Forecasting International Regional Tourist Arrivals to China

Doctor of Philosophy Thesis

Volume I

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Special Tribute

I dedicate this thesis to

Ian, my late husband for his love, support and inspiration;

Zhiwei, my late father for always having faith in me;

and

Minnie and Walter, my late parents-in-law for welcoming me with open arms into the Grundy family.

Abstract

This study develops models to forecast international arrivals to regional China, using time series as well as causal explanatory methods. The nine quantitative forecast methods applied in this study are Holt, Exponential Smoothing, Naïve, ARMA, Neural, and Basic Structural Model (BSM) with and without intervention, and the causal explanatory forecast models are the Time-Varying Parameter (TVP) with and without dummy variables.

China was chosen as the country of study primarily due to its geographic size and the availability of data in a reasonably long range time-series, using international guest arrivals at accommodation establishments from the 13 most popular tourist source countries dating back to 1994 and through to 2007. These top 13 countries account for 92% of total international arrivals to China in 2007. The research allows for forecast analyses of a fairly wide variety of data patterns, as well as vigorous model testing and performance comparisons in the testing process.

In summary, this research has demonstrated a pressing need for advancing and expanding, international tourism forecasting from the current national based approach, to include regional forecasting. This research has only touched the surface of a field that has immense potential for international tourism forecasting at the sub-national level, not only for regions in China but for a wide variety of regions around the world.

Declaration

I, Yvonne Zhou-Grundy, declare that the Doctorate of Philosophy thesis entitled "Forecasting International Regional Tourist Arrivals to China" no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma, except where otherwise indicated, this thesis is my own work".

Signature: ________________

Date: ____________________

Acknowledgement

I wish to acknowledge all those people who have travelled with me in my journey to complete this research study. My sincerest thanks go to my family members, friends, colleagues, academic associates, and staff of my university, faculty and school for their generous and unwavering emotional support, encouragement and inspiration during the course of this study.

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Chapter 1
Introduction

Tourism has become one of the world's largest and fastest growing industries. The economic development of world regions has been linked increasingly to tourism development and particularly to the volumes of tourist arrivals (Song and Witt, 2000, Song et al., 2009). Global international tourism has become one of the major economic exports and a significant contributor to many national economic development strategies. International tourism as an export income provides employment opportunities and affects living standards through external economic benefits that flow into many sectors of a national economy.

In 2007, international tourism arrivals grew by 6% in 2007, to 898 million international tourist arrivals, as compared to 2006. Against the background of a strong growth of above 7% per year since 2000, the Asia and the Pacific region is also seeking international tourism and attracted 185 million visitors in 2008 (refer to UNWTO World Tourism Barometer, 2008).

The World Tourism Organisation 2020 Vision forecasts that worldwide international arrivals are expected to reach over 1.6 billion by the year 2020. The top three receiving regions will be Europe (717 million tourists), East Asia which includes China and the Pacific (397 million tourists) and the Americas (282 million tourists). The average annual growth rate for the period of 1995 to 2020 for East Asia is 6.5%, compared to the world average of 4.1 %; East Asia is expected to share 25.4% of the global tourist market (refer to Table 1.1.1).

Table 1.1.1 World Tourist Arrivals 1995 – 2010

	Base Year 1995	Forecasts 2010	Forecasts 2020	Market share (%) 1995	Market share (%) 2020	Average annual growth rate (%) 1995-2020
	(Million)					
World	565	1006	1561	100	100	4.1
Africa	20	47	77	3.6	5.0	5.5
Americas	110	190	282	19.3	18.1	3.8
East Asia and the Pacific	81	195	397	14.4	25.4	6.5
Europe	336	527	717	59.8	45.9	3.1
Middle East	14	36	69	2.2	4.4	6.7
South Asia	4	11	19	0.7	1.2	6.2

Source: UNWTO's Tourism 2020 Vision.

According to the World Tourism Barometer October 2007 published by the World Tourism Organisation, 846 million international tourist arrivals were recorded in 2006 (6.5% growth a year between 1950-2006) with international tourism receipts totalling US$ 733 billion, or 2 US$ billion a day; tourism represents around 35% of the world's exports of services and over 70% in Least Developed Countries (LDCs) (refer to World Tourism Barometer Vol 5, No 3 October 2007 UNWTO). International tourism receipts grew by 15.4% from 2006 to 2007 to reach US$856 billion (Turner and Witt, 2009). Tourism is also changing with the capacity of destinations to manage larger volumes of internationally diverse tourist populations, with new markets opening for tourists. International tourists are increasingly penetrating regional areas beyond entry ports of destination countries. As such, the forecasting of international regional tourist arrivals has become a more pressing issue in recent years for governments at all levels, in order to reliably estimate tourism growth and the economic benefits generated by expanding tourism activities. Increasingly, international tourism arrival volumes and hence receipts, have impacted on regions within countries that now compete amongst themselves to increase returns from tourism (VU and Turner, 2006). Tourism growth can no longer be simply measured at a country or national level, as regional governments seek regional forecast information for economic, transport and infrastructure planning for their regions, to enable a greater share of the growing world tourism receipts to be earned in their regions.

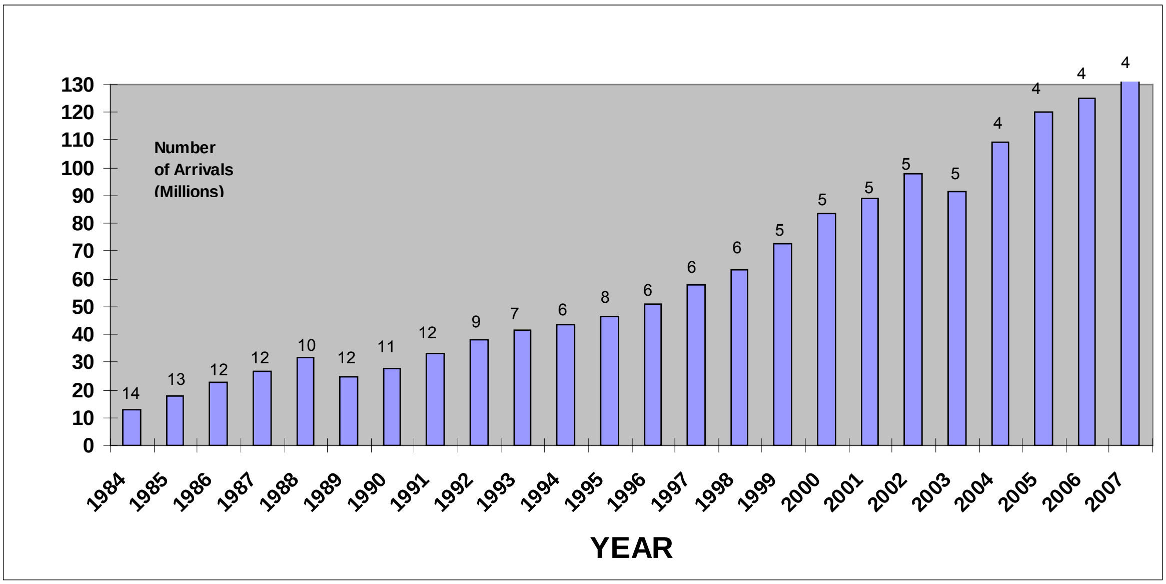
In the tourism forecasting literature, international tourism demand is generally measured in terms of the number of tourist visits from an origin country to a destination country (Song and Witt, 2000, Song et al., 2009). Forecasts of regional international arrivals have not gained the same recognition as national tourism forecasting. This may be due to unavailability of regional data required for such forecasting to take place, or a lack of urgency for regional forecasts in the past.

As this study branches away from the traditional country of destination based forecast to a regional specific forecast, the concept of regional forecasting and the forecast models that work best with regional data need to be developed and tested. The economic factors that influence tourism changes at the regional level need to be identified and examined in the development process. Although similar models to those used for national forecasting may be appropriate, no such assumption can be made. The available data may not be the same, the quality of the arrivals data may not be as good, and new processes need to be compared with known national forecasting models in a study framework capable of determining the most appropriate methodology for regional tourist arrival forecasting.

China has been chosen as the country of study for many reasons including: China has been predicted by the World Tourism Organization to become the world's top tourism destination by 2020. The number of foreign visitors to China reached 54.7 million in 2007 (UNWTO), from just 300,000 in 1978, with the Olympics as a launch pad and amid a rising global fascination in all things Chinese, China is expected to replace France as the world's top tourism destination by 2014 (refer to China Daily, 02/072007); China is a large country and a rapidly developing economy with 31 regions and 2 Special Administrative Regions (SARs); only recently, international regional tourist arrival data have become available in reasonably long range time-series based on regional guest arrivals at accommodation establishments dating back to 1994; there is significant increased industry demand for regional tourist forecasts in China stimulated initially from the 2008 Beijing Olympic Games and 2010 Shanghai World Expo, and evidenced by the recent translation and publication by PATA (Turner and Witt, 2008) by the China

National Tourism Organization. Finally China was ranked 4th in the world's top 10 tourism destinations in 2004 and has retained this position through to 2007.

Figure 1.1.1 Annual international tourist arrivals yearly world ranking



Source: China Statistic Yearbook 1996 – 2008 and CNTA website.

The need for regional forecasting has also been accelerated by the Chinese Central Government's initiative in developing the western and central regions, in order to ease social pressure and economic imbalance between the coastal developing regions and the inland and under developed regions in China. Many studies investigate the success and impact of rural and regional tourism development in China including Gao et al., (2009), Hu (2008), Lew and Yu (1995), Lew et al., (2003), Li (2008), Liu (2008) and Pine (2002), although there are also studies underlining the economic costs of tourism to developing countries (Sahli and Nowak, 2007). The national government of China considers openness in tourism trade as one significant way that economic development can be spread.

In summary, this research has taken a new direction in the research of tourism forecasting by looking into international tourism forecasting at the sub-national level in China, and by examining new models that may work best with regional data. Because this research is on the leading edge of the current literature in international tourism forecasting, it makes a significant contribution to the literature as well as providing a platform for further research on regional forecasting for other countries, as similar data increasingly becomes available at the regional level, including most immediately Australia, Canada, India, Japan, New Zealand, Thailand and the USA. The first regional forecasts for Canada and the USA were published by Turner and Witt (2008) although using new econometric time-series models only.

1.1 Overview of the Thesis

Chapter 1 provides a statement of the research problem, outlines aims and objectives of the research and its methodology.

Chapter 2 conducts a comprehensive review of the literature on tourism development in China as well as a literature review of tourism forecasting and model development including traditional time series modelling, ARIMA seasonal and non-seasonal modelling, structured time series and artificial neural networks as well as econometric modelling.

Chapter 3 provides detailed background information on the administrative divisions (six geographic regions) and the provinces, municipalities and autonomous regions within these geographic divisions in China.

Chapter 4 identifies the problems, issues and challenges that this study is facing and explains various research methods undertaken in order to achieve the objectives set out for this study. The details of possible data and model selection are discussed.

Chapters 5 embarks upon a vigorous and detailed process of data analysis, regional forecasting, model development and testing using various time series methods including Naive, Holt and Winter's, Exponential Smoothing, Box Jenkins, Basic Structural Model with and without interventions, and a Neural model.

Chapter 6 identifies and examines suitable economic causal variables for regional forecasting using the Time Varying Parameter model with and without dummy variables for forecast analysis.

Chapter 7 compares the performance of the different analytic models developed in Chapter 5 and Chapter 6 and concludes upon the aims and objectives of the thesis.

1.2 The Research Problem

Global tourists are no longer the visitors of major cities. More and more tourists are dispersed into regional areas beyond the major ports of entry. Regions within countries are competing to attract these tourists to encourage greater direct regional export income. It is imperative for the regional government to know when and where tourists will travel to their regions and how tourists will consume and spend their money. Regional governments and the tourism industry sectors want to have access to tourism forecasts in order to address tourism policy issues and plan investment on infrastructure, transportation and tourism related goods and services.

Over the past few decades, researchers and practitioners have placed a great deal of effort on tourism forecasting and model development. The literature review shows that the focus of these studies has been on tourism at the country or national level. There have been few studies based upon regional forecasting. In spite of the importance of China's role in the future world tourism market, literature in foreign languages about China's tourism development remains limited, (Xu, 1995, Lew and Yu, 1995, Wen and Tisdell, 2001). Forecasts of inbound tourism into China are even fewer in number including Turner et al., (2002), Turner and Witt (2008).

The main research problem of this study is to develop new models that can be recommended for forecasting international regional tourism demand accurately, by using international guest arrivals at accommodation establishment data. This research differs from current approaches to international tourism demand analysis that measure and forecast only the number of tourist visits from an origin country to a destination country.

Vu and Turner's 2006 study based on Thailand suggests that regional arrival data could be useful for accurately forecasting regional tourism demand for geographically larger countries such as China and India, where regional data have recently become available.

The second aspect of the research problem is to test and compare the performance of new models developed for international regional tourism forecasting with current models that are used for national forecasting. The current national forecasting has been widely accepted as useful by the tourism industry and researchers, as is evidenced by the production, publication and referencing of current studies. Consequently, one benchmark comparison is whether regional forecasting accuracy levels can be achieved that compare favourably with current national levels of accuracy (Vu and Turner, 2006).

The third aspect of the research problem is to identify and examine economic causal variables suitable for regional forecasting. According to Song and Turner (2006) explanatory variables that are widely accepted and commonly used for national tourist demand forecasting are: population and income per capita in the origin country of tourists generating, own price – the cost of travel to the destination and the cost of living for tourists in the destination, the exchange rate adjusted consumer price index, substitute prices in competing destinations, expenditures on marketing and advertising to attract tourists, and habit persistence relating to 'word of mouth' recommendations that play a key role in destination selection, as opposed to commercial advertising. Dummy variables such as 'one off events', are often entered into forecasting equations of international tourism demand. These 'one off events' such as the hosting of the Olympic Games and World Expo are likely to stimulate tourism activities whilst wars, terrorist attacks and health scares could negatively impact upon travel. It remains unclear whether these measures are also suitable for regional forecasting, or whether such data are available at a regional level. Causal variables specific to regions such as, the number of tourist attractions in the region, weather patterns, connectivity in terms of air and road travel to and out of the region, need to be carefully identified and examined for their use in regional forecasting.

In summary, this research aims to develop new models that can be used for forecasting international regional tourism demand accurately, by using international guest arrivals at accommodation establishment data. To test and compare the performance of new models developed for international regional tourism forecasting, with current models used for national forecasting, and to identify and examine potential economic causal variables suitable for regional forecasting.

1.3 Aims and Objectives

The specific aim of this study is to develop new models to forecast international tourism at the sub-national level in China, by using international guest arrival data at accommodation establishments, and to compare the performance of these new models with forecasts from other quantitative models currently used for national forecasting. This study is focused on the development of models using regional factors affecting international regional tourism in responding to demand from governments, particularly regional governments and tourism related industry for accurate regional forecasts that are increasingly underpinning the future success of tourism development, in the developing as well as under developed regions.

The objective of this study is to determine whether regional forecasting models can be used as a viable alternative to current national based tourism forecasting. In attempting to achieve this objective the study examines whether the new models can be used to accurately forecast international regional arrivals with regional data.

Figure 1.1.2 Map of China

Source: maps-of-china.com

1.4 Overview of International Tourism in China

The first record of travel outside of China was in 128 BC as noted by Fitzgerald (1969). But it is the most remarkable achievements of China's international tourism in recent decades that has attracted the world's attention. Table 1.4.1 indicates that the growth of international visitors (overnight visitors) to China, from 720,000 in 1978, the year when China adopted an 'open door policy' under the leadership of Deng Xiaoping, increasing to 54.7 million in 2007. The average annual growth rate is 16.1% for this period. Foreign exchange earnings were US$260 million in 1978 and increased to US$41.9 billion in 2007 with average annual growth of 19.2% for this period.

Table 1.4.1 International visitors and foreign exchange earnings 1978 - 2007 (10,000 people and US$100 million)

Year	Total Number	Total Earnings	Year	AAGR% Number	AAGR% Earnings
1978	72.0	2.6	1978-2007	16.1	19.2
1990	1048.4	22.2	1990-2007	10.2	18.9
2000	3122.9	162.2	2000-2007	8.3	14.5
2005	4680.9	293.0			
2006	4991.3	339.5			
2007	5472.0	419.2			

Source: China Statistic Yearbook 1996 - 2008.

1.4.1 Foreign Exchange Earnings and its Composition

Table 1.4.2 lists a basket of items of international tourist expenditure in 2006 and 2007. The items that have increased in 2007 from 2006 are: travel by air, rail, road and waterway, sightseeing, entertainment and post and communication services. The other items show slight decreases: accommodation, local transport, and food and beverage.

Table 1.4.2 Foreign exchange earnings and its composition 2005 - 2007 (US$100 million)

Year	2005		2006		2007	
Item	Value	%	Value	%	Value	%
Total	29296	100.0	33949	100.0	41919	100.0
Long Distance Transportation	8294	28.3	7376	21.7	11143	26.6
Civil Aviation	5928	20.2	6663	19.6	8791	21.0
Railway	904	3.1	279	0.8	771	1.8
Highway	718	2.5	310	0.9	694	1.7
Waterway	744	2.5	124	0.4	887	2.1
Sightseeing	1227	4.2	986	2.9	1800	4.3
Accommodation	3775	12.9	4867	14.4	5938	14.2
Food and Beverage	2748	9.4	3512	10.3	3748	8.9
Shopping	6378	21.8	11207	33.0	10494	25.0
Entertainment	1702	5.8	1253	3.7	2110	5.0
Post and Communication Services	844	2.9	511	1.5	761	1.8
Local Transportation	1030	3.5	1201	3.5	1242	3.0
Other Services	3299	11.3	3006	8.9	4683	11.2

Source: China Statistic Yearbook 2006 - 2008.

1.4.2 Composition of International Tourism to China

It should be noted that according to the 2008 China Statistical Yearbook international tourism refers to 2 major types of visitors: foreign visitors and compatriots from Hong Kong, Macau and Taiwan. Table 1.6 indicates the composition percent of each group. Although nearly 80% of international visitors to China are compatriots from Hong Kong, Macau and Taiwan, foreign visitors have increased from 12.7% in 1978 to 19.8% in 2007.

Table 1.4.3 Composition of international tourists 1978 - 2007

Type of visitors	1978	1990	2000	2006	2007
Foreigners	12.7%	6.4%	12.2%	17.8%	19.8%
Hong Kong and Macau Compatriots	*8.6%	89.95	845.0	78.7%	76.7%
Taiwan Compatriots		3.5%	3.7%	3.5%	3.5%

Note: *8.6% combined for Hong Kong, Macau and Taiwan.
Source: China Statistic Yearbook 1996 - 2008.

1.4.3 Top 13 Tourist Source Countries for China

Table 1.4.4 summarises the top 13 tourist source markets for China between 1995 and 2007 and they are Japan, South Korea, Malaysia, Singapore, Thailand, Philippines, UK, Germany, France, USA, Canada and Russia. These 13 countries generated a total of 19.9 million tourists to China in 2007, representing 92% of the total foreign tourists to China (21.6 million) at an average annual increase rate of 34% for the period.

Table 1.4.4 Top 13 tourist source markets for China 1995 - 2007 (10,000 people)

	Jap	M'sia	Phil	Spore	Korea	Thai	UK	Germ	France	Russia	Can	USA	Aust	Total
1995	131	25	22	26	53	17	18	17	12	49	13	51	13	447
1999	186	37	30	35	99	21	26	22	16	83	21	74	20	670
2000	220	44	36	40	134	24	28	24	19	108	24	90	23	815
2001	239	47	41	42	168	30	30	25	20	120	25	95	26	906
2002	293	59	51	50	212	39	34	28	22	127	29	112	29	1086
2003	225	43	46	38	195	28	29	22	16	138	23	82	25	909
2004	333	74	55	64	284	46	42	37	28	179	35	131	38	1346
2005	339	90	65	76	355	59	50	45	37	222	43	156	48	1585
2006	375	91	70	83	392	59	55	50	40	241	50	171	54	1731
2007	398	106	83	92	478	61	61	56	46	300	58	190	61	1990
Total	2738	617	500	545	2371	384	374	326	256	1568	321	1152	336	11485

Source: China Statistic Yearbook 2006 – 2008 and CNTA website.

As shown by Table 1.4.5, during 1995 to 2007, these 13 countries generated a total of 11,485 million tourists to China. Japan is the largest source market (23.8%); whilst France was the smallest with 2.2% of the total arrivals from 13 countries in this period (refer to Table 1.4.5).

Table 1.4.5 Rank of the top 13 source countries and visitors to China 1995 - 2007 (10,000 people)

Ranking	Country	Total visitors to China 95-07	% Total
1	Japan	2738	23.8
2	Korea	2371	20.6
3	Russia	1568	13.6
4	USA	1152	10.0
5	Malaysia	617	5.4
6	Singapore	545	4.7
7	Philippines	500	4.4
8	Thailand	384	3.3
9	UK	374	3.3
10	Australia	336	2.9
11	Germany	326	2.8
12	Canada	321	2.8
13	France	256	2.2
	Total	11485	100

Source: China Statistic Yearbook 2006 - 2008 CNTA website.

1.4.4 International Tourists by continent /region

In 2007 China recorded visits by more than 21.6 million foreign visitors, or an average annual growth rate of 11.4% from 1995 to 2007. Over 74% of the tourists to China were from Asia; followed by Europe with 28.8% and North America 11.9%. In terms of the market growth rate during 1995 and 2007, Table 1.4.6 indicates that Africa has become an emerging source market with an AAGR of 20.4%, followed by Asia 13.9%, 13.5% for Oceanic and Pacific Islands, 12.2% for North America, 12% for Europe and 9.4% for Latin America.

Table 1.4.6 Foreign visitors by continent / region 1995 - 2007
(10,000 people)

Region	1995	2000	2002	2004	2006	2007	% Total 2007	AAGA% 95-07
Total	588.7	1016.0	1344.0	1693.3	2221.0	2161.0		11.4
Asia	338.3	610.2	864.4	1073.7	1358.8	1606.1	74.3	13.9
Africa	4.1	6.6	9.9	17.3	29.4	37.9	1.8	20.4
Europe	159.1	248.9	282.6	377.6	528.0	621.7	28.8	12.0
L. America	5.4	8.3	9.7	13.3	19.6	16.0	0.7	9.5
N. America	64.4	113.3	141.3	165.7	221.0	256.2	11.9	12.2
Oceanic and P.Islands	15.9	28.2	35.4	45.2	63.9	72.6	3.4	13.5
Others	1.7	0.7	0.8	0.5	0.4	0.3	0.01	-13.2

Note: Foreigners refer to foreign nationals (exclude compatriots from Hong Kong, Macau and Taiwan).
Source: China Statistic Yearbook 1996 - 2008.

1.4.5 Top 10 Chinese Regions for International Visitors

Table 1.4.7 lists the top 10 most popular Chinese provinces (regions) for international visitors to China and the earnings generated from tourism activities in 2007. These provinces (regions) account for 42.4% of the total international arrivals to China and 72.8% of currency earnings. Guangdong tops the nation with 18.7% of China’s total international tourists and 20.8% of total earnings. However, it is noted that most of these provinces (regions) are along the east, northeast and south coastal area of China, except for Yunnan and Guangxi which are inland provinces in the south and southwest of China, and are known for their unique minority cultures and scenery.

Table 1.4.7 Top 10 Chinese provinces for international visitors and earnings 2007 (10,000 people and US$ million)

Ranking	Province	Number	% China	Province	Earnings	% China
1	Guangdong	2461	18.7	Guangdong	8706	20.8
2	Shanghai	520	3.9	Shanghai	4673	11.1
3	Jiangsu	513	3.9	Beijing	4580	10.9
4	Zhejiang	511	3.9	Jiangsu	3469	8.3
5	Beijing	435	3.3	Zhejiang	2708	6.5
6	Fujian	269	2.0	Fujian	2169	5.2
7	Shandong	250	1.9	Shandong	1352	3.2
8	Yunnan	222	1.7	Liaoning	1228	2.9
9	Guangxi	206	1.6	Yunnan	860	2.1
10	Liaoning	200	1.5	Tianjin	779	1.9
Total		5586	42.4		30524	72.8
China total		131873			41919	

Source: China Statistic Yearbook 2008.

1.4.6 Domestic Tourism in China

Table 1.4.8 indicates that China's domestic tourist market has also grown at a steady pace from 2000 to 2007. Domestic tourists totalled 1,610 million in 2007 with 13.7% growth per year from 2000. Earnings from domestic tourism were 777.1 billion RMB yuan in 2007 with 16.1 % growth per year for the same period.

Table 1.4.8 Domestic tourists and earnings 2000 - 2007 (million people and 100 million RMB yuan)

	2000	2001	2002	2003	2004	2005	2006	2007	AAGR %
Tourists	744	784	878	870	1102	1212	1394	1610	13.7
Earnings	3176	3522	3878	3442	4711	5286	6230	7771	16.1

Source: China Statistic Yearbook 2008.

As shown by Table 1.4.9 an Table 1.4.10, China's total domestic tourism market comprises 612 million urban residents (38%) and 998 million rural residents (62%) in 2007. Total earnings are 777 billion RMB yuan, with 555 billion RMB yuan for urban (71.4%) and 222 billion RMB yuan (28.6%) for rural tourists. Urban tourists also had higher per capita expenditure of 907 RMB yuan compared to rural residents with 223 RMB yuan.

Table 1.4.9 Chinese domestic tourism market 1994 - 2007
(million people)

Year	Domestic Tourists	Urban Residents	Rural Residents
1994	524	205	319
1995	629	246	383
1996	640	256	383
1997	644	259	385
1998	695	250	445
1999	719	284	435
2000	744	329	415
2001	784	375	409
2002	878	385	493
2003	870	351	519
2004	1102	459	643
2005	1212	496	716
2006	1394	576	818
2007	1610	612	998
AAGR%	9.02	8.78	9.17
Total %		38.0	62.0

Source: China Statistic Yearbook 2006 - 2008.

Table 1.4.10 Domestic tourism earnings 1994 - 2007
(100 million RMB yuan)

Year	Tourism Earning	Urban Residents	Rural Residents	Per Capita Expenditure (Yuan)	Urban Residents	Rural Residents
1994	1024	848	175	195.3	414.7	54.9
1995	1376	1140	236	218.7	464	61.5
1996	1638	1368	270	256.2	534.1	70.5
1997	2113	1552	561	328.1	599.8	145.7
1998	2391	1551	876	345	607	197
1999	2832	1748	1084	394	614.8	249.5
2000	3176	2235	940	426.6	678.6	226.6
2001	3522	2652	871	449.5	708.3	212.7
2002	3878	2848	1030	441.8	739.7	209.1
2003	3442	2404	1038	395.7	684.9	200

2004	4711	3359	1352	427.5	731.8	210.2
2005	5286	3656	1630	436.1	737.1	227.6
2006	6230	4415	1815	446.9	766.4	221.9
2007	7771	5550	2220	482.6	906.9	222.5
AAGR%	16.9	15.5	21.6	7.2	6.2	11.4
Total %		71.4	28.6			

Source: China Statistic Yearbook 2006 - 2008.

1.4.7 Outbound Chinese Tourists

Since 2000, the number of Chinese nationals travelling overseas has been growing exponentially. Table 1.4.11 indicates that over 10.47 million Chinese travelled overseas in 2000 increasing to 40.95 million in 2007, with an average annual growth rate of 22% for the period (refer to Table 1.4.11). The Chinese outbound tourism market will continue to grow due to relaxed government policies and increased personal disposable income (Li et al., 2010).

Table 1.4.11 Outbound Chinese tourists 1994 - 2007
(10,000 people)

Year	2000	2001	2002	2003	2004	2005	2006	2007	AAGR%
Number	1047	1213	1660	2022	2885	3103	3452	4095	22

Source: China Statistic Yearbook 2008.

1.4.8 Tourism in China's National Economy

China became the fourth largest inbound tourist receiving country in the world and fifth in terms of foreign currency earnings (refer to Table 1.4.12 and Table 1.4.13).

Table 1.4.12 World's top 10 tourist destination 2007
(million people)

Rank	Country	Arrivals	% Market Share
1	France	81.9	9.1
2	Spain	59.2	6.6
3	USA	56.0	6.2
4	China (PRC)	54.7	6.1
5	Italy	43.7	4.8
6	UK	30.7	3.4
7	Germany	24.4	2.7
8	Ukrine	23.1	2.6
9	Turkey	22.2	2.5
10	Mexico	21.4	2.4

Source: Turner and Witt (2009) p7- 8.

Table 1.4.13 World's top 10 tourism receipts
(US$ billion)

Rank	Country	Receipts	% Market Share
1	USA	96.7	11.3
2	Spain	57.8	6.8
3	France	54.2	6.3
4	Italy	42.7	5.0
5	China (PRC)	41.9	4.9
6	UK	37.6	4.4
7	Germany	36.0	4.2
8	Australia	22.2	2.6
9	Austral	18.9	2.2
10	Turkey	18.5	2.2

Source: Turner and Witt (2009) p7- 8.

After SARS, China recovered rapidly in 2004. In 2007 international arrivals totalled 54.7 million with US$41.9 billion in tourism receipts.

As shown in the Table 1.4.14 tourism receipts in 2000 were US$16.2 billion, 1.4% of national GDP, rising to US$41.9 billion in 2007 to represent 1.3% of GDP. However, the percentage of tourism income in overall national GDP is still low.

Table 1.4.14 International tourism receipts proportion to Chinese National GDP

Year	GDP RMB 100 mil	Conversion CNY/USD	GDP US$ 100 mil	Tourism Receipts US$ 100 mil	Tourism Receipts % GDP (US$)
2000	99215	8.2784	11985	162	1.4
2001	109655	8.2770	13248	178	1.3
2002	120333	8.2770	14538	204	1.4
2003	135823	8.2770	16410	174	1.1
2004	159878	8.2768	19316	257	1.3
2005	183868	8.1917	22446	293	1.3
2006	211924	7.9718	26584	339	1.3
2007	249530	7.6040	32816	419	1.3

Source: China Statistic Yearbook 2006 - 2008.

The growth for international tourism is likely to continue, due to China's successful hosting of the 2008 Beijing Olympic Games, and the 2010 Shanghai World Expo. Both events have brought larger volumes of international tourists to China and significant current and future world recognition. In addition, China's accession to the World Trade Organisation in 2001 will also serve as a stimulator to a further increase in business and investment related tourism into China. As noted by Kulendran and Shan (2002), as China increasingly moves through the early WTO concessions and controls are freed up, investment restrictions in the future will be lessened.

1.4.9 Tourist Hotels

During 2000 and 2007, the tourism industry witnessed a vigorous development in tourist hotel construction. Additionally, on 24 July 2004 China implemented the Law on Administration Licensing for Star-Rated Hotels aimed at standardising the hotel industry. According to the China Star-Rated Hotel Guide 2008-2009, there were a total of 13,583 star-rated hotels in China in 2007, an increase of 7,554 hotels from 2000, with an annual increase of 14.5% for this period. The percentage of the 5-star hotels is 2.7% and 4-star hotels is 11.7% of the total hotels in China in 2007.

Table 1.4.15 China star-rated hotels 2000 – 2007

Star - rated hotels	2000	% total	2007	% total	AAGR% 2000 - 2007
Total	6029		13583		14.5
5-star	117	1.9	369	2.7	21.1
4-star	352	5.8	1595	11.7	28.6
3-star	1899	31.5	5307	39.1	18.7
2-star	3061	50.8	5718	42.1	11
1-star	600	10.0	594	4.4	-0.2

Source: CNTA WEBSITE internet and China Statistic Yearbook 2008.

Compared with 2000 (refer to Table 1.4.15), the average annual increase in the number of 5-star hotels was 21.1% for the period 2000 to 2007, and 28.6% for 4-star hotels. Noticeably, the greatest increase is in the upper end of the market with 4 and 5 star hotels and this reflects the growth of international visitors to China in recent years, as well as increased domestic living standards. The international market is less likely to use smaller local hotels, and hotels not offering a wide range of services.

1.4.10 Tourism Infrastructure

The summary figures in Table 1.4.16 indicate that in recent years, China has made great efforts to improve rail, road and air transport networks. During 2002 to 2007, the total volume of passengers handled by railways increased at an annual growth rate of 5.1%, with highways including expressways 6.8%, and airlines 16.7%.

Table 1.4.16 Rail, road and air passengers handled 2002 – 2007
(10,000 kilometres and 10,000 people)

China total	2002	2003	2004	2006	2007	AAGR % 2002 - 2007
Railways		7	7	8	8	1.7
Total passengers	105606	97260	111764	125656	135670	5.1
Highways & expressways	177	181	187	346	358	15.2
Total passengers	1475257	1464335	1624526	1860487	2050680	6.8

Civil aviation routes	164	175	205	211	234	7.4
Total passengers	8594	8759	12123	15968	18576	16.7

Source: China Statistic Yearbook 2008.

Air transport plays a pivotal role in tourism development by bringing international visitors to China including to regional China. Over the period of 1990 to 2007 (as shown by Table 1.4.17) there has been tremendous growth in the number of new airports, aircraft, airlines and routes in China's aviation sector. The average annual growth rate was 7.5% for opening up new air routes, of which 11.7% was for the international sector, 7% for the domestic sector and 11.1% for the regional sector. Growth for new airports was 2.6%, and 7.6% for new aircraft. The growth for total passengers handled was 15.3%, of which 17.2% was for international, 16% for domestic and 6% for regional passengers.

Table 1.4.17 Civil airport, aviation routes and passenger volumes 1990 – 2007 (New routes and 10,000 people)

	1990	1995	2000	2005	2006	2007	AAGR % 90-07
Total routes	437	797	1165	1257	1336	1506	7.5
International	44	85	133	233	268	290	11.7
Domestic	385	694	1032	1024	1068	1216	7.0
Regional	8	18	42	43	43	48	11.1
Total civil airports	94	139	139	135	142	148	2.7
Total civil aircrafts	503	852	982	1386	1614	1813	7.8
Total passengers	1660	5117	6722	13827	15968	18576	15.3
International	114	368	690	1225	1415	1692	17.2
Domestic	1346	4419	6031	12602	14553	16884	16.0
Regional	200	330	403	509	536	541	6.0

Note: Since 1997, regional routes to/from Hong Kong and Macau are accounted as domestic routes.
Source: China Statistic Yearbook 2006 - 2008.

The most recent Civil Aviation Administration of China (CAAC) statistics indicate that more than a third of China's 133 airports are now capable of handling one million passengers a year, with a further 55 hubs expected by 2020, it is expected that China will surpass Japan to become the world's second largest national aviation market as early as 2010, with projected passenger figures of 950 million by 2020. CAAC statistics predict that three airports per year will be constructed in China through to 2020, in order to accommodate growing passenger figures (refer to www.airport-technology.com).

The Airport Council International's (ACI) annual report on airport traffic data 2007 worldwide, shows that Beijing Capital International Airport has been ranked in 9th position among the top 30 world's airports in 2006, in terms of passengers served (53.58 million), up by 10% from 2006 (refer to July 29, 2008 Rank City (Airport) www.aci.aero). Shanghai and Guangzhou are among the world's top 10 growth airports with consistent growth of over 10% for 2005 and 2006 (refer to IATA 2007, 51st Edition, p. 49).

1.4.11 China's 11th Five-Year Tourism Plan for 2006-2010

According to media reports from the General Administration of Civil Aviation of China (CAAC), western China will have an additional 37 airports during the 11th Five-year Plan period (2006-2010), of which six are relocated, and 31 others rebuilt or extended. The overall airport reconstruction project in the western China region will cost 52 billion yuan (6.5 billion US dollars). In 2006, the CAAC and western provinces and autonomous regions agreed upon a blueprint for "airport construction" during the 11th Five-year Plan Period, which includes construction of new airports in Tibet, Qinghai, Xinjiang, and Inner Mongolia (refer to www.Chinadaily.online).

1.4.12 Conclusion

China's achievements in the development of international tourism have been truly remarkable as shown by the figures and tables presented in this Chapter. It is evident that China has benefited economically and socially from the growth of inbound tourism and the growing significance of foreign exchange earnings (US$41.9 billion in 2007) generated by international tourism and the increased proportion of tourism earnings to

China’s national GDP (1.28% in 2007). However, the review also indicates that overall employment (185,800 people) by the hotel and catering sector is less than 1% (0.78%) of the total employment of the tertiary industry sector (249,170,000) (refer to China Statistic Yearbook 2008, p.113 and p.116). This remains a challenge for China to train a sufficient workforce, ready to service the growing international visitors predicted to reach 37.2 million in 2010 and 45.7 million in 2011 (Turner and Witt, 2009).

Chapter 2
Literature Review

2.1 The History of Tourism Development in China

2.1.1 Introduction

As the focus of this study is on the forecasting of international regional tourism in China, it is pertinent to review the history of China's tourism, and its development so far, in order to gain an appreciation of how travel and tourism has been unfolding from Ancient China to the twenty-first century. As noted by Guo et al., (2002) tourism is not a new stage in China's economic development, but is a renaissance and reinvigoration of established economic activity that has roots dating far back into history.

The literature review shows that there have been limited foreign language publications on Chinese tourism, and even fewer on the subject of forecasting. A book written by Zhang et al., (2005) titled "Tourism and Hotel Development in China" gives a very comprehensive overview of the history and development of tourism and the hotel industry in China. According to Zhang et al., (2005), 1978 marked an important turning point for China's tourism and hotel development when China embarked on economic reform and "opened its door" to the outside world, and tourism came to be considered an economic activity for earning foreign currency. Post 1949 to 1978 prior to the "open door policy" the attitude was that travel was only for political and diplomatic purposes.

In his book titled 'Tourism and Local Economic Development in China" Xu (1999) researched three Chinese cities, Guilin, Suzhou and Beidaihe as case studies on the economic, social-cultural and environmental effects of tourism development in China from the period of the early 1980s to early 1990s. The author also discussed the role of tourism in balancing sub-national development (Xu, 1999). He argued that in tourism studies most attention is given to the key factor of tourism and its contribution to the "balance-of-payments" in earning foreign currency in the tourism host countries, whilst issues of revenue distribution within host societies have received comparatively little attention (Xu, 1999, Xu, 1995). Wen and Tisdell (2001) discussed issues relating to regional economic growth, reducing spatial economic disparity, as well as, possible social and economic impacts resulting from the expansion of tourism (primarily international tourism) in China since 1978, the year when 'China opened up to the outside world' through to the end of the 20th century. This book pays particular attention to the regional distribution of China's tourism development and the possible impact of this development on China's regional economic growth. Some recent studies by Li (2008), Gao et al., (2009) and Hu (2008) reveal the successes and impacts of rural (regional) tourism development in China. Moreover, tourism as a service industry potentially provides the means for developing countries such as China to move toward a service economy based around tourism (Vu and Turner, 2009).

2.1.2 Travel in Ancient China

Travel in ancient China was mainly conducted by five groups of people: emperors and royal families; mandarins and officials, scholars and scientists, clerics and worshippers as well as traders. Travel in ancient times also served the needs of peace and war. Emperors' orders and communication between feudal states had to be transported physically. During periods of war, scholars (philosophers) frequently travelled between feudal states to spread their philosophy of peace and a harmonious society.

Before the second century BC, there is very little historical record on whether the Chinese had any contact with distant foreign people. The first record of travel outside of China was in 128 BC when the envoy Chang Ch'en was chosen by Emperor Wu (140-87 BC) to carry a mission to forge an alliance with a tribe called Yuen-Chih with whom China shared a common enemy – the Hsiung-Nu Tartars. As noted by Fitzgerald (1969) the original reason for making contact with the lands of the west was for military purposes.

As symbols of dynastic authority, power and prosperity, Chinese emperors often travelled in a large entourage of people and carried luxury goods. To facilitate travel of such magnitude, huge travel infrastructure was constructed to accommodate the travel needs of emperors and their royal families. The Grand Canal, a total of 1,801 kilometres long, the world's longest man-made canal, starts from Beijing in the north to Hangzhou in the South. The construction started in the 5^{th} century BC and was continuously extended through the following Qin and Shi dynasties, as noted in a study by Guo et al., (2002). The emperors and their royal families were the frequent users of the Canal, during summer time, travelling from north to South for leisure. The Canal also served as a major water way for the transportation of goods and armies between the north and south.

2.1.3 Travel for Trade and Economic Prosperity

The first contact with Western Asia was the result of trade. The trail used by early traders has later become known as the Silk Road from Chang'an (the capital city of the Tang Dynasty, present Xi'an in Shaanxi Province) through to the Shaanxi-Gansu Plateau, Passing Wushao Ridge, Wuwei in Gansu and crossing the Hexi Corridor to Dunhuang, the then communication hub between Chang'an and the West. The Silk Road went further west through the Taklimakan Desert in Xinjiang Uygur Autonomous Region into Central Asia. The Silk Road thus linked China with Central and Western Asia, and with the Greek and Roman civilisations (Foreign Language Press, 1958). The Chinese traded silk and spices in return for horses and other tradable items. Through the northern route the Polo brothers reached Turfan and Hami, and then headed south-east to Dunhuang. Along the Hexi Corridor, they finally reached the new capital of the Great Khan, Beijing in 1266 and 10 years later, at the end of the year 1271, the Polos once again set out from Venice on their journey to the east. They took with them 17-year-old Marco Polo and two friars. They passed through Armenia, Persia, and Afghanistan, over the Pamir, and all along the Silk Road to Cathay (China) (refer to 'Marco Polo and His Travels' www.silk-road.com/artl/marcopolo).

The traders, themselves became international visitors to China (Menzies, 2002) and Marco Polo (1254 - 1324) is probably the most famous of these Western travellers to travel on the Silk Road. He exceeded all the other travellers in his writing and his influence. His journey through Asia lasted 24 years, reached further than any of his predecessors, beyond Mongolia to China proper became a confidant of Kublai Khan (1214 - 1294), travelled the whole of China and returned to tell the tale, which then became the greatest travelogue in history.

The Tang Dynasty was regarded as the most prosperous dynasty in Chinese imperial history (Nourse, 1944) and its capital city was Chang'an (today's Xi'an). It is also the longest dynasty stretching almost 300 years. The ever lasting prosperity and glory of the Tang Dynasty was credited to Emperor T'ai Tsung of Tang, who unlike his predecessor, set an example of living a simple life and treating his people well. He adopted modest taxing policies that aimed at increasing wealth to peasants who in return stimulated economic growth (Haw, 1995, Foreign Language Press, 1958, Nourse, 1944).

During the Tang and Song Dynasties, foreign traders contributed greatly to China's economic prosperity. China traded with neighbouring countries such as Japan, Korea and the more distant lands of Asia including India as well as Africa and Southeast Asia. The Chinese were master navigators and had established well mapped routes from China into the Indian Ocean by sea. On return voyages they often carried envoys and merchants from the trading countries to visit China. Many Arabs travelled to China and stayed for long periods, with large colonies in the Southern ports along with communities of Jews. Historically, it can be said that the origins of international tourism directly relate to the development of international trade.

During the period of the Tang Dynasty, China developed as the world's most powerful nation economically and intellectually. China was also the centre of economic and cultural intercourse for Asia, and a major trading nation in the Indian Ocean. During this period, many foreigners travelled to China and many Chinese travelled overseas.

2.1.4 Travel and Social Stability

Social stability is one of the most important conditions required for the development of travel and tourism. Whenever China became stable and united, travel and trade enjoyed a steady increase as in the case of the Tang Dynasty. After a long period of trade with the outer world, the economically strong and socially stable dynasties continued from Tang to Song, Yuan and the early Ming empires. In sharp contrast to the attitude of the Tang and Song empires, a spirit of self sufficiency and a stay at home complacency began to dominate China in the later Ming Dynasty (15^{th} Century). Foreign visitors to China were discouraged. The Ming government was not interested in communicating with the outside world, and refused to establish diplomatic relations with other countries. Foreign trade during the late Ming dynasty was restricted to a single port – Canton.

The later Ming government also stopped travel overseas. China's door was effectively closed in 1423 (Menzies, 2002) to the outside world. This stopped the Silk Road trade, and in particular the very important spice trade. After the Ming Dynasty imposed this isolation from the outside world, the Portuguese and Spanish set out to find the Spice Islands with the aim of regenerating the spice trade. This European exploration resulted in opening up the western world including the Americas, Africa and Australia. It is ironic to note that the maps used by the Europeans to discover the Americas and the spice islands some 100 years later, were made as a result of the Chinese circum-navigation of the known world during the period 1421 to 1423 (Menzies, 2002).

The next major opening up occurred after the 1860s' Opium War, when the then disunited and destabilised Qin Dynasty lost the war to British capitalists who wanted to profit from their trade with China by importing manufactured goods to China in exchange for industrial raw materials at low prices. As a result of losing the Opium War to the British, China's door was forced to reopen for foreign trade and travel (Pan, 1990). The resulting concessions granted to foreign governments including America, Britain, France, Germany, Italy, Portugal, Japan and Belgium created entry points for tourism and trade from those countries.

China again closed its doors to the outside world during 1949 to 1978 when China endured a long period of isolation from the western world, partly due to an economic embargo imposed by the USA, when Mao led the communist established People's Republic of China. On the other hand, the communist Chinese adopted a self sufficient independence policy which was free of foreign involvement. Mao's ideological policies lasted three decades and impacted strongly on tourism development in China.

2.1.5 Travel in Mao's Era (from 1949 to 1978)

After Mao's Communists defeated the Japanese and drove the Nationalists out of China to Taiwan, the People's Republic of China was established in 1949. For the first time in centuries China was united and ruled by a strong Chinese government. From the experience of war and the reality of the 20 year embargo imposed on China after 1949 by the USA, the economic development policy built an independent, centralised and self-reliant Chinese Nation that was free of foreign domination. In a real sense, the structure of the government was fundamentally identical to governments in imperial dynasties. Mao's ideological policies did not recognise tourism as an economic activity and source of national income. Inbound and outbound travel and foreign visits were strictly separated and handled by authorised and dedicated travel organisations. Official travel organisations such as CITS (China International Travel Service) and CTS (China Travel

Service) were set up for the arrangement of inbound travel under the leadership of the Ministry of Foreign Affairs. CITS was dedicated to service foreign guests, experts and friends whilst CTS was a separate travel service for overseas Chinese. The travel activity was centred on "people to people diplomacy" seeking no economic benefit for the country. These foreign guests and overseas Chinese were treated as VIPs, with endless banquets and meetings with government officials.

During this time and up to 1978, the concept of tourism did not fit into China's socialist ideology. Travel was considered only for diplomatic needs, and people to people exchange for better diplomacy that served political goals rather than economic gains. Mao's socialist ideology resulted in an inadequate tourism infrastructure and further limited the development of both an international and domestic tourism industry. Additionally, excessive pressure to expand the population size reduced the impact of economic growth, and left China with a significant problem of over population and economic underdevelopment.

2.1.6 Tourism Development Post 1978 (the Open Door Policy)

The year 1978 had great significance for the Chinese people and the history of China. In December that year, a meeting held by the Central Committee of the Chinese Communist Party launched China's economic reform and Open Policy. After 30 years Mao's socialist ideology of economic equality finally gave way to a new ideology that promoted the building of a modern China, with Chinese characteristics, strong economic growth and permission for part of the population to become wealthy (which was unthinkable during Mao's rule).

Soon after 1978, China's leaders began to set targets for quadrupling production per capita by the end of the century. In the wake of the new economic reform, the old paradigm of "social stability comes from economic equality" was replaced by the new theory of “China’s political stability can only be maintained if economic prosperity is achieved.” Many political ideologies were broadened to include economic development as the key element. Since 1978, China’s economic growth rate has been among the worlds highest. China’s average annual growth has been well over 8% for more than two decades. Moreover, China’s open policy and continuing economic reforms have greatly contributed to the development of inbound and outbound tourism in China. Modern international tourism and the tourism industry in China started after 1978, although the first travel agencies such as Thomas Cook and Sons recorded operations in 1923 in Shanghai (Yang and Jiang, 1983, Hibbert, 1990), this was short-lived due to civil war in the 1930s and the Sino-Japanese war of the 1940s, and only truly began post 1978.

2.1.7 Conclusion

This brief review of travel and tourism development in China has revealed that openness in China and its social stability are critical to travel and tourism development. The impact of tourism is directly linked with trade and exports, earning of foreign currency, provision of employment and hence the role of contributing to improving living standards. In more recent years the development of travel may also be linked to policy development and in particular the development of political influence by China to the wider world.

The review of travel also indicates that there has been limited foreign language studies published on China’s tourism development. Similarly, the literature regarding the forecasting of tourism demand in China is also rare. In the wake of China’s growing position in global tourism, the demand for accurate tourism forecasting has been growing strongly. Although there are studies forecasting international country to country travel that include China there is now increasing demand to forecast regional travel within China as a fist step in measuring its economic and social impact. Regional forecasts have become the interest of both regional as well as national governments in China, for the planning of tourism related infrastructure, transport, hotel accommodation and other tourism goods and services. These developments are primarily needed for economic reasons and relate to the potential for regional economic expansion, and also to aid in balancing and equalising regional growth disparity.

The focus of this study is on international regional tourism because of its capacity to generate export trade increases directly to the regional level. There is equally an important domestic travel trade. However, currently the data required to study these phenomena are primarily limited to international travel.

Consequently, it is important for the purpose of this research to conduct a review of the relevant literature in tourism forecasting in the second part of Chapter 2, and to examine past research developments and their relevance to the regional forecasting in this study.

2.2 Tourism Forecasting Literature Review

2.2.1 Introduction

A forecast is a statement of prediction made at the present time into a possible occurrence of future events. Tourism forecasting may be generated by either quantitative approaches or qualitative approaches (Flechtling, 2001). The prime focus of tourism demand studies is modelling tourism demand to analyse the effects of various determinants, and accurate forecasting of future tourism demand. Forecasting could be made based on speculation, expert opinions, surveyed outcomes, qualitative or quantitative analysis of historical data or records (Li et al., 2005). However, forecasts in this thesis use quantitative techniques because of the scientific methods that can be applied including rigorous error measurement that cannot occur with qualitative methods. This approach is considered most appropriate at an early stage in the investigation of travel in China. Quantitative forecasting methods estimate future trends in a system based on historical behaviour patterns or relationships in past time series. If behaviour patterns of the past can be identified in the past data series, future values of the series can be forecast to some extent, assuming that the historical pattern will reoccur in the future. However, due to unforeseen reasons such as political and economic uncertainties, social and environmental changes, criminal activity such as terrorist attacks and major health scares, the historical behaviour patterns do not always reappear in the exact same patterns in the future as they did in the past. These uncertainties make it difficult for any forecast to have absolute accuracy. In spite of these uncertainties, over the past few decades, practitioners and researchers have developed a series of quantitative methods to provide useful and meaningful forecasts to government and industry for tourism planning and policy formulation. Moreover, forecasting is not limited by unforeseen events because one additional use of forecasting is the capacity they provide to also measure the impact of shocks – this being the difference between forecast arrivals and the arrivals after shocks. Quantitative forecasting provides a first stage platform for the study of tourism demand, and in subsequent research given greater data penetration, such an approach can be followed with more specific non-quantitative approaches.

In recent years, several review articles on tourism demand forecasting have been published including Crouch (1995), Li et al., (2005), Lim (1997ab), Lim (1999), Witt and Witt (1995), Song and Turner (2006) and, Song and Li (2008). Song and Turner (2006) conclude that the majority of published studies use quantitative methods to forecast tourism demand. The quantitative approaches can be categorised into two major groups namely time-series methods and econometric methods. Prior to the 1990s, the traditional regression approaches were widely used in analysing and forecasting the demand for tourism, but this trend changed from the mid-1990s as more researchers began to use more modern econometric techniques to model and forecast tourism demand (Wong et al., 2006).

Several of the researchers using more modern econometric models include Song and Turner (2006), Kulendran and King (1997a), Smeral and Webber(2000), Kulendran and Witt (2001), Song et al., (2003b) and, Fernando (2005). Non-conventional neural network models have also been applied by Law and Au (1999), Uysal and Roubi (1999), and Chandra and Menezes (2001) in the field of tourism data analysis and have been shown to be a viable alternative to the traditional time series and econometric models. Studies by Fernando (2005), Kon and Turner (2005) and, Burger et al., (2001) suggest that neural networks can perform more accurately in a forecasting comparison with the naïve, moving average, decomposition, single exponential smoothing, ARIMA, multiple regression and genetic regression models.

