ratio, maximum visitor accommodation and desirable growth

rates, and probable scenarios for Oahu tourism. The results show few significant differences in responses among the groups, and confirmed expectations about convergence and consistency of managerial responses with statistical projections and existing trends.

Yong et al. (1989) used the Delphi method to project the future of Singapore's tourism industry from two different panels, one consisting of people from the local tourist industry and the other consisting of an international group of business executives. The conclusions highlighted (a) positive future trends that include: (1) increased purchasing power for leisure and travel services for individuals from developed countries, (2) better access to travel information, (3) fewer constraints for cross-border travel movements, and (4) higher pressure for regional collaboration in tourism-related activities, and (b) negative trends which include the imposition of more stringent exit taxes and a decrease in business travellers.

Miller (2001) presented the results of a two-round Delphi study conducted utilizing expert opinion on the development of indicators for sustainable tourism. The results of this Delphi survey show considerable disagreement over 'sustainability' and where the border of the concept lies.

2.2.3 Surveys

The two survey approaches in qualitative tourism forecasting are: (1) national or regional surveys of tour operators, travel agencies and airlines, and (2) surveys of visitors or potential visitors as to whether they anticipate a trip to the tourism destination areas. The analysis of these surveys often provides valuable insights into emerging tourism trends in the short to medium-term. However, the survey approach is time-consuming and expensive, and the conclusions drawn can be biased or incorrect due to (a) sampling errors, (b) non-response errors, and (c) response errors.

In summary, qualitative forecasting methods have more value applied to medium and long-range forecasting, and are considered to be less rigorous than the quantitative forecasting methods. However, they are appropriate where data is insufficient or unreliable for the application of quantitative forecasting methods (Archer (1987), Var

and Lee (1993)). Sheldon and Turgut (1985) in their review of empirical research on tourism forecasting concluded expert-opinion methods are useful when data are unavailable.

2.3 Quantitative Tourism Forecasting Methods

Quantitative forecasting methods are based on historical patterns or relationships in past activity used to estimate future behaviour. The basic divisions of the quantitative forecasting methods are causal (econometric) methods and time series methods. Causal methods include regression analysis, error correction models, the multivariate structural model and leading indicator methods. The quantitative time series methods or non-causal methods reviewed include the naïve method, moving average, decomposition, exponential smoothing, Box-Jenkins (ARIMA), basic structural model and neural network model.

2.3.1 Causal Methods

During the past three decades, several econometric models have been developed in the tourism literature to identify the relationship between tourist arrivals in a particular country, and those factors that influence arrivals.

Econometric models search for cause and effect relationships between independent variables and the dependent variable. Causal methodology used in tourism economics is focused upon penetrating the structure of a cause and effect relationship, in order to reproduce that structure in the future to forecast tourism flows, once a set of independent measures have been identified.

Most international tourism demand studies in the past have been based on this demand function approach, using tourism demand as the dependent variable and one or more variables including price, income, substitutes and travel costs (airfare) as independent variables.

Forecasting research using consumer choice theory explains that the demand for a given commodity depends on consumer income, prices and other variables specific to the commodity in question. Consequently, the demand function becomes:

$$Q = f(Y, P, PS, AF \dots)$$

Tourism demand for a given country Q (Measured by number of visitors) to a given destination may be expressed as a function of : Y - the tourists' disposable income, P - the price of tourism goods and services at the destination, PS - the price of competing/substitute destinations, AF - cost of transport/airfare cost. However, the list of independent variables has expanded over time and now includes:

Income:

A tourist's income earned in the source country is a vital factor which influences demand for tourism to a particular destination. As the income of a source country's resident population increases, more people can afford to visit other countries as tourists. Where demand for holidays or visits to friends and relatives are concerned, the appropriate proxy of the income variable is personal disposable income or private consumption (Dwyer et al. (1998), Syriopoulos (1995)), if the attention is on business visits, then a more general income variable (such as national income or GDP) is used (Song and Witt (2000)). Since international tourism is regarded as luxury product, (Li et al. (2004)), the tourism demand rises at a more rapid percentage rate than income. In order to capture the income variable in forecasting, real GDP or per capita can be used (Song and Witt (2000)).

Price of tourism:

Prices in the destination country relative to prices in the origin country assume that a tourist looking for a holiday decides whether to spend the vacation in a particular international destination or in his or her own country. Tourism prices are the costs of goods and services that tourists are likely to pay while at the destination, e.g. accommodation, local transportation, food and entertainment. In tourism demand studies, tourism prices are normally expressed in relative a term that is relative prices. Demand theory hypothesizes that the demand for travel is an inverse function of

relative prices, that is, the greater the cost of living in the destination country relative to the origin country, the lower the tourism demand, all else being equal. Ideally a 'tourism price index' would be an appropriate measure of differences in inflation rates which affect the price of goods and services consumed by the tourist. However, constructing such a price index is difficult because of the complex nature of the tourist product and the unavailability of reliable data (Ong (1995)). The consumer price index (CPI) of the destination country is usually used as a proxy for tourism prices in aggregate. Gonzalez and Morál (1995) consider the consumer price index to be a proxy for the price of tourism, and use the ratio of the consumer price index of the destination country to that of the tourist's home country (the source country) adjusted by exchange rates. Use of the CPI is justified on the grounds of convenience (the data are readily available) and the argument that tourist spending is spread over a wide part of the economy, and so may approximate the general average consumer spending used to weight prices in the CPI, or that at least the CPI will track tourism closely (Morley (1994)). As potential tourists base their decisions on costs at the destination measured in terms of their local currency, the destination price variable should be adjusted by the exchange rate between the origin and destination country currencies (Song and Witt (2000)). It is worth to mention that CPI is not a perfect indicator for price of tourism as it has some limitations, like (I) the expenditure pattern of a tourist can be different from the average household expenditure in the tourist origin and destination country (II) the CPI of tourist origin and destination country may not reflect the prices of goods actually purchased by a tourist. However as mentioned, CPI is commonly used as a proxy for tourism price.

Substitute Price:

In addition to the relative prices between the destination and origin countries, economic theory requires the inclusion of the prices of relevant substitute destinations in the tourism demand model. Tourists most likely compare the price of a holiday in a particular foreign destination with the price of a domestic holiday as well as with other similar foreign destinations.

Two main forms of substitute prices are normally used in tourism demand functions: one allows for substitution between the destination and a number of separate

competing destinations (Kim and Song (1998) and Song et al. (2000)), and the other calculates the cost of tourism in the destination under consideration relevant to a weighted average cost of living in various competing destinations. This index is also adjusted by the relevant exchange rates. The weight is the relevant market share (arrivals or tourist spending) of each competing destination (Song et al. (2003b)). Further just as tourists' living cost in substitute destinations are likely to influence the demand for tourism to a given destination, travel cost to substitute destinations may also be expected to have impact. However although some theoretical attraction has been paid to substitute destinations' travel cost they do not often feature in tourism demand functions (Turner and Witt (2003)).

Travel Cost /Airfare:

Travel costs refer to the cost of return-trip travel between the origin and destination countries. This is different to other goods because the consumer (tourist) has to be transported to the product (destination) rather than the reverse. Hence, for a visitor to decide which destination to travel to, travel cost (airfare) plays an important role. Regional tourism as against travel to distant destinations is becoming more popular due to increasing airfares and other reasons, so airfare could be a good explanatory variable in a tourism demand model (Turner and Witt (2003)).

Exchange rate:

Exchange rate is sometimes used as an explanatory variable in the tourism demand model. This variable may appear in the tourism demand model alone or be represented in the cost of tourism variable. The reason this variable is sometimes used as the sole representation of tourist living costs is that tourists have ready access to information on fluctuations in exchange rates, whereas information on price changes in destinations is generally not known in advance. However, if both exchange rate and price of tourism are included together as independent variables, this may lead to a multicollinearity problem. Also, use of exchange rates alone in the demand function can be misleading because the exchange rate at the destination country can be offset by a relatively high inflation rate (Song et al. (2000)). According to Martin and Witt

(1987), the exchangerate-adjusted consumer price index might be a reasonable proxy for the cost of tourism included in a tourism demand function.

Marketing expenditure:

Marketing can have a persuasive impact on the decision of a potential tourist to visit a destination. Some authors highlight the importance of marketing expenditure as a determinant of tourism demand, but only a few studies have included it (O'Hagan and Harrison (1984), Papadopoulos and Witt (1985) and Kulendran and Dwyer (2008)), due to issues with the availability of relevant data (Witt and Martin (1987)). According to Song and Witt (2000), tourism-related marketing activities are not specific to a particular destination and have little impact on the demand for tourism to that destination.

Dummy variables:

Dummy variables can be included in an international tourism demand study where appropriate. They can be included to check the effect of seasonality, special events and crises (i.e. Olympics, SARS, natural disaster). Dummy variables have also been used to account for other changes, such as the use of different data sources or discontinuities in recording methods. In cross-sectional studies, dummy variables have occasionally been incorporated to facilitate the estimation of different demand coefficients by country of origin or destination (Crouch (1994)).

Song et al. (2000) estimated the demand function for tourism demand as the price of tourism, substitute destination price, level of income in the tourist's country of origin, consumer tastes in country of origin, advertising expenditure, and a disturbance term that captures other factors which may influence demand.

Turner and Witt (2001a) considered the following as possible explanatory variables: destination living costs, airfare, retail sales, new car registration, gross domestic product, survey of future manufacturing, survey of consumer confidence, survey of overall prospects, trade openness, exports, imports, domestic loans and number of working days. Lagging of independent variables was also tested though the number of lags was difficult to hypothesize, and there was little difference in the empirical

results. The explanatory variables that were found to be significant in some of the tests included: destination living costs, retail sales, new car registrations, gross domestic product, trade openness, exports, and domestic loans.

Witt and Witt (1991) suggest, as explanatory variables, per capita real income as measured by personal disposable income; cost at the destination as measured by the consumer price index specified in real terms in the currency of the country of origin and referred to as own price; cost of transport as measured by airfares; substitute prices as measured by cost of transport and cost of living in alternative destinations; promotional activity for the destination as measured by real promotional expenditure in the country of origin's currency; and habit persistence as measured by lagged tourist arrivals.

Turner et al. (1997) identified leading indicators from among national variables: income, unemployment, forward exchange rate, money supply, price ratio, industrial production, imports and exports.

The causal literature indicates that certain variables are more commonly used by researchers, with the most commonly used being income in the tourist country of origin, cost of living in the destination country, travel cost, exchange rates, substitute prices for alternative destinations and special events. These variables can be identified as the most used measures of tourism demand fluctuations. The finding by Li et al. (2005) is that no single model outperforms others for all series. This may well reflect a fundamental flaw in the current practice of assuming that all series can be forecast using the same generic independent variables, when in fact some series have different causal influences.

Other studies using a variety of mixed independent variables discussed above include: Gapinski and Tuckman (1976), Paraskevopoulos (1977), Witt (1980), Fujii et al. (1985), Quayson and Var (1982), Witt (1983), Hagen and Harrison (1984), Uysal and Crompton (1984), Edwards (1985), Guandhi and Boey (1986), Chadee and Mieczkowski (1987), Witt and Martin (1987), Brady and Widdows (1988), Martin and Witt (1987 and 1988), Johnson and Thomas (1991), Witt and Witt (1990), Crouch (1992), Witt et al. (1992), Anthony and Bojanic (1993), Morris et al. (1995),

Jorgensen and Solvoll (1996), Kulendran (1996), Kulendran and King (1997), Lim (1999), Song and Witt (2003), Song et al. (2003b) and Kulendran and Dwyer (2008).

2.3.1.1 Regression analysis

The linear regression method is one of the major original approaches to causal modelling in tourism demand forecasting (Frechtling 1996). The regression line is a linear time trend regression of the data series designed to minimize the sum of squared vertical departures (i.e. residuals) of the data from the regression line.

Crouch (1994), summarized the past empirical studies and found Ordinary Least-Squares (OLS) multivariable regression analysis was the most widely-used approach from 1960 to 2000.

Examples of linear regression applications in tourism include: Witt and Martin (1987) using a marketing expenditure variable to determine international tourism demand; Smeral et al. (1992) specifying a complete system of econometric demand equations to generate forecasts of tourism imports and exports for various major geographical areas; Crouch et al. (1992) estimating the impact of the international marketing activities of the Australian Tourist Commission (ATC) on the number of tourist arrivals to Australia and concluding that marketing activities significantly influence inbound tourism to Australia; Qu and Isabella (1997) applying regression analysis to determine what exogenous variables best explain demand for Mainland Chinese' travel to Hong Kong and finding 'disposable income per capita' and the 'relaxation of visa requirements' are key variables; Kulendran and Wilson (2000) attempting to identify economic variables that influence business tourism to Australia and finding that economic variables vary from country to country.

Recent research has questioned the validity of the assumption of regression analysis based on Ordinary Least Squares (OLS) (Skene (1996), Morley (1997)). In particular, the suggestion has been made that the time series used in ordinary least squares regression analysis may be non-stationary, and, therefore, the validity of standard statistical testing may be in doubt. As a consequence, more recent analysis has been done using co-integration methodology (Lathiras and Siriopoulos (1998), Kulendran (1996), Kulendran and King (1997), Song and Witt 2003)).

2.3.1.2 Error Correction Model

Time series data are measurements of a variable taken at regular intervals over time, in a stationary time series the mean, variance and covariance will not change through time. If the time series analyzed is non-stationary, using a regression model with the assumption of stationarity will give misleading results. This is called the spurious regression problem. A configuration technique was developed by Engle and Granger (1987) together with the error correction mechanism, whereby they proposed a solution to the spurious regression problem when non-stationary time series are used in tourism demand modelling. Song et al. (2003a) provide a detailed description of the cointegration and error correction mechanism.

In terms of forecasting accuracy, the error correction mechanism has been shown to perform well for medium and long-term forecast horizons (Engle and Granger (1987)). Further Clements and Hendry (1995) showed the importance of sample size and the representation of data for forecasting performance. Applications of the co-integration and error correction mechanism for tourism forecasting include: Lathiras and Siriopoulos (1998), Kulendran (1996), Kulendran and King (1997), Lathiras et al. (1998), Kim and Song (1998), Song et al. (2000) and Kulendran and Witt (2001).

2.3.1.3 Multivariate structural model

The single equation multivariate regression model assumes that the only causality is from each explanatory variable to the forecasting variable, and does not capture feedback and the cross-dependencies that might be present in estimating the model. Accordingly, structural models which are systems of independent equations including time elements and economic measures have been developed to more fully represent the independencies of the variables in the real world (Frechtling 2001). As such, these models (described in their basic form as the Basic Structural Model) are usually grouped under time series models.

Key limitations of the multivariate structural models are: (a) their complexity, (b) their vulnerability to the 'specification problem' (c) there is no standard way to build these models, and they may require a large amount of input data. Some Multivariate Structural Model applications are: Gonzalez and Moral (1995) who analyze the

external demand for Spanish tourist services; Turner et al. (1998) who examine various demand determinant impacts on the purpose of visit; and Turner and Witt (2001b) who study the factors effecting New Zealand inbound tourism.

An alternative to the multivariate structural modelling concept is the use of Structural Equation Modelling (SEM) Structural Equation Modeling is a multivariate statistical analysis technique that is used to analyze structural relationships (Reisinger and Turner (1999), Turner and Witt (2001b)). Structural equation modeling technique is the combination of factor analysis and multiple regression analysis, and it is used to analyze the structural relationship between measured variables and latent constructs. Structural equation modeling is preferred by the researcher because it estimates the multiple and interrelated dependence in a single analysis. In structural equation modeling, two types of variables are used endogenous variables and exogenous variables. In structural equation modeling, endogenous variables are equivalent to dependent variables. In structural equation modeling, exogenous variables are equal to the independent variable. Some Structural Equation Modeling applications are

2.3.1.4 Logit / Probit Models

The Logit and Probit models are regression models with dummy dependent variables, taking the value 1 or 0. These models the dependent variable is the logarithm of the ratio of the probability that a particular event will occur to the probability that the event will not occur.

There are very limited applications of the Logit and Probit models in tourism, and most of the research has been carried out with survey data. In tourism, these qualitative choice models are based on questionnaires, and rely either on binomial or multinomial Logit and Probit models. Examples of studies in the literature that use the binomial Logit model are Fleischer and Pizam (2002) who determine the constraints of senior Israeli tourists; De la Vina and Ford (2001) who describe the demographic and trip factors of potential cruise passengers based on a sample of individuals who previously requested travel information; Costa and Manente (1995) who investigate the characteristics of visitors to the city of Venice with respect to their origin and socio-economic profile, their preferences and their holiday decisions; Sheldon (1995) who examines the travel incentive among US corporations; and Stynes and Peterson

(1984) who propose the Logit model to estimate recreational choices. Kockelman and Krishnamurthy (2004) propose a micro economically rigorous method to characterize travel demand across a great variety of choice dimensions, including trip generation. Witt (1983) constructed a binary choice model (Probit) to explain foreign holiday distribution; the approach assumes that the individual's decision-making behaviour is based on the comparison of costs and benefits associated with foreign holiday destination.

However, standard multinomial Logit models require discretion in choices (e.g., peak vs. no-peak, trip vs. no trip); this causes a loss of cardinality and continuity which determine many travel choices, such as time of day and number of trips made (Kockelman and Krishnamurthy (2004). Examples of the multinomial Logit model are Luzar et al. (1998) who investigate socio-economic and psychographic factors, which influence Louisiana tourists' decisions to participate in nature-based tourism and Morley (1994) who assesses the independent effects of price factors on potential tourists.

The Logit model is used in other disciplines such as finance and macroeconomics, in order to predict turning points. But in tourism economics, this model has never been used for turning point forecasting. The applications of this model for turning point forecasting in other disciplines are discussed in section 2.5.2 of this chapter.

2.3.1.5 Leading Indicator Method

Future changes in some aggregate economic activity (such as the demand for international tourism) are often foreshadowed by changes in other time series variables. These latter economic variables are known as leading (economic) indicators. The business world relies heavily on leading indicators for predicting both the turning points and future values of economic variables. The leading indicator approach involves identifying a repetitive sequence of events within business cycles and using it for forecasting. Traditionally, the main interest in leading indicator forecasting has been to forecast turning points in economic activity, but leading indicators can be, and are being, used in other areas too (Lahiri and Moore, 1991).

The leading indicator approach is sometimes referred to as measurement without theory, because of the freedom in selecting explanatory variables. However, relevant economic theory often provides the necessary guidelines and justification for the selection of economic variables. In the past, the search for leading indicators in forecasting tourism demand has included: tourist origin country's GDP, unemployment rate, imports, exports, exchange rates, trade weighted index, stock prices, new car registrations, number of total constructions, and the overnight interbank rate.

A Bureau of Tourism Research Australia study (1995) indicated that leading indicators are simpler to update once the important variables are identified and the approach is better at predicting turning points than other available forecasting methods. Turner et al. (1997) applied the leading indicator approach to study quarterly tourism demand to Japan, Australia and New Zealand and included origin country income, exchange rates and relative prices as indicators. Kulendran and Witt (2003) investigated the use of leading indicators to study international tourism demand from the UK to six major destinations. The American Express Travel Related Service and The Tourism Council of Australia (1998) also examined turning points in Australian inbound tourism demand growth rates, using a tourism leading indicator approach. Choi et al. (1999) examined the cyclical patterns of business activity in the hotel industry and indicated that further research is required to develop an indicator for the hotel industry. To forecast turning points in monthly tourism demand growth rates Rossello-Nadal (2001) successfully examined the leading indicator approach and concluded that the leading indicator methodology outperformed time-series models such as ARIMA and naïve models in turning point prediction. Furthermore, Kulendran and Wong (2006) constructed a composite leading indicator from a set of leading indicators and predicted quarterly tourism demand growth, directional changes and turning points in Hong Kong tourism demand growth rates using a single input leading indicator model, and assessed the forecasting performance against the ARIMA model and the naïve model. Recently Kulendran and Wong (2009) used composite leading indicators to forecast the directional changes and turning points in Hong Kong tourism demand growth. Further Niemira and Klein (1995) indicate that

the bottom line in developing a good leading indicator comes down to selecting appropriate leading indicators that are timely, stable and significant.

Though most of the causal methods discussed claim accuracy in forecasting tourism demand, the causal methods also have drawbacks. The important and common difficulty is to forecast demand for the future, requiring the future values of the causes of travel demand (i.e. income, price or substitute price etc.). Time series methods are normally used to find these future values. Furthermore, the assumption that the chosen causal variables are the only correct relevant variables is difficult to sustain, as the relationships that are found could be spurious (that is, caused by some other unknown variable related to the independent variable being used).

2.3.2 Time Series Models

A time series refers to observations of a variable that occur in a time sequence. A time series is deterministic if it can be predicted accurately. Time series models predict the future from past values of the same series, whereby the methodology attempts to discern the historical pattern in the time series, so that the pattern can be extrapolated into the future. The main disadvantage of the time series method is the inherent assumption that changes in particular patterns are slow rather than rapid and develop from past events rather than occur independently. The main advantage is that there is no need to forecast causal variables except for the multivariate structural model. The basic strategy in time series forecasting is:

- (a) Identify a data pattern based on the historical time series. This can be done by dividing the time series into data components, such as average level, trend, seasonality, cycle and residuals.
- (b) Make forecasts by extrapolating the data pattern. Thus time series forecasting methods are fundamentally extrapolative, unless specific interruptions in the time series can be related to specific events that have occurred, or to specific time periods, and are included as dummy variables.

Frechtling (1996, 2001) highlights five patterns in a tourism time series: (a) seasonality (b) stationarity, (c) linear trend, (d) non-linear trend, and (e) stepped series. Because tourist arrivals time series typically exhibit seasonal, trend and irregular data components, they make time series forecasting methods a reasonable forecasting choice. The different time series forecasting methods employed in tourism demand forecasting are discussed below.

2.3.2.1 Naïve Forecasting Method

In the naïve or no-change forecasting method, the forecast value is equal to the actual value of the last period. This simple forecasting method can be used as a benchmark in comparing other methods. Though simple, the naïve model can outperform more complex forecasting models for tourism demand as highlighted by Witt et al. (1992), in the short term it can be argued that unless a forecasting model can outperform the naïve model the forecasting accuracy is problematic.

2.3.2.2 Simple Moving-Average Method

The moving-average method is one of the simplest time series methods. In this method, a given number of periods are selected for the averaging process in an attempt to obtain a better forecast for the next period. As a general principle, the longer the average period, the slower the response to demand changes. Therefore, a longer period has the advantage of providing stability in the forecast, but has the disadvantage of responding more slowly to real changes in the demand level. Thus, the appropriate trade-off between stability and response of the forecast must be made by selecting a workable average length. The results of a questionnaire survey by Martin and Witt (1988) indicated that the moving-average was the most popular technique for short-term forecasting.

2.3.2.3 Decomposition Model

The classical decomposition approach decomposes a time series into four components: trend, cyclical, seasonal, and irregular components. The principle is to identify these components and develop the forecast based on these components.

The Census X-11 model developed for the US Bureau of the Census (Shiskin (1967)) is an example of the decomposition method. The X-11 program is used to deseasonalise quarterly or monthly data, thereby producing detailed analyses of seasonal factors, and trend-cycle and irregular variations. The main disadvantage of X-11 is its inflexibility, as the same procedure is essentially applied irrespective of the properties of the time series.

2.3.2.4 Exponential smoothing methods

Intermediate extrapolative forecasting methods (Frechtling (1996), (2001)) include: (1) simple exponential smoothing, (2) double exponential smoothing, and (3) autoregression.

The single exponential smoothing forecasting method is applicable to stationary time series with no seasonality, thus, it cannot always be applied directly for tourism arrivals forecasting because of seasonal effects that are often present in a tourist arrivals data series. Differencing is used to derive stationarity and to pre-process the seasonal data series before using single exponential forecasting to generate the forecast values.

The double exponential smoothing method (Brown (1963)) was developed for trended time series, but its disadvantage is that it cannot deal with seasonality, which is common in tourism data series. The triple exponential smoothing method (Holt (1957), Winters (1960)) was developed for a seasonal time series with trend.

Martin and Witt (1989) tested the exponential smoothing method against the naïve model for outbound tourism for France, Germany, the UK and the USA for six main destinations, and concluded that the naïve model generates the most accurate results compared with the exponential smoothing method.

2.3.2.5 Basic Structural Model

The Basic Structural time series model (BSM) was introduced by Harvey and Todd (1983) with non-stationary data being handled directly without the need for explicit differencing operations.

Basic Structural time series models (Engle (1978), Nerlove

et. al. (1979), Kitagawa (1981), Harvey (1989)) are models that are formulated directly in terms of components such as trend, seasonality and cycle. Structural time series models offer clear interpretations through the decomposition of components (Kendall and Ord (1990)). This decomposition ability of structural models is a major attraction for time series forecasting.

Turner et al. (1995a) compared the forecasting performance of the ARIMA model and Basic Structural Model (BSM) with intervention variables and found that the BSM model demonstrated a consistently high performance against the ARIMA model. Further, Turner and Witt (2001b) applied the BSM to forecast inbound tourism to New Zealand from Australia, Japan, the UK and the USA and concluded that the structural time series model is reasonably accurate and outperformed both the seasonal naïve model and the multivariate structural time series model.

2.3.2.6 Neural Networks

The Artificial Neural Networks (ANNs) consists of a number of processing elements, normally arranged in layers. Each processing element is linked to elements in the previous layer by connections that have an adaptable strength or weight, the adaptation of which is performed by a learning algorithm (refer to Kon and Turner (2005))

The application of Artificial Neural Networks (ANNs) in forecasting is well reviewed by Hill et al. (1994) and Warner and Misra (1996). Denton (1995) highlighted that Neural Networks offer an alternative to multiple regression for performing causal forecasts, and that, in particular under less than ideal conditions, Neural Networks do a better job, i.e, the Neural Network forecasting method eliminates the ambiguities present in selecting the appropriate independent variables needed in defining a

multiple regression model. This is important as performing statistical regressions with a misspecified model can result in biased and inconsistent parameter estimates.

Hill et al. (1996) examined time series forecasting produced by neural networks compared with the forecasts from six statistical time series methods generated in a major forecasting competition (Makridakis et al. (1982)). The traditional method forecasts are estimated by experts in the particular techniques. It was found that across monthly and quarterly time series, the Neural Network did significantly better than the traditional methods. Refenes et al. (1994) also highlighted that traditional statistical techniques for forecasting have reached their limitations in applications with non-linearities in the data set, such as in stock indices.

Some applications of the Artificial Neural Network are: Aiken (1999) forecasting the Consumer Price Index (CPI) in the USA; Fernando et al. (1999) using Neural Networks to forecast tourist arrivals to Japan from the USA and finding that the univariate and multivariate Neural Network forecasts generate results very close to the actual arrival figures; Uysal and Roubi (1999) comparing the use of ANN against multiple regression in tourism demand analysis and demonstrating the usefulness of ANNs in tourism demand studies; Yao and Tan (2000) forecasting the option prices of Nikkei; Moshiri and Cameron (2000) studying the inflation rate; and Tkacz (2001) forecasting Canadian GDP growth.

However, there is no formal systematic ANN model building approach (Qi and Zhang (2001)). For instance, there is no standard formula for calculating the number of layers and nodes needed in the hidden layer (Lippman (1987), Gorr et al. (1994), Jeng et al. (1996)). In particular, the parameters of the backpropagation algorithm, as well as the Neural Network design need to be adjusted for optimal performance. Kon and Turner (2005) provide an in-depth study on the use of Neural models in tourism forecasting and conclude it has high forecasting performance.

2.3.2.7 Box-Jenkins Method (ARIMA)

The Box-Jenkins process (Box and Jenkins (1976), Vandaele (1983), uses the autoregressive and moving-average methods to suggest the most appropriate form of a

forecasting model (Frechtling (1996)). The acronym ARIMA is used to indicate the Auto Regressive Integrated Moving Average method. ARIMA models are flexible and widely used in time series analysis. ARIMA combines three types of processes: Autoregressive (AR), Integration (I) and Moving-Average (MA). Autoregressive models were originally developed by Yule in 1926 and Moving-Average (MA) models by Slutsky in 1937 (Makridakis and Hibon (1997)). They were combined into the ARIMA model and introduced by Box and Jenkins in 1970. The ARIMA approach is an empirical method for identifying, estimating and forecasting a time series. It does not assume any particular pattern in the historical data but uses an iterative method for selecting an appropriate model, by investigating the shapes of the distribution of autocorrelation coefficients and partial autocorrelation coefficients of the time series, without making assumptions about the number of terms required in the model.

An examination of the application of ARIMA in tourism demand forecasting includes Turner et al. (1997) who found that the AR model produced better forecasts than the ARIMA with non-periodic seasonal data, and also found that ARIMA forecasts are better than the naïve forecast. Lim and McAleer (2002) found that ARIMA forecasts for Malaysia and Hong Kong were not as accurate as the forecasts for arrivals from Singapore to Australia. Dharmaratne (1995) obtains accurate forecasts using ARIMA, but concludes that customized model building may be highly rewarding in terms of accurate forecasts, compared with using standard or simple methods. Kulendran and Witt (2003) found that the leading indicator model does not outperform the univariate ARIMA model and that there is no advantage in moving from a univariate ARIMA model to a more complex leading indicator model. However Turner et al. (1997) show that the leading indicator model outperforms the ARIMA model for some source countries.

Initially researchers used the more sophisticated Box Jenkins methodology (Geurts and Ibrahim (1975)). However, more recent research, discussed above, includes an assessment of less sophisticated methods such as exponential smoothing and naïve models in the comparison. These studies lead to the suggestion by Witt et al. (1992) that within-sample naïve forecasts were more accurate than formal forecasting methodologies. However, more recent studies that re-examine the performance of

different time series methods, including the Box Jenkins approach (Turner et al. (1995a,1995b)) and newer structural models (Turner et al. (1997)) dispute this finding. After analyzing the different types of time series models and their application, it is notable that as with causal models a single method has not emerged as the most suitable forecasting technique for all situations.

2.3.2.8 GARCH Model

Another extension of the univariate time-series analysis of tourism demand has been the application of Bollerslev's (1986) Generalized Autoregressive Conditional Heteroskedastic (GARCH) model. If an autoregressive moving-average model (ARMA model) is assumed for the error variance, the model is a generalized autoregressive conditional heteroskedastic (GARCH) model.

GARCH models were developed to explain volatility clustering. In the GARCH model, the innovation (or residual) distributions are assumed to be a standard normal distribution, despite the fact that this assumption is often rejected empirically. For this reason, GARCH models with non-normal innovation distribution have been developed.

GARCH models have been widely used in many financial modelling contexts to investigate the volatility of a time series. Chan et al. (2005) applied three multivariate GARCH models in tourism demand to examine the volatility and the effects of various shocks in tourism demand series.

2.4 Summary of the Literature

From the summary of the causal and non-causal quantitative methods above, it can be seen that tourism demand modelling and forecasting research rely heavily on economic secondary data in terms of model construction and estimation. Although the explanatory variables included in tourism demand models vary enormously depending on the research objectives and research backgrounds, the employment of certain indicators for the measurement of tourism demand variables in modelling and forecasting tourism demand have become less controversial, as suggested by Witt and Song (2000). Importantly, the tourist arrivals variable remains the most popular

measure of tourism demand over the past few years. This variable is measured as total tourist arrivals from an origin to a destination and has not been replaced by alternatives such as receipts (Sheldon and Var (1985)) or growth rates. The tourism forecasting literature discussed above explains that existing forecasting methods, causal methods and time series models, can be used to forecast the number of tourist arrivals successfully, but they are not appropriate for predicting turning points (with the exception of the leading indicator method).

In summary, five main types of forecasting exercises have been identified (Song and Li (2008)):

1. *Ex post* forecasting

This is normally carried out to evaluate out-of-sample forecasting accuracy. In this forecasting, the values of the explanatory and dependent variables over the forecasting period are known, and the comparison of *ex post* forecasts between different models allows for comparison between forecast values and known values, to determine which model produces the best forecasts.

2. *Ex ante* forecasting

This is basically forecasting of future demand, values or behaviours. Practitioners and managers are extremely interested in knowing about the ‘unknown’ future changes. Beyond current time, forecasts are called *ex ante* forecasts. In this case, the values of the explanatory variables if used are not known, and they have to be forecasted before the forecast of the tourism demand variable can be obtained.

3. Forecasting competition (FC)

In a forecasting competition, different models/methods are used to forecast tourism demand and the results compared. Researchers can conclude which model performs better in forecasting tourism demand. Normally most researchers use out-of-sample (*ex post*) results. This process assumes the competitors are equally competent in applying methodology but also allows for specialists to use particular methods to maximize their power.

4. Directional change forecasting (DCF)

Forecasting directional change and trend change is important in tourism forecasting. There are limited studies available in this area (Witt and Witt (1989, 1991), Petropoulos et al. (2005)). Researchers are basically looking at above and below the trend demand and demand changes, in other words, positive and negative tourism demand growth.

5. Turning point forecasting (TPF)

Forecasting turning points is a process of identifying the points at which demand turns from contraction to expansion (referred to as upturn) and from expansion to contraction (referred to as downturn). The aim of this study is to predict these turning points in the Australian inbound tourism demand growth rate, which occur due to economic factors. In looking at past studies of tourism forecasting under the five sub-areas, the turning point forecasting area is the most neglected area, with very few studies. According to Song and Li (2008) recent review of forecasting studies since 2000, there has only been one study (Rosselló-Nadal (2001)) with the sole purpose of forecasting turning points. Rosselló-Nadal (2001) uses the leading indicator approach to forecast the turning points of international visitor arrivals to the Balearic Islands from the UK and Germany. Most recently, Kulendran and Wong (2009) use composite leading indicators to forecast the directional changes and turning points in Hong Kong tourism demand.

However, there are also a few studies in the literature looking at turning points together with directional change and tourism cycles. To forecast turning points or directional changes in annual tourism demand, Witt and Witt (1989, 1991) and Witt et al. (2003) examine econometric models and time series models. These studies conclude that econometric models outperform time-series models in terms of directional change forecasting, further stressing that econometric models are capable of producing good forecasts around turning points (Witt and Witt (1989)).

Gouveia and Rodrigues (2005) attempted to identify tourism growth cycles using data from main source markets on monthly tourist nights spent in hotel accommodation in

the Algarve. The study concludes that there is a time lag between tourism demand cycles and economic cycles. Further, Petropoulos et al. (2005) show that a model incorporating technical analysis techniques outperforms classic time series models in directional change forecasting competition.

In the case of Australian tourism demand, no attempt has been made to forecast turning points using econometric models and time series models.

2.5 Literature from Other Disciplines

This section reviews the various turning point forecasting methods used in other disciplines such as finance and macroeconomics, in order to predict turning points. Irrespective of the discipline, the graphs of different series often indicate the presence of a cycle in the series, indicating these series are going through expansion or contraction periods. According to Layton and Karsuura (2001) all expansions have unique features, and, without exception, all finally come to an end. These changes are extremely important to policy makers, markets and various institutions requiring some advance warning of when the inevitable contraction is likely to occur.

It is natural that attempts would be made to summarize the visual evidence in some way in order to learn and identify the characteristics of such cycles. Burns and Mitchell (1946) set out methods to do this, and these finally became established through the institution of the NBER (National Bureau of Economic Research) committee that is responsible for the dating (identifying) of US business cycle turning points. NBER uses various methods for this purpose, and this is due to the fact that there is no single measure of 'aggregate economic activity' (Harding and Pagan (2003)).

A number of past studies have sought to characterize the nature of the long-term trend in GNP and its relation to business cycles. Researchers such as Beveridge and Nelson (1981), Nelson and Plosser (1982), Campbell and Mankiw (1987) explored this using ARIMA models and the ARMA process around a deterministic trend. Harvey (1985), Watson (1986) and Clark (1987) based their analyses on linear unobserved component models. A third approach employs the co-integrated specification of Engle

and Granger (1987) whose relevance for business cycle research is examined in a paper by King and Rebelo (1987).

In contrast, there are methods which proceed by first fitting a statistical model to the data, and then utilizing the estimated parameters of that model to come up with some turning point dates. The best known example of such research was Hamilton's (1989) use of a Markov Switching (MS) model fitted to quarterly US GDP.

Layton and Karsuura (2001) indicated that it is likely that important information about the likelihood and timing of the next turning point will be found in leading indicators, which have proven over many years, and in many countries to be reliable in anticipating business cycle turns.

Estrella and Mishkin (1998) modelled the probability of recession using a non-linear Probit specification. This is a fundamentally different approach to that described above in the model specification (while non-linear in the sense that the model specification chosen is of Probit form) in that there is only one time-invariant mechanism generating the probability of recession. Another very common alternative to the Probit specification used in applied forecasting is the Logit specification.

Consequently, different modelling approaches to forecasting turning points are suggested: the ARIMA model, the Leading Indicator method, the Markov Switching model and the Logit and Probit models. As leading indicators and ARIMA have already been discussed, the following section will discuss the Markov Switching, Logit and Probit models.

2.5.1 Markov-Switching Autoregressive (MS-AR) model

After Hamilton (1989) first introduced the Markov Regime-Switching model formulation to macroeconomics, the model has been increasingly used by business cycle researchers to assist in the dating and forecasting of turning points in the business cycle. Hamilton (1989) used the switching idea to define changes in the economy between fast and slow growth regimes. Since then this model has become increasingly popular in the areas of business cycles, industrial production, interest rates, stock prices and unemployment rates (Layton and Karsuura (2001)).

This model allows the parameters to switch between two regimes. For example, the appropriate measure of the business cycle is regarded as having a certain probability of switching unexpectedly among a number of regimes. In the case of the business cycle we might expect say, two regimes, one corresponding to expansions and the other to contractions. The mechanism thought to be generating the observed data on the variable of interest is conceived as being regime-specific. In the same way, the phases of the tourism growth cycle (expansions and contractions) could be captured by this non-linear, Markov Regime Switching model. Non-linearity refers to the fact that the behaviour of the series describing the cycle depends on the phase in which it evolves (contraction and expansion). The important ability of the model is that it describes the presence of a regime shift together with the fact that the regime can shift suddenly, allowing the model to be fundamentally non-linear in nature.

Since Hamilton's (1989) introduction of regime shifts in autoregressive time series models, there have been enormous advances in formally modelling regime shifts in a rigorous statistical framework. To understand this model, it is useful to begin with a simple linear time series framework for the growth rate of some measure of economic activity, y_t :

$$y_t - \mu_{s_t} = \phi(y_{t-1} - \mu_{s_t}) + \varepsilon_t,$$

where S_t indicates when,

$s_t=0$ (Contraction period),

$s_t=1$ (Expansion period),

and $\varepsilon_t \sim N(0, \sigma^2)$.

$$(1) \quad y_t - \mu_0 = \phi(y_{t-1} - \mu_0) + \varepsilon_t,$$

$$(2) \quad y_t - \mu_1 = \phi(y_{t-1} - \mu_1) + \varepsilon_t.$$

In the above model, the growth rate of economic activity has a mean denoted by μ (μ_0 and μ_1 denotes the mean of two regimes). Deviations from the mean growth rate are created by the stochastic disturbance ε_t .

The probability process driving s_t is captured by the following four transition probabilities.

$$P(s_t = 1 | s_{t-1} = 1) = p$$

$$P(s_t = 0 | s_{t-1} = 1) = 1 - p$$

$$P(s_t = 0 | s_{t-1} = 0) = q$$

$$P(s_t = 1 | s_{t-1} = 0) = 1 - q$$

A complete time series model would therefore include a description of the probability law governing the change from $s_t=0$ to $s_t=1$, suggesting the process is influenced by an unobserved random variable s_t , which will be called the state or regime that the process was in at date t . If $S_t=0$, then the process is in regime 0, while $S_t=1$ means that the process is in regime 1 (Hamilton (1989)).

Some of the important applications of the Markov-Switching Autoregressive (MS-AR) model include Lahiri and Wang (1994) who provided the first illustration of the Markov-Switching model applied to predict business cycle turning points using the US Commerce Department's Composite Leading Index (CLI). Boldin (1994) fitted the Hamilton model to an alternative measure of economic activity, namely, the unemployment rate. Layton (1996) found this basic model to be quite useful in dating the US business cycle using the coincident index as compiled by the Economic Cycle Research Institute (ECRI).

Since the introduction of Hamilton's model, a large number of alternative Markov-Switching models of business cycles have been studied. It has been extended in two ways: extending the model and extending the application.

Hansen (1992) allowed for regime-switching in parameters other than the mean growth rate, such as the residual variance or autoregressive parameters. The model

was modified to allow for additional phases in business cycle dynamics by Sichel (1994) and Kim and Nelson (1999). Importantly, Diebold and Rudebusch (1996), Chauvet (1998) and Kim and Yoo (1995), Kim (1994) extended the Hamilton model to a multivariate framework, estimating a coincident index of economic activity with a regime-switching mean growth rate.

2.5.2 Logit and Probit models

The Logit and Probit models are regression models with dummy dependent variables, taking the value 1 or 0. The unique nature of these models is that the dependent variable is of the type that elicits a ‘yes’ or ‘no’ response; which means, it is dichotomous in nature. But the basic equation represents the general regression structure:

$$Y_i^* = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots + \varepsilon_i$$

Using this binary ‘yes’ or ‘no’ response of the Logit and Probit models, some macro economic and financial researchers have attempted to predict turning points and economic phases, where if the economy is in expansion period $Y=1$, and if the economy is in contraction $Y=0$, and X_i are potential explanatory variables that cause turning points (Layton and Karsuura (2001), Bodart and Shadman (2005), Sensier et al. (2004), Harding and Pagan (2006).

2.5.2.1 Binomial Logit model

The binomial Logit model is an estimation technique with dummy dependent variables that avoids the unboundedness problem of linear models by using variants of the cumulative logistic function (Studenmund (2001, p.442)). In Logit models the dependent variable is the logarithm of the ratio of the probability that a particular event will occur to the probability that the event will not occur. The Logit model is based upon a cumulative distribution function and the error ε_i is not normally distributed because P_i can only take on the values of 0 and 1, and the error ε_i is dichotomous as well.

This ratio is the likelihood, or odds, of obtaining a successful outcome ($P_i=1$). The log of this ratio obtained on the left side of the equation has become the standard approach to dummy dependent variable analysis:

$$\ln \left[\frac{P_i}{(1 - P_i)} \right] = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \varepsilon_i.$$

(Studenmund (2001)).

Forecasts of P_i from this model have the interpretation of probability forecasts of P_i being either 0 or 1, conditional on the values of the explanatory variables in the model. In the binomial Logit model the parameters of the model are estimated by maximum likelihood estimation (MLE).

Therefore the binomial Logit model avoids the major problem that the linear model encounters in dealing with dummy dependent variables. This is quite satisfying to most researchers because it turns out that real world data are often described well by S- shaped patterns (Studenmund (2001, p.434 -449)).

An important extension of this basic binomial Logit model is the so-called multinomial Logit model. In this extension, the dependent variable is allowed to have more than two values.

2.5.2.2 Binomial Probit Model

The Binomial Probit model is an estimation technique for equations with dummy dependent variables using a variant of the cumulative normal distribution (Studenmund (2001, p.449)).

The probability distribution can be represented as:

$$P_i = F(\alpha + \beta X_i) = F(Z_i)$$

(Pindyck and Rubinfeld (1991, p.254)),

where: P_i = the probability that the dummy variable $P_i = 1$

$$P_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots$$

The Probit model assumes that Z_i is a normally distributed random variable, so that the probability that Z_i is less than (or equal to) one, can be computed from the cumulative normal probability function.

As with the Logit model, the Probit model can also be extended to a multinomial version to have more than two values.

Both the Logit and Probit models are a cumulative distributive function which means that the two models have similar properties, and the functional forms of both the Logit and Probit models guarantee that the estimated probabilities which result from the models are between 0 and 1. Further, both can be estimated using the maximum likelihood (ML) method.

Logit and Probit models give close results, but the estimates of the parameters of the two models are not directly compatible. The biggest difference is that the Probit model uses a cumulative standard normal distribution functional form, whereas the Logit model uses a cumulative logistic function. The other difference between the Logit and Probit models is that the Logit model has flatter tails. The differences between them occur in their behaviour in the extremities of the 0-1 probability range, but this does not imply one should be preferred over the other (Layton and Katsuura (2001)).

Due to the advantages, already discussed, of the Logit and Probit models some macro econometric and financial researchers use this model to check for turning points and economic phases. The prediction of P_i from this model has the interpretation of probability whether the economy is in an expansionary phase ($P_i=1$) or contracting phase ($P_i=0$), which is conditional on the values of the explanatory variables in the model.

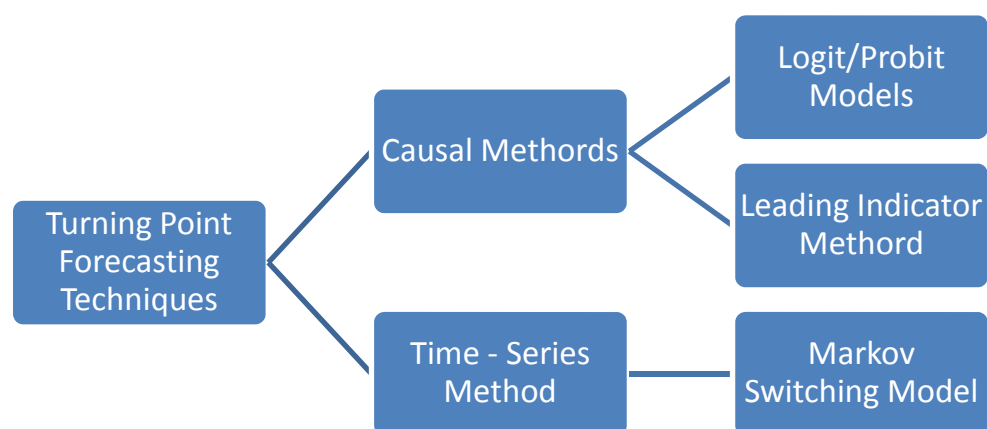
Some applications of this approach to predicting turning points are: Layton and Karsuura (2001) who forecast US business cycle turning points, Bodart and Shadman

(2005) who forecast Belgian business cycle turning points, Sensier et al. (2004) who applied this model together with the leading indicator method to identify the variables in predicting a classical business cycle regime. Additionally, Hoetker (2007) uses Logit and Probit models to research critical issues in strategic management. Harding and Pagan (2006) apply the methodology to predict recessions in Australia. Lennox (1999) uses these models to examine bankruptcy cases in UK listed companies between 1987 to 1994. Falcetti and Tudela (2008) apply the Probit model to investigate cases of currency crisis in emerging markets.

Currently, the literature from finance and macroeconomics contains a number of research papers on the Markov Switching model together with Logit/Probit models, and for Markov Switching, many researchers use leading indicator data as their main data series, and for Logit and Probit models the same leading indicators are used as independent variables (Layton and Karsuura (2001), Bodart and Shadman (2005), Sensier et al. (2004), Harding and Pagan (2006), Lennox (1999), Marianne and Kouparitsas (2005)).

Markov Switching and Logit /Probit models are non-linear models. Importantly, both models can estimate the probability of an economy being in expansion or contraction in a particular period using maximum likelihood estimation.

Figure 2.2: Possible Turning Point Forecasting Techniques Discussed



2.6 Gaps in the Literature

In conclusion, two main quantitative methods have been identified from past studies. They are causal methods and time series methods. In tourism economics apart from the leading indicator method, the other methods do not specifically attempt to forecast turning points.

Tourism turning point forecasting is an important aspect of tourism forecasting research and has a high practical value because tourism-related firms are keen to know not only the overall trends of tourism demand, but also the timing of turning points in tourism growth. This knowledge can contribute to the effectiveness of both business planning in the private sector and macroeconomic policy-making in the public sector (Song and Li (2008)).

Song and Li (2008) have conducted a comprehensive analysis of past tourism forecasting studies and have highlighted the importance of turning point forecasting and the lack of research in this area. Witt and Witt (1991) and Witt et al. (2003) have stressed the importance of further study to identify turning points in inbound tourism demand growth. Existing methods do not satisfy the investment and planning needs of government and the tourism sector. The main reason for this inadequacy is that the current econometric and time series methods used in tourism forecasting are fundamentally linear methods and the ability to forecast non-linear patterns using these methods is very limited.