In terms of forecast performance, earlier studies on tourism forecasting in the literature did not focus on the evaluation of the performance of different methodologies (Archer, 1980 and Van Doom, 1982) but rather focused upon presenting the theory of the various methodologies available. As tourism studies developed rapidly so has the pressure increased for accurate tourism forecasting from all levels of government and industry, in order to provide for adequate planning for tourism infrastructure and facilities to capture tourism growth, and avoid shortages or surpluses in tourism goods and services. The benefits of accurate forecasts are well documented in the forecasting literature (De Mello and Nell, 2005, Flechtling, 1996, Cho, 2003, Oh and Morzuch, 2005). As a result, later studies have engaged a much wider discussion on model performance and forecast accuracy including Sheldon and Var (1985), Witt and Witt (1989), Witt and Turner (2002), and Lt et al.,(2006). Tourist arrivals and tourist expenditures are still the common measure of tourism demand in the past decade (Li et al., 2005). Forecast evaluation and model performance are based on the level of error magnitude exhibited by the models. Mean absolute percentage error (MAPE), absolute percentage error and root mean square error (RMSE) are among the most popular approaches used for measuring forecast performance. In addition, in the forecasting performance comparison, the naïve one model, which is also known as the no change model, is often used as a benchmark (Song and Turner, 2006) in forecast comparison.

Questions arise whether demand volume can affect forecasting accuracy by (Vu, 2006). In this study, Vu explored the topic by examining the relative accuracy of forecasting different characters of time-series such as flow volumes, volatility and seasonality for a wide range of large to small countries with the volume of tourists varying from large to small. Vu pointed out that the forecasting of international tourist arrivals is normally done on a per country basis, and the volume of tourist flow varies widely among countries depending on their population size, as well as openness to travel overseas. She theorised that there has been an assumption made that forecasting smaller volumes is more difficult for measuring accuracy, because small errors can make up large proportions of the total volume. Her study results indicate that it is not the volume of tourist arrival flow that determines the difference in the accuracy of forecasts, between different countries, either in total or source market flows. Other variations such as the degree of seasonality and volatility are equally important. Vu concludes that forecasting arrivals from small flow volumes such as for island states, versus large volume of tourist flows such with the USA and UK, does not always suggest a decrease in forecast accuracy.

Vu also linked her findings to the question of the disaggregation of data prior to forecasting with the objective of increasing overall forecast accuracy. Previous studies have indicated the usefulness of data disaggregation in tourism demand forecasting in terms of country of origin and purpose of travel (Blackwell, 1970, Martin and Witt, 1989a, Vu and Turner, 2005). Further studies also show the usefulness of breaking down data by country for predicting regional forecast flows and disaggregation by purpose of visit, age and gender have been considered potentially useful for increasing forecast accuracy (Turner et. al., 1995, Vu and Turner, 2005). The study by Vu and Turner (2005) found that total arrivals forecasting is not more accurate when the data used is the sum of forecast disaggregated series, as opposed to direct forecasts of total arrivals. Vu's study (2006) further examined the disaggregation by volume, volatility, type of travel and gender and has found no significant increased forecasting accuracy when using substantive univariate modelling techniques. She concludes that it is unlikely that breaking down arrival series into constituent parts will yield simpler series that could be more accurately forecast. It should also be noted that in both Turner and Vu's studies that the analysis of disaggregated data is considered more costly, and as such they support the current practices of both the World Trade Organisation (WTO) and the Pacific Asia Travel Association (PATA) of not forecasting disaggregated series.

More recently, some new research directions have emerged, that include methods such as forecast combination and integration of both statistical and non-statistical approaches to achieve forecasting accuracy for tourism demand. Forecasting combination and model integration is used in several studies and the effectiveness of these studies is included in a review by Wong et al., (2006) who found that the average accuracy improves as the number of combined single methods increases. Palm and Zellner (1992) concluded that combining forecasts can reduce forecasting error and that a simple average combination may be more robust than weighted average combinations. The performance of simple average combination methods was found to be superior to the single forecasts by Fang (2003). Following these research findings, a string of more sophisticated model combination methods have developed including: the regression-based combination by Granger and Ramanathan (1984); the Bayesian shrinkage framework, which incorporates prior information in the estimation of the combination weights; while Hendry and Clements (2004) summarised five situations that have the potential for explaining the accuracy improvement using forecast combination approaches. The five situations are: (i) the combination can better reflect all the information if two models provide partial, not completed overlapping explanations; (ii) combination of forecasts may be useful, when there is a structural break over the forecasting period; (iii) combination can reduce variance when all models are miss-specified; (iv) combination has an alternative interpretation of intercept correction that is known to improve forecasting performance; and (v) combination can be regarded as shrinkage estimation. Wong et al., (2007) tested the combination of modern econometric techniques with four modelling techniques – SARIMA, ADL, ECM and VAR to forecast tourist flows to Hong Kong. Additionally, research on the frontier is looking at methods to combine forecasts from several methods to derive a “composite” forecast and bring together different methods (Blake et al., 2006) in the context of major shocks or multiple changes that occur concurrently.

Many of these studies suggest that forecast combination can significantly improve forecasting accuracy over single forecast approaches. However, the competition between alternative methods shows that some degree of relative forecast accuracy occurs under specific situations, and no single method can outperform others on all occasions (Wong et al., 2007).

One such study by Turner et al., (2002) for inbound tourism to China uses an integrative approach combining both time-series and econometric methodologies, termed structural integrated time-series econometric analysis (SITEA). The SITEA model starts with a time-series approach, the underlying series is fitted to form a mathematical projection of the cyclical and trend and then the influence of economic and dummy variables is added sequentially to adjust these time-series components. Further observations involve removal of incorrectly signed and insignificant variables, or change in the mix of variables until the variables show the “correct” sign according to economic theory and become statistically significant at the 5% level. Such an interactive decision process is based on correct statistical methodology and forms a different approach to combining existing methods.

Despite the consensus on the need to develop accurate forecasts, and the recognition of their corresponding benefits, various studies have found that there is no single model that outperforms other models in terms of forecasting accuracy (Witt and Witt, 1995, Law and Au, 1999, Li et al., 2005).

There have been many literature reviews of tourism demand forecasting in the history of tourism demand forecasting studies. The major literature reviews include: - Grouch (1994), Witt and Witt (1995), Lim (1997ab), Li et al., (2005), Song and Turner (2006) and, Song and Li (2008). These literature reviews show that tourism forecasting has been based upon the development of a series of methodologies focused upon national tourist arrivals using cross-border ‘immigration’ data. However, it is noted by Song and Turner (2006) that the number of tourist nights spent by residents in the destination is an alternative tourism demand measure.

As far as tourism forecasting is concerned, there have been only a few studies for China, including a study by Tang et al., (2007) that attempt to establish the causal link between foreign direct investment (FDI) and tourism in China by using the Granger causality test under a VAR methodology proposed by Zapata and Rambaldi (1997). This study employed various time series econometric techniques including a unit root test, co-integration and causality. The results of this study show that there is a one-way causal relationship between FDI and tourism in the direction of FDI to tourism, but there is no econometric evidence to substantiate the causal relationship between FDI and tourism in the reverse direction of tourism to FDI. The study also pointed out that as the regional economic development and regional distribution of FDI inflows in China are very unbalanced, a policy to encourage more FDI into these regions should be encouraged in order to assist the development of tourism resources in these regions, and promote regional international tourism activities.

In her Doctorate of Philosophy thesis, Huo (2002) completed a study on Modelling and Forecasting International Tourism Demand to China. She examined her subject by using both modern time-series econometric techniques and the Vector Autoregression (VAR) approach to forecasting tourism demand from Japan, the USA and Australia to China for the period of 1978 to 1998. Her study found that the VAR models provide a practical framework to analyse international tourism demand to China from the selected market sources, hence the model may have more general application for forecasting tourism demand in other market sources. Additionally, a two-way trade between China and these three tourist generating countries was shown to be one of the most important determinants of tourist demand to China, thus trade between tourist destination and country of origin may be considered as a variable in international tourism demand studies. Using the diagnostic test of directional change, the VAR models seemed too outperforms ARIMA and naïve models for forecasting demand one and two years ahead.

A study by Shan and Wilson (2001) reveals causality between trade and tourism in China. Another study was completed by Kulendran and Shan (2002) on forecasting China's monthly inbound travel demand. Their study concluded that tourism growth in China may be seen as the result of China's increased openness to international tourism including tourism related bilateral trade agreements between China and Southeast Asian countries, USA and Australia, and increased awareness of China due to more increased openness to international trade.

In relation to international regional tourism demand, the literature review shows only a few studies have examined this area, including the study by Turner et al., (2002) on large-scale regional forecasts for China. Another time-series based study was undertaken by Vu and Turner (2006) for Thailand. Vu and Turner's study focuses upon nine city-based regions in Thailand, using data on guest arrivals at accommodation establishments. Results of this study show that the Box Jenkins ARIMA model is more accurate in the case of total guest arrival data, and Basic Structural model (BSM) is more accurate in the case of total international arrivals. In addition, the overall accommodation data (total guest arrivals) yield more accurate forecasts than the average regional data (overall average). Vu and Turner's study concluded that the regional forecast of tourist arrivals (both international and domestic) is at least as accurate as the national cross-border data when used to forecast overall arrivals using similar forecasting models (Vu and Tuner, 2006). Their study recommends that regional arrival data could be useful for forecasting of regional tourism demand for other countries such as China and India where regional data have just become available. However, the study by Turner et al., (2002) and Vu and Turner (2006) are limited by their use of national level forecasting methodology, and are mainly valid for opening up the question of regional forecasting, rather than addressing its specific practice.

2.2.2 Univariate Time Series Models

Time-series models predict the future by identifying the historical pattern in a given time-series and extrapolating that pattern into the future. Since time series models only require historical observation of a variable, it is less costly in data collection, forecasting and model estimation. As such, time series approaches are among the most popular methods for tourism demand forecasting. Several studies have examined times series methodology in depth including Geurts and Ibrahim (1975), Wandner and Van Erden (1980), Geurts (1982), Martin and Witt (1989a), Sheldon (1993), Turner et al., (1997) and Kulendran and King (1997a). Unlike econometric models, a time series model cannot help to explain interdependent relationships among tourism demand and other related factors that often cause fluctuation of tourism demand, and are major concerns of business and government.

In recent years and in many published empirical research papers, time series models including the naïve no-change (Witt, 1991a, Witt, 1991b, Witt, 1992, Martin and Witt, 1989a, Martin and Witt, 1989b) and a variation of the Box-Jenkins (1994) ARIMA models have been used in conjunction with other forecasting models such as econometric models (Song and Turner, 2006), as a benchmark to assess and compare forecasting performance. Time series analysis can be a valuable tool for short-term tourism forecasting. They allow the forecast to view trends in visitor's behaviour, both seasonally and cyclically. Cyclical and seasonal effects can distinctly be seen in tourism time series as well as long-term upward or downward trends. Time series methods are also easy to implement (Burger et al., 2001). Several studies have examined time series models including Geurts and Ibrahim (1975), Kulendran and King (1997), Geurts (1982), Martin and Witt (1989a), Turner et al., (1995), Turner et al., (1997b), Burger et a., (2001), Lim and McAleer (2002), Du Preez and Witt (2003), De Mello and Nell (2005), Oh and Morzuch (2005) and, Wong et al., (2007).

2.2.3 Autoregressive Models

The ARIMA model building methods were introduced by Box Jenkins in 1970, using differencing to make a series stationary. The method is also known as the Box-Jenkins autoregressive integrated moving average (ARIMA) method. Slutsky presented it in the form of Autoregressive (AR) and Moving Average (MA) components in 1937 (Makridakis and Hibon, 1997). The ARIMA approach is the most widely used univariate forecasting model. It uses an interactive method of an empirically driven equation to systematically identify, estimate, diagnose, and forecast time series (Delurgio, 1998).

Since the introduction of the ARIMA methods, extensive studies on the building of ARIMA models for tourism forecasting have been carried out over the past decade. Makridakis and Hibon (1997) argue that the use of differencing in the ARIMA techniques to make data stationary, results in more accurate forecasts by the ARMA(1,1) model. Turner et al., (1997) discovered that the AR model with periodic data gave better forecasts than the ARIMA with non-periodic seasonal data. Chu's study (1998b) compared the use of an ARIMA and sine wave nonlinear regression combined model with the ARIMA model, and found that the combined model had relatively lower forecast errors. Chu's study (2004) went a step further to compare ARIMA forecasts with a cubic polynomial model and also found that ARIMA forecasts had lower errors. Importantly, these studies show that ARIMA models may not be the most accurate forecasting models even though they may be the best fitting model.

In recent years, modelling and forecasting of seasonality in tourism demand forecasting has gathered momentum. Several papers have been published (Bar On, 1975, Sutcliffe and Sinclair, 1980, Bulter, 1994, Lim and McAleer, 2000, Kim, 2001, Kulendran and Wong, 2005, Lim and McAleer, 1999, Koc and Altinay, 2007) and a review of seasonality by Koenig-Lewis and Bischoff (2005). Seasonality in tourism edited by Baum and Lundtorp (2001) contains 11 papers on this area. These studies have raised awareness of the positive and negative impacts caused by the fluctuation of seasonal change to tourism demand caused by changes in policy, ecology, society and culture as well as employment in tourist destination countries or regions.

One of the popular aspects of the ARIMA model proposed by Box and Jenkins (1976) is its capacity for generating seasonal tourism demand forecasts. Various studies have suggested that the seasonal ARIMA methods have been regarded as better forecasting models than either the econometric or other time-series models (Preez and Witt, 2003, Chu, 1998, Gonzales, 1996, Kulendran and King, 1997b).

Multiplicative seasonal ARIMA modelling contains many forecasting models, of which $ARIMA_{1,4}$ and $ARIMA_{1}$ are the most common. $ARIMA_{1,4}$ is used for modelling stochastic non-stationary seasonality which requires first and fourth differences to achieve stationarity; whilst $ARIMA_{1}$ uses only the first differences and seasonality is modelled with a constant and three seasonal dummies. The best models are selected depending on the forecasting accuracy of the models. There are numerous studies on modelling seasonality and performance comparisons using ARIMA, in comparison with other forecasting models (Geurts and Ibrahim, 1975, Gonzales, 1995, Lim and McAleer, 1999, Chu, 1998, Goh and Law, 2002 , Kulendran and Shan, 2002a, Kulendran and Witt, 2003b, Turner and Witt, 2001, Kulendran and Wong, 2005). A study by Kulendran and Wong (2005) suggests that $ARIMA_{1}$ provides more accurate forecasts for a time series that has fewer seasonal variations, whereas $ARIMA_{1,4}$ provides more accurate forecasts for a time series that has strong seasonal variation. But this study is limited to one quarter ahead forecasting.

Compared to simple time series models, the Box-Jenkins model (Box and Jenkins, 1976) is more complex in function and form and has more stringent validity tests and data requirements than other non-causal techniques. ARIMA time series models have been criticized for their ambiguity and inability to address the determinants of tourism demand necessary for policy assessment (Lim and McAleer, 2000, Kulendran and King, 1997a, Kulendran, 1996). Nevertheless, ARIMA models have the advantage of not being limited by the need for accurate economic causal variable forecasts that in some cases are difficult to obtain.

The use of the ARIMA model for short-term forecasts has been widely accepted in tourism forecasting studies for its versatility and accuracy (Delurgio, 1998, Harvey and Todd, 1983, Flechtling, 1996). A study by Lim and McAleer (1999) compares ARIMA with the seasonal Autoregressive Integrated Moving Average model. Gonzalez and Moral (1996), Kulendran and King (1997b) and, Kulendran and Witt (2001) compare the seasonal ARIMA and basic structural time-series models (BSM), structural causal models, no change models, and error-correction models. Chan et al. (2005) use ARMA and GARCH methods on tourism demand to Australia and related volatility. Studies on model comparisons (Martin and Witt, 1989a, Kulendran and King, 1997a, Kulendran and Witt, 2001) suggest that time-series models and the “no change” model are capable of generating more accurate tourism forecasts than econometric models. A study by Louvieris (2002) successfully used a multiplicative seasonal autoregressive integrated moving average (SRIMA) model to forecast Greece’s inbound tourism in the medium/long-term. The findings of his study support the assertion that the ARIMA methods are accurate, not only for the short term, but also for medium/long term forecasting. His study suggests that there are situations, where the normally accepted restriction of imposing artificial short-term forecasting horizons on ARIMA modelling methods can be relaxed (Louvieris, 2002).

2.2.4 Basic Structural Time Series Model

The Basic Structural Time Series Model (BSM) was introduced by Harvey and Todd (1983) and the model assumes that a time-series possesses some structure, which is the sum of independent trend, seasonal and irregular components. The Basic Structural Model is well-know in the literature of tourism demand forecasting and its approach to tourism demand forecasting primarily focuses on univariate time varying data with trend and seasonal components. Greenidge (2001) employed the BSM to analyse and forecast tourist arrivals to Barbados from USA, UK, Canada and other arrivals. The study shows that the BSM is the preferred forecasting model for its ability in capturing most of the information that is normally left in the residuals of the common tourism demand regression. A study by Kulendran and Shan (2002b) forecast monthly inbound travel demand to China. This study compares the forecasting performance of the BSM model, and also shows the importance of using different but appropriate explanatory variables for forecasting different types of tourism series. A previous study by Turner et al., (1997) also shows that the BSM model has been a highly accurate forecasting model in comparison to the univariate ARIMA model. VU and Turner (2006) discussed the performance of the BSM and ARIMA models and found that that the BSM model is significantly more accurate for the forecasting of total international arrivals, based on immigration records, whilst ARIMA is more accurate for total guest arrival data, based on accommodation data that included domestic tourist arrivals.

2.2.5 Econometric Models

Econometric approaches involve the use of statistical analysis, combined with economic theory, to analyse data (Allen and Fildes, 2001).

Song et al., (2009) and Song and Witt (2000) describe the term 'Tourism demand' for a particular destination as the quantity of the tourism product (i.e. a combination of tourism goods and services) that consumers are willing to purchase during a specified period under a given set of conditions. Earlier econometric approaches in tourism demand forecasting for a particular destination are represented by a single-equation demand forecasting model as:

$$Q_{ij} = f(P_{i,}P_{s,}Y_{j,}T_{j,}A_{ij,}E_{ij}).$$

Where Q_{ij} is the quantity of the tourism product demanded in destination i by tourism from country j;

P_i is the price of tourism for destination I,

Ps is the price of tourism substitute destinations,

Y_j is the level of income in origin country j,

T_j is consumer tastes in origin country j, Where*:* A_{ij} is advertising expenditure on tourism by destination *i* in origin country of *j; and*

E_{ij} is the disturbance term that captures all other factors which may influence the quantity of the tourism product demanded in destination *i* by residents of origin country *j*.

But according to Allen and Fildes (2001), this simple demand model failed in comparison with extrapolative methods because it paid too little attention to the dynamic structure of time series. It is noted by Song and Witt (2000) and Kulendran (1996) that the simple demand model does not take into account the long-run cointegration of relationships in the estimation of the models. Hence it raises questions regarding the quality of empirical forecast results.

It is widely acknowledged in studies by Artus (1972), Loeb (1982), Flechtling (1996) and Wong and Song (2002) that the econometric methods and in particular the modern econometric models have been playing an important role in tourism demand forecasting for planning and policy formulation. Song and Witt (2000) and, Song et al., (2009) systematically introduce a number of modern econometric techniques into tourism demand analysis. Since then, further research has developed the application of modern econometric methods in tourism demand modelling and forecasting including Song and Witt (2006), Kulendran and Witt (2001), Lim and McAleer (2001a), Lim and McAleer (2002), Song et al., (2000), Song et al., (2003), Dritsakis (2004), Blake et al., (2006), Patsuratis (2005) and, Han et al., (2006).

Econometric models are causal models and because of this they are regarded by some researchers as superior to time series techniques because the model construction is more directly based on economic theory. The specification of the model allows assessment of the underlining causes that influence changes to demand. A large number of researchers have examined causal modelling over a long period of time (Gray, 1966, Artus, 1970, Witt, 1980ab, White, 1985, Darnell et al., 1990, Morris et al., 1995, Kulendran, 1996, Lim, 1999, Lim and McAleer, 2001, Song and Witt, 2003, Blake et al., 2006). The most recent studies pay more attention to the question of stationarity in the data series

(Kulendran and King, 1997a, Kulendran, 1996, Song and Witt, 2003, Vu and Turner, 2006).

In the econometric literature, the use of demand variables and their reliability is paramount. The most commonly used and versatile variables in measuring tourism demand described by Song and Witt (2000) and Song et al., (2009) are: population of the tourist generating country, income in tourists' country of origin, own price including cost of living in the destination country, and travel cost to destination, exchange rate, expenditure, substitute prices for alternative destinations, marketing and promotion expenditure. In addition, a lagged dependent variable and an autoregressive term can be justified on the grounds of habit persistence and supply of tourism related goods and services. Some qualitative elements including dummy variables are often used in international tourism demand functions to measure 'one of events' such as the Olympic Games, SARS, Asian Tsunami and wars.

In terms of price variables, consumer price indices have been regarded as a reasonable proxy (Martin and Witt, 1987) in tourism demand forecasting. However, a study by Han et al., (2006) examines the use of the Stone Price Index, the Laspeyres Index and the Paasche Index as alternative indices within tourism demand modelling. This study shows that the use of different price indices affects the results only marginally.

A study by Turner et al., (1997b) identified leading indicators from among national variables of income, unemployment, forward exchange rate, money supply, price ratio, industrial production, imports and exports. A study by Kulendran and Wilson (2000) identified a causal relationship existed between the level of trade openness of the destination country and international travel to that country. Trade openness has been further examined and shown to be a viable variable by Kulendran and Wilson (2000), Huo (2002), Kulendran and Shan (2002) and, Rang et al., (2007). Hanly and Wade (2007) use demographic variables such as age groups to capture specific tourism money contributions in Ireland by tourists from North America. Their study revealed that the age group over 45 years old shows an increase in expenditure growth. Consequently, as a result of changing demographics, the baby boomer generation presents a huge tourism potential for Ireland. Tourism investment is used as an indicator of hotel capacity in a study by Choyakh (2008) on tourists to Tunisia from France, Germany, Italy and the UK. Goh et al., (2008) employed two non-economic variables, climate and leisure into the forecasting framework of long-haul U.S. and U.K. tourism demand for Hong Kong.

2.2.6 Artificial Neural Networks (ANNs)

In recent years, the study of artificial neural networks (ANN) has aroused great interest in fields as diverse as biology, psychology, medicine, economics, mathematics, statistics and computing Palmer et al., (2006) provides a step-by-step methodology for designing a neural network for tourism time series forecasting. As Law (2000) states, a neural network contains many simple processing units known as ‘nodes’ operating in parallel with a central control node, and the connections between these nodes have numeric weights that can be adjusted in the learning process. ANN’s function as approximators capable of mapping any linear or non-linear function and have been used by researchers in tourism related forecast in recent years including Uysal and Roubi (1999), Tang et al. (1991), Tsaur et al., (2002), Wang (2004) and, Wang and Hsu (2008). According to Zhang (2004), ANNs are data driven nonparametric methods that do not require many restrictive assumptions on the underlying process from which data are generated. This “learning from data or experience” makes ANNs, a highly effective forecast method. In addition, neural networks are shown to have the universal approximation function to capture relationships between the variable to be predicted and other relevant variables (Zhang, 2004).

Neural network models have been used as a statistical technique in the main fields of tourism research, such as demand and consumer behaviour forecasting (Burger et al., 2001, Law, 2000, Law, 2001, Law and Au, 1999, Kon and Turner, 2005, Fernando, 2005, Palmer et al., 2006). The unique features of ANNs such as the ability to adapt to imperfect data, nonlinearity, and arbiter function mapping, make this method a useful alternative to regression forecasting models.

Some improved ANNs continue to appear in recent years. Burger et al., (2001) employs a variety of time series techniques to forecast the US demand for travel to Durban, South Africa. Model comparisons include naïve, moving average, decomposition, single exponential smoothing, ARIMA, multiple regression as well genetic regression and neural networks. Burger et al., found that the neural method performs best. Law and Au (1999) used a feed-forward neural network to model the demand for Hong Kong tourism by Japan. Kon and Turner (2005) provide a detailed description and literature review of neural models. They point out the failure of many articles to specify their modelling procedure and the importance of doing so. Their findings indicate that different neural models have different levels of success in accurately forecasting arrivals for different series, and that neural models have potentially high levels of accuracy. Fernando (2005) combined artificial neural networks and fuzzy logic, and compared the performance of this model with other quantitative time-series methods to forecast tourism demand in Japan. Fernando (2005) established the potential for neural-fuzzy models to be used in tourism forecasting in the future. A recent study by Chen and Wang (2007) develops an approach using support vector regression (SVM) with genetic algorithms in tourism forecasts to China from 1985 to 2001. The SVM formulation seeks to minimize an upper bound of the generalization error rather than minimize the prediction error on the training set (Chen and Wang, 2007). This study shows the superior application of artificial neural methods in forecasting of time series with linearity. A study by Wang and Hsu (2008) developed a novel fuzzy times series model to forecast tourism from Taiwan to the United States using a relatively short-term annual data series of 1991 to 2001. This study demonstrated that the improved fuzzy time series uses a logical relationship to judge the upward or downward movement of the forecast curve, and then yields the forecast value. Empirical results show that the fuzzy time series are suitable for short-term predictions. Furthermore, as noted by Wang and Hsu (2008) unlike traditional forecasting methodologies, fuzzy time series can overcome the limitations of other methods and produce accurate short-term forecasts.

However, due to their flexibility, neural networks lack a systematic procedure for model building, and obtaining a reliable neural model involves selecting a large number of parameters experimentally through trial and error (Palmer et al., 2006). Song and Turner (2006) concluded that the application of neural network models and other univariate time series techniques including Box Jenkins ARIMA (Turner et al., 1995), BSM (Turner and Witt, 2001b) and simpler methods such as Holt Winters (Grubb and Mason, 2001) to tourism forecasting, has been limited by their inability to provide policy implications, as the construction and estimation of the models are not based on solid economic theories.

There are several methods ranging from simple time-series models (exponential smoothing) through to more complex time series methods (BSM, ARIMA and Neural) along with regression models that account for stationarity (ECM, Time Varying Parameter) that are available for use in tourism demand forecasting.

2.2.7 Conclusion

In recent years, methods used in analysing and forecasting the demand for tourism have been more diverse. There is no literature that applies a whole range of methods to regional tourist arrival data and no study applied to regional arrivals in China. However, there is an increasing urgency to examine regional tourist arrivals for economic planning purposes, especially in larger countries such as China where regional impacts are more evident.

China has been chosen as the country of study for many reasons including: China has been predicted by the World Tourism Organization to become the world's top tourism destination by 2020. China was ranked 4th in the world’s top 10 tourism destinations in 2004 and has retained this position through to 2007. China is a large country and a rapidly developing economy with 31 regions and 2 Special Administrative Regions

(SAR) with 55% rural population; eight of the top 10 Chinese provinces are coastal provinces in the east of China and these provinces account for over 40% of the total international arrivals to China and 72.8% of currency earnings. China has significant increased industry demand for regional tourist forecasts stimulated initially from the 2008 Beijing Olympic Games and 2010 Shanghai World Expo.

The need for regional forecasting has also been accelerated by the Chinese Central Government's initiative in developing the western and central regions, in order to ease social pressure and economic imbalance between the coastal developing regions and the inland and under developed regions in China. Many studies have investigated the success and impact of rural and regional tourism development in China (Gao et al., 2009, Hu, 2008, Lew and Yu, 1995, Lew et al., 2003, Li, 2008, Zhao, 2008, Pine, 2002). The national government of China considers openness in tourism trade as one significant way that economic development can be spread.

In summary, this study has taken a new direction in the research of tourism forecasting by looking into international tourism forecasting at the sub-national level in China, and by examining new models that may work best with regional data. Because this research is on the leading edge of the current literature in international tourism forecasting, it makes a significant contribution to the literature as well as providing a platform for further research on regional forecasting for other countries, as similar data increasingly become available at the regional level, including most immediately Australia, Canada, India, Japan, New Zealand, Thailand and the USA.

Chapter 3
International Arrivals to Chinese Regions

3.1 Introduction

China has a land size of 9.65 million square kilometres, which is nearly one-fifteenth of the world's land. It is the world's third largest country by size after Russia and Canada. With a land boundary of 22,800 km, China is bordered by Korea to the east; Mongolia to the north; Russia to the northeast; Kazakhstan, Kyrgyzstan and Tajikistan to the northwest; Afghanistan, Pakistan, India, Nepal and Bhutan to the west and Southwest; and Myanmar, Laos and Vietnam to the South. Across the seas to the east and Southeast are the Republic of Korea, Japan, the Philippines, Brunei, Malaysia and Indonesia. The territory of China extends 5,500 kilometres from north to South, and 5,200 kilometres from west to east.

China is the world's largest country by population (1.31 billion) compared with India's population of 1.06 billion (July 2004 est. refer to iloveindia.com). Over 90 % of the total population are Han nationality and less than 10% of the population are ethnic minorities who are descendants of 55 ethnic tribes living across 20 provinces/autonomous regions in China (refer to China Statistical Yearbook 2008). Administrative divisions under the Central National Government are in the form of 22 provinces, 5 autonomous regions, 4 municipalities and 2 special administrative regions (Hong Kong and Macau SAR).

Hong Kong and Macau are not included in the mainland regions for this study because they have very different tourism structures that have been open to foreign travel for a much longer time than mainland China, and require a separate passport for entry by Chinese citizens. As such they have been treated in current research as separate countries and often included in current national published forecasting research as separate national areas. Consequently, this research treats the 31 regional areas as "provinces", including the 5 autonomous regions and 4 municipalities covering mainland China.

3.2 Divisions of Chinese Regions

Figure 3.1.1

Source: maps of China.com

According to their geographic locations, the 33 administrative divisions (22 provinces, 5 autonomous regions, 4 municipalities and 2 special administrative regions), are divided into 7 geographic regions namely North China (Beijing and adjacent provinces/municipalities and autonomous region), Northeast China, East China (Shanghai and adjacent 6 provinces), South China, Southwest China, Northwest China and Hong Kong and Macau Special Administrative Regions.

Table 3.1 provides a list the 7 geographic regions and related 33 administrative divisions). It also provides a list of the provincial capital cities, their territory and populations in relation to the total of China's territory and population. The size of the 7 geographic regions and their population varies markedly, for example, the North China Region (16% of total China's territory) and (12% of total China's population), the Northeast China Region (8% of China's land) and (8% of total population); the East China Region (8% of total China's territory) and (29% of total China's population); the South China Region (10.6% of total China's land) and (28% of total population); the Southwest China Region (25% of total China's land) and (15% of total China's population); the Northwest China Region (25% of total China's land) and (7% of total China's population); Hong Kong SARS and Macau SARS with less than (0.12% of total China's land) and (1% of total population).

Since the establishment of the People's Republic of China in 1949, China has always regarded itself as a country with a high percentage of peasants (rural) population (80%). Since then and particularly in the past two decades, there has been a shift towards urbanization in China. A large volume of rural people are moving to major cities for a better life and the gap between the two populations have drawn closer at 44.9% (urban) to 55.1% (rural) in 2007.

Table 3.1.1 Regional (provincial) population and territory 2007

(10,000 people and 10,000 square kilometers)

	Capital City	Area	Total Population	Urban Population	%	Rural Population	%
National Total		960	132129	59379	45	72750	55
Region/Province							
North China							
Beijing	Beijing	2	1633	1380	85	253	16
Tianjin	Tianjin	1	1115	851	76	264	24
Hebei	Shijiazhuang	19	6943	2795	40	4148	60
Shanxi	Taiyuan	16	3393	1494	44	1899	56
Inner Mongolia	Hohhot	120	2405	1206	50	1199	50
Regional total		157	15489	7726	50	7763	50
% ChinaTotal		16	12	13		11	
Northeast China							
Liaoning	Shenyang	15	4298	2544	59	1754	41
Jilin	Changchun	19	2730	1451	53	1279	47
Helongjiang	Harbin	47	3824	2061	54	1763	46
Regional total		80	10852	6057	56	4795	44
% ChinaTotal		8	8	10		7	
East China							

Shanghai	Shanghai	1	1858	1648	89	210	11
Jiangsu	Nanjing	10	7625	4057	53	3569	47
Zhejiang	Hangzhou	10	5060	2894	57	2166	43
Anhui	Hefei	14	6118	2368	39	3750	61
Fujian	Fuzhou	12	3581	1744	49	1837	51
Jiangxi	Nanchang	17	4368	1738	40	2630	60
Shandong	Jinan	15	9367	4379	47	4988	53
Regional total		79	37977	18828	50	19149	50
% ChinaTotal		8	29	32		26	
South China							
Henan	Zhengzhou	17	9360	3214	34	6146	66
Hubei	Wuhan	19	5699	2525	44	3174	56
Hunan	Changsha	21	6355	2571	40	3784	60
Guangdong	Guangzhou	19	9449	5966	63	3483	37
Guangxi	Nanning	24	4768	1728	36	3040	64
Hainan	Haikou	3	845	399	47	446	53
Regional total		102	36476	16402	45	20074	55
% ChinaTotal		11	28	28		28	
Southwest China							
Chongqing	Chongqing	8	2816	1361	48	1455	52
Sichuan	Chengdu	49	8127	2893	36	5234	64
Guizhou	Guiyang	17	3762	1062	28	2700	72
Yunnan	Kunming	39	4514	1426	32	3088	68
Tibet	Lhasa	127	284	80	28	204	72
Regional total		241	19503	6824	35	12679	65
% ChinaTotal		25	15	11		17	
Northwest China							
Shaanxi	Xi'an	21	3748	1522	41	2226	59
Gansu	Lanzhou	45	2617	827	32	1790	68
Qinghai	Xining	72.00	552	221	40	331	60
Ningxia	Yinchuan	6	610	269	44	341	56
Xinjiang	Urumqi	166	2095	820	39	1275	61
Regional total		237	9622	3659	38	5963	62
% ChinaTotal		25	7	6		8	
HK SAR		0.1104	693.00				
% China Total		0.01	0.52				
Macau SAR		0.0027	53.00				
% China Total		0.00	0.04				

Source: China Statistical Yearbook 2008 and CNTA internet.

3.3 Gross Regional Product (GRP)

Table 3.1.2 summarises the growth of Gross Regional Product (GRP) for all 31 provinces included in this research, for the period of 2001 to 2007 as well as their percentage contribution to China's total GDP. The North China Region leads the country with the highest GRP growth rate of 17.9% (AAGR) and the Northeast China Region has the lowest AAGR of 14.2%. The East China Region makes up 41.7% of China's total GDP and the Northwest China Region makes only 5.3% of China's total GDP. Overall, all regions have recorded an impressive annual growth during this period.

Table 3.1.2 Gross regional product 2007

(GRP RMB 100 million and NGDP RMB 100 billion)

	2001	2003	2005	2007	% NGDP	AAGR % 2001-2007
NGDP	109655	135823	183868	251483		14.8
PC GDP	8622	10542	14103	18934		14.0
North China						
Beijing	3711	5024	6886	9353	3.7	16.7
Tianjin	1919	2578	3698	5050	2.0	17.5
Hebei	5517	6921	10096	13710	5.5	16.4
Shanxi	2030	2855	4180	5733	2.3	18.9
Inner Mongolia	1714	2388	3896	6091	2.4	23.5
Regional total	14890	19767	28755	39938	15.9	17.9
Northeast China						
Liaoning	5033	6003	8009	11023	4.4	14.0
Jilin	2120	2662	3620	5285	2.1	16.4
Heilongjiang	3390	4057	5512	7065	2.8	13.0
Regional total	10544	12722	17141	23373	9.3	14.2
East China						
Shanghai	5210	6694	9164	12189	4.8	15.2
Jiangsu	9457	12443	18306	25741	10.2	18.2
Zhejiang	6898	9705	13438	18780	7.5	18.2
Anhui	3247	3923	5375	7364	2.9	14.6
Fujian	4073	4984	6569	9249	3.7	14.6
Jiangxi	2176	2807	4057	5500	2.2	16.7
Shandong	9195	12078	18517	25966	10.3	18.9
Regional Total	40256	52634	75425	104790	41.7	17.3
South China						
Henan	5533	6868	10587	15012	6.0	18.1
Hubei	3881	4757	6520	9231	3.7	15.5
Hunan	3832	4660	6511	9200	3.7	15.7
Guangdong	12039	15845	22367	31084	12.4	17.1
Guangxi	2279	2821	4076	5956	2.4	17.4
Hainan	558	693	895	1223	0.5	14.0
Regional total	28122	35644	50956	71706	28.5	16.9
Southwest China						
Chongqing	1766	2273	3070	4123	1.6	15.2
Sichuan	4293	5333	7385	10505	4.2	16.1
Guizhou	1133	1426	1979	2742	1.1	15.9
Yunnan	2138	2556	3473	4741	1.9	14.2
Tibet	146	189	251	342	0.1	15.2
Regional total	9477	11777	16159	22453	8.9	15.5

Northwest China						
Shaanxi	2011	2588	3676	5466	2.2	18.1
Gansu	1125	1400	1934	2702	1.1	15.7
Qinghai	300	390	543	784	0.3	17.3
Ningxia	337	445	606	889	0.4	17.5
Xinjiang	1492	1886	2604	3523	1.4	15.4
Regional total	5265	6709	9363	13364	5.3	16.8

Source: China Statistical Yearbook 2006 - 2008.

3.4 Regional Employment

Tourism has become an important job creator in the Chinese national economy as well as an alternate indicator of an improved living standard for the Chinese. Table 3.1.3 summarises regional employment in hotel and catering, and culture, sports and entertainment sector in 2007. There are nearly 770 million people employed in China, of which 0.24% is directly in hotel and catering services, with an additional 0.16% in the culture, sports and entertainment sectors.

The East China Region leads the country with 28%, the highest percentage of employment in overall services relating to tourism compared to the Northwest China Region with only 6.1%. South China has 27% of the total employment, Southwest China 15%, and North China 10.1%. The South China Region makes up 29% of total employment in the hotel and catering sector, followed by the East China Region 27%, the North China Region and Northeast Region 21.5% and 13% respectively, the Southwest and Northwest Regions are below 10%.

Within these regions, Beijing has the highest employment number (40 million) in overall employment relating to tourism services, followed by Guangdong 30 million, Henan 17 million, Shandong 17 million, Zhejiang 16 million, Jiangsu 14 million and Shanghai 12 million, which compares starkly with some of the provinces in the southwest and northwest, for example, Tibet, Qinghai, Ningxia and Gansu with only 10,000 to 40,000 in the same sector.

Table 3.1.3 Regional employment by sectors 2007

(10,000 people)

	Total Employed	Hotels and Catering	Culture, Sports and Entertainment
National total	76990.0	185.8	125.0
% of national total		0.24	0.16
Region			
North China			
Beijing	1111.4	24.9	14.5
Tianjin	432.7	3.6	1.9
Hebei	3567.2	4.9	4.7
Shanxi	1550.1	4.0	4.5
Inner Mongolia	1081.5	2.6	3.2
Regional total	7742.9	40.0	28.8
% China total	10.1	21.5	23.0
Northeast China			
Liaoning	2071.3	6.4	4.9
Jilin	1096.2	2.9	3.8
Heilongjiang	1659.9	3.7	3.8
Regional total	4827.4	13.0	12.5
% China total	6.3	7.0	10.0
East China			
Shanghai	876.6	8.2	4.4
Jiangsu	4193.2	9.1	5.1
Zhejiang	3615.4	11.4	5.3
Anhui	3597.6	3.1	3.5
Fujian	1998.9	5.6	3.4
Jiangxi	2195.6	1.9	3.7
Shandong	5262.2	11.2	5.8
Regional total	21739.5	50.5	31.2
% China total	28.2	27.2	25.0
South China			
Henan	5772.7	10.0	7.2
Hubei	2763.0	4.6	5.0
Hunan	3749.3	7.2	4.4
Guangdong	5292.8	23.9	8.8
Guangxi	2759.6	4.5	3.1
Hainan	414.8	3.7	1.2
Regional total	20752.2	53.9	29.7
% China total	27.0	29.0	23.8
Southwest China			
Chongqing	1789.5	3.6	2.3
Sichuan	4778.6	5.1	4.3
Guizhou	2283.0	2.7	2.1
Yunnan	2600.8	5.8	3.4
Tibet	153.7	0.4	0.6
Regional total	11605.6	17.6	12.7
% China total	15.1	9.5	10.2
Northwest China			
Shaanxi	1922.0	4.8	3.8
Gansu	1374.4	2.1	2.2

Qinghai	276.3	0.4	0.7
Ningxia	309.5	0.6	0.9
Xinjiang	800.8	2.7	2.5
Regional total	4683.0	10.6	10.1
% China total	6.1	5.7	8.1

Source: China Statistical Yearbook 2008.

3.5 Regional International Tourists and Currency Earnings

Table 3.1.4 indicates that during the period of 1995 to 2007, all regions had strong growth in international tourist arrivals and foreign exchange earnings. China received more than 131 million international visitors with earnings of nearly US$ 42 billion. The East China Region leads the nation with receipts of US$14.9 billion (35.6% of China's total), followed by the South China Region with US$11 billion (26.1% of China's total), the North China and the Northeast China Region with US$6.4 billion (15.4% of China's total) and US$2 billion (4.9%) respectively. The two regions in the southwest and northwest have US$2 billion (4.8% of China's total) and US$863 million (2.1% of China's total).

Within these regions, Guangdong leads the nation with the highest number of arrivals (24.6 million) and tourist earnings of US$8.7 billion, followed by Shanghai with US$4.7 billion earnings (5.2 million arrivals) and Beijing US$4.6 billion (4.4 million arrivals). Ningxia, Qinghai and Gansu provinces in the Northwest Region received only US$70 million, US$16 million, and US$3 million earnings with (30,000, 160,000 and 700,000) international tourists respectively.

Table 3.1.4 Regional international tourist arrivals and earnings 2007

(10,000 people and US$ million)

	1995 number	1995 earning	2000 number	2000 earning	2007 number	2007 earning	AAGR % 95 - 07 number	AAGR % 95 - 07 earning
China Total	1728	8249	8344	16224	13187	41919	18.5	14.5
Region								
North China								
Beijing	207	2182	282	2768	435	4580	6.4	6.4
Tianjin	20	133	36	232	103	779	14.6	15.9
Hebei	17	42	41	142	82	309	14.3	18.1

Shanxi	7	21	17	50	74	222	21.5	21.7
Inner Mongolia	30	91	39	126	149	545	14.3	16.1
Regional total	281	2469	415	3318	844	6435	9.6	8.3
% China total	16.2	29.9	5	20.5	6.4	15.4		
Northeast China								
Liaoning	26	189	61	383	200	1,228	18.4	16.9
Jilin	16	41	22	58	54	179	11.0	13.1
Heilongjiang	16	61	55	189	141	643	19.8	21.7
Regional total	58	291	139	630	396	2,050	17.3	17.7
% China total	3.4	3.5	0.1	3.9	3.0	4.9		
East China								
Shanghai	137	939	181	1613	520	4673	11.8	14.3
Jiangsu	77	260	161	724	513	3469	17.1	24.1
Zhejiang	67	236	113	514	511	2708	18.4	22.5
Anhui	14	31	32	86	106	344	18.2	22.2
Fujian	91	484	161	894	269	2169	9.5	13.3
Jiangxi	7	25	16	62	66	196	20.1	18.7
Shandong	45	154	72	315	250	1352	15.3	19.8
Regional total	438	2129	737	4208	2235	14911	14.5	17.6
% China total	25.4	25.8	8.8	25.9	16.9	35.6		
South China								
Henan	22	60	33	124	88	318	12.3	14.9
Hubei	27	73	45	146	132	413	14.1	15.5
Hunan	18	65	45	221	121	642	17.3	21.0
Guangdong	621	2393	1199	4112	2461	8706	12.2	11.4
Guangxi	42	121	123	307	206	577	14.2	13.9
Hainan	29	81	49	109	75	302	8.4	11.6
Regional total	758	2793	1494	5019	3082	10958	12.4	12.1
% China total	43.9	33.9	17.9	30.9	23.4	26.1		
Southwest China								
Chongqing	*	*	27	138	76	382	16.2	15.7
Sichuan	38	125	46	122	171	512	13.4	12.5
Guizhou	14	29	18	61	43	129	10.0	13.2
Yunnan	60	165	100	339	222	860	11.6	14.7
Tibet	7	11	15	52	37	135	15.1	23.2
Regional total	118	330	206	712	548	2018	13.7	16.3
% China total	6.8	4.0	2.5	4.4	4.2	4.8		
Northwest China								
Shaanxi	44	139	71	280	123	612	8.9	13.1
Gansu	9	21	21	55	33	70	11.4	10.6
Qinghai	1	2	3	7	5	16	11.7	18.9
Ningxia	0	1	1	3	1	3	8.1	9.6
Xinjiang	20	74	26	95	44	162	6.6	6.7
Regional total	75	237	122	440	206	863	8.7	11.4
% China total	4.4	2.9	1.5	2.7	1.6	2.1		

Note: Chongqing data was unavailable for 1995.

Source: China Statistical Yearbook 2006 - 2008.

The data shown in the Table 3.1.4 also indicates significant imbalance in the number of international visitors and earnings generated from international tourism between regions in the east and the west. In June 1999, former President Jiang Zhemin addressed the need for a dedicated and large scale economic development in China's western regions. In March 2000, the Chinese Central Government issued bonds under the "Go West Campaign" for a total sum of US$72.6 billion specifically earmarked for the development of tourism infrastructure in the western region of China (refer to(Zhang et al., 2005). As a result, the western regions are expecting to see some great changes and development in the tourism sector.

3.6 Regional Star-Rated Hotels

The distribution of star-rated hotels in regional China in 2007 is shown in Table 3.1.5 The East China Region has a total of 4,121 hotels or 30.3% of the total hotels in China, followed by the South China Region with a total of 3,485 hotels or 25.7% of total hotels in China. The North China Region has 1,891 hotels or 13.9% of the total, the Southwest China Region has 1,962 (14.4%) and the Northwest China Region has 1,099 or 8.1% of China's total star-rated hotels. The East China Region has 127 5-star hotels, the highest number of high grade hotels in the country, compared to the Northwest China Region with only 16 5-star hotels.

Within these regions, Guangdong has a total of 225 hotels in the 5-star and 4-star category, followed by Beijing 156 and Shanghai 79, which compares sharply to Tibet and Ningxia with only 3 and 5 of the 4-star hotels respectively, and no 5-star hotels.

As shown by Table 3.1.5, one of the major differences between the regions in the east and west is the upper level accommodation, which is needed to meet any growth in international tourist numbers.

Table 3.1.5 Regional start-rated hotels 2007

	Total	5-star	4-star	3-star	2-star	1-star
China Total	13583	369	1595	5307	5718	594
North China						
Beijing	806	42	114	257	338	55
Tianjin	112	6	20	55	27	4
Hebei	412	4	66	184	149	9
Shanxi	324	7	43	109	163	2
Inner Mongolia	237	4	12	61	141	19
Regional total	1891	63	255	666	818	89
% China	13.9	17.1	16.0	12.5	14.3	15.0
Northeast China						
Liaoning	530	13	60	259	166	32
Jilin	219	5	34	71	100	9
Helongjiang	276	3	31	106	122	14
Regional total	1025	21	125	436	388	55
% China	7.5	5.7	7.8	8.2	6.8	9.3
East China						
Shanghai	320	32	47	128	105	8
Jiangsu	843	33	132	366	310	2
Zhejiang	1094	24	122	370	519	59
Anhui	391	6	52	140	181	12
Fujian	421	10	65	192	144	10
Jiangxi	325	5	43	152	125	0
Shandong	727	17	89	346	266	9
Regional total	4121	127	550	1694	1650	100
% China	30.3	34.4	34.5	31.9	28.9	16.8
South China						
Henan	522	4	53	219	239	7
Hubei	589	8	50	192	311	28
Hunan	541	12	41	198	271	19
Guangdong	1169	58	167	575	338	31
Guangxi	401	11	32	183	166	9
Hainan	263	14	53	118	66	12
Regional total	3485	107	396	1485	1391	106
% China	25.7	29.0	24.8	28.0	24.3	17.8
Southwest China						
Chongqing	240	7	35	90	99	9
Sichuan	507	15	63	181	229	19
Guizhou	250	2	19	76	123	30
Yunnan	887	11	45	177	520	134
Tibet	78	0	3	35	36	4
Regional total	1962	35	165	559	1007	196
% China	14.4	9.5	10.3	10.5	17.6	33.0
Northwest China						
Shaanxi	303	5	24	152	117	5
Gansu	267	2	25	91	135	14
Qinghai	105	1	9	35	52	8
Ningxia	51	0	5	34	12	0
Xinjiang	373	8	41	155	148	21
Regional total	1099	16	104	467	464	48
% China	8.1	4.3	6.5	8.8	8.1	8.1

Source: China Star-Rated Hotel Guide 2008 – 2009.

3.7 Regional Transport Network

Table 3.1.6 indicates the total railways and highways in all regions and their relative percentage of China's total rail and road network. The North China Region has the longest railway network (21.1% of China's total), followed by the South China Region with 19% of China's total railway network.

Within these regions, Inner Mongolia has the longest railway network (8.6% of China's total railways), followed by Helongjiang (7.4% of China's total). Henan leads the other provinces with the longest highway network of 6.7% of the nation's total, followed by Shandong and Yunnan at 5.9% and 5.6% respectively.

Table 3.1.6 Regional railways and highways 2007

(Kilometers)

	Total railways	% China	Total express and highways	% China
National Total	77966		3583715	
North China				
Beijing	1120	1.4	20754	0.6
Tianjin	694	0.9	11531	0.3
Hebei	4838	6.2	147265	4.1
Shanxi	3115	4.0	119869	3.3
Inner Mongolia	6694	8.6	138610	3.9
Regional total	16461		438029	
% China total	21.1		12.2	
Northeast China				
Liaoning	4201	5.4	98101	2.7
Jilin	3622	4.6	85445	2.4
Helongjiang	5755	7.4	140909	3.9
Regional total	13578		324455	
% China total	17.4		9.1	
East China				
Shanghai	331	0.4	11163	0.3
Jiangsu	1619	2.1	133732	3.7
Zhejiang	1319	1.7	99812	2.8
Anhui	2387	3.1	148372	4.1

Fujian	1616	2.1	86926	2.4
Jiangxi	2566	3.3	130515	3.6
Shandong	3302	4.2	212237	5.9
Regional total	13141		822757	
% China total	16.9		23.0	
South China				
Henan	4042	5.2	238676	6.7
Hubei	2565	3.3	183780	5.1
Hunan	2899	3.7	175415	4.9
Guangdong	2175	2.8	182005	5.1
Guangxi	2734	3.5	94202	2.6
Hainan	388	0.5	17789	0.5
Regional total	14803		891867	
% China total	19.0		24.9	
Southwest China				
Chongqing	1291	1.7	104705	2.9
Sichuan	2999	3.8	189395	5.3
Guizhou	2012	2.6	123247	3.4
Yunnan	2308	3.0	200333	5.6
Tibet	550	0.7	48611	1.4
Regional total	9160		666291	
% China total	11.7		18.6	
Northwest China				
Shaanxi	3185	4.1	121297	3.4
Gansu	2435	3.1	100612	2.8
Qinghai	1652	2.1	52626	1.5
Ningxia	789	1.0	20562	0.6
Xinjiang	2761	3.5	145219	4.1
Regional total	10823		440316	
% China total	13.9		12.3	

Source: China Statistical Yearbook 2008.

China's passenger transportation has experienced a rapid growth in passenger volumes since 2002. Table 3.1.7 indicates an average annual growth rate of 16.7% in total passengers handled from 2002 to 2007. Of all passengers travelling, the AAGR is 5.1% for railways, 6.8% for roads, and 16.7% for air transportation.

Table 3.1.7 Passenger numbers handled by railways, expressways and air 2002 - 2007

(10,000 kilometers and 10,000 people)

China total	2002	2003	2004	2006	2007	AAGR % 2002 - 2007
Railways		7.3	7.4	7.7	7.8	1.7
Total passengers	105606	97260	111764	125656	135670	5.1

Highways & expressways	176.5	181.0	187.1	345.7	358.4	15.2
Total passengers	1475257	1464335	1624526	1860487	2050680	6.8
Civil aviation routes	163.8	175.0	204.9	211.4	234.3	7.4
Total passengers	8594	8759	12123	15968	18576	16.7

Source: China Statistical Yearbook 2006 - 2008.

Regional air services, also known as feeder-line services, operate flights between medium and small cities, with routes typically between 600 and 1,200 kilometres long. The services usually use aircraft seating less than 100 passengers. Due to the increased growth of tourism from major cities, regional aviation in China is speeding up. According to the "Summit of Airport Construction in West China" on 27 May 2007, China has announced the building of 28 new regional airports, as well as revamping and expanding 27 existing airports in west China (aVbuyer.com.cn/news). Table 3.1.8 shows growth in air transportation and increases in passenger volumes since 1990.

Table 3.1.8 Passenger volumes by air 1990 - 2007

(10,000 people)

	1990	% total	1995	% total	2000	% total	2005	% total	2007	% total	AAGR % 90-07
Total	1660		5117		6722		13827		18576		15.3
International	114	6.9	368	7.2	690	10.3	1225	8.9	1692	9.1	17.2
Domestic	1346	81	4419	86	6031	90	12602	91	16884	90.9	16.0
Regional	200	12.0	330	6.4	403	6.0	509	3.7	541	2.9	6.0

Note: Since 1997, regional routes to/from Hong Kong and Macau are accounted as domestic routes.

Source: China Statistical Yearbook 2008.

Table 3.1.9 shows Beijing, Shanghai, Guangzhou and Hong Kong airports are amongst the world's top 10 growth airports in terms of passenger volumes in 2006.

Table 3.1.9 World's top 10 growth airports - passengers handled 2006

	Passengers Handled a						Movements c	
Airport	Terminal b Number	% Change	Int'l Number	% Change	Domestic Number	% Change	Number	% Change
Beijing	48,501,102	18.3	11,127,702	18.8	37,373,400	18.2	376,340	10.2
Dubai	28,788,726	16.2	27,925,522	16.7			236,325	8.8
Shanghai	26,790,826	12.9	16,073,367	10.4	10,530,470	17.2	231,993	13.1
Guangzhou	26,222,057	11.3	3,610,244	12.3	22,423,912	11.1	232,404	10
Barcelona	29,999,937	10.5	15,856,708	13.5	13,979,031	7.6	327,636	6.4
Jakarta	30,663,806	10.4	6,116,150	5.5	22,880,529	10.7	250,303	3.5
Istanbul	23,259,577	10.1	12,171,980	3.3	9,091,693	21	241,375	10.2
Bangkok	42,799,532	9.8	29,587,773	10.3	11,423,247	10.5	290,916	1.9
Hong Kong	44,020,000	9.1	43,453,000	9.0			290,199	6.2
Denver	47,324,844	9.1	1,898,046	18.1	45,426,798	8.7	597,290	6.7

Source: 2006 'IATA 51 edition 2007' ACI.

a. Preliminary ranking, April 2007.

b. Terminal passengers are arriving and departing passengers. The number include transfer passengers who are counted twice (on arrival and on departure from the airport). Direct transit passengers are counted once.

c. Total movements: landing and take off of an aircraft.

3.8 Conclusion

The regional background information provided in this chapter indicates that as a result of strong growth in international tourism during 1995 and 2007, an increase in earnings of foreign exchange has been stimulated, and in return this has aided regional economic development. Although all regions have benefited from visits of international tourists, it is evident that gaps exist between coastal regions and inland regions in their level of economic benefit from international tourism. This is also reflected in lower infrastructure provision and particularly upper level star-rated hotels and services in some inland regions and cities.

3.9 North China Region (Beijing and Adjacent Provinces)

3.9.1 Introduction

The North China Region consists of the Beijing Municipality (Capital City of People's Republic of China), Tianjin Municipality, Hebei Province, Shanxi Province and Inner Mongolia Autonomous Region. This region occupies 16% of China's total territory and 12% (154.89 million) of China's total population. The percentage of urban and rural population is 50% and 50% respectively (refer to Table 3.9.1).

Table 3.9.1 North China region population and territory 2007

(10,000 people & 10,000 square kilometers)

	Capital City	Area	Total Population	Urban Population	%	Rural Population	%
National Total		960	132129	59379	45	72750	55
Region/Province							
North China							
Beijing	Beijing	2	1633	1380	85	253	16
Tianjin	Tianjin	1	1115	851	76	264	24
Hebei	Shijiazhuang	19	6943	2795	40	4148	60
Shanxi	Taiyuan	16	3393	1494	44	1899	56
Inner Mongolia	Hohhot	120	2405	1206	50	1199	50
Regional total		157	15489	7726	50	7763	50
% ChinaTotal		16	12	13		11	
Northeast China							

Source: China Statistical Yearbook 2008 and CNTA internet.

3.9.2 North China Gross Regional Product (GRP)

Table 3.9.2 indicates the total GRP for the North China Region combined for the period of 2001 to 2007. The average regional growth rate over this period was 17.9% compared to China's national GDP of 14.8%. In 2007, the North China Region made up 15.9% of China's total GDP.

In this region, Hebei contributes 5.5% of national GDP, followed by Beijing and Inner Mongolia each at 3.7% and 2.4% respectively. As shown by Table 3.9.2, all provinces had a growth rate of over 16% with the exception of Inner Mongolia which leads the region with an average growth rate of 23.5%.

Table 3.9.2 North China region gross regional product 2007

(100 million & NGDP RMB 100 billion)

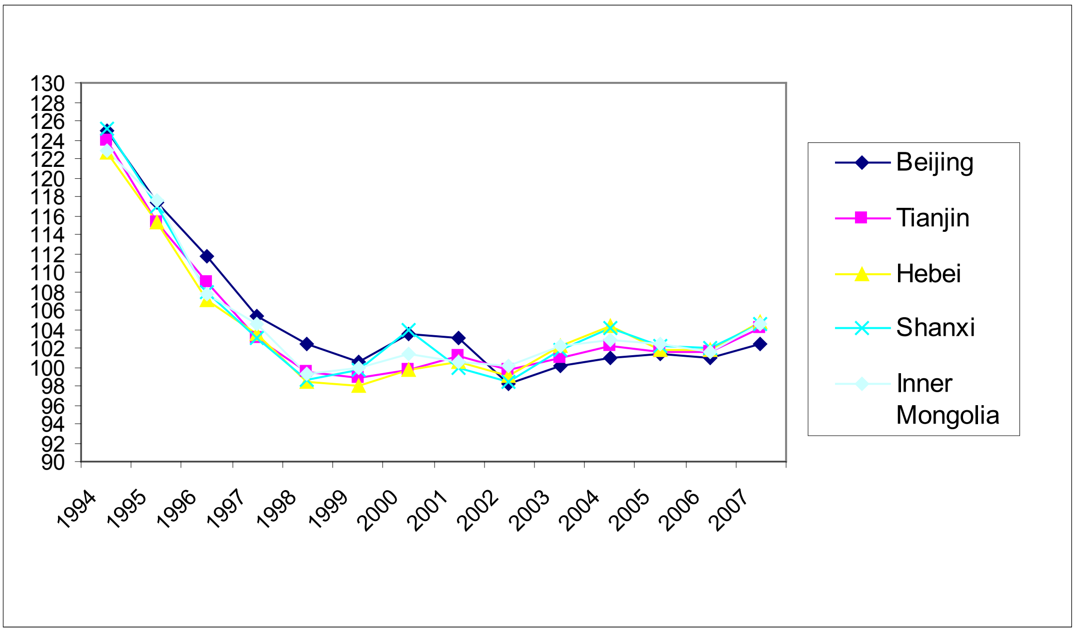
	2001	2003	2005	2007	07 GRP	AAGR % 2001-2007
NGDP	109655	135823	183868	251483	%	14.8
PC GDP	8622	10542	14103	18934	07 NGDP	14.0
North China						
Beijing	3711	5024	6886	9353	3.7	16.7
Tianjin	1919	2578	3698	5050	2.0	17.5
Hebei	5517	6921	10096	13710	5.5	16.4
Shanxi	2030	2855	4180	5733	2.3	18.9
Inner Mongolia	1714	2388	3896	6091	2.4	23.5
Regional Total	14890	19767	28755	39938	15.9	17.9

Source: China Statistical Yearbook 2006 - 2008.

3.9.3 North China Region Consumer Price Index

Figure 3.9.1 indicates that the Consumer Price Index fell by more than 20 points during the period of 1994 to 1998 followed by some small increases, particularly in Shanxi Province during 1999 to 2001. From 2001, it remained relatively stable through to 2006, trending up marginally in 2007.

Figure 3.9.1 North China Region – CPI 1994 - 2007



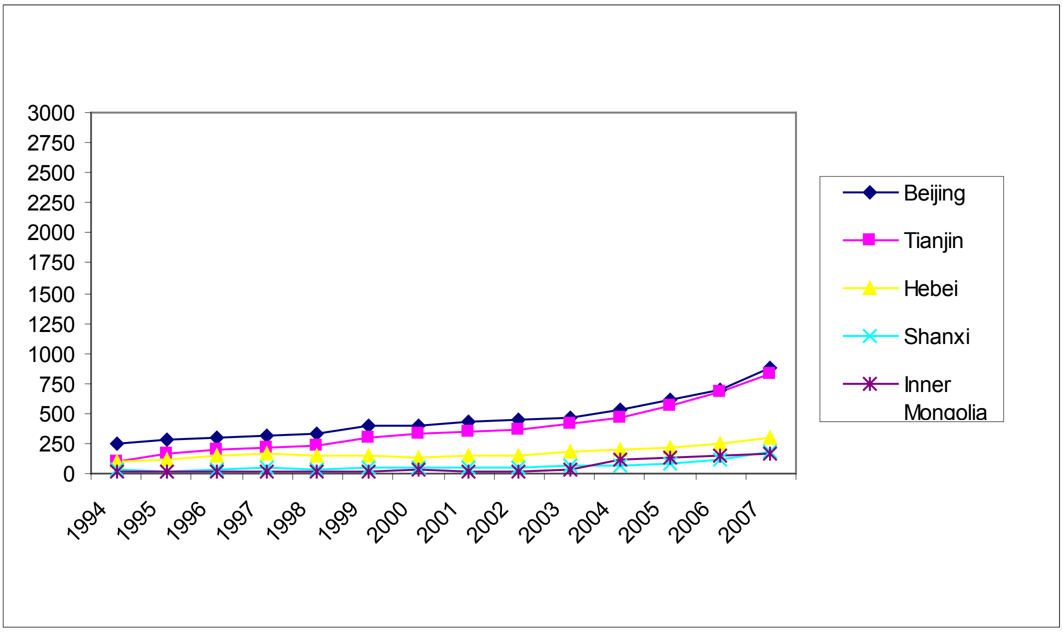
Source: China National Bureau of Statistics.

3.9.4 North China Region Registered Foreign Enterprises

Figure 3.9.2 indicates that the investment by registered foreign enterprises in the region increased steadily from 1994. Led by Beijing (US$244 in 1994 to US$876 million in 2007) and Tianjin (US$96 million in 1994 to US$829 million in 2007), and followed by Hebei (US$95 to US$291 million), and Shanxi with (US$28 million to US$178 million). Inner Mongolia received far less investment (US$17 million in 1994 to US$171 million in 2007) than other provinces in the region.

Figure 3.9.2 North China Region – RFE 1994 – 2007

(US$100 million)



Source: China National Bureau of Statistics.

3.9.5 North China Region Employment

Table 3.9.3 summarises regional employment including the hotel, catering, culture, sports and entertainment sectors in 2007. There are over 77.4 million people employed (10% of China's total), of which 21.5% of the employment are directly in hotel and catering services with an additional 23% of people employed by the culture, sports and entertainment industry.

Within this region, Beijing has the highest employment number (249,000) of the region's total in the hotel and catering sector.

Table 3.9.3 North China Region employment by sectors 2007
(10,000 people)

	Total Employed Number	Hotels and Catering	Culture, Sports and Entertainment
National total	76990	185.8	125.0
% of national total		0.24	0.16
North China			
Beijing	1111.4	24.9	14.5
Tianjin	432.7	3.6	1.9
Hebei	3567.2	4.9	4.7
Shanxi	1550.1	4.0	4.5
Inner Mongolia	1081.5	2.6	3.2
Regional total	7742.9	40.0	28.8
% China total	10.1	21.5	23.0

Source: China Statistical Yearbook 2008.

3.9.6 North China Region Tourists and Exchange Earnings

Table 3.9.4 indicates the growth of international tourists to the North China Region for the period of 1995 to 2007, with an AAGR of 9.6% for the period. The region makes up 6.4% of the total China's international tourists, and it has a higher percentage of foreign tourists (28.5% of China's total).

Within this region, Beijing received 4.35 million international visitors followed by Inner Mongolia 1.49 million and Tianjin 1.03 million in 2007. All provinces have enjoyed a steady growth in international arrivals since 1995.

Table 3.9.4 North China Region foreign tourist arrivals 2007

(10,000 people)

	1995		2000		2007		AAGR %	AAGR %
	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign
China total	1728	589	83344	1016	13187	2611	18.5	13.2
North China								
Beijing	207	167	282	238	435	383	6.4	7.2
Tianjin	20	16	36	32	103	95	14.6	15.9
Hebei	17	14	41	36	82	74	14.3	15.1
Shanxi	7	5	17	12	74	45	21.5	19.8

Inner Mongolia	30	29	39	39	149	147	14.3	14.4
Regional total	281	231	415	356	844	744	9.6	10.2
% China total	16.2	39.2	0.5	35.1	6.4	28.5		

Note: Foreign tourists are foreign nationals exclude compatriots from Hong Kong, Macau and Taiwan.

Source: China Statistical Yearbook 2006 - 2008.

Table 3.9.5 indicates the increases in international arrivals and exchange earnings received by the North China Region for the period of 1995 to 2007, with an AAGR of 9.6% for international arrivals (8.4 million) and AAGR of 8.3% for earnings (US$6.4 billion). Within this region, Shanxi has the highest AAGR of 21.7% for international arrivals and 21.5% for earnings. Beijing leads the region with earning at US$4.6 billion in 2007, followed by Tianjin and Inner Mongolia at UD$779 million and US$545 million respectively for the same period.

Table 3.9.5 North China Region international tourist arrivals and earnings 2007

(10,000 people and US$ million)

	1995 number	earning	2000 number	earning	2007 number	earning	AAGR % 95 - 07 number	AAGR % 95 - 07 earning
China total	1728	8249	8344	16224	13187	41919	18.5	14.5
North China								
Beijing	207	2182	282	2768	435	4580	6.4	6.4
Tianjin	20	133	36	232	103	779	14.6	15.9
Hebei	17	42	41	142	82	309	14.3	18.1
Shanxi	7	21	17	50	74	222	21.5	21.7
Inner Mongolia	30	91	39	126	149	545	14.3	16.1
Regional total	281	2469	415	3318	844	6435	9.6	8.3
% China total	16.2	29.9	5.0	20.5	6.4	15.4		

Source: China Statistical Yearbook 2008.

3.9.7 North China Region Star-Rated Hotels

According to China's Star-Rated Hotel Guide 2008, there are a total of 1,891 hotels (13.9% of China's total hotels) in the North China Region. Table 3.9.6 shows the breakdown of 5 to

1 star-rated hotels and their percentage, relative to the whole of China. Beijing makes up 4.2% of the total hotels in the region, followed by Hebei with 3% and Shanxi with 2.2%. Beijing has 156 hotels in the 5 and 4-star category whilst Inner Mongolia has only 16 hotels in these categories.

Table 3.9.6 North China Region star-rated hotels 2007

	Total	5-star	4-star	3-star	2-star	1-star
China total	13583	369	1595	5307	5718	594
North China						
Beijing	806	42	114	257	338	55
Tianjin	112	6	20	55	27	4
Hebei	412	4	66	184	149	9
Shanxi	324	7	43	109	163	2
Inner Mongolia	237	4	12	61	141	19
Regional total	1891	63	255	666	818	89
% China	13.9	17.1	16.0	12.5	14.3	15.0

Source: China Hotel Guide 2008 – 2009.

3.9.8 North China Regional Transport Network

Table 3.9.7 indicates that the North China Region collectively has 21% of the nation's total railways, and over 12% of the nation's total highways. Within this region, Inner Mongolia has 8.6% of China's total railways and 3.9% of China's highways; followed by Hebei has 6.2% of China's railways and 4.1% of China's highway network.

Table 3.9.7 North China Region transport network 2007

	Total railways	% China	Total express and highways	% China
National Total	77966		3583715	
North China				
Beijing	1120	1.4	20754	0.6
Tianjin	694	0.9	11531	0.3
Hebei	4838	6.2	147265	4.1
Shanxi	3115	4.0	119869	3.3
Inner Mongolia	6694	8.6	138610	3.9
Regional total	16461		438029	
% China total	21.1		12.2	

Source: China Hotel Guide 2008 - 20009.

3.9.9 Conclusion

One of the clear benefits for the North China Region is their proximity to Beijing, the capital of China. Some of the key economic data for 2007 indicate that the urban and rural population is 50% split. The region has 13.9% of China's total hotels, while 16.8% of the region's hotels are in the 5 and 4-star category. The North China Region attracts 6.4% of China's total international arrivals (8.4 million), and 15.4% of the nation's exchange earnings (US$6.4 billion). There are over 77.4 million people employed (10% of China's total), of which 21.5% of the employment is directly in hotel and catering services with an additional 23% of people employed by the culture, sports and entertainment sector.

3.10 Northeast China Region

3.10.1 Introduction

The Northeast China Region consists of 3 provinces. In the north is Helongjiang Province, bordering with Russia, followed by Jilin and Liaoning Province. The Korean Peninsular is in the northeast and Japan islands are in the east. This region occupies 8% of China's total territory and 8% of the nation's population (108 million). The percentage of urban and rural population of the region is 56 % to 44% (refer to Table 3.10.1). Within this region, Liaoning's population is close to 43 million and Jilin has relatively less than 28 million. Northeast China is known as China's old heavy industrial engine.

Table 3.10.1 Northeast China region population and territory 2007

(10,000 people and 10,000 square kilometers)

	Capital City	Area	Total Population	Urban Population	%	Rural Population	%
National Total		960	132129	59379	45	72750	55
Northeast China							
Liaoning	Shenyang	15	4298	2544	59	1754	41
Jilin	Changchun	19	2730	1451	53	1279	47
Helongjiang	Harbin	47	3824	2061	54	1763	46

Regional total	80	10852	6057	56	4795	44
% China total	8	8	10		7	

Source: China Statistical Yearbook 2008.

3.10.2 Northeast China Gross Regional Product (GRP)

Table 3.10.2 indicates the total GRP for the Northeast China Region combined for the period of 2001 to 2007. The average growth rate over this period was 14.2% compared to 14.8% for national GDP and comprises 9.3% of China's total GDP. All three provinces enjoyed an average growth rate of above 13% during this period. Liaoning makes up 4.4% of national GDP.

Table 3.10.2 Northeast China region gross regional product 2007

(100 million and NGDP RMB 100 billion)

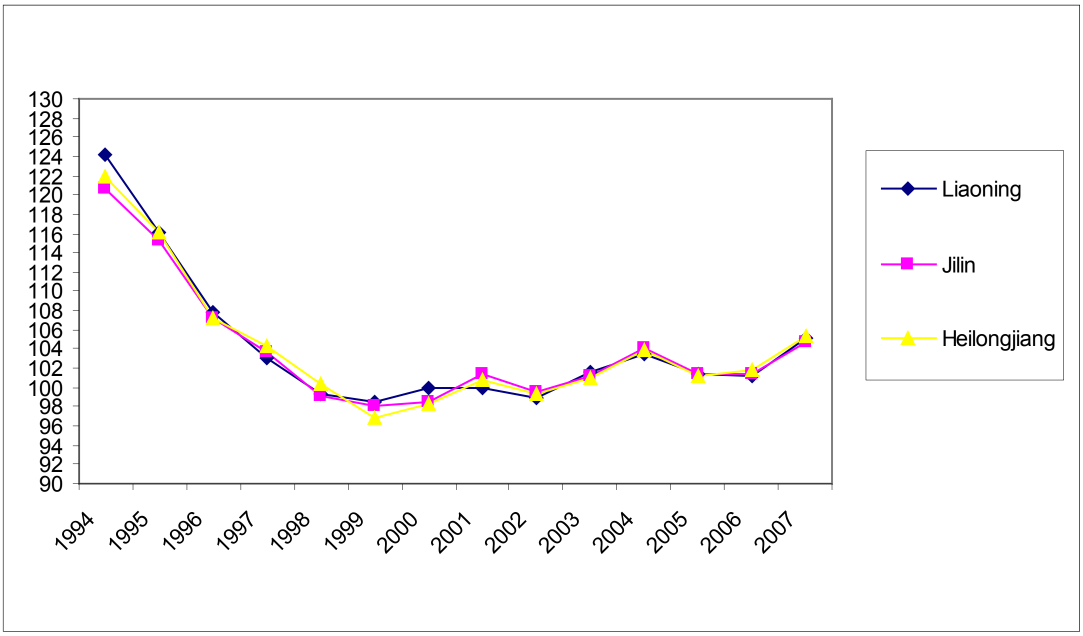
	2001	2003	2005	2007	07 GRP	AAGR (%) 2001-2007
NGDP	109655	135823	183868	251483	%	14.8
PC GDP	8622	10542	14103	18934	07 NGDP	14.0
Northeast China						
Liaoning	5033	6003	8009	11023	4.4	14.0
Jilin	2120	2662	3620	5285	2.1	16.4
Heilongjiang	3390	4057	5512	7065	2.8	13.0
Regional total	10544	12722	17141	23373	9.3	14.2

Source: China Statistical Yearbook 2006 - 2008.

3.10.3 Northeast China Region Consumer Price Index

Figure 3.10.1 indicates that the Consumer Price Index fell nearly 25 points during the period 1994 to 1998 followed by some small increases through to 2006 and a marginal increase in 2007. Percentage of CPI differences between provinces in the region was marginal.

Figure 3.10.1 Northeast China Region – CPI 1994 - 2007



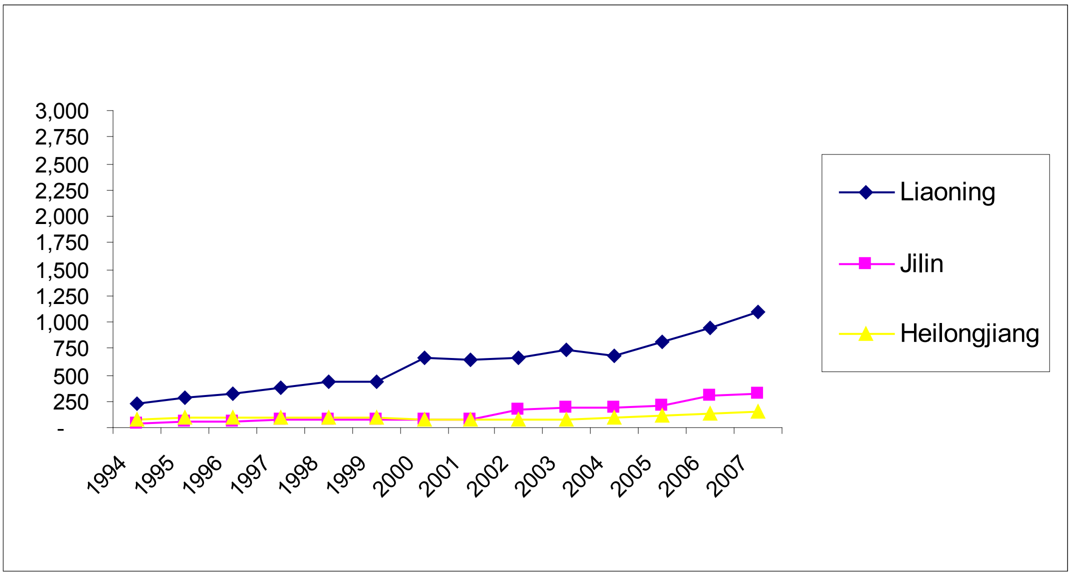
Source: China National Bureau of Statistics.

3.10.4 Northeast China Region Registered Foreign Enterprises

Figure 3.10.2 indicates that the investment by registered foreign enterprises in the region has steadily increased from 1994. Led by Liaoning Province, which received foreign investment between US$228 in 1994 to US$1088 million in 2007, Helongjiang Province at US$76 million in 1994 to US$145 million in 2007, and Jilin is a relatively smaller recipient of investment at US$39 million in 1994 to US$313 million in 2007.

Figure 3.10.2 Northeast China Region – RFE 1994 – 2007

(US$100 million)



Source: China National Bureau of Statistics.

3.10.5 Northeast China Region Employment

Table 3.10.3 indicates that there are nearly 48 million people (6.3% of the China's total) employed in the Northeast China Region, of which 7% of the total employment is directly in hotel and catering services and 10% is in the sports and entertainment sector.

Table 3.10.3 Northeast China Region employment by sectors 2007

(10,000 people)

	Total Employed Number	Hotels and Catering	Culture, Sports and Entertainment
National Total	76990.0	186	125
% of national total		0.24%	0.16%
Northeast China			
Liaoning	2071.3	6.4	4.9
Jilin	1096.2	2.9	3.8
Heilongjiang	1659.9	3.7	3.8
Regional total	4827.4	13.0	12.5
% China total	6.3	7.0	10.0

Source: China Statistical Yearbook 2008.

3.10.6 Northeast China Region Tourism and Exchange Earnings

Table 3.10.4 indicates the growth of international tourists to the Northeast China Region during a five year interval from the period of 1995 to 2007. It shows an AAGR of 17.3% in international tourist arrivals and 17.6% for foreign tourists. Helongjiang tops the Northeast China Region with an AAGR of 19.8% in international arrivals and 20.8% of foreign arrivals. The region makes up 3% of total international tourists, but has a relatively higher percentage (13.4%) of total foreign tourists to China in 2007. Liaoning received 2 million international visitors, followed by Helongjiang 1.4 million and Jilin received just over half a million international tourist arrivals.

Table 3.10.4 Northeast China Region foreign tourist arrivals 2007

(10,000 people)

	1995		2000		2007		AAGR %	AAGR %
	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign
China total	1728	589	83344	1016	13187	2611	18.5	13.2
Northeast China								
Liaoning	26	21	61	50	200	171	18.4	18.9
Jilin	16	14	22	19	54	44	11.0	9.7
Helongjiang	16	14	55	50	141	134	19.8	20.8
Regional Total	58	50	139	120	396	349	17.3	17.6
% China Total	3.4	8.5	0.2	11.8	3.0	13.4		

Source: China Statistical Yearbook 2006 - 2008.

Table 3.10.5 indicates increases in international arrivals and exchange earnings by the Northeast China Region for the period of 1995 to 2007. It recorded an AAGR of 17.7% in earnings from international tourist arrivals. The Northeast China Region contributed 4.9% of total international tourism exchange earnings for China in 2007. Within this region, Liaoning received 2 million visitors with earnings at US$1.2 billion, followed by Helongjiang with 1.4 million visitors and earnings at USD643 million and Jilin had just over half a million visitors with earnings at US$179 million for the same period.

Table 3.10.5 Northeast China Region international tourist arrivals and earnings 2007

(10,000 people and US$ million)

	1995 number	1995 earning	2000 number	2000 earning	2007 number	2007 earning	AAGR % 95 - 07 number	AAGR % 95 - 07 earning
China total	1728	8249	8344	16224	13187	41919	18.5	14.5
Northeast China								
Liaoning	26	189	61	383	200	1228	18.4	16.9
Jilin	16	41	22	58	54	179	11.0	13.1
Heilongjiang	16	61	55	189	141	643	19.8	21.7
Regional total	58	291	139	630	396	2050	17.3	17.7
% China total	3.4	3.5	1.7	3.9	3.0	4.9		

Source: China Statistical Yearbook 2006 - 2008.

3.10.7 Northeast China Region Star-Rated Hotels

According to China's Star-Rated Hotel Guide 2008-2009, there are a total of 1,025 hotels (7.5% of China's total hotels). Table 3.10.6 shows the breakdown of 5 to 1 star-rated hotels. Liaoning makes up 51.7% of the total hotels (530) in the region as well as having the highest percentages (50%) for 5-star (13) and 4-star (60) hotels, followed by Helongjiang with a total of 276 hotels (26.9%) with 3 hotels rated 5-star and 31 hotels in the 4-star category, and Jilin has a total of 219 (21.4%) hotels with 5 hotels in the 5-star and 34 hotels in the 4-star category.

Table 3.10.6 Northeast China Region star-rated hotels 2007

	Total	5-star	4-star	3-star	2-star	1-star
China total	13583	369	1595	5307	5718	594
Northeast China						
Liaoning	530	13	60	259	166	32
Jilin	219	5	34	71	100	9
Helongjiang	276	3	31	106	122	14
Regional total	1025	21	125	436	388	55
% China	7.5	5.7	7.8	8.2	6.8	9.3

Source: China Hotel Guide 2008 – 2009.

3.10.8 Northeast China Region Rail and Road Network

Table 3.10.7 indicates that the Northeast China Region collectively has 17.4% of the nation's total rail network and 9.1% of the nation's total expressways and highways. Helongjiang has 7.4% of national total railways and 3.9% of nation's highways.

Table 3.10.7 Northeast China Region transport network 2007

(Kilometers)

	Total railways	% China	Total express and highways	% China
National Total	77966		3583715	
Northeast China				
Liaoning	4201	5.4	98101	2.7
Jilin	3622	4.6	85445	2.4
Helongjiang	5755	7.4	140909	3.9
Regional total	13578		324455	
% China total	17.4		9.1	

Source: China Statistical Yearbook 2008.

3.10.9 Conclusion

The Northeast China Region has a long winter period at below 20 degrees. This region is known as China's old heavy industrial region. Some of the 2007 economic data indicate that the urban and rural population is split in half. Helongjiang has close ties with Russia, Jilin with both North and South Korea and has promoted itself as the capital of the winter ice arts festival. The region made up 3% of total international tourists and 13.4% of the total foreign tourists to China in 2007 and generated 4.9% of China's total tourism earnings. Employment in hotel and catering services was 6.9% and 10.3% for the sports and entertainment sectors. 14% of its hotels are in the 5-star and 4-star category.

3.11 East China Region

3.11.1 Introduction

The East China Region is also known as East China with 6 provinces (Jiangsu, Zhejiang, Anhui, Jiangxi, Fujian and Shandong) and 1 municipality (Shanghai). Shanghai Municipality is situated in the far-east, bordering with Jiangsu Province in the northwest and Zhejiang Province in the Southwest. Shanghai, Jiangsu and Zhejiang form the East Delta Regions. Shandong Province is in the north of Jiangsu Province, Anhui Province is in the west of the region, Jiangxi Province is in the Southwest and Fujian Province is along the east coast line next to the Taiwan Straight. The East China Region occupies 8% of China's total territory and 29 % of China's population (379.8 million). The percentage of urban and rural population in the Region is close to 50% split (refer to Table 3.11.1).

Table 3.11.1 East China region population and territory 2007

(10,000 people and 10,000 square kilometers)

	Capital City	Area	Total Population	Urban Population	%	Rural Population	%
National Total		960	132129	59379	45	72750	55
East China							
Shanghai	Shanghai	1	1858	1648	89	210	11
Jiangsu	Nanjing	10	7625	4057	53	3569	47
Zhejiang	Hangzhou	10	5060	2894	57	2166	43
Anhui	Hefei	14	6118	2368	39	3750	61
Fujian	Fuzhou	12	3581	1744	49	1837	51
Jiangxi	Nanchang	17	4368	1738	40	2630	60
Shandong	Jinan	15	9367	4379	47	4988	53
Regional total		79	37977	18828	50	19149	50
% ChinaTotal		8	29	32		26	

Source: China Statistical Yearbook 2008.

3.11.2 East China Region Gross Regional Product (GRP)

Table 3.11.2 indicates the total GRP for the East China Region combined for the period of 2001 to 2007. The average regional growth rate over this period was 17.3% compared with

14.8% for China's national GDP. In 2007, this region collectively made up 41.7% of China's total GDP, the largest regional contributor to the nation's total GDP in China. The East China Region has 2 provinces (Jiangsu and Shandong) that are among the nation's largest GDP contributors with more than 10% each.

Table 3.11.2 East China region gross regional product 2007

(100 million and NGDP RMB 100 billion)

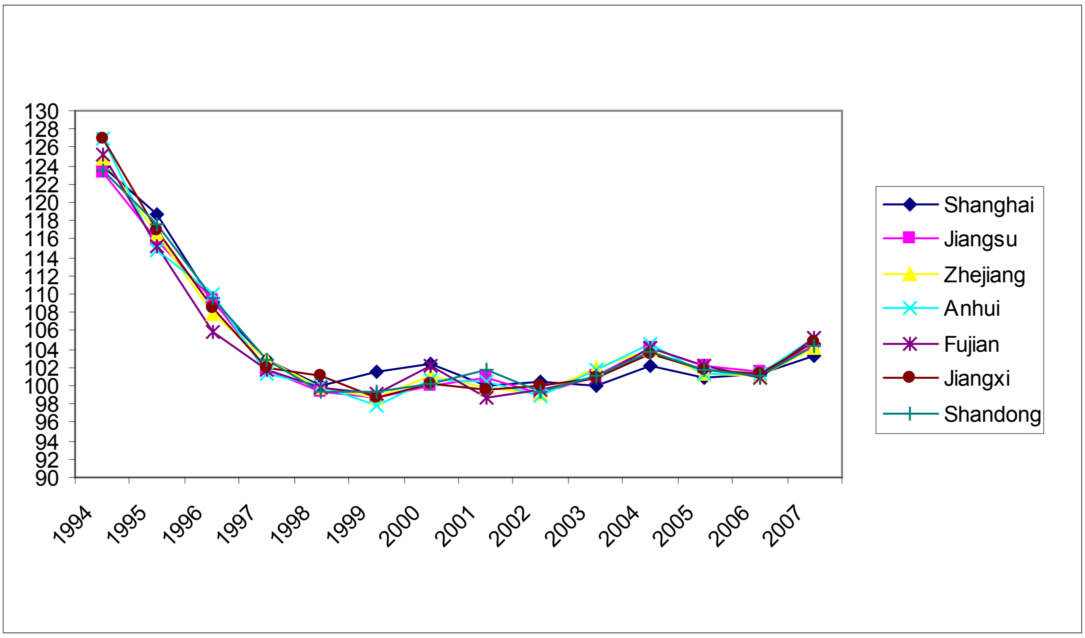
	2001	2003	2005	2007	07 GRP	AAGR (%) 2001-2007
NGDP	109655	135823	183868	251483	%	14.8
PC GDP	8622	10542	14103	18934	07 NGDP	14.0
East China						
Shanghai	5210	6694	9164	12189	4.8	15.2
Jiangsu	9457	12443	18306	25741	10.2	18.2
Zhejiang	6898	9705	13438	18780	7.5	18.2
Anhui	3247	3923	5375	7364	2.9	14.6
Fujian	4073	4984	6569	9249	3.7	14.6
Jiangxi	2176	2807	4057	5500	2.2	16.7
Shandong	9195	12078	18517	25966	10.3	18.9
Regional Total	40256	52634	75425	104790	41.7	17.3

Source: China Statistical Yearbook 2006 - 2008.

3.11.3 East China Region Consumer Price Index

Figure 3.11.1 indicates that the Consumer Price Index fell by more than 20 points during the period 1994 to 1998 followed by some small increases through to 2007. Shanghai had a noticeably higher increase (1.5% in 1999 and 2.5% in 2000) than other provinces.

Figure 3.11.1 East China Region – CPI 1994 - 2007



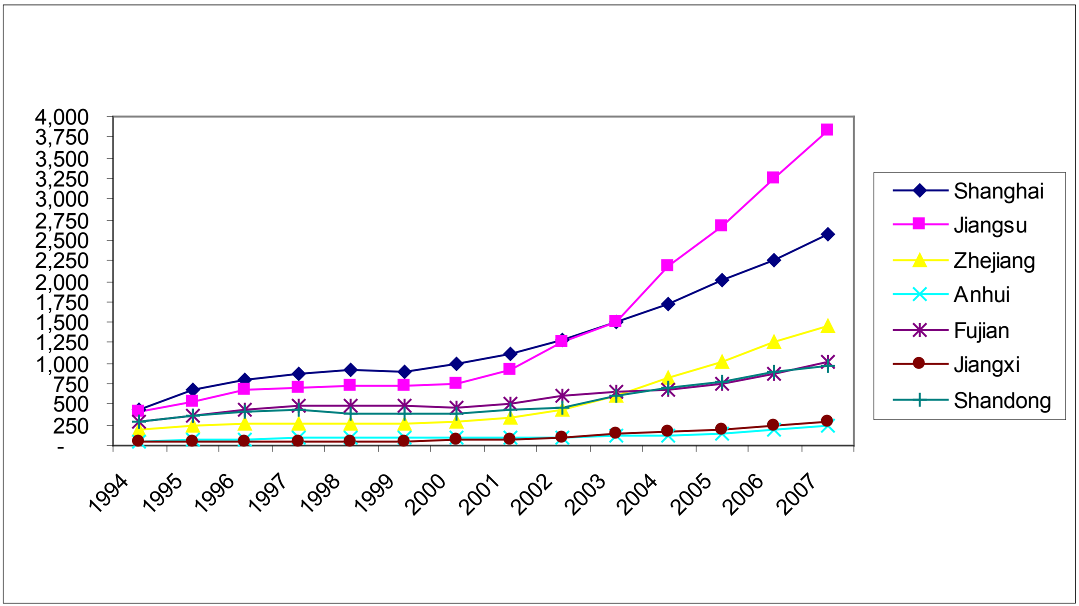
Source: China National Bureau of Statistics.

3.11.4 East China Region Registered Foreign Enterprises

Figure 3.11.2 indicates that the investment by Registered Foreign Enterprises in the region increased steadily from 1994. Led by Jiangsu Province (US$406 in 1994 to US$3,820 million in 2007) and Shanghai (US$442 million in 1994 to US$2,570 million in 2007), followed by Zhejiang Province (US$182 million in 1994 to US$1,457 million in 2007), Fujian (US$283 million and US$1087 million), Shandong (US$297 million to US$963 million), Jiangxi (US$44 million to US$290 million). Anhui Province received far less investment (US$44 million in 1994 to US$238) than other provinces in the region for the same period.

Figure 3.11.2 East China Region – RFE 1994 – 2007

(US$100 million)



Source: China National Bureau of Statistics.

3.11.5 East China Region Employment

Table 3.11.3 indicates that there are over 217 million people (28.2% of China's total) employed in the East China region. Of the total employment 27.2% is directly in hotel and catering services and an additional 25% is in the sports and entertainment sector. Within this region, Jiangsu has the highest employment (42 million people), but Zhejiang has the highest percentage (11.4%) in the hotel and catering sectors, while Shandong has 11.2% and 5.8% in both areas of employment, Shanghai has 8.2% and 4.4% of the employment respectively in these two major tourism sectors.

Table 3.11.3 East China Region employment by sectors 2007

(10,000 people)

	Total Employed Number	Hotels and Catering	Culture, Sports and Entertainment
National Total	76990.0	186	125

% of national total		0.24%	0.16%
East China			
Shanghai	876.6	8.2	4.4
Jiangsu	4193.2	9.1	5.1
Zhejiang	3615.4	11.4	5.3
Anhui	3597.6	3.1	3.5
Fujian	1998.9	5.6	3.4
Jiangxi	2195.6	1.9	3.7
Shandong	5262.2	11.2	5.8
Regional total	21739.5	50.5	31.2
% China total	28.2	27.2	25.0

Source: China Statistical Yearbook 2008.

3.11.6 East China Region Tourism and Exchange Earnings

Table 3.11.4 indicates the growth of international tourists to the East China Region during 1995 and 2007; it recorded an AAGR of 14.5% in international tourist arrivals and 16.3% for foreign tourists. The region makes up 16.9% of total international tourists and 59.6% (nation's highest percentage) of total foreign tourists to China in 2007. Shanghai, Jiangsu and Zhejiang provinces each received more than 5 million international tourist arrivals in 2007, followed by Fujian and Shandong which received between 1 and 2 million arrivals respectively.

Table 3.11.4 East China Region foreign tourist arrivals 2007

(10,000 people)

	1995		2000		2007		AAGR %	AAGR %
	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign
China total	1728	589	83344	1016	13187	2611	18.5	13.2
East China								
Shanghai	137	108	181	144	520	443	11.8	12.5
Jiangsu	77	49	161	98	513	369	17.1	18.4
Zhejiang	67	37	113	65	511	344	18.4	20.5
Anhui	14	7	32	17	106	74	18.2	21.4
Fujian	91	22	161	50	269	101	9.5	13.3
Jiangxi	7	2	16	6	66	24	20.1	21.4
Shandong	45	30	72	48	250	202	15.3	17.1
Regional Total	438	255	737	427	2235	1557	14.5	16.3
% China Total	25.4	43.4	0.9	42.0	16.9	59.6		

Source: China Statistical Yearbook 2006 - 2008.

Table 3.11.5 indicates increases in international arrivals and exchange earnings by the East China Region from 1995 to 2007, with an AAGR of 14.5% in international arrivals and 17.6% in earnings. Within this region, Jiangxi led with the highest AAGR of 22.1% for international arrivals and Jiangsu with the highest AAGR of 22.6% for earnings. The region contributed 35.6% of total international tourism exchange earnings for China in 2007. Shandong, Fujian, Zhejiang, Jiangsu and Shanghai received earnings ranging from US$1.34 billion to US$4.67 billion respectively in 2007.

Table 3.11.5 East China Region international tourist arrivals and earnings 2007

(10,000 people and US$ million)

	1995 number	earning	2000 number	earning	2007 number	earning	AAGR % 95 - 07 number	AAGR % 95 - 07 earning
China total	1728	8249	8344	16224	13187	41919	18.5	14.5
East China								
Shanghai	137	939	181	1613	520	4673	11.8	14.3
Jiangsu	77	260	161	724	513	3469	17.1	24.1
Zhejiang	67	236	113	514	511	2708	18.4	22.5
Anhui	14	31	32	86	106	344	18.2	22.2
Fujian	91	484	161	894	269	2169	9.5	13.3
Jiangxi	7	25	16	62	66	196	20.1	18.7
Shandong	45	154	72	315	250	1352	15.3	19.8
Regional total	438	2129	737	4208	2235	14911	14.5	17.6
% China total	25.4	25.8	8.8	25.9	16.9	35.6		

Source: China Statistical Yearbook 2006 - 2008.

3.11.7 East China Region Star-Rated Hotels

According to China's Star-Rated Hotel Guide 2008-2009, there are a total of 4,121 hotels (30.3% of China's total hotels) in the Region. Table 3.11.6 shows the breakdown of 5 to 1 star-rated hotels and their percentage, relative to the whole of China. Zhejiang takes up 26.5% of the total hotels in the region, followed by Jiangsu 20.5% and Shandong 17.6%.

Jiangsu also has the highest percentage (26%) of 5-star hotels followed by Shanghai (25%) in contrast to Jiangxi with less than 4%.

Table 3.11.6 East China Region star-rated hotels 2007

	Total	5-star	4-star	3-star	2-star	1-star
China total	13583	369	1595	5307	5718	594
East China						
Shanghai	320	32	47	128	105	8
Jiangsu	843	33	132	366	310	2
Zhejiang	1094	24	122	370	519	59
Anhui	391	6	52	140	181	12
Fujian	421	10	65	192	144	10
Jiangxi	325	5	43	152	125	0
Shandong	727	17	89	346	266	9
Regional total	4121	127	550	1694	1650	100
% China	30.3	34.4	34.5	31.9	28.9	16.8

Source: China Hotel Guide 2008 – 2009.

3.11.8 East China Region Transport Network

Table 3.11.7 indicates that the East China Region collectively has nearly 16.9% of the nation's total railways and 23% of the nation's express and highways. Shandong has 4.2% of China's railways and 5.9% of the highways; followed by Anhui an inland province with 3.3% of China's railways and 4.1% of the highway network.

Table 3.11.7 East China Region transport network 2007

(Kilometers)

	Total railways	% China	Total express and highways	% China
National Total	77966		3583715	
East China				
Shanghai	331	0.4	11163	0.3
Jiangsu	1619	2.1	133732	3.7
Zhejiang	1319	1.7	99812	2.8
Anhui	2387	3.1	148372	4.1
Fujian	1616	2.1	86926	2.4
Jiangxi	2566	3.3	130515	3.6
Shandong	3302	4.2	212237	5.9
Regional total	13141		822757	

% China total	16.9	23.0

Source: China Statistical Yearbook 2008.

3.11.9 East China Region Air Transportation

According to statistics compiled by the Aviation Council of International in April 2007, Shanghai Pudong International Airport has been ranked number 3 in the world's top 10 airports with 26.7 million passengers handled in 2007, a 10% increase over the previous year (refer to Table 3.1.8).

3.11.10 Conclusion

Some of the 2007 economic data indicate that the East China Region is the nation's leading region for tourist arrivals and provision of tourism related services. Most of the provinces in this region are amongst the first group of "special economic zones" established during mid 1980's. This region has benefited greatly from the special economic polices developed by the Central Government. The urban and rural population is split in half. It is the largest contributor (41.7%) of China's total GDP, and collectively made up 16.9% of total international tourists and 59.6% of total foreign tourists to China in 2007. International tourism generated 34% of China's total tourism earnings for this region. Employment in hotel and catering services was at 17.9% of China's total and 17.4% of China's total for the sports and entertainment sectors. Thirty four percent of the nation's 5 and 4-star hotels are in this region. Shanghai Pudong Airport is amongst the world's top 10 airports for passengers handled in 2007. Anhui and Jiangxi are the two inland provinces that have lagged behind the coastal provinces such as Shanghai, Jiangsu, Zhejiang and Shandong.

3.12 South China Region

3.12.1 Introduction

The South China Region consists of 6 provinces (Henan, Hubei, Hunan, Guangdong, Guangxi and Hainan) in the Southeast of China. It occupies 11% of China's total territory and has 28 % of China's population (364.8 million). The percentage of urban and rural population is 45% to 55%.

Table 3.12.1 South China region population and territory 2007

(10,000 people and 10,000 square kilometers)

	Capital City	Area	Total Population	Urban Population	%	Rural Population	%
National Total		960	132129	59379	45	72750	55
South China							
Henan	Zhengzhou	17	9360	3214	34	6146	66
Hubei	Wuhan	19	5699	2525	44	3174	56
Hunan	Changsha	21	6355	2571	40	3784	60
Guangdong	Guangzhou	19	9449	5966	63	3483	37
Guangxi	Nanning	24	4768	1728	36	3040	64
Hainan	Haikou	3	845	399	47	446	53
Regional total		102	36476	16402	45	20074	55
% ChinaTotal		11	28	28		28	

Source: China Statistical Yearbook 2008 and CNTA internet.

3.12.2 South China Region Gross Regional Product (GRP)

Table 3.12.2 indicates the total GRP for the South China Region for the period 2001 to 2007. The average regional growth rate over this period was 16.9% compared to 14.8% for China's national GDP. In 2007, the region made up 28.5% of China's total GDP, the second highest after the East China Region (41.7%). Guangdong Province made up 12.4% of NGDP, compared to Hainan Province with only 0.5% of NGDP.

Table 3.12.2 South China region gross regional product 2007

(100 million and NGDP RMB 100 billion)

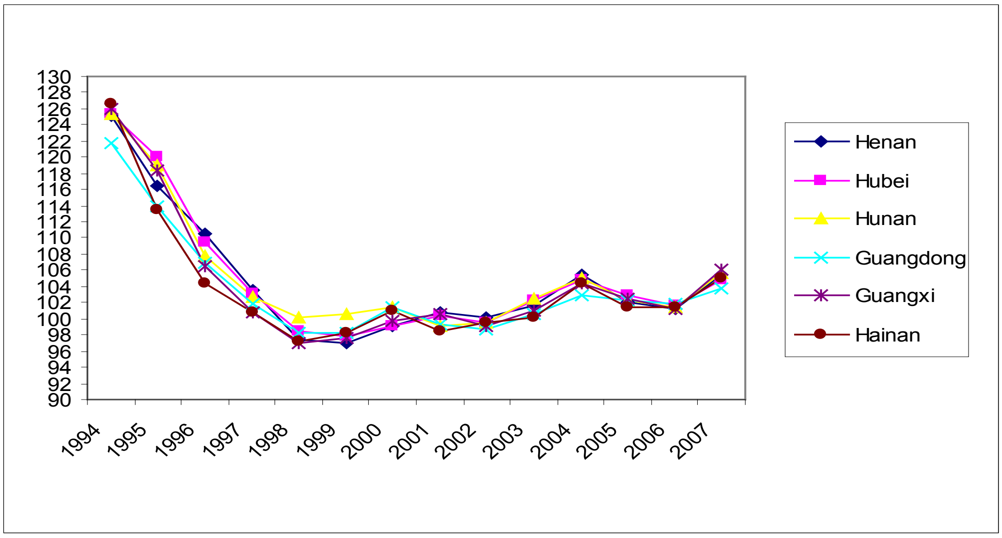
	2001	2003	2005	2007	07 GRP	AAGR (%) 2001-2007
NGDP	109655	135823	183868	251483	%	14.8
PC GDP	8622	10542	14103	18934	07 NGDP	14.0
South China						
Henan	5533	6868	10587	15012	6.0	18.1
Hubei	3881	4757	6520	9231	3.7	15.5
Hunan	3832	4660	6511	9200	3.7	15.7
Guangdong	12039	15845	22367	31084	12.4	17.1
Guangxi	2279	2821	4076	5956	2.4	17.4
Hainan	558	693	895	1223	0.5	14.0
Regional total	28122	35644	50956	71706	28.5	16.9

Source: China Statistical Yearbook 2007 - 2008.

3.12.3 South China Region Consumer Price Index

The graph indicates that the CPI for the South China Region over the period 1994 to 1998 was trending downwards. During this period Hainan Province had the highest CPI at 21.6% to 9% and Guangdong Province the lowest at 18.9% to 1.8%. From 1998 the trend stayed fairly flat with a small increase in 2004 and 2007. The percentage CPI difference between the provinces in this region was marginal.

Figure 3.12.1 South China Region – CPI 1994 - 2007



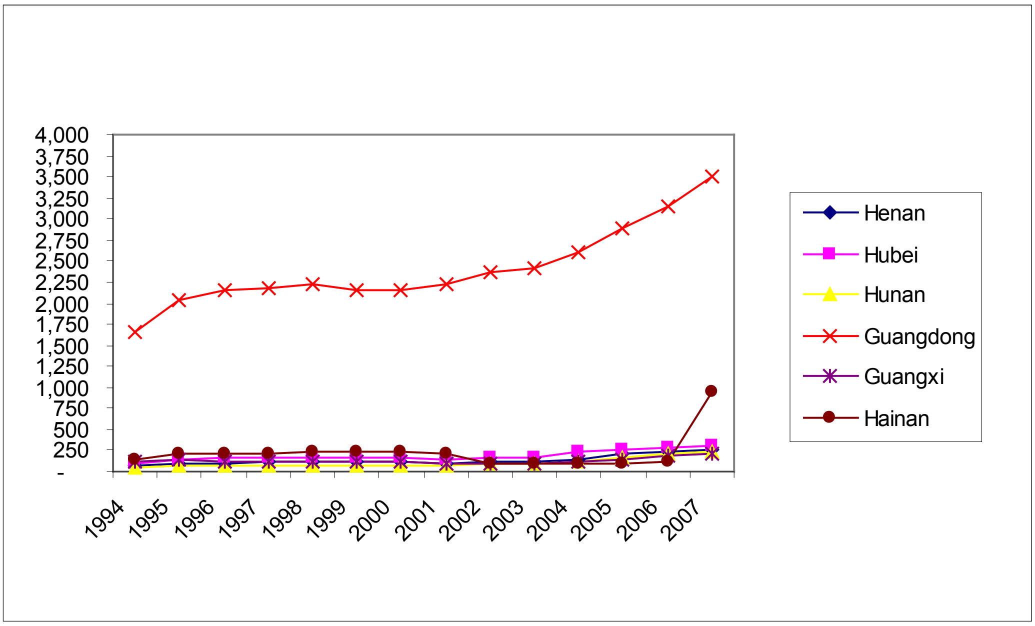
Source: China National Bureau of Statistics.

3.12.4 South China Region Registered Foreign Enterprises

Figure 3.12.2 indicates that the investment by Registered Foreign Enterprises in the region increased steadily from 1994. Led by Guangdong Province with US$1,659 million in 1994 increasing to US$ 3,507 million in 2007, followed by Hainan at 154 million in 1994 to 941 million, Hubei with US$104 million to US$313 million, Henan US$73 million to US$257 million, and Guangxi US$126 million to US$219 million.

Figure 3.12.2 South China Region – RFE 1994 – 2007

(US$100 million)



Source: China National Bureau of Statistics.

3.12.5 South China Region Employment

Table 3.12.3 indicates that there are over 200 million people (27% of China's total) employed in 2007, of which 29% of the total employment in the South China Region is directly in the hotel and catering industry and an additional 23.8% is in the sports and entertainment sector.

This region shows the highest employment number in China in the hotel and catering sector. Guangdong has the second highest employment (239,000) in the hotel and catering sector in China after Beijing (249,000) in 2007.

Table 3.12.3 South China Region employment by sectors 2007

(10,000 people)

	Total Employed Number	Hotels and Catering	Culture, Sports and Entertainment
National Total	76990.0	185.8	125.0
% of national total		0.24%	0.16%
South China			
Henan	5772.7	10.0	7.2
Hubei	2763.0	4.6	5.0
Hunan	3749.3	7.2	4.4
Guangdong	5292.8	23.9	8.8
Guangxi	2759.6	4.5	3.1
Hainan	414.8	3.7	1.2
Regional total	20752.2	53.9	29.7
% China total	27.0	29.0	23.8

Source: China Statistical Yearbook 2008.