On the other hand, the literature from other disciplines shows that models like Markov Switching, Logit and Probit models are suitable and are currently in use to forecast turning points in other economic sectors, the main reason for this being the non-linear nature of these models. The Markov Switching model can be described as a non-linear model due to the fact that the mechanism thought to be generating the observed data on the variable of interest is conceived as being regime-specific. This feature, together with the fact that the regime can shift suddenly, characterises the model as fundamentally non-linear in nature. On the other hand, Logit and Probit models are non-linear methods because the dependent variable (D_i) is bounded by 1 and 0, $\hat{D}_i$ approaches 1 and 0 very slowly (asymptotically). Therefore these models avoid the

major problems that linear models encounter in dealing with dummy dependent variables (Studenmund (2001, p.434-449)). Importantly, none of the above non-linear models have been used to forecast turning points in tourism demand.

Chapter 3

Research Process and Methodology

3.1 Introduction

The objective of this chapter is to discuss the process, and the methods used in this research, to identify and forecast turning points. The chapter will also discuss the model evaluation methods used, in order to evaluate forecast accuracy between models.

3.2 Objective of the Study

As discussed in Chapter 2, one of the main causes of tourism demand change is the dynamic nature of world economies. Further, available literature in tourism economics has used economic variables/factors for demand forecasting and has identified the influence of economic factors on tourism demand (Turner et al. (1997), Witt and Witt (1991), Song and Witt (2000), Song et al. (2000), Turner and Witt (2001a)). Hence, focusing on economic factors could be a good starting point and will make the comparisons easy in this relatively new study area of ‘turning point forecasting’ in tourism economics. Therefore, specifically, the aim of this study is to forecast turning points in Australian inbound tourism demand caused by ‘economic factors’ in the tourism-originating or destination country.

3.3 Main Methods Used to Forecast Turning Points

The existing literature indicates that a new approach is required to forecast turning points in tourism demand due to the limitations of the current linear methods. Techniques identified from other disciplines may provide an insight into what is thus required. These techniques include Markov Switching, Logit and Probit models and leading indicators. The advantage of Logit and Probit models is that leading indicators can be used as dependent variables to estimate the Logit and Probit models and,

further, the Logit and Probit models can also be estimated using potential economic independent variables.

These methods can then be used to calculate the probability that tourism demand will be in expansion or in contraction at a certain date in the future. The normal state of tourism demand is considered to be expansion because of the historical economic growth in tourism since 1975, and accordingly the focus is to concentrate on calculating the probability of contraction. If the probability of contraction exceeds a predetermined threshold (e.g. 0.5), a signal is defined that indicates tourism demand is moving from expansion to contraction (downturn). On the other hand, if the probability of contraction is below the threshold, it signals the end of the contraction (beginning of an expansion-upturn).

3.4 Data Used in the Study

This study will use the quarterly time series of tourist arrivals to Australia from 1975 (quarter 1) to 2007 (quarter 4), and will examine four major tourist-generating countries to Australia, namely: New Zealand, the United Kingdom, Japan, and the USA. The reason for selecting these four countries is that they are the major tourism source markets and contribute more than 50% of inbound tourism to Australia. Quarterly inbound tourism data are collected from the Australian Bureau of Statistics (ABS) and the Tourism Australia website. Quarterly data are collected in preference to yearly data because of the importance of a larger sample size and the need to measure sensitive changes in the series. The economic variables, including income, exchange rates and relative prices, are obtained from the International Financial Statistics published by the International Monetary Fund (IMF) and DX data.

3.5 Smoothing Tourist Arrivals Data

The objective of data smoothing is to create an approximating function that attempts to capture important patterns in the data, while leaving out noise. Extracting the smoothed tourism demand growth for each tourism origin country is a prerequisite for identifying true turning points.

The extraction of a smoothed growth varies from single differences to more complicated higher order moving averages. A discussion of the methods used in calculating smoothed growth, using different approaches, is given in Niemira and Klein (1994) who point out two important features in the selection of a smoothing method:

- (1) The smoothing process should not distort the original pattern.
- (2) The smoothed pattern should not be adversely affected by outliers, that is, the method should be robust.

Further Niemira and Klein (1994) discuss different approaches to smoothing data including the simple growth rate, annualized growth rate, growth rate over time (Geometric Mean), 6 month smoothed annualized rate (SMSAR) and 2-quarter smoothed annualized rate (TQSAR). According to Niemira and Klein (1994, p. 94) other non-statistical methods such as single differences and moving-average methods are more volatile compared to a 6-month smoothed growth rate method (SMSAR) and 2-quarter smoothed annualized rate (TQSAR). Layton and Moore (1989) and Rossello-Nadal (2001) adopted the 6-month smoothed annualized rate in their studies. Kulendran and Wong (2006) examined the 2-quarter smoothed annualized rate method in order to predict turning points for quarterly Hong Kong inbound tourism demand growth.

In recent years, the statistical modelling approach of ‘unobserved components’ has been used to extract the trend derivative (slope), and this method has become very popular in the area of finance and economics. One example of successful implementation is Garcia-Ferrer and Bujosa-Burn (2000) who recommended that if the trend is smooth and without irregular components, this can be considered as both an indicator of underlying growth as well as an anticipative tool for predicting turning points in seasonal economic time series. The trend derivative of the unobserved trend component could be obtained in two ways: (1) a filter approach and (2) a statistical modelling approach.

In the filter approach, the trend derivative is obtained from the extraction of a trend component using the Hodrick-Prescott (HP) filter smoothing method. This is widely

used among macroeconomists to obtain a smoothed estimate of the long-term trend component of a series (EView 4.0). However the weaknesses of this approach are: (a) the end point estimation is unstable; (b) the cyclical signal may display considerable erraticity; (c) as is common with ad-hoc filters, it may be inadequate for certain series, raising the possibility of generating spurious results (Kaiser and Maravall (2002)).

The second approach is the statistical modelling method, or the Basic Structural Model (BSM) (Harvey (1989)). The use of the BSM model to extract the trend derivative has been successfully implemented in Garcia-Ferrer and Bujosa-Burn (2000). This smoothing method is used in other disciplines and has been successful with times series data. In tourism economics, Kulendran and Wong (2009) adopted this method to smooth Hong Kong inbound tourism data.

Considering the literature above, and the quarterly nature of the data, this study applies three different smoothing methods in order to select the most suitable one, namely:

(I) 2-quarter smoothed annualized rate (TQSAR) method (Niemira and Klein (1994)).

(II) Hodrick-Prescott (HP) filter smoothing method.

(III) Basic Structural Model (BSM) (Trend Derivative (Slope) approach).

After applying these three methods to the historical tourism arrivals data, a decision is made concerning which method is most suitable for this study based on the smoothed graph (visual inspection) and the ability to highlight significant turning points (volatility levels). The three smoothing methods above are examined in the next chapter.

3.6 Selecting a Cycle Pattern

Once the tourist arrivals time series is smoothed, the next step is to apply the smoothed time series to an appropriate cyclical pattern in order to identify significant turning points. Presently there is no generally accepted industry cycle model in economics.

Distinguishing different types of cycles is vital for making decisions in selecting an appropriate cycle pattern as cycle pattern is extremely important in the process of identifying and forecasting turning points. In macroeconomics GDP, GNP or unemployment rates are commonly used to construct the cycle. In tourism research and particularly in this study, the number of tourist arrivals (smoothed) is used to develop an appropriate cycle pattern.

The following three types of cyclical patterns are common in the literature to monitor turning points: (1) classical business cycles (2) growth cycle and (3) growth rate cycle.

3.6.1 Classical Business Cycle

Classical business cycles are characterized by absolute expansions and contractions in the levels of aggregate sector (economic) activity.

According to Burns and Mitchell (1946, p.3) “Business cycles are a type of fluctuation found in aggregate economic activity of nations”. A cycle consists of an expansion occurring at the same time for any set of economic activities, followed by a similar general recession/contraction. This process is recurrent but not periodic. The duration of a business cycle varies from more than one year to twelve years.

By the end of the 1960s, many industrial economies had not experienced a recession for many years. This led some observers to question whether the business cycle was still in existence (Bronfenbrenner (1969)). Subsequently, there was a move towards studying the growth cycle based on cyclical deviations in economic activity from trend (Mintz (1969)). A few years later when the OECD developed leading indicators for its member countries, it decided to monitor these growth cycles.

In tourism economics Rossello-Nadal (2001) applied the business cycle using monthly tourist growth to forecast turning points in the Balearic Islands. Leading indicators were originally used to anticipate traditional cyclical downturns and upturns in economic activity (i.e., contraction and expansion).

3.6.2 Growth Cycle

The growth cycle refers to deviations from the long-term trend in the growth rate of the economy. The expression ‘growth cycle’ is not a strictly correct term because it creates confusion with the cycle of the growth rate (discussed below), introduced by the OECD in the 1960s. In recent years, more emphasis has been placed on forecasting turning points in the growth cycle. Growth cycles are a short-term fluctuation in the aggregate economy and can be divided into two phases: high growth (expansion: above-average trend growth) and low growth (contraction: below-average trend growth). A growth cycle is a pronounced deviation around the trend change. Thus, this definition pertains to periods of accelerating and decelerating rates of growth in the economy.

Taylor (1998) pointed out that growth cycles tend to lead business cycles and, consequently, they are useful precursors of major change in the level of economic activity. As stated by Garcia-Ferrer et al. (2001), compared to classical business cycles, growth cycles are more likely to represent the present stage of economic activity. The identification of a growth cycle involves estimation of the long-term trend using the phase average trend method (Boschan and Ebanks (1978)) and it is expressed as the deviation from trend.

The difficulties of measuring the growth cycle on a real-time basis are discussed in Banerji and Hiris (2001). Layton and Moore (1989) state: “Although the procedure works well historically, there are uncertainties about measuring the trend currently and problems with revision as more recent data become available”.

3.6.3 Growth Rate Cycle

An alternative approach is to analyze growth rates directly rather than looking at the deviation from trend. Cyclical turns in these growth rates define the growth rate cycles. By the late 1980s, the use of growth rate cycles for the measurement of a series which manifested few actual cyclical declines but did show cyclical slowdowns, was introduced (Layton and Moore (1989)). Like the ‘step cycle’ introduced by Mintz (1969), the growth rate cycle was based on the growth rate of

economic activity (meaning growth rate of the economy). However, unlike the step cycle, it did not presume that the growth rate changed in steps. The peak represents the maximum growth rate and the trough indicates that the growth has reached its lower value. Importantly, with the growth rate cycle it is harmful to mention 'slowdown' when the growth begins to decrease. For example, when the tourism demand growth rate decreases from 3% to 2%, it does not mean that tourism demand is moving into recession (it is not a slowdown) because growth remains above the trend growth it is only a growth slowdown. The growth rate cycle avoids the problem of trend estimation evident in the growth cycle procedure, while on the other hand it shares the key cyclical characteristics exhibited by the business cycle (Banerji and Hiris (2001)). The main difference in growth rate cycle compared to growth cycle is, when the growth rate goes up from -2% to -1%, it correspond to a phase of decreasing activity (contraction) in growth cycle, even though the growth rate goes up. Due to this basic attribute, growth rate cycle is not suitable for short-term cycles, as it is too difficult estimate.

In tourism economics, Kulendran and Wong (2009) used the growth cycle to construct leading indicators to forecast Hong Kong tourism demand.

After considering three cycle patterns, this study will use the growth cycle due to its simplicity ($(Y_t = Y_t - Y_{t-4})$), due to evidence of its use in past studies in tourism and, importantly, because the main objective of this study is to forecast turning points rather than detect slower growth and faster growth.

3.7 Detecting Turning Points/Dating Turning Points

Once the data is smoothed and the cyclical pattern is established, the next step is to identify the significant turning points in the tourism demand growth. This is called the 'dating' process or establishing reference chronology. Once the significant turning point in the actual arrivals series is established (once the turning point chronology is established), it can be used in empirical studies to classify and to validate a forecasting method.

According to Boldin (1994), turning points are peaks, the period immediately preceding a decline/contraction in real activity, while the troughs are the period

immediately preceding an upturn or expansion. Boldin (1994) highlighted two main conditions for a dating technique to qualify as useful: (1) careful and clear documentation of the data that is examined and (2) a means to distinguish recession from expansion (known as the pattern recognition problem). Boldin (1994) further mentions that flexibility in identifying a turning point can be useful since business cycles are irregular in periodicity, and each recession has some unique factors and conditions.

The detection and description of any cycle is accomplished by first isolating turning points in the series, after which those dates are used to mark off periods of expansion and contraction. The location of turning points can sometimes be done visually, and the eye is very good at filtering out ‘false turning points’, that is movements which are either short-lived or of insufficient amplitude (Harding and Pagan (2000)).

Translating visual judgments into an algorithm has proved to be challenging. At the very least, such an algorithm needs to have three attributes:

1. The ability to determine a potential set of turning points, i.e. the peaks and troughs in a series.
2. Demonstrate a procedure for ensuring that peaks and troughs alternate.
3. Possess a set of rules that re-combine the turning points established after steps one and two in order to satisfy pre-determined criteria concerning the duration and amplitudes of phases and complete cycles - what we will refer to as ‘censoring rules’ (Harding and Pagan (2000)).

As discussed above a proper dating method is required to identify true turning points in quarterly inbound tourism demand growth. There is no research facility/institute that dates turning points in tourism demand locally or internationally, and there are only a few studies in tourism economics that attempt to identify turning points in tourism demand (Kulendran and Wong (2006)). However the literature from macroeconomics indicates that in this field dating turning points is a popular subject area which uses parametric and non-parametric methods.

In macroeconomics there have been many attempts to establish turning point dates by translating the graphical inspection approach into a procedure, either parametric or non-parametric. An important feature is that all these procedures must be flexible enough to take into account certain non-linearities of the cycle, such as different duration, amplitudes and cumulative movements of its phases. Non-linearity refers to the fact that behaviour of the series describing the cycle depends on the phase in which it evolves (contraction or expansion).

There are a variety of definitions that exist for turning points and they differ according to the period under study. Zellner et al. (1991) and Witt and Witt (1991) observed that in an annual time series four consecutive observations are used to characterize downturns and upturns, whereas in a quarterly time series Oller and Tallbom (1996) point out that a turning point is observed when a seasonal logarithmic difference, $(\nabla 4yt)$, changes sign and maintains the change for at least four quarters. Several other studies such as Lesage (1992), Birchenhall et al. (2001), Harding and Pagan (2003) and Gouveia and Rodrigues (2005) use the definition to identify turning points in growth rates of quarterly and monthly data. To identify the turning points in the monthly tourist growth rate, a Rossello-Nadal (2001) study used the traditional National Bureau of Economic Research (NBER) method accomplished by means of a visual inspection (or using a computer program). The Birchenhall et al. (2001) study used rules implying that a peak is identified at t if the variable Y_t is strictly greater than the values for the subsequent two quarters $t+1$ and $t+2$, while also being at least as large as all values within the past year, and in the future, troughs are defined in an analogous manner. An alternative approach to defining turning points is the use of dummies, which is discussed in Hales (1999).

To summarize the past research and theory in dating turning points, the following popular non-parametric and parametric dating methods are presented.

Non-parametric Dating Methods

3.7.1 The NBER Business Cycle Dating Committee approach

In the United States, the NBER (National Bureau of Economic Research) Business Cycle Dating Committee is widely recognized as the authority for determining the

peaks and troughs of the classical business cycle. The NBER turning point selection method has largely been carried out by visual inspection or can be done using a computer program. But the method is no less effective in summarizing the cyclical movement of a time series than turning points from special analysis or some other purely statistical technique (Niemira and Klein (1994)). The Committee's method for selecting turning point dates is pragmatic since it requires a consensus among members who tend to hold differing views and use different methods to analyze macroeconomic conditions and trends.

3.7.2 Gross Domestic Product (GDP) rule of thumb

Many economists believe that two consecutive quarters of negative growth define the start of an official recession. This is called the '2- quarter GDP' rule and although the NBER and 2- quarter GDP rule dates are not exactly the same, they are very close.

3.7.3 Peaks and troughs of the Commerce Department's business cycle indicators

The Commerce Department's Bureau of Economic Analysis (BEA) computes three popular series for business cycle analysis: the coincident (CI), leading (LI), and lagging (LGI) indicators. The construction methodology for these series is based on research that began with Burns and Mitchell (1946) and was continued by other NBER economists. The monthly percentage change in each indicator is a weighted average growth in individual components. In this method it is found that the peaks and troughs coincide almost exactly with NBER dates (Boldin (1994)).

3.7.4 Stock and Watson's experimental business cycle indices

This was initiated as an NBER supported project. Stock and Watson (S-W (1989)) developed an experimental coincident indicator (XCI) of the business cycle. They used roughly the same data sources as the BEA's (Bureau of Economic Analysis) coincident indicator (CI), the only difference being that 'hours worked' is substituted for the 'employment count' (Boldin (1994)).

All the methods discussed above attempt to establish turning point dates by translating a graphical inspection into an algorithm. For example, the NBER Committee's decision process seems to closely adhere to Burns and Mitchell's (1946) concept of business cycle theory, in that:

- (1) A full cycle is required lasting over one year and those lasting less than two years warrant scepticism.
- (2) Chooses later (as opposed to earlier) turning point dates, both in periods of flatness and multiple spikes (unless the spikes show a clear downward or upward pattern).

3.7.5 Bry and Boschan (BB) Algorithm

The most famous non-parametric algorithm (procedure) is the Bry and Boschan (1971) procedure. This is still in use in many countries to estimate business cycle turning points.

Although there are many sub-stages, the important step is a definition of a local peak (trough) as occurring at time t whenever $\{y_t > (<) y_{t \pm k}\}$, $k=1, \dots, K$, where K is generally set to five. The other important criteria are that a phase must last at least six months and a complete cycle should have a minimum duration of 15 months.

When the data is measured at a quarterly frequency, an analogue to the first step of the BB algorithm would be to put $K=2$, i, as this ensures that y_t is a local maximum relative to the two quarters (6 months) on either side of y_t . Later, this quarterly version of the BB algorithm, combined with some censoring rules, is described as BBQ. An even simpler 'sequence' rule is available from the idea that a turning point in a graph at time t requires that the derivative change sign at t . Thus, treating Δy_t as a measure of the derivative of y_t with respect to t , leads to the use of the sequence $\{\Delta y_t > 0, \Delta y_{t+1} < 0\}$ as signalling a peak. The problem with the latter is that it would conflict with the requirement that a phase must be at least six months in length.

A minor modification is given to the Bry and Boschan (BB) approach by Lesage (1992) in order to identify the potential turning points in the growth rate of quarterly data. Lesage slightly changed the quarterly version of the BB algorithm, just adding

one more quarter, meaning $K=3$, as this ensures that y_t is a local maximum relative to the three quarters (9 months) on either side of y_t .

Lesage (1992) applied the following definition for the downturn (DT) and upturn (UT):

DT at $t := \{(Y_{t-3}, Y_{t-2}, Y_{t-1} < Y_t > Y_{t+1}, Y_{t+2}, Y_{t+3})\}$,

UT at $t := \{(Y_{t-3}, Y_{t-2}, Y_{t-1} > Y_t < Y_{t+1}, Y_{t+2}, Y_{t+3})\}$.

Where: Y_{t-3} , Y_{t-2} , and Y_{t-1} are past values of growth and Y_{t+1} , Y_{t+2} , and Y_{t+3} , are the future values of growth.

In tourism economics this method has been applied by Kulendran and Wong (2009). According to Harding and Pagan (2000) this Bry and Boschan non-parametric algorithm method captures most of the NBER turning points.

Of all the non-parametric approaches discussed above, this study will apply the modified Bry and Boschan (BB) algorithm used by Lesage (1992) in order to date/identify the turning points in the Australian inbound tourism demand growth cycle because it has already been tested with tourism data by Kulendran and Wong (2009).

In Chapter 4, to identify the significant turning points in tourism demand, and in Chapter 7, to identify the significant turning points of leading indices, this non-parametric modified BB algorithm method will be applied.

Parametric Dating Methods

Apart from the non-parametric approaches discussed above, a number of parametric models have been developed lately to identify significant turning points in the business cycle. These parametric methods are mainly based on the Markov-Switching model proposed by James Hamilton (1989).

3.8 Markov Switching Model

This is the latest parametric dating method introduced by Hamilton (1989) for business cycle analysis. Hamilton's MSM (Markov Switching model) specification captured distinct periods of high (positive) and low (negative) growth in quarterly GNP. Later Boldin (1992) expanded this research to monthly data.

These models take into account a type of non-stationarity inherent in some economic and financial time series that cannot be captured by classical linear models. Non-linearity refers to the fact that the behaviour of the series describing the cycle depends on the phase in which it evolves (contraction and expansion).

Hamilton's Two State Model

Hamilton (1989) used the switching idea to define changes in the economy between fast and slow growth regimes, the two states representing expansion and contraction phases of the business cycle.

In the same way, in this study the phases of the tourism growth cycle (expansions and contractions) can be captured by this non-linear Markov Regime Switching model. Specifically, this study uses the two phases of tourism demand, to define switching between fast and slow tourism demand growth regimes.

Hamilton's model (1989) can be represented in general using the following form:

$$y_t = \mu_{s_t} + \phi_1(y_{t-1} - \mu_{s_{t-1}}) + \phi_2(y_{t-2} - \mu_{s_{t-2}}) + \phi_3(y_{t-3} - \mu_{s_{t-3}}) + \phi_4(y_{t-4} - \mu_{s_{t-4}}) + \varepsilon_t,$$

Since this study considers only two states, the model is:

$$y_t = \mu_{s_t} + \varepsilon_t,$$

where y_t is the logarithm of the smoothed growth of tourist arrivals data (at time t), and μ_{s_t} takes two values, μ_0 when $s_t=0$ and μ_1 when $s_t=1$, where s_t is an unobserved binary variable representing the system (or demand growth) at time t known as the state of the system.

The probability process driving s_t is captured by the following four transition probabilities:

$$\begin{aligned} P(s_t = 1 | s_{t-1} = 1) &= p \\ P(s_t = 0 | s_{t-1} = 1) &= 1 - p \\ P(s_t = 0 | s_{t-1} = 0) &= q \\ P(s_t = 1 | s_{t-1} = 0) &= 1 - q \end{aligned}$$

The Markov Switching output will generate the smoothed probabilities of the unobserved states s_t . This will give the probability of each quarter being in an expansion (or contraction) regime. Normally 0.5 probability values form a cut off point between the expansion and contraction regime. When the tourism demand probability changes from greater than 0.5 to less than 0.5, or vice versa, it is considered a regime change, or turning point.

As mentioned, the significant turning points are identified in the next chapter (Chapter 4) using the non-parametric modified BB algorithm. Chapter 5 introduces and applies parametric Markov Switching to identify significant turning points and compares the accuracy of the parametric and non parametric dating methods.

3.9 Leading Indicators

From the existing literature, the leading indicator method is identified as one of the most acceptable methods in macroeconomics, as well as in tourism economics, to forecast turning points.

A common question raised about composite leading indicators is: Why go through this procedure when a simple regression model would establish the associated coefficients based on an optimal statistical relationship compared with some dependent variable of interest? But the difference is that a composite leading index is often a turning point indicator with no true ‘dependent’ variable, which means turning points can happen due to many different reasons. The second difference is that a regression model normally would assume a fixed timing relationship between a

dependent and independent variable. The leading indicator approach forecasts the timing relationship between indicator changes over time and the business cycle (in this study the tourism cycle), hence the indicators are entered with a concurrent relationship, which assumes that the information is simply today's information about the future or present (Niemira and Klien (1994)).

This study constructs a composite leading indicator for tourism demand taking into account the past leading indicator studies in tourism economics (Turner et al. (1997), Kulendran and Witt (2003), Rossello-Nadal (2001)). The potential leading indicators for Australian inbound tourism demand are selected from the following economic variables: tourist origin country income measured by gross domestic product (GDP), the exchange rate between tourist origin country and destination country (EX), the relative price (CPI), share price (SP), total exports (TEP), total imports (TMP), and the unemployment rate (UN). In order to discover whether these economic indicator variables lead Australian inbound tourism demand, the cross-correlation function is examined (which describes the extent to which two series are correlated) for inbound tourism demand and these economic variables.

In addition to the constructed Composite Leading Indicator (CLI), two more readily available potential leading indicators are used in this study, namely: (1) CLI available for OECD countries through DX data and (2) Business Survey index available in DX data. To assess the forecasting performance of these three indicators, the previously discussed parametric and non-parametric turning point detection methods will be used.

3.10 Logit and Probit Models

Logit and Probit models are possible non-linear econometric models, which have binary dependent variables. These models have been used to forecast turning points in business cycles, but not to forecast turning points in the tourism context.

Using the binary 'yes' or 'no' response of the Logit and Probit models, some macro economic and financial researchers have attempted to predict turning points and economic phases. If the economy is in an expansion period the independent variable $Y = 1$, and if the economy is in contraction, $Y = 0$. The dependent variables are the

potential variables that cause turning points (Layton and Karsuura (2001), Bodart and Shadman (2005)). Importantly, these models can give the probability of the economy being in expansion (or contraction) in a particular time period and the point where the probability value passes a specific cut-off value (e.g. 0.5) that identifies a turning point. But the basic equation represents the general regression structure.

$$Y_i^* = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots + \varepsilon_i$$

Due to their relevance and previously discussed features, this study will apply Logit and Probit models to forecast turning points in Australian inbound tourism demand growth. In this study, Y can be predicted, with the interpretation of Y=1 when tourism is in an expansion phase (increasing tourism demand) and Y=0 when tourism is in a contracting phase (decreasing tourism demand), with explanatory variables. The explanatory variables for the Logit and Probit models are selected based on the recognised tourism demand model (Chapter 2.3.1) and past tourism demand studies.

Consumer choice theory postulates that the demand for a given commodity depends on consumer's income, prices and other variables specific to the commodity in question. Many past studies have identified the potential independent variable's effect on tourism demand. Song and Turner (2006 p.90), Li et al. (2004), Lim (1997), Song and Witt (2000), Song et al. (2003b), Kulendran and King (1997), Kim and Song (1998), Lathiras and Siriopoulos (1998), Witt and Witt (1991, 1992), Lim and McAleer (2001, 2002), Dritsakakis (2004), Turner and Witt (2003), Witt and Martin (1987), Crouch et al. (1992) and Ledesma-Rodriguez et al. (2001) have all identified different independent variables for tourism demand including destination price, income, population, substitute price, marketing expenditure, travel cost and dummy variables in order to account for the impact of one-off events. Considering the availability of data and the aim of this study, inbound tourism demand for Australia may be expressed as a function of income, price, the price of a competing substitute and airfare:

$$TD = f(Y, PT, AF, SP, D_1, D_2),$$

Where:

TD: represents the actual tourism demand growth; $TD = 1$ if the actual tourism demand growth is in expansion, and $TD = 0$ if the actual tourism demand growth is in contraction.

Income (Y): is the growth of tourist origin country income (measured in real GDP).

Price of Tourism (PT): is the growth of the tourist destination country's prices (to calculate the price of tourism products in Australia, the Australian consumer price index (CPI) is divided by the origin country CPI and multiplied by the bilateral exchange rate).

Airfare (AF): is the growth of airfare prices measured in real terms.

Substitute Price (SP): is the growth of substitute destination prices measured by substitute destination price, (CPI) adjusted with exchange and adjusted with tourist origin country price (CPI).

It is not easy to find a close substitute destination, for a country like Australia due to its unique characteristics that is also located distant to other countries. To select the substitute destination for USA, UK Japan and New Zealand tourists, attributes such as geographic location, culture, travel distance, climate and destination highlights need to be considered. After carefully considering the potential substitutes for Australia, and taking in to account past studies, in this study Hawaii is selected for Japanese tourists as a substitute destination due to similarities between both locations such as sandy beaches and climate. Queensland (the major Japanese destination in Australia) and Hawaii have many similar characteristics to Australia (Kulendran and Divisekara 2007). For USA tourists the UK is considered a substitute destination since the UK has some similar characteristics to Australia and a history of high levels of USA travel to the UK. For UK tourists the USA is considered a substitute destination due to its size, diverse offerings and a long-term history of high levels of UK travel to the USA. For New Zealand there is no substitute selected, because it is virtually impossible to find a substitute destination for New Zealand due to its close proximity to Australia and other cultural and political links (Kulendran and King (1997), (Kulendran and Divisekara (2007))).

Though the aim of this study is to forecast turning points caused by economic factors, two dummy variables (two random events) are used to check the effects on tourism demand (whether they create significant turning points), (1) 2000 Sydney Olympics which had a positive effect on tourism demand and (2) 2001 September 11th terrorist attack on New York which had negative effects on tourism demand.

Moreover, in Chapter 8 the explanatory power of leading indicators to predict expansion and contraction (1 and 0) will be checked when estimating Logit/Probit models, using leading indicators as dependent variables.

3.10.1 Diagnostic tests

Diagnostic tests are important in determining a model's statistical acceptability. In a major review of empirical research on tourism forecasting, Witt and Witt (1995) conclude that "The lack of diagnostic checking in econometric studies considered clearly limits the usefulness of the empirical results".

Like other regression models, with Logit and Probit models care is needed to deal with the following problems:

- (1) **Heteroscedasticity** - which implies that the residuals do not maintain constant variance throughout the time series. The White test can be used to identify a heteroscedasticity problem.
- (2) **Multicollinearity** - which refers to the correlation among explanatory variables. This was "the most common methodological problem encountered" as highlighted by Crouch (1994) in his review of 85 tourism demand forecasting models. Simple cross correlation tests can be carried out to identify multicollinearity problems.
- (3) **Autocorrelation** - In regression models, error terms or residuals are assumed to be an independent white noise sequence with zero mean which has constant variance, independence, and normality assumptions. The autocorrelation of error terms or residuals can lead to an inappropriate model (Cook and Weisberg (1982)). The presence of autocorrelated

residuals may be detected by using residual plots and the Durbin-Watson statistic d test (Durbin and Watson (1951)).

3.10.2 Tests to check the overall significance of the Logit and Probit models

In Chapter 6 Logit and Probit models are discussed in detail. To understand tests applied to check the overall significance, the basic Logit and Probit models are given below.

Logit Model

The Logit model can be presented as:

$$\ln \left[\frac{P_i}{1 - P_i} \right] = Z_i = \alpha + \beta X_i,$$

where the dependent variable is the logarithm of the ratio of the probability that a particular event will occur to the probability that the event will not occur. The Logit model is based upon a cumulative distribution function and the error ε_i is not normally distributed because $P(Y_i)$ can only take on the values of 0 and 1.

Probit Model

The probability distribution can be represented as:

$$P_i = F(\alpha + \beta X_i) = F(Z_i),$$

where: P_i = the probability that the dummy variable $P_i = 1$

$$P_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots$$

The Probit model assumes that Z_i is a normally distributed random variable, so that the probability that Z_i is less than (or equal to) one can be computed from the cumulative normal probability function.

Likelihood tests

A 'likelihood' is a probability that the observed values of the dependent variable may be predicted from the observed values of the independent variables. Like any probability, the likelihood varies from 0 to 1.

(I) Log likelihood

The log likelihood (LL) is the log of likelihood and varies from 0 to minus infinity (it is negative because the log of any number less than 1 is negative). LL is calculated through iteration, using maximum likelihood estimation (MLE). In model refinement, when models are compared, the highest LL value is the value closest to zero. Log likelihood is the basis for tests of a logistic model. This shows the maximum value of the likelihood function assisted by our estimated parameter value of $l(\hat{\beta})$.

(II) Average log likelihood

This shows the average maximum value of the likelihood function obtained by dividing the log likelihood by the sample size (n).

(III) Restr. log likelihood

Restr. log likelihood shows the maximum value of the likelihood function when all the slope coefficients are set to zero, $l(\tilde{\beta})$. This is the likelihood function value obtained when the model is estimated with just the intercept. The estimate of the intercept is equal to the unconditional mean probability that $Y=1$.

Likelihood Ratio Tests

The likelihood ratio test is based on -2LL (deviance). The likelihood ratio test is a test of the significance of the difference between the likelihood ratio (-2LL) for the researcher's model, minus the likelihood ratio for a reduced model.

(I) LR statistics

The LR statistics test the joint null hypothesis that all the coefficients except the intercept are zero. The formula that is used to obtain LR is $-2(l(\tilde{\beta}) - l(\hat{\beta}))$.

This statistic, which is only reported when a constant is included in the specification, is used to test the overall significance of the model. The number in parentheses indicated the degrees of freedom, which is the number of restrictions under the test.

(II) Prob (LR statistics)

When the reduced model is the baseline model with only the constant, the likelihood ratio test tests the significance of the researcher's model as a whole. A well-fitting model is significant at the .05 level or better, meaning the researcher's model is significantly different from the one with only the constant.

The probability (LR statistics) shows the probability values for the LR statistic. If the probability value is 0.0014, the chance of obtaining these coefficient estimates when the true population values are zero is only 0.0014.

The McFadden R-squared

Unlike other regression models, in Logit and Probit models R^2 is not an accurate measure of overall fit and it tells very little about the overall fit, because the model uses dummy dependent variables (Studenmund (2001 p. 442)). An R^2 measure seeks to make a statement about the 'percent of variance explained', but the variance of a dichotomous or categorical dependent variable depends on the frequency distribution of that variable. For a dichotomous dependent variable, for instance, variance is at a maximum for a 50-50 split and the more lopsided the split, the lower the variance. This means that R-squared measures for logistic regressions with differing marginal distributions of their respective dependent variables cannot be compared directly, and comparison of Logit and Probit R-squared measures with R^2 from OLS regression is also problematic. But, as the name suggests, this is an analogy to R^2 reported in linear regression models. It has the property that it always lies between zero and one.

3.10.3 Interpreting Coefficients

The coefficient in the Logit and Probit models are not interpreted in the same way that the coefficients are interpreted in the standard regression model. In the regression

model the coefficients describe the marginal impact of an X variable on the Y variable when the other X variables are fixed.

(I) Marginal Effect

Coefficient which appear in the output of the Logit and Probit models cannot be interpreted directly since the interpretation of the coefficients' values is complicated by the fact that the estimated coefficients are from a binary model.

The marginal effect of x_i on the conditional probability is given by:

$$\frac{\partial E(y_i | x_i \beta)}{\partial x_{ij}} = f(-x_i' \beta) \beta_j ,$$

where $f(x) = dF / dx$ is the density function corresponding to F . The β_j is weighted by a factor f that depends on the values of all the regressions in x . The direction of the effect of change in x_j depends only on the sign of the β_j coefficient. Positive values of β_j imply that increasing x_j will increase the probability of the response while a negative value implies the opposite (EViews6 User Guide).

Since only the Logit model transforms the estimated function into a logistic probability using the logistic cumulative distribution function, the marginal effect can be obtained only with the Logit model. Furthermore, the marginal effects calculation is not provided as a built-in view or procedure, it has to be separately computed as the marginal effect of each variable using EViews.

(II) Relative impact

Other than the above, the output coefficients' values directly state the relative impact on the turns of unit changes in each independent variable (i.e. $\beta_1 / \beta_2 = 10/5=2$), meaning in any quarter the impact of the changes in β_1 have twice the impact compared to β_2 .

3.10.4 Establishing accuracy

Once the Logit and Probit models are finalized for each country, the next step is to check whether the final model gives accurate predictions. For that purpose the Expectation-prediction and Hosmer-Lemeshow (HL) tests can be used.

(I) Expectation-prediction (classification table)

The Expectation-prediction (classification) table shows how accurately the model forecasts each observation by quarter. In other words, the Y value of 1 or 0 will be checked against the probability value for each period. The default critical probability level (cut-off value) to determine a correct forecast is 0.5. This table tallies the correct and incorrect estimates, and in a perfect model the overall percentage correct will be 100.

(II) Goodness of fit test (Hosmer-Lemeshow)

This is a non-parametric Chi-square test which compares the actual or observed values with the values which we expect if the model is correct for different types of groups. The test divides subjects into deciles based on predicted probabilities, and then computes a chi-square value from observed and expected frequencies. Then a probability (p) value is computed from the chi-square distribution with 8 degrees of freedom to test the fit of the logistic model. If the H-L goodness-of-fit test statistic is greater than 0.05, as is required in well-fitting models, and the null hypothesis is not rejected, then there is no difference between the observed and model-predicted values, implying that the model's estimates fit the data at an acceptable level. That is, well-fitting models show non-significance on the H-L goodness-of-fit test, meaning if the chi-square goodness of fit is not significant, then the model has an adequate fit. By the same token, if the test is significant, the model does not adequately fit the data.

3.11 Model Evaluation Methods

While the cost of forecasting must be balanced against the accuracy obtained, the most important forecasting performance criterion is the accuracy of the prediction that is generated by the forecasting method or model, as compared to the actual

observation. As highlighted by Nimera and Klein (1994, p.201), “.... accuracy is the bottom line for the professional forecaster”. Carbone and Armstrong (1982) also concluded that forecasting accuracy is the most important forecasting performance criterion, relative to other criteria such as ease of interpretation, cost/time, and ease of use/ implementation.

In this study, different methods are progressively used to identify and forecast turning points:

1. Identify turning points:

- (I) Modified Bry and Boschan (BB) algorithm will be applied to historical tourism arrivals data (smoothed growth).
- (II) Markov Switching model will be estimated with historical tourism arrivals data (smoothed growth).

Once the significant (actual) turning points of tourism demand are established using the above methods the next step is to forecast turning points.

2. Forecast turning points:

- (I) Logit and Probit models will be estimated with potential economic explanatory variables to forecast turning points.
- (II) Logit and Probit models will be estimated using three leading indicators (Constructed Composite Leading Indicators, OECD Leading Indicator and Business Survey index) as explanatory variables.
- (III) Non-parametric BB algorithm will be applied to identify turning points in the same three leading indicators (Constructed CLI, OECD CLI and Business Survey index).

It is very important to assess which model forecast captures the actual turning points of the tourism arrivals growth rate, which is identified by the BB algorithm or Markov Switching model. In macroeconomics Captured Ratio, False Ratio and Quadratic Probability Score (QPS) are commonly used methods for evaluating the accuracy of different turning points’ forecasting models/methods, (Bodart and Shadman (2005), Layton and Karsuura (2001)).

In order to check the accuracy of each model/method used in this study the following model evaluation methods are used:

(I) Captured ratio

The ratio of captured turns to the total number of true turns (the ratio of the turning points identified by the model against the actual turning points of tourist arrivals growth). A good model needs to have a high captured ratio to be able to claim that the model is a better model than others.

(II) False ratio (the ratio of false alarms)

This is a ratio of the turning points which are detected by the model, but not recognised as actual turning points. A good model needs to have a low false ratio in order to be able to claim that the model is a better model than others (lower false signals).

In the ratio calculations above, this study uses the actual tourist arrivals turning points established using the BB algorithm and MS model. Moreover, Markov Switching and Logit and Probit models normally use 0.5 (50%) as the probability threshold to distinguish a contraction from an expansion. Therefore, when the probability drops/raises above or below this 0.5 (50%) threshold, that point could be a potential turning point.

(III) MAD (Mean Absolute Deviation)

This is a simple method to evaluate model accuracy. In this method, the model predicted date (quarter) is compared with the actual turning point date (quarter) to obtain the difference (error) measured in the number of quarters. Therefore, if the model predicted turning point is beyond one quarter of the actual turning point, it is +1, or if it is before one quarter it is -1, and if the model predicted the exact turning point date as the actual turning point (perfect capture) it is zero.

In this method all the errors of captured turning points are added as absolute values (without '+' and '-', for example, 1+1+0), and divided by the number of turning

points. Thus, indicating how close (accurate) the predicted turning points are to the actual turning points (the lower the MAD value (error) better the model).

(IV) Quadratic Probability Score (QPS)

The QPS is the unique scoring rule for a function of divergence between predictions and realizations (Diebold and Rudebusch (1989)).

This Quadratic Probability Score (QPS) is a widely-used measure introduced by Diebold and Rudebusch (1989) and further developed by Layton and Karsuura (2001).

QPS is defined as:

$$QPS = \frac{1}{T} \sum_{t=1}^T (P_t - D_t)^2$$

Where D_t is the binary reference cycle chronology (takes the value 1 during expansion and 0 during contraction, as identified by the actual tourism growth). P_t is the model-derived probability for the corresponding observation. The QPS results vary from 0 to 2, with a score of 0 corresponding to perfect accuracy, so that the closer this measure is to zero, the better the fit to the actual turning point.

3.12 Software Used in the Study

This study uses following software:

To smooth the data using the Trend Derivative (Slope) approach: STAMP 7/GiveWin,

To estimate the Logit and Probit models: EViews,

To estimate the Markov Switching model: Gauss Program,

To run the cross correlation for leading indicators: SAS,

For the diagrams, tables and for other formula calculations: MS Excel.

Chapter 4

Identifying Turning Points

4.1 Introduction

The objective of this chapter is to identify the actual/significant turning points in Australian inbound tourism demand from 1975 to 2007 for the USA, the UK, New Zealand and Japan. The previous chapter recognized the growth cycle as the most suitable cyclical pattern and the modified BB algorithm as the suitable non-parametric method to identify turning points. As smoothing is a prerequisite to detect significant turning points, this chapter examines three different smoothing methods to select the most suitable smoothing method for tourism arrivals data used in this study.

The chapter has three main sections. The first section examines three different smoothing methods that can be considered to select the most suitable smooth growth cycle. Section two identifies the significant turning points using the non-parametric BB algorithm. Section three examines the timing relationships of turning points in each country.

4.2 Data Smoothing

In the previous chapter different smoothing methods, their importance and their applications were discussed. As mentioned in Chapter 3, extracting the smoothed tourism demand for each tourism origin country is a prerequisite for identifying significant turning points (dating). Tourism data contain high seasonal, random and trend components. The actual tourist arrivals data to Australia from the USA, New Zealand, the UK and Japan was examined and a high degree of volatility/noise was observed.

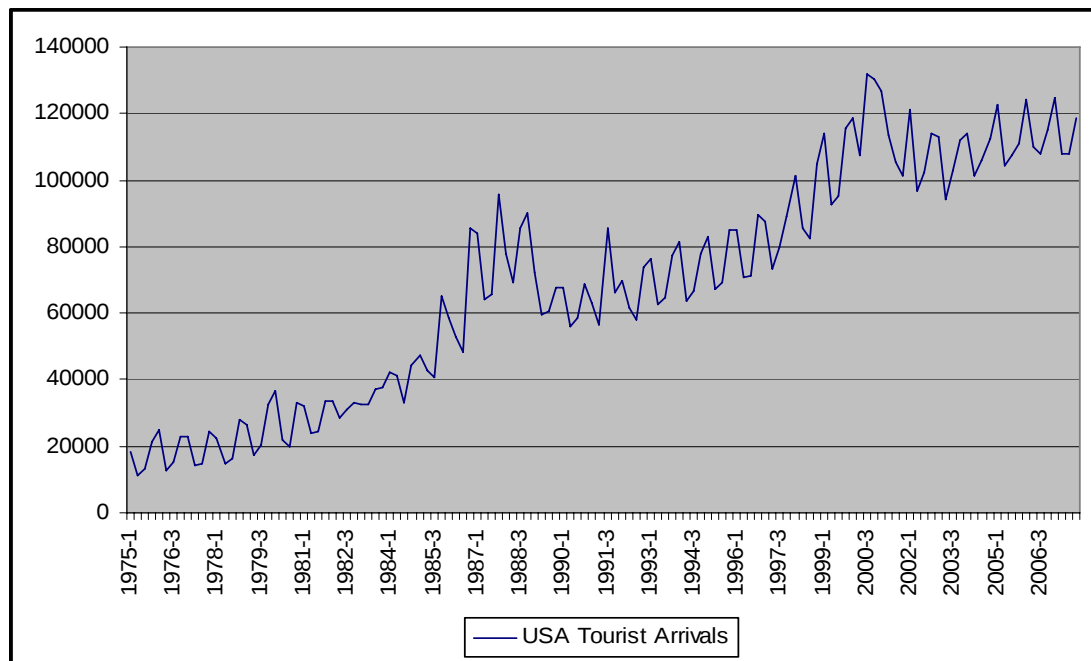
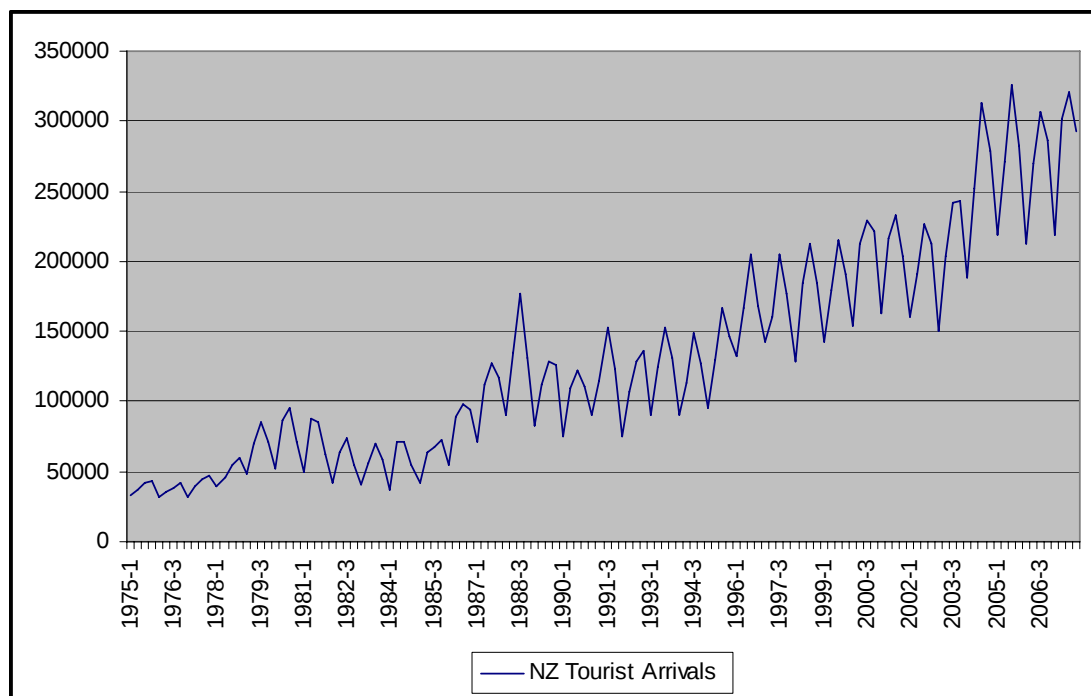
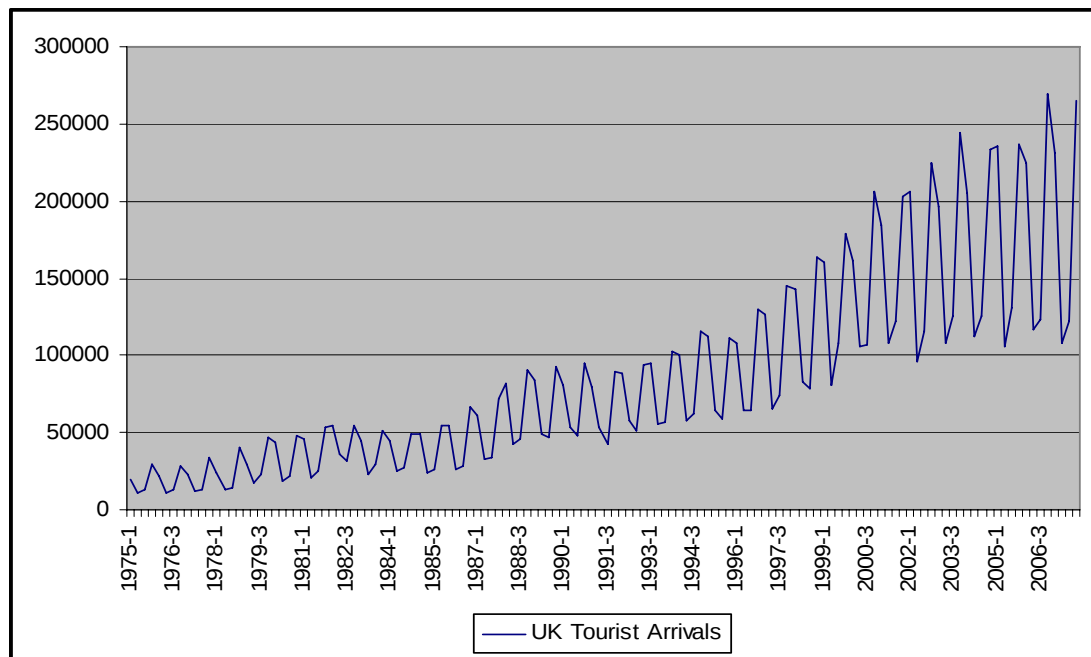
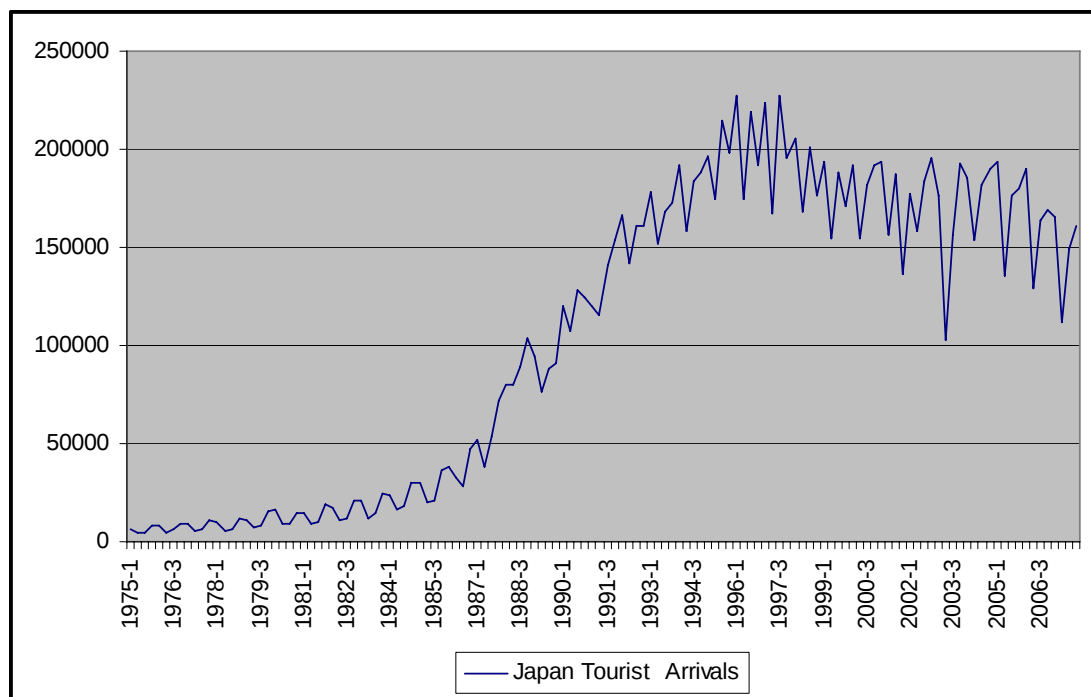
Figure 4.1**USA Tourist Arrivals Data From 1975 – 2007****Figure 4.2****New Zealand Tourist Arrivals Data From 1975 – 2007**

Figure 4.3**UK Tourist Arrivals Data From 1975 – 2007****Figure 4.4****Japan Tourist Arrivals Data From 1975 – 2007**

The Figures 4.1, 4.2, 4.3 and 4.4 demonstrate the volatility of tourist arrivals data mainly caused by seasonal, trend and random effects, and shows the importance of smoothing the data. In tourism time series data the most volatile component is the seasonal factor, and the diagrams above clearly show the seasonality in the inbound tourism data.