3.12.6 South China Region Tourism and Exchange Earnings

Table 3.12.4 indicates the growth of international tourists to the Northeast China Region during a five year interval from 1995 to 2005 and through to 2007, it recorded an AAGR of 23.4% in international tourist arrivals and 40.7% for foreign tourists. The region makes up 21% of total international tourists and 41.8% of total foreign tourists to China in 2007. Guangdong leads in international tourist arrivals (24.6 million) in 2007, compared to Henan and Hainan with 880,000 and 750,000 arrivals respectively for the same year. Guangxi received over 2 million international visitors, of which over half were foreign tourists.

Table 3.12.4 South China Region international tourist arrivals 2007

(10,000 people)

	1995		2000		2007		AAGR %	AAGR %
	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign

China total	1728	589	83344	1016	13187	2611	18.5	13.2
South China								
Henan	22	9	33	18	88	56	12.3	16.3
Hubei	27	17	45	36	132	108	14.1	16.7
Hunan	18	7	45	16	121	88	17.3	23.2
Guangdong	621	122	1199	213	2461	629	12.2	14.6
Guangxi	42	31	123	51	206	125	14.2	12.4
Hainan	29	6	49	9	75	59	8.4	21.5
Regional Total	758	192	1,494	343	3082	1063	12.4	15.3
% China Total	43.9	32.6	1.8	33.7	23.4	40.7		

Source: China Statistical Yearbook 2006 - 2008.

Table 3.12.5 indicates increases in international arrivals and exchange earnings by the South China Region for a five year interval from 1995 to 2005, and growth continued through to 2007 with a record AAGR of 12.4% in international arrivals and 12.1% in earnings. This region contributed 26% of total international tourism exchange earnings for China in 2007. Guangdong received US$8.7 billion in tourism exchange earnings, the number one recipient in China in 2007, compared to Henan and Hainan at US$318 million and US$302 million respectively.

Table 3.12.5 South China Region international tourist arrivals and earnings 2007

(10,000 people and US$ million)

	1995 number	earning	2000 number	earning	2007 number	earning	AAGR % 95 - 07 number	AAGR % 95 - 07 earning
China total	1728	8249	8344	16224	13187	41919	18.5	14.5
South China								
Henan	22	60	33	124	88	318	12.3	14.9
Hubei	27	73	45	146	132	413	14.1	15.5
Hunan	18	65	45	221	121	642	17.3	21.0
Guangdong	621	2393	1199	4112	2461	8706	12.2	11.4
Guangxi	42	121	123	307	206	577	14.2	13.9
Hainan	29	81	49	109	75	302	8.4	11.6
Regional total	758	2793	1494	5019	3082	10958	12.4	12.1
% China total	43.9	33.9	17.9	30.9	23.4	26.1		

Source: China Statistical Yearbook 2006 - 2008.

3.12.7 South China Region Star-Rated Hotels

According to China's Star-Rated Hotel Guide 2008-2009, there were a total of 3,485 hotels (25.7% of China's total hotels) in the region. Table 3.12.6 shows the breakdown of 5 to 1 star-rated hotels and their percentage, relative to the whole of China. Guangdong has 33.5% of the total hotels in this region, followed by Hubei with 16.7% and Henan 15.5%. Hainan on the other hand has a relatively small number of hotels but the highest percentage (13.3%) of 5-star hotels, and 13.3% of the 4-star hotels.

Table 3.12.6 South China Region star-rated hotels 2007

	Total	5-star	4-star	3-star	2-star	1-star
China total	13583	369	1595	5307	5718	594
South China						
Henan	522	4	53	219	239	7
Hubei	589	8	50	192	311	28
Hunan	541	12	41	198	271	19
Guangdong	1169	58	167	575	338	31
Guangxi	401	11	32	183	166	9
Hainan	263	14	53	118	66	12
Regional total	3485	107	396	1485	1391	106
% China	25.7	29.0	24.8	28.0	24.3	17.8

Source: China Hotel Guide 2008 – 2009.

3.12.8 South China Region Rail and Road Transport Network

Table 3.12.7 indicates that the South China Region collectively has 19% of the nation's total railways and 24.9% of the nation's total expressways and highways. Henan in the central China has 5.2% and 6.7% of China's railways and highways, compared with Hainan only with 0.5% of China's railways and highways.

Table 3.12.7 South China Region transport network 2007

	Total railways	% China	Total express and highways	% China
National Total	77966		3583715	
South China				
Henan	4042	5.2	238676	6.7
Hubei	2565	3.3	183780	5.1
Hunan	2899	3.7	175415	4.9
Guangdong	2175	2.8	182005	5.1
Guangxi	2734	3.5	94202	2.6
Hainan	388	0.5	17789	0.5
Regional total	14803		891867	
% China total	19.0		24.9	

Source: China Statistical Yearbook 2008.

3.12.9 South China Region Air Transportation

According to statistics compiled by the Aviation Council of International in April 2007, Guangzhou Beiyun International Airport has been ranked number 4 in the world's top 10 airports with 26 million passengers handled in 2007, a 12.3% increase over the previous year (refer to Table 3.1.8).

3.12.10 Conclusion

The South China Region includes Henan, China's largest populated province (94 million), Guangdong, the third largest province (93 million) and Hainan (8 million), one of China's smallest provinces by population. The urban and rural population is 44% to 56%. The South China Region makes up 28 % of China's total GDP, second highest after the East China Region (41.7%). It also has a higher percentage (23.4% of China's total) of international tourist arrivals in 2007 and 26% of China's total tourism earnings. Employment in hotel and catering services is 29% of China's total, and 23.8% of China's total for the sports and entertainment sectors. It has 29% of China's 5-star hotels and 25% of the 4-star hotels. Guangzhou Airport is amongst the world's top 10 airports for passengers handled in 2007. Within this region, except for Guangdong, the provinces have a higher number of 3-star and 2-star accommodation and received only 0.4% (Hainan) to 1.4% (Guangxi) of total China's international visitors in 2007.

3.13 Southwest China Region

3.13.1 Introduction

The Southwest China Region consists of 1 municipality (Chongqing), 3 provinces (Sichuan, Guizhou and Yunnan) and 1 Autonomous Region (Tibet). The region occupies 25% of China's total territory and has 15% (195 million) of China's population. The percentage of rural population is relatively higher than other regions at 65%. Sichuan is the fourth largest province in China in terms of population (81.3 million). The region has various minority tribes including the Zhuang, Miao, Hui, Dai and Muslims.

Table 3.13.1 Southwest China region population and territory 2007

(10,000 people and 10,000 square kilometers)

	Capital City	Area	Total Population	Urban Population	%	Rural Population	%
National Total		960	132129	59379	45	72750	55
Southwest China							
Chongqing	Chongqing	8	2816	1361	48	1455	52
Sichuan	Chengdu	49	8127	2893	36	5234	64
Guizhou	Guiyang	17	3762	1062	28	2700	72
Yunnan	Kunming	39	4514	1426	32	3088	68
Tibet	Lhasa	127	284	80	28	204	72
Regional total		241	19503	6824	35	12679	65
% ChinaTotal		25	15	11		17	

Source: China Statistical Yearbook 2008 and CNTA internet.

3.13.2 Southwest China Region Gross Regional Product (GRP)

Table 3.13.2 shows the GRP for the Southwest China Region for the period of 2001 to 2007. The average regional growth rate over this period was 15.5% compared to China's national GDP of 14.8%. In 2007, this region made up 8.9% of the nation's total GDP, one of the smallest regions compared with regions in the east. Within this region, Sichuan is the highest contributor (4.2%) of the nation's GDP in 2007, with Tibet at 0.1% of the NGDP in the same year.

Table 3.13.2 Southwest China region gross regional product 2007

(100 million and NGDP RMB 100 billion)

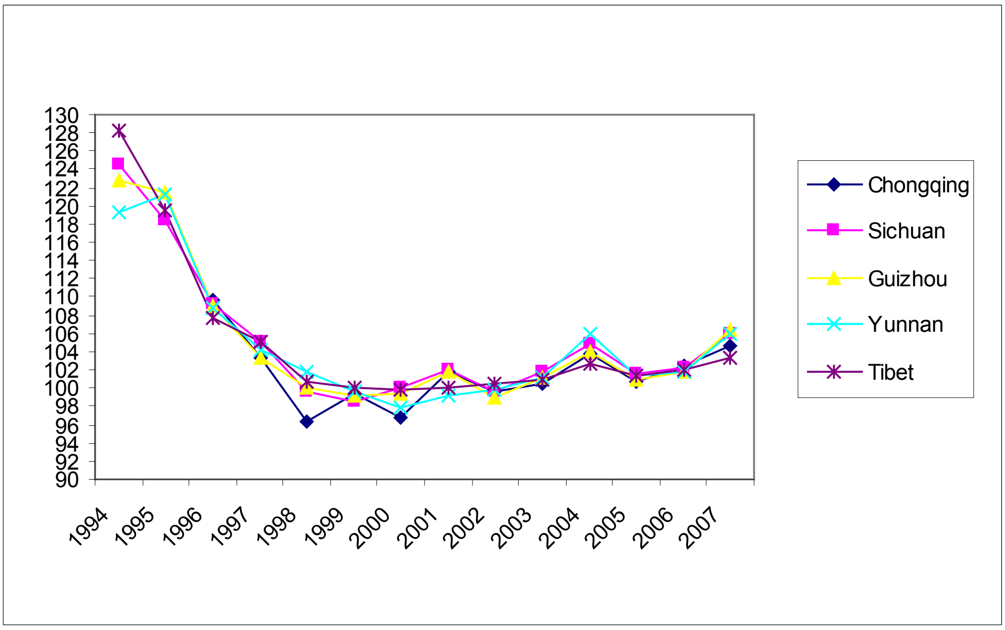
	2001	2003	2005	2007	07 GRP	AAGR (%) 2001-2007
NGDP	109655	135823	183868	251483	%	14.8
PC GDP	8622	10542	14103	18934	07 NGDP	14.0
Southwest China						
Chongqing	1766	2273	3070	4123	1.6	15.2
Sichuan	4293	5333	7385	10505	4.2	16.1
Guizhou	1133	1426	1979	2742	1.1	15.9
Yunnan	2138	2556	3473	4741	1.9	14.2
Tibet	146	189	251	342	0.1	15.2
Regional total	9477	11777	16159	22453	8.9	15.5

Source: China Statistical Yearbook 2006 - 2008.

3.13.3 Southwest China Region Consumer Price Index

The graph indicates that the CPI for the South China Region over the period 1994 to 1999 was trending downwards. During this period Tibet had the highest CPI of 28.3% to 1.5% and Yunnan Province the lowest at 19.2% to 1.4%. From 1998 the trend was stable through to 2006 with small increases shown in 2001, 2004 and 2007. Chongqing had the lowest CPI in 1998 and 2000 than other provinces since its inception in 1997. The percentage of CPI differences between the provinces in the region was marginal.

Figure 3.13.1 Southwest China Region – CPI 1994 – 2007



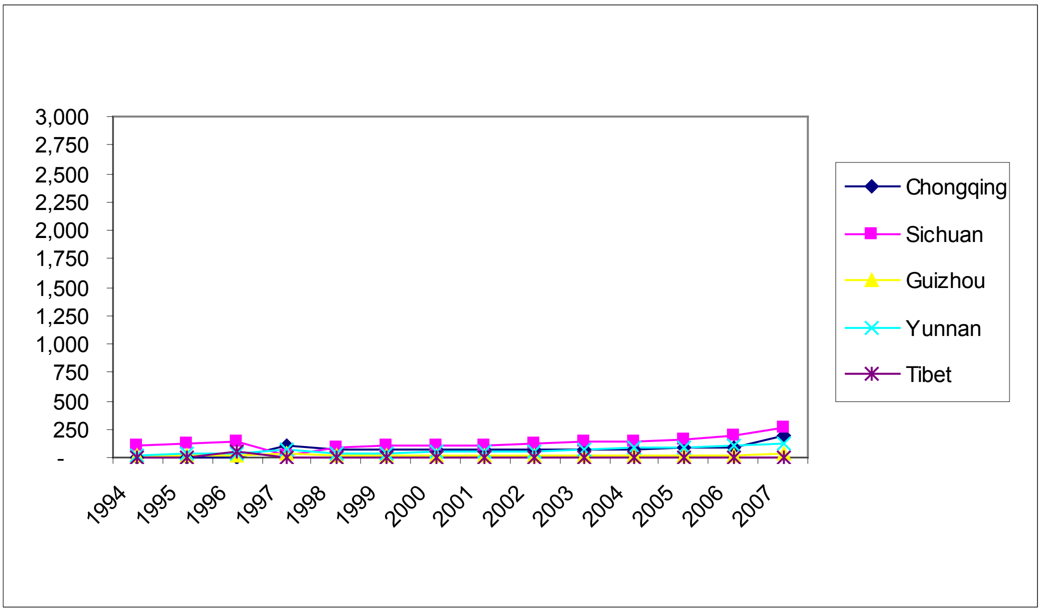
Source: China National Bureau of Statistics.

3.13.4 Southwest China Region Registered Foreign Enterprises

Figure 3.13.2 indicates that the investment by Registered Foreign Enterprises in the Southwest China Region was sluggish compared to other coastal regions from 1994. Tibet received the smallest investment in China at US$2 million in 1994 to 5 million in 2007, except for 1996 when a RFE of US$56 million was recorded. Chongqing started with US$100 million in 1997 and slowly increased to US$198 million in 2007. Sichuan, Yuan and Guizhou indicate positive but modest growth in RFE.

Figure 3.13.2 Southwest China Region – RFE 1994 – 2007

(US$100 million)



Source: China National Bureau of Statistics.

3.13.5 Southwest China Region Employment

Table 3.13.3 indicates that there were over 116 million people (15% of China's total) employed in the Southwest China Region, of which 9.5% of the total employment is directly related to hotel and catering services, and an additional 10.2% is in the sports and entertainment sectors. Yunnan has 26 million people employed in 2007, of which 58,000 people are employed by the hotel and catering sector, compared to Tibet with only 4,000 people working in this sector for the same year.

Table 3.13.3 Southwest China Region employment by sectors 2007

(10,000 people)

	Total Employed Number	Hotels and Catering	Culture, Sports and Entertainment
National Total	76990.0	185.8	125.0
% of national total		0.24%	0.16%

Southwest China			
Chongqing	1789.5	3.6	2.3
Sichuan	4778.6	5.1	4.3
Guizhou	2283.0	2.7	2.1
Yunnan	2600.8	5.8	3.4
Tibet	153.7	0.4	0.6
Regional total	11605.6	17.6	12.7
% China total	15.1	9.5	10.2

Source: China Statistical Yearbook 2008.

3.13.6 Southwest China Region Tourism and Exchange Earning

Table 3.13.4 shows the growth of international tourists to the Southwest China Region during a five year interval from 1995 to 2005 and through to 2007, and the region recorded an AAGR of 13.7% in international tourist arrivals and 12.7% in foreign tourists. Most of the provinces in this region indicate a steady growth of international arrivals ranging from an AAGR of 10% to 16%. The region makes up 4% of total international tourists but attracts 13.9% of total foreign tourists to China in 2007. Yunnan received over 2.2 million international tourists in 2007, compared to Guizhou and Tibet with 430,000 and 370,000 visitors respectively.

Table 3.13.4 Southwest China Region foreign tourist arrivals 2007

(10,000 people)

	1995		2000		2007		AAGR %	AAGR %
	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign
China total	1728	589	83344	1016	13187	2611	18.5	13.2
Southwest China								
Chongqing	nil	nil	27	19	76	62	16.2	18.2
Sichuan	38	25	46	20	171	107	13.4	13.1
Guizhou	14	8	18	7	43	15	10.0	5.9
Yunnan	60	47	100	67	222	145	11.6	9.8
Tibet	7	7	15	14	37	34	15.1	14.7
Regional Total	118	86	206	127	548	364	13.7	12.7
% China Total	6.8	14.6	0.2	12.5	4.2	13.9		

Source: China Statistical Yearbook 2006 - 2008.

Table 3.13.5 shows an increase in international arrivals and exchange earnings by the Southwest China Region for a five year interval from 1995 to 2005 and this continued through to 2007. This region recorded an AAGR of 13.7% in international arrivals and 16.3% in earnings. It contributed 4.8% of total international tourism exchange earnings for China in 2007. Yunnan tops the region for earnings at US$860 million in 2007, compared to Guizhou and Tibet at USD129 million and US$135 million respectively for the same year.

Table 3.13.5 Southwest China Region international tourist arrivals and earnings 2007

(10,000 people and US$ million)

	1995 number	earning	2000 number	earning	2007 number	earning	AAGR % 95 - 07 number	AAGR % 95 - 07 earning
China total	1728	8249	8344	16224	13187	41919	18.5	14.5
Southwest China								
Chongqing	*	*	27	138	76	382	16.2	15.7
Sichuan	38	125	46	122	171	512	13.4	12.5
Guizhou	14	29	18	61	43	129	10.0	13.2
Yunnan	60	165	100	339	222	860	11.6	14.7
Tibet	7	11	15	52	37	135	15.1	23.2
Regional total	118	330	206	712	548	2018	13.7	16.3
% China total	6.8	4.0	2.5	4.4	4.2	4.8		

Source: China Statistical Yearbook 2006 - 2008.

3.13.7 Southwest China Region Star-Rated Hotels

According to China's Star-Rated Hotel Guide 2008-2009, there are a total of 1,962 hotels (14.4% of China's total hotels) in the region. Table 3.13.6 shows the breakdown of 5 to 1 star-rated hotels and their percentage, relative to the whole of China. Yunnan has 45% of the total hotels in the region with a higher percentage of lower level hotels, followed by Sichuan at 25.8%. Tibet is at other end of the spectrum with only 4.1% of the total hotels in the region. There is non 5-star hotel in Tibet. Sichuan has 15 hotels in the 5-star category with the highest percentage (42.8%) in the region, compared to Guizhou with only 2 hotels in the 5-star category.

Table 3.13.6 Southwest China Region star-rated hotels 2007

	Total	5-star	4-star	3-star	2-star	1-star
China total	13583	369	1595	5307	5718	594
Southwest China						
Chongqing	240	7	35	90	99	9
Sichuan	507	15	63	181	229	19
Guizhou	250	2	19	76	123	30
Yunnan	887	11	45	177	520	134
Tibet	78	0	3	35	36	4
Regional total	1962	35	165	559	1007	196
% China	14.4	9.5	10.3	10.5	17.6	33.0

Source: China Hotel Guide 2008 - 20009.

3.13.8 Southwest China Region Rail and Road Network

Table 3.13.7 shows that the Southwest China Region has 11.7% of the nation's total railways and 18.6% of the nation's total expressways and highways. Sichuan has 3.8% of the nation's railways and 5.4% of the nation's highway networks, compared to Tibet with less than 1% of China's railways and 1.4% of the highways.

Table 3.13.7 Southwest China Region transport network 2007

(10,000 kilometers)

	Total railways	% China	Total express and highways	% China
National Total	77966		3583715	
Southwest China				
Chongqing	1291	1.7	104705	2.9
Sichuan	2999	3.8	189395	5.3
Guizhou	2012	2.6	123247	3.4
Yunnan	2308	3.0	200333	5.6
Tibet	550	0.7	48611	1.4
Regional total	9160		666291	
% China total	11.7		18.6	

Source: China Statistical Yearbook 2008.

3.13.9 Conclusion

The Southwest China Region is distinctively different to the regions in the east of China. Some of the 2007 economic data indicates that this region occupies a quarter of China's total territory, but only 14.9 % (195 million) of China's population. It has a relatively larger rural population (66%). In terms of regional GDP the ratio to the National GDP was significantly smaller ranging from 0.1% (Tibet) to 1.1% (Guizhou), except for Sichuan which was 4.2% of NGDP. Regional employment in the hotel and catering sectors was between 0.4% (Tibet) and 2.7% (Guizhou) of China's total. Only 4.2% of the total international tourists to China visited the Southwest China Region. Regional earnings from international tourism were 4.8% of China's total. There are higher percentages of lower level accommodation in this region in the southwest of China. However, the Southwest China Region offers an abundance of tourism attractions including Yunnan and Tibet with unique sceneries and minority cultures.

3.14 Northwest China Region

3.14.1 Introduction

The Northwest China Region consists of 3 provinces (Shaanxi, Gansu and Qinghai) and 2 Autonomous Regions (Ningxia Hui and Xinjiang). It occupies nearly one third (32%) of total China's territory and has only 7% (9.6 million) of China's population. The percentage of urban and rural population is 38% to 62%.

Table 3.14.1 Northwest China region population and territory 2007

(10,000 people and 10,000 square kilometers)

	Capital City	Area	Total Population	Urban Population	%	Rural Population	%
National Total		960	132129	59379	45	72750	55
Northwest China							
Shaanxi	Xi'an	21	3748	1522	41	2226	59
Gansu	Lanzhou	45	2617	827	32	1790	68
Qinghai	Xining	72	552	221	40	331	60

Ningxia	Yinchua	6	610	269	44	341	56
Xinjiang	Urumqi	166	2095	820	39	1275	61
Regional total		309	9622	3659	38	5963	62
% ChinaTotal		32	7	6		8	

Source: China Statistical Yearbook 2008 and CNTA internet.

3.14.2 Northwest China Region Gross Regional Product (GRP)

Table 3.14.2 indicates the total GRP for the Northwest China Region for the period of 2001 to 2007. Although the average regional growth rate over this period for this region was 16.8% compared to China's national GDP of 14.8 %, it contributed only 5.3% of China's total GDP. All provinces in the region have the smallest percentage of GRP in 2007, ranging from Qinghai 0.3% to Shaanxi 2.2%, relative to the nation's GDP, compared to other provinces in the east, northeast and south regions of China.

Table 3.14.2 Northwest China region gross regional product 2007

(100 million and NGDP RMB 100 billion)

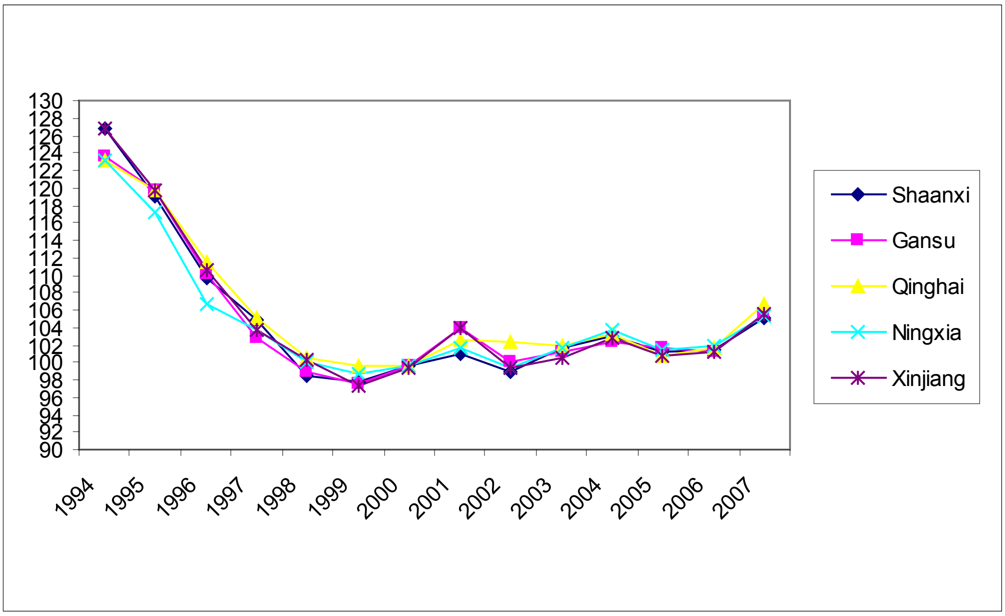
	2001	2003	2005	2007	07 GRP	AAGR (%) 2001-2007
NGDP	109655	135823	183868	251483	%	14.8
PC GDP	8622	10542	14103	18934	07 NGDP	14.0
Northwest China						
Shaanxi	2011	2588	3676	5466	2.2	18.1
Gansu	1125	1400	1934	2702	1.1	15.7
Qinghai	300	390	543	784	0.3	17.3
Ningxia	337	445	606	889	0.4	17.5
Xinjiang	1492	1886	2604	3523	1.4	15.4
Regional total	5265	6709	9363	13364	5.3	16.8

Source: China Statistical Yearbook 2006 - 2008.

3.14.3 Northwest China Region Consumer Price Index

The graph indicates that the CPI for the Northwest China Region over the period 1994 to 1999 was trending downwards. During this period Shaanxi and Xinjiang had the highest CPI of 27.6% to 1.2%. From 1998 the trend stayed fairly flat through to 2006, with small increases shown in 2004 and 2007. The percentage of CPI differences between the provinces in the region was marginal.

Figure 3.14.1 Northwest China Region – CPI 1994 - 2007



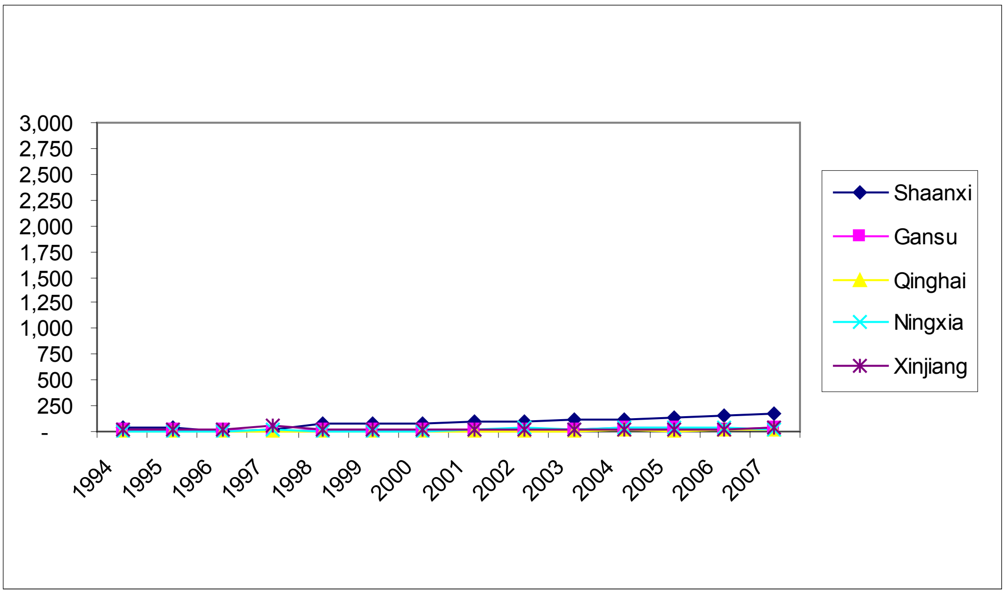
Source: China National Bureau of Statistics.

3.14.4 Northwest Region Registered Foreign Enterprises

Table 3.14.2 indicates that the investment by Registered Foreign Enterprises in the region increased steadily from 1994. Led by Shaanxi Province where investment in RFE was US$38 million in 1994 increasing to US$165 million in 2007, Gansu (11 million to 31 million); Qinghai (US$1 million to US$24 million), Ningxia (US$4 million to US$22 million); and Xinjiang (US$13 million to US$31 million). The Northwest China Region received far less investment compared to the costal regions of China.

Figure 3.14.2 Northwest China Region – RFE 1994 – 2007

(US$100 million)



Source: China National Bureau of Statistics.

3.14.5 Northwest China Region Employment

Table 3.14.3 indicates that there were nearly 46 million people (6% of China's total) employed in the Northwest Region of China. Some 6% of the total employment was directly in the hotel and catering services sectors and an additional 8% was in the sports and entertainment services sectors. This is the lowest employment in China in these sectors. Within the region, Shaanxi has 48,000 people employed in the hotel and catering sector, compared to Qinghai and Ningxia with only 4,000 and 6,000 respectively.

Table 3.14.3 Northwest China Region employment by sectors 2007
(10,000 people)

	Total Employed Number	Hotels and Catering	Culture, Sports and Entertainment
National Total	76990.0	185.8	125.0
% of national total		0.24%	0.16%
Northwest China			
Shaanxi	1922.0	4.8	3.8
Gansu	1374.4	2.1	2.2
Qinghai	276.3	0.4	0.7
Ningxia	309.5	0.6	0.9
Xinjiang	800.8	2.7	2.5
Regional total	4683.0	10.6	10.1
% China total	6.1	5.7	8.1

Source: China Statistical Yearbook 2008.

3.14.6 Northwest China Region Tourism and Exchange Earnings

Table 3.14.4 shows the growth of international tourists to the Northwest China Region during a five year interval from 1995 to 2005 and through to 2007, it recorded an AAGR of 8.7% in international tourist arrivals and 7.9% for foreign tourists. The region makes up 1.6% of total international tourists and 6.4% of total foreign tourists to China in 2007. Shaanxi attracted a total of 1.23 million international tourists, compared to Qinghai (50,000) and Ningxia (10,000) in 2007.

Table 3.14.4 Northwest China Region international tourist arrivals 2007

(10,000 people)

	1995		2000		2007		AAGR %	AAGR %
	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign	Total Int'l	Foreign
China total	1728	589	83344	1016	13187	2611	18.5	13.2
Northwest China								
Shaanxi	44	40	71	58	123	98	8.9	7.8
Gansu	9	7	21	14	33	23	11.4	10.5
Qinghai	1	1	3	1	5	4	11.7	12.6
Ningxia	0	0	1	1	1	1	8.1	9.6
Xinjiang	20	19	26	21	44	40	6.6	6.7

Regional Total	75	67	122	96	206	166	8.7	7.9
% China Total	4.4	11.3	0.1	9.4	1.6	6.4		

Source: China Statistical Yearbook 2006 - 2008.

Table 3.14.5 shows that although there have been increases in international arrivals and exchange earnings by the Northwest China Region for a five year interval from 1995 to 2005, and it continued through to 2007, the region suffers from a lack of tourism activity and consequent export earnings from international tourism. This region contributed only 2.1% of the total international tourism exchange earnings for China in 2007. Shanxi recorded earnings with US$139 million in 1995 to US$612 million in 2007, compared with Qinghai with only US$2 million to US$16 million, and Ningxia showing earnings from US$1 million in 1995 to US$3 million in 2007.

Table 3.14.5 Northwest China Region international tourist arrivals and earnings 2007

(10,000 people and US$ million)

	1995 number	earning	2000 number	earning	2007 number	earning	AAGR % 95 - 07 number	AAGR % 95 - 07 earning
China total	1728	8249	8344	16224	13187	41919	18.5	14.5
Northwest China								
Shaanxi	44	139	71	280	123	612	8.9	13.1
Gansu	9	21	21	55	33	70	11.4	10.6
Qinghai	1	2	3	7	5	16	11.7	18.9
Ningxia	0.4	1	1	3	1	3	8.1	9.6
Xinjiang	20	74	26	95	44	162	6.6	6.7
Regional total	75	237	122	440	206	863	8.7	11.4
% China total	4.4	2.9	1.5	2.7	1.6	2.1		

Source: China Statistical Yearbook 2006 - 2008.

3.14.7 Northwest China Region Star-Rated Hotels

According to China's Star-Rated Hotel Guide 2008-2009, there are a total of 1,099 hotels (8% of China's total hotels) in the region. This region in China's northwest has a lower number of 5-star (4.3% of China's total) and 4 star (6.5% of China's total) hotels but a larger number of hotels in the 3-star to 1-star category. Table 3.14.6 shows the breakdown of 5 to 1 star-rated hotels and their percentage, relative to the whole of China. Xinjiang makes up 34% of the total hotels in the region, followed by Shaanxi 27.6%. Ningxia is at other end of the spectrum with only 4.6% of the region's total hotels and has no hotel in 5-star category.

Table 3.14.6 Northwest China Region star-rated hotels 2007

	Total	5-star	4-star	3-star	2-star	1-star
China total	13583	369	1595	5307	5718	594
Northwest China						
Shaanxi	303	5	24	152	117	5
Gansu	267	2	25	91	135	14
Qinghai	105	1	9	35	52	8
Ningxia	51	0	5	34	12	0
Xinjiang	373	8	41	155	148	21
Regional total	1099	16	104	467	464	48
% China	8.1	4.3	6.5	8.8	8.1	8.1

Source: China Hotel Guide 2008 - 20009.

3.14.8 Northwest China Region Rail and Road Network

Table 3.14.7 indicates that the Northwest China Region has 13.9% of the nation's total railways in operation and 12.3% of the nation's total expressways and highways. Shaanxi has 4% of nation's railways and 3.4% of the highways, Xinjiang in the far northwest of China, has 3.5% of the railways and 4% of the nation's highways.

Table 3.14.7 Northwest China Region transport network 2007

	Total railways	% China	Total express and highways	% China
National Total	77966		3583715	
Northwest China				
Shaanxi	3185	4.1	121297	3.4
Gansu	2435	3.1	100612	2.8
Qinghai	1652	2.1	52626	1.5
Ningxia	789	1.0	20562	0.6
Xinjiang	2761	3.5	145219	4.1
Regional total	10823		440316	
% China total	13.9		12.3	

Source: China Statistical Yearbook 2008.

3.14.9 Conclusion

In contrast to the regions in the east of China, as shown by some of the 2007 economic data, this region occupies nearly one third of China's total territory but only has 7 % (over 9.5 million) of China's population. It has a larger rural population (55%). In terms of the regional GDP ratio relative to the national GDP the region was significantly smaller ranging from 0.3% (Qinghai) to 2.2% (Shaanxi). Regional employment in the hotel and catering sectors was 5.7% of China's total. Only 1.6% of the total international tourists to China visit this region in the Northwest of China. The Northwest China Region received far less investment compared to the costal regions of China. Regional earnings from international tourism were 2% of China's total in 2007, but this region has a rich history and unique tourism attractions including the Silk Road, Terracotta Warriors, Dunhuang Grotto and the remains of the western end of the Great Wall.

Chapter 4
Research Methodology

The regional data available for international tourist arrivals into China is based upon annual recorded accommodation use, and dates from 1994 to 2007. Regional data is available by province including the autonomous regions and municipalities that make up the 31 governing provincial areas of mainland China. The two special economic regions of Hong Kong and Macau collect their own data, and operate under passport to China for Chinese travel. These two areas are commonly treated as independent national units and are not included here as part of mainland provincial China. The data is published by the China National Tourism Organisation (CNTA) and is available only for the top 13 major source markets of Japan, Korea, Malaysia, Philippines, Singapore, Thailand, USA, Canada, UK, France, Germany, Russia and Australia (in order of volume) covering more than 92% of current total international arrivals to China. Additional data used for the econometric causal models includes per capita income, the consumer price index and exchange rates for the data series for these top 13 major tourist generating countries to China. These data are collected from the DX (Econ) data base published by the IMF, EU and OECD. Other variables consist of economic, social, transport, connectivity, weather and tourist attractions in China and are sourced for the 31 Chinese regions, from a variety of published sources within China.

In the econometric literature, the most commonly used independent variables for predicting arrivals (Song and Witt, 2000, Song et al., 2009) are: population of the tourist generating country, income in tourists' country of origin, own prices including cost of living in the destination country and travel cost to destination, exchange rate, substitute prices for alternative destinations, marketing and promotion expenditure and transport costs. In addition, a lagged dependent variable and an autoregressive term can be justified on the grounds of habit persistence and supply of tourism related goods and services. Most recent examples of the use of these variables can be found in Cortes-Jimenez and Blake (2010) who used structural time-series techniques modelled separately by purpose of visit and nationality pairings against results from models for expenditure treated on a more aggregate basis, and Andraz et al., (2009) who apply a diffusion index model, proposed by Stock and Watson (1999, 2002), to forecast the UK tourism growth cycle in Algarve Portugal. The information contained in a large set of variables is summarized through the use of dynamic factor models, where a small number of unobserved common factors may capture co-movements across series. The improved forecasting performance obtained in their study has raised prospects of using the diffusion index approach to construct leading indicators for tourism demand; and the importance of addressing the problem of selecting the initial data set. The economic cycle can introduce asymmetry in tourism variables.

Some qualitative elements including dummy variables are often used in international tourism demand functions to measure ‘one off events’ such as the Olympic Games, SARS, Asia Tsunami and wars.

In terms of price variables, consumer price indices have been regarded as a reasonable proxy (Martin and Witt, 1987) in tourism demand forecasting. However, a study by Han et al., (2006) examines the use of the Stone Price Index, the Laspeyres Index and the Paasche Index as alternative indices within tourism demand modelling. This study shows that use of the different price indices affects the results only marginally.

A study by Turner et al., (1997b) identified leading indicators from among national variables of income, unemployment, forward exchange rate, money supply, price ratio, industrial production, imports and exports. A study by Kulendran and Wilson (2000) identified a causal relationship existed between the level of trade openness of the destination country and international travel to that country. Trade openness has been further examined and shown to be an explanatory variable by Turner et al., (1998), Kulendran and Wilson (2000), Kulendran and Shan (2002) and Huo (2002).

Fewer studies have focused on regional tourist arrivals and the causal variables to be used, and no formal testing has been done for regional independent variables. Causal variables suitable for national level forecasting do not necessarily have the same affect when they are used for regional based forecasts. No assumption can be made that is based upon research findings that causal variables for international tourism demand are also relevant for sub-national (regional) areas. Furthermore, data mining seems inadequate, and in any case there is no large data base available to enable the random selection of causal variables for regional forecasting. These reasons impact upon the choice of the selection of suitable regional causal variables for the tourism series in China. For international country based tourism, economic utility theory has suggested the use of the variables listed above. However, for international tourists who have already selected China as their international destination, it is not clear that utility theory based upon variation in price is adequate to explain why tourists travel to particular regions.

Population variation can be expected to relate to the base regional size and therefore reflect trade variations. However, regional (provincial) populations tend not to change in volume relatively through time, and not to correlate with the growth evident in international tourism. Population variations are not used in current international country forecasts, and there is no particular reason to expect such a variable would directly relate to changes in provincial tourist arrivals. However, structural change within a given population is possibly important. In China the greatest structural change is urbanisation, the movement from rural to urban areas, and the rural/urban mix and its change may be important.

Disposable income in the source country suggests that increased disposable income will relate to increased expenditure on travel. Consequently, an increase of disposable income for the 13 source countries remains an important independent variable regardless of whether the outbound travel is to countries or to regions within countries.

Own price is a comparative measure of the cost to tourists travelling to particular destinations. The cost of living varies significantly between countries and most international long distance tourism is from developed countries to under developed countries with lower costs. It is unclear whether costs vary greatly between the provinces of China, but they may do so. Consequently, own price remains a variable to be included into a regional analysis.

Exchange rates are best included with own prices as discussed in the literature review so that exchange rate measures are required to adjust cost of living variations between the 13 countries to China.

Substitute prices are used to measure alternative cost choices between countries where tourists may readily substitute one destination country for another. In China the 31 provinces do offer substitute options, where an international tourist may select one province over another under certain conditions. However, it seems unlikely the choice would be based upon the cost of living in different regions within China. It is not likely that tourist costs in one part of China will be markedly discounted for the same product. Moreover, there is no research to indicate what regions might substitute for each other, and it is difficult to select groups of provinces that have the same attractions or tourist experiences. Consequently, it is not perceived that measuring substitution between the 31 provinces is a practical or theoretically valid exercise.

Whilst the choice of independent variables can to some degree be guided by theory, current research and reasonable construct development, the actual variables used must depend in the end on availability and subsequent testing.

Data availability is a constant problem in all tourism forecasting research and is evident throughout the literature. For example, many studies have no measure of marketing or transport cost Song and Witt (2000), Song and Turner (2006). Some studies measure per capita income directly, and others use a measure of income divided by population size and so forth. This study is also limited by data availability. It is also limited by the annual nature of the tourist arrival series which may favour time-series over econometric methods because the model requirements in some cases are less rigorous.

In selecting the independent variables for this research it is possible to identify from the current research that disposable income and own price (including exchange rates) are likely to be relevant independent variables. Additionally, some measure of economic size (as an alternative to population size or trade openness) may be required. Measures for provincial international inbound and outbound trade by foreign country and province are not available. Consequently, a measure of regional GDP (which is available) is suggested as a possible independent variable, to capture changes in the economic base of the provinces.

Theoretically, economic factors must be included and current research indicates what measures are recommended. However, there is no research that is specific to regional independent variables and the study must explore possible theoretical implications that indicate other variables. It is clear that apart from economic factors there are potential social, transport and weather elements (the later not being captured here with seasonal data). Social factors include changes in the character of the population mix and the level of tourist attraction development in provinces, transport factors excluding direct cost (as discussed above) can potentially include the degree of connectivity, time and ease of access to different provinces. Weather elements must be considered because China covers several climate zones from extreme cold in the north to a tropical climate in the south, and desert environment in the west to coastal Mediterranean climate in the east. Weather would be best measured using seasonal arrivals data, but such data as average sunshine, temperatures and so forth could be explored instead. The difficulty in using such data is that it is not likely to vary through time for use as an independent measure on annual basis and must remain a broader indicator relevant to overall arrivals growth.

The following data sources have been examined in China:

- Comparative Statistical Data and Materials on 50 Years of New China;
- China Statistic Yearbook 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007 and 2008;
- China Hotel Guide 2004 – 2005 and 2008 – 2009;
- The Essential China Airports Book 2004 Edition (Centre for Asia Pacific Aviation) ;
- Monthly Essential China Airports 2009 publications by the Centre for Asia Pacific Aviation;
- China National 5A to A Tourist Attractions by region; (http://bbs.cnzozo.com/forumdisplay)

- Government and industry websites including: airport-technology.com; AVbuy.com.cn; cnta.gov.cn (China National Tourism Administration); china.org.cn; world-tourism.org; chinadaily.com.cn; carnoc.com (Civil Aviation Resource Net of China); bcia.com.cn (Beijing Capital International Airport); aci.org (Airports Council International)
- ‘World Airport Transport Statistics’ IATA 2007, 51st Edition
- The Yearbook of China Tourism Statistics 1995, 1996, 1998, 1999, 2000, 2001 (Supplement) , 2002, 2003(Supplement), 2004, 2005, 2006 and 2007
- China Population Statistics Yearbook 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007 and 2008;
- National Tourism Administration of PRC;
- “China Tourism Industry” by China Knowledge Press Pty Ltd.
- CNTA 11th Five-Year Plan for Travel – A synopsis prepared for PATA by Ren Publishing

Additional economic measures have been identified as

- Gross regional product
- Capital formation

Gross regional product provides the regional equivalent to GDP at the national level, and measures changes in the economic base of a local province. Capital formation potentially measures changes in the investment in infrastructure that in turn reflects upon the economic tourism base and the facilities growth available to local tourism operators.

An additional social variable has been identified as:

- Ratio of urban and rural population

As China develops it can be expected that urbanisation will shift the relative volume of the population from rural to urban activities. This variable may well distinguish between provinces in their degree of development that is socially based, and in turn reflect upon the level of attraction to international tourists.

Additional transport variables have been identified as:

- Length of highways
- Connectivity

There are several measures of transport development available at a regional level including length of highways and railways. One measure is the growth in highways and this variable is selected to represent the rapid overall growth in transport accessibility for each province.

Transport costs are potentially relevant for travel between provinces. However, an examination of air costs by example from Beijing to the capital in each province (refer to Table 4.1) indicates two issues. First, the overall costs of domestic travel are low for international tourists relative to their income, and second the costs do not vary greatly between provinces. Consequently, it is unlikely that direct transport cost will distinguish between provinces in terms of cost for international tourists. However, cost and ease of transport are different variables and the time taken to travel to different provinces may remain relevant as a cost and is measured in the variable connectivity.

Connectivity is measured as the time taken to travel from Beijing to the capital city of each province divided by the number of flights available per week. Longer travel is more difficult and costly to build into a travel itinerary, but made easier if there is a wider selection of travel times available.

However, because connectivity does not change much over time it cannot be used as an independent measure and along with weather as discussed below must remain a broader indicator variable relevant to overall growth.

Table 4.1.1 Weekly flights from capital Beijing airport to the 30 Chinese provinces

	Flight Time (minutes)	Weekly Flights (oneway)
Tianjin		0
Hebei	42	2
Shanxi	50	522
Inner Mongolia	60	149
Liaoning	70	550
Jilin	100	469
Helongjiang	100	144
Shanghai	125	2900
Jiangsu	110	335
Zhejiang	115	577
Anhui	105	249
Fujian	155	1046
Jiangxi	135	569
Shandong	75	236
Henan	85	452
Hubei	115	334
Hunan	140	820
Guangdong	180	1773
Guangxi	190	537
Hainan	210	662
Chongqing	150	831
Sichuan	150	1173
Guizhou	210	633
Yunnan	195	1934
Tibet	255	86
Shaanxi	105	211
Gansu	130	265
Qinghai	255	158
Ningxia	110	178
Xinjiang	245	236
Total		18031

Source: Beijing capital airport website.

Additional variables related to weather are included as:

- Sunshine in regional capital cities

Although it is unclear if any variation in weather is focal to the volume of international travel, it is possible that some provinces will suffer fewer arrivals because of their climate. A study by Saayman and Saayman (2008) shows a positive link between climate and arrivals to South Africa. Variations in seasonal travel would be a measure to include if seasonal arrivals were available as a data set, as is evidenced by current research. However, current research has not been focused upon regional arrivals and does not examine the volume of annual weather based variables (because seasonal data is normally available). The choice is made to use sunshine as the single measure because it is reflective of temperature, humidity, rainfall and cloud cover in one measure. Although it is possible for a cold climate to have high sunshine levels, it is argued that in that instance the issue of temperature is less important.

Marketing is a potentially important independent variable and would also be potentially relevant at the regional, as well as the international scale. However, within China individual provinces are not free to directly market internationally. Indirectly, marketing occurs through mass media exposure. Hence, Beijing received significant marketing by holding the Olympic Games and Shanghai by holding the World Expo. It is not possible to accurately measure indirect marketing and an attempt is not proposed here.

Habit persistence may also be relevant in China, but there is a very low level of repeat travel, apart from business travel. Consequently, there is currently little evidence for the need to include habit persistence as a variable that distinguishes between international source countries or specific provinces.

Dummy variables measure sharp shocks within arrival series that relate to particular events such as specific attractions (Olympic Games) and detractions (SARS). Since the provinces in China have been variously affected by two major impacts – SARS and September 11, it is necessary to consider the use of dummy variables at least for these two events.

Forecast methods used in this study range from exponential smoothing to the more complex Basic Structural model (with and without interventions), the ARMA model, and the neural model as well as the time varying parameter model (TVP), using causal measures. The software used includes SPSS 10.1, Eviews 7, STAMP, Excel and SAS.

The discussion of forecast accuracy it is a subjective debate as to what level of MAPE is considered accurate. A MAPE value of 10% or less is considered highly accurate in the literature generally. Values between 10% and 20% are often discussed but not specified as of a particular level of accuracy. Statistically, it could be argued that there is a 50% chance of guessing the forecast accurately so that values above 50% are inaccurate and below 50% have some degree of accuracy. It has been subjectively decided to use bands between 0% to < 10%, >10% to < 20%, >20% to < 30% as useful levels of accuracy. Values above 30% are considered inaccurate. Although subjective it is both reasonable and conservative to select these levels of accuracy and in doing so there is a greater capacity to assess the accuracy of a wide range of quantitative models.

Chapter 5
Time-Series Regional Forecasting

5.1 Introduction

This chapter consists of a regional forecast analysis for international arrivals generated by the top 13 countries to 31 regional provinces in China. The data series covers 14 periods from 1994 to 2007. Forecasts were done by using some of the most modern time-series forecasting methods given in the literature including the Holt, Naïve (No Change), Exponential smoothing, ARMA model, the Basic Structural Model and Neural model, with an ex ante forecasting period of 2006 to 2007. The main objective of this chapter is to examine whether these models are capable of accurately forecasting regional tourist arrivals in the short term of two years ahead, and to compare the forecasting performance of these univariate methods to establish new propositions for future regional forecasting for other countries, where regional data are increasingly becoming available. Longer term forecasting would also be useful to test for the accuracy of the models in different forecasting horizons. However, at this stage data availability in China is limited to the annual 1994 to 2007 series and a two year ahead forecast (leaving only 12 periods for the model to use for extrapolation) and therefore, forecasting far ahead is not possible while still maintaining sufficient data for use in the modelling process.

The top 13 tourist generating countries (for which published data are available) to China are Japan, Korea, Malaysia, Singapore, Thailand, United States of America, Canada, United Kingdom, France, Germany, Russia, Australia and Philippines. These countries in 2007 comprised more than 92% of total foreign arrivals to China.

The annual regional tourist arrival data collected at accommodation establishments from 1994 to 2007 are sourced from the China National Tourism Organisation (CNTO). These data are available late in the year one year after the arrivals so the 2007 data became available in December 2008. Unlike the national cross-border flow data collected at immigration on entry to China, the regional data are currently available only in a shorter time series. These regional data have the same consistency as the national arrival data in methods of data recording and collecting, where the data are collected. However, these data fail to capture foreign visits to relatives and friends (which is not fully accepted as an appropriate form of international travel in China, and is quite a small fraction of arrivals), arrivals to private accommodation (which is usually owned by business organisations in China) and arrivals to local Chinese accommodation. The reliability of data for accommodation establishments cannot be assumed to equal that of Thailand. However, the evidence from Thailand provides a positive incentive to use this data source (Vu and Turner, 2006).

The research has identified that the data series under study contain several events which cause impacts on global international tourism arrivals (Kuo et al., 2009). Two major events (shocks) causing severe downturns to international tourist arrivals to China were the ‘9.11’ terrorist attacks to the USA in 2001, and the Severe Acute Respiratory Syndrome (SARS) in China in 2003. Other less significant events were the Asian Financial Crisis in 1997; Falungong movement and increased violence and social disturbances in China prior to China’s accession to the WTO in late 2001; Asia Tsunami on Boxing Day 2004; Avian Flu in late 2003 and 2007; the anti Japanese movement in the years leading up to 2008 Beijing Olympics; anti Chinese government uprising in Tibet and the Xinjiang Autonomous Region in South West and North West China. Table 5.1 shows a list of the main international and Chinese internal shocks during 1994 to 2005.

Table 5.1.1 Major Shocks (events) 1994 to 2005

	Year	Event
1	1997	Asian financial crisis
2	2001	September 11, terrorist attacks in USA
3	2001	China’s accession into WTO
4	2001	Falungong movement (violence and social disturbances)
5	2003	SARS spread across China
6	2004	Boxing Day Tsunami (the effect of 2004 Tsunami fell in 2005)
7	2005	Avian influenza (spread worldwide from late 2003 to 2007)

8	2005	Anti Japanese movement

Although the two major shocks of Sept 11 and SARS impacted in most provincial regions, each of these shocks did not impact equally across the 31 provinces. In some instances, an opportunity existed for some regional tourist attractions to draw visitors that previously selected better-known destinations such as Beijing (Gut and Jerrell, 2007), while destinations external to China, received increased tourism revenues (Hanly and Wade, 2007). Table 5.1.2 displays the relatively few exceptions to this situation for the Chinese provinces.

Table 5.1.2 Chinese provinces showing no decreases of international tourist arrivals during the 11 Sept & SARS event

Country										
Korea			Jiangsu							
Thailand				Fujian						
Canada					Inner Mongolia	Hainan				
Russia	Liaoning	Helongjiang	Shanxi	Zhejiang	Anhui	Shandong	Hubei	Guizhou	Tibet	Gansu
Australia	Xinjiang									
Philippines	Inner Mongolia	Shanghai	Jiangsu	Hainan	Inner Mongolia	Qinghai				

International travel has become increasingly sensitive to the political stability and economic conditions of both tourist generating and destination countries. There have been numerous studies on crisis impact, and increased attention has been given to quantifying the effects of these external shocks on tourism demand using various forecast methods. Studies include Law (2001) who used various forecasting techniques to study the impact of the Asian Financial Crisis on Japanese tourists to Hong Kong; Goh and Law (2002) who examined the use of SARIMA and ARMA models with interventions to quantify the influences of the Asian Financial Crisis, along with other one-off events on inbound tourists to Hong Kong; Lim and McAleer (2002) who investigated SARMA models to analyse the effects of the one-off events on the demand for tourists to Australia by Asian travellers. Huang and Min (2002) and Min (2005) who examined the devastation caused by an earthquake and the tourism recovery in Taiwan and the effect of SARS on tourism demand; Eugenio-Martin et al., (2005) who employed causal structural time series models to qualify the effects of the

September 11 terrorist attack and foot and mouth disease on the demand for Scottish tourism among French, American and German tourists. The demand forecast effects of this type of one-off event has raised a great challenge to model specification, and forecast performance is often determined by the level of impact these shocks have on the analysis. This has also led to recent work on the uncertainty and volatility of tourism series by Shareef and McAleer (2007), Vu (2006), and Kim and Wong (2006). Kuo et al., (2009) use the panel data method to estimate the impacts of avian flu on global tourism and for more studies on 'one of events' refer to Turner et al., (2006), Ritchie et al., (2009), Smeral (2009ab) and, Song and Lin (2009).

Forecasts for the time-series models selected in this research (Naïve-no change, Exponential Smoothing, Holt-Winters model, Basic Structural model, ARMA and Neural model are explained in the following sections of this chapter, and a broad comparison is made of the overall accuracy of these models. The initial models used are the Naïve, Exponential Smoothing, Holt and BSM model. These models do not include dummy measures or specific methods to account for the shocks of SARS or September 11. As such these models are the less sophisticated of the time series models and are used initially to test whether elementary models can forecast the series accurately. This broad comparison provides a starting point for the more detailed Box Jenkins, BSM with interventions and the Neural models which are more capable of handling shocks. The comparative tables presented here give MAPE error values and the RMSE tables are given in Appendix IV. More detailed comparison of the performance of the models is given in the following chapters.

5.2 Naïve Forecast for the 13 Countries to the 31 Chinese Provinces

5.2.1 Introduction

Naïve methods are direct extrapolations from immediate past data into the future. The Naïve One process is the most commonly used method of the naïve processes in that the arrivals Y_t are equal to the arrivals of Y_{t-1}. Other variants extrapolate growth rates immediately. The Naïve One method used here constitutes an educated guess, because it involves no other information than the number of previous arrivals. In some instances arrivals are slow to change, and volumes of arrivals are low, so that naïve processes can be an accurate educated guess. Since quantitative models are variously more complex to calculate than naïve processes, and the simplest solution is the best solution, a quantitative model must be able to outperform an educated guess as a basic starting point, to validate the effort involved in producing the forecast. Consequently, Naïve One is used as a comparative benchmark process.

Naïve One uses the actual value of the current period as the forecast value of the next period ahead. This simple forecast has no mathematical involvement of modelling and computer simulation. It has been wildly used in tourism forecasting for its accuracy, particularly by Martin and Witt (1989a), and Witt and Witt (1992).

The forecasts are first calculated within sample and not extrapolated ahead into the future. Consequently, the following tables show the results for the fitting of each method to the actual data from 1994 to 2005. If the results of such an analysis are not accurate then it would follow that any forecast beyond the time period of the actual data would also not be accurate, and may not be worth conducting.

The simplest naïve technique is shown by the following equation:

$$Y_{t+1} = Y ,$$

Where: $Y_t = 1$ is the forecast made in time t for time $t+1$.

For horizons greater than 1 year, the actual value of a particular year in the previous year of the horizon is used as the forecast for the corresponding year.

As a result, any forecasting model that does not perform at least as well or, better than Naïve One, cannot be regarded as adequate or parsimonious.

5.2.2 Results of Naive Forecasting for the 13 Countries to the 31 Chinese Provinces

Table 5.1.3 shows Malaysia has the lowest overall MAPE average of 21.3%, and Canada has the highest overall MAPE average of 30.2%. The overall MAPE average for all provinces is 25.3%.

Table 5.1.3 MAPE for naïve forecast for all countries to the 31 Chinese provinces 2006 - 2007

	Jap	Kor	M'sia	S'pore	Thai	USA	Can	UK	France	G'many	Rus	Aust	Phi	T/A
Beijing	12.5	5.7	17.5	14.9	0.8	12.0	17.9	9.5	8.9	8.5	26.6	18.7	18.4	13.2
Tianjin	13.5	11.1	11.7	16.4	24.8	15.7	NC	28.1	24.8	29.9	16.8	17.7	29.2	20.0
Hebei	2.6	11.9	3.1	11.0	16.3	24.2	19.1	7.2	16.5	14.2	16.2	17.6	22.0	14.0
Shanxi	50.2	46.5	46.0	42.5	12.5	49.0	53.4	55.5	17.7	49.5	37.5	51.7	53.5	43.5
Inner Mongolia	33.1	31.0	37.6	36.6	65.4	28.2	9.5	19.1	47.8	9.7	10.9	35.2	71.3	33.5
Liaoning	15.9	20.5	20.8	16.1	16.2	19.0	23.5	32.0	29.0	19.3	28.0	22.8	27.1	22.3
Jilin	15.4	16.0	12.8	13.0	6.1	16.1	NC	88.6	2.6	8.5	21.4	37.1	30.9	22.4
Heilongjiang	10.8	19.1	39.2	28.6	46.1	21.2	21.0	14.7	33.8	14.1	26.3	24.0	32.9	25.5
Shanghai	2.8	15.5	18.9	4.7	3.4	6.0	18.0	10.9	12.1	1.7	17.9	9.0	9.9	10.1
Jiangsu	15.5	12.8	4.8	18.3	5.2	25.8	28.1	32.8	24.4	28.3	37.4	31.4	15.7	21.6
Zhejiang	19.8	13.9	8.1	8.2	11.4	19.3	24.3	20.0	19.5	15.6	25.4	22.0	12.1	16.9
Anhui	28.4	24.5	19.3	18.4	29.6	22.7	35.7	43.2	24.9	23.4	59.7	29.3	28.0	29.8
Fujian	9.2	18.9	4.8	11.8	7.5	24.3	38.2	22.3	15.1	6.5	13.6	21.7	11.6	15.8
Jiangxi	15.6	33.9	29.0	25.0	37.0	20.5	31.5	27.6	29.7	28.4	28.4	28.9	34.8	28.5
Shandong	16.7	23.3	13.4	22.6	18.8	26.9	23.2	29.5	23.2	18.1	23.6	29.6	21.1	22.3
Henan	11.5	37.1	14.0	23.0	16.3	26.3	29.2	11.6	24.7	60.3	21.2	6.4	20.0	23.2
Hubei	17.2	6.4	41.0	51.9	33.7	8.7	43.0	23.4	21.0	21.2	49.1	44.6	41.2	31.0
Hunan	31.9	7.1	19.1	29.7	87.5	6.8	29.8	35.6	21.9	34.0	62.6	20.7	40.4	32.9
Guangdong	13.2	21.8	20.7	14.5	6.8	21.2	26.3	15.1	9.6	22.6	19.7	26.9	10.6	17.6
Guangxi	39.7	26.4	14.0	17.0	6.1	15.0	30.9	29.7	21.4	14.7	25.6	25.9	33.2	23.0
Hainan	15.4	41.5	57.3	26.9	1.6	12.5	17.8	41.0	5.9	12.0	90.0	7.7	61.2	30.1
Chongqing	27.7	17.9	28.7	42.5	32.0	18.0	23.2	14.1	18.4	21.0	36.8	20.4	11.1	24.0
Sichuan	26.3	31.7	33.8	7.4	26.5	20.3	36.3	40.7	24.3	21.5	27.3	31.7	35.3	27.9
Guizhou	22.0	21.3	19.0	24.7	19.2	23.1	21.0	16.1	34.5	15.8	17.5	18.8	24.9	21.4
Yunnan	23.8	18.2	19.9	15.0	18.5	15.2	17.1	26.0	18.9	17.8	30.1	15.5	37.9	21.1
Tibet	71.6	57.3	60.5	71.4	60.2	34.1	50.5	39.9	29.9	37.6	63.4	48.6	51.9	52.1
Shaanxi	9.6	4.1	15.7	19.2	12.6	10.1	21.8	12.0	10.3	12.5	19.9	11.3	12.1	13.2
Gansu	3.8	39.2	14.4	22.8	40.3	25.5	35.9	20.6	37.0	21.0	50.4	25.3	17.7	27.2
Qinghai	67.3	44.5	12.0	35.5	NC	38.6	83.7	30.0	29.4	71.2	65.9	78.2	43.8	50.0
Ningxia	15.1	14.7	3.0	19.4	81.1	54.5	41.2	15.0	32.3	38.4	36.1	40.0	NC	32.6
Xinjiang	31.6	14.9	1.0	15.2	22.2	12.2	25.1	13.6	23.1	24.2	28.0	7.5	9.9	17.6
MAPE Overall	22.3	22.9	21.3	23.4	25.5	21.7	30.2	26.6	22.3	23.3	33.3	26.7	29.0	25.3

Note: NC means not calculable for values over 100.

Although there are a handful of single digit MAPE values scattered through Table 5.2 the vast majority of MAPE values are over 20% error, and the forecast accuracy can be considered low (Lewis, 1982). However, given the simplicity of the forecasting methodology the results are generally useable with a large 290 values below 30% error, so that when used as a benchmarking process these results set a reasonably high benchmark level.

Table 5.1.4 Summary MAPE counts for naïve forecast for all countries to the 31 Chinese provinces

Number of forecasts <10%	47
Number of forecasts >10% <20%	129
Number of forecasts >20% <30%	114
Number of forecasts >30% <50%	77
Number of forecasts >50%	32

5.3 Exponential Smoothing Forecasting for the 13 Countries to the 31 Chinese Provinces

5.3.1 Introduction

Exponential smoothing is a procedure for continually revising an estimate in the light of more recent experiences. This method is based on averaging (smoothing) past values of a series in a decreasing (exponential) manner (Hanke and Reitsch, 1992). The smoothing coefficient value assigned is the key to the analysis, and chosen to create stable predictions and to smooth random variations. Exponential smoothing is a variant of the Holt method that places greatest importance on the most recent past known value, and has less importance on earlier known values. The smoothing constant (α) serves as the weighting factor. The actual value of α determines the extent to which the most current observation influences the forecast value.

As noted by Li et al., (2006), the exponential smoothing method has been used frequently for tourism forecasting in the 1980s, with satisfactory accuracy in both directional change and trend change forecasting.

Exponential smoothing can be extended to include a seasonal coefficient (Winters model) for seasonal data. The data available in China is not seasonal and this extension cannot be applied (Cho, 2003).

5.3.2 Results of Exponential Smoothing Forecasting for the 13 Countries to the 31 Chinese Provinces

Table 5.1.5 shows that Japan has the lowest overall MAPE average of 26.4%, and Russia the highest overall MAPE average of 46.6%. The overall MAPE average for all provinces is 34.1% and the MAPE values are all high.

Table 5.1.5 MAPE for exponential smoothing forecast for all countries to the 31 Chinese provinces 2006 - 2007

	Jap	Kor	M'sia	S'pore	Thai	USA	Can	UK	Fra	G'many	Rus	Aust	Phi	T/A
Beijing	15.5	8.2	8.3	22.1	11.5	24.9	31.5	19.6	21.4	20.7	46.1	35.4	33.8	23.0
Tianjin	23.7	12.7	77.5	23.6	21.9	12.7	15.5	15.5	14.8	31.2	73.7	18.8	91.8	33.3
Hebei	10.3	22.4	3.1	27.7	31.8	38.1	15.5	27.9	37.7	26.0	37.7	36.2	36.3	27.0
Shanxi	53.4	39.1	57.0	26.5	51.8	60.6	66.1	61.5	58.0	59.2	50.2	62.6	66.3	54.8
Inner Mongolia	31.5	42.3	18.4	43.1	54.8	38.9	38.9	15.7	74.2	18.3	37.9	53.4	31.2	38.3
Liaoning	23.4	37.4	28.6	24.1	25.3	29.3	15.5	42.0	41.0	28.6	15.5	32.0	42.1	29.6
Jilin	27.9	35.3	NC	35.5	17.7	17.8	NC	74.1	20.2	40.2	47.8	21.3	29.9	48.0
Helongjiang	12.4	13.0	11.1	26.1	29.6	15.2	14.1	29.1	26.5	20.5	44.2	25.3	35.1	23.2
Shanghai	8.1	27.3	15.6	13.5	11.4	20.6	30.6	30.9	21.6	13.5	45.2	25.3	29.5	22.5
Jiangsu	27.3	25.2	8.9	30.1	14.3	40.7	43.5	46.9	39.7	44.2	15.5	44.7	7.7	29.9
Zhejiang	31.2	29.8	15.5	25.4	24.3	33.6	15.5	36.0	36.1	30.0	50.9	39.2	27.8	30.4
Anhui	31.1	49.2	13.6	14.3	32.7	32.7	44.7	55.0	40.3	31.1	71.1	41.4	36.0	37.9
Fujian	15.5	14.6	7.6	18.9	25.6	40.4	48.2	33.3	28.0	18.8	37.8	27.5	15.5	25.5
Jiangxi	31.0	52.5	40.9	40.8	41.1	44.6	20.9	23.6	28.0	46.2	50.5	32.3	54.5	39.0
Shandong	25.9	41.2	18.6	28.5	17.0	36.6	31.6	41.3	34.5	30.3	46.1	37.9	27.1	32.0
Henan	10.4	53.2	25.0	18.9	13.3	41.2	47.5	28.4	43.9	59.8	44.2	27.4	37.2	34.7
Hubei	13.4	8.4	55.0	56.8	47.3	25.6	78.9	40.4	32.0	38.8	66.0	61.2	54.3	44.5
Hunan	46.4	24.9	44.3	51.2	27.2	29.1	16.4	49.7	44.8	55.7	38.2	41.4	46.7	39.7
Guangdong	22.1	36.5	35.2	29.3	25.3	34.0	40.4	25.8	24.2	32.7	15.5	45.6	28.3	30.4
Guangxi	13.5	29.4	12.5	38.5	24.6	27.5	47.4	45.5	40.6	27.4	42.9	43.9	47.9	34.0
Hainan	15.5	57.1	37.8	40.2	12.5	32.0	38.4	52.5	39.8	36.3	54.6	32.6	38.0	37.5
Chongqing	15.9	18.6	42.5	15.5	43.4	35.6	25.1	13.4	39.7	36.3	74.1	35.1	34.7	33.1
Sichuan	39.0	48.5	15.2	24.8	19.4	34.5	36.3	54.7	51.4	41.0	55.5	15.5	21.8	35.2
Guizhou	35.2	40.1	30.7	29.4	20.2	39.6	36.4	27.7	27.9	27.9	52.8	34.1	20.1	32.5
Yunnan	27.9	34.3	21.6	21.4	20.4	28.2	28.4	36.1	37.8	32.1	45.8	35.2	49.6	32.2

Tibet	61.7	61.5	68.3	75.4	67.0	37.2	61.3	40.4	27.2	37.7	55.0	54.9	39.9	52.9
Shaanxi	5.6	3.5	19.3	31.3	12.8	24.9	32.5	32.9	31.3	93.5	46.5	21.2	17.5	28.7
Gansu	8.6	54.4	9.6	31.9	19.5	32.1	21.1	16.7	26.2	26.6	40.7	14.6	12.2	24.2
Qinghai	71.5	42.5	15.4	33.1	93.5	48.4	47.7	37.7	22.6	48.0	44.3	50.1	29.3	44.9
Ningxia	15.5	21.4	23.6	24.4	52.6	85.3	26.8	15.4	22.2	44.0	64.0	59.2	78.2	41.0
Xinjiang	46.7	24.2	1.1	8.5	18.6	10.9	14.5	15.3	14.9	13.7	33.8	6.3	12.8	17.0
MAPE Overall	26.4	32.5	30.1	30.0	29.9	34.0	36.7	35.0	33.8	35.8	46.6	35.9	36.5	34.1

Note: NC means not calculable for values over 100.

Although there are a handful of single digit MAPE values scattered through Table 5.3 the vast majority of MAPE values are over 20% error and the forecast accuracy can be considered low (Lewis, 1982). The performance of this model is generally less accurate than the naïve process with only 183 forecasts below 30% error.

Table 5.1.6 Summary MAPE counts for exponential smoothing forecast for all countries to the 31 Chinese provinces

Number of forecasts <10%	15
Number of forecasts >10% <20%	74
Number of forecasts >20% <30%	94
Number of forecasts >30% <50%	158
Number of forecasts >50%	60

5.4 Holt Forecasting for the 13 Countries to the 31 Chinese Provinces

5.4.1 Introduction

Holt's two-parameter method has been used frequently in handling a linear trend in (Hanke and Reitsch, 1992). Holt's technique gives more flexibility in selecting the rates at which the trend and slope are tracked. Holt model forecasting was conducted for the 13 tourist countries to the 31 Chinese regions using ForecastX Wizard (Book Version) 6.0a.

5.4.2 Results of the Holt Forecasting for the 13 Countries to the 31 Chinese Provinces

Table 5.1.7 shows Japan has the lowest overall MAPE of 25.8%, and Russia has the highest overall MAPE of 59.9%. The overall MAPE average for all provinces is 33.9%.

Table 5.1.7 MAPE for Holt forecast for all countries to the 31 Chinese provinces 2006 - 2007

	Jap	Kor	M'sia	S'pore	Thai	USA	Can	UK	Fra	G'many	Rus	Aust	Phi	T/A
Beijing	16.8	6.6	7.6	21.5	17.1	19.6	36.4	16.2	23.2	31.8	41.0	24.1	40.1	23.2
Tianjin	26.0	57.6	NC	17.2	13.4	4.6	NC	12.7	8.0	47.3	41.0	26.4	NC	19.5
Hebei	4.6	17.2	7.4	48.8	46.6	58.2	34.0	41.2	52.0	4.9	43.8	45.3	44.8	34.5
Shanxi	60.4	24.1	74.4	11.5	16.8	70.5	75.3	62.4	48.3	63.5	47.9	73.0	78.3	54.3
Inner Mongolia	31.8	28.3	34.3	68.5	NC	40.7	28.9	12.3	65.1	7.7	61.0	54.0	54.9	37.5
Liaoning	2.8	36.1	23.9	4.6	13.4	20.6	19.8	34.3	35.7	2.7	68.1	19.6	36.8	24.5
Jilin	1.0	43.9	88.9	22.5	35.6	56.6	NC	NC	42.3	48.9	60.2	73.8	95.1	43.8
Helongjiang	32.5	11.0	28.0	18.0	11.8	7.4	29.5	33.1	26.4	12.0	49.9	26.2	47.7	25.7
Shanghai	19.1	7.6	13.4	19.4	30.3	20.2	5.2	30.7	10.2	36.4	80.0	26.0	29.5	25.2
Jiangsu	10.0	6.6	13.6	12.6	12.4	28.4	28.9	32.6	25.3	32.3	71.5	33.9	37.4	26.6
Zhejiang	8.6	6.7	23.0	1.2	7.8	6.1	24.9	8.2	7.1	6.6	64.7	6.7	4.4	13.5
Anhui	22.0	37.8	12.3	13.6	31.1	23.7	37.1	50.8	22.4	9.8	71.7	39.0	43.9	31.9
Fujian	8.9	40.7	31.6	28.8	37.7	27.7	39.1	19.9	9.5	22.9	51.1	25.3	39.1	29.4
Jiangxi	10.6	17.8	28.8	23.4	43.6	57.0	70.5	99.5	18.3	49.9	59.8	16.4	57.5	42.5
Shandong	11.3	18.5	6.2	27.3	13.1	36.0	28.9	25.5	25.1	4.9	58.4	30.9	29.9	24.3
Henan	6.2	49.6	26.9	11.6	16.7	46.8	56.7	17.8	54.2	56.2	38.5	38.6	42.5	35.6
Hubei	3.8	51.5	47.4	64.3	51.0	14.2	50.9	35.2	38.9	33.9	77.3	59.0	63.9	45.5
Hunan	55.1	71.1	67.7	58.0	20.1	37.1	56.3	52.9	55.3	72.5	60.2	38.3	43.0	52.9
Guangdong	8.8	15.7	43.1	24.6	10.9	26.8	47.2	3.2	11.7	32.7	59.4	52.3	30.8	28.3
Guangxi	78.1	25.0	87.6	11.1	27.7	33.7	56.2	61.2	59.3	35.9	46.7	52.6	50.2	48.1
Hainan	33.6	58.0	NC	49.3	6.9	8.5	37.6	29.6	5.9	26.4	90.0	6.1	65.1	32.1
Chongqing	38.0	45.0	46.8	47.2	44.7	38.5	18.2	14.4	47.7	31.6	70.7	3.8	3.4	34.6
Sichuan	32.0	16.0	NC	24.3	16.1	40.5	36.3	43.0	33.6	27.5	73.4	30.3	26.0	30.7
Guizhou	48.5	6.9	31.8	60.1	35.3	46.8	25.6	36.6	35.1	33.2	32.9	10.2	19.8	32.5
Yunnan	31.9	15.2	24.1	22.4	38.1	33.2	23.8	33.4	17.5	25.1	68.2	4.3	59.7	30.5
Tibet	54.6	59.9	77.1	79.8	71.9	34.2	74.6	39.7	29.0	37.4	84.9	62.8	33.3	56.9
Shaanxi	5.1	26.5	98.5	40.9	24.2	41.8	32.5	56.0	51.2	16.8	64.1	4.5	24.5	37.4
Gansu	8.2	51.5	9.5	28.3	15.8	28.5	21.5	12.6	22.9	45.1	64.9	52.2	8.0	28.4
Qinghai	81.4	44.7	25.3	37.7	60.2	48.2	36.9	31.0	23.5	33.5	59.9	65.7	49.8	46.0
Ningxia	13.7	12.8	19.7	20.8	53.9	86.1	34.1	14.5	17.3	49.8	58.9	73.7	NC	35.0
Xinjiang	33.2	7.6	9.1	11.4	23.0	18.2	17.2	7.6	25.4	15.1	36.2	43.9	20.0	20.6
MAPE Overall	25.8	29.6	32.5	30.0	27.3	34.2	35.0	31.2	30.6	30.8	59.9	36.1	38.0	33.9

Note: NC means not calculable for values over 100.

These MAPE values are all high and larger than those calculated using the Naïve no-change process. Only one province, Zhejiang has a highly accurate forecast result across several markets. Overall, the results are over 30% error and can be considered poor forecast results (Lewis, 1982).

Table 4.1.8 Summary MAPE counts for Holt forecast for all countries to the 31 Chinese provinces

Number of forecasts <10%	49
Number of forecasts >10% <20%	61
Number of forecasts >20% <30%	66
Number of forecasts >30% <50%	124
Number of forecasts >50%	94

5.5 BSM Forecasting for the 13 Countries to the 31 Chinese Provinces

5.5.1 Introduction

The basic structural time-series (BSM) technique has been widely used in more recent years. The structural time-series model can also represent causal relationships among variables, using independent variables, causal structural modelling (CSM) is sometimes referred to as structural time series modelling (STSM). Here the term CSM will be used below. Turner and Witt (2001a) compared BSM and CSM models to examine the relationships between a set of explanatory variables for disaggregated tourist flows (holidays, business visits and VFR). Their study showed the potential for both models to forecast tourism arrivals accurately.

A study by Black et al., (2006) on forecasting of tourism in Scotland has demonstrated the ways in which an integrated model, combining the structural time-series model (CSM) and quantifiable forecasts from a computable general equilibrium (GGE) model, can be used to examine combinations of the events and forecasting future tourism demand. It was noted by Blake et al., (2006), that the CSM has an established tradition of providing forecasts of tourism demand at both the sub-national and national levels (for example, Gonzalez and Moral, 1996, Greenidge, 2001, Papatheodorou and Song, 2005).

Preez and Witt (2003) noted that in previous research in tourism forecasting where the accuracy of short-term forecasts generated by multivariate models (incorporating explanatory variables) is compared with the accuracy of forecasts generated by univariate models, that the extra complexity of multivariate tourism forecasting models does not necessarily lead to an improvement in performance. For example, the univariate ARMA model (Garcia-Ferrer and Queralt, 1997) is shown to outperform the causal structural time series model (CSM); and the ‘no change’ (random walk) model (Song and Witt, 2000, Kulendran and Witt, 2001) has outperformed the error correction model. However, the study by Smeral and Wȕger (2005), in the case of Austria, concludes that complexity does matter in designing short-term tourism forecast modelling, and that variations in tourism demand can be influenced by the combination of complex data adjustment methods, and adequate model structures will significantly improve forecast results, and the simpler approaches are decidedly outperformed by complex methods.

The BSM was introduced by Harvey and Todd (1983). The model assumes that a time-series possesses some structure, which is the sum of independent trend, seasonal and irregular components. The BSM is well-know in the literature of tourism demand forecasting for its approach in decomposing the data into components and using the Kalman filter to evaluate the function. Often the components of a time series are not fixed but are stochastic by nature and the basic structural model consists of components including stochastic trend, cyclical change, seasonality and an error term. The trend component changes from the previous period by the amount of the slope, where the slope allows for stochastic changes from period to period. The model can allow for seasonal change but can also be used on non-seasonal data. The model manages the issue of non-stationarity without the need for differencing.

As explained by Harvey and Todd (1983), the main identification tools in the Box-Jenkins approaches are the functions of autocorrelation and partial auto correlation. However, these counterparts are not always very informative, in particular when dealing with small samples. Furthermore, a series with differencing adds additional difficulties and the risk of over-differencing. Consequently, they suggested formulating models directly in terms of trend cycle, seasonal and irregular components.

Turner and Witt (2001b) argue that univariate structural time series models are capable of providing reasonably accurate forecasts. However, their study could not show improvement in the accuracy of BSM when extended to include explanatory variables (CSM).

The BSM is represented as $y_t = \mu_t + \pi_t + c_t + \alpha_t$ where = μ is the stochastic trend component, π_t the seasonal component, c_t the cyclical component, and α_t the error term.

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

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

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

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

The seasonal component π is additive and totals to zero over s seasons in the year as follows:

$$\pi_t = \sum_{j-1}^{s-1} \pi_{t-j} + \omega_{t.} .$$

The parameters $\alpha_t, \alpha_{1t,} \alpha_{2t}$ and ω_t are all stochastic, independent, white noise error terms with expected values of zero.

In this study the BSM forecasts were obtained using STAMP software. The cyclical component comprises a damping factor p in the range 0<p>1, λ as the frequency in (radians) in the range $0 \le \lambda \le \pi$ and two mutually uncorrelated disturbances K with zero mean and a common variance. There may be two additional cycles of the same form incorporated into the model.

A first-order auto regressive AR (1) process is also available. The auto regressive component acts as a limiting case on the stochastic cycle when λ is equal to ϕ or π. It is not a limiting case in CSM modelling.

5.5.2 Results of BSM Forecasting for the 13 Countries to the 31 Chinese Provinces

Each BSM model has the slope, level and irregular components tested using the q-ratio of the variance of each component to the largest variance of these components. The component with the largest variance will have a q-ratio of unity. Components with no variance will have q-ratio of zero, indicating absence of that component in the data.

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

H_0: Independent error terms,

H_1: Error terms are not independent.

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

Table 5.1.9 shows that Japan has the lowest overall MAPE average of 28.3%, and Russia has the highest overall MAPE average of 48.7%. Total MAPE average for the 13 source countries to the 31 Chinese regions is 35.6%.

Table 5.1.9 MAPE for BSM forecast for all countries to the 31 Chinese provinces 2006 - 2007

	Jap	Kor	M'sia	S'pore	Thai	USA	Can	UK	Fra	G'many	Rus	Aust	Phi	T/A
Beijing	16.4	9.3	15.6	32.9	18.1	20.8	35.5	9.9	13.7	28.9	15.3	18.9	51.3	22.0
Tianjin	12.4	40.5	NC	17.6	97.4	9.8	NC	11.4	18.3	8.6	82.1	21.1	NC	31.9
Hebei	9.4	9.7	49.2	70.3	61.6	51.1	32.6	55.7	61.1	34.0	16.5	54.8	62.9	43.8
Shanxi	72.0	12.1	48.8	43.1	74.4	69.7	76.8	64.0	63.6	61.4	56.5	73.0	85.8	61.6
Inner Mongolia	36.3	47.2	30.2	68.5	NC	22.6	24.9	44.8	74.9	NC	8.2	34.8	86.0	43.5
Liaoning	4.0	21.6	11.4	2.2	10.8	15.7	23.5	28.6	30.2	13.2	69.8	17.5	25.3	21.1
Jilin	14.3	56.2	NC	52.0	67.8	9.8	157.5	NC	40.5	66.7	49.0	15.4	68.2	54.3
Helongjiang	88.6	27.6	33.7	13.1	62.1	9.5	18.9	48.1	33.0	27.5	60.8	25.7	50.7	38.4
Shanghai	28.8	23.6	12.6	15.5	48.6	39.2	4.9	4.4	18.8	48.3	14.7	19.7	35.7	24.2
Jiangsu	11.9	32.3	31.7	7.0	40.8	16.8	14.7	23.5	14.0	27.0	62.6	29.8	41.9	27.2
Zhejiang	5.0	31.1	18.3	8.8	35.9	1.8	36.1	5.7	9.4	27.5	46.8	11.2	3.9	18.6
Anhui	18.0	42.1	19.4	13.3	31.4	13.8	20.4	41.1	15.0	3.5	68.6	31.6	46.1	28.0
Fujian	9.8	67.4	1.5	16.5	84.7	23.9	39.7	13.8	2.4	27.1	9.3	11.7	11.3	24.5
Jiangxi	7.9	22.6	32.7	37.9	43.6	45.3	NC	NC	9.2	37.7	44.1	14.0	54.7	31.8
Shandong	8.9	17.6	3.9	14.4	11.5	34.4	27.4	13.3	24.1	12.2	58.4	31.9	44.5	23.3
Henan	16.3	53.9	15.2	54.4	20.8	36.3	29.7	37.8	57.5	83.1	20.0	20.0	7.6	34.8
Hubei	3.5	65.9	38.4	58.2	42.9	6.3	41.5	5.1	33.9	4.2	74.9	66.2	54.7	38.1
Hunan	55.7	59.2	72.8	75.4	43.3	41.8	71.3	64.7	16.0	78.5	57.4	19.0	50.2	54.2
Guangdong	18.7	10.0	37.0	23.2	40.2	21.3	49.7	9.5	59.1	33.7	52.0	47.7	31.8	33.4
Guangxi	13.6	23.2	71.7	21.7	61.9	35.7	57.7	60.9	10.1	42.1	9.7	51.5	51.6	39.3
Hainan	16.6	6.2	NC	52.3	18.0	12.3	28.7	28.6	9.9	13.8	88.8	47.0	61.8	32.0
Chongqing	27.7	57.8	36.6	44.4	43.1	29.9	15.8	76.0	51.2	6.7	36.5	42.2	36.6	38.8
Sichuan	28.2	14.9	NC	17.6	22.8	9.8	26.9	34.7	23.8	18.7	34.1	22.7	48.4	25.2
Guizhou	52.0	8.8	55.0	61.8	23.6	57.4	25.1	45.0	43.3	39.7	NC	5.9	23.2	36.7
Yunnan	40.7	13.8	11.5	26.4	39.6	28.9	24.6	31.6	16.8	10.6	15.9	21.5	52.0	25.7
Tibet	63.5	65.8	80.8	80.5	76.1	33.6	73.0	44.2	40.6	33.3	82.8	55.0	28.3	58.3
Shaanxi	37.3	22.0	NC	48.5	24.9	60.1	57.4	69.7	74.1	71.7	79.6	32.2	59.2	53.1
Gansu	17.2	47.4	21.9	23.3	14.7	17.9	22.9	11.3	22.4	40.5	74.8	95.9	32.7	34.1
Qinghai	85.4	50.1	50.4	34.3	51.9	46.9	56.1	29.4	26.0	33.2	52.5	27.4	43.5	45.2
Ningxia	16.2	12.1	20.0	20.1	58.2	36.3	33.9	9.9	15.8	57.4	80.2	66.8	NC	35.6
Xinjiang	41.9	8.0	18.6	9.5	11.9	26.2	15.7	20.8	30.7	23.0	40.4	52.1	17.6	24.3
MAPE Overall	28.3	31.6	32.3	34.3	42.8	28.5	39.4	32.5	30.9	33.8	48.7	35.0	43.7	35.6

Note: NC means not calculable for values over 100.

Table 5.1.10 Summary MAPE counts for BSM forecast for all countries to the 31 Chinese provinces

Number of forecasts <10%	47
Number of forecasts >10% <20%	131
Number of forecasts >20% <30%	123
Number of forecasts >30% <50%	69
Number of forecasts >50%	32

The results of the BSM analysis are not highly accurate for any province and the overall error exceeds 30% (35.6%), and when compared with the previous analyses Holt (Average MAPE of 33.9%) and the Exponential Smoothing model (Average MAPE of 34.1%) shows the most accurate overall forecast result is the Naïve (Average MAPE of 25.3%). However, the number of results below 30% error far exceeds to exponential smoothing and Holt results and exceeds the results for the Naïve model.

5.6 Conclusions on Preliminary Analysis

Overall MAPE results from the Naïve, Exponential Smoothing, Holt and BSM forecasts are all above 25%. Throughout the time series there are obvious impacts that cause a reduction of international tourist arrivals to all 31 regions including wide spread impacts immediately after September 11 in 2001 and SARS in 2003. The severity of these impacts on the arrival of international tourists to the 31 regions varies, ranging from the less affected regions in the east and southeast to the more badly affected regions in the west and northwest of China. Because there are potentially 13 source countries x 31 regions = 403 graphs, a small sample is selected below to indicate this issue. Beijing, Liaoning, Shanghai, Guangdong, Yunnan and Shaanxi are regions in the north, northeast, east, south, southwest and northwest of China.

Figure 5.1 shows the decrease in Japanese tourists to Beijing in the north China region, during both September 11, 2001 (Period 8) and a larger drop of Japanese tourists in 2003 due to SARS (Period 10).

Figure 5.1.1 Japanese tourist arrivals to Beijing 1994 - 2007

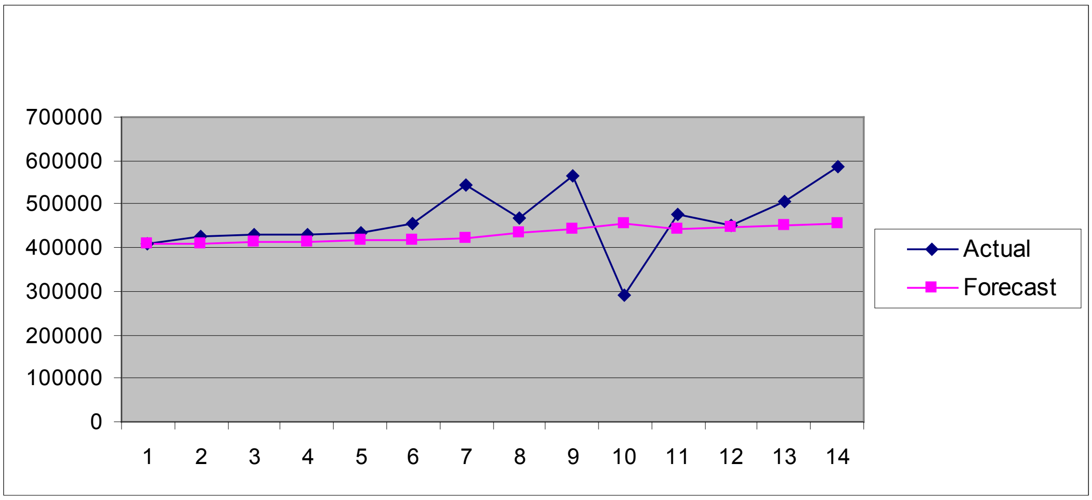


Figure 5.1.2 shows that Liaoning in the northeast of China had a decrease in Japanese tourist arrivals during September 11 (period 8) and SARS (period 10).

Figure 5.1.2 Japanese tourist arrivals to Liaoning 1994 - 2007

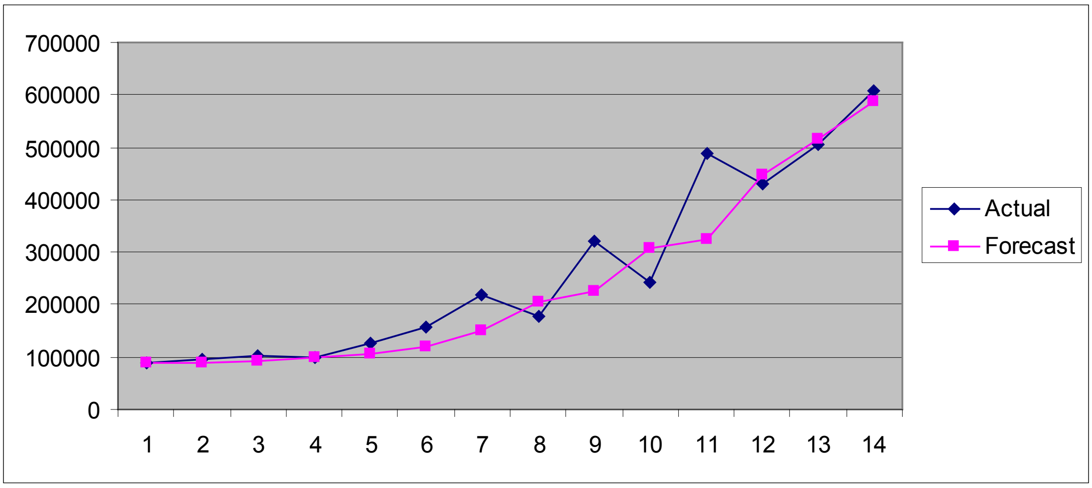


Figure 5.1.3 shows that Japanese arrivals to Shanghai in the east of China, were less impacted by September 11 (period 8) and SARS (period 10) with tourist arrivals recovering immediately after these two events in periods 9 and 11.

Figure 5.1.3 Japanese tourist arrivals to Shanghai 1994 - 2007

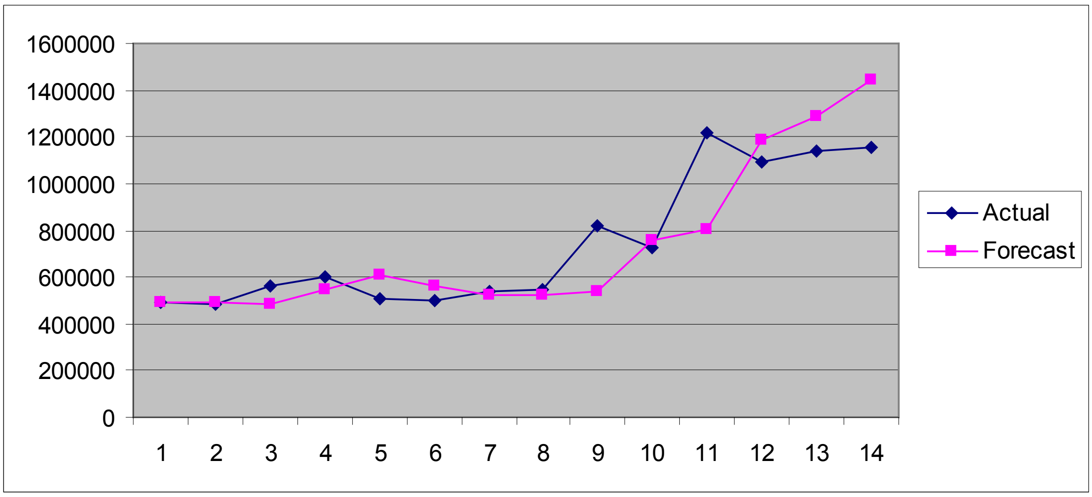


Figure 5.1.4 shows that Japanese arrivals to Guangdong in the south of China, received no impact from September 11 (period 8) but had a decrease in Japanese visitors during SARS (period 10).

Figure 5.1.4 Japanese tourist arrivals to Guangdong 1994 - 2007

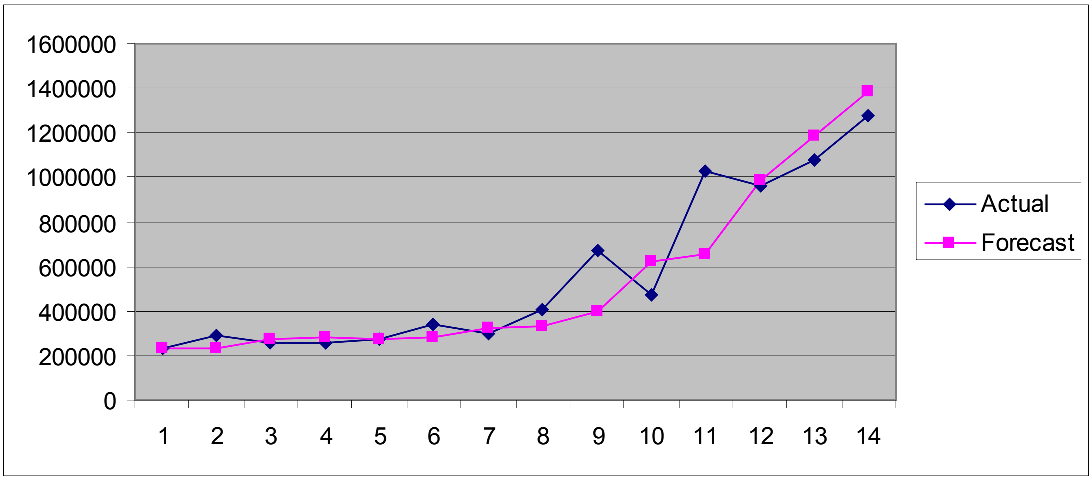


Figure 5.1.5 shows that Yunnan in the southwest of China, received very severe impacts for both shocks and a major downturn of arrival volume for an extended period after SARS (period 10).

Figure 5.1.5 Japanese tourist arrivals to Yunnan 1994 - 2007

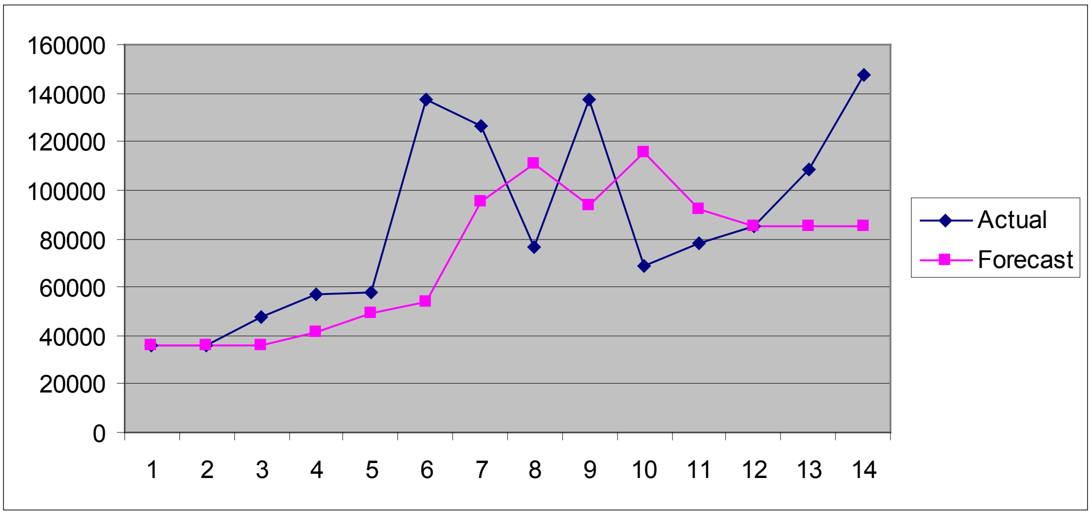
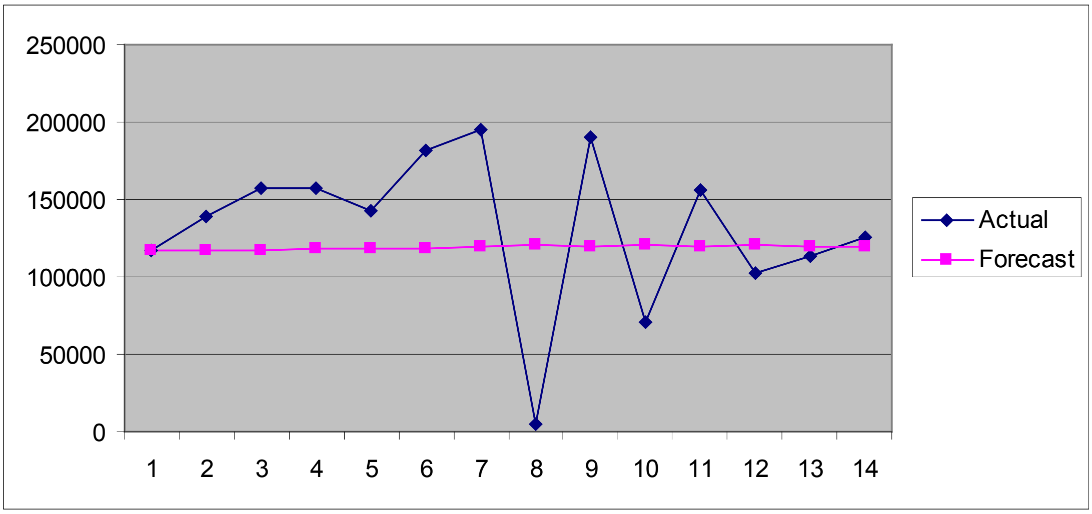


Figure 5.1.6 shows that Shaanxi in the northwest of China, had a severe downturn of arrival volume during September 11 (period 8) as well as SARS (period 10), and another shock in period 12 due to the Avian influenza and the anti Japanese movement.

Figure 5.1.6 Japanese tourist arrivals to Shaanxi 1994 - 2007



However, even the best fitted of the preliminary model which is the BSM model is inaccurate overall and has high error. The inaccuracy of the models are likely caused by the high volatility in many of the series caused by the shocks of September 11 and SARS and to a lesser extent other shocks such as the financial crisis of 1997, Tsunami in 2004, Avian influenza and anti Japanese movement in 2005. Models selected to forecast these time series need to be more sophisticated, and to be capable of managing shock in the original data series. From the literature the most evident models to select first is the Box Jenkins ARMA model, the BSM model with interventions, and the neural model.

5.7 ARMA and ARIMA Forecasting for 13 Countries to the 31 Chinese Provinces

5.7.1 Introduction

ARMA and ARIMA model building is an empirical technique for systematically identifying, estimating and forecasting a time series and it is widely used for univariate forecasting. The well known Box Jenkins (1976) ARMA model and extended ARIMA model has dominated much of the tourism forecasting in the past, depending on the frequency of the time series, either simple ARMA includes models with only autoregressive terms, moving average terms, or with a combination of the auto-regression component and the moving average term or ARIMA (and seasonal ARIMA-SRIMA) with an interactive component. The forecast approach of this model does not assume any particular pattern in the historical data, but uses an interactive method in identifying a suitable model from a group of possible models by investigating the shapes of the distributions of autocorrelation coefficients and partial autocorrelations coefficients of a time series. The identified model is then compared against historical data to verify whether it describes the series correctly.

The ARIMA (and seasonal ARIMA-SRIMA) approach is a process of transforming a series into a stationary covariance condition, it then identifies, estimates, diagnoses and forecasts the series. Details of the analysis of the methods and their application can be found in Chu (1998b), Kim and Moosa (2003), Louvieris (2002), Lim and McAleer (2002), Goh and Law (2002) and Wong et al., (2007).

A study by Chu (1998b) employed seasonally adjusted data to overcome problems of controlling stochastic seasonality and a lack of ability to determine cycles.

ARMA and ARIMA forecasting is used, and no seasonal model (SRIMA) can be used because the data contains no seasonal measurement as stated earlier, the data available on international tourist arrivals at the accommodation establishments in China have been collected on an annual basis.

Multiplicative ARMA and ARIMA modelling here tests the models including (1,0,0) (1,1,0) (1,1,1) (0,1,1) (0,0,1). These options test for a moving average or both a moving average and auto regressive analysis coupled with either a stationary or non stationary series, where the order of differencing to achieve stationary is one. The best models are selected depending on the forecasting performance of the models.

The non-seasonal autoregressive model of order *p is* of the form*:*

$$Z_t = \delta + \phi_1 z_{t-1} + \phi_2 z_{t-2} + ...\phi_\rho z_{t-\rho} + \alpha_t ,$$

Where: $Z_t = \nabla^d y_t$ for an undifferenced time series y_t and an order of differencing d , ϕ_i 's are the parameters relating to the Z_{t-1} 's, and α_t is the residual error term.

The autoregressive moving average model (ARMA) of order (p,q) is of the form:

$$Z_t = \delta + \phi_1 z_{t-1} + \phi_2 z_{t-2} + ...\phi_\rho z_{t-\rho} + q_t - \theta_1 q_{t-1} - \theta_1 q_{t-1} - \theta_2 \alpha_{t-2} + ...\theta_q \alpha_{t-q} \ .$$

When stationarity is achieved by differencing, a non-seasonal model of the order ARIMA (p,d,q) is represented using the back shift operator as:

$$\phi(\mathrm{B})\nabla^d y_t = \delta + \theta(\mathrm{B})\mathrm{E}_t .$$

Where: $\phi(\mathrm{B}) = 1 - \phi_1 \mathrm{B} - \phi_2 \mathrm{B}^2 - ...\phi_p \mathrm{B}^p$, and: $\theta(\mathrm{B}) = 1 - \theta_1\mathrm{B} - \theta_2\mathrm{B}^2 - ...\theta_q\mathrm{B}^q$.

The adequacy of the model is checked statistically by testing the significance of the model parameters using *t* statistics in a conditional least squares estimation. Terms in the model with non-significant parameters are removed.

Compared with the simple time series models analysed earlier, the Box-Jenkins model (1976) is more complex in function and form, and it has more stringent validity tests and data requirements than the previous methods. ARMA and ARIMA time series models have been criticized for their ambiguity and inability to address the determinants of tourism demand necessary for policy assessment (Lim and McAleer, 2000, Kulendran and King, 1997, Kulendran, 1996). There are also questions raised in using differencing to remove stationarity and the concern for over differencing. Studies carried out including Chu (1998), Goh and Law (2002) extend the ARIMA (p,d,q) to a seasonal ARIMA $(p,d,q)(P,D,Q)$ to overcome the situation in which the time series is seasonally non-stationary.

The use of the ARIMA model for short-term forecasts has been widely accepted in tourism forecasting studies for its versatility and accuracy (Frechtling, 1996, Delurgio, 1998). In most analyses in tourism it is the seasonal SARIMA model that is tested using smoothed data. A study by Louvieris (2002) successfully used a multiplicative seasonal autoregressive integrated moving average (SRIMA) model to forecast Greece's inbound tourism in the medium/long-term. The findings of his study support the assertion that the ARIMA methods are accurate, not only for the short term, but also for medium/long term forecasting. However, Smeral and Wüger (2005) found that the Naïve One (no-change) model outperformed both the ARIMA and SRIMA models. In an early study in 1995 Turner et al., compared the Winters and ARIMA models and found that in cases where there is regular trend and even but highly variable seasonal components between the extremes of summer and winter, the Winters model was more accurate than the ARIMA model (Turner, et al., 1995). However, other studies have found improved forecast accuracy in using the Box Jenkins model (Kulendran and Witt, 2003, Veloce, 2004, Kon and Turner, 2005, Vu, 2006).

Multivariate time series forecasting has also been developed to examine the involvement of additional “parallel” time series, for example tourism demand for a destination by a number of source markets, and how this may contribute to the improvement of forecast performance. Goh and Law (2002) introduced a multivariate SRIMA model including an intervention function to capture the potential spill-over effects of the additional demand series on a particular time series. The study showed that the multivariate (MSRIMA) model significantly improved the forecasting performance of the univariate model (SRIMA) as well as other simple time series models. However, in studies by Du Preeze and Witt (2003) the multivariate ARIMA failed to outperform its univariate rival model. Furthermore, a study by Chan et al., (2005) examined three multivariate Generalised Autoregressive Conditional Heteroskedastic (GARCH) models and discovered that tourism demand was affected by the conditional variances of the models that underpin the demand for Australian tourism, by the four leading tourist generating countries. However, the performance of the GARCH forecast was not the focus of their study.

Additionally, the use of an Egarch Model has become more popular outside tourism research and particularly in finance research. The reason is that the conditional variance is an exponential function and this removes some constraints on the parameters that are used in GARCH models, to have a positive conditional variance. The Egarch model also permits asymmetries as an additional term in the model.

Model selection for the ARIMA analysis here is made using forecasting accuracy on a trial and error basis. The model choice for the most accurate model is also checked on the basis of the Akaike Information Criteria and Schwartz Bayesian Criteria for comparison of model accuracy. These measures of model accuracy are widely used and accepted in the tourism forecast literature. Some conflict can occur between results for the two criteria and the choice here is based on the Akaike measure and the Schwartz measure is used only when there is conflict between forecast accuracy (MAPE) and the Akaike criteria.

In this study, ForecastX Wizard (Book Version) V6.0a was used to obtain the ARMA forecasts.

5.7.2 Results of ARMA Forecasting for the 13 Countries to the 31 Chinese Provinces

Table 5.1.11 shows that Japan has the lowest overall MAPE average of 38.7%, and Russia has the highest overall MAPE average of 69.5%. Total MAPE average for the 13 source countries to the 31 Chinese regions is 48.7%.