Seasonality

Seasonality is strongly linked to tourism demand. Though tourism flows to destinations and regions are conditioned by a complex array of factors that influence and impact on visitor behaviour, seasonality is one of the most predominant features of tourism demand. According to Rodrigues and Gouveia (2004), seasonality in tourism is an issue that is recognized as an important concern in tourism research. The main factors causing seasonality in tourism demand are climate factors, such as temperature and sunshine, religious festivals, school or industrial holidays, choice of particular sporting or leisure pursuits and persistence of established habits.

Thomas and Wallis (1971) defined seasonality as: “Seasonality is the systematic, although not necessarily regular, intra-year movement in economic time series which are often caused by non-economic phenomena, such as climatic changes and regular timing of religious festivals”.

In recent years, modelling seasonal variation in international tourism demand has become an important issue in tourism forecasting (Kulendran and Wong (2005)). According to Kulendran and King (1997) seasonality is an important feature in a tourist arrivals time series and requires careful handling to improve the accuracy of (quarterly or monthly) tourism demand forecasts (Kulendran and King (1997)).

Since smoothing eliminates the noise from the series and makes the cyclical signal clearer, it is important to select the most appropriate smoothing method to smooth the tourist arrivals data. There are many methods to remove seasonal and other variations in time series to obtain smoothed growth cycles. In the previous chapter three different smoothing methods in the literature which are useful for this study were discussed briefly. They are:

- (1) 2-quarter smoothed annualized rate (TQSAR) method (Niemira and Klein (1994)),
- (2) Hodrick-Prescott (HP) filter smoothing method,
- (3) Basic Structural Model (BSM) (Trend Derivative (Slope) approach).

4.2.1 2-quarter smoothed annualized rate (TQSAR) method

According to Niemira and Klein (1994, p. 94) other non-statistical methods such as single differences and moving-average methods are more volatile compared to the 2-quarter smoothed annualized rate (TQSAR). This method is based on the ratio of the current value of the series to its average during the previous four quarters, expressed as the smoothed annualized rate (Niemira and Klein (1994, p.94)) and it is given in the equation:

$$\text{Smoothed Growth Rate} = 100 \times \left(\left(X_t / \sum_{i=t-1}^{i=t-5} X_i \right)^{(4/2.5)} - 1 \right)$$

X_t = Values of previous quarters

The 2.5 in the above equation is average lag in quarters (formula span is five quarters and half of that is average lag).

Once the data is smoothed using the TQSAR method, the fourth difference (due to quarterly data) of the smoothed series will produce the smoothed growth cycle. The following smoothed growth cycle is found when the TQSAR method is applied. The TQSAR Model was estimated using MS Excel software.

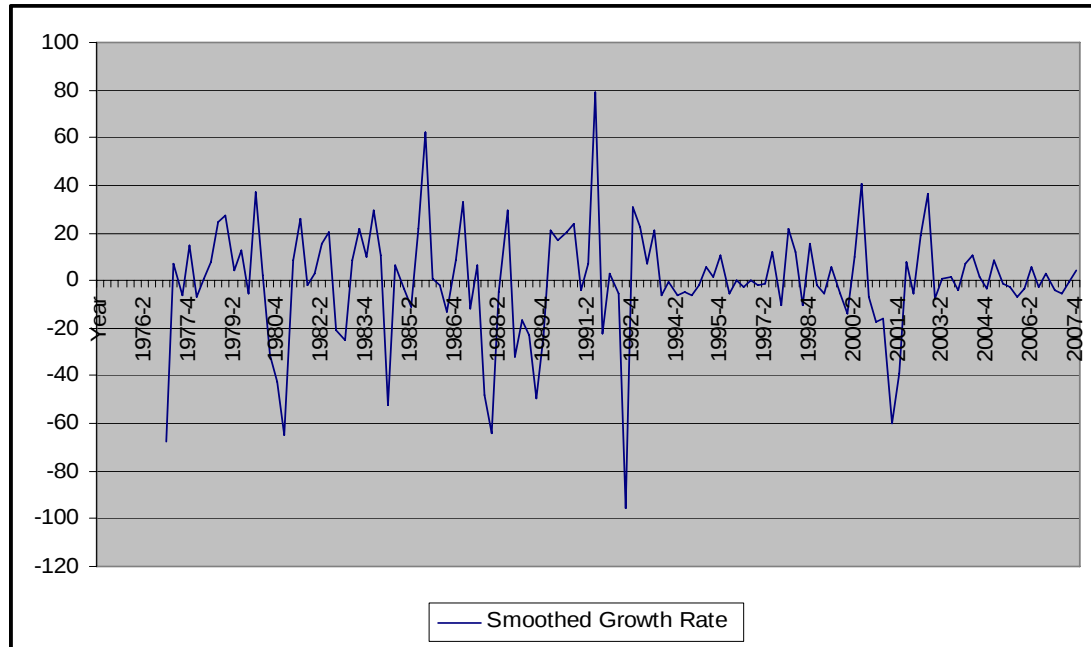
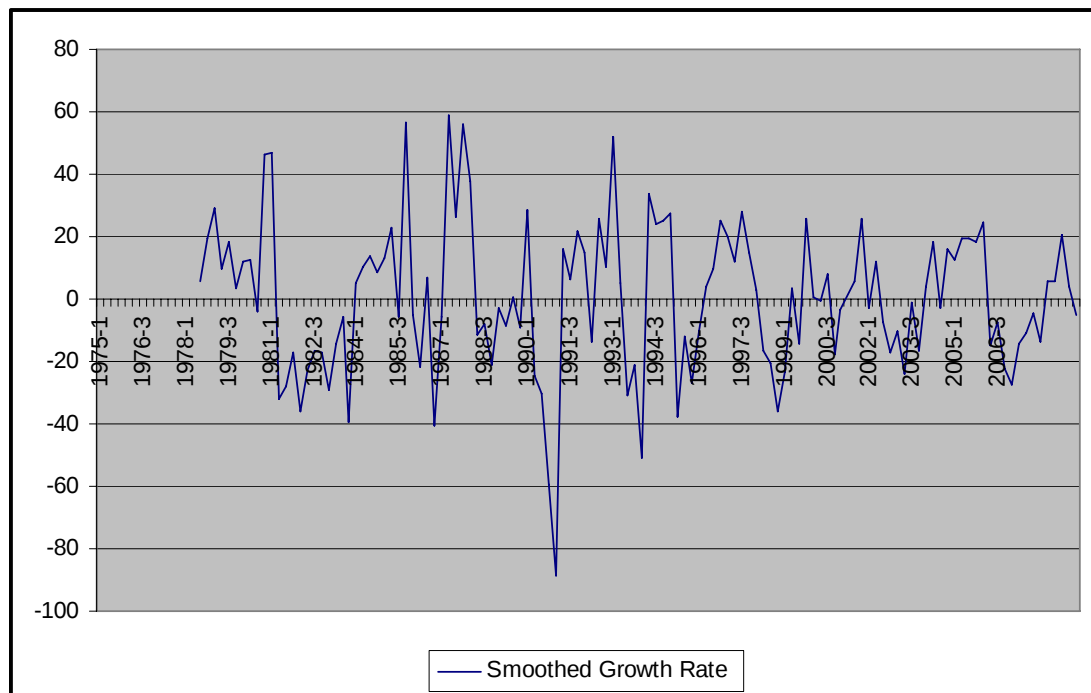
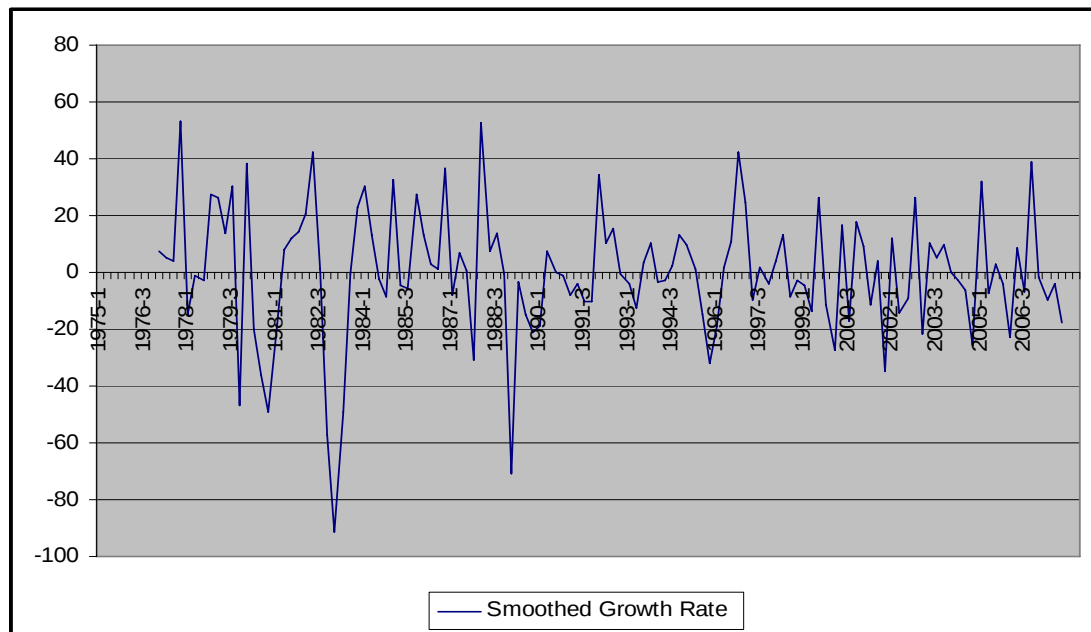
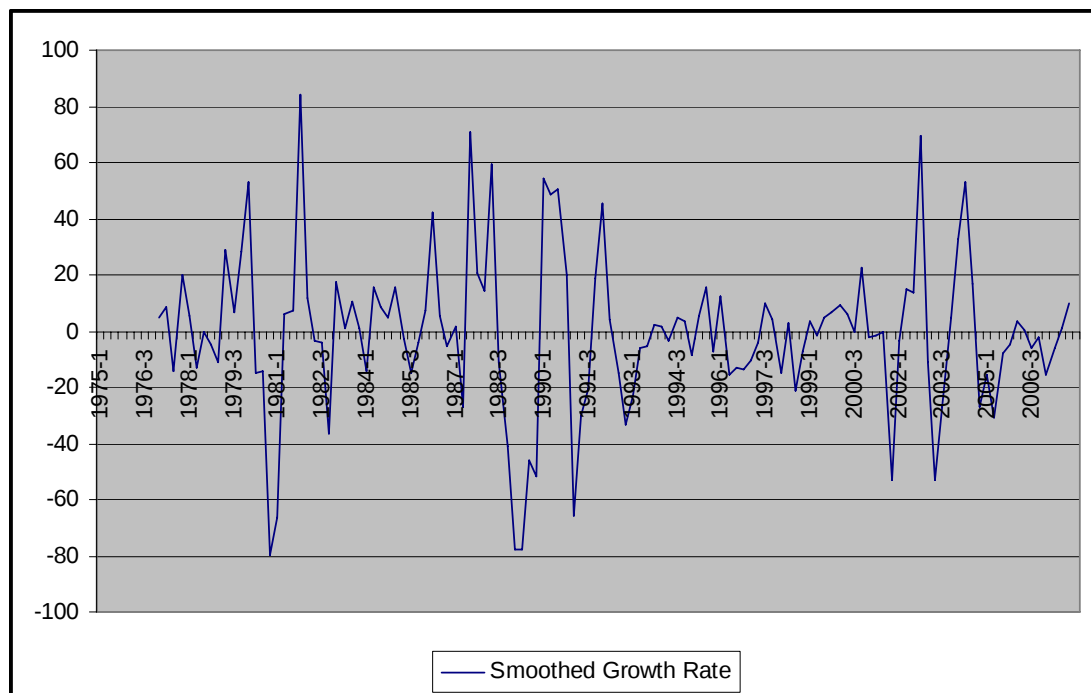
Figure 4.5**USA Smoothed Tourist Arrivals Growth Using TQSAR Method****Figure 4.6****New Zealand Smoothed Tourist Arrivals Growth Using TQSAR Method**

Figure 4.7**UK Smoothed Tourist Arrivals Growth Using TQSAR Method****Figure 4.8****Japan Smoothed Tourist Arrivals Growth Using TQSAR Method**

4.2.2 Trend Derivative of Unobserved Component

The Unobserved Components Model represents a framework in which phenomena like periodic behaviour, such as trend, seasonality, cyclical (economic), and economic cycles in particular, may be modelled and forecast naturally. In recent years, the statistical modelling approach of unobserved components has been used to extract the trend derivative (slope), and has become very popular especially in the area of finance and macroeconomics. This method is successfully implemented in Garcia-Ferrer and Bujosa-Burn (2000).

The smoothed tourism demand growth used to identify the significant turning points could be obtained from the trend derivative (slope) method. Trend is smooth and does not contain higher frequencies. In the past, the trend derivative of the unobserved trend component has been considered both as an indicator of underlying growth rate as well as an anticipative tool for predicting turning points in seasonal economic time series (Garcia-Ferrer and Queralt (1998)).

The trend derivative of the unobserved trend component could be obtained in two ways: (1) a filter approach and (2) a statistical modelling approach. In the filter approach, the trend derivative is obtained from the extraction of the trend component using the Hodrick-Prescott (HP) filter smoothing method. The HP filter is widely used among macroeconomists to obtain a smooth estimate of the long-term trend component of the series. The second approach is the statistical modelling method known as Basic Structural Modelling (BSM) (Harvey, 1989). The use of the BSM model to extract the trend derivative has been successfully implemented in Garcia-Ferrer and Bujosa-Burn (2000).

4.2.2 (a) Hodrick-Prescott (HP) Filter Smoothing Method

In this section, the trend derivative is obtained from the extraction of the trend component, using the Hodrick-Prescott (HP) filter approach. Since it was originally proposed by Hodrick-Prescott (1980) in the context of business-cycle estimation, the Hodrick-Prescott (HP) filter has been the subject of considerable discussion and criticism, for example, King and Rebelo (1993) and Kaiser and Maravall (2001). But it was admired by Kydland and Prescott (1982) and Prescott (1986) because it offers a simple and visually appealing solution to a very basic need of economic policy and monitoring. The popularity of the HP filter among applied macroeconomists results from its flexibility to accommodate these needs, since the implied trend line resembles what an analyst would draw by hand through the plot of the data (Kydland and Prescott (1990)).

The HP filter is a linear filter aimed at removing low frequency variation from a series. This has become the most widely-used procedure to estimate business cycles in applied work, including the work performed at important economic institutions such as the International Monetary Fund (1993), Giorno et al. (1995) for the OECD, European Commission (1995), and European Central Bank (2000).

The selection mechanism that economic theory imposes on the data via the HP filter can be justified using the statistical literature on curve fitting (Wabha (1980)). In this framework the HP filter optimally extracts a trend which is stochastic, but moves smoothly over time and is uncorrelated with the cyclical component. The assumption that the trend is smooth is imposed by assuming that the sum of squares of the second differences of S_t is small. An estimate of the secular component is obtained by minimizing:

$$\sum_{t=1}^T (y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1} ((s_{t+1} - s_t) - (s_t - s_{t-1}))^2$$

where T is the sample size and λ is a parameter that penalizes the variability of trend.

The penalty parameter λ controls the smoothness of the series σ . The larger the λ , the smoother the σ , as $\lambda \rightarrow \alpha$, σ approaches a linear trend. As λ increases, the penalty imposed for large fluctuations in the secular component increases and the path for $\hat{s}_t$ becomes smoother. In this context, the ‘optimal’ value of λ is $\lambda = \sigma_s^2 / \sigma_y^2$, where σ_s and σ_y are the standard deviations of the innovations in the trend and in the cycle.

Users of the HP filter select λ a priori to isolate those cyclical fluctuations, which belong to the specific frequency band the researcher wants to investigate. With quarterly data, $\lambda=1600$ is typically chosen and the filter leaves in the data cycles with an average duration of 4–6 years (Fabio (1998) and Eview 6.0, p.360).

However, the weakness in this approach is that the end point estimation is unstable, the cyclical signal may display considerable erraticity as it characterises ad-hoc filters and it may be inadequate for certain series, raising the possibility of generating spurious results (Kaiser and Maravall (2002)).

The data is smoothed using the HP method and the growth cycle is obtained for the USA, New Zealand, the UK and Japan. The smoothed growth cycle plots are given in Figures 4.9, 4.10, 4.11 and 4.12. The HP model is estimated using EView6.

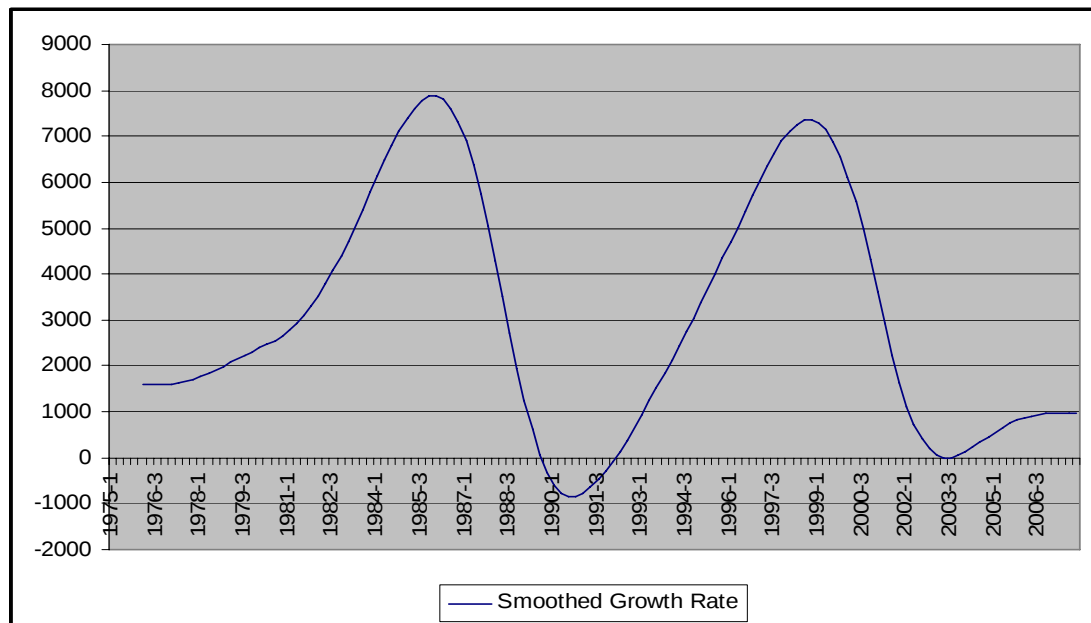
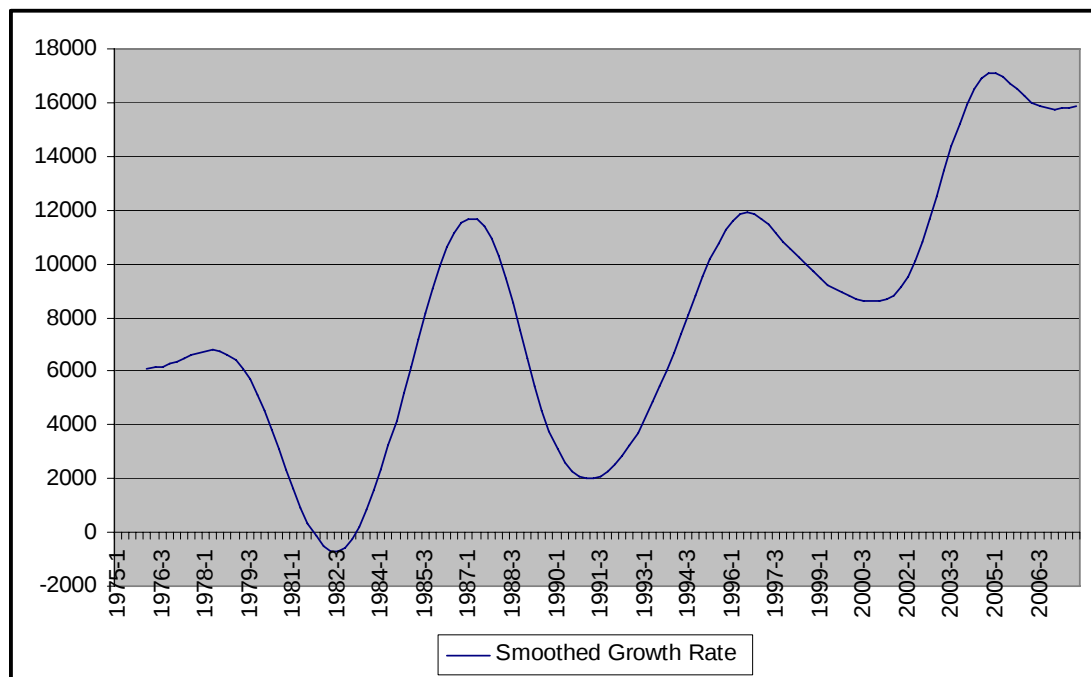
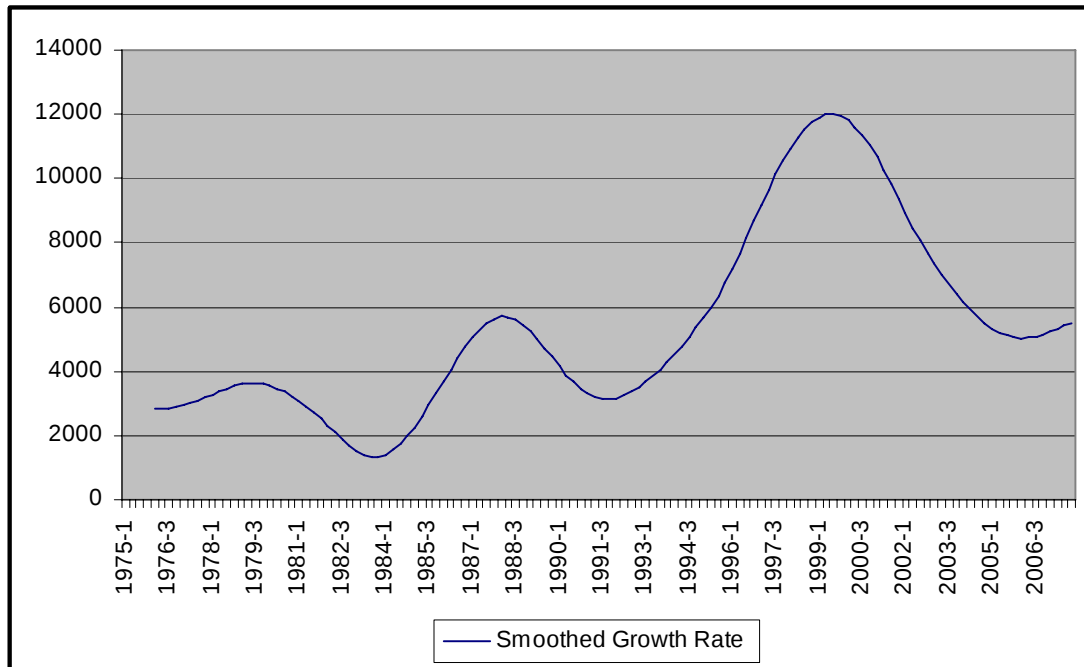
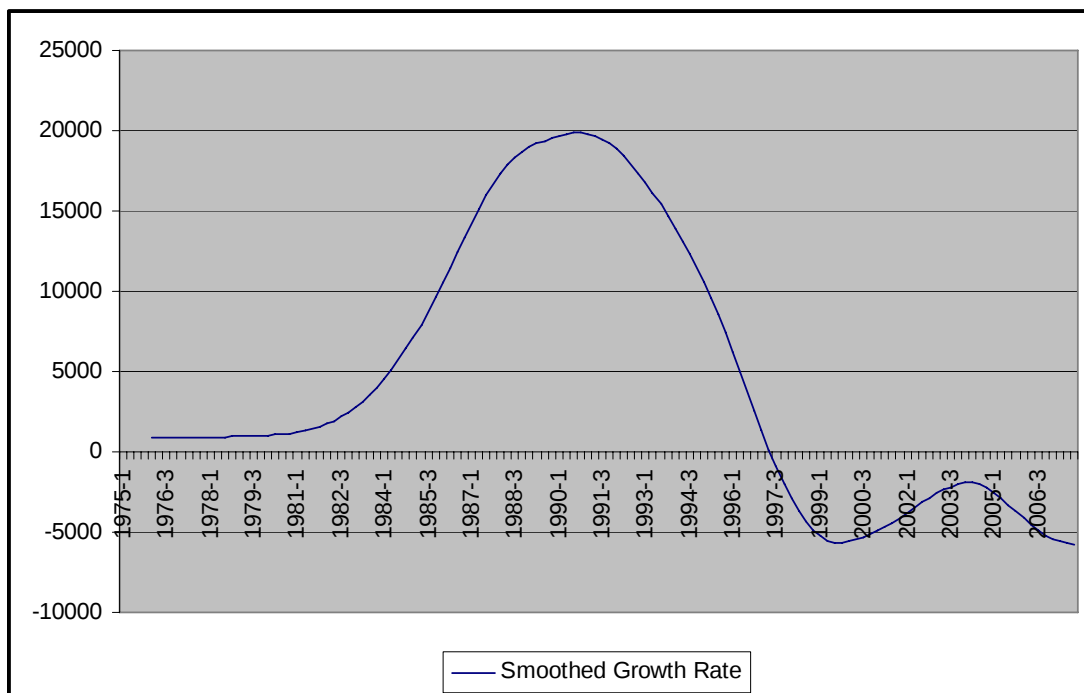
Figure 4.9**USA Smoothed Tourist Arrivals Growth Cycle Using HP Method****Figure 4.10****New Zealand Smoothed Tourist Arrivals Growth Cycle Using HP Method**

Figure 4.11**UK Smoothed Tourist Arrivals Growth Cycle Using HP Method****Figure 4.12****Japan Smoothed Tourist Arrivals Growth Cycle Using HP Method**

4.2.2 (b) Basic Structural Model (BSM) /Trend Derivative (Slope) Approach

To obtain the trend derivative of the unobserved component, the other approach is the Basic Structural Model (BSM) introduced by Harvey and Todd (1983). This model deals with univariate time varying data with a trend and seasonal component. This model decomposes the data into their components. In tourism, Turner et al. (1995a) compared the forecasting performance of the ARIMA model and the BSM model and found that the BSM model had higher performance against the ARIMA model. Turner and Witt (2001a) used the BSM to forecast inbound tourism to New Zealand by purpose of visit. Greenidge (2001) used the BSM to forecast tourist arrivals to Barbados. Moreover, the use of the BSM model to extract the trend derivative has been successfully implemented in Garcia-Ferrer and Bujosa-Burn (2000) and Kulendran and Wong (2009).

In the Basic Structural Model (BSM) (Harvey, 1989) the unobserved component can be written as:

$$(1) Y_t = T_t + S_t + \varepsilon_t$$

where the Y_t is the log of the quarterly series, T_t is the Trend component, S_t is the Seasonal component, ε_t is an Irregular component which is normally distributed with $(0, \sigma_\varepsilon^2)$.

Each component of the series can be modelled in several ways. A very simple specification for the trend component consists of a global deterministic linear trend.

The trend component T_t is then specified as:

$$(2) T_t = T_{t-1} + \beta_{t-1} + \eta_t$$

$$(3) \beta_t = \beta_{t-1} + \xi_t$$

where $\eta_t \sim \text{NID}(0, \sigma_\eta^2)$, $\xi_t \sim \text{NID}(0, \sigma_\xi^2)$, and β is the slope of the trend. T and β denote the level and the slope. However, the assumption of deterministic trend limits the application of these models. The stochastic formulation proposed for the trend component is a flexible one since it allows the level T and slope β to evolve slowly over time (Harvey and Todd (1983)):

The seasonal component is specified in seasonal dummy form as:

$$(4) S_t = \sum_{j=1}^{s-1} S_{t-j} + \omega_t, t=1, \dots, N,$$

where $\omega_t \sim \text{NID}(0, \sigma_\omega^2)$.

An alternative way of modelling such a pattern is by a set of trigonometric terms at the seasonal frequencies (Harvey (1989)).

The model composed by Equations (1), (2), (3) and (4) constitutes the Basic Structural Model, and is extensively illustrated in Harvey (1989).

In such a model the slope β ($T_t - T_{t-4} = \Delta T_t = \beta_{t-1}$ for the annual/four quarter difference) represents the trend derivative which is usually very smooth, thus making the dating particularly easy for defining a contraction (or expansion) at time T when $\Delta T_t = \beta_{t-1} < (>) 0$ (Bruno and Otranto (2004)).

Once the data is smoothed using the BSM method, the growth cycle is obtained for the USA, New Zealand, the UK and Japan and given in Figures 4.13, 4.14, 4.15 and 4.16. The Basic Structural Model (BSM) was estimated using the STAMP (5.0) Program.

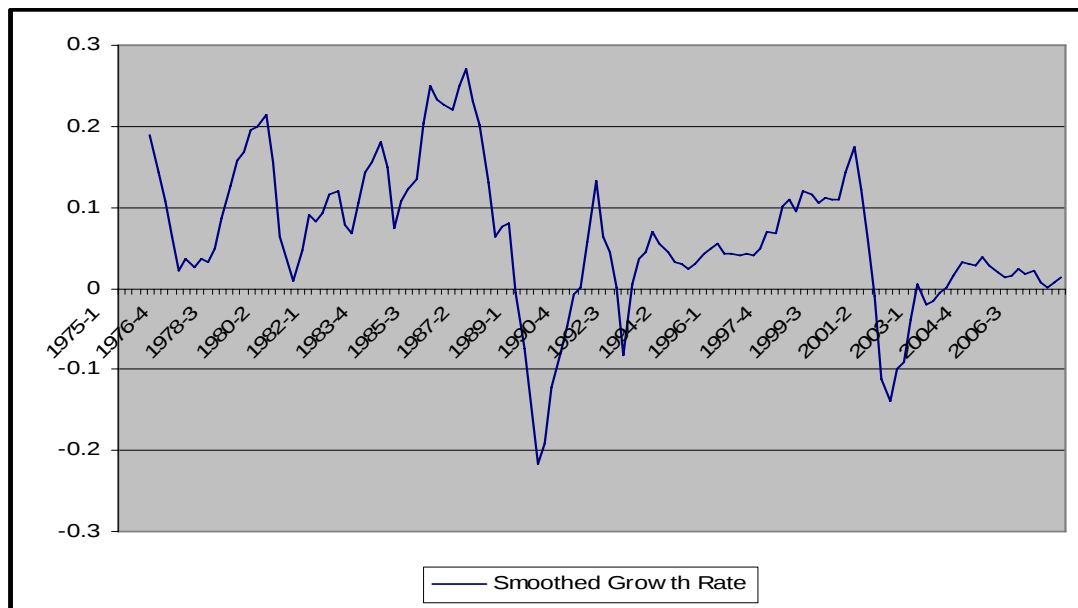
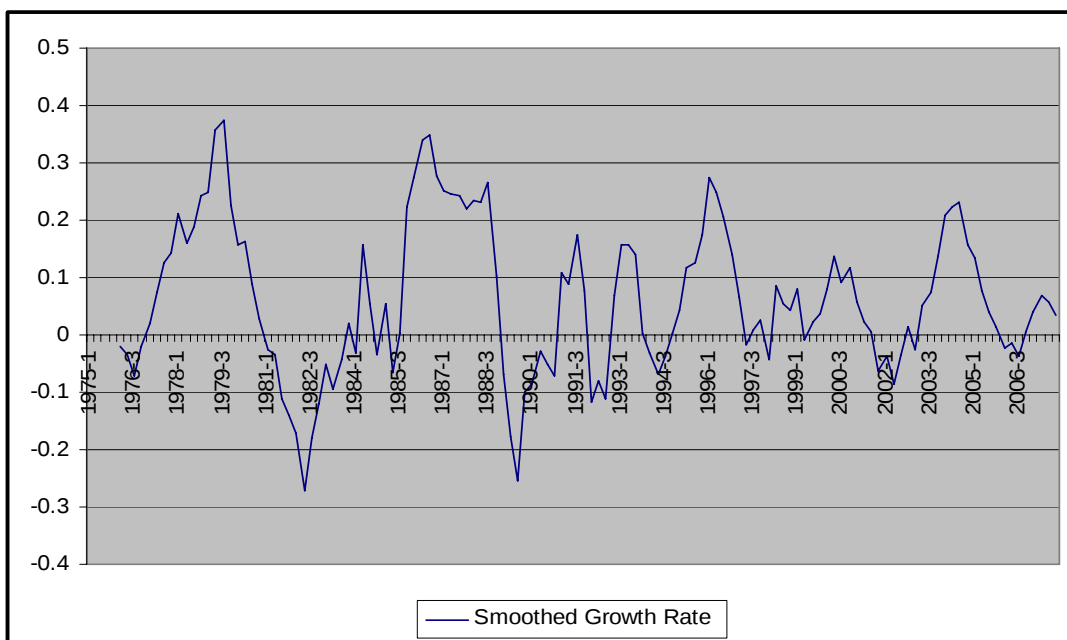
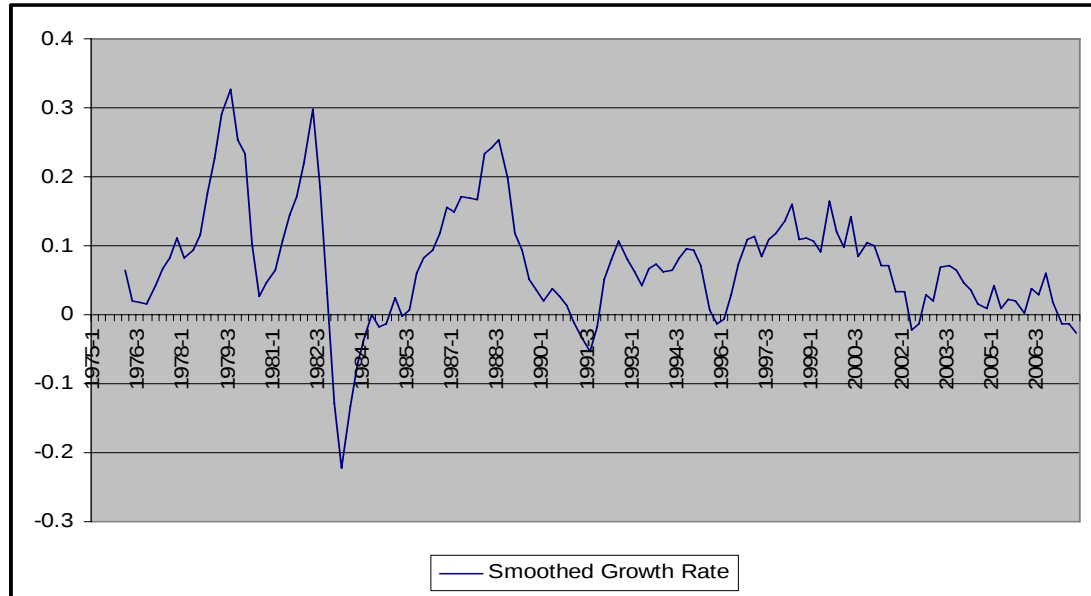
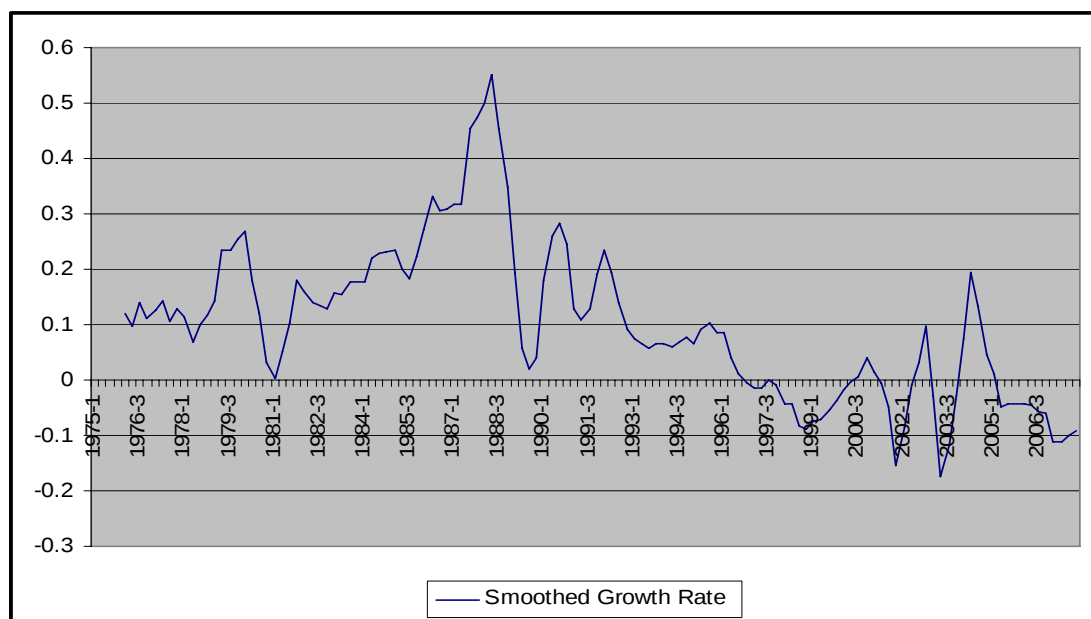
Figure 4.13**USA Smoothed Tourist Arrivals Growth Using BSM Method****Figure 4.14****New Zealand Smoothed Tourist Arrivals Growth Using BSM Method**

Figure 4.15**UK Tourist Smoothed Tourist Arrivals Growth Using BSM Method****Figure 4.16****Japan Smoothed Tourist Arrivals Growth Using BSM Method**

4.3 Selecting a Suitable Smoothing method

As is seen in the figures above (Figure 4.5 to Figure 4.16), the three examined smoothing series are illustrated, namely the 2-quarter smoothed annualized rate (TQSAR), the Hodrick-Prescott (HP) filter smoothing method and the Basic Structural Model (BSM), each producing a different smoothed series. The following figure (4.17) displays all three methods in one diagram, in order to identify the most suitable method through visual examination.

Figure 4.17

USA Smoothed Tourist Arrivals Growths

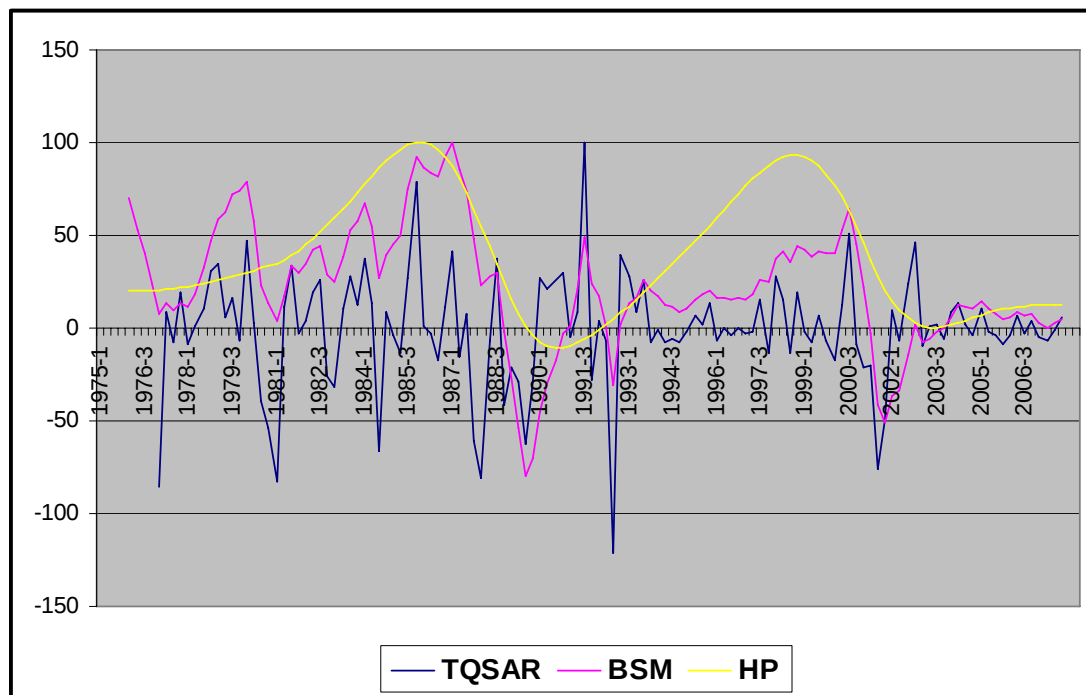


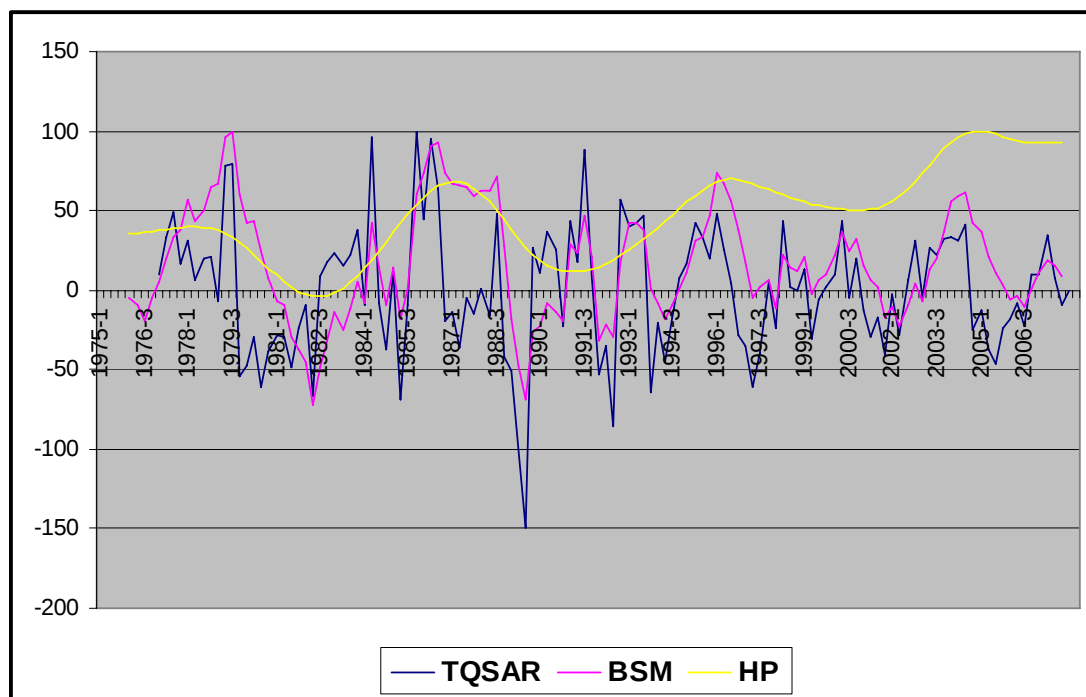
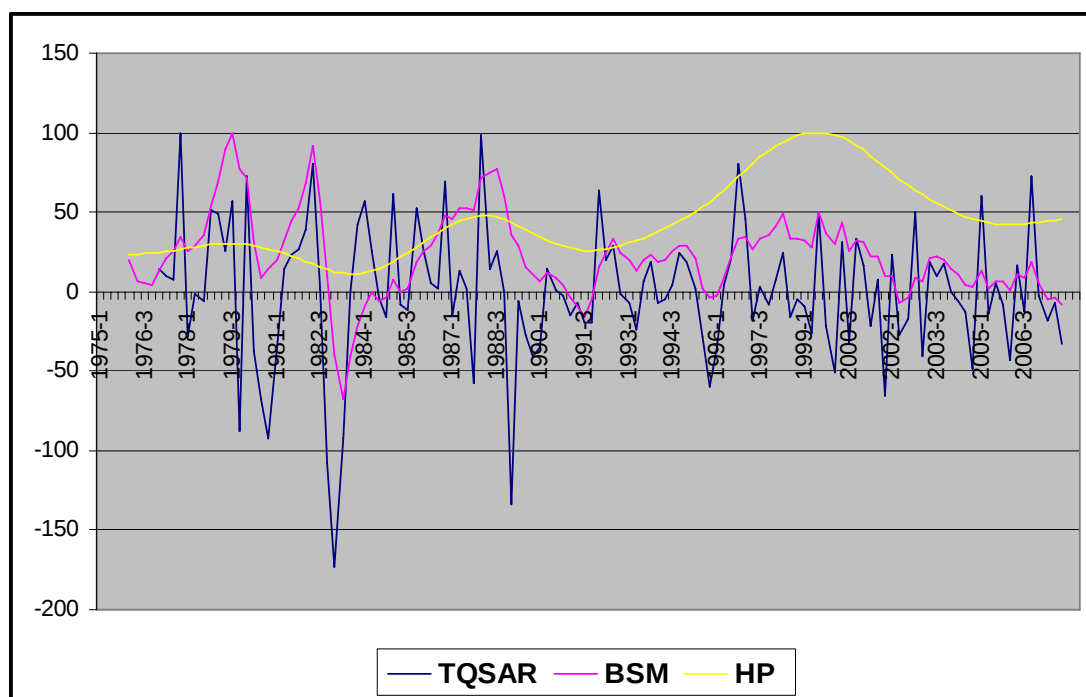
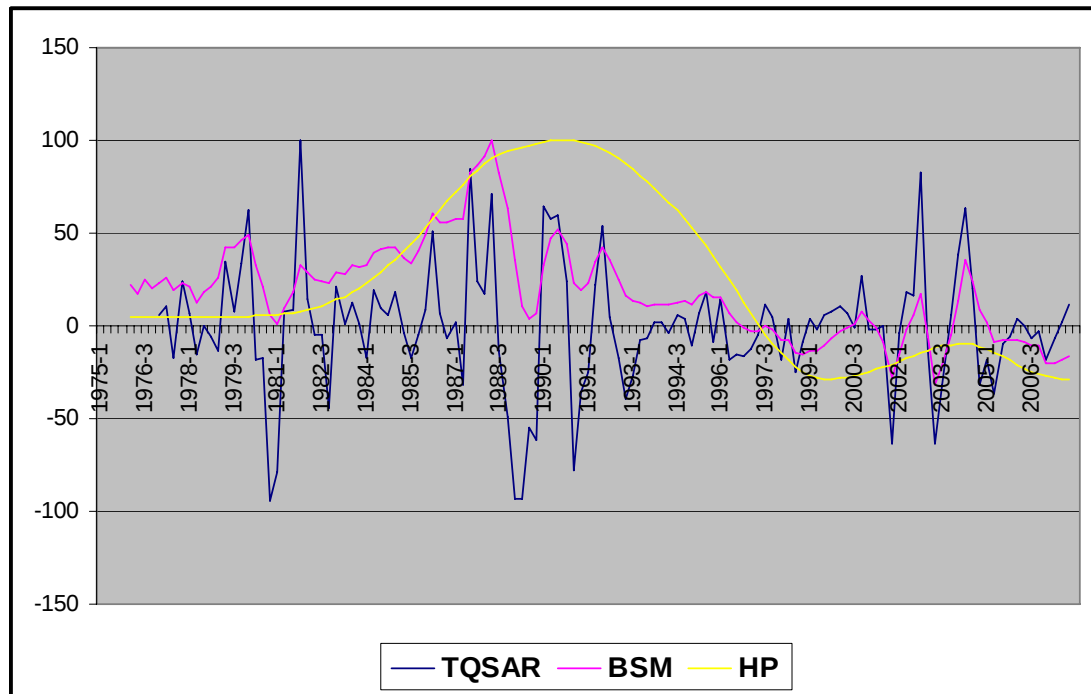
Figure 4.18**New Zealand Smoothed Tourist Arrivals Growths****Figure 4.19****UK Smoothed Tourist Arrivals Growths**

Figure 4.20**Japan Smoothed Tourist Arrivals Growths**

As the prime task is to select the most appropriate method to extract the smoothed growth, and since it has a direct impact upon identifying the significant turning points, other than the volatility factor, it is necessary to look at a method that does not distort the original pattern, and a method which is not adversely affected by outliers.