Table 5.1.11 MAPE for ARMA forecast for all countries to the 31 Chinese provinces 2006 - 2007

	Jap	Kor	M'sia	S'pore	Thai	USA	Can	UK	Fra	G'many	Rus	Aust	Phi	T/A
Beijing	17.8	18.9	8.5	20.8	40.3	28.7	39.1	16.7	34.5	38.7	59.6	34.8	55.3	31.8
Tianjin	14.2	16.3	11.7	23.4	29.3	20.8	NC	22.3	19.4	34.1	NC	17.0	19.8	20.8
Hebei	10.3	18.3	56.7	NC	71.9	73.4	80.2	82.5	84.0	48.4	65.3	82.7	69.4	61.9
Shanxi	61.0	57.5	64.1	NC	64.5	71.3	84.1	69.9	64.1	65.9	69.1	73.3	75.1	68.3
InnerMongolia	39.7	61.2	53.6	58.8	NC	49.7	89.7	17.9	14.1	31.2	68.1	21.5	87.4	49.4
Liaoning	91.7	41.9	33.3	96.1	32.7	28.1	31.6	43.8	41.1	26.7	65.3	30.1	51.4	47.2
Jilin	36.1	42.4	NC	NC	5.7	NC	90.3	70.8	5.4	42.8	88.5	63.4	31.4	47.7
Helongjiang	40.7	42.1	60.9	19.1	47.5	51.9	84.9	35.0	35.3	31.0	82.7	63.9	52.4	49.8
Shanghai	43.6	21.1	15.9	97.7	57.8	11.0	23.7	82.7	28.9	2.7	80.0	4.8	50.0	40.0
Jiangsu	52.4	15.2	3.1	25.9	14.5	41.1	37.6	49.4	64.4	41.8	75.2	47.4	52.3	40.0
Zhejiang	90.5	17.8	5.2	5.6	23.3	30.8	42.6	35.8	32.6	23.9	70.4	32.3	28.6	33.8
Anhui	27.8	49.3	28.6	NC	37.9	31.1	44.3	51.3	35.7	32.3	79.2	47.1	67.9	44.4
Fujian	83.5	12.1	46.6	84.6	94.6	42.8	50.4	32.9	23.6	4.7	57.8	33.4	38.6	46.6
Jiangxi	23.9	49.0	39.2	NC	54.9	49.7	NC	24.3	19.8	50.1	57.8	22.7	64.2	41.4
Shandong	20.1	32.7	16.7	82.1	69.2	34.6	26.4	41.8	31.2	27.7	74.9	36.3	52.9	42.1
Henan	19.4	NC	32.4	82.5	80.6	41.9	55.5	18.8	49.5	64.0	52.4	47.7	37.3	48.5
Hubei	39.0	18.1	79.7	45.0	88.1	37.0	59.8	52.2	27.0	50.4	82.4	69.8	81.6	56.2
Hunan	56.9	54.5	88.4	65.1	60.1	73.3	72.1	73.1	77.0	82.5	85.0	48.4	59.5	68.9
Guangdong	16.5	75.4	58.6	97.8	74.5	34.8	53.6	21.2	59.3	54.0	66.1	60.6	54.9	55.9
Guangxi	31.0	NC	23.9	NC	88.1	48.3	65.0	71.3	73.0	44.4	41.8	47.7	58.7	53.9
Hainan	33.9	68.1	NC	45.4	70.3	32.0	45.5	50.7	45.1	48.3	95.8	26.4	72.3	52.8
Chongqing	17.7	88.5	83.8	42.1	85.2	83.7	26.8	13.5	56.0	49.9	70.4	28.9	40.6	52.9
Sichuan	59.5	62.7	32.6	93.8	95.8	65.2	47.6	57.6	53.8	46.4	80.6	45.6	13.1	58.0
Guizhou	49.2	NC	8.2	NC	36.4	70.4	72.7	74.6	50.4	64.0	53.5	79.9	49.2	55.3
Yunnan	33.5	63.6	34.4	92.3	99.6	28.3	31.3	44.6	35.8	30.8	42.0	35.4	64.3	48.9
Tibet	49.5	NC	88.9	NC	45.3	33.8	84.8	57.1	29.1	37.3	90.4	69.2	71.1	59.7
Shaanxi	5.9	80.4	46.4	88.5	80.3	75.9	86.5	64.1	70.2	67.7	60.5	80.1	83.8	68.5
Gansu	12.2	77.7	2.7	55.4	33.5	28.8	21.7	13.8	26.8	54.2	89.9	15.4	63.6	38.1
Qinghai	82.1	NC	53.6	NC	40.6	53.8	65.9	50.7	12.1	30.9	68.1	36.9	77.8	52.0
Ningxia	11.6	NC	79.8	NC	52.5	45.7	34.9	27.0	25.2	58.8	NC	70.3	56.5	46.2
Xinjiang	28.3	60.6	27.2	29.8	18.5	18.7	21.1	8.6	48.4	19.2	43.8	19.1	27.2	28.5
MAPE Overall	38.7	45.8	40.9	59.6	56.5	44.6	54.1	44.4	41.1	42.1	69.5	44.9	55.1	48.7

Note: NC means not calculable for values over 100.

Table 5.1.12 Summary MAPE counts for ARMA forecast for all countries to the 31 Chinese provinces

Number of forecasts <10%	47
Number of forecasts >10% <20%	131
Number of forecasts >20% <30%	123
Number of forecasts >30% <50%	69
Number of forecasts >50%	32

The results of ARMA analysis overall are not highly accurate, in that the overall error exceeds 48.7% and when compared with the previous analyses Holt (Average MAPE of 33.9%), the Exponential Smoothing model (Average MAPE of 34.1%), and BSM (Average MAPE of 35.6) shows the most accurate overall forecast result is the Naïve (Average MAPE of 25.3%). However, the number of forecasts below 30% error is high, and compares well with the results from the earlier BSM analysis (best of the initial time-series models) and far better than the Naïve result.

5.8 Neural Forecasting for 13 Countries to the 31 Chinese Provinces

5.8.1 Introduction

The Artificial intelligence based data mining methods in tourism demand forecasting began in the late 1990's when the first two studies by Uysal and El Roubi (1999) identified the method as a data mining methodology. In their study, a preliminary neural network is build by using Canadian tourism expenditure in the United States as a dependent variable and four economic and seasonal dummy variables as independent variables. This study found that the neural network achieved higher accuracy with high adjusted correlations and low errors; Law and Au (1999) developed a trained (supervised) feed-forward neural network to forecast Japanese tourists to Hong Kong using six social economic dependent variables. Their findings show that use of the neural network yielded lowest average MAPE when compared with four other econometric models including naïve one, moving average, single exponential smoothing and multiple regression models.

The artificial neural (ANN) method is a computing technique that tries to imitate the learning process of a human brain (Law, 2000). Neural network technology is a new option in many application areas in business, especially when the problem largely involves classification, recognition and prediction (Li et al., 2004). The unique features of ANNs include their ability to adapt imperfect data, nonlinearity and artificial function mapping, making this method a potentially useful alternative to regression forecasting models where the objective is to provide accurate forecasts as opposed to reasons for the forecasts.

As Law (2000) states, a neural network contains many simple processing units known as 'nodes' operating in parallel with no central control and the connections between these nodes have numerical weights that can be adjusted in the learning process. ANN's function as approximators capable of mapping any linear or non-linear function and are powerful methods for tasks involving pattern classification, estimating continuous variables and forecasting (Zhang, 2004).

Some improved ANNs continue to appear in recent years. Burger et al., (2001) employ a variety of time series techniques to forecast the US demand for travel to Durban, South Africa. Models include naïve, moving average, decomposition, single exponential smoothing, ARMA, multiple regression as well genetic regression and neural networks. Their study found that the neural method performs best. Law et al., (1999) used a feed-forward neural network to model the demand for Hong Kong tourism by Japan. A follow on study by Law (2001) used the same variables as in an earlier study Law (1999) but with updated data, on Japanese tourists to Hong Kong, during the Asian financial crisis in 1997, the neural network outperformed other forecasting models when there was a sudden environmental change. A study by Wang and Hsu (2008) uses short-term series data forecasting tourism from Taiwan to the United States. This study found that the fuzz time series are suitable for short-term predictions.

Neural network models have been used as a statistical technique in the main fields of tourism research, such as demand and consumer behaviour forecasting Burger et al., (2001); Kon and Turner (2004) provide a detailed description and literature review of neural models. They point out the failure of many articles to specify their modelling procedure and the importance of doing so. Their findings indicate that different neural models have different levels of success in accurately forecasting arrivals for different series, and that neural models have potentially high levels of accuracy. Zhang (2004) indicated that due to the fact that a real world problem is often complex in nature any single model may not be able to capture different patterns under study. Researchers in recent years have been trying to combine different models to increase forecast accuracy. His study demonstrated that combining the linear ARMA model and nonlinear neural network technique provides better forecasting performance than individual models used separately. Fernando (2005) concluded in his Doctorate Thesis research that neural-fuzzy models can be used effectively in tourism forecasting.

However, due to their flexibility, neural networks lack a systematic procedure for model building and obtaining a reliable neural model involves selecting a large number of parameters experimentally through trial and error (Palmer et al., 2006).

This study undertook forward stepping neural forecasting for the 13 tourist countries to the 31 Chinese regions using PASW Statistics 18.

5.8.2 Results of Neural Forecasting for the 13 Countries to the 31 Chinese Provinces

Table 5.1.13 shows that Japan and Singapore have the lowest overall MAPE average of 17.3%, and Australia has the highest overall MAPE average of 40.3%. Total MAPE average for the 13 source countries to the 31 Chinese regions is 27.3%.

Table 5.1.13 MAPE for neural forecast for all countries to the 31 Chinese provinces 2006 -2007

	Jap	Kor	M'sia	S'pore	Thai	USA	Can	UK	Fra	G'many	Rus	Aust	Phi	T/A
Beijing	0.1	22.9	0.6	2.5	2.1	12.0	25.1	8.3	8.1	12.5	46.0	51.3	28.8	16.9
Tianjin	2.8	2.6	1.5	1.2	3.4	9.1	36.2	7.2	8.6	29.5	13.2	40.4	3.2	12.2
Hebei	1.1	30.2	0.6	7.0	1.0	42.3	52.6	22.9	39.5	37.6	58.3	14.3	1.6	23.8
Shanxi	26.2	8.8	79.9	4.5	14.8	54.5	65.0	45.6	59.4	44.9	21.0	70.0	21.9	39.7
Inner Mongolia	14.1	73.2	1.0	21.3	4.5	52.5	72.8	67.6	48.8	73.3	37.1	63.1	47.1	44.3
Liaoning	25.3	15.5	18.2	14.8	18.0	54.5	40.7	31.7	64.5	39.9	57.3	30.0	25.3	33.5
Jilin	37.2	15.5	24.9	18.7	38.0	55.6	58.5	27.9	69.5	15.4	29.3	55.5	35.1	37.0
Helongjiang	3.8	12.4	16.0	4.5	1.8	7.3	0.7	1.9	0.5	2.5	29.0	24.3	0.5	8.1
Shanghai	20.4	36.3	8.8	18.4	33.8	13.5	32.1	68.4	7.8	32.5	7.3	36.8	15.4	25.5
Jiangsu	38.8	36.3	10.9	24.9	29.4	37.4	42.1	67.1	57.4	59.4	52.3	58.3	28.7	41.8
Zhejiang	35.5	36.1	24.0	7.3	41.1	47.8	45.1	38.6	47.8	58.7	55.9	53.3	34.0	40.4
Anhui	11.1	75.1	5.1	0.9	12.2	47.6	35.6	56.3	52.5	47.6	41.2	22.7	12.9	32.4
Fujian	6.0	12.7	2.2	2.6	68.5	20.2	53.2	45.2	43.0	29.9	19.2	31.6	2.9	25.9
Jiangxi	59.0	72.8	49.2	50.6	13.3	35.0	57.7	55.2	32.3	40.4	31.0	36.3	70.0	46.4
Shandong	22.1	37.9	9.5	21.1	37.3	52.5	38.5	39.8	49.9	31.9	48.0	49.1	2.8	33.9
Henan	1.4	59.3	16.4	8.7	9.1	36.2	19.9	28.0	39.2	14.5	47.6	4.4	20.5	23.5
Hubei	0.4	15.3	41.6	30.3	34.8	2.8	32.5	11.0	29.6	7.0	55.5	70.4	35.0	28.1
Hunan	2.7	53.1	26.1	21.2	3.8	3.1	2.2	22.1	19.5	49.5	11.6	2.1	1.4	16.8
Guangdong	26.1	46.4	29.9	18.1	35.7	38.3	40.6	40.1	32.9	50.8	25.5	47.1	6.6	33.7
Guangxi	0.9	1.9	49.8	56.8	38.8	22.5	33.8	34.4	35.4	5.2	33.0	27.8	30.3	28.5
Hainan	11.7	55.2	1.3	26.3	12.0	58.1	57.0	49.6	64.4	65.1	84.6	65.3	58.0	46.8
Chongqing	12.0	12.0	48.3	37.7	49.6	32.8	19.4	6.9	12.4	5.1	1.7	61.5	58.9	27.6
Sichuan	68.2	68.2	22.4	53.5	8.6	31.0	42.2	59.3	30.7	22.1	47.5	59.8	34.0	42.1
Guizhou	15.6	56.3	1.2	0.8	4.5	33.8	15.9	22.7	9.0	8.9	76.4	67.4	9.5	24.8
Yunnan	3.5	34.3	8.9	2.2	1.3	25.7	30.4	11.2	53.7	29.6	32.5	54.6	9.4	22.9
Tibet	35.5	13.8	63.4	54.0	37.4	9.4	59.1	12.8	5.4	6.9	60.8	31.9	1.7	30.2
Shaanxi	7.3	0.1	15.9	10.3	3.5	6.2	14.4	4.4	5.0	0.3	20.0	19.6	4.5	8.6
Gansu	0.1	50.0	3.8	1.3	11.9	16.3	5.0	7.2	13.5	10.4	51.1	10.6	0.1	14.0
Qinghai	45.1	44.7	3.2	3.8	17.5	46.7	7.1	8.7	1.3	9.9	20.3	21.5	1.6	17.8
Ningxia	0.6	1.4	28.9	10.9	5.1	20.1	11.6	1.4	16.1	6.2	10.7	57.0	16.9	14.4
Xinjiang	3.5	15.1	0.5	1.3	6.4	0.6	3.4	1.3	13.4	1.4	4.0	12.2	2.0	5.0
MAPPE VERALL	17.3	33.3	19.8	17.3	19.8	30.8	33.9	29.2	31.3	27.4	36.4	40.3	19.7	27.3

Note: NC means not calculable for values over 100.

Table 5.1.14 Summary MAPE counts for all countries to the 31 Chinese provinces

Number of forecasts <10%	47
Number of forecasts >10% <20%	131
Number of forecasts >20% <30%	123
Number of forecasts >30% <50%	69
Number of forecasts >50%	32

The results of Neural analysis are not highly accurate in that the overall error exceeds 25% when compared with the previous analyses ARMA Average MAPE of 48.7%, Holt (Average MAPE of 33.9%), the Exponential Smoothing model (Average MAPE of 34.1%), and BSM (Average MAPE of 35.6) shows the most accurate overall forecast result is the Naïve (Average MAPE of 25.3%). However, in overall terms the neural model has come close to the benchmark naïve process in regard to accuracy and provides a reasonably accurate model for several provinces. In terms of the number of forecasts below 30% error the same results occur for the Neural as the ARMA and BSM models.

5.9 BSM Forecasting with Structural Interventions for the 13 Countries to the 31 Chinese Provinces

5.9.1 Introduction

The BSM was introduced by Harvey and Todd (1983). The model assumes that a time-series possesses some structure, which is the sum of independent trend, seasonal and irregular components. Harvey (1989) developed the structural times series models (CSM) by decomposing the data into components and using the Kalman filter to evaluate the function. Often the components of a time series are not fixed but are stochastic by nature and the basic structural model consists of components including stochastic trend, cyclical change, seasonality and an error term. The trend component changes from the previous period by the amount of the slope, where the slope allows for stochastic changes from period to period. The model can allow for seasonal change but can also be used on non-seasonal data. The model manages the issue of non-stationarity without the need for differencing. Kulendran and King (1997) used the basic CSM in conjunction with the regression method to form multivariate structural time series models. Further studies relating to this approach include Turner et al., (1997b), Greenidge (2001), Kulendran and Witt (2001), Turner and Witt (2001a), Du Preeze and Witt (2003), and Kulendran and Witt (2003). Kon and Turner's study (2005) found the BSM and neural model to be more accurate than the naïve and Holt Winters models. Vu's study (2006) found both Winters and BSM forecasts outperform the naïve model.

As shown in earlier analyses, none of the forecasting methods (Exponential Smoothing, Holt, BSM, ARMA and neural models) has yielded an overall MAPE average below the naïve average of 25%. Therefore an alternative method using BSM with structural intervention has been considered in order to examine whether or not the volatilities of shocks in the time series under this study were the cause of the relatively overall inaccurate forecast results. The major shocks that caused significant reduction of tourists from the 13 countries to the 31 Chinese regions were examined by using Stamp 7.

5.9.2 Results for BSM Forecasting with Structural Interventions for 13 Countries to the 31 Provinces in China

The structural time series modelling procedure used for the structural modelling in section 5.5 is extended here to include intervention variables to account for the impact of Sept. 11 and SARS on the arrivals series. In the few cases where these variables did not impact on the series (refer to the Table 5.2) the model reverts to a BSM model.

The interventions used in this analysis were input as "outliers" occurring at a particular time and measured as the value one, at the time of the event (outlier) and zero otherwise.

Table 5.1.15 shows that Japan has the lowest overall MAPE average of 16.8%, and Russia has the highest overall MAPE average of 25.5%. Three of the 13 countries have a total MAPE average of below 20%. Total MAPE average for the 13 source countries to the 31 Chinese regions is 22.1%, which is lower than the previous analyses. The ARMA Average MAPE of 48.7%, Holt (Average MAPE of 33.9%), the Exponential Smoothing model (Average MAPE of 34.1%), BSM (Average MAPE of 35.6), Neural (Average MAPE of 27.3%), Naïve (Average MAPE of 25.3%), shows the most accurate overall forecast result is the BSM with intervention (Average MAPE of 22.1%). The number of forecast errors below 30% is also high and slightly higher than the preceding analyses for the BSM, ARMA and Neural models, which were the best forecasts results above, indicating that the BSM intervention model is the best performing model of the time-series methods.

Table 5.1.15 MAPE for BSM forecast with intervention for all countries to the 31 Chinese provinces 2006 - 2007

	Jap	Kor	M'sia	S'pore	Thai	USA	Can	UK	Fra	G'many	Rus	Aust	Phi	T/A
Beijing	14.5	1.1	7.9	12.2	3.1	6.9	10.5	5.7	8.7	15.7	11.5	9.8	28.0	10.4
Tianjin	24.8	13.2	9.0	17.6	11.4	4.6	NC	11.4	17.3	8.6	7.4	4.1	22.9	19.4
Hebei	10.0	7.7	4.9	6.8	29.7	10.1	6.3	21.2	21.8	16.9	9.5	16.5	22.2	14.1
Shanxi	52.7	19.9	48.8	37.7	64.0	61.8	68.1	56.0	63.6	49.8	48.1	63.4	66.8	53.9
Inner Mongolia	21.4	17.2	16.5	54.9	NC	22.6	18.8	5.3	18.5	NC	8.2	29.4	38.8	34.7
Liaoning	12.7	3.3	9.5	2.2	10.7	7.7	16.5	24.7	13.9	5.9	22.9	9.2	10.6	11.5
Jilin	4.9	29.4	3.7	11.8	16.9	9.8	NC	79.0	3.9	6.8	38.2	15.4	35.2	27.3
Helongjiang	4.0	12.3	33.7	13.1	60.0	9.5	13.8	43.8	31.4	13.3	18.0	21.1	50.7	25.0
Shanghai	3.5	6.5	12.6	11.3	40.8	24.0	4.9	4.4	11.1	23.3	14.7	19.7	10.0	14.4
Jiangsu	27.1	28.7	11.6	7.0	40.8	13.0	10.0	23.5	10.6	23.6	29.4	21.7	24.9	20.9
Zhejiang	8.5	15.7	12.6	8.8	5.9	1.8	31.2	5.7	9.4	14.4	16.6	6.2	3.9	10.8
Anhui	13.2	11.5	15.5	13.3	27.4	13.8	12.6	28.2	8.7	3.5	45.1	11.7	8.6	16.4
Fujian	13.3	60.2	1.5	10.5	65.1	17.4	25.8	12.0	2.4	27.1	9.3	11.7	11.3	20.6
Jiangxi	12.1	13.5	18.1	19.7	29.0	21.2	NC	19.0	9.2	7.7	11.7	14.0	7.1	21.7
Shandong	2.0	7.9	3.9	14.4	11.5	17.0	10.9	13.3	16.0	12.2	25.5	18.7	14.2	12.9
Henan	8.7	16.0	15.2	33.9	6.5	7.5	20.3	34.7	37.8	65.9	19.2	20.0	7.6	22.6
Hubei	4.9	22.6	38.4	58.2	25.0	6.3	37.8	5.1	4.4	4.2	47.0	44.4	54.7	27.2
Hunan	23.5	42.7	50.7	25.6	13.1	8.9	26.7	25.9	16.0	18.3	47.6	9.3	21.6	25.4
Guangdong	2.2	10.0	13.0	1.2	8.5	14.9	33.0	5.1	25.5	12.7	22.7	37.3	1.6	14.4
Guangxi	11.9	23.1	71.7	21.7	6.4	9.3	42.4	16.4	10.1	16.2	9.7	20.5	6.0	20.4
Hainan	9.3	6.2	NC	32.6	9.6	12.3	17.6	27.7	8.1	13.8	20.9	36.5	49.2	26.5
Chongqing	23.0	43.8	34.4	44.4	26.0	2.5	15.8	12.8	32.0	6.7	12.8	14.6	27.2	22.8
Sichuan	8.5	14.9	88.5	17.6	22.6	5.6	2.4	21.1	18.9	13.7	34.1	14.8	46.7	23.8
Guizhou	3.2	8.8	29.7	43.7	8.9	5.2	14.2	9.9	14.0	13.3	15.2	5.9	17.9	14.6
Yunnan	6.3	2.8	10.9	12.7	12.1	11.6	10.9	11.2	16.8	10.6	15.9	10.1	27.0	12.2
Tibet	48.9	55.4	68.4	80.5	24.7	33.6	26.5	25.4	25.5	32.3	76.5	46.4	28.3	44.0
Shaanxi	21.9	22.0	10.9	11.2	14.3	4.8	15.6	4.0	6.7	17.9	16.9	19.7	15.8	14.0
Gansu	3.2	45.4	6.3	5.3	14.7	17.7	10.6	11.3	22.4	20.8	27.5	67.2	26.3	21.4
Qinghai	77.1	47.6	18.3	28.1	43.8	46.9	50.6	1.3	25.6	25.9	31.2	27.4	34.6	35.3
Ningxia	10.7	12.1	5.9	20.1	58.2	19.8	33.9	9.9	15.8	53.9	44.8	66.0	60.3	31.7
Xinjiang	33.1	7.3	4.0	8.7	11.9	14.7	15.7	11.9	5.6	14.0	32.7	24.0	7.3	14.7
MAPE OVERALL	16.8	20.3	25.0	22.2	26.5	14.9	29.1	18.9	17.2	21.6	25.5	23.8	25.4	22.1

Note: NC means not calculable for values over 100.

Table 5.1.16 Summary MAPE counts for BSM forecast with intervention for all countries to the 31 Chinese provinces

Number of forecasts <10%	104
Number of forecasts >10% <20%	135
Number of forecasts >20% <30%	78
Number of forecasts >30% <50%	50
Number of forecasts >50%	31

Overall MAPE results from the Naïve, Exponential Smoothing, Holt and BSM forecasts, ARMA and Neural are all above 25% except the BSM forecast with interventions which are below 25%. Throughout the time series there are obvious impacts that cause a reduction of international tourist arrivals to all 31 regions including wide spread impacts immediately after September 11 in 2001 and SARS in 2003. The severity of these impacts on the arrival of international tourists to the 31 regions varies, ranging from the less affected regions in the east and southeast to the more badly affected regions in the west and northwest of China, as shown by earlier analyses. However, the preliminary time-series models are relatively inaccurate and these results suggested that the use of interventions may be worthwhile. The inaccuracy of the earlier models is caused by the high volatility in many of the series caused by the shocks of September 11 and SARS and to a lesser extent other shocks such as the financial crisis of 1997, Tsunami in 2004, Avian influenza and anti Japanese movement in 2005 and the high degree of variability between the source markets and the 31 provinces.

Models selected to forecast these time series potentially need to be more sophisticated, and to be capable of managing shock in the original data series. In the case of the time-series methods used in this chapter the BSM intervention model appears to be the most obvious model, and indeed this model has performed better than the other selected methods. Moreover, from the literature, the most evident causal model to select is the Time Varying Parameter (TVP) model, because it will allow for explanatory variables to provide additional causal theory to account for data variation, while not maintaining fixed parameters that might be unable to adjust to the changing arrivals series and shocks known to exist in these series. The following Chapter 6 examines the use of the TVP model.

Chapter 6

Demand Forecasting for Regional China

6.1 Introduction

Econometric approaches involve the use of statistical analysis, combined with economic theory, to analyse data (Allen and Fildes, 2001).

Song and Witt (2000) and Song et al., (2009) describe the term ‘Tourism demand” for a particular destination as the quantity of the tourism product (i.e. a combination of tourism goods and services) that consumers are willing to purchase during a specified period under a given set of conditions. Earlier econometric approaches in tourism demand forecasting for a particular destination are represented by a single-equation demand forecasting model as:

$$Q_{ij} = f(P_{i,} P_{s,} Y_{j,} T_j A_{ij,} E_{ij}).$$

Where Q_{ij} is the quantity of the tourism product demanded in destination i by tourism from country *j*;

P_i is the price of tourism for destination *i*;

P_s is the price of tourism substitute destinations;

Y_j is the level of income in origin country *j*;

T_j is consumer tastes in origin country *j*;

A_{ij} is advertising expenditure on tourism by destination i in origin country of j;

Eij is the disturbance term that captures all other factors which may influence the quantity of the tourism product demanded in destination i by residents of origin country j.

But according to Allen and Fields (2001), this simple demand model failed in comparison with extrapolative methods, because it paid too little attention to the dynamic structure of a time series. It is noted by Song and Witt (2000) and Song et al., (2009) that the simple demand model does not take into account the long-run cointegration of relationships in the estimation of the models. Hence it raises questions regarding the quality of the empirical forecast results.

Econometric models are causal models and because of this they are regarded by some researchers as superior to time series techniques, because the model construction is more directly based on economic theory. The specification of the model allows assessment of the underlining causes that influence changes to demand. A large number of researchers have examined causal modelling over a long period of time, including: Gray (1966), Artus (1970), Witt (1980a), Witt (1980b), White (1985), Witt and Martin (1987), Darnell,et al., (1990), Syriopoulous and Sinclair (1993), Morris,et al., (1995), Witt and Witt (1995), Lim and McAleer (1999), Lim and McAleer (2001), Song and Witt (2003), Song et al., (2003), Dritsakis (2004) and, Tang et al., (2007). The most recent studies pay more attention to the question of stationarity in the data series: Kulendran (1996), Kulendran and King (1997), Song and Witt (2003) and, Vu and Turner (2006). A study by Morley (2009) on the dynamics in specification of tourism demand models leads to the recommendation of the ARIMAX model which includes an ARIMA model with explanatory variables, autocorrelated errors and autoregressive terms.

One of the distinction problems in short and long-run models is the notion of equilibrium; that is the long-run is the state of equilibrium where economic forces are in balance and there is no tendency to change, while the short-run depicts the disequilibrium state where adjustment to the equilibrium is occurring (Harris and Sollis, 2003, p39). Equilibrium is synonymous with the concept of cointegration when dealing with non-stationary data. Harris and Sollis (2003) warned that failure to establish cointegration often leads to spurious regressions that do not reflect long-run economic relationships, but rather reflect the 'common trends' contained in most non-stationary time series. Furthermore, as pointed out by Harris and Sollis (2003) cointegration is also linked very closely to the use of short-run Equilibrium (or Error) Correction Models, thus providing a useful and meaningful link between the long- and short-run approach to econometric modelling.

A discussion of the advances made in econometric modelling of tourism demand is given in the literature review (Chapter 2). The problem of non-stationarity was examined from 1995 onwards using several methods including unit root testing and differencing, and more recently the Engel-Granger method to determine the lag length. Engle and Granger developed the error-correction model (ECM) containing both long and short-run equilibrium adjustment.

As discussed previously models based upon ECM and vector autoregression (VAR) assume constant coefficients through the time series. The time varying parameter model (TVP) was first introduced in tourism demand studies by Song and Witt (2000) on the basis of the Kalman (1960) filter technique. The TVP approach allows for structural instability to occur in the tourism demand analysis, and therefore to theoretically improve forecast performance.

The TVP model has been developed to reduce the restriction of parameter constancy and takes account of the possibility of parameter changes through time, and consequently theoretically improves forecast accuracy. A study by (Song et al., 2003) shows that the TVP model has better forecasting results over other models for short-term forecasting when the data contains structural instability. In recent years, the TVP model has been widely used by many researchers including Song et al., (2003), Li et al., (2006), Shen et al., (2008) and, Song et al., (2009). These studies found that the TVP model generated more accurate forecast results than other econometric models.

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

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

Where p is the lag length, which is determined by the data and usually decided by the Aikake Information Criterion (AIC) and Schwarz-Bayesian Criterion (SBC); k is the number of explanatory variables and ε_t is the error term which is assumed to be white noise: distributed with zero mean and constant variance σ^2. This study contains annual data and a lag of one is employed.

The TVP method uses a recursive estimation process in which the more recent event is weighted more heavily than the earlier event. With the restriction p = 0 imposed on the coefficients in the equation (1), the TVP model is written as follows:

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

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

Where:

y_t : a vector of tourism demand,

x_t : a row vector of k explanatory variables,

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

Φ : a $k \times k$ matrix initially assumed to be know,

$R_{t:}$ a $k \times g$ matrix,

$u_{t:}$ a residual with zero mean and constant covariance matrix H_t, and

$e_{t:}$ a $g \times 1$vector of serially uncorrelated residuals with zero mean and constant covariance matrix Q_t.

Equation (2) is the measurement equation or system equation, and equation (3) is known as the transition equation or state equation, and the assumptions in both equations are that the initial vector β_0 has a mean of b_0 and a covariance matrix $P_{0,}$ and the residual terms u_t and e_t are not correlated.

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

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

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

Another possible form of the transition equation is:

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

Where μ is the mean of β_t and a stationary process is shown.

The transition equation is determined through a process of experimentation using the goodness of fit and the predictive power of the model. Once the state space (SS) model is constructed, a convenience algorithm, know as the Kalman Filter (KF), can be used to estimate the SS model, refer to Harvey and Todd (1983) and Harvey (1989) for details. The final values from the Kalman Filter are then used for the forecasting of *b,p* and y.

Dummy variables could also be used to capture impacts caused by shocks or a 'one off event' such as the terrorist attack on Sept 11, 2001 and SARS in 2003, and the TVP approach seems a good alternative in these situations (Song et al., 2009).

However, the previous time series analysis has highlighted the high level of volatility in the Chinese regional data caused by external shocks. In fact the naïve model compares well against each model introduced, until the neural and structural model with interventions are used. The advantage of the structural and neural time-series models over other time series methods is the capacity of the parameters of the model to vary in time.

Consequently, an econometric model that will allow the coefficients to vary through time would be an obvious method to consider. The time-varying parameter (TVP) model provides such an option, because it will allow for explanatory variables to provide additional causal theory, to account for data variation while not maintaining fixed parameters that might be unable to adjust to the changing arrivals series. As discussed in the literature review the TVP model has been found to out perform other econometric forecasting models. The TVP model is selected as the most suitable and advanced model for use here.

As mentioned earlier, this is the first major study on regional international tourist arrivals to 31 Chinese regions, and there have been limited references available on the types of variables suitable for regional forecasting. Furthermore, variables available at the regional level vary compared to broader national causal variables, that have been well examined and tested in the context of national level forecasting.

Additional data used for the econometric causal models include income per capita and the consumer price index, for the data series for the top 13 major tourist generating countries to China, and whilst other variables including economic, social, transport and connectivity and weather are sourced for the 31 Chinese regions, the final list of measures available and theoretically justified is limited by data availability. The independent variables used are discussed in detail in Chapter 4.

6.2 TVP forecasting without dummy variables for the 31 Chinese provinces

The TVP model developed here is based upon the modelling procedure provided in the Eviews 6 software package. This analysis provides a dynamic system in state space form. The state space form allows the unobserved variables (state variables) to be estimated along with the observable model. It also allows use of the recursive Kalman filter algorithm used before with the time-series structural modelling in Section 5.5. The Kalman filter is used to calculate one-step ahead estimates of the state and associated mean square error matrix once initial values for the state mean and covariance values are determined. In this analysis Eviews sets these initial values by most commonly setting them arbitrarily high to reflect uncertainty.

The TVP forecast analysis in this study uses two approaches one with two dummy variables (Sept 11 and SARS) and the other one, without involvement of dummy variables. It remains unclear whether interventions are needed in the analysis given the variable parameter capacity of the TVP model.

6.3 Results of TVP forecasting without dummy variables for the 13 source countries to the 31 Chinese provinces

Table 6.1.1 shows Malaysia has the lowest overall MAPE average of 24.1%, and Australia has the highest overall MAPE average of 49.5%. The overall MAPE average for all provinces is 38%.

Table 6.1.1 MAPE for TVP forecast without dummy variables for all countries to the 31 Chinese provinces 2006 - 2007

Province	Jap	Kor	M'sia	S'pore	Thai	USA	Canada	UK	Fra	G'many	Rus	Aust	Phi	T/A
Beijing	28.0	5.6	29.7	49.0	NC	18.4	10.4	11.4	89.9	29.7	NC	3.4	72.0	31.6
Tianjin	NC	20.4	40.0	47.8	13.3	20.5	NC	18.3	24.5	19.8	9.6	77.3	25.0	28.8
Hebei	95.7	39.1	35.0	74.7	95.5	49.7	NC	NC	NC	50.8	NC	63.7	NC	63.0
Shanxi	44.1	31.7	44.7	59.8	12.7	73.5	97.5	57.3	77.8	47.0	52.9	47.1	50.3	53.6
Inner Mongolia	6.6	36.9	5.4	22.7	39.1	47.6	87.9	87.8	NC	72.3	88.8	38.5	6.1	45.0
Liaoning	NC	21.8	14.2	38.3	NC	NC	39.7	NC	24.4	46.4	NC	52.7	59.0	37.1
Jilin	52.5	46.9	3.5	39.4	66.0	13.3	NC	93.9	NC	29.3	4.6	69.1	NC	41.8
Helongjiang	11.8	27.4	55.7	20.2	NC	NC	NC	NC	NC	39.8	52.1	8.7	20.1	29.5
Shanghai	4.5	18.8	32.9	18.4	NC	NC	NC	39.8	35.7	NC	31.1	NC	29.1	26.3
Jiangsu	11.4	21.8	21.2	22.2	17.0	20.2	35.2	16.1	56.7	16.0	16.5	56.2	18.7	25.3
Zhejiang	12.8	6.3	1.5	34.4	NC	8.1	16.6	NC	NC	4.9	22.6	44.6	24.5	17.6
Anhui	8.1	21.9	7.6	27.1	52.5	3.2	23.1	12.5	32.7	20.1	22.7	51.0	37.9	24.6
Fujian	18.2	8.8	24.8	19.5	15.2	18.4	65.5	NC	82.0	7.4	66.6	51.6	55.4	36.1
Jiangxi	26.3	27.8	34.5	13.2	20.4	66.1	12.1	NC	48.2	46.2	NC	39.8	12.7	31.6
Shandong	22.9	16.4	10.0	20.6	4.9	54.0	42.5	NC	52.8	46.8	NC	61.4	18.0	31.8
Henan	18.1	59.3	48.4	26.9	42.3	9.6	79.7	59.9	NC	19.2	17.0	NC	61.3	40.1
Hubei	51.1	44.6	8.9	25.2	63.1	63.8	54.1	40.7	61.9	98.1	33.3	75.9	67.2	52.9
Hunan	68.1	50.7	27.5	41.4	62.4	47.6	44.0	61.3	69.9	28.8	61.0	32.3	52.6	49.8
Guangdong	46.4	15.9	4.1	29.9	13.7	43.7	49.7	43.6	61.4	52.7	10.5	47.7	6.7	32.8
Guangxi	15.1	7.3	31.9	40.8	21.2	43.5	4.7	11.7	NC	80.0	61.7	30.3	9.5	29.8
Hainan	14.7	65.8	10.4	97.3	67.9	24.0	23.1	69.4	21.6	88.7	8.6	NC	42.9	44.5
Chongqing	60.0	19.9	25.4	17.1	96.0	NC	55.7	NC	26.1	47.8	13.9	NC	NC	40.2
Sichuan	19.3	18.3	17.2	72.7	27.3	34.3	21.8	31.6	35.2	42.1	63.1	46.2	25.8	35.0

Guizhou	57.0	8.9	41.1	29.6	41.1	49.6	11.6	87.9	8.6	13.7	NC	52.1	12.9	34.5
Yunnan	3.8	10.0	10.2	20.1	6.8	10.8	7.0	36.2	37.1	18.6	15.3	34.7	18.0	17.6
Tibet	56.5	33.6	30.4	48.9	64.8	33.1	42.2	33.5	45.5	26.1	57.6	60.5	23.2	42.7
Shaanxi	NC	99.0	NC	97.5	NC	NC	NC	60.8	NC	NC	NC	NC	NC	85.8
Gansu	37.7	47.1	23.1	22.7	56.4	NC	60.9	85.7	31.5	38.4	NC	79.3	17.0	45.4
Qinghai	64.2	NC	26.4	13.8	85.9	76.9	NC	NC	50.0	NC	54.8	NC	NC	53.2
Ningxia	44.9	22.0	26.2	42.8	NC	53.0	58.3	NC	88.8	42.7	71.9	98.8	NC	54.9
Xinjiang	28.0	13.6	30.1	14.8	19.8	20.1	38.0	23.0	47.1	17.6	13.3	14.1	13.4	22.5
MAPEOVERALL	33.1	28.9	24.1	37.1	41.9	36.1	40.9	46.8	48.2	39.0	36.9	49.5	31.2	38.0

Note: NC means not calculable for values over 100.

Table 6.1.2 Summary MAPE counts for TVP forecast without dummy variables for all countries to the 31 Chinese provinces

Number of forecasts <10%	33
Number of forecasts >10% <20%	60
Number of forecasts >20% <30%	57
Number of forecasts >30% <50%	94
Number of forecasts >50%	95

Although there are a handful of single digit MAPE values scattered through Table 6.1 the vast majority of MAPE values are over 20% error, and the forecast accuracy can be considered low (Lewis, 1982), relatively to the naïve model.

6.4 Results of TVP forecasting with dummy variables for the 13 source countries to the 31 Chinese Provinces

Table 6.2 shows Korea has the lowest overall MAPE average of 28.1%, and France has the highest overall MAPE average of 52.4%. The overall MAPE average for all provinces is 37.9%, compared to the overall MAPE for the forecast with no dummy variables (38%); this analysis does not seem to yield better results.

Table 6.1.2 MAPE for TVP with dummy variables forecast for all countries to the 31 Chinese provinces 2006 – 2007

Province	Jap	Kor	M'sia	S'pore	Thai	USA	can	UK	Fra	G'many	Rus	Aust	Phi	T/A
Beijing	28.0	8.7	29.4	48.3	NC	37.9	7.4	37.1	88.4	7.2	NC	3.9	22.7	29.0
Tianjin	38.5	8.2	41.0	9.6	54.5	18.0	83.3	18.3	24.5	9.1	9.6	NC	27.8	28.5
Hebei	95.7	37.7	9.6	17.0	NC	38.8	NC	NC	NC	NC	44.7	NC	17.2	37.2
Shanxi	45.3	69.4	24.5	34.4	12.5	47.4	33.6	76.6	60.3	27.3	64.8	10.7	58.2	43.5
InnerMongolia	99.7	55.3	18.0	30.8	52.0	31.8	16.4	30.0	NC	72.3	NC	50.7	NC	45.7
Liaoning	NC	20.4	5.7	14.0	NC	NC	NC	61.3	67.0	34.9	15.8	52.7	52.4	36.0
Jilin	8.9	67.1	9.0	16.2	34.5	32.1	NC	NC	81.4	35.0	8.7	79.7	77.2	40.9
Helongjiang	NC	22.9	60.7	33.1	17.3	16.1	33.3	55.9	NC	NC	40.6	8.7	NC	32.1
Shanghai	4.5	9.6	34.4	11.8	3.2	15.9	14.3	8.1	25.8	NC	30.9	NC	24.4	16.6
Jiangsu	NC	13.9	9.4	43.7	21.9	14.5	14.9	30.7	NC	6.5	53.1	48.6	17.2	24.9
Zhejiang	1.3	8.4	22.1	55.2	23.9	39.3	3.2	NC	NC	30.8	31.0	44.6	1.6	23.8
Anhui	17.8	27.2	74.7	29.9	NC	25.1	54.2	56.1	NC	NC	36.8	45.6	54.7	42.2
Fujian	NC	4.9	9.0	21.1	17.6	NC	53.6	NC	82.5	15.0	32.1	55.3	33.0	32.4
Jiangxi	42.2	27.8	50.6	8.1	8.6	58.1	22.4	69.6	56.2	66.3	25.4	9.9	12.2	35.2
Shandong	88.4	49.9	10.0	72.7	23.4	54.0	80.3	63.7	NC	NC	NC	33.4	45.6	52.1
Henan	65.1	9.7	28.2	26.2	20.8	50.3	NC	NC	NC	19.2	NC	57.7	45.8	35.9
Hubei	13.4	31.4	8.9	40.1	87.7	36.5	56.5	55.1	NC	93.8	NC	95.2	NC	51.9
Hunan	60.9	55.5	22.4	9.4	29.4	49.8	55.2	69.0	67.3	61.9	NC	76.9	64.6	51.9
Guangdong	12.8	27.3	25.1	35.3	10.1	86.7	26.4	62.0	25.6	47.0	NC	NC	33.6	35.6
Guangxi	13.5	9.5	7.6	39.6	54.2	26.2	6.8	50.4	58.6	56.0	26.9	10.2	2.4	27.8
Hainan	NC	12.3	5.5	85.8	20.5	NC	NC	71.4	11.9	40.5	NC	NC	NC	35.4
Chongqing	29.5	6.9	94.1	19.0	36.2	NA	25.1	NC	NC	NC	47.7	NC	NC	36.9
Sichuan	53.9	25.5	30.2	54.6	NC	9.0	25.7	NC	33.3	24.1	NC	64.8	NC	35.7
Guizhou	2.2	12.4	61.1	29.6	19.4	27.4	NA	15.8	8.6	20.7	60.1	55.9	NC	28.5
Yunnan	13.2	10.2	10.2	11.0	11.6	27.7	5.8	35.3	38.2	43.5	17.1	24.7	36.6	21.9
Tibet	76.7	43.1	35.4	71.4	70.2	34.7	46.2	53.1	71.2	40.3	59.3	NC	37.0	53.2
Shaanxi	NC	45.0	98.1	31.5	7.5	24.1	43.4	60.8	58.1	46.2	NC	NC	NC	46.1
Gansu	NC	43.1	25.6	23.3	NC	34.7	8.6	73.8	28.0	98.6	NC	76.1	NC	45.8
Qinghai	64.4	74.7	35.6	82.0	31.7	47.3	80.2	NC	80.6	NC	55.2	40.3	79.1	61.0
Ningxia	22.8	32.3	11.2	49.7	NC	10.1	58.3	NC	90.7	25.2	13.3	NC	39.7	35.3
Xinjiang	47.6	0.0	20.9	26.0	39.9	35.6	39.7	23.0	42.2	73.2	48.0	24.9	39.0	35.4
MAPE Overall	39.4	28.1	29.9	34.8	29.5	34.4	35.8	48.9	52.4	41.4	36.0	44.1	37.4	37.9

Note: NC means not calculable for values over 100.

Although there are a handful of single digit MAPE values scattered through Table 6.1.2 the vast majority of MAPE values are over 20% error, and the forecast accuracy can be considered low (Lewis, 1982).

Table 6.1.3 Summary MAPE counts for TVP (with dummy variables) forecast for all countries to the 31 Chinese provinces

Number of forecasts <10%	42
Number of forecasts >10% <20%	45
Number of forecasts >20% <30%	54
Number of forecasts >30% <50%	89
Number of forecasts >50%	96

Chapter 7
Conclusion

7.1 Introduction

Most of the studies in tourism forecasting have been predominately concentrated on tourist arrivals at the national level using tourist arrival data collected at the immigration counter. A review of the tourism literature shows that the export of tourism services to attract a wider range and greater number of tourists exerts a great influence on a country's economic development and trade balance sheet. Regions within countries are increasingly competing for a greater share of earnings from these tourism exports to create more jobs and improve living standards in local areas. The emerging needs for regional tourism forecasts are potent, not only for the national government but also for the regional governments, in order to facilitate a broader level of economic planning, particularly to aid the planning of tourism related infrastructure, transport, employment, hotels, catering and entertainment services. A review of the tourism literature has demonstrated a pressing need for advancing and expanding international tourism forecasting from the current national based approach, to include regional forecasting. The review also shows that there have been very few studies on regional tourism forecasting (refer to Chapter 2). The purpose of this study is to explore a new forecasting approaching for regional tourism that differs from the traditional method of country based tourism forecasting, and in so doing identifies best practice for regional forecasting. Additionally, the aim is to explore for new causal independent variables that play a critical role in attracting tourists to one particular region over another.

China was chosen as the country of study for regional tourism forecasting, primarily due to its geographic size (31 provinces and 1.3 billion people) and the availability of data in a reasonably long range time-series, using guest arrivals at accommodation establishments dating back to 1994 and through to 2007. China is one of the few countries to publish data for tourist arrivals at hotel and accommodation establishments, for international visitors. These data are annual arrivals of international guests staying at registered accommodation establishments. Visitor arrivals from the 13 most popular tourist source countries to the 31 Chinese provinces (regions) were used to incorporate a fairly wide variety of data patterns in the testing and analysis process.

The aim of this study is to develop new models to forecast inbound tourism to the 31 Chinese provinces (regions). There are nine forecasting models applied in this study including the Naïve, the Exponential Smoothing, the Holt, the Autoregressive Moving Average (ARMA) no seasonal component, the Neural, the Basic Structural Model (BSM) with and without intervention and the Time Varying Parameter (TVP) with and without dummy variables. Annual data from 1994 to 2005 are used as within sample data for model development, and the data from 2006 to 2007 are used as out of sample data, for testing and comparing the forecasting accuracy of the models. For each data series, forecasts are made for one-year ahead and two-year ahead lead periods.

This study uses 13 country based sets of source data to the 31 Chinese provinces (regions) making a total of 403 analyses for each of the nine forecasting models.

MAPE and RMSE values are the two most commonly used methods for measuring forecasting performance. When comparing alternative forecasting methods, the model that demonstrates the lowest MAPE in forecasts is judged as the better model. Other criteria used for measuring forecasting performance are the number of forecasts with less various levels of percentage error of MAPE, and the mean MAPE for all forecasts. In the analysis the t-test does not always indicate significant differences, because of variance in the sample data primarily caused by the two events SARS and September 11. Consequently, BSMI (the Basic Structure Model with intervention) and TVPD (the time-varying parameter model with dummy variables) were incorporated into the research.

Forecasts from the naïve model are used as the benchmark for model comparison to help determine the relative accuracy of model performance. If a model cannot outperform a naïve forecast, the given model is not considered better, or more adequate, for tourism forecasting, than a simple naïve guess.

Section 7.2 of this Chapter provides a summary of the best forecasting performance (MAPE) comparison of all models for the 13 source countries to the 31 Chinese provinces (regions); Section 7.3 shows comparisons of the other eight models against the naïve forecast model for the 13 countries to the 31 Chinese provinces (regions); Sections 7.4 to 7.16 show a paired significance hypothesis analysis of the means to test the significance of the differences between the analyses for each of the 13 source markets; Section 7.17 presents a conclusion summary on the causal modelling for each of the 13 source countries. Section 7.31 shows the optimal models based on MAPE for each of the top 10 arrival provinces. In the latter part of this chapter conclusions are made upon the objectives and aims of this study followed by a short discussion of the research limitations and possible recommendations for future research.

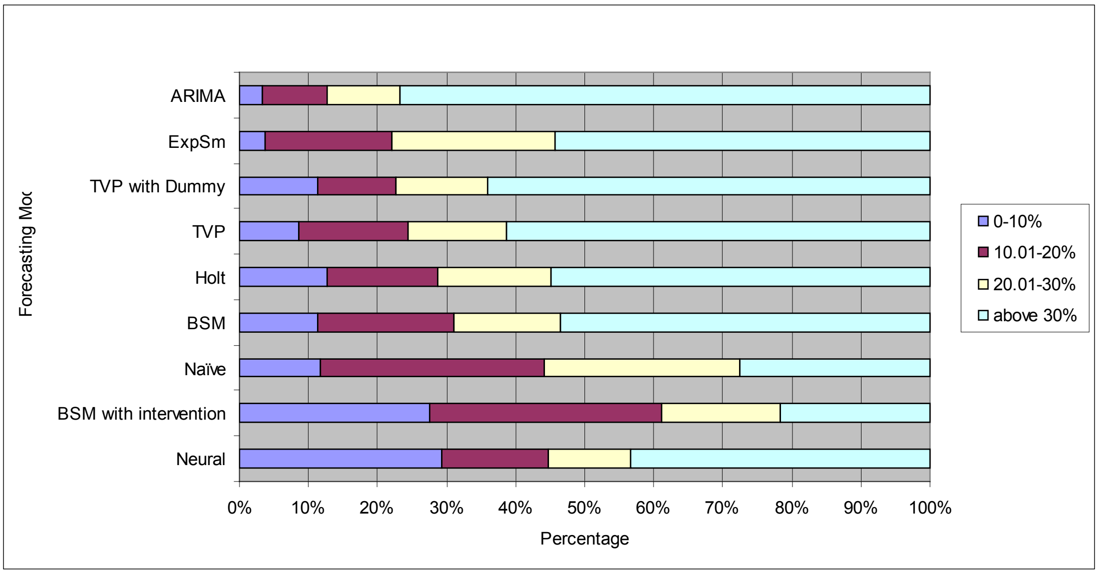
7.2 Best MAPE Counts of All Models for Arrivals from the 13 Source Countries to the 31 Chinese Provinces

Table 7.2.1 summarises MAPE performances for all models for the arrivals from the 13 source markets to the 31 Chinese provinces. There are a total of 31 x 13 = 403 forecast series. For example, the Neural forecast has 118 of the best MAPE counts between 0% to < 10% compared with the ARMA method which only has 13 overall MAPE counts in this band. These comparisons are also shown graphically in Figure 7.2.1.

Table 7.2.1 Forecast performance (MAPE) comparison of all models for arrivals from the 13 source countries to the 31 Chinese provinces

Forecast models	0-10%	10.01-20%	20.01-30%	above 30%	Total
Neural	118	62	48	175	403
BSM with intervention	111	135	70	87	403
Naïve	47	131	114	111	403
BSM	46	79	62	216	403
Holt	51	65	66	221	403
TVP	35	63	58	247	403
TVP with Dummy	46	45	54	258	403
ExpSm	15	74	95	219	403
ARMA	13	38	43	309	403
Total	364	630	562	1668	

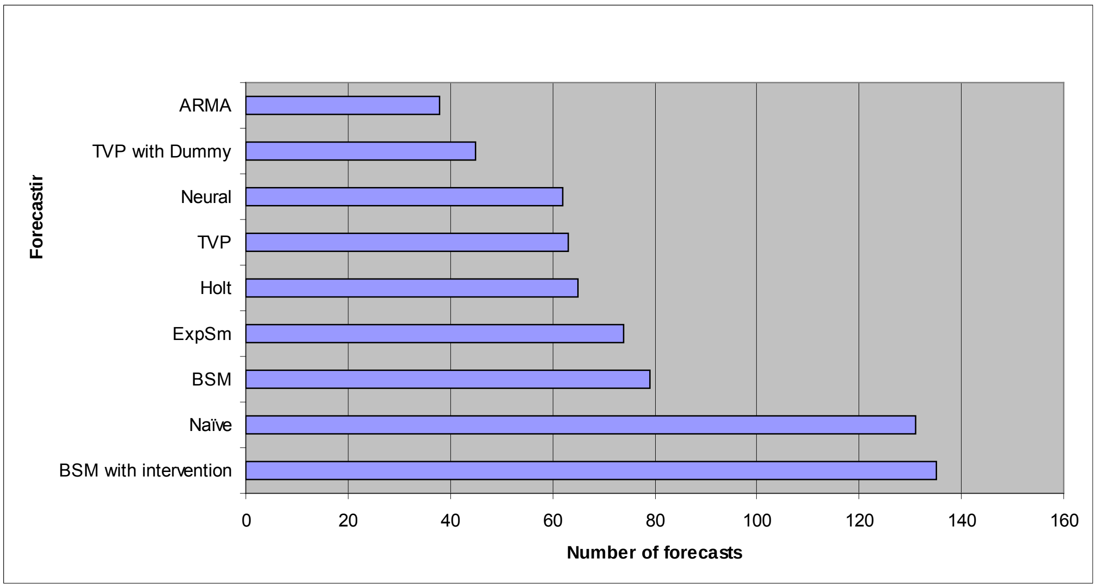
Figure 7.2.1 Forecast performance (MAPE) comparisons for arrivals from the 13 source countries to the 31 Chinese provinces



The findings indicate that accurate forecasting of all 13 source markets into the wide ranging 31 Chinese provinces is not possible using any one model. There is a large number of (3,627) time series with a forecasting accuracy above 20% MAPE error. Given the large number of highly diverse provinces in China and the highly variable flow of international tourists from 13 source countries it is not surprising that accurate forecasting is illusive on the grand scale. It is necessary to examine where forecasting is and is not accurate in more detail.

From Table 7.2.1 and Figure 7.2.1 there is one other outstanding issue, the most accurate of the nine models appears to be the BSM with interventions (BSMI) method which forecasts more than half of the 403 series at or below 20% (refer to Figure 7.2.2). This model is followed by the naïve benchmark and the neural models. A considerable way back the remaining models have far lesser accuracy, with the ARMA model the worst performing method.

Figure 7.2.2 Forecast performance (MAPE) comparisons of all models for arrivals from the 13 source countries to the 31 Chinese provinces with MAPE below 20%



The potential comparisons that can be made with such a large matrix of results are extensive. At the country level Table 7.3.1 shows for example, that for flows from Japan to the provinces the Holt model has the lowest overall mean. However, none of the methods outperform the naïve process overall or are statistically and significantly better methods than the naïve process overall at 95%.

7.3 Comparison of All Models Against the Naïve Model Using MAPE for Arrivals from the 13 Source Countries to the 31 Chinese Provinces

Table 7.3.1 shows that apart from arrivals from Russia, each market has a model that will produce accurate forecasts below 12% error MAPE. Moreover there is the potential for models to outperform the naïve process except for Russia and possibly Thailand. The more complex time-series models perform best including the Neural and BSM methods, while the causal models perform poorly. Overall, none of the models are statistically significantly better than the Naïve model, as shown by the p values above 0.05 which compare the model outputs against the Naïve model in each case. However, this finding is an overall assessment and Table 7.3.1 indicates that there is no overall best performing model and the finding is consistent with that outcome.

Table 7.3.1 Forecast performance (MAPE) comparison summary of all models against the naïve model

Country	Holt	ExpSm	ARMA	Neural	BSM	BSM I	TVP	TVP D	Naïve
Australia	12.8	25.4	33.4	10.9	21.0	16.5	28.9	28.1	22.8
Canada	15.8	27.3	33.7	9.6	21.6	41.0	40.9	35.8	24.1
France	27.3	40.9	47.4	20.5	9.1	20.0	39.0	41.4	18.1
Germany	22.6	38.3	35.4	21.3	11.6	23.2	24.1	29.9	16.9
Japan	4.4	19.1	25.2	4.9	16.1	8.7	33.1	39.4	14.1
Korea	8.5	43.4	24.1	30.9	44.7	52.2	36.9	36.0	15.8
Malaysia	3.7	18.6	17.5	6.8	30.5	12.4	37.1	34.8	7.1
Philippines	18.3	27.3	13.8	2.4	11.4	13.4	46.8	35.8	13.3
Russia	55.9	63.5	73.2	20.7	36.0	46.8	59.6	44.1	23.9
Singapore	7.7	16.0	25.8	5.1	9.6	8.8	41.9	29.5	15.6
Thailand	10.3	14.6	21.5	2.7	30.2	17.2	48.2	52.4	6.4
UK	12.5	26.2	25.6	9.4	24.9	35.6	31.2	37.4	20.3
US	238.0	185.8	202.4	3.1	49.0	66.7	36.1	34.4	241.7
p-value	0.96	0.21	0.07	0.24	0.55	0.69	0.79	0.87	
Count of MAPE ≤10%	0		0	8	2	2	0	0	2

7.4 Comparison of All Models Against the Naïve Model for Arrivals from Australia to the 31 Chinese Provinces

The following tables in sections 7.4 to 7.16 follow though with the complex and detailed testing of all countries for all models, and all regions, to determine whether there is a statistically significant performance by any of the models against the naïve benchmark. Discussion of the result is given at the end of these detailed tables.

Table 7.4.1 Paired comparison of all models against the naïve model for arrivals from Australia to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.67	0.11	0.43	0.23	0.95	0.07	0.65	0.40
Tianjin p-value	0.87	0.87	0.73	0.30	0.72	0.30	0.40	0.23
Hebei p-value	0.17	0.01	0.19	0.78	0.13	0.76	0.03	0.38
Shanxi p-value	0.60	0.62	0.64	0.64	0.60	0.72	0.52	0.13
Inner Mongolia p-value	0.14	0.23	0.23	0.30	0.90	0.70	0.04	0.04
Liaoning p-value	0.69	0.20	0.53	0.50	0.40	0.12	0.23	0.57
Jilin p-value	0.54	0.74	0.53	0.24	0.32	0.33	0.43	0.47
Helongjiang p-value	0.11	0.22	0.38	0.11	0.12	0.23	0.84	0.61
Shanghai p-value	0.19	0.15	0.00	0.05	0.20	0.20	0.46	0.99
Jiangsu p-value	0.25	0.30	0.49	0.35	0.99	0.53	0.30	0.02
Zhejiang p-value	0.06	0.06	0.49	0.21	0.09	0.04	0.02	0.29
Anhui p-value	0.62	0.36	0.49	0.82	0.85	0.30	0.20	0.35
Fujian p-value	0.73	0.46	0.47	0.49	0.23	0.23	0.32	0.17
Jiangxi p-value	0.65	0.34	0.55	0.18	0.51	0.38	0.59	0.59
Shandon p-value	0.82	0.37	0.66	0.35	0.76	0.44	0.08	0.25
Henan p-value	0.01	0.13	0.06	0.60	0.18	0.21	0.68	0.91
Hubei p-value	0.56	0.34	0.45	0.45	0.46	0.90	0.03	0.22
Hunan p-value	0.40	0.06	0.33	0.12	0.26	0.08	0.44	0.35
Guangdong p-value	0.29	0.13	0.27	0.39	0.31	0.47	0.21	0.15
Guangxi p-value	0.21	0.06	0.23	0.80	0.22	0.27	0.17	0.13
Hainan p-value	0.55	0.18	0.00	0.02	0.34	0.35	0.97	0.81
Chongqing p-value	0.09	0.01	0.41	0.11	0.22	0.30	0.00	0.27
Sichuan p-value	0.90	0.07	0.28	0.19	0.04	0.08	0.28	0.23
Guizhou p-value	0.17	0.12	0.03	0.04	0.34	0.17	0.42	0.41
Yunnan p-value	0.10	0.02	0.20	0.14	0.24	0.22	0.36	0.31
Tibet p-value	0.43	0.45	0.36	0.54	0.01	0.90	0.33	0.25
Shaanxi p-value	0.33	0.18	0.01	0.31	0.11	0.18	0.12	0.49
Gansu p-value	0.27	0.64	0.47	0.88	0.27	0.32	0.15	0.10
Qinghai p-value	0.31	0.41	0.48	0.70	0.52	0.57	0.50	0.59
Ningxia p-value	0.47	0.42	0.51	0.67	0.53	0.54	0.11	0.06
Xinjiang p-value	0.18	0.26	0.06	0.24	0.20	0.16	0.70	0.98

7.5 Comparison of All Models Against the Naïve Model for Arrivals from Canada to the 31 Chinese Provinces

Table 7.5.1 Paired comparison of all models against the naïve model for arrivals from Canada to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.24	0.07	0.25	0.53	0.25	0.13	0.34	0.23
Tianjin p-value	0.27	0.27	0.80	0.23	0.03	0.60	0.98	0.97
Hebei p-value	0.34	0.20	0.11	0.20	0.22	0.11	0.45	0.50
Shanxi p-value	0.59	0.57	0.50	0.73	0.57	0.66	0.89	0.33
Inner Mongolia p-value	0.12	0.24	0.24	0.07	0.54	0.81	0.76	0.76
Liaoning p-value	0.56	0.19	0.51	0.30	0.92	0.43	0.12	0.58
Jilin p-value	0.02	0.07	0.51	0.12	0.00	0.82	0.47	0.29
Helongjiang p-value	0.67	0.71	0.15	0.31	0.89	0.52	0.49	0.46
Shanghai p-value	0.08	0.01	0.47	0.20	0.17	0.11	0.50	0.75
Jiangsu p-value	0.31	0.21	0.61	0.50	0.24	0.18	0.77	0.28
Zhejiang p-value	0.86	0.23	0.36	0.32	0.33	0.06	0.02	0.00
Anhui p-value	0.77	0.31	0.54	0.86	0.22	0.02	0.23	0.75
Fujian p-value	0.75	0.23	0.41	0.36	0.70	0.15	0.05	0.03
Jiangxi p-value	0.26	0.44	0.27	0.15	0.30	0.31	0.91	0.57
Shandon p-value	0.34	0.13	0.66	0.24	0.38	0.00	0.15	0.77
Henan p-value	0.39	0.27	0.43	0.76	0.94	0.08	0.15	0.50
Hubei p-value	0.57	0.34	0.41	0.73	0.91	0.83	0.26	0.07
Hunan p-value	0.23	0.09	0.01	0.28	0.14	0.58	0.16	0.27
Guangdong p-value	0.25	0.11	0.23	0.39	0.24	0.52	0.20	0.53
Guangxi p-value	0.21	0.07	0.19	0.71	0.21	0.24	0.11	0.29
Hainan p-value	0.34	0.11	0.30	0.24	0.43	0.48	0.67	0.65
Chongqing p-value	0.10	0.31	0.54	0.17	0.16	0.21	0.23	0.82
Sichuan p-value	0.56	0.19	0.37	0.48	0.67	0.10	0.15	0.47
Guizhou p-value	0.47	0.07	0.06	0.18	0.27	0.08	0.40	0.50
Yunnan p-value	0.11	0.11	0.11	0.10	0.10	0.22	0.46	0.44
Tibet p-value	0.43	0.45	0.31	0.65	0.44	0.21	0.13	0.11
Shaanxi p-value	0.14	0.02	0.03	0.07	0.08	0.18	0.65	0.01
Gansu p-value	0.56	0.72	0.51	0.97	0.57	0.85	0.08	0.90
Qinghai p-value	0.68	0.60	0.48	0.88	0.52	0.55	0.95	0.93
Ningxia p-value	0.49	0.49	0.44	0.79	0.33	0.34	0.76	0.76
Xinjiang p-value	0.32	0.83	0.44	0.95	0.51	0.14	0.87	0.16

7.6 Comparison of All Models Against the Naïve Model for Arrivals from France to the 31 Chinese Provinces

Table 7.6.1 Paired comparison of all models against the naïve model for arrivals from France to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.00	0.14	0.05	0.51	0.01	0.81	0.86	0.84
Tianjin p-value	0.58	0.58	0.72	0.26	0.06	0.05	0.12	0.17
Hebei p-value	0.17	0.04	0.10	0.31	0.15	0.54	0.11	0.52
Shanxi p-value	0.05	0.15	0.21	0.08	0.04	0.05	0.37	0.25
Inner Mongolia p-value	0.48	0.21	0.21	0.27	0.04	0.23	0.29	0.29
Liaoning p-value	0.59	0.22	0.48	0.27	0.82	0.34	0.30	0.31
Jilin p-value	0.20	0.17	0.11	0.01	0.26	0.33	0.10	0.61
Helongjiang p-value	0.24	0.41	0.55	0.35	0.86	0.96	0.59	0.50
Shanghai p-value	0.39	0.27	0.07	0.99	0.36	0.45	0.47	0.67
Jiangsu p-value	0.11	0.11	0.49	0.21	0.05	0.09	0.15	0.16
Zhejiang p-value	0.11	0.03	0.27	0.15	0.22	0.37	0.29	0.04
Anhui p-value	0.33	0.04	0.28	0.14	0.28	0.15	0.37	0.64
Fujian p-value	0.34	0.05	0.47	0.18	0.04	0.05	0.11	0.59
Jiangxi p-value	0.39	0.38	0.58	0.30	0.80	0.76	0.17	0.91
Shandon p-value	0.74	0.18	0.55	0.23	0.83	0.37	0.28	0.53
Henan p-value	0.27	0.14	0.30	0.50	0.25	0.45	0.27	0.27
Hubei p-value	0.25	0.19	0.68	0.54	0.28	0.05	0.94	0.95
Hunan p-value	0.01	0.19	0.12	0.65	0.00	0.00	0.69	0.05
Guangdong p-value	0.86	0.20	0.04	0.00	0.57	0.23	0.30	0.20
Guangxi p-value	0.26	0.15	0.15	0.54	0.24	0.50	0.62	0.79
Hainan p-value	0.17	0.04	0.03	0.11	0.31	0.27	0.12	0.04
Chongqing p-value	0.15	0.02	0.13	0.00	0.14	0.23	0.04	0.44
Sichuan p-value	0.95	0.11	0.30	0.93	0.03	0.00	0.02	0.12
Guizhou p-value	0.09	0.06	0.01	0.27	0.08	0.08	0.43	0.36
Yunnan p-value	0.21	0.17	0.06	0.03	0.33	0.70	0.49	0.65
Tibet p-value	0.17	0.46	0.17	0.46	0.16	0.15	0.48	0.38
Shaanxi p-value	0.02	0.19	0.05	0.36	0.01	0.18	0.63	0.64
Gansu p-value	0.57	0.76	0.59	0.93	0.61	0.33	0.81	0.88
Qinghai p-value	0.47	0.44	0.90	0.89	0.27	0.33	0.34	0.45
Ningxia p-value	0.96	0.60	0.37	0.88	0.93	0.62	0.64	0.69
Xinjiang p-value	0.83	0.64	0.16	0.59	0.61	0.23	0.02	0.83

7.7 Comparison of All Models Against the Naïve Model for Arrivals from Germany to the 31 Chinese Provinces

Table 7.7.1 Paired comparison of all models against the naïve model for arrivals from Germany to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.04	0.14	0.04	0.23	0.05	0.06	0.84	0.85
Tianjin p-value	0.82	0.82	0.81	0.92	0.12	0.67	0.05	0.04
Hebei p-value	0.18	0.03	0.03	0.13	0.02	0.14	0.09	0.54
Shanxi p-value	0.68	0.65	0.72	0.99	0.71	0.92	0.32	0.19
Inner Mongolia p-value	0.33	0.27	0.27	0.07	0.34	0.32	0.02	0.02
Liaoning p-value	0.13	0.24	0.58	0.28	0.07	0.15	0.10	0.35
Jilin p-value	0.07	0.23	0.23	0.12	0.10	0.65	0.20	1.00
Helongjiang p-value	0.16	0.16	0.06	0.57	0.15	0.18	0.38	0.40
Shanghai p-value	0.23	0.22	0.25	0.01	0.27	0.31	0.05	0.10
Jiangsu p-value	0.04	0.28	0.57	0.35	0.98	0.76	0.41	0.28
Zhejiang p-value	0.09	0.01	0.37	0.09	0.21	0.20	0.16	0.93
Anhui p-value	0.29	0.38	0.57	0.29	0.08	0.03	0.20	0.48
Fujian p-value	0.17	0.11	0.56	0.09	0.18	0.76	0.34	0.70
Jiangxi p-value	0.13	0.04	0.07	0.18	0.09	0.19	0.31	0.12
Shandon p-value	0.16	0.16	0.54	0.39	0.09	0.61	0.34	0.34
Henan p-value	0.94	0.88	0.83	0.41	0.56	0.77	0.14	0.05
Hubei p-value	0.37	0.08	0.14	0.34	0.00	0.10	0.48	0.48
Hunan p-value	0.14	0.02	0.10	0.29	0.13	0.34	0.50	0.34
Guangdong p-value	0.45	0.24	0.30	0.32	0.42	0.87	0.53	0.70
Guangxi p-value	0.13	0.06	0.07	0.02	0.10	0.69	0.88	0.34
Hainan p-value	0.12	0.01	0.04	0.14	0.94	0.09	0.04	0.76
Chongqing p-value	0.44	0.12	0.16	0.28	0.15	0.17	0.98	0.62
Sichuan p-value	0.63	0.13	0.33	0.94	0.68	0.40	0.51	0.70
Guizhou p-value	0.04	0.19	0.09	0.47	0.02	0.17	0.31	0.87
Yunnan p-value	0.11	0.17	0.09	0.00	0.28	0.56	0.37	0.52
Tibet p-value	0.28	0.25	0.29	0.54	0.94	0.62	0.51	0.49
Shaanxi p-value	0.52	0.03	0.19	0.12	0.15	0.09	0.57	0.09
Gansu p-value	0.34	0.36	0.24	0.86	0.37	0.59	0.70	0.84
Qinghai p-value	0.42	0.45	0.44	0.84	0.42	0.53	0.85	0.84
Ningxia p-value	0.63	0.66	0.49	0.29	0.52	0.48	0.23	0.45
Xinjiang p-value	0.66	0.44	0.39	0.10	0.98	0.25	0.07	0.07

7.8 Comparison of All Models Against the Naïve Model for Arrivals from Japan to the 31 Chinese Provinces

Table 7.8.1 Paired comparison of all models against the naïve model for arrivals from Japan to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.52	0.41	0.46	0.12	0.55	0.35	0.98	0.98
Tianjin p-value	0.23	0.23	0.27	0.40	0.07	0.08	0.16	0.95
Hebei p-value	0.69	0.17	0.28	0.05	0.38	0.13	0.02	0.02
Shanxi p-value	0.75	0.83	0.79	0.66	0.60	0.46	0.24	0.09
Inner Mongolia p-value	0.99	0.73	0.73	0.34	0.71	0.22	0.13	0.13
Liaoning p-value	0.00	0.15	0.06	0.31	0.08	0.61	0.56	0.50
Jilin p-value	0.06	0.02	0.57	0.18	0.16	0.07	0.27	0.19
Helongjiang p-value	0.04	0.28	0.43	0.07	0.05	0.06	0.12	0.50
Shanghai p-value	0.13	0.04	0.03	0.08	0.16	0.12	0.44	0.44
Jiangsu p-value	0.43	0.21	0.20	0.30	0.70	0.72	0.53	0.33
Zhejiang p-value	0.13	0.12	0.09	0.30	0.09	0.58	0.01	0.08
Anhui p-value	0.73	0.69	0.92	0.24	0.02	0.42	0.22	0.31
Fujian p-value	0.11	0.01	0.06	0.37	0.15	0.13	0.06	0.50
Jiangxi p-value	0.06	0.14	0.10	0.03	0.04	0.71	0.16	0.03
Shandon p-value	0.41	0.18	0.76	0.61	0.19	0.02	0.35	0.07
Henan p-value	0.53	0.38	0.42	0.75	0.03	0.69	0.55	0.20
Hubei p-value	0.51	0.81	0.40	0.45	0.02	0.60	0.58	0.82
Hunan p-value	0.30	0.16	0.28	0.13	0.02	0.00	0.02	0.04
Guangdong p-value	0.10	0.02	0.59	0.22	0.03	0.07	0.44	0.18
Guangxi p-value	0.49	0.58	0.86	0.47	0.61	0.62	0.71	0.47
Hainan p-value	0.41	0.23	0.44	0.83	0.91	0.76	0.82	0.51
Chongqing p-value	0.40	0.71	0.87	0.77	0.55	0.53	0.79	0.75
Sichuan p-value	0.64	0.25	0.31	0.83	0.81	0.67	0.41	0.43
Guizhou p-value	0.19	0.06	0.20	0.39	0.17	0.38	0.05	0.12
Yunnan p-value	0.49	0.48	0.44	0.07	0.34	0.32	0.23	0.31
Tibet p-value	0.82	0.93	0.97	0.08	0.84	0.40	0.44	0.41
Shaanxi p-value	0.27	0.43	0.58	0.04	0.01	0.08	0.50	0.17
Gansu p-value	0.14	0.26	0.13	0.86	0.03	0.29	0.94	0.51
Qinghai p-value	0.51	0.60	0.50	0.74	0.47	0.47	0.20	0.20
Ningxia p-value	0.02	0.19	0.09	0.51	0.23	0.19	0.33	0.61
Xinjiang p-value	0.97	0.30	0.65	0.01	0.75	0.24	0.61	0.33

7.9 Comparison of All Models Against the Naïve Model for Arrivals from Korea to the 31 Chinese Provinces

Table 7.9.1 Paired comparison of all models against the naïve model for arrivals from Korea to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.62	0.33	0.04	0.39	0.07	0.07	0.11	0.06
Tianjin p-value	0.28	0.28	0.36	0.10	0.05	0.05	0.49	0.49
Hebei p-value	0.40	0.28	0.39	0.09	0.83	0.26	0.91	0.61
Shanxi p-value	0.62	0.87	0.76	0.40	0.41	0.43	0.17	0.14
Inner Mongolia p-value	0.32	0.39	0.39	0.31	0.56	0.81	0.80	0.80
Liaoning p-value	0.20	0.00	0.30	0.37	0.58	0.26	0.57	0.20
Jilin p-value	0.15	0.05	0.30	0.61	0.12	0.15	0.11	0.15
Helongjiang p-value	0.02	0.52	0.23	0.18	0.06	0.12	0.28	0.25
Shanghai p-value	0.38	0.25	0.11	0.08	0.30	0.29	0.72	0.06
Jiangsu p-value	0.16	0.01	0.68	0.15	0.18	0.18	0.87	0.49
Zhejiang p-value	0.15	0.08	0.53	0.12	0.22	0.20	0.69	0.44
Anhui p-value	0.16	0.08	0.12	0.09	0.07	0.04	0.84	0.40
Fujian p-value	0.27	0.42	0.40	0.56	0.28	0.29	0.90	0.33
Jiangxi p-value	0.21	0.13	0.45	0.23	0.29	0.34	0.76	0.01
Shandon p-value	0.12	0.00	0.47	0.28	0.04	0.10	0.61	0.50
Henan p-value	0.41	0.16	0.52	0.34	0.32	0.78	0.39	0.65
Hubei p-value	0.17	0.32	0.48	0.10	0.23	0.25	0.68	0.47
Hunan p-value	0.19	0.17	0.54	0.03	0.87	0.27	0.60	0.49
Guangdong p-value	0.29	0.09	0.54	0.10	0.21	0.18	0.50	0.53
Guangxi p-value	0.29	0.04	0.52	0.56	0.24	0.27	0.31	0.53
Hainan p-value	0.55	0.37	0.43	0.62	0.07	0.02	0.33	0.50
Chongqing p-value	0.07	0.30	0.47	0.29	0.14	0.14	0.46	0.06
Sichuan p-value	0.14	0.04	0.34	0.11	0.18	0.19	0.89	0.68
Guizhou p-value	0.14	0.08	0.51	0.10	0.39	0.25	0.64	0.14
Yunnan p-value	0.09	0.04	0.39	0.21	0.19	0.19	0.77	0.89
Tibet p-value	0.73	0.63	0.53	0.09	0.61	0.56	0.12	0.06
Shaanxi p-value	0.31	0.35	0.15	0.30	0.48	0.26	0.46	0.50
Gansu p-value	0.37	0.13	0.72	0.46	0.42	0.70	0.50	0.50
Qinghai p-value	0.36	0.39	0.49	0.50	0.24	0.24	0.54	0.54
Ningxia p-value	0.35	0.21	0.52	0.48	0.20	0.14	0.65	0.67
Xinjiang p-value	0.52	0.36	0.31	0.98	0.22	0.35	0.79	0.21

7.10 Comparison of All Models Against the Naïve Model for Arrivals from Malaysia to the 31 Chinese Provinces

Table 7.10.1 Paired comparison of all models against the naïve model for arrivals from Malaysia to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.96	0.86	0.99	0.73	0.69	0.94	0.30	0.30
Tianjin p-value	0.19	0.19	0.17	0.73	0.07	0.21	0.14	0.29
Hebei p-value	0.28	0.17	0.08	0.55	0.00	0.44	0.13	0.15
Shanxi p-value	0.49	0.58	0.65	0.44	0.85	0.65	0.13	0.36
Inner Mongolia p-value	0.78	0.22	0.22	0.81	0.72	0.66	0.59	0.59
Liaoning p-value	0.63	0.27	0.37	0.80	0.14	0.11	0.89	0.57
Jilin p-value	0.04	0.22	0.45	0.27	0.12	0.17	0.25	0.88
Helongjiang p-value	0.78	0.49	0.40	0.53	0.93	0.51	0.12	0.06
Shanghai p-value	0.36	0.67	0.49	0.81	0.30	0.30	0.97	0.69
Jiangsu p-value	0.38	0.29	0.84	0.17	0.23	0.25	0.29	0.54
Zhejiang p-value	0.38	0.30	0.47	0.12	0.46	0.45	0.17	0.10
Anhui p-value	0.02	0.47	0.53	0.17	0.03	0.20	0.77	0.50
Fujian p-value	0.00	0.07	0.01	0.13	0.16	0.11	0.31	0.38
Jiangxi p-value	0.91	0.09	0.36	0.24	0.37	0.05	0.31	0.39
Shandon p-value	0.39	0.45	0.82	0.75	0.09	0.01	0.71	0.47
Henan p-value	0.09	0.05	0.04	0.42	0.01	0.11	0.63	0.54
Hubei p-value	0.68	0.33	0.31	0.86	0.99	0.85	0.03	0.02
Hunan p-value	0.05	0.12	0.01	0.37	0.05	0.05	0.94	0.41
Guangdong p-value	0.10	0.04	0.10	0.34	0.08	0.13	0.20	0.86
Guangxi p-value	0.24	0.30	0.36	0.06	0.29	0.27	0.02	0.08
Hainan p-value	0.45	0.59	0.42	0.21	0.34	0.39	0.20	0.17
Chongqing p-value	0.51	0.34	0.22	0.48	0.68	0.69	0.35	0.35
Sichuan p-value	0.30	0.49	0.88	0.20	0.32	0.48	0.10	0.04
Guizhou p-value	0.22	0.04	0.34	0.31	0.12	0.34	0.30	0.30
Yunnan p-value	0.32	0.35	0.14	0.96	0.82	0.79	0.58	0.93
Tibet p-value	0.49	0.51	0.35	0.72	0.45	0.62	0.14	0.05
Shaanxi p-value	0.23	0.53	0.11	0.30	0.28	0.34	0.11	0.38
Gansu p-value	0.57	0.44	0.93	0.95	0.29	0.70	0.32	0.34
Qinghai p-value	0.23	0.35	0.01	0.96	0.38	0.00	0.35	0.06
Ningxia p-value	0.17	0.16	0.02	0.06	0.19	0.63	0.05	0.13
Xinjiang p-value	0.17	0.28	0.06	0.04	0.15	0.34	0.13	0.17

7.11 Comparison of All Models Against the Naïve Model for Arrivals from Philippines to the 31 Chinese Provinces

Table 7.11.1 Paired comparison of all models against the naïve model for arrivals from Philippines to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.32	0.15	0.19	0.56	0.24	0.17	0.56	0.53
Tianjin p-value	0.24	0.24	0.62	0.16	0.00	0.05	0.42	0.42
Hebei p-value	0.31	0.15	0.13	0.16	0.18	0.92	0.18	0.39
Shanxi p-value	0.58	0.59	0.64	0.58	0.51	0.70	0.21	0.67
Inner Mongolia p-value	0.51	0.21	0.21	0.37	0.21	0.52	0.68	0.68
Liaoning p-value	0.53	0.21	0.35	0.99	0.93	0.22	0.50	0.52
Jilin p-value	0.26	0.27	0.54	0.00	0.32	0.76	0.36	0.29
Helongjiang p-value	0.68	0.83	0.60	0.53	0.62	0.56	0.29	0.10
Shanghai p-value	0.05	0.11	0.42	0.38	0.05	0.11	0.87	0.28
Jiangsu p-value	0.26	0.43	0.19	0.20	0.42	0.66	0.35	0.54
Zhejiang p-value	0.39	0.15	0.08	0.05	0.34	0.01	0.55	0.55
Anhui p-value	0.26	0.20	0.00	0.07	0.24	0.10	0.32	0.14
Fujian p-value	0.13	0.22	0.13	0.99	0.21	0.14	0.36	0.41
Jiangxi p-value	0.09	0.05	0.05	0.12	0.06	0.32	1.00	0.69
Shandon p-value	0.18	0.32	0.34	0.65	0.29	0.78	0.50	0.52
Henan p-value	0.29	0.12	0.40	0.94	0.03	0.01	0.21	0.50
Hubei p-value	0.48	0.43	0.35	0.92	0.59	0.57	0.11	0.61
Hunan p-value	0.65	0.33	0.28	0.34	0.39	0.08	0.06	0.13
Guangdong p-value	0.14	0.05	0.10	0.60	0.13	0.08	0.86	0.54
Guangxi p-value	0.27	0.07	0.22	0.95	0.25	0.22	0.33	0.81
Hainan p-value	0.37	0.31	0.35	0.42	0.38	0.49	0.52	0.36
Chongqing p-value	0.54	0.22	0.03	0.02	0.38	0.44	0.62	0.53
Sichuan p-value	0.46	0.45	0.74	0.33	0.42	0.42	0.89	0.63
Guizhou p-value	0.37	0.44	0.17	0.39	0.83	0.09	0.18	0.65
Yunnan p-value	0.50	0.48	0.45	0.41	0.58	0.64	0.49	0.24
Tibet p-value	0.87	0.98	0.30	0.74	0.84	0.31	0.72	0.50
Shaanxi p-value	0.13	0.09	0.07	0.27	0.01	0.42	0.52	0.52
Gansu p-value	0.68	0.43	0.09	1.00	0.23	0.28	0.94	0.78
Qinghai p-value	0.98	0.51	0.08	0.04	0.63	0.39	0.50	0.68
Ningxia p-value	0.36	0.60	0.75	0.64	0.45	0.72	0.12	0.14
Xinjiang p-value	0.42	0.50	0.29	0.49	0.48	0.88	0.33	0.33

7.12 Comparison of All Models Against the Naïve Model for Arrivals from Russia to the 31 Chinese Provinces

Table 7.12.1 Paired comparison of all models against the naïve model for arrivals from Russia to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.50	0.13	0.34	0.41	0.30	0.30	0.09	0.06
Tianjin p-value	0.27	0.27	0.36	0.37	0.12	0.71	0.15	0.25
Hebei p-value	0.14	0.05	0.06	0.12	0.22	0.33	0.05	0.05
Shanxi p-value	0.64	0.40	0.22	0.62	0.50	0.61	0.01	0.24
Inner Mongolia p-value	0.14	0.05	0.05	0.10	0.36	0.24	0.43	0.43
Liaoning p-value	0.17	0.23	0.19	0.24	0.16	0.63	0.13	0.13
Jilin p-value	0.13	0.05	0.09	0.53	0.01	0.28	0.15	0.74
Helongjiang p-value	0.22	0.04	0.08	0.73	0.16	0.30	0.14	0.14
Shanghai p-value	0.11	0.04	0.11	0.15	0.00	0.04	0.50	0.04
Jiangsu p-value	0.31	0.19	0.13	0.41	0.22	0.39	0.12	0.21
Zhejiang p-value	0.17	0.01	0.11	0.25	0.19	0.07	0.11	0.11
Anhui p-value	0.40	0.23	0.30	0.55	0.43	0.20	0.51	0.38
Fujian p-value	0.19	0.01	0.26	0.72	0.39	0.44	0.61	0.61
Jiangxi p-value	0.14	0.02	0.11	0.69	0.13	0.08	0.24	0.26
Shandon p-value	0.21	0.04	0.03	0.30	0.20	0.80	0.17	0.23
Henan p-value	0.48	0.12	0.13	0.39	0.05	0.09	0.51	0.77
Hubei p-value	0.38	0.28	0.27	0.69	0.39	0.91	0.13	0.10
Hunan p-value	0.50	0.41	0.36	0.77	0.50	0.50	0.86	0.75
Guangdong p-value	0.16	0.22	0.02	0.65	0.16	0.03	0.67	0.50
Guangxi p-value	0.16	0.04	0.32	0.42	0.10	0.12	0.58	0.52
Hainan p-value	0.34	0.26	0.28	0.39	0.34	0.14	0.27	0.50
Chongqing p-value	0.34	0.24	0.38	0.16	0.93	0.27	0.35	0.59
Sichuan p-value	0.27	0.15	0.26	0.51	0.73	0.55	0.65	0.64
Guizhou p-value	0.24	0.18	0.09	0.02	0.37	0.50	0.04	0.15
Yunnan p-value	0.07	0.11	0.05	0.60	0.18	0.18	0.07	0.47
Tibet p-value	0.43	0.35	0.35	0.82	0.44	0.53	0.27	0.96
Shaanxi p-value	0.15	0.02	0.44	0.95	0.12	0.77	0.54	0.58
Gansu p-value	0.22	0.40	0.13	0.25	0.19	0.46	0.37	0.36
Qinghai p-value	0.29	0.18	0.18	0.65	0.29	0.36	0.88	0.75
Ningxia p-value	0.03	0.23	0.53	0.53	0.12	0.12	0.77	0.60
Xinjiang p-value	0.48	0.37	0.27	0.13	0.38	0.61	0.48	0.39

7.13 Comparison of All Models Against the Naïve Model for Arrivals from Singapore to the 31 Chinese Provinces

Table 7.13.1 Paired comparison of all models against the naïve model for arrivals from Singapore to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.46	0.15	0.49	0.12	0.01	0.06	0.12	0.12
Tianjin p-value	0.19	0.19	0.03	0.53	0.09	0.00	0.54	0.29
Hebei p-value	0.11	0.06	0.06	0.90	0.09	0.59	0.11	0.56
Shanxi p-value	0.49	0.68	0.10	0.36	0.92	0.97	0.55	0.14
Inner Mongolia p-value	0.80	0.60	0.60	0.74	0.52	0.53	0.47	0.47
Liaoning p-value	0.02	0.09	0.04	0.86	0.10	0.06	0.51	0.50
Jilin p-value	0.34	0.25	0.02	0.39	0.07	0.16	0.74	0.36
Helongjiang p-value	0.12	0.32	0.17	0.05	0.25	0.11	0.54	0.56
Shanghai p-value	0.21	0.21	0.00	0.06	0.24	0.18	0.48	0.33
Jiangsu p-value	0.14	0.14	0.53	0.56	0.10	0.47	0.82	0.83
Zhejiang p-value	0.43	0.17	0.08	0.20	0.35	0.22	0.49	0.15
Anhui p-value	0.11	0.41	0.04	0.33	0.17	0.09	0.01	0.54
Fujian p-value	0.14	0.07	0.05	0.04	0.37	0.75	0.55	0.53
Jiangxi p-value	0.24	0.02	0.03	0.17	0.10	0.04	0.16	0.36
Shandon p-value	0.69	0.50	0.13	0.97	0.49	0.46	0.00	0.95
Henan p-value	1.00	0.41	0.01	0.88	0.33	0.32	0.72	0.31
Hubei p-value	0.50	0.56	0.96	0.48	0.60	0.60	0.24	0.64
Hunan p-value	0.03	0.16	0.03	0.40	0.04	0.13	0.71	0.50
Guangdong p-value	0.06	0.06	0.04	0.38	0.06	0.14	0.77	0.57
Guangxi p-value	0.10	0.09	0.02	0.23	0.17	0.19	0.91	0.89
Hainan p-value	0.23	0.08	0.25	0.92	0.21	0.52	0.88	0.25
Chongqing p-value	0.59	0.17	0.81	0.93	0.68	0.60	0.27	0.34
Sichuan p-value	0.12	0.05	0.05	0.09	0.15	0.24	0.39	0.48
Guizhou p-value	0.29	0.56	0.13	0.02	0.24	0.40	0.07	0.01
Yunnan p-value	0.20	0.08	0.02	0.41	0.12	0.25	0.27	0.06
Tibet p-value	0.54	0.55	0.02	0.86	0.53	0.52	0.32	0.27
Shaanxi p-value	0.09	0.10	0.03	0.29	0.02	0.17	0.50	0.37
Gansu p-value	0.60	0.27	0.15	0.03	0.89	0.20	0.29	0.51
Qinghai p-value	0.50	0.76	0.00	0.44	0.95	0.21	0.34	0.51
Ningxia p-value	0.06	0.20	0.11	0.15	0.11	0.69	0.48	0.51
Xinjiang p-value	0.57	0.91	0.24	0.90	0.33	0.65	0.92	0.61

7.14 Comparison of All Models Against the Naïve Model for Arrivals from Thailand to the 31 Chinese Provinces

Table 7.14.1 Paired comparison of all models against the naïve model for arrivals from Thailand to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.05	0.21	0.11	0.07	0.04	0.71	0.27	0.38
Tianjin p-value	0.33	0.33	0.24	0.04	0.23	0.45	0.11	0.11
Hebei p-value	0.24	0.06	0.10	0.63	0.16	0.30	0.64	0.51
Shanxi p-value	0.52	0.12	0.12	0.12	0.12	0.12	0.15	0.12
Inner Mongolia p-value	0.72	0.67	0.67	0.27	0.38	0.57	0.52	0.52
Liaoning p-value	0.78	0.16	0.26	0.69	0.66	0.42	1.00	0.69
Jilin p-value	0.22	0.23	0.34	0.02	0.26	0.24	0.48	0.09
Helongjiang p-value	0.48	0.69	0.89	0.24	0.65	0.66	0.52	0.50
Shanghai p-value	0.32	0.28	0.13	0.05	0.30	0.31	0.15	0.27
Jiangsu p-value	0.26	0.17	0.08	0.04	0.22	0.22	0.14	0.41
Zhejiang p-value	0.12	0.04	0.26	0.11	0.20	0.19	0.53	0.50
Anhui p-value	0.17	0.03	0.07	0.58	0.17	0.28	0.47	0.64
Fujian p-value	0.17	0.10	0.04	0.05	0.04	0.25	0.20	0.22
Jiangxi p-value	0.46	0.46	0.28	0.13	0.45	0.49	0.08	0.05
Shandon p-value	0.41	0.58	0.03	0.07	0.54	0.18	0.28	0.52
Henan p-value	0.60	0.40	0.05	0.50	0.61	0.68	0.50	0.50
Hubei p-value	0.38	0.18	0.15	0.81	0.49	0.39	0.75	0.53
Hunan p-value	0.49	0.61	0.33	0.72	0.99	0.62	0.31	0.41
Guangdong p-value	0.19	0.07	0.06	0.14	0.25	0.52	0.75	0.18
Guangxi p-value	0.21	0.12	0.03	0.08	0.30	0.01	0.87	0.73
Hainan p-value	0.64	0.24	0.01	0.07	0.42	0.70	0.10	0.57
Chongqing p-value	0.35	0.12	0.13	0.28	0.33	0.29	0.74	0.48
Sichuan p-value	0.75	0.21	0.11	0.85	0.25	0.28	0.76	0.85
Guizhou p-value	0.12	0.59	0.12	0.38	0.35	0.18	0.53	0.53
Yunnan p-value	0.08	0.35	0.04	0.70	0.10	0.52	0.70	0.69
Tibet p-value	0.51	0.49	0.22	0.54	0.45	0.04	0.20	0.30
Shaanxi p-value	0.18	0.03	0.02	0.49	0.34	0.02	0.50	0.03
Gansu p-value	0.67	0.52	0.32	0.79	0.73	0.40	0.61	0.93
Qinghai p-value	0.82	0.79	0.48	0.82	0.79	0.69	0.91	0.74
Ningxia p-value	0.34	0.60	1.00	0.40	0.77	0.67	0.41	0.41
Xinjiang p-value	0.80	0.68	0.85	0.31	0.15	0.98	0.18	0.20

7.15 Comparison of All Models Against the Naïve Model for Arrivals from UK to the 31 Chinese Provinces

Table 7.15.1 Paired comparison of all models against the naïve model for arrivals from UK to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.10	0.09	0.24	0.13	0.52	0.02	0.56	0.88
Tianjin p-value	0.19	0.19	0.71	0.02	0.20	0.09	0.17	0.03
Hebei p-value	0.05	0.22	0.08	0.04	0.03	0.21	0.53	0.10
Shanxi p-value	0.74	0.69	0.67	0.93	0.71	0.86	0.29	0.13
Inner Mongolia p-value	0.77	0.58	0.58	0.12	0.15	0.20	0.59	0.59
Liaoning p-value	0.76	0.30	0.49	0.90	0.86	0.50	0.16	0.20
Jilin p-value	0.01	0.03	0.76	0.18	0.01	0.59	0.86	0.75
Helongjiang p-value	0.12	0.18	0.05	0.60	0.15	0.14	0.09	0.50
Shanghai p-value	0.15	0.08	0.02	0.07	0.12	0.23	0.03	0.42
Jiangsu p-value	0.25	0.27	0.47	0.28	0.48	0.64	0.14	0.13
Zhejiang p-value	0.15	0.09	0.36	0.33	0.09	0.01	0.08	0.13
Anhui p-value	0.45	0.18	0.49	0.39	0.96	0.07	0.33	0.25
Fujian p-value	0.84	0.15	0.44	0.24	0.26	0.16	0.19	0.11
Jiangxi p-value	0.25	0.39	0.29	0.14	0.30	0.29	0.85	0.78
Shandon p-value	0.82	0.27	0.51	0.55	0.92	0.80	0.04	0.16
Henan p-value	0.08	0.10	0.33	0.11	0.25	0.23	0.65	0.76
Hubei p-value	0.37	0.09	0.12	0.47	0.09	0.11	0.60	0.44
Hunan p-value	0.09	0.27	0.07	0.66	0.07	0.34	0.65	0.26
Guangdong p-value	0.01	0.14	0.62	0.21	0.10	0.08	0.24	0.05
Guangxi p-value	0.27	0.17	0.15	0.72	0.26	0.17	0.14	0.05
Hainan p-value	0.01	0.02	0.24	0.29	0.18	0.16	0.45	0.54
Chongqing p-value	0.14	0.45	0.45	0.36	0.16	0.16	0.42	0.40
Sichuan p-value	0.71	0.21	0.38	0.38	0.57	0.01	0.17	0.93
Guizhou p-value	0.08	0.19	0.09	0.06	0.02	0.22	0.54	0.51
Yunnan p-value	0.50	0.15	0.31	0.09	0.55	0.00	0.18	0.12
Tibet p-value	0.81	0.76	0.23	0.11	0.61	0.34	0.37	0.20
Shaanxi p-value	0.06	0.12	0.06	0.08	0.05	0.02	0.58	0.50
Gansu p-value	0.38	0.44	0.96	0.78	0.65	0.29	0.82	0.51
Qinghai p-value	0.83	0.34	0.36	0.05	0.93	0.13	0.50	0.90
Ningxia p-value	0.40	0.36	0.15	0.88	0.48	0.35	0.54	0.94
Xinjiang p-value	0.33	0.36	0.26	0.93	0.12	0.28	0.73	0.13

7.16 Comparison of All Models Against the Naïve Model for Arrivals from US to the 31 Chinese Provinces

Table 7.16.1 Paired comparison of all models against the naïve model for arrivals from USA to the 31 Chinese provinces

Province	Holt	ExpSm	ARMA	Neural	BSM	BSMI	TVP	TVPD
Beijing p-value	0.03	0.11	0.11	0.94	0.01	0.16	0.64	0.29
Tianjin p-value	0.90	0.90	0.84	0.79	0.73	0.52	0.57	0.59
Hebei p-value	0.13	0.02	0.09	0.23	0.14	0.24	0.13	0.11
Shanxi p-value	0.58	0.57	0.60	0.82	0.58	0.68	0.74	0.26
Inner Mongolia p-value	0.40	0.49	0.49	0.43	0.99	0.61	0.66	0.66
Liaoning p-value	0.75	0.14	0.45	0.06	0.05	0.05	0.20	0.20
Jilin p-value	0.01	0.29	0.52	0.76	0.07	0.00	0.07	0.98
Helongjiang p-value	0.23	0.37	0.22	0.06	0.04	0.26	0.51	0.61
Shanghai p-value	0.16	0.09	0.43	0.08	0.22	0.18	0.50	0.37
Jiangsu p-value	0.07	0.22	0.49	0.38	0.41	0.24	0.32	0.14
Zhejiang p-value	0.03	0.02	0.36	0.17	0.16	0.07	0.19	0.70
Anhui p-value	0.82	0.21	0.55	0.89	0.26	0.48	0.04	0.23
Fujian p-value	0.71	0.17	0.04	0.06	0.78	0.28	0.45	0.58
Jiangxi p-value	0.14	0.02	0.17	0.20	0.14	0.30	0.19	0.69
Shandon p-value	0.44	0.50	0.56	0.26	0.48	0.50	0.92	0.92
Henan p-value	0.32	0.18	0.42	0.53	0.46	0.09	0.26	0.34
Hubei p-value	0.20	0.07	0.05	0.37	0.21	0.02	0.65	0.64
Hunan p-value	0.04	0.13	0.07	0.96	0.03	0.00	0.30	0.52
Guangdong p-value	0.54	0.15	0.39	0.35	0.93	0.45	0.37	0.79
Guangxi p-value	0.09	0.05	0.09	0.33	0.10	0.04	0.53	0.09
Hainan p-value	0.21	0.01	0.26	0.14	0.17	0.16	0.70	0.52
Chongqing p-value	0.15	0.24	0.05	0.12	0.33	0.52	0.57	0.40
Sichuan p-value	0.20	0.00	0.10	0.30	0.19	0.11	0.74	0.34
Guizhou p-value	0.22	0.01	0.08	0.40	0.14	0.05	0.31	0.16
Yunnan p-value	0.18	0.03	0.23	0.36	0.22	0.54	0.03	0.34
Tibet p-value	0.66	0.13	0.67	0.45	0.26	0.23	0.47	0.59
Shaanxi p-value	0.01	0.16	0.06	0.27	0.02	0.25	0.51	0.13
Gansu p-value	0.29	0.00	0.36	0.28	0.10	0.15	0.51	0.60
Qinghai p-value	0.65	0.49	0.56	0.70	0.67	0.57	0.98	0.51
Ningxia p-value	0.49	0.48	0.32	0.28	0.30	0.28	0.28	0.24
Xinjiang p-value	0.41	0.39	0.40	0.73	0.11	0.51	0.16	0.31

The outputs have been kept small by just showing the p-value. The tables are important in the context of determining whether the naïve process is statistically inferior to the quantitative models, and to determine the extent of this comparison in terms of the source markets and the provinces.

Overall the p-values are large and generally above .05 at 95% significance, and this again confirms that there is no statistically superior single model or country that has models that outperform the naïve process. Statistically, the main reason for this is that the standard deviations are too high. Even in cases where it appears that the MAPE value for a particular model for a particular source market to a particular province is far lower than the naïve result, the standard deviation of the error term is large, and often yields an acceptance of the null hypothesis; that is the particular quantitative model does not have a lower value of MAPE than in the naïve case. The reason for the generally large standard deviation is that the arrivals series are volatile and contain interventions, mainly SARS and Sept. 11.

7.17 Conclusion Summary on Causal Modelling

Apart from the BSMI model with intervention variables, that are dummy measures used to account for special events (namely Sept 11 and SARS), the only analyses to use causal variables are the TVP and TVPD (with dummy variables) models. One of the important issues raised in the thesis regarding the overall accuracy between methods, is whether significant causal variables can be found, and whether they differ from the causal variables currently used in national arrivals forecasting research.

The causal variables applied in this study are: PCI (Per Capita Income of Tourist Generating Country), GRP (Gross Regional Product), RFDI (Regional Foreign Direct Investment), GCF (Gross Capital Formation), UR (Urban and Rural Ratio), Sun (Regional Average Monthly Sunshine), Own (Own Price), Road (Regional Road Network), and two dummy variables are: 9.11 (Dummy variable 1) and SARS (Dummy variable 2).

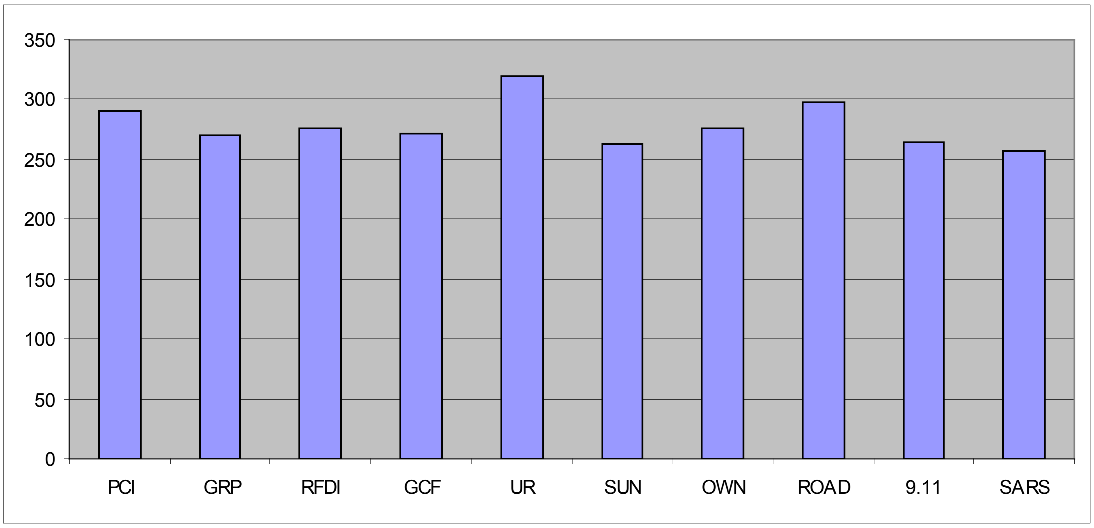
As shown in Table 7.17.1, the variable of UR (Urban and Rural Ration) has been identified as the most widely significant causal variable for the TVP forecasting to the 31 Chinese provinces, followed by Road (Regional Road Networks). Both variables are new and show significant contribution to the regional (provincial) forecast.

Table 7.17.1 Identifying significant variables for forecasting regional arrivals using TVP analysis with intervention

Country	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS
Australia	18	19	19	20	22	18	21	19	21	20
Canada	23	24	25	26	25	24	24	29	22	22
France	24	25	23	24	27	24	25	26	22	22
Germany	17	18	15	17	23	15	16	18	19	18
Japan	19	13	15	14	21	12	12	18	18	20
Korea	28	22	24	26	26	22	24	25	20	20
Malaysia	15	12	12	9	17	12	10	12	21	13
Philippines	25	25	24	25	28	22	27	27	22	22
Russia	24	25	25	21	28	24	24	23	21	21
Singapore	21	16	19	20	24	18	19	21	14	14
Thailand	28	26	25	25	30	26	28	27	25	25
UK	25	23	26	24	25	24	25	27	21	21
USA	23	22	24	21	24	22	21	25	19	19
Total	**290**	**270**	**276**	**272**	**320**	**263**	**276**	**297**	**265**	**257**

Figure 7.17.1 shows that UR (Urban and Rural Ration) is the most useful independent variable appearing in 320 regional (provincial) forecasting analyses in the TVP modelling with intervention, followed by the Road (Regional Road Networks) variable appearing in 297 forecast analyses, and variables such as GRP (Gross Regional Product), RFDI (Regional Foreign Direct Investment) and GCF (Gross Capital Formation) appearing in 270 forecasting analyses. However, it is interesting to note that all the independent variables are useful in the causal modelling overall.

Figure 7.17.1 Rank of most useful causal variables in provincial (regional) forecasting



More specific examination is required to determine whether some provinces have a wide range of significant causal measures and some do not.