Having examined the three smoothing methods and their plots, it is clear that the 2-quarter smoothed annualized rate (TQSAR) method is excessively volatile, while the Hodrick-Prescott (HP) filter smoothing method is too heavily smoothed between 2 - 5 turning points for most countries for the entire period between 1975 - 2007. Considering these factors and following a close visual examination, this study selects the Basic Structural Model (BSM) due to its ability to represent most of the turns without being too smooth or too volatile. Importantly, the BSM smooth growth cycle, in most cases, does not contradict the results generated by the other two methods.

4.4 Identifying/Dating Turning Points

Having constructed the smooth growth cycle using the BSM method, the next step is to identify the significant turning points in the smoothed growth cycle. In macroeconomics this is called the ‘dating’ process or the process of constructing a reference turning point chronology. However, a turning point has to be clearly defined. In this study a ‘turning point’ is a particular point of the series (a particular quarter) where tourism demand changes from faster growth to slower growth (called a downturn or peak) or slower growth to faster growth (called an upturn or trough). In short, a point of a series where tourism demand changes from expansion to contraction is a peak and a change from contraction to expansion is a trough.

Also, contraction means decreasing or reducing demand, and the demand does not need be in negative growth. Therefore, when identifying a turning point, it does not consider whether the demand is in a negative growth or positive growth period, meaning it can find a significant upturn (trough) within the positive growth period.

4.5 Importance of ‘Dating’ or ‘Reference Chronology’ in Tourism Demand Research

Establishing a cycle turning point chronology (list of actual turning points) is important to find links between the cycles (actual arrivals growth cycle) and diverse economic aggregates. Dating is an *ex post* exercise, but accuracy of the dating method is also important in order to use different economic series or models to forecast turning points. Importantly, established arrivals growth cycle reference chronology (dating) can be used in empirical studies to classify economic series according to their type (leading, coincident or lagging) or to validate another forecasting method.

As has been discussed previously, the non-parametric method initiated by Bry and Boschan (BB) (1971) and subsequently modified by Lesage (1992) is recognised as the most appropriate method to identify the significant turning points in tourism demand growth.

According to Lesage (1992), the downturn (DT) and upturn (UT) are as follows:

DT at t (Peak): = $\{(Y_{t-3}, Y_{t-2}, Y_{t-1} < Y_t > Y_{t+1}, Y_{t+2}, Y_{t+3})\}$,

UT at t (Trough): = $\{(Y_{t-3}, Y_{t-2}, Y_{t-1} > Y_t < Y_{t+1}, Y_{t+2}, Y_{t+3})\}$.

where: Y_{t-3} , Y_{t-2} , and Y_{t-1} are past values of the growth and Y_{t+1} , Y_{t+2} , and Y_{t+3} , are the future values of the growth.

According to the above algorithm, the minimum cycle period is seven quarters (peak to peak or trough to trough) and the minimum phase period is three quarters (expansion or contraction period).

4.6 Significant Turning Points

The above definition/algorithm was applied to the tourist arrivals data smoothed by the BSM method to identify the significant turning points. Significant troughs (upturns) and peaks (downturns) were identified in the Australian inbound tourism demand for the USA, New Zealand, the UK and Japan from 1975 to 2007.

Table 4.1

Significant Turning Points of All Four Countries from 1975 to 2007

USA		New Zealand		UK		Japan	
Trough(UT)	Peak(DT)	Trough(UT)	Peak(DT)	Trough(UT)	Peak(DT)	Trough(UT)	Peak(DT)
1977-1			1979-3	1976-4			1977-2
1981-1	1980-1	1982-2	1984-2	1980-3	1979-3	1978-2	1980-1
1984-3	1982-3	1985-2	1986-3	1983-2	1982-2	1981-2	1988-2
1989-3	1985-4	1989-3	1993-1	1991-3	1988-3	1989-3	1992-1
1992-3	1991-3	1994-2	1996-1	1995-4	1992-3	1993-3	1995-3
1994-4	1993-3	1999-2	2000-2	2002-2	1998-2	1999-1	2000-4
2001-4	1998-4	2002-2	2004-3	2006-1	2003-3	2001-4	2004-2
	2006-2	2006-3					

Table 4.1 explains the turning points of each country from 1975 to 2007, and shows also that there were between 13 to 14 turning points for each country during this 32-year period.

4.7 Significant Turning Points and Timing Relationship

The following Tables 4.2, 4.3, 4.4 and 4.5 show the identified significant turning points (turning point chronology) and their timing relationship (in quarters) for the USA, New Zealand, the UK and Japan.

Table 4.2

Significant Turning Points and Cyclical Relationship of USA Tourism Demand

Trough(T)	Peak(P)	Trough to Trough	Peak to Peak	Expansion (T-P)	Contraction (P-T)
1977-1					
1981-1	1980-1	16		12	4
1984-3	1982-3	14	10	6	8
1989-3	1985-4	20	13	5	15
1992-3	1991-3	12	23	8	4
1994-4	1993-3	9	8	4	5
2001-4	1998-4	28	21	16	12
	2006-2		30	18	
Mean		16.50	17.50	9.85	8.00

Table 4.3**Significant Turning Points and Cyclical Relationship of New Zealand Tourism Demand**

Trough(T)	Peak(P)	Trough to Trough	Peak to Peak	Expansion (T-P)	Contraction (P-T)
1979-3					
1982-2	1984-2		19	8	11
1985-2	1986-3	12	9	5	4
1989-3	1993-1	17	26	14	12
1994-2	1996-1	19	12	7	5
1999-2	2000-2	20	17	4	13
2002-2	2004-3	12	17	9	8
2006-3		17			8
Mean		16.16	16.66	7.83	8.71

Table 4.4**Significant Turning Points and Cyclical Relationship of UK Tourism Demand**

Trough(T)	Peak(P)	Trough to Trough	Peak to Peak	Expansion (T-P)	Contraction (P-T)
1976-4					
1980-3	1979-3	15		11	4
1983-2	1982-2	11	11	7	4
1991-3	1988-3	33	25	21	12
1995-4	1992-3	17	16	4	13
2002-2	1998-2	26	23	10	16
2006-1	2003-3	15	21	5	10
Mean		19.5	19.2	9.66	9.83

Table 4.5**Significant Turning Points and Cyclical Relationship of Japan Tourism Demand**

Trough(T)	Peak(P)	Trough to Trough	Peak to Peak	Expansion (T-P)	Contraction (P-T)
1977-2					
1978-2	1980-1		11	7	4
1981-2	1988-2	12	33	28	5
1989-3	1992-1	33	15	10	5
1993-3	1995-3	16	14	8	6
1999-1	2000-4	22	21	7	14
2001-4	2004-2	11	14	10	4
Mean					
		18.80	18	11.66	6.33

The tables above (4.2, 4.3, 4.4 and 4.5) explain the identified peaks (downturns) and troughs (upturns) for the cycle period for 128 quarters (from 1975 to 2007), and in summary:

- The USA has an average cycle period (trough to trough or peak to peak) of 17 quarters (4.25 years), an average expansion of 10 quarters (2.5 years) and an average contraction of 8 quarters (2 years).
- New Zealand has an average cycle period (trough to trough or peak to peak) of 16 quarters (4 years), an average expansion of 7 quarters (1.75 years) and an average contraction of 8 quarters (2 years).
- The UK has an average cycle period (trough to trough or peak to peak) of 19 quarters (4.75 years), an average expansion of 9 quarters (2.25 years) and an average contraction of 9 quarters (2.25 years).
- Japan has an average cycle period (trough to trough or peak to peak) of 18 quarters (4.5 years), an average expansion of 12 quarters (3 years) and an average contraction of 6 quarters (1.50 years).

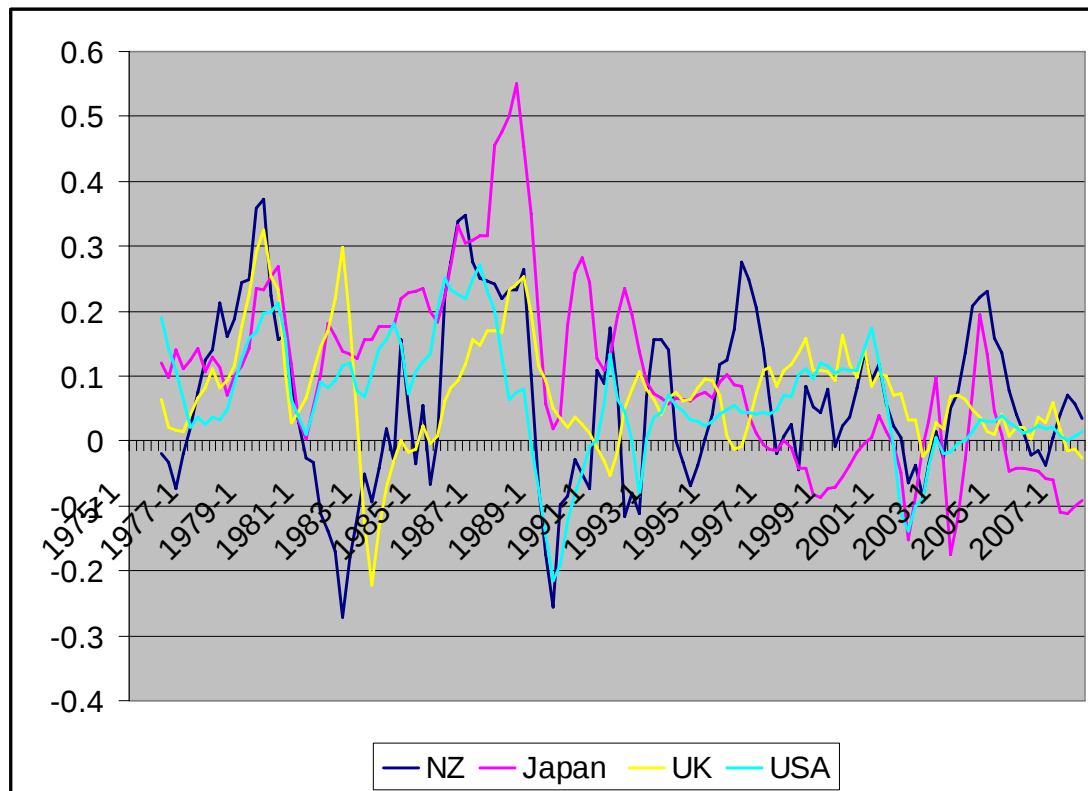
Overall, the mean duration of the tourism demand growth cycle (trough to trough or peak to peak) is between 14 to 20 quarters (3.5 years to 5 years) for the four countries. The mean duration for the tourism demand growth cycle expansion is around 9 quarters (2.25 years) and the contraction is about 8 quarters (2 years).

Further, the average longest cyclical period (trough to trough or peak to peak) is for the UK, and the shortest average cyclical period is for the USA. Except for New Zealand, all the countries have longer expansion periods than contraction periods, while for New Zealand the contraction period is greater than the expansion period.

When identifying significant turning points, different dating procedures can lead to different dating results. Hence, keeping the dating results of this non-parametric method as a bench mark, this research uses a parametric Markov Switching model (in the next chapter) to compare and to establish the accuracy of this method.

4.8 Relationship of Turning Points Between Countries

It is worth observing the relationships of the turning points between the four countries. The above tables (Table 4.2, Table 4.3, Table 4.4 and Table 4.5) and Figure 4.21 below show that in certain time periods there is a degree of relationship between the turning points of the four countries, although the relationships are not identical and consistent throughout the time series.

Figure 4.21 Smoothed Growth of All Four Countries Using BSM Method

As mentioned above, Figure 4.21 highlights some relationships between the turning points, for instance, most of the countries experienced a peak between 1979-Q3 to 1980-Q1 and a trough between 1981-Q1 to 1983-Q2. From the mid 70s to late 80s there is a similarity in the relationship between the four countries, but after the early 90s the relationship is weak, especially for Japan, with a long contraction period and New Zealand with volatile behaviour after the early 90s. But the UK and USA have a long-term relationship in their arrivals pattern.

These relationships could be purely coincidence or could be due to common global economic and social factors. The relationships could also be due to the economic and social factors of the destination country (Australia), since these may affect all four countries' tourist arrivals. Alternatively, they may be purely due to factors in the tourism origin countries, or due to a mix of factors. This study does not investigate all four countries as a single series, but as individual countries with individual potential economic factors.

Chapters 6 and 8 will investigate relevant economic factors and economic indicators in the tourist origin and destination countries to identify their influence on turning points, and to forecast turning points for each country.

Chapter 5

Markov Switching Model

5.1 Introduction

In the previous chapter, the turning points of Australian tourism demand, from 1975 Quarter 1 to 2007 Quarter 4 is identified using the non-parametric algorithm (modified Bry and Boschan (BB) rule). This chapter uses the parametric Markov Switching (MS) model to identify/date the significant turning points for the same smoothed arrivals growth of the four countries.

The first section of this chapter briefly discusses the theoretical aspects of the Markov Switching model including Hamilton's maximum likelihood estimation routine. The second section estimates the Markov Switching model in order to identify/date the significant turning points. In the third section, the significant turning points are identified using the parametric MS. The results will be compared with the turning points identified using the non-parametric algorithm in Chapter 4. The strengths and weaknesses of each model will be assessed and the final section discusses the ability of each method to identify significant turning points.

5.2 Markov Switching Model

The structure of time series cycles is better captured by non-linear models as discussed in the literature review chapter (Chapter 2). Regime Switching models are one type of these non-linear models. As mentioned previously, the Markov Switching model is a very popular method of identifying turning points, especially in the macroeconomic area (turning points in GDP or GNP). The ability of the MS model to identify/describe the presence of a structural switching shift in the level of an economic data series, such as GDP, may explain the behaviour of a business cycle. This shift may not happen only once in the data recorded through the life of the series, but may switch between two or more values several times. Thus regime switching

models, which contain components that switch between different values according to a Markov process, are suitable to describe and quantify this type of switching behaviour. In this chapter, the Markov Switching model is applied to tourism data to check whether it can capture the significant turning points in tourism demand growth.

5.2.1 MS General Model

In the next few sections, the theoretical aspects of the MS model (particularly Hamilton's two state model) are discussed.

In general form, let s_t be a random variable that can assume only an integer value $\{0, 1, \dots, N\}$. Suppose that the probability that s_t equals some particular value j depends on the past most recent value of s_{t-1} which is equal to (i) :

where s_t is governed by a Markov chain of order 1

$$P\{s_t = j | s_{t-1} = i, s_{t-2} = k, \dots\} = P\{s_t = j | s_{t-1} = i\} = p_{ij} \quad (5.1)$$

The simplified form of the above equation is:

If,

$$P(s_t | s_{t-1}, \dots, s_{t-n}) = P(s_t | s_{t-1}) \quad (5.2)$$

As can be seen above, in the general form, the state s_t can define more than two phases. The above process is described as the N -state Markov Chain with transition probabilities $\{p_{ij}\}_{i,j=0,1,\dots,N}$. The transition probability p_{ij} gives the probability that the state i will be followed by state j .

Further, it is often convenient to collect the transition probabilities in a $(N \times N)$ matrix $\mathbf{P}$ known as the *transition matrix* (TM):

$$\mathbf{P} = \mathbf{T}\mathbf{M} = \begin{bmatrix} p_{11} & \cdots & p_{N1} \\ \vdots & \ddots & \vdots \\ p_{1N} & \cdots & p_{NN} \end{bmatrix}, \quad (5.3)$$

The row i , column j element of $\mathbf{P}$ is the transition probability p_{ij} :

All elements p_{ij} are between 0 and 1, and the sum of each column is equal to 1.

$$p_{i0} + p_{i1} + \dots + p_{iN} = 1. \quad (5.4)$$

5.2.2 Hamilton's Two State Model

Hamilton (1989) used the switching idea to define changes in the economy between fast and slow growth regimes, the two states representing expansion and contraction phases of the business cycle.

In the same way, in this study the phases of the tourism growth cycle (expansions and contractions) can be captured by this non-linear Markov Regime Switching model. Specifically, this study uses the two phases of tourism demand to define switching between fast and slow tourism demand growth regimes.

Hamilton's model (1989) can be represented in general using the following form:

$$y_t = \mu_{s_t} + \phi_1(y_{t-1} - \mu_{s_{t-1}}) + \phi_2(y_{t-2} - \mu_{s_{t-2}}) + \phi_3(y_{t-3} - \mu_{s_{t-3}}) + \phi_4(y_{t-4} - \mu_{s_{t-4}}) + \varepsilon_t, \quad (5.5)$$

Since this study considers only two states, the model is:

$$y_t = \mu_{s_t} + \varepsilon_t, \quad (5.6)$$

where y_t , is the logarithm of the smoothed growth of tourist arrivals data (at time t), and μ_{s_t} takes two values μ_0 when $s_t=0$ and μ_1 when $s_t=1$, where s_t is an unobserved binary variable representing the system (or demand growth) at time t known as the state of the system.

The probability process driving s_t is captured by the following four transition probabilities:

$$\begin{aligned}
 P(s_t = 1 | s_{t-1} = 1) &= p \\
 P(s_t = 0 | s_{t-1} = 1) &= 1 - p \\
 P(s_t = 0 | s_{t-1} = 0) &= q \\
 P(s_t = 1 | s_{t-1} = 0) &= 1 - q
 \end{aligned} \tag{5.7}$$

5.2.3 Hamilton's Parameter Estimates

This model contains two types of parameters which require estimation. They are estimated using an iterative approach. Firstly, the parameter $\lambda = (\mu_0, \mu_1, p, q, \sigma)$ is obtained using a numerical maximum likelihood method. Secondly, the unobserved states s_t are estimated by the smoothed probabilities.

Estimation is made using the Markov Switching model (using GAUSS software) which will generate λ using the numerical maximum likelihood method.

μ_0 – Mean value of the contraction regimes of the entire series.

μ_1 – Mean value of the expansion regimes of the entire series.

p = Probability (overall probability) that tourism demand will remain in the contraction regime/state.

q = Probability (overall probability) that tourism demand will remain in the expansion regime/state.

σ = ‘Standard deviation’.

As mentioned above, μ_0 and μ_1 will give the mean value of the expansion and contraction regimes of the entire series, and the mean arrivals smoothed growth data series will lie within these two mean values. The importance of these mean values is that the MS model uses these mean values as one of the main factors to decide whether a particular time period is in expansion or contraction.

The p and q values give the long-term probability that tourism demand will stay in an expansion or contraction regime/state. Higher probability (close to 1) for p (contraction) indicates, on the other hand a higher probability for q (expansion). These higher probabilities for p and q indicate the certainty of expansion and contraction periods, whereas low probabilities (e.g. 0.4, 0.5, 0.6...) reduce the certainty of being a particular regime. Therefore, a higher p and q means a higher probability (higher certainty) of tourism demand being in a particular regime.

With regard to errors, the objective is to reduce the errors as much as possible; in this scenario a lower standard deviation (σ) indicates a better model. Importantly, a ‘good’ model should generate smaller errors (standard deviation) than the original dataset’s arrivals smoothed growth standard deviation.

Refer to Appendix 1 for a detail description of filtered probabilities and smoothed probabilities.

5.2.4 Estimating Unobserved States (s_t)

The next important step is estimating the unobserved states s_t . These are estimated by the smoothed probabilities:

$$P(s_t | Y_N, \lambda), \quad (5.8)$$

where Y_N represents the whole observed data.

To obtain these probabilities and the likelihood function, Hamilton (1989) devised an iterative procedure to compute the filtered probability at time $t+1$, $P(s_{t+1}|Y_{t+1}, \lambda)$, from the filtered probability at time t , $P(s_t|Y_t, \lambda)$. Here, Y_t means the observed data up to, and including, the current date t . These probabilities are calculated assuming λ is known. To simplify notation, hereafter λ is suppressed from Equation (5.8) and all other expressions of probabilities, although it is implicit in all the following expressions.

5.2.5 Likelihood Estimation

In the previous sub-sections, the vector of population parameters λ was regarded as known. Given Y_t and λ , the question was where did the changes in regime seem to occur? In the course of answering this question, the conditional densities $f(y_t|Y_{t-1}, \lambda)$ need to be calculated. These calculations are used to obtain the value of the likelihood function for a given value of λ using:

$$L(\lambda|Y_N) = f(Y_N|\lambda) = \prod_{j=k+1}^N f(y_j|Y_{j-1}, \lambda). \quad (5.9)$$

The maximum likelihood estimate of λ can be found by maximising (5.9) by numerical methods.

5.3 Estimating the Markov Switching Model

When the MS model is estimated to identify turning points in tourism demand growth, it generates important parameter estimates. The following table (Table 5.1) presents the estimated parameters $\lambda = (\mu_0, \mu_1, p, q, \sigma)$ from the MS model for the four countries. Further, the mean value (μ) and the standard deviation (σ) of the smoothed growth data series are also given for comparison.

Table 5.1 **Estimated MS Model Results**

	μ of the series	μ_0	μ_1	p	q	σ of the series	σ
USA	0.06203	0.00755	0.13842	0.95382	0.93773	0.09015	0.06104
New Zealand	0.06224	-0.00342	0.213322	0.94693	0.87031	0.12969	0.08226
UK	0.07255	0.04540	0.20159	0.96943	0.84307	0.84300	0.05968
Japan	0.10098	-0.00478	0.193955	0.99115	0.99163	0.13930	0.09706

When analysing the MS results above (Table 5.1), the higher probability values for p and q and lower standard deviation (σ) can be seen, compared to the original data's standard deviation. As expected, the series mean is between the given expansion mean (μ_1) and the contraction mean (μ_0), but, importantly, the range of the two means (μ_1 and μ_0) is very high for all four countries.

5.3.1 Smoothed Probabilities and Regime Change

The Markov Switching output will generate the smoothed probabilities of the unobserved states s_t . This will give the probability of each quarter being in an expansion (or contraction) regime. Normally 0.5 probability values form a cut-off point between the expansion and contraction regime. When the tourism demand probability changes from greater than 0.5 to less than 0.5, or vice versa, it is considered a regime change, or turning point.

Other than the smoothed probabilities, the MS output will also generate a series with a combination of 0's and 1's for each quarter to show whether the tourism demand is in a contraction regime or an expansion regime. To decide on 1 or 0, MS uses 0.5 as the cut-off point, meaning that if the smoothed probability value is greater than 0.5 its category is 1, and if the value is less than 0.5 it is considered 0. Most macroeconomic turning point researchers use this change over point as the turning point. But just a one quarter (1 period) jump up or down does not register as a regime change. MS theory expects at least two periods to be in the same regime before it can be considered to be in the next regime. It is worth mentioning here that these smoothed probabilities and the 1's and 0's are by-products of MS output and the dating is not a natural outcome of the MS model.

Plotting these 1 and 0 values and smoothed probability values against actual tourism arrivals growth will give an indication of the accuracy and the ability of the MS model to capture expansion and contraction regimes.

(Note: The following graphs are produced using the probabilities of tourism demand in the expansion phase ($S_{t=1}$)).

Figure 5.1

USA Tourist Arrivals Growth vs. Markov Switching Expansions and Contraction Regimes

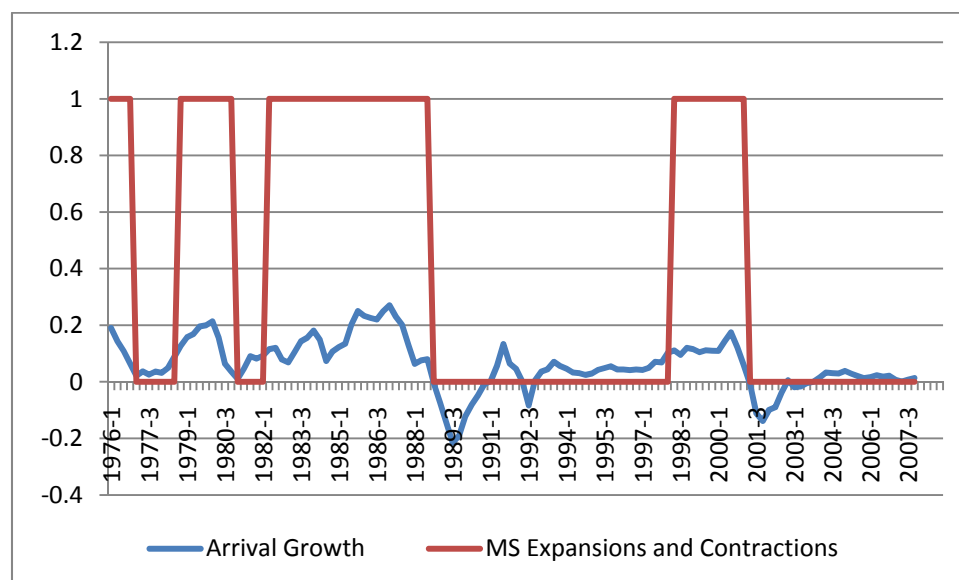


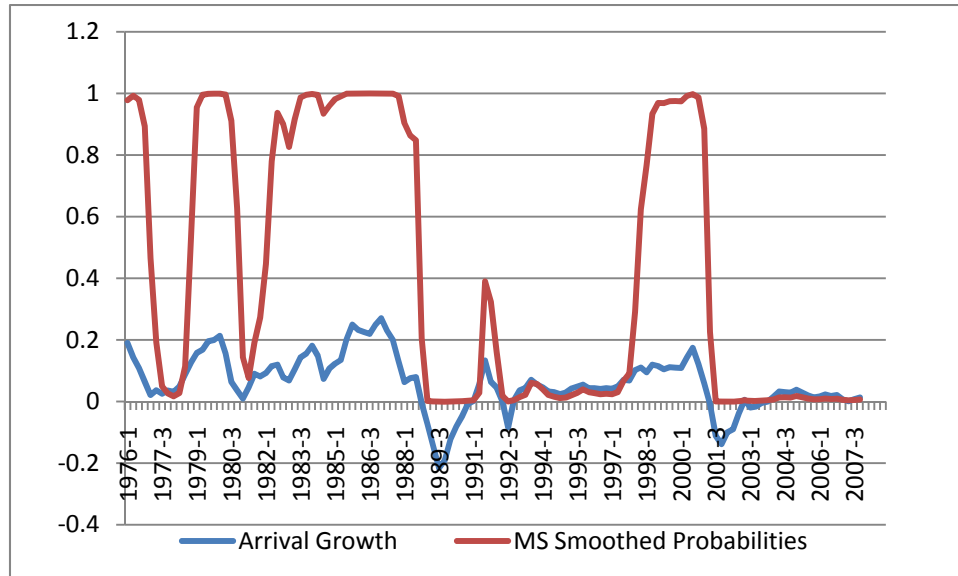
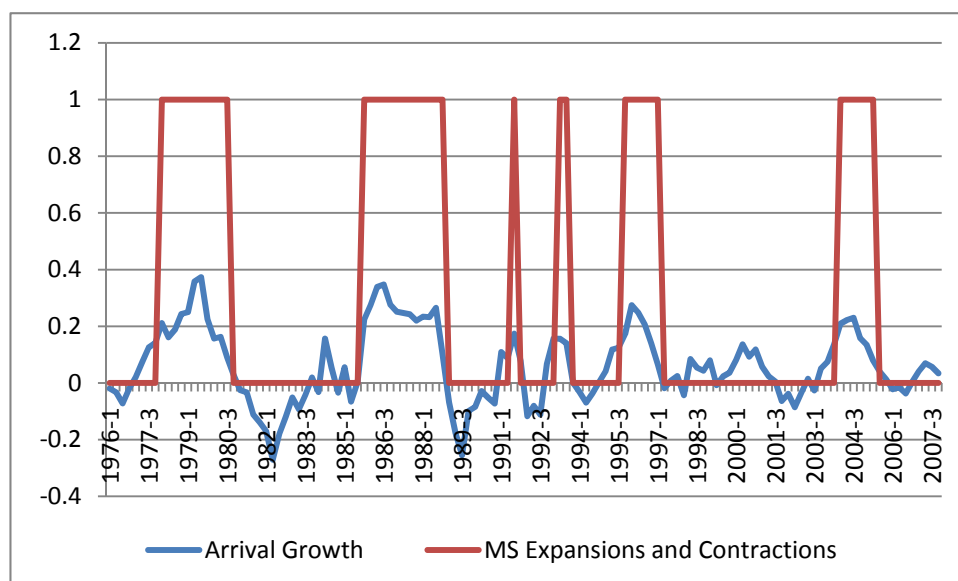
Figure 5.2**USA Tourist Arrivals Growth vs. Markov Smoothed Probabilities****Figure 5.3****New Zealand Tourist Arrivals Growth vs. Markov Switching Expansion and Contraction Regimes**

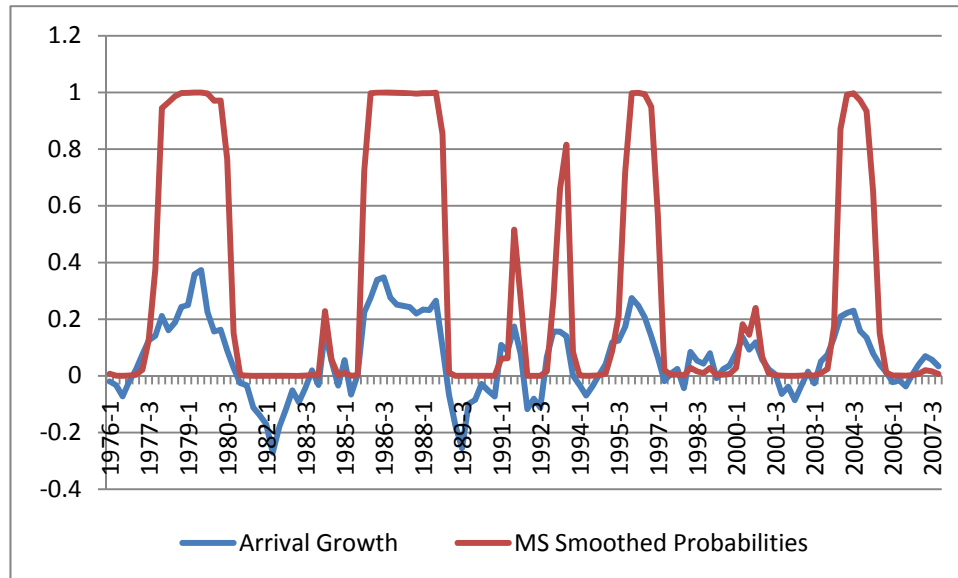
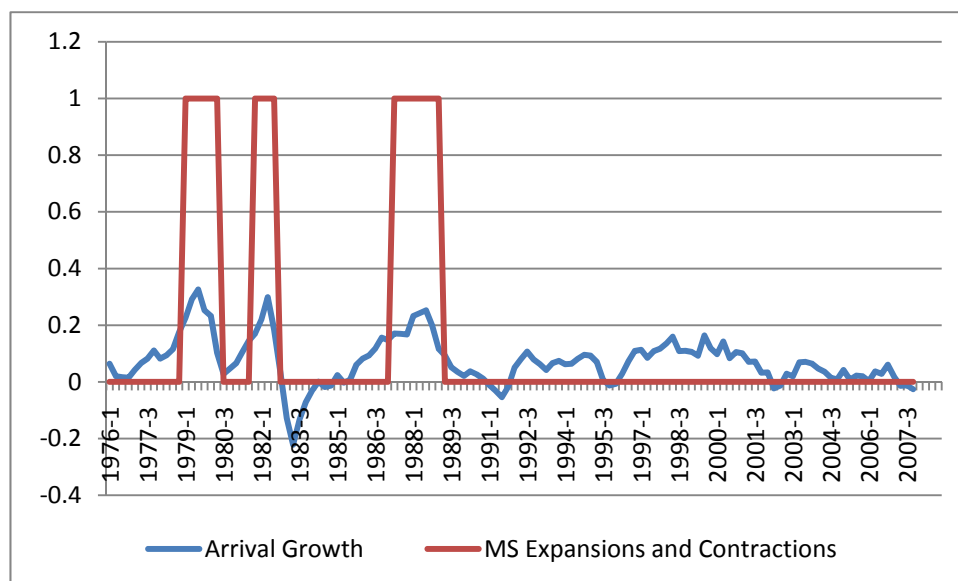
Figure 5.4**New Zealand Tourist Arrivals Growth vs. Markov Smoothed Probabilities****Figure 5.5****UK Tourist Arrivals Growth vs. Markov Switching Expansion and Contraction Regimes**

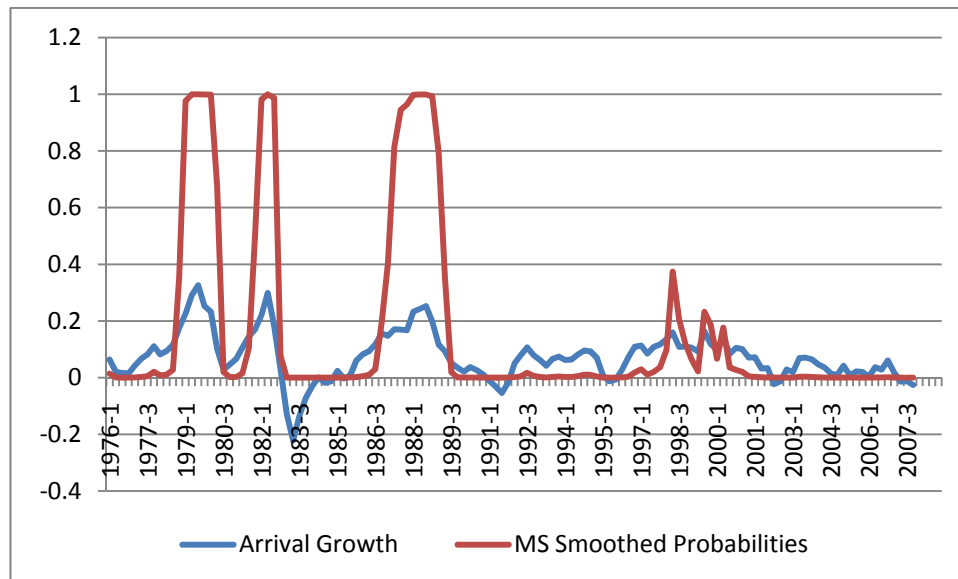
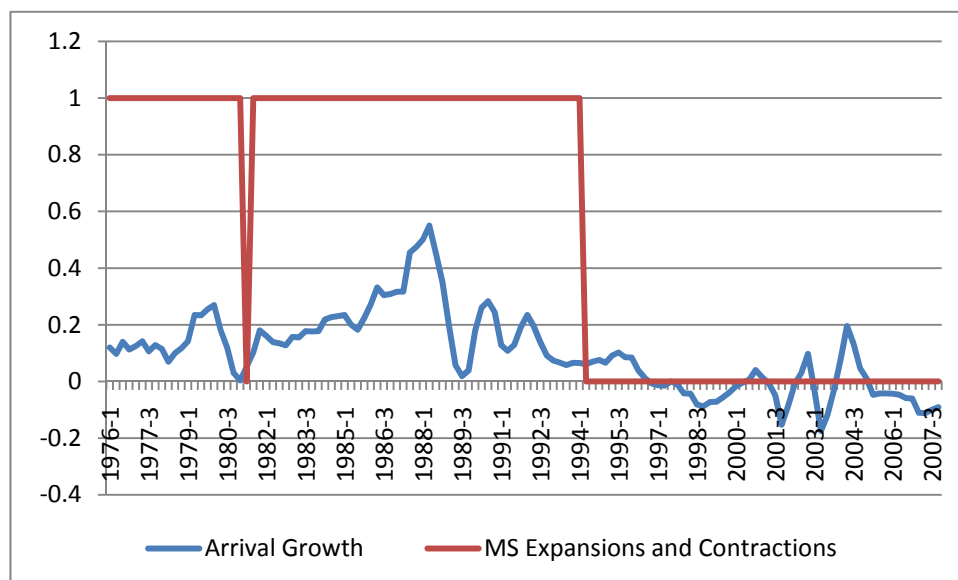
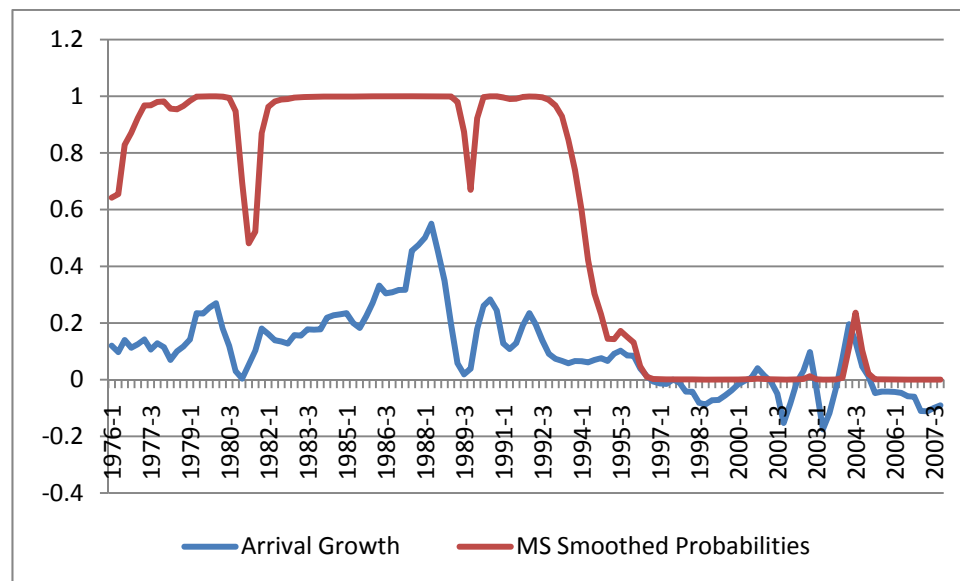
Figure 5.6**UK Tourist Arrivals Growth vs. Markov Smoothed Probabilities****Figure 5.7****Japan Tourist Arrivals Growth vs. Markov Switching Expansion and Contraction Regimes**

Figure 5.8**Japan Tourist Arrivals Growth vs. Markov Smoothed Probabilities****5.4 Parametric MS versus Non-parametric BB Algorithm**

The objective of this section is to compare the turning points identified by the parametric MS and the turning points identified in Chapter 4 using the non-parametric BB algorithm. This analysis is helpful to conclude which method/model is better in identifying significant turning points in tourism demand.

In addition to the non-parametric BB method and parametric MS models, this study introduces a third method called the Mix method. The Mix method (Highest Probability method) is a combination of the two main methods tested in this study (Section 4.5 and 5.3) and is an optional dating method.

In order to decide as to the most suitable method to date turning points in tourism demand, other than by capturing, factors such as transparency, robustness, simplicity and explicability must also be considered.

Before a comparison is made it is important to re-examine the basics of these three methods:

(I) Modified BB (Bry and Boschan) Non-Parametric Algorithm:

(A) The cycle in a series Y_t can be expressed in terms of its turning points, which are local maxima and minima in a sample path:

DT at $t := \{(Y_{t-3}, Y_{t-2}, Y_{t-1} < Y_t > Y_{t+1}, Y_{t+2}, Y_{t+3})\}$,

UT at $t := \{(Y_{t-3}, Y_{t-2}, Y_{t-1} > Y_t < Y_{t+1}, Y_{t+2}, Y_{t+3})\}$,

where: Y_{t-3} , Y_{t-2} , and Y_{t-1} are past values of the smoothed arrivals growth and Y_{t+1} , Y_{t+2} , and Y_{t+3} are the future values of the smoothed arrivals growth.

(B) The minimum phase period (expansion or contraction) needs to be three quarters.

(C) The minimum cycle period (expansion to contraction and contraction to expansion) needs to be seven quarters.

(II) Parametric MS Model:

(A) Identify turning points using the smoothed probabilities generated by the MS output.

(B) Turning point or regime change period is a quarter where the smoothed probability changes from the 0.5 threshold.

(C) To be considered as a turning point/regime shift, a series needs to be in the same regime for at least two quarters.

(D) If a series produces more than one turning point in a regime, select the highest value (probability) as the turning point.

i.e. **(a)** $Y_t > 0.5$ and **(b)** $Y_{t-2}, Y_{t-1} > 0.5 > Y_{t+1}, Y_{t+2}$.

(III) Mix Method (Highest Probability Method)

Recalling the aim of the research which is to identify the turning points irrespective of the negative or positive growth and irrespective of the magnitude of the phase where tourism demand changes from faster growth to slower growth, called a downturn (DT), or from slower growth to faster growth, called an upturn (UT).

Examining Figure 5.1 to 5.8 for tourist arrivals growth and smoothed probabilities, it can be observed visually that though the MS method captures most of the expansion and contraction periods, it does not capture the exact points of upturn (UT) and downturn (DT) of tourism growth. Further, it is seen that there are increasing (expansion) growth periods as well as decreasing (contraction) growth periods within the same regime.

A further option to be considered in identifying the turning points is a combination of the parametric output (MS output) of smoothed probabilities and the application of the non-parametric formula on the MS smoothed probability, while keeping the basic rules of both methods alive.

In this combined mix method, the smoothed probabilities are generated by the Markov Switching output, and the non-parametric formula is applied to each regime to identify the highest probability value for each regime, which would be the turning point. Here it is assumed that the highest probability in each regime is the peak or trough point.

To select a point as a turning point (UT or DT) using smoothed probability values, it is important that the basic theoretical conditions of Markov switching are met and that the 0.5 probability threshold rule of identifying expansion/contraction and the non-parametric basic turning point rules are used.

Therefore, the combined conditions for the method would be:

(A) Identify turning points using smoothed probabilities generated by MS output.

(B) Determine whether the phase is in expansion or contraction by using the 0.5 threshold.

(C) A turning point (UT or DT) is the observation at time t with the highest smoothed probability in the regime (highest probability in the expansion regime is the DT and highest probability in the contraction regime is the UT).

(D) To identify a highest probability value in the smoothed probabilities, non-parametric rules are used:

(a) DT at $t := \{(Y_{t-3}, Y_{t-2}, Y_{t-1} < Y_t > Y_{t+1}, Y_{t+2}, Y_{t+3})\}$,

UT at $t := \{(Y_{t-3}, Y_{t-2}, Y_{t-1} > Y_t < Y_{t+1}, Y_{t+2}, Y_{t+3})\}$,

where: Y_{t-3} , Y_{t-2} , and Y_{t-1} are past values of the MS smoothed probabilities and Y_{t+1} , Y_{t+2} , and Y_{t+3} , are the future values of the MS smoothed probabilities.

(b) Minimum regime period (expansion or contraction) needs to be seven quarters.

(c) If it produces more than one turning point in a regime, select the highest probability value of that regime.

In this chapter, three methods have been discussed to identify turning points, namely, the non-parametric algorithm, the parametric MS method, and the Mix method (highest smoothed probability). The table below summarises the three methods (Table 5.2).

Table 5.2 Summary of the Three Methods for Identifying Turning Points

	Non-Parametric Algorithm	Parametric MS Regime Switching (MS)	Mix method (highest smoothed probability)
Countries	USA, New Zealand, UK and Japan	USA, New Zealand, UK and Japan	USA, New Zealand, UK and Japan
Data	Smoothed arrivals growth	Smoothed arrivals growth	Smoothed arrivals growth
Series used to identify TP	Smoothed arrivals growth	MS output-smoothed probabilities for each quarter	MS output-smoothed probabilities for each quarter
Basic Rules	Period t is a downturn (DT) if (a) DT at $t = \{(Y_{t-3}, Y_{t-2}, Y_{t-1} < Y_t > Y_{t+1}, Y_{t+2}, Y_{t+3})\}$ Period t is an upturn (UT) if (a) UT at $t = \{(Y_{t-3}, Y_{t-2}, Y_{t-1} > Y_t < Y_{t+1}, Y_{t+2}, Y_{t+3})\}$	Period t is a downturn (DT) regime shift if (a) $Y_t > 0.5$ (b) $(Y_{t-2}, Y_{t-1} > 0.5 > Y_{t+1}, Y_{t+2})$ (To be considered as a regime shift it needs to be in the same regime at least 2 quarters) (c) In the presence of double DT highest probability value is chosen Period t is an upturn(UT) regime shift if (a) $Y_t < 0.5$ (b) $(Y_{t-2}, Y_{t-1} < 0.5 < Y_{t+1}, Y_{t+2})$ (To be considered as a regime shift it needs to be in the same regime at least 2 quarters) (c) In the presence of double UT lowest probability value is chosen	Period t is a downturn (DT) if (a) $Y_t > 0.5$ (b) Y_t should be the highest probability of the regime (c) $(Y_{t-3}, Y_{t-2}, Y_{t-1} < Y_t > Y_{t+1}, Y_{t+2}, Y_{t+3})$ Period t is an upturn (UT) if (a) $Y_t < 0.5$ (b) Y_t should be the lowest probability of the regime (c) $(Y_{t-3}, Y_{t-2}, Y_{t-1} > Y_t < Y_{t+1}, Y_{t+2}, Y_{t+3})$
Minimum phase period	Three quarters	Two quarters	Three quarters
Minimum cycle period	Seven quarters	Four quarters	Seven quarters (minimum regime period)

The following tables and figures present the turning points identified using the three methods above for the four countries from 1975 to 2007.

Table 5.3

USA Turning Points Using Non-Parametric, MS and MS Highest Probability Methods

Non-Parametric Algorithm		Parametric MS Regime Switching (MS)		Mix method (highest smooth probability)	
Up Turn	Down Turn	Up Turn	Down Turn	Up Turn	Down Turn
			1976-3		
1977-1	1980-1	1978-3	1980-4	1978-1	1980-1
1981-1	1982-3	1982-1		1981-2	
1984-3	1985-4		1988-3		1985-4
1989-3	1991-3			1989-3	
1992-3	1993-3				
1994-4	1998-4	1999-1	2001-1		2000-3
2001-4	2006-2			2001-4	

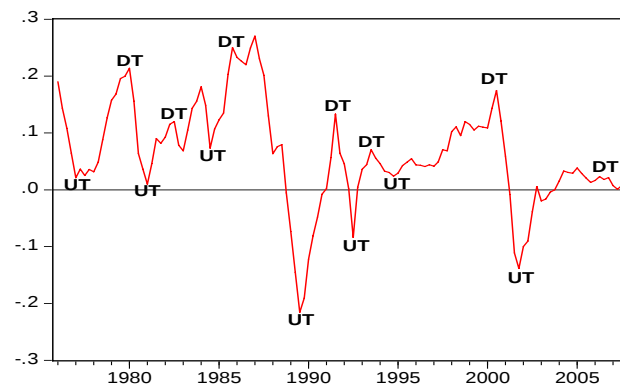
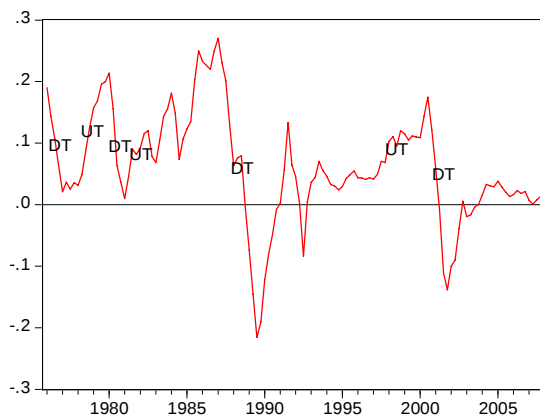
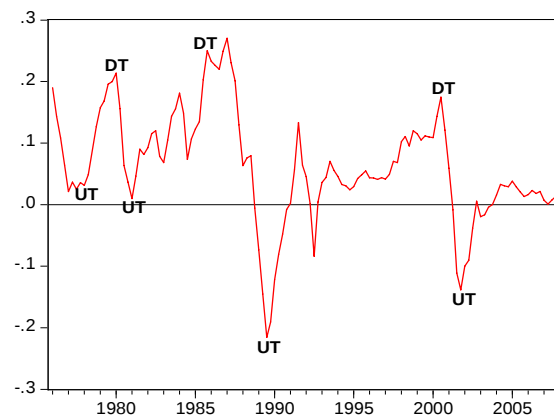
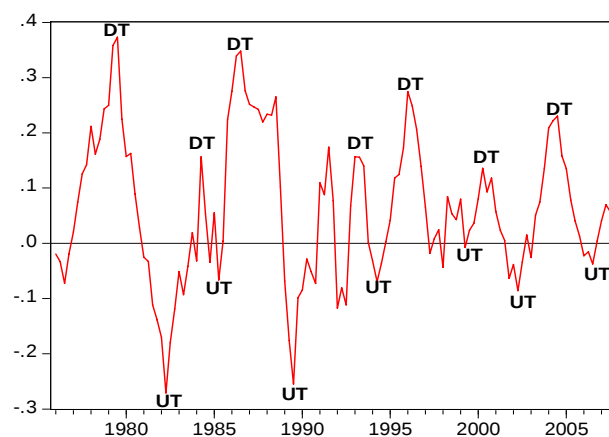
Non-Parametric Algorithm**Parametric Regime Switching****Mix method**

Table 5.4

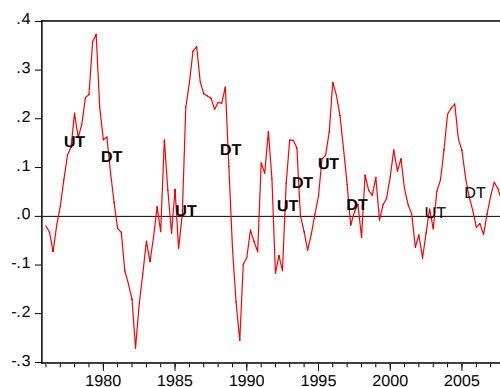
New Zealand Turning Points Using Non-Parametric, MS and MS Highest Probability Methods

Non-Parametric Algorithm		Parametric MS Regime Switching (MS)		Mix method (highest smoothed probability)	
Up Turn	Down Turn	Up Turn	Down Turn	Up Turn	Down Turn
	1979-3	1977-4	1980-3		1979-3
1982-2	1984-2	1985-3	1988-4	1982-2	
1985-2	1986-3	1993-1	1993-3		1986-3
1989-3	1993-1	1995-3	1997-1	1989-3	
1994-2	1996-1	2003-4	2005-2		1996-2
1999-2	2000-2			1998-1	
2002-2	2004-3				2004-3
2006-3				2006-3	

Non-Parametric Algorithm



Parametric Regime Switching



Mix method

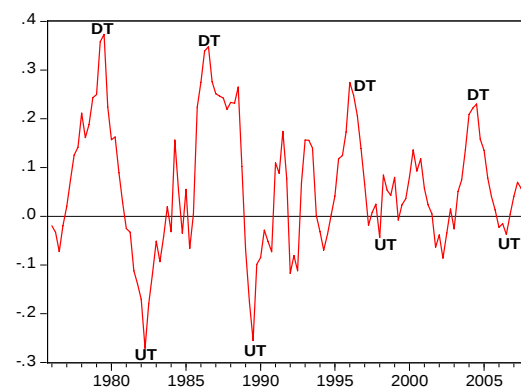
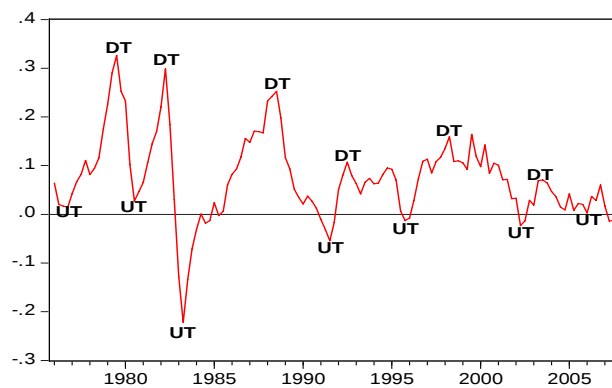


Table 5.5

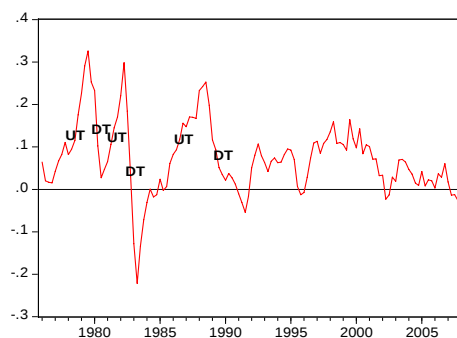
UK Turning Points Using Non-Parametric, MS and MS Highest Probability Methods

Non-Parametric Algorithm		Parametric MS Regime Switching (MS)		Mix method (highest smoothed probability)	
Up Turn	Down Turn	Up Turn	Down Turn	Up Turn	Down Turn
1976-4	1979-3	1978-4	1980-2	1976-4	1979-3
1980-3	1982-2	1981-3	1982-3	1980-4	1982-2
1983-2	1988-3	1987-1	1989-1	1983-2	1988-3
1991-3	1992-3			1991-3	
1995-4	1998-2				
2002-2	2003-3				
2006-1					

Non-Parametric Algorithm



Parametric Regime Switching



Mix method

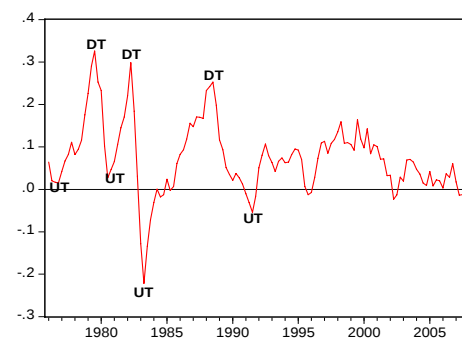
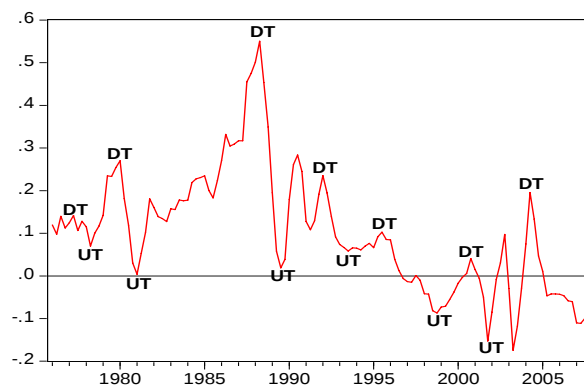


Table 5.6

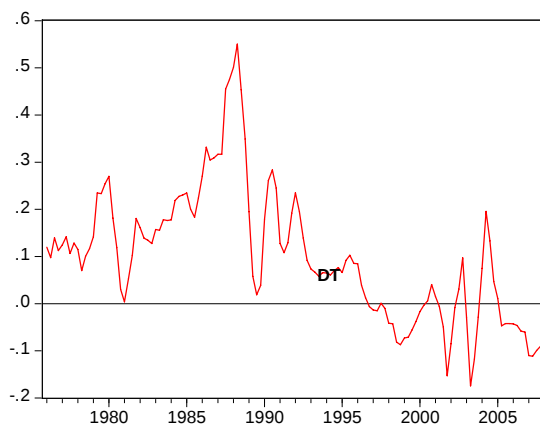
Japan Turning Points Using Non-Parametric, MS and MS Highest Probability Methods

Non-Parametric Algorithm		Paramedic MS Regime Switching (MS)		Mix method (highest smoothed probability)	
Up Turn	Down Turn	Up Turn	Down Turn	Up Turn	Down Turn
	1977-2				
1978-2	1980-1				
1981-2	1988-2				1988-1
1989-3	1992-1		1994-1		
1993-3	1995-3				
1999-1	2000-4				
2001-4	2004-2				

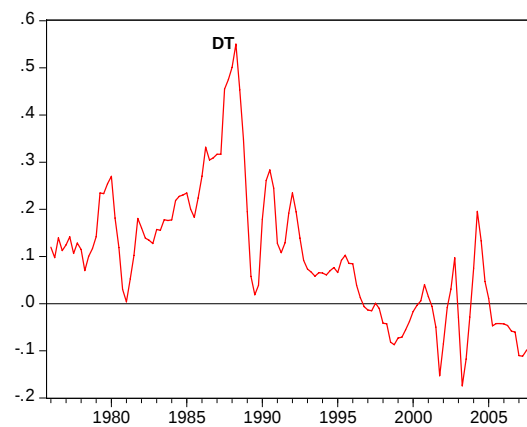
Non-Parametric Algorithm



Parametric Regime Switching



Mix method



5.4.1 Results of the Three Dating Methods

Tables 5.3, 5.4, 5.5 and 5.6 above compare the significant turning points captured by each method for the four countries. When analysing the results of the main two methods (MS and BB) for the purpose of identifying turning points, it is clear that the timing of turning points is not the same in the parametric MS method and non-parametric algorithm. But it is clear that the mixed method identifies most of the turning points identified by the non-parametric algorithm method, but the mixed method only identifies the turning points with high amplitudes. Of the three methods used, visual observation confirms that the non-parametric algorithm method captures almost all the possible turning points during the period 1975 to 2007.

Many macroeconomic turning point researchers have used the parametric MS and non-parametric BB algorithm method to identify and compare turning points and most have obtained similar results, with both methods identifying the same turning point, but in this study they have not always been the same. Therefore it is worth investigating the reasons for not getting close results from these two methods for the tourism demand growth data in this study.

5.4.2 Difference Between the Parametric and Non-parametric Methods

This section attempts to identify the possible reasons for getting different results from the parametric and non-parametric methods, by investigating the basic differences between the methods and their application.

It is obvious that there are many differences between the parametric and non-parametric methods. Fundamentally, the parametric method goes through a complex statistical process and the non-parametric method uses a simple formula. However it is important to investigate reasons that may be specific to the tourism arrivals data in this study.

The MS regime change recognition uses the entire data set (in this study 1975 Q1 to 2007 Q4) and calculates the mean value of all the expansion periods (μ_1) and the

mean value of all the contraction periods (μ_0). To decide whether a particular quarter/value stays or shifts from one regime to another regime, the MS model checks whether the value of that quarter is close to the expansion mean or the contraction mean. If a particular value/quarter is close to the expansion mean and the series is already in the expansion regime, the particular value/quarter stays in the same regime (no regime change). If tourism demand is in a contraction regime and the particular quarter/value is close to the expansion mean, and the immediate past (S_{t-1}) values carry contraction probability, it will stay in the contraction regime.

If tourism is in a contraction regime, and the particular quarter/value is close to the expansion mean and the immediate past (S_{t-1}) value is in an expansion probability, then the regime will shift from contraction to expansion. This characteristic of the model clearly explains that the preselected mean value for expansion and contraction plays a major role in deciding the regime.

Moreover, it is known that macroeconomic data, especially data like GDP and GNP, are mainly in an expansion period and only occasionally experience contractions of a few quarters, and the contractions do not carry very high amplitude (depth) or phase (duration).

However, the tourist arrivals data in this study is highly volatile, not only due to its high seasonality (which was addressed by smoothing), but mainly because tourism demand is highly sensitive to economic and political factors in the tourist origin or destination countries. Moreover, events occur such as epidemics, natural disasters, sporting events and terrorist attacks. Due to these factors the turning points have high amplitudes (higher peaks and deep troughs). In other words, the smoothed tourism demand growth rate has higher positive values and higher negative values, and at times the entire cycle can lie within the positive growth period or negative growth period. This will clearly affect the MS process when it tries to decide to which regime each quarter belongs, based on the mean value for expansions and recessions.

In contrast, the non-parametric algorithm only validates three periods before, and three periods after, when considering a particular point as a turning point. This

technique only takes seven quarters into consideration at a time when deciding whether a turning point occurs and never considers the depth or the amplitude of the data/turning point. Also, the non-parametric algorithm eliminates (sacrifices) the three quarters at the beginning and the end of the series.

The non-parametric method can identify turning points without regard to negative or positive growth and can directly identify an upturn (trough) within a positive growth period and downturn (peak) within a negative growth period.

The importance of the MS method is that it considers the entire series during regime selection. Therefore the probability value given by the MS for a quarter/period (in this case 1975- 2007) indicates whether a particular quarter is in an expansion or contraction regime. Hence the MS probability values are useful in deciding whether each quarter is being in an expansion or contraction. Consequently, the MS model can give probability values up to the last observation without losing any time period.

In discussing the different characteristics of the different methods, the next section will identify the most suitable turning point detection method (dating method). Selection of the most suitable method mainly depends on the ability to identify true turning points, the research objective and each model's characteristics such as transparency, robustness, simplicity and explicability.

5.5 Selecting the Most Suitable Method

It is important to decide the most suitable method to recognise significant turning points in a tourism demand growth series. These turning points then become the benchmark turning points to check the accuracy of forecasting methods.

There is no tourism organization or institution that provides official turning point dating on tourism demand. In macroeconomics however, organisations like NBER in the USA (National Bureau of Economic Research) and ISEA in Italy (Istituto Di Studi E Analisi Economica) give official turning point dates and researchers use them as bench marks to check their dating accuracy. Therefore, given there are no official

benchmarks to use in tourism demand research, the following criteria are used to determine the best method: (1) Visual observation which can be applied to check the capturing capability of the method (using the smoothed growth diagram). (2) Deciding whether the dating method helps to achieve the objective of the study. (3) Whether the method has important characteristics of a good dating method such as transparency, robustness, simplicity and explicability (Harding and Pagan (2003)).

The main reasons for applying parametric MS method is to identify turning points in this study are: (1) MS method is the latest, most commonly and widely used non-linear method to identify turning points in macroeconomics (2) The ability of the MS model to identify/describe the presence of a structural switching shift in the level of an economic data series, such as GDP, may explain the behaviour of a tourism cycle. (3) As MS model can generate the appropriate measure of the business cycle is regarded as having a certain probability of switch between two regimes, this method may compatible with the other econometric models used in this study (Logit and Probit models also generate probabilities of being in expansion or contraction)

The objective of this study is to identify and predict turning points, not to investigate the amplitude or the depth of the turning points, span/duration of the turning points or negative growth and positive growth.

With regard to the parametric MS method, the results have higher p and q values and lower σ values, and the method has captured turning points but not as many as by visual observation. It has captured the quarter as turning points where the demand growth comes close to a positive/negative threshold.

As observed in Tables 5.3 to 5.6, visual observation demonstrates that the non-parametric algorithm captures all the turning points irrespective of the magnitude of the turning point, and, as mentioned above, it clearly meets the aim of the study. Furthermore, this method is simple to apply, and is transparent compared to the MS method. Also it is highly robust, and turning point dates do not change with the number of observations, amplitude or range of the data (high negative low positive values). Moreover, according to Harding and Pagan (2003), *“the main advantage of the non parametric algorithm over the parametric method is its robustness and*

simplicity. In general the problem with the MS model dating technique is that it is not very transparent". Since the objective is not to look at negative growth periods and positive growth periods, this research identifies the non-parametric BB algorithm method as the most suitable dating method to use to identify turning points as benchmarks with which to check the accuracy of forecasting methods (discussed in Chapter 6).

Chapter 6

Forecasting Turning Points Using Logit and Probit Models

6.1 Introduction

The objective of this chapter is to forecast turning points in tourism demand using non-linear econometric models. Logit and Probit models are possible non-linear econometric models which have binary dependent variables. Though these models have been used in macroeconomics, they have never been used in the tourism context to forecast turning points. The first section of this chapter discusses the theoretical aspects of Logit and Probit models and the second section will apply Logit and Probit models in order to forecast turning points. Thirdly the models' validity for each country is assessed using different tests. Finally, in the fourth section the forecasted turning points using Logit and Probit models are compared with the benchmark turning points identified, using the BB non-parametric algorithm. This allows a discussion of the ability of the Logit and Probit models to forecast turning points in Australian tourism demand.

6.2 Logit and Probit Models

Standard econometric models are based on an implicit assumption that the value of the dependent variable Y can take any value between plus infinity and minus infinity. But the Logit and Probit models are designed to deal with situations where the Y variable represents a qualitative measure with a limited number of possible values, where Y mainly takes two different values, 1 or 0.

Therefore the Logit and Probit models are regression models with dummy dependent variables, taking a value of 1 or 0. The unique nature of these models is that the dependent variable is of the type that elicits a 'yes' or 'no' response, which means it's dichotomous in nature. But the basic equation represents the general regression structure:

$$Y_i^* = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots + \varepsilon_i$$

Using this binary ‘yes’ or ‘no’ response for the Logit and Probit models, some macro economic and financial researchers have attempted to predict turning points and economic phases, where if the economy is in an expansion period $Y = 1$, if the economy is in a contraction period $Y = 0$, and where X_i are potential explanatory variables that cause turning points (Layton and Karsuura (2001), Bodart et al. (2005), Sensier et al. (2004), Harding and Pagan (2006), Lennox (1999), Marianne and Kouparitsas (2005)). In the same way, this study predicts Y with the interpretation of $Y = 1$ when tourism is in an expansion phase (increasing tourism demand growth) and $Y = 0$ when tourism is in a contracting phase (decreasing tourism demand growth), with X_i being potential economic explanatory variables.

6.3 Tourism Demand Model and Explanatory Variables

One of the major advantages of the Logit and Probit regression models over the time series models lies in their ability to analyse the causal relationships between the tourism demand (dependent) variable and its influencing factors (explanatory variables). But the great challenge is to select the relevant explanatory variables for these models. Though the Logit and Probit models have never been examined in tourism economics for turning point forecasting (as previously discussed in Chapters 2 and 3) previous econometric studies have broadly identified potential explanatory variables for tourism demand.

In this study, use is made of the same tourism demand approach with non-linear Logit and Probit models to predict turning points in tourism demand (discussed in Chapter 3 which deals with methodology).

Consumer choice theory postulates that the demand for a given commodity depends on consumer's income, prices and other variables specific to the commodity in question, hence tourism demand for a given country may be expressed as a function of income, price, the price of a competing substitute and airfare:

$$TD = f(Y, PT, AF, SP, D_1, D_2),$$

Where:

TD represents the actual tourism demand growth; TD = 1 if the actual tourism demand growth is in expansion, and TD = 0 if the actual tourism demand growth is in contraction.

Y is the growth of income in the tourists' country of origin (Measured in Real GDP).

PT is the growth of the destination country's prices (to calculate the prices of tourism products in Australia, the Australian consumer price index (CPI) is divided by the CPI of the tourists' country of origin and divided by the bilateral exchange rate):

$$PT = \frac{\text{Consumer Price Index}_{\text{Australia}}}{\text{Consumer Price Index}_{\text{ForeignCountry}}} \times \frac{1}{\text{ExchangeRate}_{\text{ForeignCurrency / Australia}}}$$

AF is growth of airfare prices measured in real terms.

SP is the growth of substitute destination price - to calculate the substitute destination price, the substitute destination's consumer price index (CPI) is divided by the tourists' country of origin CPI and multiplied by the bilateral exchange rate (same as in the PT calculation above).

(As the above growth variables are used, the letter 'G' will be placed in front of independent variable names, and thereafter they will be referred to as, GY, GPT, GAF and GSP).

As discussed in the methodology chapter (Chapter 3), it is not easy to select a substitute destination for Australia due to its location and unique characteristics. To select a substitute destination for USA, UK, Japan and New Zealand tourists, attributes such as geographic location, culture, distance of travel, climate and the substitute destination's highlights need to be considered.

Chapter 3.10 also explains that for USA tourists the UK is considered to be a substitute destination. For UK tourists the USA is considered to be the substitute destination. For Japanese tourists, Hawaii will be regarded as a substitute country for Australia (Kulendran and Divisekara (2007)). For New Zealand tourists there is no substitute destination for Australia as it is very difficult to find a close substitute due to the close proximity and other cultural and political links between the two countries (Kulendran and King (1997)).

Further, two dummy variables (refer Chapter 3.10), D_1 and D_2 , are used to check the effect of random events in creating turning points as against economic variables. In this study use was made of the following two events:

D_1 is for the 2000 Sydney Olympics which had a positive effect on tourism demand.

D_2 is for the September 11, 2001 attack on New York which had a negative effect on tourism demand.

6.4 Logit Model

The binomial Logit model is an estimation technique, which uses dummy dependent variables and thus avoids the unboundedness problem that occurs in linear models by using a variant of the cumulative logistic function (Studenmund (2001, p.442)).

The Logit model transforms the estimated function into a logistic probability model. The logistic cumulative distribution function is:

$$F(Z_i) = \frac{1}{1 + e^{-Z_i}}, \quad (6.1)$$

where e is the base of natural logarithms and $F(Z_i) = P_i$. In the Logit model, P_i is the probability of the i^{th} individual choosing the first response. It is expressed as a function of $(\alpha + \beta X_i)$, which is then substituted for Z_i in the Logit model. The transformed Logit model then becomes:

$$F(Z_i) = F(\alpha + \beta X_i),$$

$$P_i = F(Z_i) = F(\alpha + \beta X_i) = \frac{1}{1 + e^{-(\alpha + \beta X_i)}} \quad (6.2)$$

To demonstrate the simple nature of the Logit model, Equation 6.2 can be expressed as:

$$P_i = \frac{1}{1 + e^{-z_i}} \quad (6.3)$$

This can be rearranged to give:

$$e^{z_i} = \frac{P_i}{1 - P_i} \quad (6.4)$$

Taking the natural logarithm of both sides results in:

$$Z_i = \ln \left[\frac{P_i}{1 - P_i} \right] \quad (6.5)$$

Substituting from Equation (6.2) gives the relationship:

$$\ln \left[\frac{P_i}{1 - P_i} \right] = Z_i = \alpha + \beta X_i, \quad (6.6)$$

where the dependent variable is the logarithm of the ratio of the probability that a particular event will occur to the probability that the event will not occur. The Logit model is based upon a cumulative distribution function and the error ε_i is not normally distributed, because $P(Y_i)$ can only take on the values of 0 and 1.

Thus, the dependent variables can be interpreted as the logarithm of the odds that a particular choice will be made. The properties of the Logit model are:

1. The distribution is symmetric about 0.
2. The variance is $\pi^2 / 3$, where $\pi = 22/7$.
3. The slope of the derivative is the greatest at $P = 0.5$. This implies that the greatest impact of the explanatory variable on the probability of choosing a given alternative will be at the midpoint of the distribution. The tails of the

distribution are flat implying that large changes are necessary in the explanatory variables to affect the probability of choice.

While X contains explanatory variables, P_i is bounded by 1 and 0, and $\hat{P}_i$ approaches 1 and 0 very slowly (i.e. asymptotically). The binomial Logit model therefore avoids the major problem that the linear model encounters in dealing with dummy dependent variables. In addition, the binomial Logit model is quite satisfying to most researchers because it turns out that real world data are often described well by S-shaped patterns (Studenmund (2001, p.434 -449)).

Further, in linear Logit models P_i is modelled directly, and there is a possibility that a prediction of P_i might be outside the probability interval of 0 to 1, but in the case of the binomial Logit model, the ratio $P_i / (1 - P_i)$ is modelled constructively. This ratio is the likelihood, or odds, of obtaining a successful outcome ($P_i = 1$). The log of this ratio obtained on the left-side of the equation has become the standard approach to the dummy dependent variable analysis.

In this study P_i is the probability that the tourism demand growth is in expansion or contraction mode. Forecasts of P_i from this model have the interpretation that the probability forecasts of P_i will be 1. This is conditional on the values of the explanatory variables in the model.

It is worth mentioning that an important extension of this basic binomial Logit model is the multinomial Logit model. In this extension the dependent variable is allowed to have more than two values.

6.5 Binomial Probit Model

The binomial Probit model is an estimation technique for equations with dummy dependent variables using a variant of the cumulative normal distribution (Studenmund (2001, p.449)).

The probability distribution can be represented as:

$$P_i = F(\alpha + \beta X_i) = F(Z_i). \quad (6.7)$$

(Pindyck and Rubinfeld (1991, p.254)).

To understand the above model (6.7), assume that it has a theoretical continuous index Z_i which is determined by an explanatory variable X . Thus the equation can be rewritten as:

$$Z_i = \alpha + \beta X_i. \quad (6.8)$$

The Probit model assumes that Z_i is a normally distributed random variable, so that the probability that Z_i is less than (or equal to) one can be computed from the cumulative normal probability function.

To obtain an estimate of the index Z_i , the inverse of the cumulative normal function can be applied to Equation 6.7:

$$Z_i = F^{-1}(P_i) = \alpha + \beta X_i. \quad (6.9)$$

The above can be elaborated as:

$$Z_i = F^{-1}(P_i) = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} \dots$$

Like the Logit model, the Probit model is also based on the cumulative distribution function but the difference is that the Probit model's error term is normally distributed. The theoretical justification for employing the Probit model is, however, somewhat limited compared to the Logit model (Pindyck and Rubinfeld (1991)). In this chapter both the Logit and Probit models will be used for the turning point prediction in tourism demand.

6.6 Estimating Logit and Probit Models

Both the Logit and Probit models are cumulative distribution functions which mean that the two have similar properties, and the functional forms of both the Logit and Probit models guarantee that the estimated probabilities which result from the models are between 0 and 1. Further, both the Logit and Probit models can be estimated using the maximum likelihood (ML) method.

6.6.1 Maximum Likelihood Estimation (MLE)

MLE is the method used to calculate the Logit and Probit coefficients. This contrasts with the use of ordinary least squares (OLS) estimation of coefficients in regression. OLS seeks to minimize the sum of squared distances of the data points to the regression line. MLE seeks to maximize the log likelihood (LL). LL reflects how likely the odds are that the observed values of the dependent variable may be predicted from the observed values of the independent variables.

MLE is an iterative algorithm which starts with an initial arbitrary ‘guesstimate’ of what the coefficients should be and the MLE algorithm determines the direction and size of the change in the coefficients, which will increase LL. After this initial function is estimated, the residuals are tested and a re-estimate is made with an improved function, and the process is repeated, until *convergence* is reached (that is, until LL does not change significantly).

The great advantage of maximum likelihood estimation is that under a broad set of conditions, parameter estimations are both consistent and (for large samples) asymptotically efficient. Further, maximum likelihood estimation assumes independence among estimates.

In this chapter, the theory of MLE estimation procedure will not be discussed, since it was discussed in the previous Markov Switching chapter (Chapter 5).

6.7 Model Estimation and Evaluation (within sample: 1975 Q1 – 2003 Q4)

This study uses quarterly data from 1975 Q1 to 2007 Q4. 1975 Q1 to 2003 Q4 will be used as the estimation period while the forecasting period is from 2004 Q1 to 2007 Q4. Further, the models are estimated using EViews version 6.0.

For Logit and Probit models, Eviews has various tests and generates important outputs in order to understand, refine, assess the models’ performance and to interpret the results of the tests (Some of the methods have already been discussed in Chapter 3.10).

The model evaluation and forecasting process summary is as follows:

1. Basic tests to understand the nature of the data.
2. Model refinement, to construct a model which can explain tourism demand changes (i.e. turning points).
3. Identify and establish the most suitable model for each country and identify the most important independent variables which cause tourism demand changes (i.e. turning points).
4. Using estimated probabilities given by the final model, check the accuracy of the turning point predictions within the sample (1975 Q1- to 2003 Q4) and out of the sample (2004 Q1 to 2007 Q4).

The tests/parameters listed in Table 6.1 can be used in the model evaluation and forecasting process:

Table 6.1

Evaluation and Forecasting Tests/Parameters

To understand the data	For model refinement	To establish the accuracy of the final model	To check the Accuracy of turning point prediction
Dependent variable frequencies	p-values of the independent variables	Significant Variables	Captured Ratio
Categorical Regressor Status	Prob LR (Likelihood Ratio statistics)	p-values of the independent variables	False Ratio
	McFadden R-squared	Prob LR (Likelihood Ratio statistics)	Mean Absolute Deviation (MAD)
	LR (Likelihood Ratio) Test	McFadden R-squared	Quadratic Probability Score (QPS)
	Log Likelihood	Marginal effect of coefficient	
		Relative impact	
		Classification Table	
		Goodness of fit test (HL) Hosmer-Lemeshow	

6.7.1 Understanding the Data

The parameters listed in Table 6.1 provide a basic outline of the data used, and are discussed in more detail below.

6.7.1.1 Dependent variable frequencies

Table 6.2 shows the percentage associated with Y (independent variable) values of 0 and 1, in other words, percentages of upturns and downturns.

Table 6.2

Dependent Variable Frequencies

Dependent Value	USA	New Zealand	UK	Japan
0 (Contractions /Decreasing Growth)	38%	51%	43%	43%
1 (Expansions /Increasing Growth)	62%	49%	57%	57%

The above dependent variable frequency table explains that in our data set, except for New Zealand, there were more upturns (expansions) than downturns (contractions). Only New Zealand had slightly more downturns than upturns.

6.7.1.2 Categorical regressor status

EView generates an output that shows the descriptive statistics (mean and standard deviation) for each regressor. They are shown for both, the entire sample and the two sub-samples associated with values of 0 and 1. The following table observes the mean values of each explanatory variable (regressor) against the dependent variables 1 and 0.

Table 6.3**Categorical Regressor Table**

Regressor (Independent Variables)	Country							
	USA		New Zealand		UK		Japan	
	Dep=0	Dep=1	Dep=0	Dep=1	Dep=0	Dep=1	Dep=0	Dep=1
GY	0.225154	0.223778	0.66906	0.60186	0.021535	0.02745	0.018505	0.023067
GPT	0.020706	-0.024763	0.02090	-0.0424	0.012371	-0.00420	0.013714	-0.03848
GPS	0.026816	-0.054354	-	-	0.028337	0.020308	0.053874	-0.05125
GAF	0.700097	-0.125939	0.00632	0.12111	0.035863	-0.00517	0.045796	-0.05746

(**GY** is the growth of income; **GPT** is the growth of the destination country's prices; **GPS** is the growth of substitute destination price; **GAF** is the growth of airfares).

Mean values could be used to get an idea of whether the mean values of each independent variable are noticeably different for the dependent variable values 0 and 1, for each variable. The variables, which have significant differences in the means, could be the significant independent variables.

The independent variables GPT, GPS and the GAF of the USA and Japan, show considerable difference in their means. For New Zealand and the UK, GPT and GAF show a significant difference in means. Overall, this indicates that in this study GPT and GAF could be potential predictors to forecast turning points (1 and 0).

6.7.2 Model Refinement (To fine tune the model)

Model refinement can be done by examining the significance of individual independent variables as well as checking the significance of the overall model.

6.7.2.1 Tests to check the significance of the independent variables

Prob values of independent variables (P-values)

The probability value gives the significance of each independent variable. This probability is also known as the *p-value*. It can be decided either to reject or accept a hypothesis of zero coefficients, if the performance test is at the 5% significance level, and a *p-value* lower than 0.05 is taken as evidence to reject the null hypothesis.

6.7.2.2 Tests to check the overall significance of the model

(I) Log likelihood

The log likelihood (LL) is the log of likelihood and varies from 0 to minus infinity (it is negative because the log of any number less than 1 is negative). In the model refinement, when models are compared, the highest LL value is the value closest to zero.

(II) LR statistics

The LR statistics test the joint null hypothesis that all the coefficients except the intercept are zero. The formula that is used to obtain LR is $-2(l(\tilde{\beta}) - l(\hat{\beta}))$

This statistic, which is only reported when a constant is included in the specification, is used to test the overall significance of the model.

(III) Probability (LR statistics)

When the reduced model is the baseline model with only the constant, the likelihood ratio test tests the significance of the researcher's model as a whole. A well-fitting model is significant at the 0.05 level or better, meaning the researcher's model is significantly different from the one with only the constant.

The probability (LR statistics) shows the probability values for the LR statistic. If the probability value is 0.0014, the chance of obtaining these coefficient estimates when the true population values are zero is only 0.0014.

(IV) The McFadden R-squared

As mentioned in Chapter 3, in Logit and Probit models R^2 is not an accurate measure of overall fit and it tells very little about the overall fit. This means that R-squared measures for logistic regressions with differing marginal distributions of their respective dependent variables. Further comparison of Logit and Probit R-squared measures with R^2 from OLS regression is problematic. But as the name suggests, this is an analogy to R^2 reported in linear regression models. It has the property that it always lies between zero and one.

Table 6.4**Test/Parameter Results for Model Refinement**

	USA		NZ		UK		Japan	
Parameter Elements	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Sig Variables and p values	GPT (0.0087)	GPT (0.0081)	GPT (0.0008)	GPT (0.0012)	GY (0.0365)	GY (0.0409)	GPT(-3) (0.0014)	GPT(-3) (0.0019)
	GAF (0.0537)	GAF (0.0424)			GPT(-4) (0.4272)	GPT(-4) (0.4281)	GY (0.0726)	GY (0.0726)
Log Likelihood(LL)	-55.2054	-54.8763	-70.8042	-70.8707	-70.6888	-70.70515	-67.1421	-67.16617
Restr. log Likelihood	-61.1134	-61.1134	-77.6146	-77.6146	-72.9973	-72.99731	-74.2219	-74.22193
Average LL	-0.60006	-0.59648	-0.63218	-0.63274	-0.65452	-0.654677	-0.61598	-0.616203
LR Statistics	11.81592	12.47422	13.62084	13.48779	4.61694	4.584328	14.15947	14.11152
Prob LR	0.002718	0.001955	0.000224	0.000240	0.099413	0.101048	0.000842	0.000862
McFadden R^2	0.096672	0.102058	.087747	0.086889	0.031624	0.031401	0.095386	0.095063

(GY is the growth of income; GPT is the growth of the destination country's prices; GPS is the growth of substitute destination price; GAF is the growth of airfares).

The above parameter estimates show that the USA has the best results over the other three countries. The USA's Probability LR (overall model) is significant at 99% and the P values of the variables for both models are significant at 95% (except Probit

GAF at 94%). In addition, the USA has the highest log likelihood and highest McFadden R^2 compared to the other three countries.

New Zealand and Japan give mixed results with Probability LR showing 99% significance for the overall model and the p value of GPT is significant at 95% while Japan's GY is significant only at the 10% level. Further, these two countries show lower log likelihood and McFadden R^2 values compared to the USA.

According to the above parameter estimates, the UK shows weak results over the other three countries. Its Probability LR shows the model is not significant at the 95% level and the p values of GPT also are not significant at 95%. Further, it has lower log likelihood (only marginally better than New Zealand) and the lowest McFadden R^2 values compared to the other three countries.

Estimated models

Once the model estimation is completed, the estimated Logit and Probit models can be presented in the following table:

Table 6.5 Estimated models

Country	Logit	Probit
USA	$\ln \left[\frac{P_i}{1 - P_i} \right] = 0.535320 - 8.7303(\text{GPT}) - 0.2828(\text{GAF})$	$P_i = 0.334890 + 4.8611(\text{GPT}) - 0.1443(\text{GAF})$
NZ	$\ln \left[\frac{P_i}{1 - P_i} \right] = -0.032878 - 6.2867(\text{GPT})$	$P_i = -0.021316 - 3.8856(\text{GPT})$
UK	$\ln \left[\frac{P_i}{1 - P_i} \right] = -0.158469 - 1.42573(\text{GPT}(-4)) + 22.3579(\text{GY})$	$P_i = -0.098057 - 0.8726(\text{GPT}(-4)) + 13.9326(\text{GY})$
Japan	$\ln \left[\frac{P_i}{1 - P_i} \right] = -0.104189 - 5.0005(\text{GPT}(-3)) + 14.4061(\text{GY})$	$P_i = -0.067110 - 3.0857(\text{GPT}(-3)) + 8.7156(\text{GY})$

6.7.3 Interpreting Coefficients

After estimating the parameters β_i , it is appropriate to check the effect of changes in any of the explanatory variables on the probabilities of any observation belonging to either of the two groups. But the coefficients in the Logit and Probit models are not interpreted in the same way that the coefficients are interpreted in the standard regression model.

(I) Marginal Effect (Impact on Probability)

The marginal effect can be used to calculate the impact on probability (probability of expansion (upturn)) occurring due to a one per cent change in the explanatory variables (GPT, GSP, GY and GAF). Since only the Logit model transforms the estimated function into a logistic probability using the logistic cumulative distribution function, the marginal effect can be obtained only with the Logit model.

In Table 6.6 below, the impact on probability section explains the change in probability (Δp) due to a one per cent change in the economic variables (independent variables), which means:

USA: The negative value for GPT indicates that increasing GPT by 1% will decrease the probability of tourism demand in expansion by 0.01519. The negative value for GAF indicates that increasing GAF by 1% will decrease probability of tourism demand in expansion by 0.00035.

New Zealand: The negative value for GPT indicates that increasing GPT by 1% will decrease the probability of tourism demand in expansion by 0.000008.

UK: The negative value for GPT indicates that increasing GPT (-4) by 1% will decrease the probability of tourism demand in expansion by 0.003551. The positive value for GY indicates that increasing GY by 1% will increase the probability of tourism demand in expansion by 0.04144.

Japan: The negative value for GPT indicates that increasing GPT (-3) by 1% will decrease the probability of tourism demand in expansion by 0.009704. The positive

value for GY indicates that increasing GY by 1% will increase the probability of tourism demand in expansion by 0.02956.

(II) Relative Impact

The relative impact values directly state the relative impact on the turns of unit changes in each independent variable.

The table below (Table 6.6) displays the relative impact of the significant variables. The relative impact can be discussed only when there is more than one significant variable available for the model. As the table shows, in the USA, the impact of GPT on upturn or downturn is 33 times more important than the GAF. With the UK, the impact of GY is 15 times more important compared to GPT, and for Japan the impact of GY is 3 times more important compared to GPT.

Table 6.6 Marginal Effect (Impact on Probability) and Relative Impact

	USA		NZ		UK		Japan	
Parameter Elements	Logit		Logit		Logit		Logit	
Impact on Probability	1% Δ GPT = -0.01519 Δ p		1% Δ GPT = -0.0000088 Δ p		1% Δ GPT(-4) = -0.003551 Δ p		1% Δ GPT(-3) = -0.009704 Δ p	
	1% Δ GAF = -0.00035 Δ p				1% Δ GY = 0.04144 Δ p		1% Δ GY = 0.02956 Δ p	
	USA		NZ		UK		Japan	
	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Relative Impact	GPT 33.67	GPT 30.87	-	-	GY 15.96	GY 15.68	GY 2.82	GY 2.88

6.7.4 Establishing the accuracy

Once the models are finalized for each country, the next step is to check whether the final model gives accurate predictions. For that purpose we can use two main outputs, namely, the Classification table and the Hosmer-Lemeshow test.

Table 6.7 below can be used to demonstrate the accuracy of the final model in order to capture upturns and downturns.

(I) Expectation-prediction (Classification table)

Table 6.7 below displays the Expectation-prediction (Classification table). This table shows how accurately the model forecasts each observation by quarter. In other words, the Y value of 1 or 0 will be checked against the probability value for each period. The default critical probability level (cut-off value) to determine a correct forecast is 0.5. This table tallies the correct and incorrect estimates, and in a perfect model the overall percentage correct will be 100.

As can be seen in the expectation versus prediction row, the USA has the best results over the Logit test (78%) and Japan has the best results over the Probit test (74%). While the USA and Japan perform well with accuracy, the UK and New Zealand are comparatively weak in their predictions compared to the USA and Japan.

(II) Goodness of fit test (Hosmer-Lemeshow)

If the H-L goodness-of-fit test statistic is greater than 0.05, as well-fitting models are required to possess, and the null hypothesis is not rejected, then there is no difference between the observed and model-predicted values, implying that the model's estimates fit the data at an acceptable level. That is, well-fitting models show non-significance on the H-L goodness-of-fit test, meaning if the chi-square goodness of fit is not significant, then the model has an adequate fit. Similarly, if the test is significant, the model does not adequately fit the data.

In this situation, the hypotheses that will be tested are:

H_0 : The model **classifies** upturns and downturns well,

H_1 : The model **does not classify** upturns and downturns well.

The large probability value (greater than 0.05) for the Hosmer-Lemeshow statistic indicates the null hypothesis should be accepted, meaning the model helps to classify upturns and downturns more accurately. The H-L test results are displayed in Table 6.7 below.

According to the H-L test or the goodness of fit test, the USA, New Zealand and the UK can accept the null hypotheses confirming, the ‘model classifies upturns and downturns well’ (as all the HL values are greater than 0.05), while Japan cannot accept the null hypothesis (as it has an HL value less than 0.05).

Table 6.7

Results of Expectation-Prediction and Hosmer-Lemeshow Tests

	USA		NZ		UK		Japan	
Parameter Elements	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Accuracy								
Expectation Vs prediction test Success cut-off = 0.5	69.57%	78.26%	61.61%	60.71%	61.11%	62.04%	74%	73%
H-L Test								
Goodness of fit test	0.0677	0.0809	0.0631	0.0642	0.8595	0.8571	0.0388	0.0392

6.8 Estimated Probabilities

Once we run the selected independent variables against our actual 1 and 0 (dependent variable), Probit and Logit models can estimate the probabilities for each quarter (observation). The probability value generated is the value for tourism demand in upturn (=1) or, in other words, the probability of getting 1.

A plot of the actual 1 and 0 (independent variable) values against the fitted probability values gives a visual observation of the accuracy and the ability of the Logit and Probit models to capture upturns (1) and downturns (0).

Figure 6.1

USA Tourist Arrivals ‘1’ (Expansions) and ‘0’ (Contractions) vs. Probit Fitted Probabilities

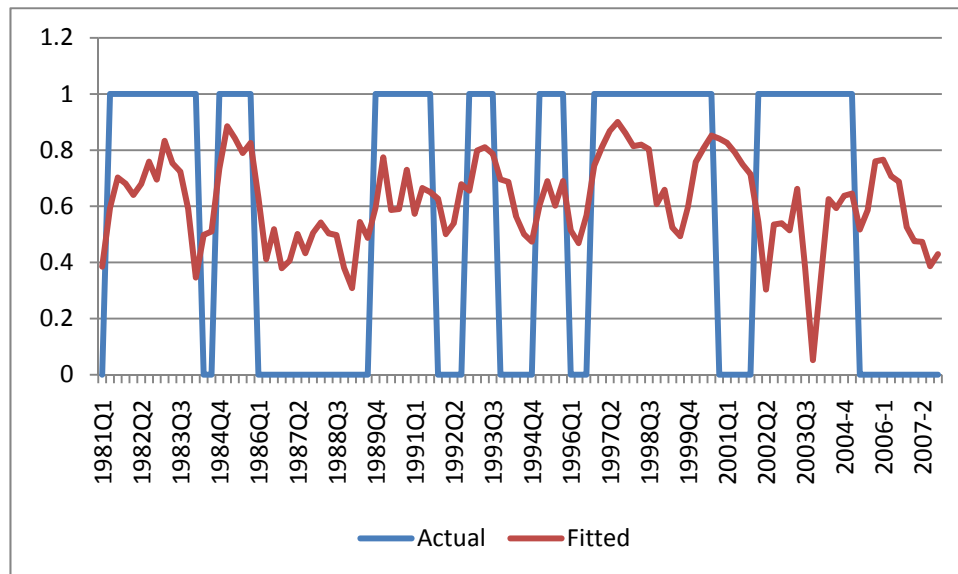


Figure 6.2

USA Tourist Arrivals ‘1’ (Expansions) and ‘0’ (Contractions) vs. Logit Fitted Probabilities

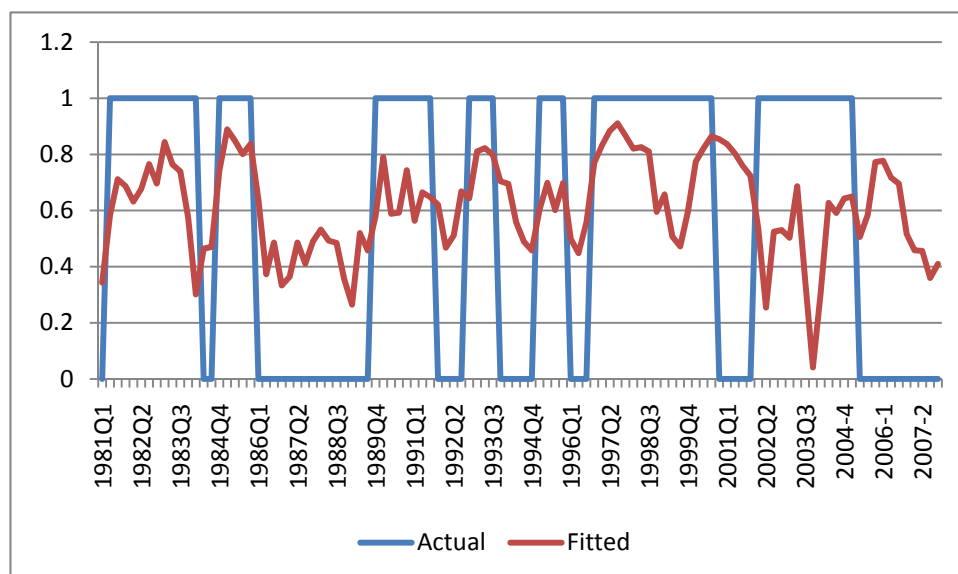
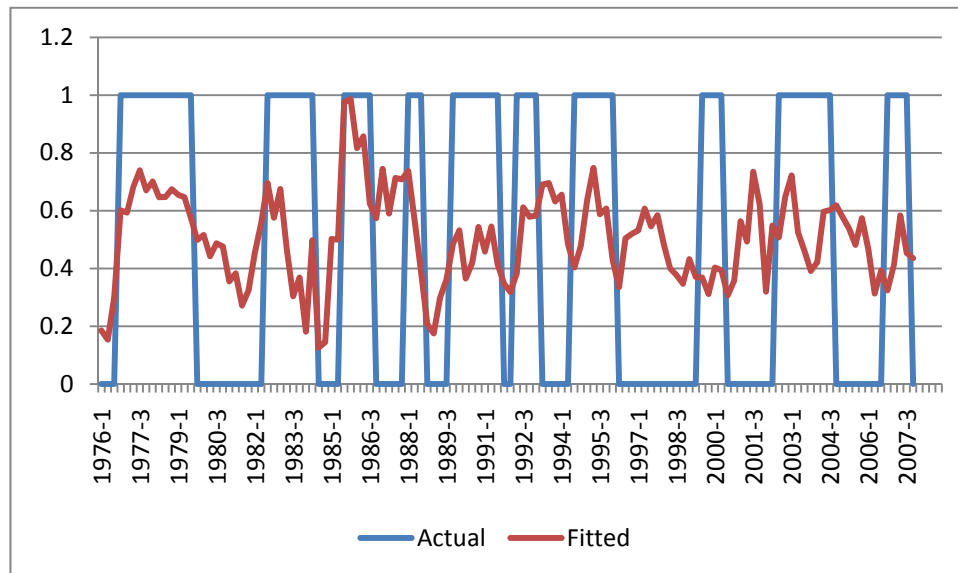


Figure 6.3

New Zealand Tourist Arrivals ‘1’ (Expansions) and ‘0’ (Contractions) vs. Probit Fitted Probabilities

**Figure 6.4**

New Zealand Tourist Arrivals ‘1’ (Expansions) and ‘0’ (Contractions) vs. Logit Fitted Probabilities

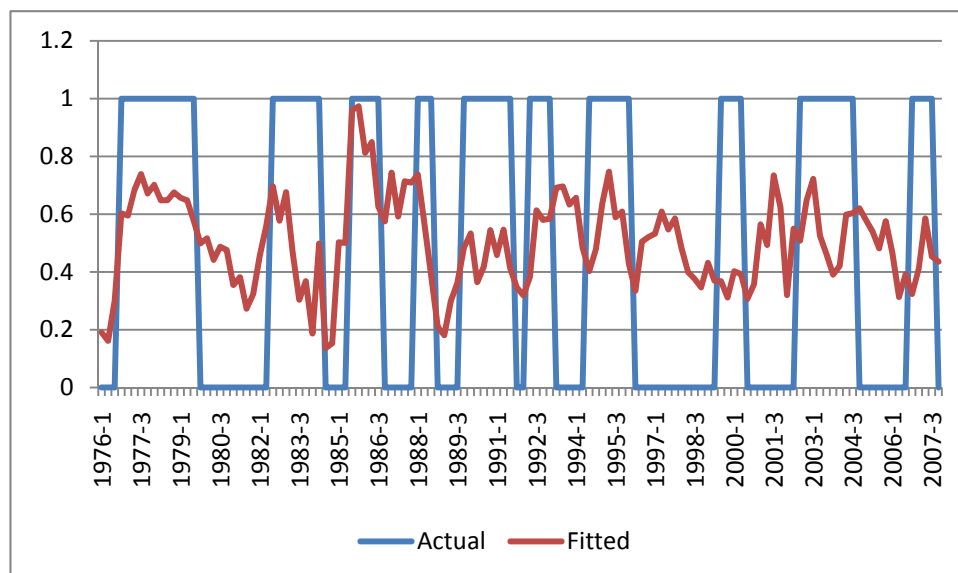
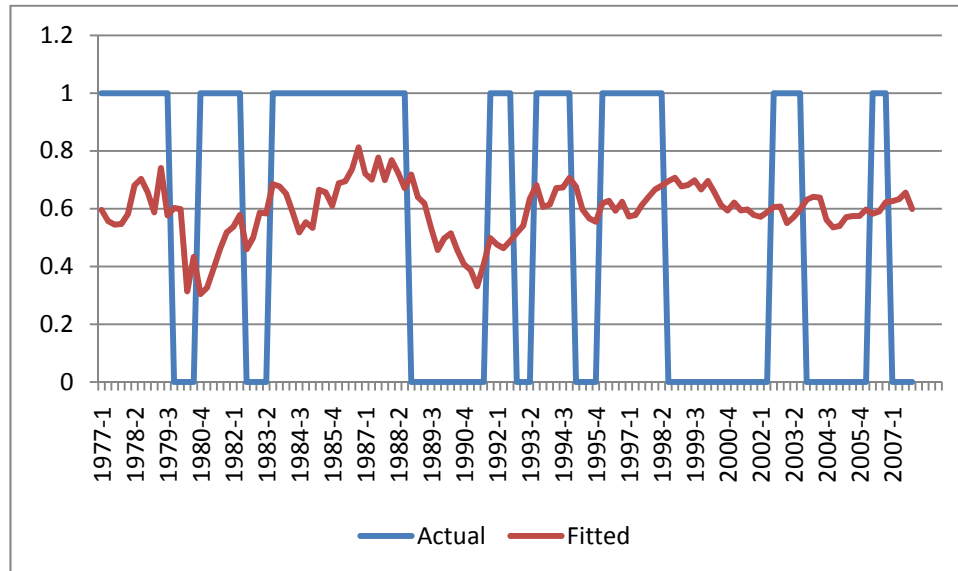


Figure 6.5

UK Tourist Arrivals ‘1’ (Expansions) and ‘0’ (Contractions) vs. Probit Fitted Probabilities

**Figure 6.6**

UK Tourist Arrivals ‘1’ (Expansions) and ‘0’ (Contractions) vs. Logit Fitted Probabilities

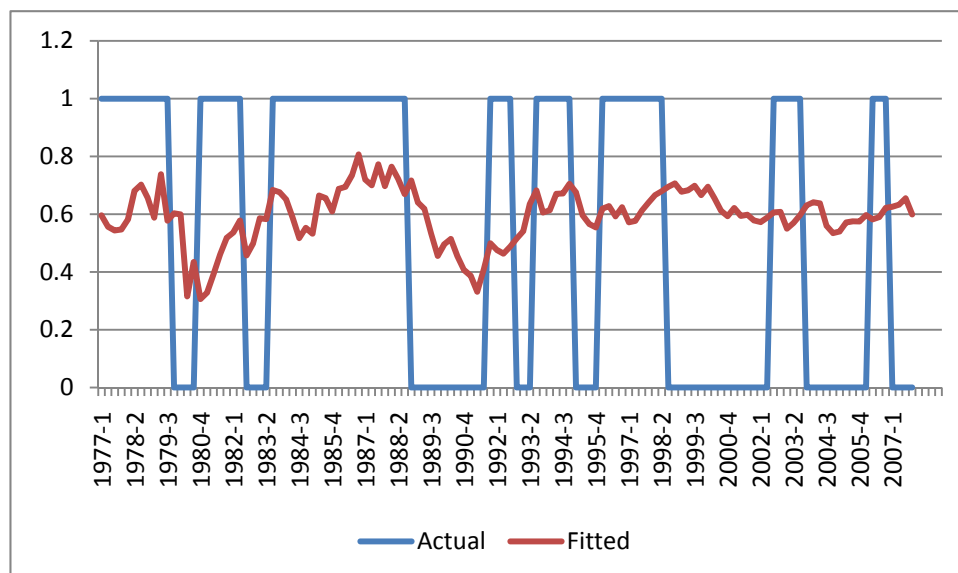
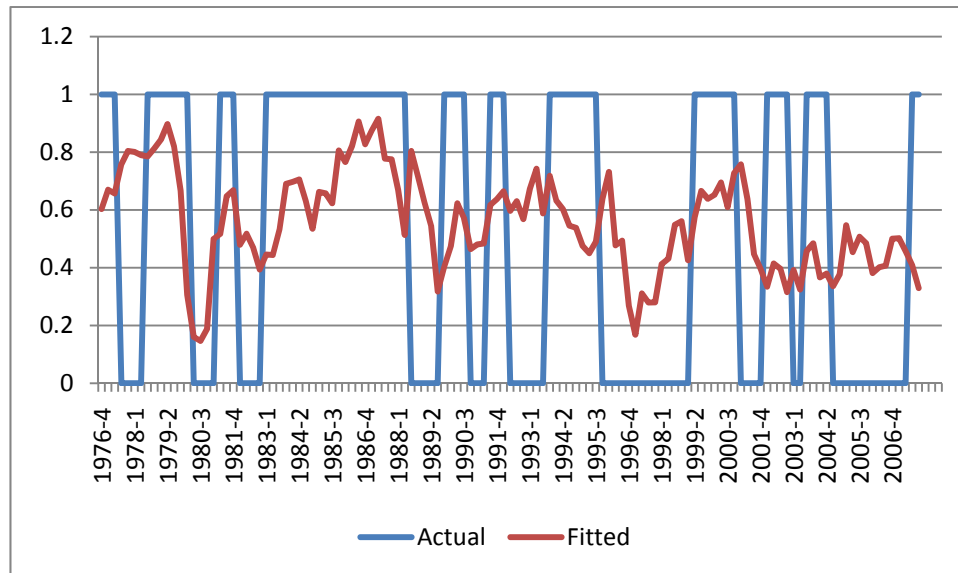
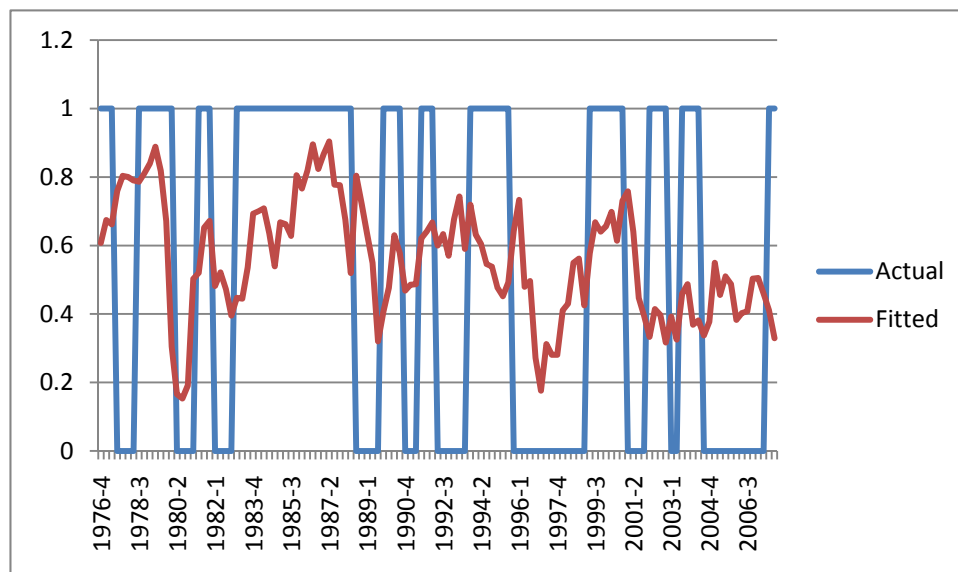


Figure 6.7

Japan Tourist Arrivals ‘1’ (Expansions) and ‘0’ (Contractions) vs. Probit Fitted Probabilities

**Figure 6.8**

Japan Tourist Arrivals ‘1’ (Expansions) and ‘0’ (Contractions) vs. Logit Fitted Probabilities



6.9 Checking the Accuracy of Turning Point Prediction

The above plots show the turning points and the estimated probabilities but these plots are useful only for visual observation. After identifying the correct model for each country and assessing the performance of each model, the most important step is to check the ability of the turning point prediction of each model for each country using the estimated probabilities.

6.9.1 Accuracy of turning point prediction within sample period (from 1975 Q1 to 2003 Q4)

Logit and Probit models generate a probability value between 0 to 1 for each observed period (quarter) being in upturn ($Y=1$), using 0.5 as a cut-off point. The point where the probability value drops below 0.5 is the downturn (Peak), while the point where the probability value rises above 0.5 is the upturn (Trough).

Tables 6.8, 6.9, 6.10 and 6.11 which follows, present the forecasting performance of the Logit and Probit models and their ability to predict the significant turning points in tourism demand. Significant turning points in tourism demand (turning point chronology) have already been identified/established in Chapter 4.

In the following table, the result 0 (zero) denotes the perfect capturing of turning points while (+) and (–) signs represent the size of the error i.e., how many quarters before (+) or after (–) the actual predicted turning point occurs. This gives an idea of how close the predicted turning point is to the actual turning point.

The probability value 0.5 is the cut-off point to identify the significant peaks and troughs with Logit and Probit model probabilities.

Table 6.8 USA - Accuracy of Turning Point Prediction

	Probit	Logit		Probit	Logit
<u>UT/Trough</u>			<u>DT /Peaks</u>		
1977-1	N/A	N/A	1980-1	N/A	N/A
1981-1	0	0	1982-3	+5	+5
1984-3	0	0	1985-4	+1	+1
1989-3	0	0	1991-3	Missing	Missing
1992-3	Missing	Missing	1993-3	+3	+3
1994-4	+1	+1	1998-4	+2	+2
2001-4	-5	-5			
False signals	1	1	False signals	1	1

Table 6.9 New Zealand - Accuracy of Turning Point Prediction

	Probit	Logit		Probit	Logit
<u>UT/Trough</u>			<u>DT /Peaks</u>		
1982-2	-1	-1	1979-3	0	0
1985-2	0	0	1984-2	+5	+5
1989-3	missing	missing	1986-3	missing	missing
1994-2	+2	+2	1993-1	+4	+4
1999-2	+8	+8	1996-1	-1	-1
2002-2	+1	+1	2000-2	+6	+6
False signals	2	2	False signals	3	3

Table 6.10 UK - Accuracy of Turning Point Prediction

	Probit	Logit		Probit	Logit
<u>UT/Trough</u>			<u>DT /Peaks</u>		
1976-4	N/A	N/A	1979-3	+2	+2
1980-3	+4	+4	1982-2	0	0
1983-2	-1	-1	1988-3	+4	+4
1991-3	+4	+4	1992-3	missing	missing
1995-4	missing	missing	1998-2	missing	missing
2002-2	missing	missing	2003-3	missing	missing
False signals	0	0	False signals	0	0

Table 6.11 Japan - Accuracy of Turning Point Prediction

	Probit	Logit		Probit	Logit
<u>UT/Trough</u>			<u>DT /Peaks</u>		
1978-2	N/A	N/A	1977-2	NA	NA
1981-2	-1	-1	1980-1	-1	-1
1989-3	+2	+2	1988-2	+3	+3
1993-3	missing	missing	1992-1	-6	-6
1999-1	-3	-3	1995-3	-4	-4
2001-4	missing	missing	2000-4	+2	+2
False signals	2	2	False signals	1	1

False Signals: Are turning point signals detected by the Logit/Probit model but which are not actual turning points (not in the turning point chronology).

Missing: Logit/Probit model has not detected the actual turning point.

N/A: Results are not available due to data problems or missed values due to smoothing or during generation of growth.

D/problem: Data are not available (applies to New Zealand only).

6.9.2 Evaluating the prediction performance

As discussed in the methodology chapter (Chapter 3.11), in order to identify and summarize the prediction performance of the Logit and Probit models, the following criteria can be used:

- (I) **Captured ratio** is the ratio of captured turns from the model (Logit/Probit) to the total number of actual turning points.
- (II) **False ratio** is the turning points that are detected by the model (Logit/Probit), but are not recognised as actual turning points (not in the turning point chronology).
- (III) **MAD (Mean Absolute Deviation)** is method where all the errors of captured turning points are added as absolute values (without '+' and '-', for example,

1+1+0), and divided by the number of turning points, this indicating how close (accurate) the predicted turning points are to the actual turning points (the lower the MAD value (error) the better the model).

(IV) **Quadratic Probability Score (QPS)** is defined as:

$$QPS = \frac{1}{T} \sum_{t=1}^T (P_t - D_t)^2$$

Where D_t takes the value 1 during expansion and the value 0 during contraction as identified by the actual tourism growth and P_t is the model-derived probability for the corresponding observation. The results vary from 0 to 2; the closer this measure is to zero, the better is the fit to the actual turning point.

Applying the above criteria, the best model can be selected based on the highest ‘captured ratio’, the lowest ‘false ratio’, the lowest MAD and the lowest QPS.

6.9.3 Summary of the within sample turning point forecast performance (1975 Q1 to 2003 Q4)

Table 6.12 Summary of Turning Point Forecast Performance

	USA		NZ		UK		Japan	
Method	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Captured ratio	83%	83%	83%	83%	54%	54%	80%	80%
False ratio	15%	15%	40%	40%	0%	0%	25%	25%
MAD	1.8	1.8	2.8	2.8	2.5	2.5	2.7	2.7

Table 6.12 above explains the turning point forecasting performance within the sample period. According to the results the USA has the best performance having the highest captured ratio, lowest false ratio and smaller MAD.

New Zealand and Japan come out as the second best performing models with captured ratios of 83% and 80%, respectively, and MAD of 2.8 and 2.7, respectively. However, compared to Japan, New Zealand has a higher false ratio.

As can be seen in the other analysis, the UK results are comparatively poor, with a lower captured ratio (54%), though the UK has a 0% false ratio which is better than the other three countries.

Table 6.13 QPS (Quadratic Probability Score) Results

	USA		NZ		UK		Japan	
Method	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
QPS	0.40458	0.39889	0.44571	0.44592	0.46301	0.46309	0.42839	0.42934

Observing the QPS values of Table 6.13 for the Logit and Probit model, again the USA has the lowest QPS values, while Japan and New Zealand have the second and third lowest values, respectively, and the UK has the highest QPS value confirming weakness in forecasting turning points within the sample period accurately.

6.9.4 Accuracy of turning point prediction in the out-of-sample period (from 2004 Q1 to 2007 Q4)

Table 6.14 USA - Accuracy of Turning Point Prediction

	Probit	Logit		Probit	Logit
<u>UT/Trough</u>			<u>DT /Peaks</u>		
No upturns	-	-	2006-2	+2	+2
False signals	1	1	False signals	0	0

Table 6.15 New Zealand - Accuracy of Turning Point Prediction

	Probit	Logit		Probit	Logit
<u>UT/Trough</u>			<u>DT /Peaks</u>		
2006-3	+1	+1	2004-3	+5	+5
False signals	1	1	False signals	0	0

Table 6.16 UK - Accuracy of Turning Point Prediction

	Probit	Logit		Probit	Logit
<u>UT/Trough</u>			<u>DT /Peaks</u>		
2006-1	missing	missing	No downturns	-	-
False signals	0	0	False signals	0	0

Table 6.17 Japan - Accuracy of Turning Point Prediction

	Probit	Logit		Probit	Logit
<u>UT/Trough</u>			<u>DT /Peaks</u>		
No upturns	-	-	2004-2	+5	+5
False signals	1	1	False signals	0	0

Tables 6.14, 6.15, 6.16 and 6.17 present the out-of-sample performance of each model in capturing actual turning points. In order to summarise the results of the Logit and Probit models the captured ratio, false ratio and MAD (mean absolute deviation) will be used.

It is important to mention that since there are very few turning points in the out-of-sample period, it is not suitable to use ratios, which might not give the correct idea and may lead to an incorrect interpretation. In order to maintain the consistency of the test, the same criteria will be used giving more attention to the QPS results.

Applying the above criteria, the best model can be assessed using the highest ‘captured ratio’, lowest ‘false ratio’, the lowest MAD and the lowest QPS.

6.9.5 Summary of the out of sample turning point forecast performance (2004 Q1 to 2007 Q4)

Table 6.18 Summary of Turning Point Forecast Performance

	USA		NZ		UK		Japan	
Method	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
QPS	0.5966	0.5997	0.5197	0.5202	0.6401	0.63976	0.5028	0.5045
Captured ratio	100%	100%	100%	100%	0%	0%	100%	100%
False ratio	100%	100%	50%	50%	0%	0%	100%	100%
MAD	2	2	3	3	-	-	5	5

Table 6.18 above provides the out-of-sample forecasts and identifies that the USA, Japan and New Zealand equally perform well with the captured ratio while the USA is best with its MAD. For the QPS values, Japan has the lowest QPS value followed by the USA and New Zealand. The UK’s results are again poor with the ratios and QPS but no false signal is given for that period.

6.10 Chapter Findings

This chapter’s overall conclusion is that with the data set used, the Logit and Probit models performed well with the USA, and the model used for the USA predicted most of the turning points in tourism demand. For the prediction of the turning points in the Japanese and New Zealand tourism demand growth cases, the Logit and Probit models performed moderately. The Logit and Probit models predicted the UK turning points poorly, however, for within and out-of-sample periods compared to the USA, Japan and New Zealand.

To summarise, the importance of this chapter is the consistency of the results, from the very outset, in the model refinement results, model evaluation results and turning

point prediction results. From the beginning, the Logit and Probit models for the USA have shown the better results while the Japan and New Zealand models have shown moderate results and the UK model has shown weak results for each stage of the analysis.

In addition, it is worth mentioning that of the six independent variables used in this study to predict turning points, the variable GPT (price of tourism) became a significant variable for all four countries. Also, the GPS (price of substitute destination) is not a significant variable for any country. The two dummy variables used (D_1 for the 2000 Sydney Olympics and D_2 for the September 11 attacks) to check the effect of random events on turning points, were not found to be significant. The reason for this could be the sudden random changes in tourism demand, which may have disappeared with the smoothing process as their effect lasted for only a few quarters.

Looking at the results of this chapter, a conclusion cannot be drawn as to the superiority of the Logit and Probit models to forecast turning points over any other method, but what can be concluded here is that using the given independent variables, the Logit and Probit models performed well for the USA, Japan and New Zealand, but didn't work well for the UK.

In this chapter economic variables are used as independent variables to estimate the Logit and Probit models. In the next chapter (Chapter 7) different leading indicators will be identified/constructed to forecast turning points in tourism demand. In Chapter 8 these leading indicators will then be used as independent variables to estimate a Logit model with tourist arrivals growth expansion and contraction represented by 1 and 0, respectively. Broader conclusions can then be made about the performance of the Logit and Probit models.

As mentioned at the beginning of the chapter, the Logit and Probit models have similar properties and they generate very close results. Further, in this chapter the Logit and Probit models have given identical turning points for both within-sample and out of sample periods. Therefore, in Chapter 8, to avoid repetition, instead of

using both the Logit and Probit models, leading indicators will be estimated using the Logit model only due to its stronger theoretical justification over the Probit model (Pindyck and Rubinfeld (1991)).

Chapter 7

Leading Indicators

7.1 Introduction

The objective of this chapter is to construct and identify potential leading indicators that can predict turning points in Australian inbound tourism demand growth. Currently leading indicators are being widely used in general business forecasting situations, but rarely in tourism contexts. In this chapter, three leading indicators are identified to forecast turning points in Australian inbound tourism demand.

The first section of this chapter will construct a composite leading indicator to predict turning points in tourism demand growth. The second section examines the potential existing indicators, namely, constructed CLI for OECD countries and ‘Business Survey index’, as leading indicators to forecast turning points in Australian inbound tourism demand. The final section will discuss the methods that are used to interpret the movement of leading indicators in order to predict turning points.

7.2 Leading Indicators (LI)

Leading economic indicators can anticipate moves in an economic process because they have a causal, reporting, or mathematical lead. As was discussed in the literature review chapter, leading indicators are well known in providing early signals of turning points (peaks (DT) and troughs (UT)). It is reasonable to suggest that the future changes in some aggregate economic activities are often forecast by changes in other time series variables. These latter economic variables are known as leading (economic) indicators. The leading indicator approach involves identifying the repetitive sequences within cycles and using them for forecasting. Traditionally, the main interest of leading economic indicator forecasting has been to forecast turning points in an economic activity. According to Niemira and Klein (1995) “composite leading indicators provide a more reliable gauge of economic activity since they can

be more comprehensive and hence, are less dependent on any single measure, even if that measure has a comprehensive coverage. This is particularly helpful when some components are subject to a lot of revision or when one indicator runs counter to several other measures”.

In the same context, leading indicators can be used to forecast turning points in tourism demand, using economic variables that can influence the changes of the demand for tourism. The basic idea here is, whatever the indicator used as the leading indicator, the series must turn before the tourism demand turns.

As discussed in the literature review, there is very little research available in turning point modelling in tourism economics. But the importance of the current chapter is that three different leading indicators are used to forecast turning points and turning point detection is done using the Logit model and the BB algorithm.

Once again, the data used in this chapter are the quarterly tourist arrivals data to Australia from the USA, NZ, the UK and Japan. The study will use 1975 Q1 to 2004 Q4 periods as the within-sample period, and the 2005Q1 to 2007 Q4 period as the out-of-sample period. In this study, the smoothed tourism demand growth cycle is used as the reference cycle for the leading indicator study, and most indicators refer to the country of origin.

Economic independent variables such as income, exchange rate and relative prices will be obtained from the International Financial Statistics, published by the International Monetary Fund (IMF), and the OECD’s Main Economic Indicators.

7.3 Constructing a Composite Leading Indicator

One of the earliest leading indicator systems was developed before World War I. This approach was known as the Harvard ABC curves. In 1937, Henry Morgenthau, the US Secretary of the Treasury, requested the NBER (National Bureau of Economic Research) to develop a system of indicators to anticipate cyclical changes in the economy. As a result, the NBER provided the treasury with a list of cyclical indicators based on timing. This research commenced the system of leading, coincident, and lagging indicators.

In the past 15 to 20 years, numerous leading indicators have been developed in many areas, but as mentioned earlier there are only a few leading indicators constructed in tourism economics for tourism forecasting.

The objective of this section is to develop a composite leading indicator to forecast turning points in Australian inbound tourism demand. The construction of a leading indicator has the following steps:

1. Select potential indicators,
2. Transfer the potential indicators to a log format and smooth them,
3. Check the relationship between the potential indicators and tourism demand,
4. Give weights to each indicator depending on their importance,
5. Construct the composite leading indicator.

7.3.1 Selecting potential indicators

The objective of this section is to identify potential variables that can create turning points in tourism demand. Since tourism demand is highly volatile due to the dynamic nature of world economies and, as the turning point can occur due to a number of reasons, it is not easy to predict turning points in tourism demand by selecting only a handful of variables.

Since the theory behind cyclical indicators is not rigid, the selection of indicators tends to be an empirical question. The selection of indicators requires some judgment and knowledge of the data series. However, in the final analysis, a theory is only as good as the ability of the indicator to predict future change in another variable. Despite all the potential problems, a good starting point is to replicate some of the already used existing composite cyclical indicators (Nimera and Klien (1994)). Though it is difficult to say what should or should not be included in a composite indicator, Niemira and Klein (1994) give some useful guidelines to the selection of cyclical indicators:

1. Search for leading and lagging indicators based on a causal relationship - they are more likely to be robust over numerous cycles.
2. Look for data with the highest frequency (for example, if there is an option use monthly data instead of quarterly data).
3. Look for the series with the longest history.
4. Do not overlook reliable coincident or lagging indicators. While these coincident and lagging indicators, by themselves, will not be helpful in forecasting, they can confirm and forecast useful results when used in other forms.

Although the leading indicator approach is sometimes referred to as measurement without theory, the above guidelines and economic theory, do give clues as to the selection of appropriate indicators.

To predict significant turning points in tourism demand, this study has selected the existing national economic indicators; most of the indicators that have been selected have been used in previous tourism studies. The selected economic indicators can be a leading indicator, a coincident indicator, or a lagged indicator for tourism demand.

Considering past studies and economic theory (as discussed in the literature review), the following economic variables were selected as potential leading indicators:

- Tourist origin country income measured by gross domestic product (GDP).
- Exchange rate between tourist origin country and destination country (EX).
- Relative price (CPI) - (Tourists' country of origin).
- Share prices (SP) - (Tourists' country of origin).
- Total exports (TEP) - (Tourists' country of origin).
- Total imports (TMP) - (Tourists' country of origin).
- Unemployment rate (UE) - (Tourists' country of origin).

All the selected variables are either physical units or deflated, and they have been seasonally adjusted.

Once the potential indicators are identified, those leading indicators are specified in logarithmic form. This is the generally accepted practice in tourism demand modelling, and is used in order to satisfy the assumption of constant variance of the error term. Further, as the volatility in the series reduces the prediction power of the leading indicator, the potential leading indicators are smoothed by using the BSM method.

7.3.2 Checking the relationship between potential indicators and tourism demand

Checking the relationship between potential indicators and tourism demand is an important step in constructing a composite leading indicator. In order to proceed with this step, the smoothed growth of tourism demand should be specified using the BSM method, and the potential indicators smoothed using the same method (discussed in Chapter 3).

Cross correlation

In order to discover whether these economic indicator variables lead Australian inbound tourism demand, this study examines the cross correlation function (which describes the extent to which two series are correlated) of inbound tourism demand and these economic variables. The cross correlation between the two series x and y defines the degree of association between values of x at time t and values of y at time $t = k$ (where $k = 0 \pm 1, \pm 2, \pm 3 \dots$). The cross correlation function can be used to check the independence of the two series, and then to discover whether one of the series may act as a leading indicator of the other. If x is a leading indicator of y , then x at time t will be positively related to y at time $t+k$ where $k=1$ or 2 or 3 , and so on.

If the two series are transformed (e.g. by differencing) in such a way that they are jointly covariance stationary, then their interrelationships can be described easily by the cross correlation function. However in the cross correlation analysis, as suggested by Haugh (1976) misleading cross correlations could occur due to the presence of autocorrelation in the series x and y (either tourism demand or the indicator series), though the series has been smoothed. As a result, the lagged cross correlation

estimates (correlation between x at time t and values of y at time $t+k$, where $k = -1, -2, -3, -4, \dots$) can be difficult to interpret. The autocorrelation present in each of the series can be inflating the variance of the cross correlation estimates. Also the cross correlation estimates at different lags will be correlated (possibly to a great extent). This can happen even if the two series are in fact independent (expected cross correlation is zero).

To avoid the problem of misleading cross correlation, seasonal Auto Regressive Integrated Moving Average (ARIMA) models were fitted to both series and the cross correlation coefficients (which measure the degree of association) of the residuals are examined. Significant cross correlation at a positive lag indicates that the economic indicator variable is a leading indicator, a negative lag indicates that the economic indicator variable is a lagging indicator, and zero lag indicates the economic indicator is a coincident variable. Once the cross correlation process is performed, the indicators can be classified as leading, coincident or lagging. Table 7.1 below presents the cross correlation results of the four countries.

For the cross correlation and the estimation of the ARIMA model this study uses the SAS program.

CLI 1: refers to CLI having a significant correlation in positive lag.

CLI 2: refers to CLI having a significant correlation in negative lag.

CLI 3: refers to CLI having a significant correlation in zero lag.

Table 7.1 Cross Correlation Results for the Four Countries

Countries	CLI	GDP	Exchange Rate	Share Prices	Unemployment Rates	Exports	Imports	CPI
USA	CLI 1	+ 4	-	+ 3	+ 4	-	+ 1	+ 1
NZ		-	-	+1	-	-	+1	-
UK		-	+4	+1	+1	-	-	-
Japan		-	-	+1	+1	-	+1	
USA	CLI 2	-	-4	-	-	-	-	-
NZ		-4	-1	-	-1	-		-2
UK		-	-	-	-	-2	-2	-3
Japan		-	-4	-	-	-1	-	
USA	CLI 3	-	-	-	-	0	-	-
NZ		-	-	-	-	0	-	-
UK		0	-	-	-	-	-	-
Japan		0	-	-	-	-	-	0

Table 7.1 shows the identified leading, lagging and coincident indicators from the cross correlation analysis. Except for the share price, no other economic variable can be identified consistently as a leading, lagging or coincident indicator for the different countries of origin. But it shows that unemployment and imports are leading indicators for three countries. The exchange rate is a lagging indicator for all three countries except the UK. Further, GDP is a coincident indicator for the UK and Japan, while exports are coincident indicators for the USA and New Zealand.

As can be seen in the cross correlation results in the above table, it is clear that all the selected indicators are not leading indicators. Some are coincident and some are lagging. The lagging indicators can be transformed into leading indicators because the inverse lagging indicator can reflect the view that the seeds of a current downturn are usually determined in a previous cycle (Niemira and Klein (1994)). However, in this study only leading indicators are used, and not the lagging indicators, to predict turning points. The above coincident and lagging indicators, by themselves, will not

be helpful to forecast, but they can confirm and forecast when used in other forms. Therefore, only the indicators with positive lags are used with statistically significant correlations.

7.3.3 Construct the composite leading indicator

Having identified relationships between tourist arrivals growth and leading indicators through cross correlation, a composite leading indicator can be constructed from a set of leading indicators that can be useful to capture the cyclical nature of the growth of tourism.

When constructing a composite leading indicator, two important issues are usually considered: the method of aggregation and the assignment of weights among the components. Before the leading indicator series are combined, as stated by Bikker and Kennedy (1999), the series must be normalized and synchronized in order to make them comparable.

Normalization implies de-trending the leading indicator series, which can be achieved through differencing (seasonal differencing Δ_4) and adjusting for their variance (on the assumption of a constant variance) to minimize the influence of any single component with high volatility.

Synchronized series have the leading indicator series lagged according to the lead time, which is identified from the cross correlation, so that on average peaks and troughs coincide.

The unemployment rate and the CPI values are in an inverted form (e.g. multiplied by -1) in order to get positive relationships for all the leading indicators against tourism arrivals growth.

Niemira and Klein (1994) provide a method to construct a composite leading indicator by summing the changes for the individual composite while accounting for the component's importance and volatility:

$$\Delta_4 \text{Composite} = \sum w_i \sigma_i \Delta_4(\text{component}) I + s - x_i.$$

where: $I = 1$ to n (n being the maximum number of components), w is the component's weight which represents the component's relative importance (considered to be the coefficient of cross correlation), σ is the standardized weight which is calculated from the inverse value of the volatility measure (the average absolute deviation around the average growth rate) to minimize the influence of highly volatile series on the composite leading indicator. The standardized weight (σ), equalizes the percentage change among the individual components by minimizing the influence from any single component dominating the overall index change. (s) is the shortest lead time (in number of quarters) among the n indicators, and (x_i) is the lead time of the indicator.

With the above steps being followed, a composite leading indicator can be constructed to predict turning points in tourism demand growth. The following figures present the plots of constructed composite leading indicators (CLI) for the four countries and the actual tourism demand growth cycle (AC).

Note: AC = Actual tourism arrivals growth.

Figure 7.1 USA, Constructed Composite Leading Indicator (CLI) and Tourism Demand Growth (AC)

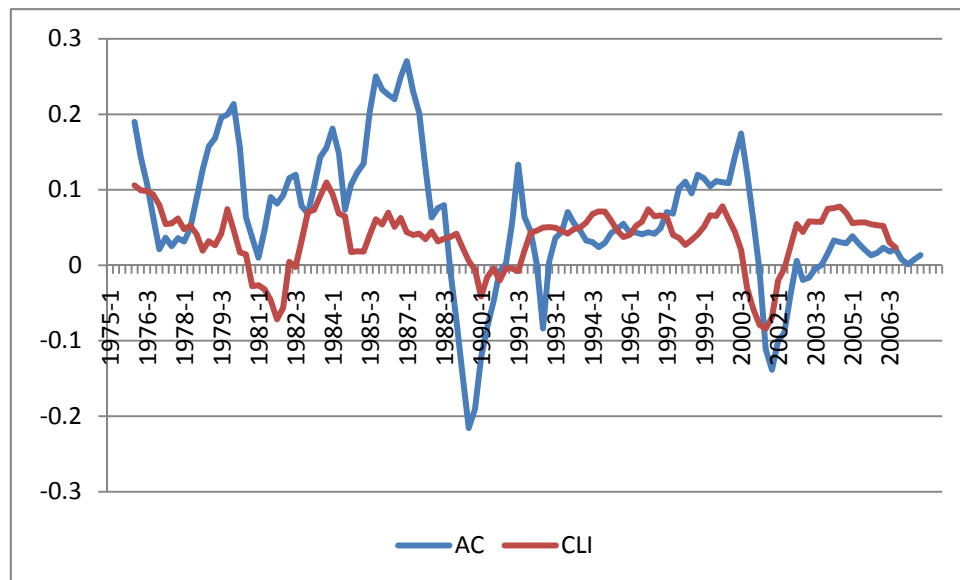
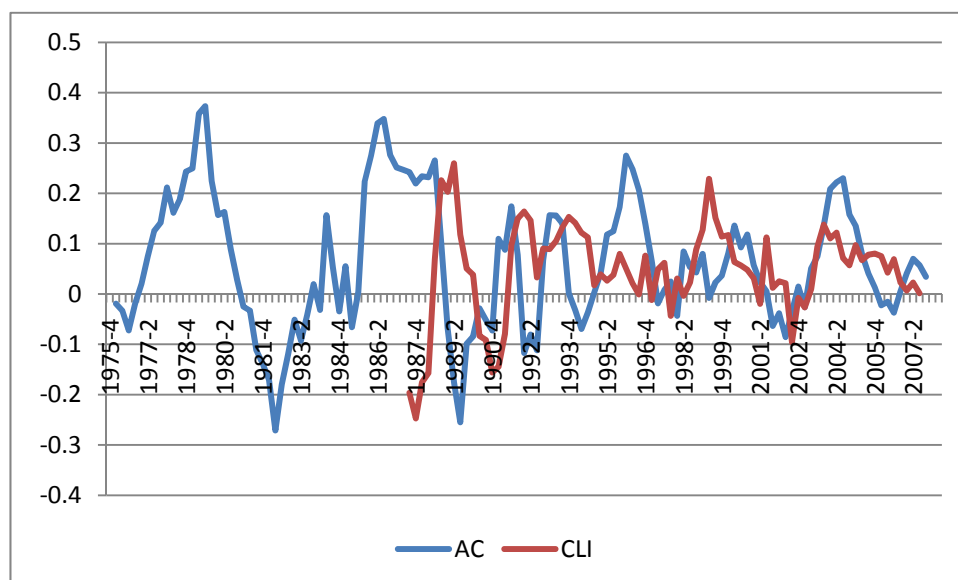


Figure 7.2 New Zealand, Constructed Composite Leading Indicator (CLI) and Tourism Demand Growth (AC)



Note: Some of the indicators used to construct New Zealand CLI are available only from 1987 Q1.

Figure 7.3 UK, Constructed Composite Leading Indicator (CLI) and Tourism Demand Growth (AC)

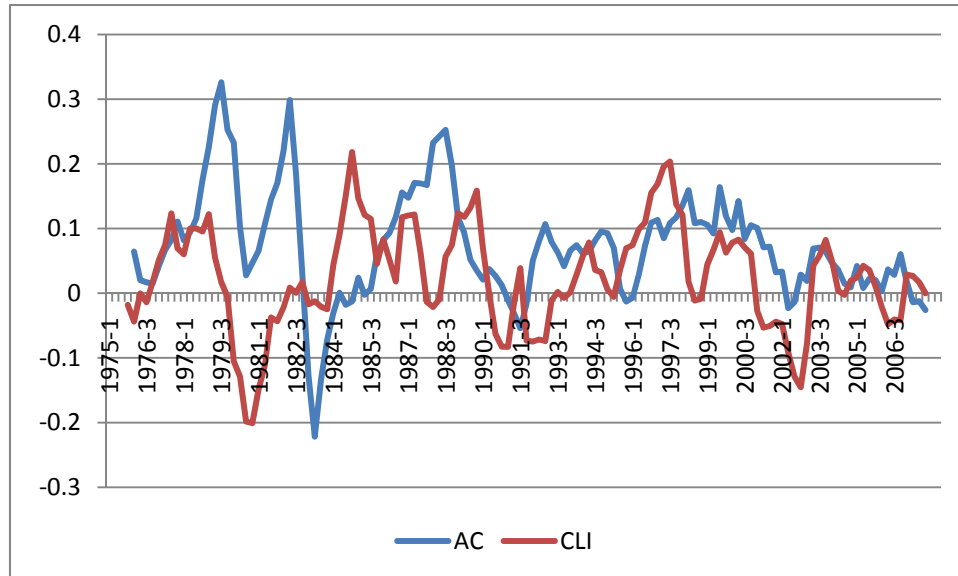
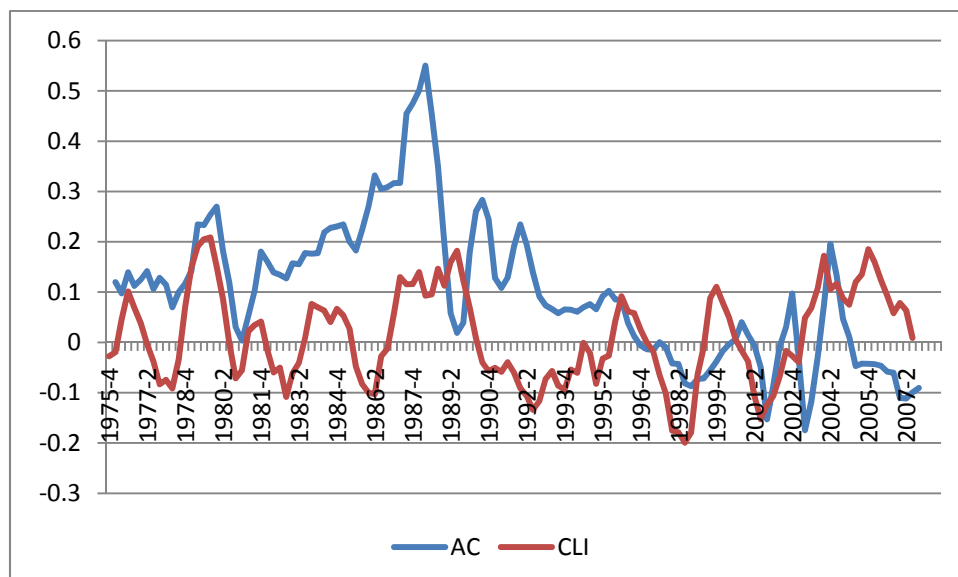


Figure 7.4 Japan, Constructed Composite Leading Indicator (CLI) and Tourism Demand Growth (AC)



7.4 Using Available Indicators for Turning Point Forecasting

In the previous section a composite leading indicator is constructed to forecast turning points in tourism demand. In this section use is made of the available leading indicators, namely the constructed CLI and Business Survey index data, as leading indicators to forecast turning points. Both these indicators are published by the OECD.

OECD (Organization for Economic Co-operation and Development)

The Organization for Economic Co-operation and Development is one of the world's largest publishers in the field of economics and public policy. The OECD provides a useful online library of statistical databases, books and periodicals that economies, businesses and researchers rely on heavily for their research and decision-making.

The OECD routinely maintains a system of business cycle indicators pertaining to its 29 member countries, six OECD non-member economies and seven country groupings, that is, the G-7 countries. In this chapter, use is made of two important leading indexes published by the OECD which are the OECD CLI and the Business Survey index.

7.4.1 OECD CLI

One important publication published by the OECD is their Composite Leading Indicator (CLI). The OECD has been publishing CLIs since 1981. This system, which is along the lines of analysis established by Burns and Mitchell (1946), comprises both a 'coincident' and 'reference' series, which represents the cycle itself, and, in addition, a leading indicator series.

The CLIs are aggregated time series. A CLI is constructed by aggregating together component series selected according to multiple criteria such as: economic significance, cyclical correspondence and data quality. Because of the multi-criteria selection process, the CLI can be used to give an early indication of turning points in the reference series but not for quantitative forecasts.

Component series are economic time series that exhibit leading relationships with reference series at the turning points. The component series are selected from a wide range of economic sectors. The number of series used for the compilation of the OECD CLIs varies for each country, with typically between five and ten series. Selection of the appropriate series for each country is made according to the following criteria: Economic significance - there has to be an *a priori* economic reason for a leading relationship with the reference series; cyclical behaviour - cycles should lead those of the reference series, without any missing or extra cycles. At the same time, the lead at turning points should be homogeneous over the whole period; Data quality - statistical coverage of the series should be broad; series should be compiled on a monthly basis rather than on a quarterly basis; series should be timely and easily available; there should not be any breaks in time series; series should not be revised frequently.

Smoothing eliminates the noise from the series, and makes the cyclical signal clearer. Up to December 2008, the component series were smoothed according to their MCD (Months of Cyclical Dominance) values to reduce irregularity. Thereafter, the OECD decided to replace the combined PAT/MCD approach with the Hodrick-Prescott (HP) filter to perform de-trending and smoothing in a single operation. The OECD CLI focuses on the 'growth cycle' concept and presents the amplitude-adjusted CLI, which means the OECD CLI data are presented in their trend-restored form. This trend restoration enables direct comparison with the reference series.

The CLI is constructed from several component series. The specific procedures used to establish the chronologies and the components used by the OECD are described in Nilsson (1987). Each of these series is smoothed in line with the month of cyclical dominance and normalized, so as to standardize the amplitude of cyclical variation. Then the composite is produced as a simple average. Although the OECD system does not impose a standard set of component series for all countries, certain types of series recur regularly in the list of leading indicators for different countries. The most frequently used are the series based on business surveys, together with monetary and financial data.

The CLI comprises a set of component series selected from a wide range of key short-term economic indicators (224 in total, about 5-10 for each country) to ensure that the indicators will still be suitable when changes in economic structures may occur in future. Those selected are known to provide an indication of future economic activity.

The following figures present the plots of OECD CLI for the four countries in this study and the actual tourism demand growth cycle (AC).

Note: AC = Actual tourism arrivals growth

Figure 7.5 USA, OECD CLI and Tourism Demand Growth (AC)

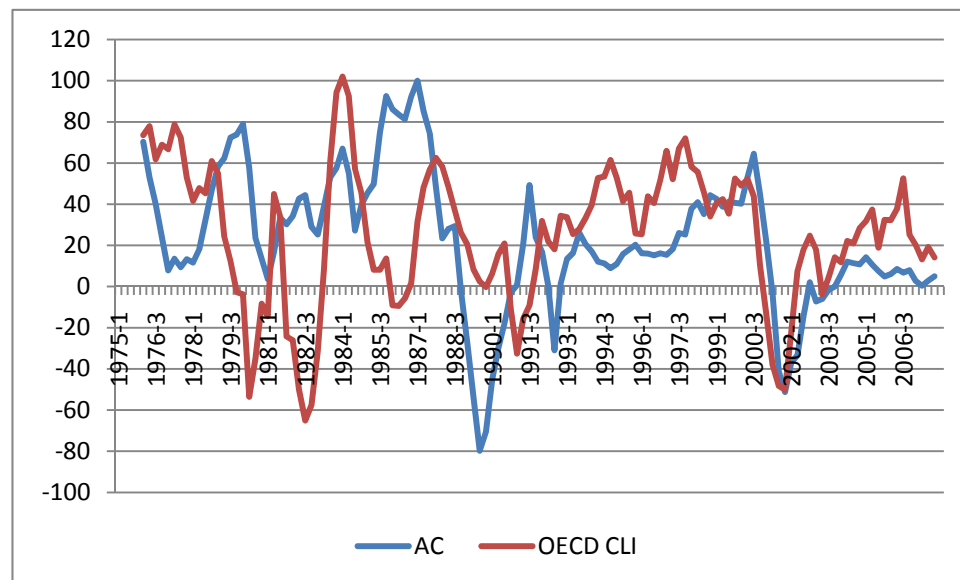


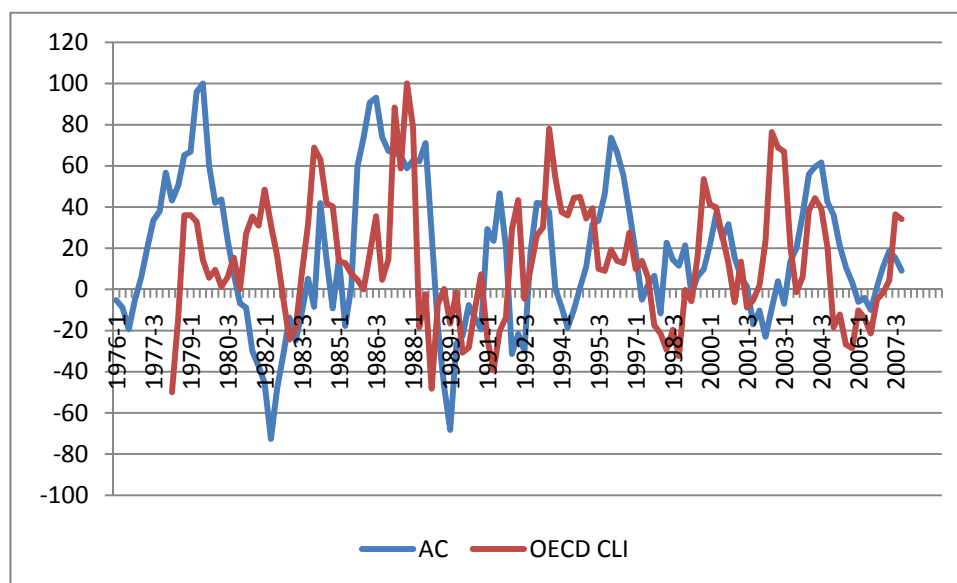
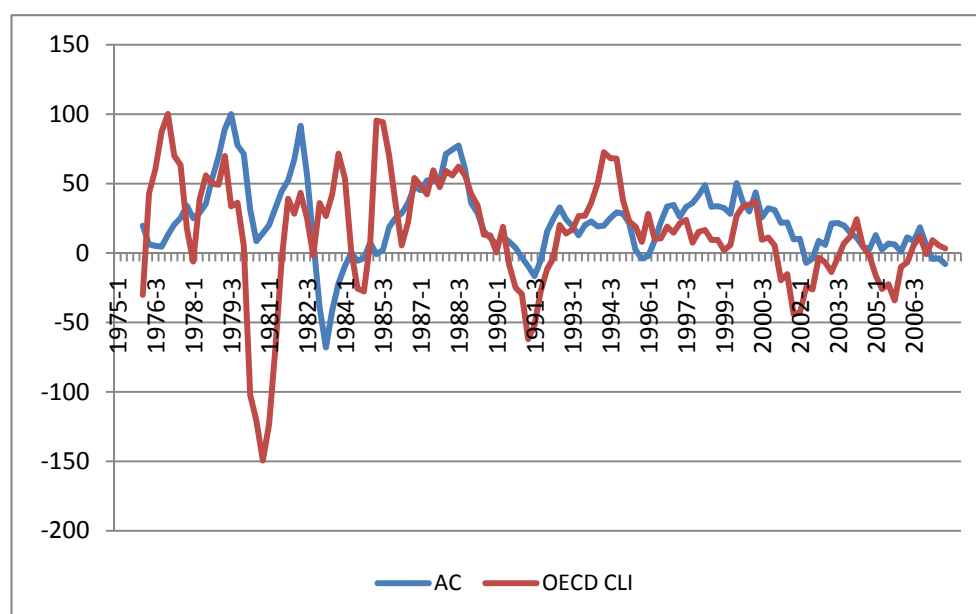
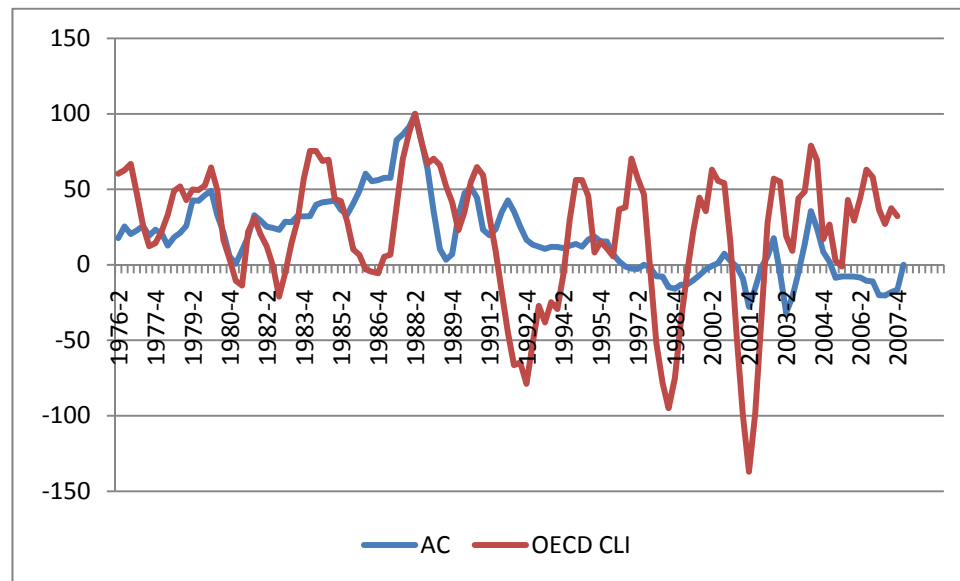
Figure 7.6 New Zealand, OECD CLI and Tourism Demand Growth (AC)**Figure 7.7 UK, OECD CLI and Tourism Demand Growth (AC)**

Figure 7.8 Japan, OECD CLI and Tourism Demand Growth (AC)

7.4.2 Business Survey index

The third leading indicator that is used for this study is the business/consumer survey data. This index is available for most OECD countries and can be obtained through DX data. In this section, the nature of the Business Survey index is discussed briefly, including the calculation and data collection methods.

Compared to traditional quantitative statistical surveys, business and consumer tendency surveys present many advantages as a source of short-term economic information. They collect information which is easier for enterprises and consumers to supply, because the answers are not based on precise records and the returns can be submitted more quickly. Business tendency surveys cover a wide range of variables selected for their ability to monitor the business cycle and include information on variables not covered by quantitative statistics, e.g. capacity utilisation and views on the overall economic situation.

The main characteristic of business opinion surveys is that instead of asking for exact figures they usually seek the respondent's assessment of the current business situation compared with the 'normal' state, i.e. they might pose a question on levels, or ask for a judgement on the direction of changes, i.e. a question on tendency.

Business tendency surveys are conducted by national statistical institutes, central banks or private research institutes of the country concerned. The tendency survey closest to international standards is the harmonised questionnaires developed by the OECD in co-operation with Eurostat and the European Commission from 1991 to 1996. They have also been adopted by many EU countries, and countries of the former USSR have implemented such surveys.

Though most countries use similar questions for a business survey, since it is conducted by each countries' statistical institutes, central bank, or private research institutes, each country has its own definition, collection and calculation method. A brief discussion of each country's definition, collection and calculation methods (for this study's four tourism-generating countries to Australia) is given below.

- **USA**

Definition: The index measures consumers' attitude towards current and expected personal finances, expected business conditions and current buying conditions for durable goods.

Collection: The indicator is compiled by the Survey Research Center of the University of Michigan using the results of a consumer survey based on interviews conducted by telephone.

Calculation: Each of the questions has three possible answers, which are 'good times', 'no change' and 'bad times'. The weights of the answers are respectively 2, 1 and 0. The index is then calculated as a simple average of individual indicators.

Coverage: Sample covers a cross-section of the USA.

- **New Zealand**

Definition: The results of the business tendency survey reflect the judgement of business men and women as to developments experienced in the past quarter and the prospects for their own firm in the following months. The questions relate to the business situation, production, orders and stocks of finished goods.

Collection: Data are compiled from the results of the Quarterly Survey of Business Opinion conducted at the end of each calendar quarter from a sample of over 1000 firms by the New Zealand Institute of Economic Research.

Calculation: All series (except firms operating at full capacity) are calculated as the balance of positive ('improve', 'up') over negative ('deteriorate', 'down') replies expressed as a percentage of total replies. The replies are weighted according to the size of enterprises.

Coverage: Firms employing six or more employees in the manufacturing and building trade are covered by the survey. Data cover the manufacturing sector of the whole country.

- **UK**

Definition: The results of the Industrial Trends Survey reflect the judgement of business men and women as to developments experienced in the recent past, the current situation and expectations for the following four to 12 month period for their own firm. Survey questions relate to total order books and actual demand.

Collection: Data are collected from the Quarterly Industrial Trends Survey and the Monthly Trends Inquiry carried out by the CBI (Confederation of British Industry).

Calculation: For all series except 'Firms operating at full capacity', data are presented as the balance of positive ('above normal', 'more than adequate', 'up') over negative ('below normal', 'less than adequate', 'down') replies expressed as a percentage of total replies. Each reply is weighted according to the proportion of manufacturing net output accounted for by the firms' size group.

Coverage: On average, 1500 replies from manufacturing enterprises are submitted each month to the Confederation of British Industry (CBI), accounting for around half of manufacturing employment and between one third and one half of the United Kingdom's manufactured exports.

- **Japan**

Definition: The business tendency survey results reflect the judgement of business men and women as to developments experienced in the recent past, the current situation and prospects for the next three or four month period for their own business. The survey questions relate to the business situation, stocks of finished goods and capacity utilisation.

Collection: Data are derived from the Bank of Japan's Quarterly Judgement Survey.

Calculation: The figures are presented as the balance of positive ('favourable', 'excessive') over negative ('unfavourable', 'insufficient') replies expressed as a percentage of total replies.

Coverage: More than 700 manufacturing enterprises whose capital is generally more than one billion yen are covered by the survey.

(Source: www.oecd.org/std/cli-ts)

The following figures present the plots of the Business Survey index for the four countries and the actual tourism demand growth cycle (AC).

Note: AC = Actual tourism arrivals growth.

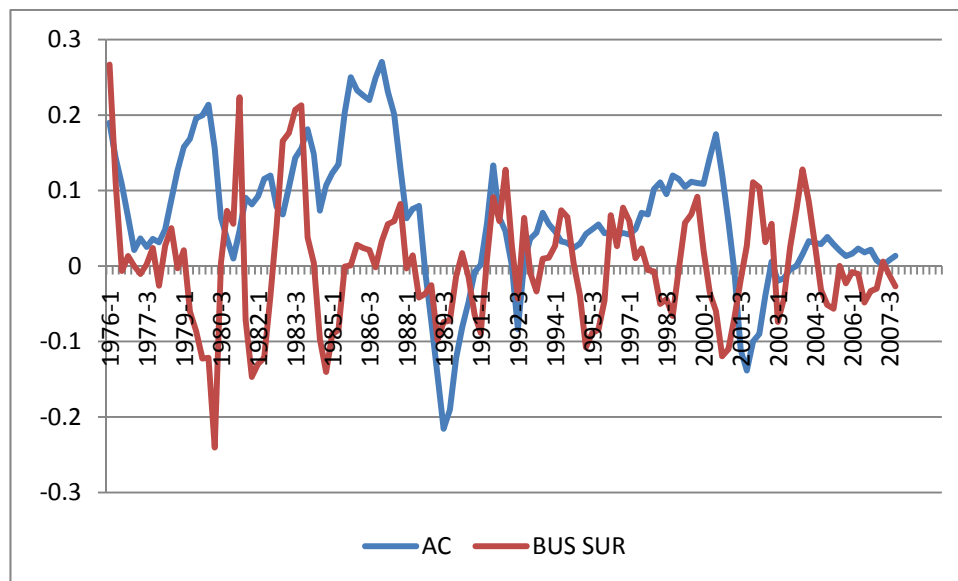
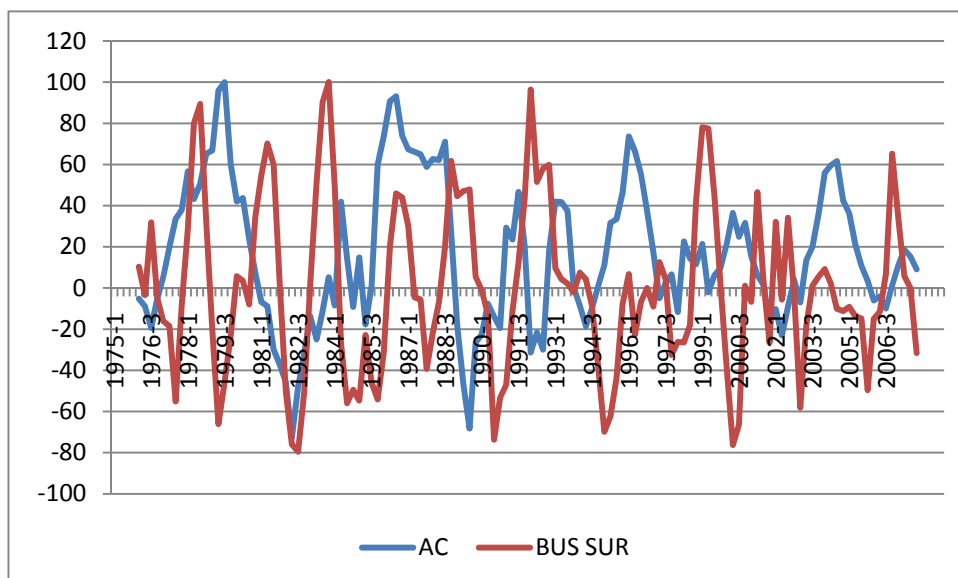
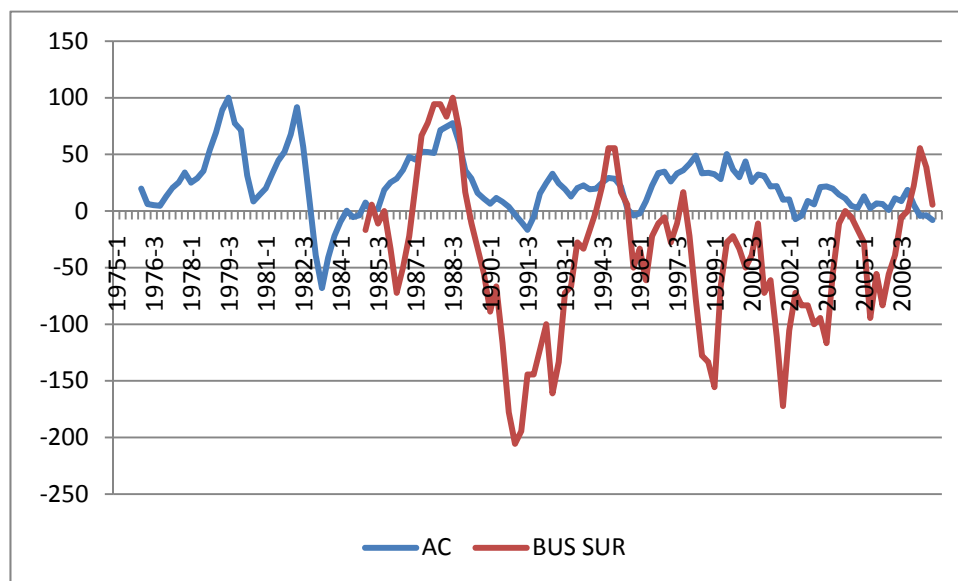
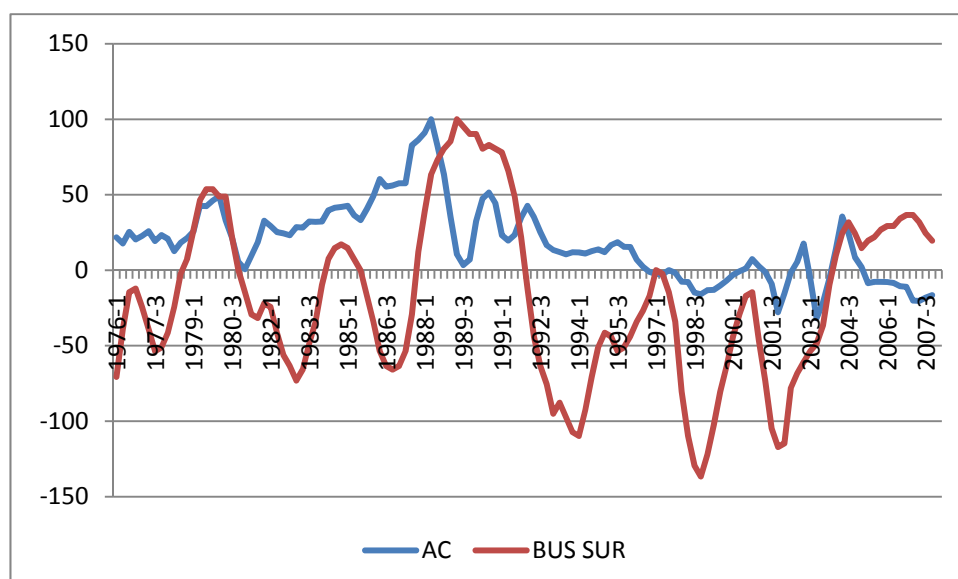
Figure 7.9 USA, Business Survey Index and Tourism Demand Growth (AC)**Figure 7.10 New Zealand, Business Survey Index and Tourism Demand Growth (AC)**

Figure 7.11 UK, Business Survey Index and Tourism Demand Growth (AC)

Note: UK Business survey data is available from 1985 Q1.

Figure 7.12 Japan, Business Survey Index and Tourism Demand Growth (AC)

7.5 Interpreting Movements in the Leading Indicators

In this chapter, three main potential leading indicators were identified, namely: (1) constructed CLI, (2) OECD CLI and (3) business/consumer survey data. Visual observation of the figures indicates that some indicators have a close relationship with tourism demand turns. However, the questions that need addressing are ‘How to interpret fluctuation of the composite leading indicators?’ and ‘How can the results of leading indicators can be compared with the actual tourism smoothed growth cycle to check their ability to predict turning points?’

While theory explains that, a turning point in the CLI signals a turning point in the reference series, in reality turning points are determined by a complicated process. Therefore, it is necessary to wait for several periods before drawing a more definite conclusion. Another concern about leading indicators is the random or short-lived changes in economic movement, where the presence of an ‘extra cycle’ on the leading indicator makes the result interpreting process more difficult.

In theory, the above problems are specified as pattern recognition issues and they are clearly stated in the pattern recognition literature (for example, Fu (1970)). According to the pattern recognition literature:

1. The first issue above is referred to as the ‘*separation problem*’. This involves both issues of whether the turning points of leading indicator (LI), which are mixed in the whole population, can be clearly separated, as well as the practical consideration of how such a separation should be implemented.
2. Following separation, each new observation needs to be classified into the turning point category which it best belongs to. This is referred to as the ‘*classification problem*’.
3. Finally, a decision rule is required, which will indicate the circumstances under which a turning point for leading indicator (LI) may be said to occur. This decision

rule provides the basis for issuing the signal of a corresponding turning point prediction for turning points in the tourism demand growth.

To address the above issues, over the years many methods have been developed. To recognize turning points in leading indicators, the first and commonly applied rule is to observe when an indicator declines (slow down) or increases (faster growth) for two or more consecutive months. This is the non-parametric BB rule. In this study the modified BB rule (see Chapter 4) is applied to identify turning points in tourism demand.

A second approach for spotting turning points is based on probability, and Neftci (1982) introduced the probability approach for this purpose. The probability approach is an important method of recognizing turning points, because in this method cyclical turning points are identified by calculating the likelihood that an economic environment has changed. A turning point probability signal is defined when the estimated probability reaches some threshold level (eg. 0.5). This second methodology statistically judges the likelihood of a turning point occurring based on information. These methods are called parametric methods; Logit and Probit models are such parametric methods, discussed in Chapter 6.

In the next chapter, to identify turning points and to interpret the movement of the leading indices, both the non-parametric BB method and the parametric Logit model will be examined.

Chapter 8

Identifying and Interpreting Turning Points in Leading Indicators

8.1 Introduction

In the previous chapter, three potential leading indicators (LIs) were identified to predict turning points in tourism demand. The objective of this chapter is to identify and interpret the turning points of those leading indicators using parametric and non-parametric methods.

In this chapter the non-parametric BB method and parametric Logit model will be used to identify and interpret the turning points in the three leading indicators, namely: the Constructed Leading Indicator (CLI), the OECD CLI and the ‘Business Survey index’, to forecast turning points in tourism demand.

This chapter is divided into two main sections. The first section attempts to identify the turning points of the leading indicators using the BB method while the second section attempts to identify the turning points of the leading indicators using the Logit model.

8.2 Identifying Turning Points Using the Non-parametric BB Algorithm

As discussed in Chapter 7, the BB (Bry and Boschan) rule is a non-parametric algorithm used to identify the significant turning points in a time series. In this chapter the modified BB algorithm is used (as discussed in Chapter 4) to identify significant turning points in three leading indicators. As discussed in Chapter 4, with the modified BB method the basic rules are, firstly, that the minimum phase period is three quarters and, secondly, that the minimum cycle period is seven quarters.

Using EViews the cross correlogram was tested, and the actual tourism demand against each leading indicator was used to check the timing relationships between LI's and tourism demand. The significant relationships were selected within five quarters in order to avoid misleading lead relationships. Table 8.1 below presents the positive leading or coincident relationships.

Table 8.1

The estimated lead time (obtained from cross correlation) for CLI, OECD CLI and Business Survey CLI against actual tourism arrivals growth.

Cross Correlation Results

Countries	CLI	OECD CLI	Bus Survey
USA	0 Qtr (0.3384)	0 Qtr (0.1967)	4 Qtr (0.1070)
NZ	3 Qtr (0.3205)	2 Qtr (0.1762)	3 Qtr (0.1602)
UK	0 Qtr (0.1340)	0 Qtr (0.2607)	0 Qtr (0.4623)
Japan	0 Qtr (0.2145)	0 Qtr (0.3543)	0 Qtr (0.3268)

In Table 8.1 most of the leading indicators have coincident relationships with tourism demand, indicating that most of the leading indicators have predicted the tourism demand change. In the case of the USA and New Zealand particularly, tourism demand has a comparatively strong relationship with Constructed CLI. Tourism demand for the UK and Japan has a comparatively strong relationship with the OECD CLI and the Business Survey index.

Having a strong relationship (higher cross correlation value) does not mean that these indicators have predicted the turning points correctly. For correct predictions to be made, the leading indicators must be adjusted according to the lead period (keeping the coincident relationship unchanged).

It is necessary to check how close the predictions of CLI turning points are to actual turning points. The following tables (Table 8.2, 8.3, 8.4 and 8.5) present the actual

turning points in tourism demand against the turning points of each leading indicator detected using the BB method.

In the following tables a 0 (zero result) denotes a perfect capture of a turning point while (+) and (–) signs indicate how many quarters before (+) or after (–) the leading indicator the turning point occurs (error). This gives an idea of how close the predicted turning point is to the actual turning point.

Note: To be able to claim that any turning point of a leading indicator is a correct prediction of tourism demand, that turning point needs to fall within + or – seven quarters (within the minimum cycle period) of the actual tourism demand turning point. Any turning point which falls outside this range will be considered a false signal.

8.2.1 Evaluating the results of three leading indicators for turning point prediction (within-sample period - from 1975 Q1 to 2003 Q4)

False Signal: These are turning points detected by the BB model, but not among the actual turning points (in the turning point chronology).

Missing: BB model has not detected the actual turning point.

N/A: Results are not available due to data problems or missed values due to smoothing or generating growth.

Table 8.2**USA Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points**

	Constructed CLI	OECD CLI	Business Survey Index		Constructed CLI	OECD CLI	Business Survey Index
<u>UT/ Trough</u>				<u>DT /Peaks</u>			
1977-1	+5	+4	Missing	1980-1	-1	-6	-2
1981-1	+3	-2	+1	1982-3	+5	-5	-1
1984-3	+1	-7	+5	1985-4	+3	-7	+5
1989-3	+2	+1	+3	1991-3	+5	-4	Missing
1992-3	+4	Missing	Missing	1993-3	+5	+5	+7
1994-4	+4	+5	+6	1998-4	+5	-4	-4
2001-4	-1	0	0				
False signals	0	2	2	False signals	1	2	3

Table 8.3**New Zealand Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points**

	Constructed CLI	OECD CLI	Business Survey Index		Constructed CLI	OECD CLI	Business Survey Index
<u>UT/ Trough</u>				<u>DT /Peaks</u>			
1982-2	D/Problem	-3	+4	1979-3	D/Problem	0	-1
1985-2	D/Problem	+5	Missing	1984-2	D/Problem	+3	+1
1989-3	+7	-1	-4	1986-3	D/Problem	+7	Missing
1994-2	+5	+7	+6	1993-1	+7	-1	-1
1999-2	-3	0	Missing	1996-1	+2	+5	+3
2002-2	-1	-1	-5	2000-2	-1	0	Missing
False signals	0	1	2	False signals	1	1	1

Table 8.4**UK Tourism Demand Turning Point Chronology vs. Leading Indicators Turning Points**

	Constructed CLI	OECD CLI	Business Survey Index		Constructed CLI	OECD CLI	Business Survey Index
<u>UT/ Trough</u>				<u>DT /Peaks</u>			
1976-4	N/A	Missing	D/Problem	1979-3	-2	-1	D/Problem
1980-3	1	+1	D/Problem	1982-2	+2	+6	D/Problem
1983-2	2	Missing	D/Problem	1988-3	+5	-4	0
1991-3	Missing	+1	-2	1992-3	Missing	Missing	Missing
1995-4	-2	Missing	Missing	1998-2	+5	+7	Missing
2002-2	-4	+3	-6	2003-3	+1	-3	Missing
False signals	2	2	1	False signals	1	1	1

Table 8.5**Japan Tourism Demand Turning Point Chronology vs. Leading Indicators Turning Points**

	Constructed CLI	OECD CLI	Business Survey Index		Constructed CLI	OECD CLI	Business Survey Index
<u>UT/ Trough</u>				<u>DT /Peaks</u>			
1978-2	0	-3	-3	1977-2	N/A	N/A	N/A
1981-2	-2	+6	+7	1980-1	+2	0	-1
1989-3	Missing	Missing	Missing	1988-2	+5	0	+4
1993-3	-4	+3	+1	1992-1	Missing	Missing	Missing
1999-1	-2	-3	-1	1995-3	+2	-3	+6
2001-4	-1	0	0	2000-4	-4	-2	0
False signals	2	1	0	False signals	2	1	0

In order to summarise the performance of each leading indicator to predict turning points which are detected by the BB method, the following criteria can be used:

- (1) **Captured ratio** is the ratio of captured turns from the model/method to the total number of actual turning points.
- (2) **False ratio** represents the turning points that are detected by the model/method, but are not recognised as actual turning points (not in the turning point chronology).
- (3) **MAD (Mean Absolute Deviation)** is the method whereby all the errors of captured turning points are added as absolute values (without '+' and '-' for example 1+1+0), and divided by the number of turning points, thus indicating how close (accurate) the predicted turning points are to the actual turning points (the lower the MAD value (error) the better the model).

Table 8.6: Summary of the Turning Point Forecast Performance (within-sample period - from 1975 Q1 to 2003 Q4)

Method	USA			NZ			UK			Japan		
	CLI	OECD CLI	Bus Sur	CLI	OEC D CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
Captured ratio	100%	92.3%	76.9%	100%	100%	66.6%	83.3%	66.6%	42.8%	83.3%	83.3%	83.3%
False ratio	7.6%	30.7%	50%	14.2%	16%	37.5%	33.3%	37.5%	66.6%	44.4%	22.2%	0%
MAD	3.38	4.33	3.4	3.71	2.75	3.12	2.66	3.37	2.66	2.44	2.22	2.55

Table 8.6 above indicates the turning point forecasting performance of leading indicators for the within-sample period. In order to evaluate the results of each leading indicator, the BB method was used as the turning point detecting/recognition method.

The best leading indicator to forecast turning points for each country can be selected based on the highest ‘captured ratio’, lowest ‘false ratio’ and the lowest MAD.

Note: the QPS probability test is only available with parametric probability methods (e.g. the Logit method) and not with the non-parametric BB method.

Most of the turning points in tourism demand have been detected by each leading indicator method. But there are only a few instances where the leading indicator detected the tourism demand turning point at the exact quarter. Also there are three turning points which were not captured by any leading indicator method, namely Japan’s upturn (trough) in 1989/3, and downturn (peak) in 1992/1 and the UK’s downturn (peak) in 1992/1993.

According to the above results, different indicators have performed well for different countries. For the USA, the constructed CLI has the best performance having the highest captured ratio, the lowest false ratio and the smallest MAD.

For New Zealand, both the constructed CLI and OECD CLI show the same results for the captured ratio. However the false ratio of the constructed CLI is marginally better (lower) than the OECD CLI, while with regard to the MAD, the OECD CLI has obtained a lower MAD compared to the Constructed CLI.

For the UK, the constructed CLI has the best performance having the highest captured ratio, the lowest false ratio and the smallest MAD.

For Japan all three leading indicators perform almost equally well, although having a zero false ratio for the Business Survey index is a better result than the other two methods.

8.2.2 Evaluating the results of three leading indicators for turning point prediction (Out-of-sample period results - from 2004 Q1 to 2007 Q4)

Table 8.7

USA Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points

	CLI	OECD CLI	Bus Sur		CLI	OECD CLI	Bus Sur
<u>UT/Trough</u>				<u>DT /Peaks</u>			
No upturns	-	-	-	2006-2	-8	+1	-5
False signals	-	0	1	False signals	0	0	0

Table 8.8

New Zealand Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points

	CLI	OECD CLI	Bus Sur		CLI	OECD CLI	Bus Sur
<u>UT/Trough</u>				<u>DT /Peaks</u>			
2006-3	-4	Missing	0	2004-3	0	-6	+1
False signals	0	0	0	False signals	0	0	0

Table 8.9

UK Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points

	CLI	OECD CLI	Bus Sur		CLI	OECD CLI	Bus Sur
<u>UT/Trough</u>				<u>DT /Peaks</u>			
2006-1	Missing	Missing	-5	No downturns	-	-	-
False signals	0	0	0	False signals	1	1	2

Table 8.10**Japan Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points**

	CLI	OECD CLI	Bus Sur		CLI	OECD CLI	Bus Sur
<u>UT/Trough</u>				<u>DT /Peaks</u>			
No upturns	-	-	-	2004-2	-1	0	+1
False signals	0	0	0	False signals	0	0	0

Tables 8.7, 8.8, 8.9 and 8.10 present the out-of-sample performance of each model in capturing actual turning points. The summary of results for the out-of-sample period is presented in Table 8.11. Since there are very few turning points in the out of sample period, it is not suitable to use ratios, which may lead to an incorrect interpretation.

Table 8.11: Summary of the Turning Point Forecast Performance (Out-of-sample period results - from 2004 Q1 to 2007 Q4)

	USA			NZ			UK			Japan		
Method	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OEC D CLI	Bus Sur
Captured ratio	100%	100%	100%	100%	50%	100%	0%	0%	100%	100%	100%	100%
False ratio	0%	0%	100%	0%	0%	0%	100%	100%	200%	0%	0%	0%
MAD	8	1	5	2	6	.5	N/A	N/A	5	1	0	1

In the out-of-sample period for the USA, the OECD CLI has performed well compared to the other two leading indicators. For New Zealand, both the constructed CLI and the Business Survey index show good results, while for the UK none of the methods have produced good results. For Japan, the performance is similar to that of the within-sample period, where all three leading indicators have performed equally well by having the highest captured ratio and lowest MAD.

In the previous leading indicator chapter (Chapter 7) visual observation showed that there were some close relationships between the actual tourist arrivals and the leading indicators. But when the BB method is used to capture the turning points, some results are not always as strong as shown by the visual relationship. This means that all the closely related figures (between tourism demand and leading indicators) do not necessarily mean they correctly predict turning points, though they correctly display most of the movements.

To conclude, the overall results of the within and out-of-sample periods for each country's (Japan, USA and New Zealand) leading indicators have performed well.

Of the three leading indicators used for Japan, the OECD CLI has the best results compared to the other two indicators. The USA indicators claim the second best results in forecasting the turning points, and all three indicators perform equally well, while the constructed CLI is marginally better than the other two indicators. For New Zealand, all leading indicators predict fairly well, while the constructed CLI has the best results out of the three indicators. However, in regard to turning points prediction for the UK's tourism demand, all three leading indicators performed poorly compared to the results of the other three countries.

8.3 Logit Model

Detection of turning points based on the probability approach was introduced by Neftci (1982). In the probability method, cyclical turning points are identified by calculating the likelihood that an economic environment or regime has changed. A turning point probability signal is defined when the estimated probability reaches some threshold

level (eg. 0.5). This method statistically judges the likelihood of a turning point based on the available data and is a parametric method by definition.

A Logit model is a parametric econometric (regression) approach based on probability and is estimated using the maximum likelihood method. To identify the turning points and to interpret the movement of the leading indices, this section uses the parametric Logit model. The results generated by this method are assessed and compared against the actual turning points (turning point chronology) of tourism demand growth, using the same diagnostics used in the previous chapters namely Captured ratio, False ratio, MAD (mean absolute deviation) and QPS (Quadratic Probability Score).

8.3.1 Estimation of the Logit model with leading indicators

In Chapter 6, different economic variables were used as explanatory variables to forecast turning points with the Logit and Probit models. In this section, the leading indices (Constructed CLI, OECS CLI and Business Survey) will be used as explanatory variables with the Logit model, using the same dependent variable, taking the value 1 for expansion in tourism demand and 0 for contraction in tourism demand.

Table 8.12 Logit Model Estimation Results

	p values of the variable	Log Likelihood (LL)	Restr. log Likelihood	Average LL	LR Statistics	Prob LR	McFadden R^2
USA							
Constructed CLI	0.0748	-78.25090	-79.88069	-0.652091	3.259585	0.071007	0.020403
OECD CLI	Not significant even at 90% level						
Business Survey Index	Not significant even at 90% level						
NZ							
Constructed CLI	0.0485	-49.81245	-51.97937	-0.664166	4.333851	0.037362	0.041688
OECD CLI	Not significant even at 90% level						
Business Survey Index	0.0886	-84.43636	-85.93412	-0.680938	-0.680938	0.083496	0.017429
UK							
Constructed CLI	0.0003	-78.33001	-86.15877	-0.626640	15.65752	0.000076	0.090864
OECD CLI	0.0004	-78.44889	-86.76425	-0.622610	16.63071	0.000045	0.095839
Business Survey Index	0.0002	-51.10395	-60.97422	-60.97422	19.74055	0.000009	0.161876
Japan							
Constructed CLI	0.0375	-83.90489	-86.15877	-0.671239	4.507769	0.033741	0.026160
OECD CLI	0.0206	-77.68394	-87.55272	-0.611685	19.73756	0.000009	0.112718
Business Survey Index	Not significant even at 90% level						

Table 8.12 presents the estimated Logit models using three different leading indicators as the explanatory variable. Out of the three indicators, the Constructed CLI manifests as a significant explanatory variable for all four countries. The OECD CLI is not a significant explanatory variable for the USA and New Zealand, while the Business Survey index is not a significant variable for the USA and Japan.

The above parameter estimates demonstrate also that all three leading indicators for the UK obtained the best results over other countries' leading indicators. The UK's

Probability Likelihood Ratio - LR (overall model) is significant at 99% and the p-values of each indicator are significant at 99%. Also, all the UK indicators obtained comparatively higher McFadden R^2 and log likelihood values.

For the USA, only the constructed CLI is significant at 90%, and the other two indicators are not significant.

For New Zealand, the OECD CLI is not significant, but the Constructed CLI and Business Survey index is significant. Of the two significant models, the constructed CLI shows better results having better p-values, log likelihood and McFadden R^2 values.

Of the three indicators for Japan, only the constructed CLI and OECD CLI are significant, while the OECD CLI shows better results with p-values, log likelihood and McFadden R^2 values.

Estimated models

The estimated Logit models are presented in Table 8.13.

Table 8.13 Estimated Logit Models Using Leading Indicators

Country	Constructed CLI	OECD CLI	Business Survey Index
USA	$\ln \left[\frac{P_i}{1 - P_i} \right] = 0.176885 +$ 8.910601 (CLI(4))	No Significant Results	No Significant Results
NZ	$\ln \left[\frac{P_i}{1 - P_i} \right] = -0.415653 +$ 6.681177 (CLI(6))	No Significant Results	$\ln \left[\frac{P_i}{1 - P_i} \right] = 0.033309 +$ 0.007699 (BUS SUR(4))
UK	$\ln \left[\frac{P_i}{1 - P_i} \right] = -0.065353 +$ 9.793031 (CLI(3))	$\ln \left[\frac{P_i}{1 - P_i} \right] = -0.111081 +$ 0.020954 (OECD(2))	$\ln \left[\frac{P_i}{1 - P_i} \right] = 0.641136 +$ 0.016623 (BUS SUR(4))
Japan	$\ln \left[\frac{P_i}{1 - P_i} \right] = 0.131162 +$ 4.184142 (CLI(2))	$\ln \left[\frac{P_i}{1 - P_i} \right] = -0.277861 +$ 0.020674 (OECD(1))	No Significant Results

Note: The number indicated within brackets next to each leading indicator (e.g. CLI (2)) represents the lead period (number of quarters) of the leading indicator.

Establishing accuracy

Once the models are finalized for each country, two main outputs, the Classification Table and the Hosmer-Lemeshow (H-L) test, are used to check the accuracy of the prediction.

Table 8.14 Classification Table (Expectation-Prediction) and Hosmer-Lemeshow Test Results

Country	Constructed CLI	OECD CLI	Business Survey Index
USA			
Accuracy Expectation vs. prediction test (cut-off = 0.5)	60.83%	No Significant Results	No Significant Results
H-L Test Goodness of fit test	0.6186	No Significant Results	No Significant Results
NZ			
Accuracy Expectation vs. prediction test (cut-off = 0.5)	64.00%	No Significant Results	53.23%
H-L Test Goodness of fit test	0.6707	No Significant Results	0.6390
UK			
Accuracy Expectation vs. prediction test (cut-off = 0.5)	61.60%	66.67%	68.18%
H-L Test Goodness of fit test	0.1392	0.476	0.4814
Japan			
Accuracy Expectation vs. prediction test (cut-off = 0.5)	62.40%	66.14%	No Significant Results
H-L Test Goodness of fit test	0.2774	0.8334	No Significant Results

Table 8.14 is used to illustrate the accuracy of the final model in capturing upturns and downturns. According to the expectation versus prediction table results, the UK indicators predict most of the turns. The UK's Business Survey index has the highest percentage (68%), but due to data limitations this percentage has been obtained using a limited data period (1985 – 2007) and not by using the entire period (1976 - 2007). The OECD CLI of the UK predicts the second highest turning points (67%). In addition, the OECD CLI for Japan and constructed CLI for New Zealand predict correct turns reasonably. However, the Business Survey index predicts New Zealand turns with comparatively less precision with a predicted ratio of 53%.

The H-L test, or the goodness of fit test, shows that all the significant models are good predictors of turning points and the above table can support (accept) the null hypotheses that the 'model classifies upturns and downturns well' (as all the p-values of the H-L statistics of all the indicators are greater than 0.05).

8.3.2 Evaluating the results of the three leading indicators for turning point prediction for the within-sample period (1975 Q1 to 2003 Q4)

After identifying the significant leading indicator model for each country and assessing the performance of each indicator, the most important step is to check the forecasting ability of each indicator for each country. First, the within-sample period from 1975 Q1 to 2003 Q4 is selected. Next, to identify the turning points, the predicted (fitted) probability values are used to generate the model. As discussed, to identify a turning point (or to separate expansion from contraction), 0.5 will be used as the cut-off point.

In the following tables, the result 0 (zero) denotes perfect capturing of turning points while (+) and (–) signs represents how many quarters there are before or after the turning point occurs. This gives an idea of how close the predicted turning point is to the actual turning point.

Note: To be able to claim that any turning point of a leading indicator is a correct prediction of tourism demand, that turning point needs to fall within + or – seven quarters of the actual tourism demand turning point. Any turning point, which falls outside this range, will be considered a false signal.

False Signals: Are turning point signals detected by the model that are not among the actual turning points.

Missing: Model has not detected the actual turning point.

N/A: Results are not available due to data problems or missed values due to smoothing or generating growth.

D/problem: Data is not available.

Table 8.15

USA Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points

	Constructed CLI	OECD CLI	Business Survey Index		Constructed CLI	OECD CLI	Business Survey Index
UT/ Trough				DT /Peaks			
1977-1	N/A	N	N	1980-1	0	N	N
1981-1	+5	0	0	1982-3	Missing	0	0
1984-3	+3	T	T	1985-4	-5	T	T
1989-3	Missing			1991-3	Missing		
1992-3	Missing	S	S	1993-3	Missing	S	S
1994-4	Missing	I	I	1998-4	+7	I	I
2001-4	+3	G	G			G	G
False signals	0			False signals	0		

Table 8.16**New Zealand Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points**

	Constructed CLI	OECD CLI	Business Survey Index		Constructed CLI	OECD CLI	Business Survey Index
<u>UT/ Trough</u>				<u>DT /Peaks</u>			
1982-2	N/A	N	+2	1979-3	N/A	N	-3
1985-2	N/A	0	+3	1984-2	N/A	0	-1
1989-3	N/A	T	-5	1986-3	N/A	T	+2
1994-2	Missing		Missing	1993-1	+6		+5
1999-2	-3	S	-3	1996-1	Missing	S	Missing
2002-2	+4	I	-5	2000-2	0	I	-2
		G				G	
False signals	1		2	False signals	0		2

Table 8.17**UK Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points**

	Constructed CLI	OECD CLI	Business Survey Index		Constructe d CLI	OECD CLI	Business Survey Index
<u>UT/ Trough</u>				<u>DT /Peaks</u>			
1976-4	N/A	N/A	D/Problem	1979-3	0	+1	D/Problem
1980-3	Missing	0	D/Problem	1982-2	Missing	+0	D/Problem
1983-2	+1	0	D/Problem	1988-3	-4	+4	+4
1991-3	-1	+4	+7	1992-3	-3	Missing	Missing
1995-4	-2	Missing	Missing	1998-2	0	+2	-1
2002-2	+3	+5	+6	2003-3	+2	+4	Missing
False signals	3	2	1	False signals	2	1	1

Table 8.18 Japan Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points

	Constructed CLI	OECD CLI	Business Survey Index		Constructed CLI	OECD CLI	Business Survey Index
UT/ Trough				DT /Peaks			
1978-2	+1	-2	N	1977-2	+0	0	N
1981-2	-1	0	0	1980-1	+2	+2	0
1989-3	Missing	Missing	T	1988-2	Missing	Missing	T
1993-3	+4	+3		1992-1	-7	+4	
1999-1	0	+1	S	1995-3	-4	-1	S
2001-4	+3	+3	I	2000-4	0	0	I
			G				G
False signals	2	2		False signals	2	2	

Summary of the within-sample period results

In order to identify and summarize the prediction performance of each indicator for each country, the following criteria can be used: (1) Captured ratio (2) False ratio (3) MAD (Mean Absolute Deviation) (4) Quadratic Probability Score (QPS).

Table 8.19 Summary of Turning Point Forecast Performance (within-sample period - from 1975 Q1 to 2003 Q4)

	USA			NZ			UK			Japan		
Method	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
Captured ratio	50 %	-	-	66%	-	83.3%	81%	81%	57%	83%	83%	-
False ratio	0%	-	-	16%	-	40%	45%	33%	50%	40%	40%	-
MAD	3.83	-	-	3.25	-	3.1	1.77	2.22	4.5	2.2	1.6	-
QPS	0.45	-	-	0.622	-	0.527	0.483	0.458	0.438	0.445	0.4523	

Applying the above criteria, the best indicator can be selected based on the highest 'captured ratio', lowest 'false ratio', the lowest MAD and the lowest QPS.

Table 8.19 above provides a summary of the turning point forecasting performance of each indicator for the four countries for the within sample period. According to the results in general, the indicators for the UK and Japan, the constructed CLI and OECD CLI, have given better results. And for New Zealand, the Business Survey index indicator has given good results. More specifically:

- For the UK all three indicators become significant, while OECD CLI has the best performance having the highest captured ratio (83%) and a comparatively low false ratio (33%), MAD (2.2) and QPS (0.4586). Constructed CLI for the UK also performed equally well, with a slightly higher false ratio (45%) and QPS (0.4830).
- For Japan the OECD CLI and constructed CLI are significant indicators and both indicators performed equally well having the highest captured ratio (83%), lower MAD and QPS. But both indicators have given a comparatively high false ratio (40%). Interestingly, Japan's OECD CLI has a lower MAD compared to the Constructed CLI while the Constructed CLI has a lower QPS compared to the OECD CLI.
- For New Zealand the constructed CLI and the Business Survey indicator are the significant indicators, while the Business Survey index has predicted more accurately than the constructed CLI. The Business Survey index has the highest captured ratio (83.3%) and lower MAD (3.1) and QPS, compared to the constructed CLI (0.5272).
- For the USA only the Constructed CLI is a significant indicator (at the 90% level) but it produced poor results with a low captured ratio (50%).

8.3.3 Evaluating the results of three leading indicators for turning point prediction for the out-of-sample period (2004 Q1 to 2007 Q4)

Tables 8.20, 8.21, 8.22 and 8.23 present the out-of-sample performance of each model in capturing actual turning points. In order to summarise the results of each estimated leading indicator using the Logit model, the captured ratio, the false ratio, and the MAD (mean absolute deviation) are used.

Table 8.20

USA Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points

	CLI	OECD CLI	Bus Sur		CLI	OECD CLI	Bus Sur
<u>UT/Trough</u>				<u>DT /Peaks</u>			
No upturns	-	N/S	N/S	2006-2	+1	N/S	N/S
False signals	0			False signals	0		

Table 8.21

New Zealand Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points

	CLI	OECD CLI	Bus Sur		CLI	OECD CLI	Bus Sur
<u>UT/Trough</u>				<u>DT /Peaks</u>			
2006-3	Missing	N/S	-1	2004-3	Missing	N/S	-1
False signals	0		0	False signals	1		0

N/S: Not Significant.

Table 8.22**UK Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points**

	CLI	OECD CLI	Bus Sur		CLI	OECD CLI	Bus Sur
<u>UT/Trough</u>				<u>DT /Peaks</u>			
2006-1	0	+1	-4	No downturns	-	-	-
False signals	0	0	0	False signals	0	0	1

Table 8.23**Japan Tourism Demand Turning Point Chronology vs. Leading Indicator Turning Points**

	CLI	OECD CLI	Bus Sur		CLI	OECD CLI	Bus Sur
<u>UT/Trough</u>				<u>DT /Peaks</u>			
No upturns	-	-	N/S	2004-2	Missing	+3	N/S
False signals	-	1		False signals	-	0	

N/S: Not Significant.

Since very few turning points were obtained in the out-of-sample period, it is not suitable to use ratios which may lead to an incorrect interpretation as percentages are calculated from one or two observations. In order to maintain consistency, the same criteria are used giving more weight to the QPS value.

Table 8.24 Summary of the Turning Point Forecast Performance (Out-of-sample period results - from 2004 Q1 to 2007 Q4)

	USA			NZ			UK			Japan		
Method	CLI	OECD CLI	Bus Sur	CLI	OEC D CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
QPS	0.6634	-	-	0.5053	-	0.4455	0.5725	0.4469	0.3951	0.7165	0.6189	-
Captured ratio	100 %	-	-	0%	-	100%	100%	100%	100%	0%	100%	-
False ratio	0%	-	-	100%	-	0%	0%	0%	100%	0%	100%	-
MAD	1	-	-	-	-	1	0	1	4	-	3	-

Table 8.24 displays the out-of-sample results of the three estimated leading indicators using the Logit model. Most of the above out-of-sample results confirm the results that were obtained from the within-sample period.

The UK's OECD CLI and Constructed CLI have provided the best prediction performance with the highest captured ratio (100%), and the lowest false ratio (0%). The OECD CLI has the lower QPS (0.44692), the Constructed CLI has the lower MAD (0). The UK's Business Survey index has the best QPS (0.39519) but a false ratio (100%) and a MAD that are comparatively high.

For Japan, the OECD CLI has performed well for the out-of-sample period with the highest captured ratio (100%), and a lower MAD (3) and QPS (0.6189) compared to the constructed CLI.

For the out-of-sample period the USA has obtained good results by capturing the only turning point of the out-of-sample period, and has obtained a high captured ratio (100%), a low false ratio (0%) and MAD (1). However, a comparatively higher QPS result (0.66344) suggests that the capture could be a coincidental result.

The above section investigated the performance of the leading indicators using the Logit model. The chapter's overall conclusion is that the within and out-of-sample results confirm the OECD CLI and the Constructed CLI performed well in forecasting turning points in the case of the UK and Japan. To forecast turning points in New Zealand tourism demand turning points, the Business Survey index works well. With the Logit model, none of the indicators were able to forecast turning points for USA tourism demand.

This chapter investigated the performance of the three leading indicators in identifying and forecasting turning points using the BB algorithm and the Logit model. In the next chapter (Chapter 9), the ability of these two methods to identify turning points will be evaluated. Additionally, the next chapter will compare all the results obtained from Chapters 6 and 8 and decide upon the most suitable model for predicting turning points in Australian inbound tourism demand for each country.

Chapter 9

Comparison of Results

9.1 Introduction

The objective of this chapter is to compare the results obtained in this study and identify the most suitable method for each country to forecast turning points. In Chapter 6 Logit and Probit models were estimated with economic independent variables and in Chapter 8, three leading indicators were estimated using the Logit model and the BB algorithm.

The first section of this chapter compares all the leading indicator results. The second section compares all the econometric results (Logit models estimated using economic independent variables and leading indicators). Finally, all results are compared to identify the best model for each country to forecast turning points.

9.2 Models Used to Forecast Turning Points

To forecast turning points, parametric Logit/Probit models and non-parametric BB algorithm methods are used in Chapters 6 and 8. More specifically, for each country the following models were tested:

- Logit models with economic variables as independent variables (Chapter 6),
- Probit models with economic variables as independent variables (Chapter 6),
- Constructed CLI with non-parametric BB method (Chapter 8),
- OECD CLI with non-parametric BB method (Chapter 8),
- Business Survey index with non-parametric BB method (Chapter 8),
- Constructed CLI with Logit model (Chapter 8),
- OECD CLI with Logit model (Chapter 8),
- Business Survey index with Logit model (Chapter 8).

The following sections examine model performance (based on country results), method performance (Logit, Probit, and BB) and the performance of each leading indicator. When selecting the best model/ method/ indicator the following criteria are used:

1. For the within-sample period the best model/method/indicator will be identified on the basis of the best of four evaluation methods, namely, captured ratio, false ratio, MAD and QPS.
2. For the out-of-sample period, since only one or two turning points are available, the two ratios could be misleading, hence more consideration is given to the QPS and MAD statistics. As mentioned earlier, the BB method does not produce QPS results.
3. Whenever the out-of-sample period has only one or two turning points giving rise to captured ratios of 100% and false ratio of 0%, both within and out-of-sample results will be considered together when selecting the best model.

9.3 Comparison of the Leading Indicator Results

In Chapter 8, the turning points of the three leading indicators were identified using the non-parametric BB method and the parametric Logit model. The following table compares the leading indicator results obtained using the BB and Logit methods.

9.3.1 Within-Sample Period (1975 Q1 - 2003 Q4)

Table 9.1 Comparison of the Leading Indicator Results (Within-Sample Period, 1975 Q1 - 2003 Q4)

	USA			NZ			UK			Japan		
	CLI	OECD CLI	Bus Sur	CLI	OEC D CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
BB Algorithm												
Captured ratio	100%	92.3%	76.9	100%	100%	66.6%	83.3%	66.6%	42.8%	83.3%	83.3%	83.3%
False ratio	7.6%	30.7%	50%	14.2	16%	37.5%	33.3%	37.5%	66.6%	44.4%	22.2%	0%
MAD	3.38	4.33	3.4	3.71	2.75	3.12	2.66	3.37	2.66	2.44	2.22	2.55
Logit Model												
Captured ratio	50%	-	-	66%	-	83.3%	81%	81%	57%	83%	83%	-
False ratio	0%	-	-	16%	-	40%	45%	33%	50%	40%	40%	-
MAD	3.83	-	-	3.25	-	3.1	1.77	2.22	4.5	2.2	1.6	-
QPS	0.4514	-	-	0.6226	-	0.5272	0.4830	0.4586	0.4380	0.4452	0.4523	-

Table 9.1 is a comparison between a parametric model (Logit) and a non- parametric method (BB) for each leading indicator. This comparison can be used to find (I) the best method (Logit or BB) for identifying the turning points in leading indicators and (II) the best leading indicator to forecast tourism demand turning points for each country.

(I) Best estimation model/method (Logit or BB)

Of the two methods used to identify turning points in leading indicators, namely, the Logit and the BB, it is clear that overall both the non-parametric BB and the parametric Logit methods perform equally well in accurately recognising turning points. Further, the Logit model identifies the turning points of the UK and Japan more accurately while the BB algorithm identifies the USA and New Zealand turning points more accurately.

(II) The best leading indicator for each country

Of the three leading indicators estimated, all four countries have found at least two leading indicators performed equally well.

For the USA, the constructed CLI and OECD CLI are equally good in predicting turning points.

For New Zealand, the OECD CLI and the Business Survey index are equally good in predicting turning points.

For the UK, the constructed CLI and OECD CLI are equally good in predicting turning points.

For Japan, the constructed CLI and OECD CLI are equally good in predicting turning points.

The results above indicate that, except in the case of New Zealand, the constructed CLI and OECD CLI are good indicators for all countries while for New Zealand the OECD CLI and the Business Survey index are good indicators.

9.3.2 Out-of-Sample Period (2004 Q1 to 2007 Q4)

Table 9.2 Comparison of the Leading Indicator Results (Out-of-Sample Period – 2004 Q1 to 2007 Q4)

	USA			NZ			UK			Japan		
	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
BB Algorithm												
Captured ratio	100%	100%	100%	100%	50%	100%	0%	0%	100%	100%	100%	100%
False ratio	0%	0%	100%	0%	0%	0%	100%	100%	200%	0%	0%	0%
MAD	8	1	5	2	6	.5	N/A	N/A	5	1	0	1
Logit Model												
Captured ratio	100%	-	-	0%	-	100%	100%	100%	100%	0%	100%	-
False ratio	0%	-	-	100%	-	0%	0%	0%	100%	0%	100%	-
MAD	1	-	-	-	-	1	0	1	4	-	3	-
QPS	0.6634	-	-	0.5053	-	0.4455	0.5725	0.44692	0.3951	0.7165	0.6189	-

Table 9.2 is a comparison between a parametric model (Logit) and a non-parametric method (BB) for the three leading indicators for the out-of-sample period.

(I) The best method (Logit or BB)

Of the two methods used to identify/estimate turning points, namely, the Logit and BB, it is clear that, even for the out-of-sample period, the non-parametric BB method and the significant Logit models give better results overall for most of the turning points in the leading indicators.

(II) Best leading indicator for each country

Of the three leading indicators estimated for the out-of-sample period, again, some countries have found that two leading indicators performed equally well in predicting turning points.

For the USA, the constructed CLI produces the best results, and the OECD CLI produces the second best results for the out-of-sample period.

For New Zealand, the Constructed CLI, OECD CLI and Business Survey indices perform well for the out-of-sample period.

For the UK, the Business Survey index shows better results over the other two indicators for the out-of-sample period (but has a higher false ratio).

For Japan, the Constructed CLI, OECD CLI and Business Survey index perform equally well for the out-of-sample period.

After careful analysis of within and out-of-sample results, a decision can be made as to the most appropriate leading indicators to predict turning points for each country. For the USA, the constructed CLI is the best indicator while the OECD CLI indicator is second best. For New Zealand, the OECD CLI and Business Survey Index are equally suitable and for the UK and Japan both the constructed CLI and the OECD CLI are equally well suited to forecasting turning points.

Considering both the within and out-of-sample results, the most suitable leading indicator for each country is nominated in the following table (Table 9.3).

Table 9.3 Suitable Leading Indicator for Each Country

Country	Suitable Leading Indicator
USA	Constructed CLI
New Zealand	OECD CLI and Business Survey Index
UK	Constructed CLI and OECD CLI
Japan	Constructed CLI and OECD CLI

9.4 Comparison of Econometric Model Results

In Chapter 6, the Logit and Probit models were estimated using potential economic explanatory variables for tourism demand. In Chapter 8, the Logit model was estimated with three leading indicators as explanatory variables. The following table compares the Logit results of Chapter 6 (obtained using economic explanatory variables) with the Logit results of Chapter 8 (obtained using a leading indicator as the explanatory variable). Since the Logit and Probit turning point results were identical in Chapter 6, the Probit model results are not used for comparison.

9.4.1 Within-Sample Period (1975 Q1 to 2003 Q4)

Table 9.4 Comparison of the Econometric Results (Economic Independent Variables vs. Leading Indicators for Logit Model – Within-Sample Period, 1975 Q1 - 2003 Q4)

Logit model with economic independent variables												
	USA			NZ			UK			Japan		
Captured ratio	83%			83%			54%			80%		
False ratio	15%			40%			0%			25%		
MAD	1.8			2.8			2.5			2.7		
QPS	0.39889			0.44592			0.46309			0.42934		
Logit model with leading Indicators												
	USA			NZ			UK			Japan		
	CLI	OECD CLI	Bus Sur	CLI	OEC D CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
Captured ratio	50%	-	-	66%	-	83.3%	81%	81%	57%	83%	83%	-
False ratio	0%	-	-	16%	-	40%	45%	33%	50%	40%	40%	-
MAD	3.83	-	-	3.25	-	3.1	1.77	2.22	4.5	2.2	1.6	-
QPS	0.4514	-	-	0.6226	-	0.5272	0.4830	0.4586	0.4380	0.4452	0.4523	

Table 9.4 above summarises the results for the Logit method, and shows turning point forecasting performance for the within-sample period. What needs to be examined here is whether the Logit model with ‘economic independent variables’ or Logit model with ‘leading indicators’ has performed better. If leading indicators are found to be performing better, which leading indicator is best to estimate with a Logit model.

Identifying the best explanatory variable for each country (Economic independent variables vs. leading indicators for the Logit model):

For the USA ‘economic independent variables’ performed well with the highest captured ratio, lowest false ratio, smaller MAD, and lowest QPS values.

For New Zealand both ‘economic independent variables’ and the ‘Business Survey index’ leading indicator performs equally well. The model with ‘economic independent variables’ can be identified as the best since it has lower MAD and QPS.

For the UK ‘OECD CLI’ has the best results compared to the other independent variables having higher captured ratio and the lowest false ratio.

For Japan ‘economic independent variables’ and the Leading Indicators ‘Constructed CLI indicator’ and ‘OECD CLI’ perform equally well. It is difficult to select a best independent variable since all three models perform equally.

9.4.2 Out-of-Sample Period (2004 Q1 to 2007 Q4)

Table 9.5 Comparison of the Econometric Results (Economic Independent Variables vs. Leading Indicators for Logit Model – Out-of-Sample Period, 1975 Q1 - 2003 Q4)

Logit model with Economic independent variables												
	USA			NZ			UK			Japan		
Captured ratio	100%			100%			0%			100%		
False ratio	100%			50%			0%			100%		
MAD	2			3			-			5		
QPS	0.5997			0.5202			0.63976			0.5045		
Logit model with leading Indicators												
	USA			NZ			UK			Japan		
	CLI	OECD CLI	Bus Sur	CLI	OEC D CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
Captured ratio	100%	-	-	0%	-	100%	100%	100%	100%	0%	100%	-
False ratio	0%	-	-	100%	-	0%	0%	0%	100%	0%	100%	-
MAD	1	-	-	-	-	1	0	1	4	-	3	-
QPS	0.6634	-	-	0.5053	-	0.4455	0.5725	0.44692	0.3951	0.7165	0.6189	-

Table 9.5 above summarises the results of the Logit method for the out-of-sample period.

For the USA ‘economic independent variables’ and ‘Constructed CLI’ have performed equally well for the out-of-sample period.

For New Zealand ‘Business Survey index’ performed well for the out-of-sample period.

For the UK ‘Constructed CLI’, ‘OECD CLI’ and ‘Business Survey index’ performed equally well for the out-of-sample period.

For Japan ‘economic independent variables’ and ‘OECD CLI’ performed equally well for the out-of-sample period.

Considering the within and out-of-sample results, the best explanatory variable for each country (Economic independent variables vs. Leading indicators for the Logit model) can be decided: For the USA ‘economic independent variables’, for New Zealand ‘Business Survey index’, for the UK ‘OECD CLI’ and for Japan the ‘economic independent variables’ can be identified as the best explanatory variables.

Table 9.6 Summary of the Best Explanatory Variable for Each Country

Country	Independent variable
USA	Economic independent variables (Price of tourism (GPT) and Airfare (GAF))
New Zealand	Business Survey Index
UK	OECD CLI
Japan	Economic independent variables (Price of tourism (GPT) and income of tourists’ origin country (GY))

9.5 Comparison of All the Obtained Results

In the previous sections, the best explanatory variable for each country was identified. In section 9.3, of the three leading indicators, the best indicators were identified for each country and the best method to estimate/identify the turning points of the leading indicators was also identified.

The following table takes the results from all the models used in this study for the within-sample period and using the captured ratio, false ratio, MAD and QPS, a conclusion is made as to the best model/method for each country to predict turning points.

9.5.1 Within-Sample Period (1975 Q1 to 2003 Q4)

Table 9.7 Comparison of All Results for Within-Sample Period (1975 Q1 to 2003 Q4)

	USA			NZ			UK			Japan		
<u>Logit Model with Economic independent variables</u>												
Captured ratio	83%			83%			54%			80%		
False ratio	15%			40%			0%			25%		
MAD	1.8			2.8			2.5			2.7		
QPS	0.42934			0.44592			0.46309			0.39889		
<u>Probit Model with Economic independent variables</u>												
Captured ratio	83%			83%			54%			80%		
False ratio	15%			40%			0%			25%		
MAD	1.8			2.8			2.5			2.7		
QPS	0.40458			0.44571			0.46301			0.42839		
	USA			NZ			UK			Japan		
	CLI	OECD CLI	Bus Sur	CLI	OEC D CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
<u>BB Algorithm with Leading Indicators</u>												
Captured ratio	100%	92.3%	76.9	100%	100%	66.6%	83.3%	66.6%	42.8%	83.3%	83.3%	83.3%
False ratio	7.6%	30.7%	50%	14.2	16%	37.5%	33.3%	37.5%	66.6%	44.4%	22.2%	0%
MAD	3.38	4.33	3.4	3.71	2.75	3.12	2.66	3.37	2.66	2.44	2.22	2.55
<u>Logit Model with Leading Indicators</u>												
Captured ratio	50%	-	-	66%	-	83.3%	81%	81%	57%	83%	83%	-
False ratio	0%	-	-	16%	-	40%	45%	33%	50%	40%	40%	-
MAD	3.83	-	-	3.25	-	3.1	1.77	2.22	4.5	2.2	1.6	-
QPS	0.4514	-	-	0.6226	-	0.5272	0.4830	0.4586	0.4380	0.4452	0.4523	

Using Table 9.7 the best forecasting model/method for each country can be found for the within-sample period. The best method for each country is selected using the four coefficients, namely, the highest captured ratio, lowest false ratio, smaller MAD and the lowest QPS values. To summarise the above table, Table 9.8 below displays the selected models for each country. To reduce the number of models for each country and to only include reasonably well-performing models, the table lists only the models with a captured ratio of 80% or more, a false ratio of 40% or less and a MAD value of less than 3.5.

Table 9.8 Selected Models for Each Country

	Model/Method	Captured Ratio	False Ratio	MAD	QPS
USA	1.Constructed CLI estimated using BB method	100%	7.6%	3.3	-
	2.Economic explanatory variables estimated using Logit and Probit method	83%	15%	1.8	0.4
NZ	1.OECD CLI estimated using BB method	100%	16%	2.7	-
	2.Economic explanatory variables estimated using Logit and Probit method	83%	40%	2.8	0.4
	3. Business Survey Index estimated using Logit and Probit method	83%	40%	3.1	0.5
UK	1.Constructed CLI estimated using BB method	83%	33%	2.6	-
	2. OECD CLI estimated using Logit and Probit method	81%	33%	2.2	0.4
Japan	1.Business Survey Index estimated using BB method	83%	0%	2.5	-
	2.OECD CLI estimated using BB method	83%	22%	2.2	-
	3.Economic explanatory variables estimated using Logit and Probit method	80%	25%	2.7	0.3
	4. OECD CLI estimated using Logit and Probit method	83%	40%	1.6	0.4
	5. Constructed CLI estimated using BB method	83%	40%	2.2	-

Comparison of all results for out-of-sample period (2004 Q1 – 2007 Q4)

In Table 9.7 all the results obtained for the within-sample period are compared to identify the best method/model for each country as summarised in Table 9.8.

Table 9.9 which follows, intakes the results from all the models used in this study for the out-of-sample period. The out of sample results are also considered when finally determining the best model/method for each country.

9.5.2 Out-of-Sample Period, 2004 Q1 to 2007 Q4

Table 9.9 Comparison of All Results for Out-of-Sample Period (2004 Q1 to 2007 Q4)

	USA			NZ			UK			Japan		
<u>Logit Model with Economic independent variables</u>												
Captured ratio	100%			100%			0%			100%		
False ratio	100%			50%			0%			100%		
MAD	2			3			-			5		
QPS	0.5997			0.5202			0.63976			0.5045		
<u>Probit Model with Economic independent variables</u>												
Captured ratio	100%			100%			0%			100%		
False ratio	100%			50%			0%			100%		
MAD	2			3			-			5		
QPS	0.5966			0.5197			0.6401			0.5028		
	USA			NZ			UK			Japan		
	CLI	OECD CLI	Bus Sur	CLI	OEC D CLI	Bus Sur	CLI	OECD CLI	Bus Sur	CLI	OECD CLI	Bus Sur
<u>BB Algorithm with Leading Indicators</u>												
Captured ratio	100%	100%	100%	100%	50%	100%	0%	0%	100%	100%	100%	100%
False ratio	0%	0%	100%	0%	0%	0%	100%	100%	200%	0%	0%	0%
MAD	8	1	5	2	6	.5	N/A	N/A	5	1	0	1
<u>Logit Model with Leading Indicators</u>												
Captured ratio	100%	-	-	0%	-	100%	100%	100%	100%	0%	100%	-
False ratio	0%	-	-	100%	-	0%	0%	0%	100%	0%	100%	-
MAD	1	-	-	-	-	1	0	1	4	-	3	-
QPS	0.6634	-	-	0.5053	-	0.4455	0.5725	0.44692	0.3951	0.7165	0.6189	-

The out-of-sample results in Table 9.9 show that there are some minor differences between the within and out-of-sample results.

Table 9.10 below displays the best forecasting models for each country for the out-of-sample period. To reduce the number of models for each country and to only include reasonably well-performing models, the following table lists only the models which (i) are selected as the best model for the within-sample period in Table 9.8 and (ii) obtain a captured ratio of more than 80%, a false ratio of less than 40% and a MAD value of less than 3.5 for the out-of-sample period.

Table 9.10 Selected Models for Each Country

	Model/Method	Captured Ratio	False Ratio	MAD	QPS
USA	1.Economic explanatory variables estimated using Logit and Probit method	100%	0%	1	0.4
NZ	1.OECD CLI estimated using BB method	100%	0%	1	-
	2. Business Survey Index estimated using Logit and Probit method	100%	0%	1	0.44
UK	1. OECD CLI estimated using Logit and Probit method	100%	0	1	0.57
Japan	1.OECD CLI estimated using BB method	100%	0%	0	-
	2.Business Survey Index estimated using BB method	100%	0%	1	-
	3.Constructed CLI estimated using BB method	100%	0%	1	-

After considering the above within-sample period results and out-of-sample period results, a final conclusion can be made as to the best model/method for each country to forecast turning points in Australian tourism demand. Table 9.11 below summarises the best model/method found in this study for each country.

Table 9.11 The best models/methods found in this study

Model/Method	
USA	1.Economic explanatory variables estimated using Logit and Probit method
	2.Constructed CLI estimated using BB method
NZ	1.OECD CLI estimated using BB method
	2.Economic explanatory variables estimated using Logit and Probit method
	3. Business Survey Index estimated using Logit and Probit method
UK	1. OECD CLI estimated using Logit and Probit method
	2.Constructed CLI estimated using BB method
Japan	1.Business Survey Index estimated using BB method
	2.OECD CLI estimated using BB method
	3.Economic explanatory variables estimated using Logit and Probit method
	4. OECD CLI estimated using Logit and Probit method
	5. Constructed CLI estimated using BB method

Table 9.11 above indicates the overall results of this study. The turning point results in this study show the relative performance of a particular turning point forecasting model. There is no single model/method that is ‘best’ for all the ‘origin-Australia’ pairs. But the parametric Logit/Probit model and the non-parametric BB method are claimed as the preferred methods for all the countries in this study.

Reiterating our conclusion, the best model for each country of this study is:

For the USA, economic independent variables are the best explanatory variables and the parametric Logit/Probit models are the best estimation methods to forecast turning points.

For New Zealand the OECD CLI is the best indicator and the non-parametric BB method is the best detection/estimation method to predict turning points.

For UK the OECD CLI is the best indicator and the parametric Logit model is the best estimation method to predict turning points.

For Japan the Business Surveys Index is the best indicator and the non-parametric BB method is the best detection/estimation method.

The above results indicate that the Logit model is good at estimating/identifying turning points in leading indicators as well as with economic independent variables. Also, the BB is good in identifying turning points in leading indicators.

The above results for the USA and the UK indicate that the Logit model is the most preferred method, while the BB method is the most preferred method for New Zealand and Japan. But it is important to mention the superiority of the parametric Logit model over the non-parametric BB algorithm.

The non-parametric BB algorithm is a formula and can only be used to identify turning points in a series. However, the Logit model being a parametric method with a theoretical background has the ability to estimate models (by evaluating the model's validity using a range of parameters). Further, the Logit model can develop models with a range of independent variables, and has the ability to forecast probabilities for each period.

Chapter 10**Conclusion**

10.1 Introduction

The aim of this thesis is to develop a model/method to forecast turning points caused by ‘economic factors’ in Australian inbound tourism demand growth. The aim has been achieved in establishing that Logit/Probit models can be used effectively in turning point forecasting in Australian tourism demand.

This chapter summarises the major findings of the thesis and highlights the contribution of this thesis to the literature. In the second part of the chapter, suggestions for future research and the limitations of the study will be discussed.

10.2 An Overview

In Chapter 1, it was identified that tourism is one of the biggest economic sectors in the world, and the economic contribution and economic importance of tourism should not be underestimated. Further, within the spectrum of tourism research, ‘tourism economics’ was identified as a vital instrument for policy-making and planning. Further, ‘tourism economics’ was recognized as a study area quite distinct from other fields of economics.

Within tourism economics, turning point forecasting was identified as an important concern due to its relevance to governments, policy makers, the airline industry, the hotel industry and other tourism-related industries for their policy-making, planning and resource allocation activities.

After identifying the importance of tourism and the importance of forecasting turning points in tourism demand in Chapter 1, the literature review chapter (Chapter 2) indicated that more attention and a new approach, should be directed to forecasting turning points in tourism demand growth, due to the limitations of current linear

methods. Consequently, this study uses non-linear econometric models (Logit and Probit) and a non-linear time series model (Markov Switching) to identify and forecast turning points, (Chapters 5, 7, 8). In the past, no attempt has been made to forecast turning points in tourism demand using non-linear econometric models. Essentially these methods are able to calculate the probability that tourism demand will be in expansion or in contraction at a certain date in the future. Since the use of leading indicators is an accepted method in tourism economics and other disciplines to forecast turning points, the leading indicator method is used in this study as the main basis for comparison.

The reason for examining the relationship between economic factors and turning points is that, as discussed in Chapter 2, one of the main causes for tourism demand change is the dynamic nature of world economies. Further, the available literature in tourism economics has used economic variables/factors for demand forecasting and has determined the influence of economic factors on tourism demand (Turner et al. (1997), Witt and Witt (1991), Song and Witt (2000), Song et al. (2000), Turner and Witt (2001a)). Consequently, using economic factors to forecast turning points is a good starting point. Specifically the aim of this study is to identify and forecast turning points in Australian inbound tourism demand, resulting from 'economic factors' in the tourism-generating or destination country.

Considering the availability of data and the aim of the study, Logit and Probit models are estimated with potential economic variables (as explanatory variables), namely, income (Y), price of tourism (PT), airfare (AF) and substitute price (SP). Two dummy variables (two random events) are also used to check the effect of random events (D1 and D2).

The leading indicator method is one of the most accepted methods in macroeconomics, as well as in tourism economics, to forecast turning points. This study constructed a composite leading indicator to forecast turning points in Australian inbound tourism demand using seven economic variables, namely, tourists' country of origin income measured by gross domestic product (GDP), exchange rate between tourists' country of origin and the destination country (EX), relative price

(CPI), share price (SP), total exports (TEP), total imports (TMP), and the unemployment rate (UN) (refer to Chapter 7).

Further, two more readily available potential leading indicators were also used namely: The Composite Leading Indicator (CLI) available for OECD countries through DX data and the Business Survey index available in DX data. To assess the forecasting performance of all three leading indicators, these indicators were estimated with the Logit model.

The countries chosen as the countries of study were the USA, New Zealand, the UK and Japan. They were chosen as they are the major tourism source markets contributing more than 50% of inbound tourism to Australia, and due to the availability and the reliability of economic and tourism data for these four countries. Past quarterly tourist arrivals data to Australia from these four countries are used in this study. Data from 1975 Quarter 1 to 2003 Quarter 4 is used as the within-sample data. The period 2004 Quarter 1 to 2007 Quarter 4 is used as the out-of-sample period for testing the forecasting accuracy of the model. The model accuracy is measured using captured ratio, false ratio, MAD and QPS (refer to Chapter 3).

Using the above-mentioned methods and data, this study attempts to achieve the following key objectives (refer to Chapter 1):

- Identify the most appropriate method to extract smoothed quarterly tourism demand growth for each tourism origin market.
- Investigate the most suitable method to identify significant turning points (dating) in Australian inbound tourism demand (to establish a chronology of the turning points in tourism demand).
- Construct a composite leading indicator to identify and predict turning points in Australian inbound tourism demand using economic indicators and check the suitability of available leading indices (OECD CLI and Business Survey index) to predict turning points.

- Identify the economic factors or economic indicators that determine the turning points in Australian inbound tourism demand growth.
- Develop a non-linear econometric model to forecast turning points in Australian inbound tourism demand.

10.3 Summary of Findings

Suitable cyclical pattern

In Chapter 3, different cycle patterns were examined, namely: classical business cycles, growth cycle and growth rate cycle. The growth cycle was identified as the most appropriate cyclical pattern that may be used to identify significant turning points in this study, due to its simplicity, evidence of use in past studies in tourism and considering the objective of the study (to forecast turning points rather than to detect slower growth and faster growth).

Appropriate smoothing method

Quarterly tourist arrivals to Australia are highly volatile due to seasonal, trend and random effects. In Chapter 4, three different smoothing methods are tested to select the best smoothing method to extract smoothed quarterly tourism demand growth for each tourism origin market, namely: (1) Basic Structural Model (BSM) (2) 2-quarter smoothed annualized rate (TQSAR) and (3) Hodrick-Prescott (HP) filter method. Having examined the three methods and their plots, this study selected the Basic Structural Model (BSM) as the most suitable smoothing method due to its ability to represent most of the turns without being too smooth or too volatile. Further, with the tourism arrivals data used in this study it is found that the 2-quarter smoothed annualized rate (TQSAR) method is excessively volatile and the Hodrick-Prescott (HP) filter smoothing method is too heavily smoothed.

Best method to identify significant turning points (dating method)

Due to the absence of benchmark turning points for Australian tourism demand, in Chapter 5 the most suitable method to identify significant turning points (dating method/to establish a chronology) in Australian inbound tourism demand is determined. For this purpose, the non-parametric Bry and Boschan (BB) formula and parametric Markov Switching models were tested. Visual observation explained that the non-parametric BB algorithm captures all the turning points irrespective of their magnitude. Further, it was found that the BB method is simple to apply and is transparent compared to the MS method. Even though the parametric MS method produces higher p and q values and lower σ values in the process of capturing the turning points, it does not capture the turning points closely when compared to visual observation. However, it captures the turning points where the demand growth becomes close to a positive/negative threshold. After comparing the MS and BB methods, this research identifies the non-parametric BB method as the most suitable dating method to use in identifying turning points for Australian inbound tourism demand growth.

Economic variables that determine the turning points in Australian inbound tourism demand

In Chapter 6, the econometric Logit and Probit models are tested with a set of six potential economic independent variables to forecast turning points. Of the six independent variables used in this study to predict turning points, the variable GPT (price of tourism) is the significant variable for all four countries. This indicates the importance of exchange rates and price levels in the tourism-originating and destination country for Australian inbound tourism. More specifically, for each country the following economic variables were identified as significant economic variables that determine the turning points in Australian inbound tourism demand growth.

- USA : Price of tourism (GPT) and Airfare (GAF),
- New Zealand: Price of tourism (GPT),
- UK: income of tourists' country of origin - measured in real GDP (GY) and Price of tourism four quarters before the travel (GPT (-4)),

- Japan: Price of tourism three quarters before the travel (GPT (-3)) and income of tourists' country of origin - measured in real GDP (GY).

The price of the substitute destination variable (GPS) is not significant as an indicator variable for the countries tested. This indicates that tourists from tourism-generating countries (USA, UK and Japan) do not consider substitute destination price as a major factor in their decision to travel to Australia (assuming the substitutes selected are correct for each country).

Effect of Random Events

Though the objective is to study the effect of economic factors, two dummy variables are included as independent variables (D_1 for the 2000 Sydney Olympics and D_2 for the September 11/2001 attacks in New York) to check the effect of random events in creating turning points. Both dummy variables were found to be not significant. The reason for this could be that the sudden random demand changes due to D_1 and D_2 in tourism demand may have disappeared with the smoothing process, because their effect lasted for only a few quarters. This means we can assume that random events like terrorist attacks or large sporting events do not create a significant turning point in tourism demand (according to the turning point definition in this study).

Logit/Probit models with economic independent variables

Given the economic independent variables used, the Logit and Probit models performed well for the USA, and the model used for the USA predicted most of the turning points in tourism demand. For the prediction of the turning points in the Japanese and New Zealand tourism demand growth, the Logit and Probit models performed moderately and for the UK the predictions were poor (refer Chapter 6).

Leading indicators to forecast turning points

In Chapter 7, three leading indicators were used to forecast turning points namely, Constructed CLI, OECD CLI and the Business Survey index. To construct a composite leading indicator, after considering past leading indicator studies in tourism the following potential indicators were selected (refer Chapter 7 page 6);

- Tourist origin country income measured by gross domestic product (GDP)
- Exchange rate between tourist origin country and destination country (EX)
- Relative price (CPI) - (Origin country of tourists)
- Share price (SP) - (Origin country of tourists)
- Total exports (TEP) - (Origin country of tourists)
- Total imports (TMP) - (Origin country of tourists)
- Unemployment rate (UE) - (Origin country of tourists)

Of the above leading indicators, share price is found to be a leading indicator for all four countries. Except for New Zealand, unemployment and imports were identified as leading indicators for Australian tourism demand for the other three tourism-generating countries.

Leading Indicators with BB method

In Chapter 8, the turning points of three leading indicators are identified using the non-parametric BB method. Of the three leading indicators used for Japan, the OECD CLI has the best results compared to the other two indicators. For the USA all three indicators performed well, while the constructed CLI is marginally better than the other two indicators. For New Zealand, all three leading indicators predict turning points fairly well, while the constructed CLI had the best results of the three indicators. However, in regard to the turning points prediction for UK tourism demand, all the three leading indicators performed poorly compared to the results of the other countries.

More importantly, the results of Chapter 7 indicate that the closely related movements between tourism demand and leading indicators don't necessarily mean they correctly predict turning points, though they correctly display most of the movements.

Leading indicators with Logit model

In Chapter 8, the three leading indicators were estimated with the Logit model: for the UK, both the Constructed CLI and OECD CLI predict actual turning points with high accuracy; for New Zealand, the Business Survey index predicts actual turning points with high accuracy; for Japan OECD CLI predicts actual turning points moderately; for the USA, the indicators have not produced strong results.

Best explanatory variable for each country

In Chapter 9, the best explanatory variable for each country was examined (Economic independent variables vs. leading indicators). The following variables were identified as the best explanatory variable for each country to predict turning points:

- For the USA the economic variables, Price of tourism (GPT) and Airfare (GAF), were identified as the best independent variables.
- For New Zealand 'Business Survey index' is the best explanatory variable.
- For the UK, the 'OECD CLI' is the best independent variable.
- For Japan the economic variables Price of tourism (GPT) and income of tourists' country of origin (GY), were identified as the best independent variables.

Best leading indicator for each country

In Chapter 9, all three leading indicator results were compared to find the most suitable leading indicator for each country. The following leading indicators were identified as the best leading indicator for each country, based on the number of actual turning points identified.

- For the USA the constructed CLI is the best indicator while the OECD CLI indicator is second best.
- For New Zealand the OECD CLI and Business Survey index performed equally well in forecasting turning points.
- For the UK the constructed CLI and OECD CLI indices can be selected as the most appropriate leading indicators to predict turning points.

- For Japan, the Constructed CLI and OECD CLI performed equally well to forecast turning points.

Best model/method for each country to forecast turning points

In Chapter 9, the results of all the models used in this study were compared to find the best model/method for each country to forecast turning points in Australian tourism demand. Table 10.1 which follows, summarises the best model/method of this study for each country.

Table 10.1 Summary of Best Methods

	Model/Method	Key Factors Create Turning Points
USA	1.Economic explanatory variables estimated using Logit and Probit methods	Price of Tourism and Airfare
	2.Constructed CLI estimated using BB method	GDP, Share Price, Unemployment Rate, Imports and CPI
NZ	1.OECD CLI estimated using BB method	OECD Composite Leading indicator
	2.Economic explanatory variables estimated using Logit and Probit methods	Price of Tourism
	3. Business Survey Index estimated using Logit and Probit methods	Business Survey/Confidence
UK	1. OECD CLI estimated using Logit and Probit methods	OECD Composite Leading Indicator
	2.Constructed CLI estimated using BB method	Exchange Rate, Share Prices and Unemployment
Japan	1.Business Survey Index estimated using BB method	Business Survey/Confidence
	2.OECD CLI estimated using BB method	OECD Composite Leading Indicator
	3.Economic explanatory variables estimated using Logit and Probit methods	Price of Tourism and Income
	4. OECD CLI estimated using Logit and Probit methods	OECD Composite Leading Indicator
	5. Constructed CLI estimated using BB method	Share Prices, Unemployment and Imports

Table 10.1 indicates that for the USA and the UK, the Logit model is the most preferred method, while the BB method is the most preferred method for New Zealand and Japan. Though there is no single model/method that is ‘best’ for all tourism-generating countries to Australia, the parametric Logit/Probit model and the non-parametric BB method are claimed as the preferred methods for each country in this study.

10.4 Contribution of the Thesis

Before discussing the contribution of the thesis to the literature, it is important to discuss the background of the research question. The problem associated with past turning point studies was that in tourism economics linear econometric and linear time series models have been used to predict turning points, when the series are fundamentally non-linear. As a result, past researchers have been unsuccessful in precisely predicting turning points in tourism growth, because tourism demand growth is both volatile and non-linear.

Based on the inability of current linear econometric and time series models to predict turning points in non-linear time series and the lack of adequate research in turning point prediction, the objective was to forecast turning points accurately by applying non-linear models such as Markov Switching and Logit/Probit models. The objective has been achieved by establishing that Logit/Probit models can be used effectively in turning point forecasting of tourism demand.

Introducing these non-linear models to tourism economics to identify and forecast turning points, and having obtained the results with higher accuracy, this research constitutes an important step in turning point forecasting in tourism economics. Thus, the main contribution of this thesis is introducing these non-linear Logit/Probit and MS models to tourism economics to identify and forecast turning points in inbound tourism demand growth. Furthermore, being the best model for the USA and the UK, the Logit/Probit model stands out as the most successful method in this study and highlights the importance and the accuracy of this non-linear method in turning point forecasting.

The other important contribution of this thesis is that although the leading indicator is already used in tourism economics, this research has taken the existing leading indicator approach in tourism forecasting to a new dimension by estimating leading indicators using the Logit model. Further, this is the first attempt in tourism economics to use the OECD CLI and the Business Survey index as leading indicators to forecast turning points in tourism demand.

Furthermore, this research establishes a number of methodological contributions to tourism economics by examining the appropriate cyclical pattern, the most suitable smoothing method and establishing the BB method as the most suitable method to identify significant turning points (dating method) in tourism demand growth.

The results obtained in this study clearly indicate that the non-linear Logit/Probit models introduced in this study with economic independent variables provide successful results. The ability of the Logit /Probit models in identifying turning points in leading indicators is also established. However, the introduced MS model performed poorly in this study. Overall, the results of this study confirm the usefulness of non-linear econometric models (Logit/Probit) to forecast turning points in tourism demand growth.

Finally, a question can be raised as to whether the findings can be replicated in other countries. The concluded cyclical pattern, smoothing method, BB dating method and non-linear Logit and Probit models can be used successfully for similar turning point research since they have produced consistent and clear results for all four countries in this study and the selected method clearly stands out in comparison with the other tested methods.

As it is clear that the Logit and Probit models are successful methods, they can be used more effectively in future turning point forecasting as well as other tourism demand studies with different independent variables. However, the economic variables and leading indicators may vary depending on the country and the specific objective of the study

10.5 Practical Implications of the Study

As mentioned in the introductory chapter, government and the various industries making up the tourism sector, including airlines, tour operators, hotels and food suppliers, need an early prediction of turning points and the economic factors that contribute to generating turning points for the purpose of investment, planning, policy analysis and to minimize the risk due to changes in demand growth. With the findings of this study all these sectors will benefit through proactive resource allocation and will be able to develop an appropriate management strategy to avoid financial and other risks.

In this context, this study makes an important contribution in terms of its practical validity/usefulness for the tourism industry as follows.

1. This study has clearly shown the importance of price of tourism, meaning the importance of exchange rates and price levels in the tourism originating and destination country to create significant turning points in Australian inbound tourism demand. Of the six independent variables used in this study to predict turning points, the variable GPT (price of tourism) is the significant variable for all four countries.
2. It is found that the share prices (of tourism generating countries), as an important leading indicator to Australian tourism demand turning points as share prices found to be a leading indicator for all four countries.
3. It is also shown the importance of level of unemployment rates (of tourism generating countries), as a vital leading indicator to Australian tourism demand turning points. Except for New Zealand, unemployment is identified as leading indicators for other three tourism-generating countries.
4. The usefulness of OECD CLI as a leading indicator and to forecast turning point in Australian in bound tourism demand is confirmed as OECD CLI becoming the significant leading indicator for all four countries examined in this study.

5. Out of the four countries tested, it had been found that the price of the substitute destination for each country is not a key factor to create significant turning points in Australian inbound tourism demand (assuming the substitutes selected are correct for each country).
6. Though the random events can create significant demand changes in tourism demand, as their effect lasted for only a few quarters (given the two random events applied) in this study it is found that the random events like terrorist attacks or large sporting events do not create a significant turning point in tourism demand (according to the turning point definition and the two events tested in this study).

10.6 Suggestions for Future Research

This research takes turning point forecasting in tourism demand to an entirely new level in obtaining successful results for non-linear Logit/Probit models. However, this research is just the first step in developing a new approach to identifying and forecasting turning points in the tourism forecasting field, a field that has immense research potential, not only in turning point forecasting but also in other related areas of tourism demand forecasting such as demand patterns, tourism cycle studies and so on:

- (1) The aim of this research is to identify/forecast turning points in tourism demand using economic variables regardless of negative and positive growth. In future research however, it would be useful to examine specific above-the-horizon and below-the-horizon turning points and the factors that contribute to these turning points.
- (2) The aim of this study is to forecast turning points caused by economic factors. Further, it might also be important to know the natural turning points created by seasonality of tourist arrivals, which means the study of natural peaks and troughs.

- (3) This study did not attempt to study the amplitude/depth of turning points, or the span (spread/duration) of turning points, including the severity and the duration of turning points. This can be left to future research.
- (4) Following on from (2) above, when analysing the arrivals growth diagrams of this study, different shapes of turning points could be identified such as a 'V' shape (sudden turns) and 'U' shape (smooth turns). Future research can be conducted to investigate the reasons for these different shapes of turning points.
- (5) Chapter 3 of this study plotted the smoothed growth of four tourism-generating countries and identified a degree of relationship between the turning points of the countries. It would be useful in future research to study the cycle and phase of the relationships between countries and within the country over a period of time. This means checking whether there is a timing relationship between countries, cycles and phases, which can be used as indicators to predict future cycle changes.
- (6) Global economic factors affect global tourism demand. Hence, the relationship between the global tourism demand cycle and the Australian tourism demand cycle can be studied to compare and check the similarities and dissimilarities of the cycle movements and to seek the reasons for these.
- (7) This study applied two most relevant and available economic indices, and in addition to these two indices there are many economic indices available for different countries and for different periods (e.g. Economic Sentiment Index). These indices can be used in future turning point forecasting studies depending on the relevance and the availability.
- (8) As discussed in this study, the price of tourism (exchange rates), income (GDP), airfare, and substitute destinations could affect inbound tourism demand to Australia from the USA, New Zealand, the UK and Japan, while the same factors could affect Australian outbound tourism to the same four countries in positive or negative relativity. Hence, it is research worthy to check the relationship between the inbound tourism demand turning points and

outbound tourism demand turning points and investigate demand magnitudes and lead or lag relationships between inbound and outbound tourism.

- (9) Though the Markov Switching model did not capture the turning points correctly over BB method, this modern non-linear method has great potential in tourism research. It can be tested with tourism cycles with different data sets as well as can be used in areas such as switching in different markets, switching of age groups and changes in proportions in arrival patterns etc.

10.7 Limitations of the Research

In order to forecast turning points, the benchmark turning point chronology is very important. One of the main limitations of this research is the unavailability of a past turning point chronology to be used as a benchmark to check the accuracy of the results. Further, in tourism economics there is no commonly accepted definition of what is meant by a 'turning point'. Hence this study has had to first establish the turning point chronology (identify significant turning points) using the MS and BB methods, and finally select the turning point chronology given by the BB algorithm. The risk here is that all the model results are compared with a chronology established within the same research. Therefore, any mistakes encountered while establishing the turning point chronology can affect the results of the study.

Another limitation experienced in this study was the selection of the independent variables for the Logit/Probit models and the selection of the potential leading indicator variables to construct the composite leading indicators. Since the Logit model has not been used to forecast turning points in tourism, the independent variables used in past tourism demand studies were used even though these studies were not focused on turning point forecasting. Since the theory behind the leading indicators is not rigid, and there is a lack of adequate research in leading indicators for tourism forecasting together with a non-availability of leading indicator data, the difficulty is to determine what should or should not be included in a composite indicator.

In this study, some particular data limitations were experienced in constructing the leading indicators. For New Zealand the unemployment, export and import data are

available only from 1986 Q1. For the UK the Business Survey index is available only from 1985 Q2. Furthermore, in this study air fare was used for the Logit/ Probit model as one of the explanatory variables. The airfare data used in this study are published airfares, and the actual discounted airfares are potentially different to the published airfares.

When comparisons are made between models, QPS is an important evaluation technique but the QPS probability test is possible only with parametric probability methods (e.g. Logit, Probit and MS methods) and not with the non-parametric BB method. This affects the selection of the best method and reduces the potency of the conclusion.

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Appendix

Appendix to Chapter 5

Hamilton's Procedure

Filtered Probabilities

Hamilton's (1989) procedure for filtering his switching regime model is composed of several steps. The basic feature of the procedure is that it is an iterative algorithm. It needs an input value, which is then updated using Bayes theorem into an output value. This output is then used as an input in the next recurrence.

The input value of the procedure is the joint conditional probability of the states at time t , $P(s_t, s_{t-1}, \dots, s_{t-k+1} | Y_t)$, and the output value is the joint conditional probability of the states at time $t+1$, $P(s_{t+1}, s_t, \dots, s_{t-k+2} | Y_{t+1})$. Each of the input and the output values is a vector consisting of 2^k elements, one for each possible combination of the k states in the joint probability (analogous to the k autoregressive lags). These 2^k elements are probabilities and always sum to unity. They represent the inference about the joint unobserved states $(s_t, s_{t-1}, \dots, s_{t-k+1})$. Note that in the general case where it has m phases, each conditional probability consists of m^k elements.

To set up the iteration, since this study looks at only two states, the procedure needs an initial value $P(s_2, s_1 | y_k)$. This value is set to equal the unconditional probability $P(s_2, s_1)$, using Bayes theorem:

$$P(s_2, s_1) = P(s_1) \times P(s_2 | s_1)$$

The first term of this product $P(s_1)$ has two elements. The first element is given by

$$P(s_1 = 1) = \pi_0,$$

where π_0 is the limiting probability of the Markov process from matrix. Evidently, the second element $P(s_1 = 0)$ is equal to $1 - \pi_0$. The value of π_0 is found by solving the equation

$$\begin{bmatrix} \pi_0 \\ 1 - \pi_0 \end{bmatrix} = TM \begin{bmatrix} \pi_0 \\ 1 - \pi_0 \end{bmatrix}$$

hence, $\pi_0 = (1 - q) / (1 - p + 1 - q)$.

The joint probability of S_1 and S_2 is obtained by multiplying $P(s_1)$ by $P(s_2|s_1)$,

$$P(s_2, s_1) = P(s_2|s_1)P(s_1).$$

This value denotes a set of four numbers, one for each possible combination of s_2 and s_1 . For example,

$$P(s_2 = 1, s_1 = 0) = P(s_2 = 1|s_1 = 0)P(s_1 = 0),$$

therefore

$$P(s_2 = 1, s_1 = 0) = (1 - q)(1 - \pi_0).$$

Then, the joint conditional densities of y_{k+1} and the $k+1$ states (s_2, s_1) are given by

$$f(y_2|s_2, s_1) = f(y_2|s_2, s_1) \times P(s_2, s_1|Y_1)$$

where we know the conditional distribution of y_{k+1} :

$$f(y_2|s_2, s_1) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(y_2 - \mu_1 s_2 - \mu_0)}$$

Note here that the word "density" will be used for continuous probability density functions, discrete probabilities, and those cases where combinations of continuous and discrete variables apply. Knowing the joint conditional densities of y_{k+1} and the $k+1$ states (s_2, s_1) , the conditional density of y_{k+1} is calculated by summing up all values of the states. Note that this is a summation of 2^{k+1} values:

$$f(y_2|s_1) = \sum_{s_2=0}^1 f(y_2|s_2, s_1)$$

We can then calculate the joint densities of the states (s_2, s_1) conditional on the data, by using the outputs from the two previous steps:

$$P(s_2, s_1 | Y_2) = \frac{f(y_2 | s_2, s_1)}{f(y_2 | s_1)}$$

Summing up the state s_1 it follows that:

$$P(s_2, s_1 | Y_2) = \sum_{s_1=0}^1 P(s_2, s_1 | Y_1)$$

We have seen how to calculate $P(s_2, s_1 | Y_2)$ from $P(s_1 | Y_1)$ the algorithm can be generalised for later periods. The following steps will be repeated to calculate $P(s_{t+1}, s_t | Y_{t+1})$ from $P(s_t, s_{t-1} | Y_t)$ for $t = k, \dots, N-1$.

Step 1: Let us assume that $P(s_t, s_{t-1} | y_t)$ is known. By adding another state to (s_t, s_{t-1}) , calculate the joint densities of (s_{t+1}, s_t, s_{t-1}) conditional on available data up to time t ,

$$P(s_2, s_1) = P(s_1) \times P(s_2 | s_1)$$

Note that $P(s_{t+1} | s_t) = P(s_{t+1} | s_t, \dots, s_{t-k+1}, Y_t)$ by the conditional independence of s_{t+1} and Y_t , and the first order Markov assumption

Step 2: Calculate the joint conditional densities of y_{t+1} and the $k+1$ states $(s_{t+1}, s_t, \dots, s_{t-k+1})$

$$f(y_2 | s_2, s_1) = f(y_2 | s_2, s_1) \times P(s_2, s_1 | Y_1)$$

where we know the conditional density of y_{t+1}

$$f(y_2 | s_2, s_1) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(y_2 - \mu_1 s_2 - \mu_0)}$$

Step 3: Calculate the conditional density of y_{t+1} by summing up all values of the states.

$$f(y_2|s_1) = \sum_{s_2=0}^1 f(y_2|s_2, s_1).$$

Step 4: Calculate the joint densities of the states conditional on the available data, by dividing the output from step 2 by the output from step 3.

$$P(s_2, s_1|Y_2) = \frac{f(y_2|s_2, s_1)}{f(y_2|s_1)}.$$

Step 5: The desired output is then obtained by summing up the two possible values of the state

$$P(s_2, s_1|Y_2) = \sum_{s_1=0}^1 P(s_2, s_1|Y_1).$$

Smoothing Probabilities

The full-sample of smoothed probabilities $P(s_t|Y_N)$ defines the state of the system, conditional on the entire series Y_N . These full-sample probabilities are obtained by calculating the smoothed probabilities $P(s_t|Y_j)$, which are probabilities about the current state s_t , based on data available through all future dates j , $j = t+1, \dots, N$.

From the output (Equation 5.21), the filtered probability $P(s_t|Y_t)$ of the current state s_t for $t > k$, based on currently available data, can be calculated using

$$P(y_t|s_1) = \sum_{s_{k+1}=0}^1 \dots \sum_{s_t=1}^1 f(y_t|s_2, s_1)$$

Using the same output for $t+1, \dots, t+k$, the probabilities $P(s_t|Y_{t+1}), \dots, P(s_t|Y_{t+k})$ can be obtained by summing the appropriate elements, for example:

$$P(y_{t+1}|s_1) = \sum_{s_{k+1}=0}^1 \dots \sum_{s_t=1}^1 f(y_{t+1}|s_2, s_1)$$

A similar algorithm to that of filtered probabilities can be run, and the full-sample of smoothed probabilities $P(s_t|Y_N)$ can be deduced from the smoothed probabilities

$P(s_t|Y_j)$ where $j > t$. The recurrence algorithm has the input $P(s_j, s_1, s_2|Y_j)$ and the output $P(s_{j+1}, s_1, s_2|Y_{j+1})$.

The algorithm assumes that $P(s_j, s_1, s_2|Y_j)$ is known where $j > t+k$. Adding another state s_{j+1} , the conditional joint probabilities are given by:

$$P(s_{j+1}, s_1, s_2|Y_{j+1}) = P(s_2|s_j) P(s_j, s_1, s_2|Y_j)$$

Then, the joint conditional density of y_{j+1} and the $k+2$ states (s_1, s_2) become:

$$f(s_j, s_1, s_2|Y_j) = f(s_{j+1}, s_1, s_2|Y_{j+1}) f(s_j, s_1, s_2|Y_j)$$

The joint conditional densities of y_{j+1} and s_t are then obtained by summing up all values of the remaining states, so that:

$$f(s_t|y_j) = \sum_{s_{j+1}=0}^1 \dots \sum_{s_{j-k+1}=0}^1 f(s_1, s_2|Y_j)$$

The joint conditional densities of the states (s_1, s_2) are obtained by normalising the previous output:

$$P(s_{j+1}, s_1, s_2|Y_{j+1}) = \frac{f(y_{j+1}, s_1, s_2|Y_j)}{f(y_{j+1}, s_t|Y_j)}$$

Summing up the state s_{j-k+1} it follows that:

$$P(s_{j+1}, s_1, s_2|Y_{j+1}) = \sum_{s_{j-k+1}=0}^1 P(s_{j+1}, s_1, s_2|Y_{j+1})$$

Once the above is computed for all t and all $j = t+1, \dots, N$, then the full-sample of smoothed probabilities $P(s_t|Y_N)$ will be known.