7.18 Causal Modelling for Australian Tourists to the 31 Chinese Provinces

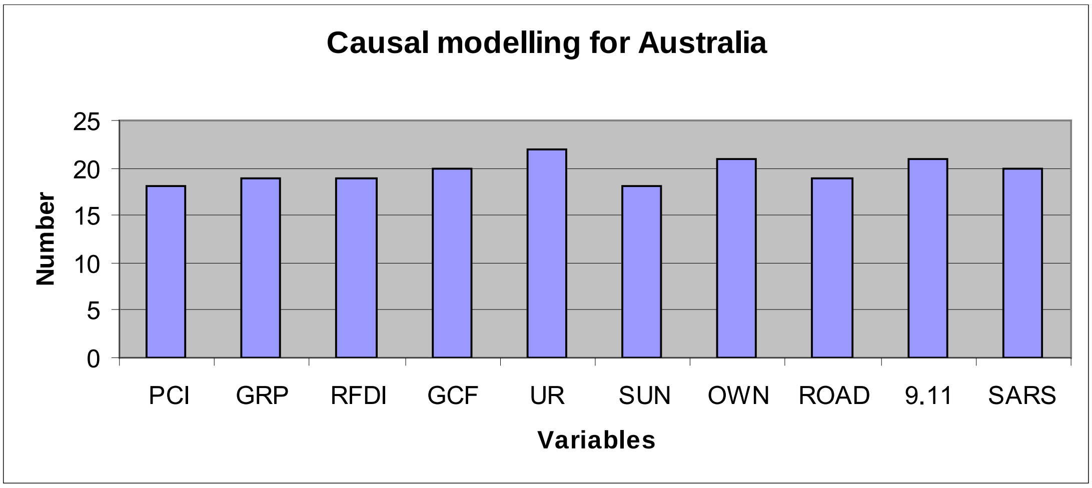
Table 7.18.1 shows that the top 3 independent variables in forecasting Australian tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.18.1 Causal modelling for arrivals from Australia to the 31 Chinese provinces

Variable / Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing	X	X	X	X	X	X	X	X	X	X	10
Tianjin	X	X		X	X	X		X	X	X	8
Hebei	X				X				X	X	4
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X	X	X	X	X	X	X	X	X		9
Liaoning				X	X						2
Jilin							X	X	X	X	4
Helongjiang		X		X							2
Shanghai			X								1
Jiangsu	X	X	X	X	X	X	X	X	X	X	10
Zhejiang			X				X	X			3
Anhui						X	X				2
Fujian			X							X	2
Jiangxi					X						1
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan							X				1
Hubei		X							X		2
Hunan	X	X	X	X	X	X	X	X	X	X	10
Guangdong	X	X	X	X	X	X	X	X	X		9
Guangxi	X	X	X	X	X	X	X	X	X	X	10
Hainan				X							1
Chongqing	X	X	X	X	X	X	X	X	X	X	10
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou					X		X		X	X	4
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10

Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai					X					X	2
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	18	19	19	20	22	18	21	19	21	20	

Figure 7.18.1 Rank of independent causal variables for forecasting analysis for arrivals from Australia to the 31 Chinese provinces



In regard to the determinant variables Beijing, Shanxi, Jiangsu, Shandong, Hunan, Guangxi, Chongqing, Sichuan, Yunnan, Tibet, Qinghai, Ningxia and Xinjiang have all variables as significant, whereas Zhejiang has three and Shanghai just one. Generally, the provinces in the Northeast and East with the exceptions of the provinces of Jiangsu and Shandong have the lower number of determinant variables. Overall the number of significant independent variables is very high with 65% (197) of the 310 possible relationships being significant.

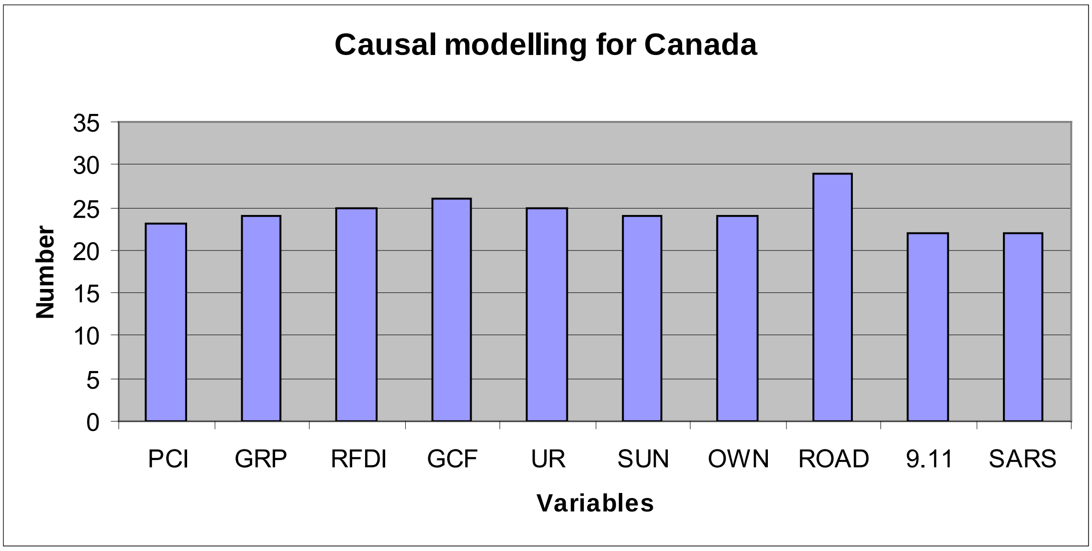
7.19 Causal Modelling for Canadian Tourists to the 31 Chinese Provinces

Table 7.19.1 shows that the top 3 independent variables in forecasting Canada tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.19.1 shows graphically the most useful independent variables in these analyses, and again there are a huge number of 244 significant relationships or 79%.

Table 7.19.1 Causal modelling for arrivals from Canada to the 31 Chinese provinces

Variable / Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing				X				X			2
Tianjin	X	X	X	X	X	X	X	X	X	X	10
Hebei	X	X	X	X	X	X	X	X	X	X	10
Shanxi			X			X					2
Inner Mongolia	X			X	X		X	X			5
Liaoning	X	X	X	X	X	X	X	X	X	X	10
Jilin	X	X	X	X	X	X	X	X	X	X	10
Helongjiang		X						X			2
Shanghai			X		X	X	X	X			5
Jiangsu	X	X	X	X	X	X	X	X	X	X	10
Zhejiang	X	X	X	X	X	X	X	X	X	X	10
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X	X	X	X	X	X	X	X	X	X	10
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan	X	X	X	X	X	X	X	X	X	X	10
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan	X	X	X	X	X	X	X	X	X	X	10
Guangdong					X			X			2
Guangxi	X	X	X	X	X	X	X	X	X	X	10
Hainan	X	X	X	X	X	X	X	X	X	X	10
Chongqing				X				X			2
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou	X	X	X	X	X	X	X	X	X	X	10
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10
Gansu		X	X								2
Qinghai				X				X			2
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	23	24	25	26	25	24	24	29	22	22	

Figure 7.19.1 Rank of independent causal variables for forecasting analysis for arrivals from Canada to the 31 Chinese provinces



In regard to the determinant variables, most are equally significant with the intervention (dummy) variations slightly less common.

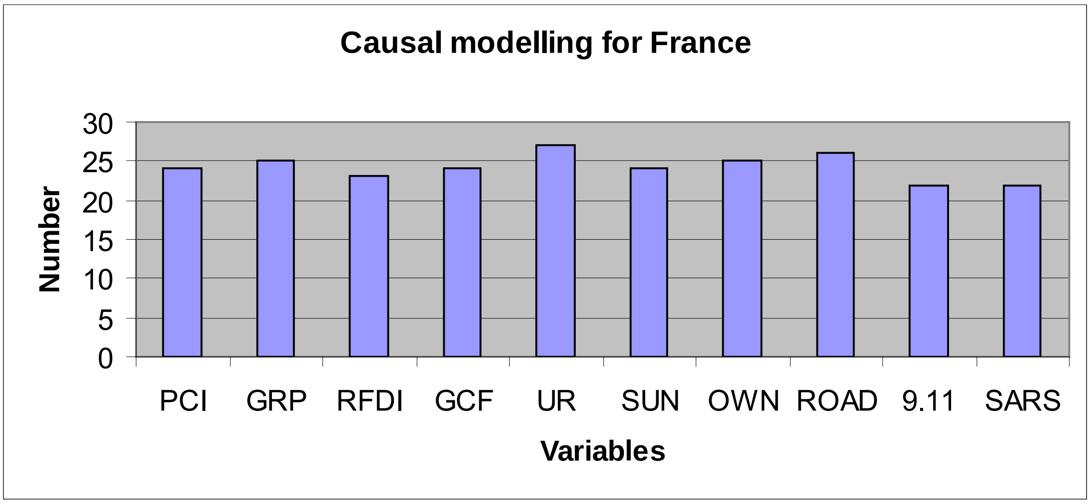
7.20 Causal Modelling for French Tourists to the 31 Chinese Provinces

Table 7.20.1 shows that the top 3 independent variables in forecasting French tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.20.1 Causal modelling for arrivals from France to the 31 Chinese provinces

Variable / Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing				X				X			2
Tianjin		X				X		X			3
Hebei	X	X	X	X	X	X	X	X	X	X	10
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia			X					X			2
Liaoning	X	X	X	X	X	X	X	X	X	X	10
Jilin	X	X	X	X	X	X	X	X	X	X	10
Helongjiang	X	X	X	X	X	X	X	X	X	X	10
Shanghai	X	X	X	X	X	X	X	X	X	X	10
Jiangsu				X				X			2
Zhejiang	X	X	X	X	X	X	X	X	X	X	10
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X	X	X	X	X	X	X	X	X	X	10
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan	X				X		X				3
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan	X	X	X	X	X	X	X	X	X	X	10
Guangdong	X	X	X	X	X	X	X	X	X	X	10
Guangxi					X		X				2
Hainan		X			X						2
Chongqing	X	X	X	X	X	X	X	X	X	X	10
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou	X	X			X	X					4
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10
Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai	X	X	X	X	X	X	X	X	X	X	10
Ningxia					X		X				2
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	24	25	23	24	27	24	25	26	22	22	

Figure 7.20.1 Rank of independent causal variables for forecasting analysis for arrivals from France to the 31 Chinese provinces



In regard to the determinant variables most of the provinces have all variables as significant, whereas Beijing, Inner Mongolia, Jiangsu, Guangdong, Hainan and Ningxia have just two. This consistent with the previous tables and again the two dummy variables are slightly less common to be significant. There are 242 (78%) significant relationships.

7.21 Causal Modelling for German Tourists to the 31 Chinese Provinces

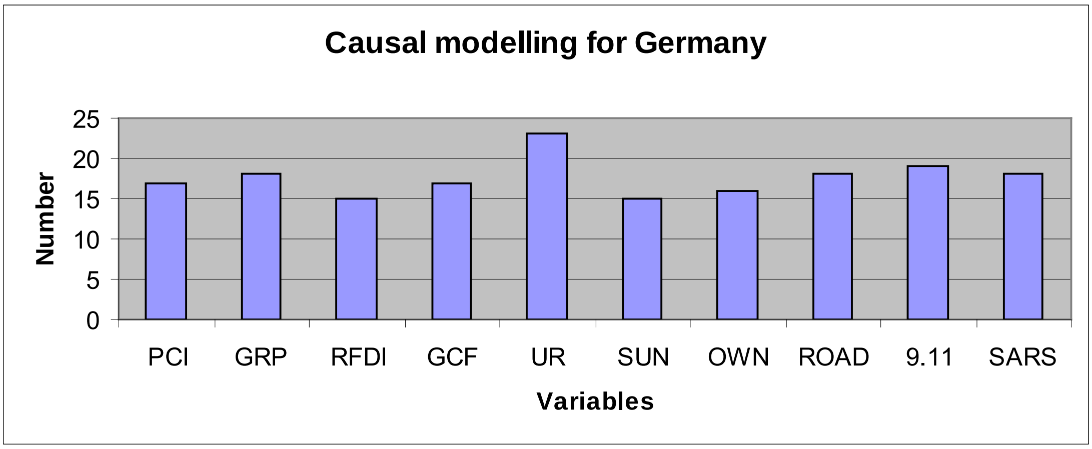
Table 7.21.1 shows that the top 3 independent variables in forecasting German tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.21.1 Causal modelling for arrivals from Germany to the 31 Chinese provinces

Variable											
Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing								X			1
Tianjin	X	X	X		X	X	X				6
Hebei				X			X		X	X	4
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X	X	X	X	X	X	X	X	X	X	10
Liaoning				X					X		2
Jilin			X		X	X	X			X	5
Helongjiang								X			1
Shanghai		X		X	X			X	X		5
Jiangsu				X				X	X		3
Zhejiang	X	X	X	X	X	X	X	X	X	X	10
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian	X				X						2
Jiangxi	X	X	X	X	X	X	X	X	X	X	10
Shandong	X				X						2
Henan	X	X	X	X	X	X	X	X	X	X	10
Hubei		X			X						2
Hunan		X			X						2
Guangdong	X									X	2
Guangxi					X		X			X	3
Hainan	X				X			X			3
Chongqing		X	X			X			X		4
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou				X				X		X	3

Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi					X				X		2
Gansu		X			X				X	X	4
Qinghai	X	X	X	X	X	X	X	X	X	X	10
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	17	18	15	17	23	15	16	18	19	18	

Figure 7.21.1 Rank of independent causal variables for forecasting analysis for arrivals from Germany to the 31 Chinese provinces



In regard to the determinant variables more than half of the provinces have all variables as significant, whereas Beijing has just one. The regions of Northeast and South China tend to have fewer relationships, and there are a smaller number of significant relationships for Germany at 191 (62%).

7.22 Causal Modelling for Japanese Tourists to the 31 Chinese Provinces

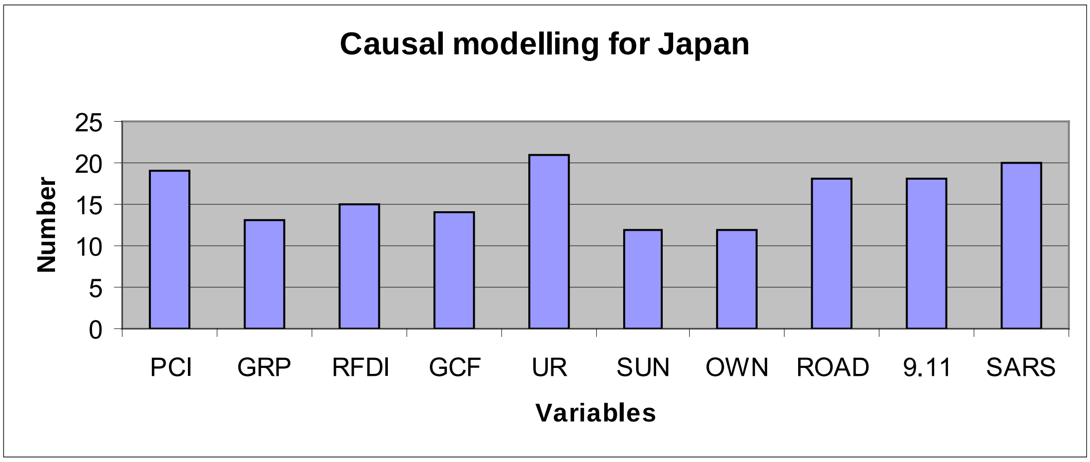
Table 7.22.1 shows that the top 3 independent variables in forecasting Japanese tourists to the 31 Chinese provinces are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF

(Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.22.1 Causal modelling for arrivals from Japan to the 31 Chinese provinces

Variable											
Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing								X	X		2
Tianjin								X	X		2
Hebei			X		X			X	X	X	5
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia					X						1
Liaoning	X	X	X	X	X	X	X	X	X	X	10
Jilin	X	X	X	X	X	X	X	X	X	X	10
Helongjiang	X	X	X	X	X	X	X	X	X	X	10
Shanghai	X										1
Jiangsu	X										1
Zhejiang	X	X	X	X	X	X	X	X	X	X	10
Anhui		X									1
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X	X	X	X	X	X	X	X	X	X	10
Shandong					X					X	2
Henan	X				X						2
Hubei			X		X			X	X	X	5
Hunan			X		X						2
Guangdong	X				X					X	3
Guangxi	X									X	2
Hainan	X	X	X	X	X	X	X	X	X	X	10
Chongqing	X									X	2
Sichuan					X			X			2
Guizhou				X						X	2
Yunnan								X	X	X	3
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi					X						1
Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai	X			X					X		3
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	19	13	15	14	21	12	12	18	18	20	

Figure 7.22.1 Rank of independent causal variables for forecasting analysis for arrivals from Japan to the 31 Chinese provinces



In regard to the determinant variables Shanxi, Liaoning, Jilin, Helongjiang, Zhejiang, Fujian, Jiangxi, Hainan, Tibet, Gansu, Ningxia and Xinjiang provinces have all variables as significant, whereas Inner Mongolia, Shanghai, Jiangsu and Shaanxi have just one. There are 163 relationship or 53% of possible relationships which makes Japan one of the source markets with the lowest number of useful causal variables.

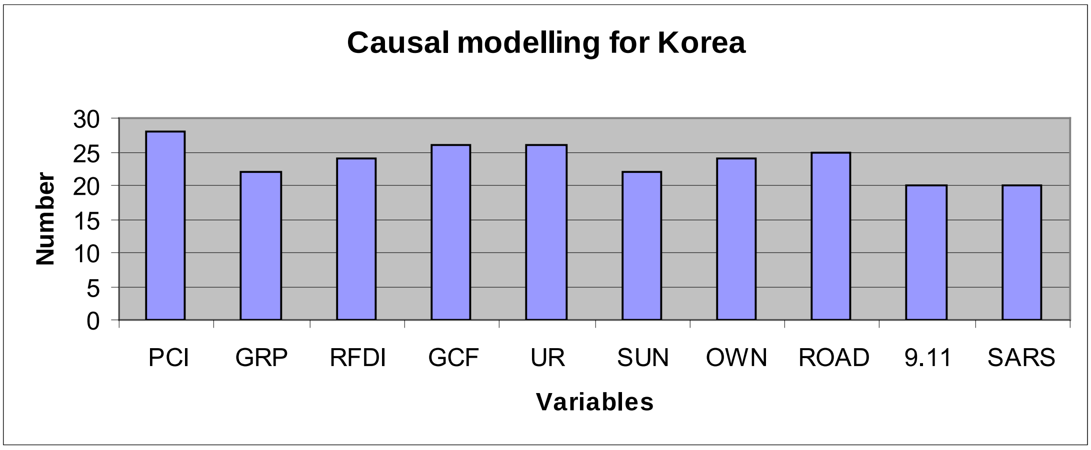
7.23 Causal Modelling for Korean Tourists to the 31 Chinese Provinces

Table 7.23.1 shows that the top 3 independent variables in forecasting Korean tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.23.1 Causal modelling for Arrivals from Korea to the 31 Chinese provinces

Variable											
Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing	X	X	X	X	X	X	X	X	X	X	10
Tianjin	X	X			X	X		X			5
Hebei	X	X	X	X	X	X	X	X	X	X	10
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X	X	X		X	X	X				6
Liaoning	X	X	X	X	X	X	X	X	X	X	10
Jilin	X		X	X	X						4
Helongjiang	X	X	X	X	X	X	X	X	X	X	10
Shanghai	X	X	X	X	X	X	X	X	X	X	10
Jiangsu							X	X			2
Zhejiang	X	X	X	X	X	X	X	X	X	X	10
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X		X	X	X						4
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan	X	X	X	X	X	X	X	X	X	X	10
Hubei			X		X		X	X			4
Hunan							X	X			2
Guangdong	X	X	X	X	X	X	X	X	X	X	10
Guangxi	X			X							2
Hainan	X	X	X	X	X	X	X	X	X	X	10
Chongqing	X			X				X			3
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou	X	X	X	X	X	X	X	X	X	X	10
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10
Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai	X			X	X						3
Ningxia	X			X							2
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	28	22	24	26	26	22	24	25	20	20	

Figure 7.23.1 Rank of independent causal variables for forecasting analysis for arrivals from Korea to the 31 Chinese provinces



In regard to the determinant variables more than half of the 31 provinces have all variables as significant, whereas Jiangsu, Hunan, Guangxi and Ningxia have just two. This is reflective of the low significance of the causal modelling. There are a large number of independent variables that have significant relationships for Korea. Of the possible 310 relationships, 237 (77%) have significant independent variables. Again the two dummy variables are slightly less often significant.

7.24 Causal Modelling for Malaysian Tourists to the 31 Chinese Provinces

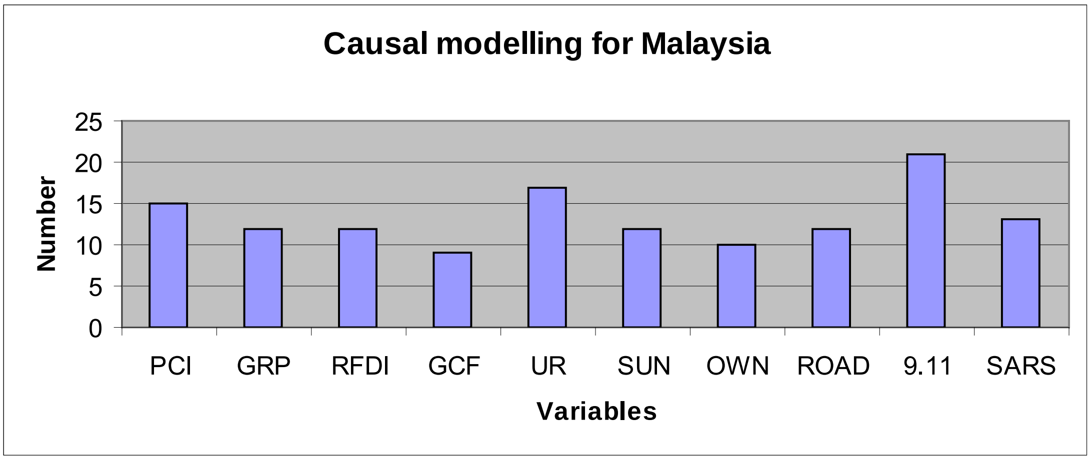
Table 7.24.1 shows that the top 3 independent variables in forecasting Malaysian tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.24.1 Causal modelling for arrivals from Malaysia to the 31 Chinese provinces

Variable											
Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing			X						X		2
Tianjin	X				X	X			X		4
Hebei	X				X	X			X		4
Shanxi		X							X	X	3
Inner Mongolia		X							X	X	3
Liaoning				X				X			2
Jilin					X		X		X	X	4
Helongjiang								X			1
Shanghai		X	X		X	X	X	X	X	X	8
Jiangsu								X	X		2
Zhejiang								X			1
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian	X					X			X		3
Jiangxi			X								1
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan			X		X		X		X	X	5
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan		X			X						2
Guangdong					X			X		X	3
Guangxi	X								X		2
Hainan		X									1
Chongqing	X			X					X		3
Sichuan	X										1

Guizhou					X						1
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X					X			X		3
Gansu	X		X								2
Qinghai					X				X		2
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	15	12	12	9	17	12	10	12	21	13	

Figure 7.24.1 Rank of independent causal variables for forecasting analysis for arrivals from Malaysia to the 31 Chinese provinces



In regard to the determinant variables Anhui, Shandong, Hubei, Hunan, Tibet, Ningxia and Xinjiang have all variables as significant, whereas Helongjiang, Zhejiang, Jiangxi, Hainan, Sichuan and Guizhou have just one. Malaysia has fewer significant independent variables being used over all, with just 133 relationships or just 43% of the possible relationships with significant independent variables.

7.25 Causal Modelling for Philippine Tourists to the 31 Chinese Provinces

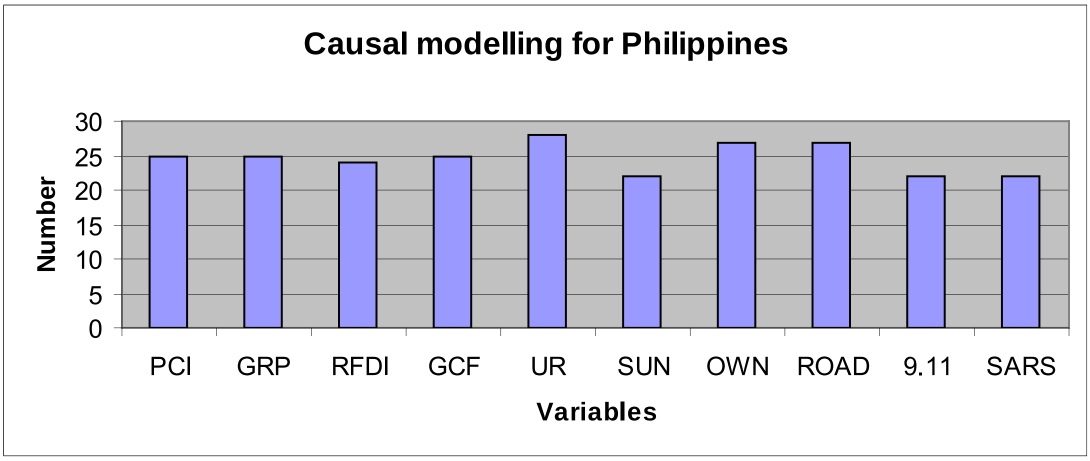
Table 7.25.1 shows that the top 3 independent variables in forecasting Philippine tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross

Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.25.1 Causal modelling for arrivals from Philippines to the 31 Chinese provinces

Variable / Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing	X	X	X	X	X	X	X	X	X	X	10
Tianjin		X			X						2
Hebei					X		X	X			3
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X			X	X		X				4
Liaoning	X	X	X	X	X	X	X	X	X	X	10
Jilin				X				X			2
Helongjiang	X	X	X	X	X	X	X	X	X	X	10
Shanghai	X		X								2
Jiangsu	X	X	X	X	X	X	X	X	X	X	10
Zhejiang					X		X	X			3
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X	X	X	X	X	X	X	X	X	X	10
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan	X	X	X	X	X	X	X	X	X	X	10
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan	X	X	X	X	X	X	X	X	X	X	10
Guangdong				X	X		X	X			4
Guangxi	X	X	X	X	X	X	X	X	X	X	10
Hainan	X	X	X	X	X	X	X	X	X	X	10
Chongqing	X	X	X	X	X	X	X	X	X	X	10
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou		X	X		X						3
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10
Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai	X	X	X	X	X	X	X	X	X	X	10
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang	X	X					X	X			4
Total	25	25	24	25	28	22	27	27	22	22	

Figure 7.25.1 Rank of independent causal variables for forecasting analysis for arrivals from the Philippines to the 31 Chinese provinces



In regard to the determinant variables most of the provinces have all variables as significant, whereas Tianjin, Jilin and Shanghai have just one. Of the 310 possible relationship 248 (80%) have significant relationships.

7.26 Causal Modelling for Russian Tourists to the 31 Chinese Provinces

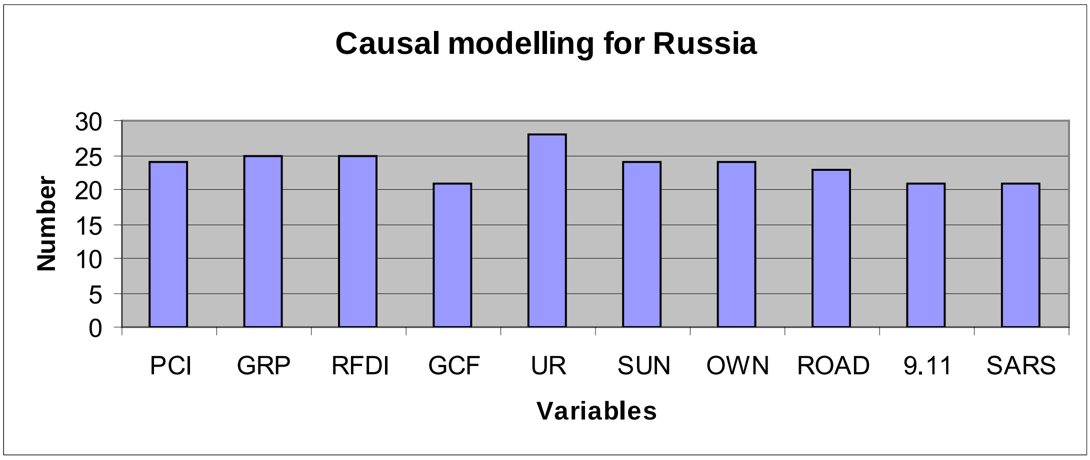
Table 7.26.1 shows that the top 3 independent variables in forecasting Russian tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.26.1 Causal modelling for arrivals from Russia to the 31 Chinese provinces

Variable / Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing	X	X	X	X	X	X	X	X	X	X	10
Tianjin	X	X	X	X	X	X	X	X	X	X	10
Hebei			X		X	X					3
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X	X	X	X	X	X	X	X	X	X	10
Liaoning	X	X				X					3
Jilin	X	X	X	X	X	X	X	X	X	X	10

Helongjiang		X			X						2
Shanghai	X	X	X	X	X	X	X	X	X	X	10
Jiangsu	X	X	X	X	X	X	X	X	X	X	10
Zhejiang		X				X					2
Anhui	X		X		X						3
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X				X						2
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan	X	X	X	X	X	X	X	X	X	X	10
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan					X		X	X			3
Guangdong	X	X	X	X	X	X	X	X	X	X	10
Guangxi			X				X				2
Hainan	X	X	X	X	X	X	X	X	X	X	10
Chongqing	X	X	X	X	X	X	X	X	X	X	10
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou	X	X	X	X	X	X	X	X	X	X	10
Yunnan			X		X		X	X			4
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10
Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai		X			X						2
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	24	25	25	21	28	24	24	23	21	21	

Figure 7.26.1 Rank of independent causal variables for forecasting analysis for arrivals from Russia to the 31 Chinese provinces



In regard to the determinant variables most of the provinces have all variables as significant, whereas Zhejiang, Jiangxi, Guangxi and Qinghai have just two. There are 237 independent determinant relationships or 77% of the total possible (310). Again the two dummy variables are slightly less commonly used.

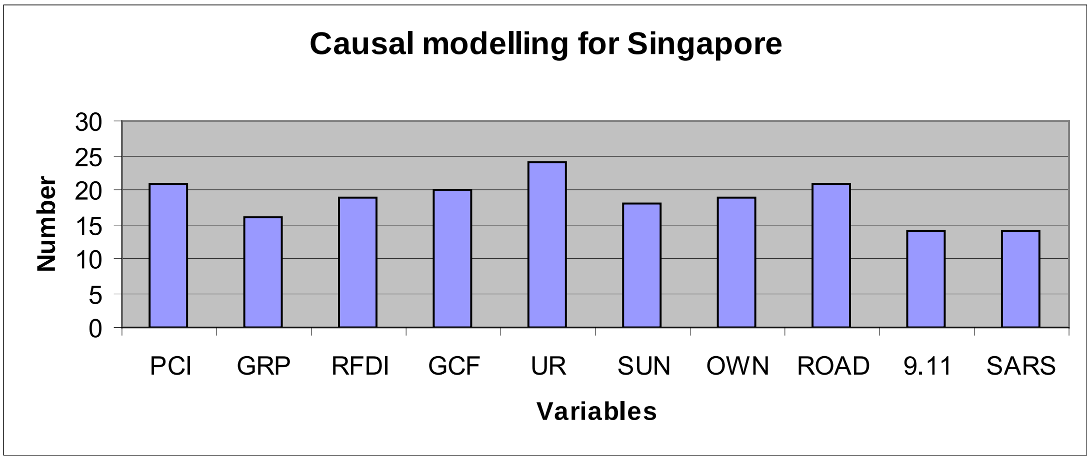
7.27 Causal Modelling for Singaporean Tourists to the 31 Chinese Provinces

Table 7.27.1 shows that the top 3 independent variables in forecasting Singapore tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.27.1 Causal modelling for arrivals from Singapore to the 31 Chinese provinces

Variable											
Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing					X			X			2
Tianjin	X				X						2
Hebei	X	X	X	X	X	X	X	X	X	X	10
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X	X	X	X	X	X	X	X	X	X	10
Liaoning			X	X	X		X	X			5
Jilin					X	X	X				3
Helongjiang				X	X		X	X			4
Shanghai		X				X	X	X			4
Jiangsu	X	X	X	X	X	X	X	X	X	X	10
Zhejiang	X				X						2
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian			X			X					2
Jiangxi	X		X	X	X	X					5
Shandong			X					X			2
Henan				X				X			2
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan	X				X						2
Guangdong					X			X			2
Guangxi	X	X	X	X	X	X	X	X	X	X	10
Hainan		X					X				2
Chongqing	X			X							2
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou	X		X								2
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10
Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai	X			X	X						3
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	21	16	19	20	24	18	19	21	14	14	

Figure 7.27.1 Rank of independent causal variables for forecasting analysis for arrivals from Singapore to the 31 Chinese provinces



In regard to the determinant variables nearly half of the provinces have all variables as significant, whereas Beijing, Tianjin, Fujian, Shandong, Henan, Hunan, Guangdong, Hainan, Chongqing and Guizhou have just two. This is reflective of the low significance of the causal modelling. There 187 (60%) of the possible relationships with significant independent variables. The two dummy variables are somewhat less commonly significant.

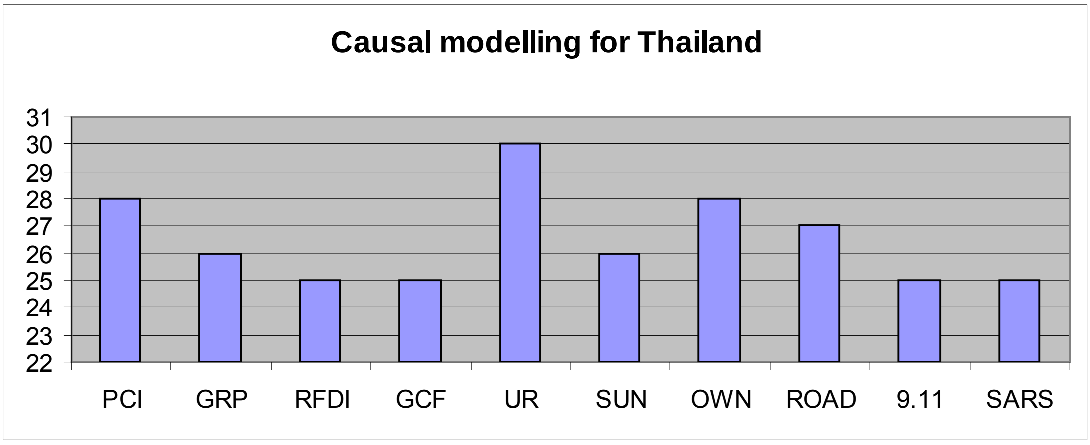
7.28 Causal Modelling for Thai Tourists to the 31 Chinese Provinces

Table 7.28.1 shows that the top 3 independent variables in forecasting Thai tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.28.1 Causal modelling for arrivals from Thailand to the 31 Chinese provinces

Variable / Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing	X	X	X	X	X	X	X	X	X	X	10
Tianjin	X	X		X	X						4
Hebei	X	X	X	X	X	X	X	X	X	X	10
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X	X	X	X	X	X	X	X	X	X	10
Liaoning	X	X	X	X	X	X	X	X	X	X	10
Jilin					X		X				2
Helongjiang	X	X	X	X	X	X	X	X	X	X	10
Shanghai	X	X	X	X	X	X	X	X	X	X	10
Jiangsu	X	X	X	X	X	X	X	X	X	X	10
Zhejiang	X	X	X	X	X	X	X	X	X	X	10
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X	X	X	X	X	X	X	X	X	X	10
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan	X	X	X	X	X	X	X	X	X	X	10
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan	X	X	X	X	X	X	X	X	X	X	10
Guangdong					X			X			2
Guangxi	X	X	X	X	X	X	X	X	X	X	10
Hainan	X	X	X	X	X	X	X	X	X	X	10
Chongqing	X	X	X	X	X	X	X	X	X	X	10
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou	X				X						2
Yunnan	X				X		X				3
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10
Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai	X	X	X	X	X	X	X	X	X	X	10
Ningxia							X	X			2
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	28	26	25	25	30	26	28	27	25	25	

Figure 7.28.1 Rank of independent causal variables for forecasting analysis for arrival from Thailand to the 31 Chinese provinces



In regard to the determinant variables most of the provinces have all variables as significant, whereas Jilin, Guangdong, Guizhou and Ningxia have just two. Of the 310 relationships, there are 266 (86%) with significant independent variables.

7.29 Causal Modelling for UK Tourists to the 31 Chinese Provinces

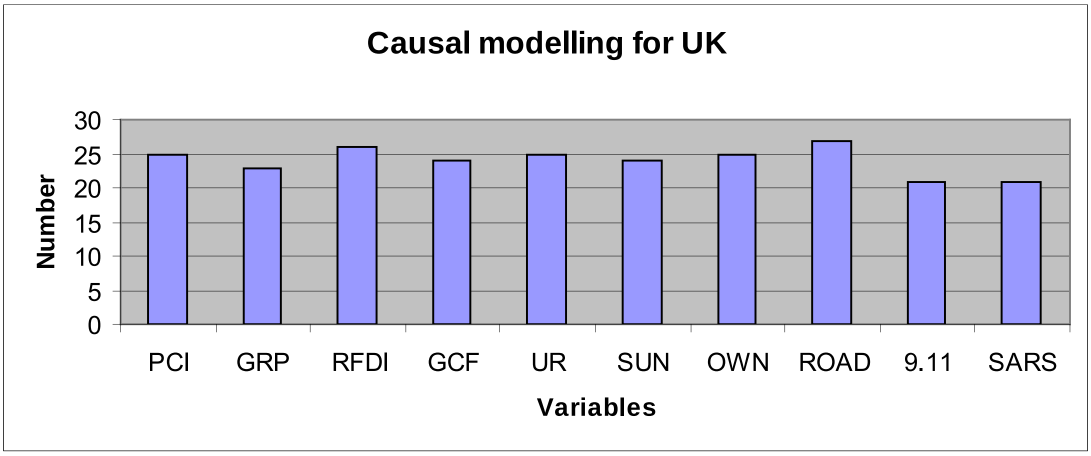
Table 7.29.1 shows that the top 3 independent variables in forecasting UK tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.29.1 Causal modelling for arrivals from the UK to the 31 Chinese provinces

Variable											
Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing							X	X			2
Tianjin	X	X		X	X	X		X			6
Hebei							X	X			2
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X	X	X	X	X	X	X	X	X	X	10
Liaoning	X	X	X	X	X	X	X	X	X	X	10
Jilin	X		X			X					3
Helongjiang	X	X	X	X	X	X	X	X	X	X	10
Shanghai	X			X	X		X				4
Jiangsu			X	X	X						3
Zhejiang			X				X	X			3
Anhui	X	X	X	X	X	X	X	X	X	X	10
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X	X	X	X	X	X	X	X	X	X	10
Shandong	X	X	X	X	X	X	X	X	X	X	10
Henan	X	X	X	X	X	X	X	X	X	X	10
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan	X	X	X	X	X	X	X	X	X	X	10
Guangdong	X					X					2
Guangxi		X	X		X			X			4
Hainan	X	X	X	X	X	X	X	X	X	X	10
Chongqing	X	X	X	X	X	X	X	X	X	X	10
Sichuan	X	X	X	X	X	X	X	X	X	X	10
Guizhou	X	X	X	X	X	X	X	X	X	X	10
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X	X	X	X	X	X	X	X	10
Gansu	X	X	X	X	X	X	X	X	X	X	10
Qinghai	X	X	X	X	X	X	X	X	X	X	10

	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	
Ningxia			X					X			2
Xinjiang	X	X	X	X	X	X	X	X	X	X	10
Total	25	23	26	24	25	24	25	27	21	21	

Figure 7.29.1 Rank of independent causal variables for forecasting analysis for arrival from UK to the 31 Chinese provinces



In regard to the determinant variables most of the provinces have all variables as significant, whereas Beijing, Hebei, Guangdong, and Ningxia have just two. Of the 310 possible causal relationship 241 (78%) have significant independent variables. The two dummy variables are slightly less commonly significant.

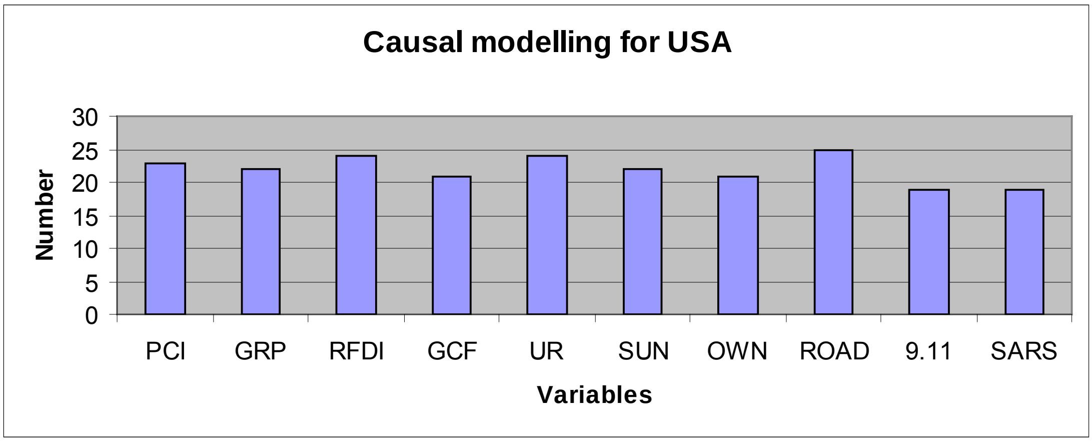
7.30 Causal Modelling for USA Tourists to the 31 Chinese Provinces

Table 7.30.1 shows that the top 3 independent variables in forecasting USA tourists to the 31 Chinese regions are in the order of the UR (Urban and Rural Ratio) followed by Own (Own Price) and Sept.11 (dummy variable 1), and GCF (Gross Capital Formation) and SARS (dummy variable 2). Figure 7.18.1 shows graphically the most useful independent variables in these analyses.

Table 7.30.1 Causal modelling for arrivals from USA to the 31 Chinese provinces

Variable / Province	PCI	GRP	RFDI	GCF	UR	SUN	OWN	ROAD	9.11	SARS	Total
Beijing	X	X	X	X	X	X	X	X	X	X	10
Tianjin	X	X				X		X			4
Hebei	X			X							2
Shanxi	X	X	X	X	X	X	X	X	X	X	10
Inner Mongolia	X		X		X						3
Liaoning	X	X	X	X	X	X	X	X	X	X	10
Jilin			X		X	X					3
Helongjiang	X	X	X	X	X	X	X	X	X	X	10
Shanghai	X	X	X	X	X	X	X	X	X	X	10
Jiangsu				X				X			2
Zhejiang	X	X	X	X	X	X	X	X	X	X	10
Anhui							X	X			2
Fujian	X	X	X	X	X	X	X	X	X	X	10
Jiangxi	X	X	X	X	X	X	X	X	X	X	10
Shandong			X		X			X			3
Henan	X	X	X	X	X	X	X	X	X	X	10
Hubei	X	X	X	X	X	X	X	X	X	X	10
Hunan	X	X	X	X	X	X	X	X	X	X	10
Guangdong	X	X	X	X	X	X	X	X	X	X	10
Guangxi	X	X	X	X	X	X	X	X	X	X	10
Hainan	X	X	X	X	X	X	X	X	X	X	10
Chongqing	X	X	X	X	X	X	X	X	X	X	10
Sichuan		X	X		X						3
Guizhou	X	X	X	X	X	X	X	X	X	X	10
Yunnan	X	X	X	X	X	X	X	X	X	X	10
Tibet	X	X	X	X	X	X	X	X	X	X	10
Shaanxi	X	X	X			X					4
Gansu							X	X			2
Qinghai	X	X	X	X	X	X	X	X	X	X	10
Ningxia	X	X	X	X	X	X	X	X	X	X	10
Xinjiang					X			X			2
Total	24	23	25	22	25	23	22	26	20	20	

Figure 7.30.1 Rank of independent causal variables for forecasting analysis for arrival from USA to the 31 Chinese provinces



In regard to the determinant variables most of the provinces have all variables as significant, whereas Hebei, Jiangxi, Anhui, Gansu, Xinjiang have just two. This is reflective of the low significance of the causal modelling. There are 231 (75%) of the relationships with significant independent variables.

7.31 Top Arrival Provinces

Although an examination of all provinces is needed in the comparison analysis, it is also the case that international tourist arrivals are focussed upon a selection of regions that is much smaller than the total of 31 provinces and regions. Table 1.9 shows that one third of arrivals (33.7%) are concentrated into the top five arrival provinces and 42.4% in the top ten provinces.

This concentration raises the question of what the modelling does in these high concentration provinces. Also the previous analysis did show that there is no one model that accurately forecasts arrivals in all cases or for select countries or select provinces. This is consistent with current literature (refer to Chapter 2) whereby it is stated that different models work accurately with different time series, and there is no known universal best model.

Table 7.31.1 summarises a comparison of the top arrival provinces (top 10) to determine which models work best for each province. In Table 7.31.1 there are several issues. There are 120 forecast error terms in Table 7.31.1 and only 11 Naïve values (9%) while the error terms are very good in most cases 81 at 10% or less (68%), so it can be concluded that it is possible to use forecast models to accurately forecast regional arrivals, for a large part of the total volume of international arrivals. However, it is also evident that a wide range of models are needed with all models represented. Again this is consistent with the findings in the literature review that no one forecasting technique is best to use across several time series. The BSM is outperformed in accuracy by the BSM with interventions (BSMI) whereby only two BSM models are most accurate, and 53 BSMI models (44%) are represented. The

BSMI is the most common model overall and this relates to the impact of SARS and Sept. 11 on the arrival series whereby the measurement of interventions become important. Most of the accurate models are the more complex and modern methods; in that there are only two exponential smoothing results, 4 ARMA results and 8 Holt models in Table 7.18. The Neural, BSM, BSMI, TVP and TVPD models account for 95 results (79%). It is also evident that despite the simple model structure of exponential smoothing models such as Holt, they can on occasion still outperform the more modern methods.

Table 7.31.1 Optimal model based on MAPE for each of the top 10 arrival provinces

Province	Guangdong		Shanghai		Jiangsu		Zhejiang		Beijing	
Market	Model	MAPE	Model	MAPE	Model	MAPE	Model	MAPE	Model	MAPE
Australia	Naïve	26.9	ARMA	4.8	BSMI	21.7	BSMI	6.2	TVP	3.4
Canada	Naive	26.3	BSMI	4.9	BSMI	10.0	TVPD	3.2	TVP	10.4
France	Naive	9.6	Neural	7.8	BSMI	10.6	Holt	7.1	Neural	8.1
Germany	BSMI	12.7	Naive	1.7	TVPD	6.5	TVP	4.9	TVPD	7.2
Japan	BSMI	2.2	Naive	2.8	Holt	10.0	TVPD	1.3	Neural	0.1
Korea	BSMI	2.2	BSMI	3.5	Holt	6.6	BSM	5.0	BSMI	1.1
Malaysia	TVP	4.1	Neural	9.6	ARMA	3.1	TVP	1.5	Neural	0.6
Russia	TVP	10.5	Neural	7.3	TVP	16.3	ExpSm	15.5	BSMI	11.5
Singapore	BSMI	1.2	Naive	4.7	BSMI	7.0	Holt	1.2	Neural	2.5
Thailand	Naive	6.8	TVPD	3.2	Naive	5.2	BSMI	5.9	Naive	0.8
UK	Holt	3.2	TVPD	8.1	TVP	16.1	BSMI	5.7	BSMI	5.7
USA	BSMI	14.9	ARMA	11.0	BSMI	13.0	BSMI	1.8	BSMI	6.9

Province	Fujian		Shandong		Yunnan		Guangxi		Liaoning	
Market	Model	MAPE	Model	MAPE	Model	MAPE	Model	MAPE	Model	MAPE
Australia	BSMI	11.7	BSMI	18.7	BSMI	10.1	TVPD	10.2	BSMI	9.2
Canada	BSMI	25.8	BSMI	17.0	TVPD	5.8	TVP	4.7	ExpSm	15.0
France	BSMI	2.4	BSMI	16.0	BSMI	16.8	BSMI	10.1	BSMI	13.9
Germany	ARMA	4.7	BSMI	12.2	BSMI	10.6	Neural	5.2	Holt	2.7
Japan	Neural	6.0	BSMI	2.0	Neural	3.5	Neural	0.9	Holt	2.8
Korea	TVPD	4.9	BSMI	7.9	BSMI	2.8	Neural	1.9	BSMI	3.3
Malaysia	BSMI	1.5	BSMI	3.9	Neural	8.9	TVPD	9.5	TVPD	5.7
Russia	BSMI	9.3	Naive	23.6	TVP	15.3	BSMI	9.7	TVPD	15.9
Singapore	Neural	2.6	BSM	14.4	Neural	2.2	Holt	11.1	BSMI	2.2
Thailand	Naive	7.5	BSMI	11.5	Neural	1.3	BSMI	6.4	BSMI	10.7
UK	BSMI	12.0	BSMI	13.3	BSMI	11.2	TVP	11.7	BSMI	24.7
USA	BSMI	17.4	BSMI	17.0	TVP	10.8	BSMI	9.3	BSMI	7.7

In concluding upon the aims and objectives of this study it can be stated that it is possible to accurately forecast regional arrivals into China. Despite the data limitations, which in particular relate to the annual nature of the series, and the limited time series length, accurate forecasts defined to be below 20% error, and preferably below 10% error, are consistently possible. It may be that it is better to concentrate forecasting to the more developed tourism regions where flows tend to be larger and less volatile. Additionally, it would be a mistake to focus only upon econometric modelling, because in this study the more modern time series methods have proven to be dominant. It is also evident that of the time series methods the more modern structural and neural models need to be used.

It remains unclear why the econometric results are not as accurate in a more widespread outcome across more provinces. It is possible as is always the case that this simply results from lack of data, including a small sample size (small degrees of freedom) for measuring the real causes of volume changes. It may also be because each province may have unique, or largely unique, causal measures. Hence the concept of using the same independent variables across all regions is not viable. However, from a management approach it is also not viable to spend large amounts of money and time isolating independent variables that only occasionally significantly outperform time series methods.

The data used in this study are accommodation measures and not cross border immigration records. One of the aims of the study was to determine whether this data could yield accurate forecasts of arrivals, and the conclusion is evident that such data can be used in tourism forecasting. In the case of China these data appear to be consistent and reliable and can be accurately used in forecasting models.

Finally, the thesis has developed a set of new models in terms of model selection, and the use of new independent variables, capable of moving regional forecasting ahead in future research. There is a new mix of currently used national measures and separate regional economic variables, and these new measures are likely to be commonly available, and provide a strong starting point for regional forecasting studies in the future.

7.32 Research Limitations

The main limitation of this research was the inability to use a larger post sample data period. Medium and long term forecasting accuracy could not be tested and the findings of the research are limited to the short-term. This constraint will slowly be removed as longer arrival series become increasingly available. Although the forecasting models selected are good examples of modern methodology, there are other methods using interventions that need testing. Although two models – the BSM and the TVP were done separately with interventions the Neural and the ARMA model may also be done this way. The original study did not anticipate that interventions would be important in the final outcome, and this is a limitation in the study.

Finally, the greatest limitation is beyond rectification at present, and that is the data are annual and not seasonal. China does not provide seasonal data although they must be originally collected. Private attempts were made through high level contacts in the China National Travel Association and PATA to obtain such data, but these data are not collected together into data sets for use at present. This may be a more general limitation for regional forecasting, as the problem does exist in India as well. Seasonal regional data would likely produce more accurate forecasts as the regions in China vary greatly in weather conditions and the peak seasons.

7.33 Recommendations for Future Research

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

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Appendix I

Table 5A.1.1
ARMA results for Australian tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-18.55
BIC	-17.58
Mean Absolute Percentage Error (MAPE)	1.50%
R-Square	46.66%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.52
T-Test For Constant	0.21

Forecast Statistics	Value
Durbin Watson(1)	1.88
Mean	4.64
Standard Deviation	0.14
Auto-Correlation	0.35
Auto-Covariance	0.01
Ljung-Box	2.21

Table 5A.1.2
ARMA results for Australian tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.13
BIC	-2.64
Mean Absolute Percentage Error (MAPE)	4.02%
R-Square	3.44%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.51

Forecast Statistics	Value
Durbin Watson(1)	1.76
Mean	3.46
Standard Deviation	0.21
Auto-Correlation	0.11
Auto-Covariance	0.00
Ljung-Box	4.91

Table 5A.1.3
ARMA results for Australian tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	230.07
BIC	231.04
Mean Absolute Percentage Error (MAPE)	178.24%
R-Square	0.00%
Adjusted R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.26
T-Test For Constant	2.84

Forecast Statistics	Value
Durbin Watson(1)	1.63
Mean	5,209.75
Standard Deviation	3,096.18
Auto-Correlation	0.02
Ljung-Box	4.70

Table 5A.1.4
ARMA results for Australian tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	2.96
BIC	3.44
Mean Absolute Percentage Error (MAPE)	6.68%
R-Square	15.27%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.37

Forecast Statistics	**Value**
Durbin Watson(1)	1.56
Mean	3.13
Standard Deviation	0.29
Auto-Correlation	0.21
Auto-Covariance	0.02
Ljung-Box	6.83

Table 5A.1.5
ARMA results for Australian tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-6.78
BIC	-6.30
Mean Absolute Percentage Error (MAPE)	4.47%
R-Square	65.36%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-1.56

Forecast Statistics	**Value**
Durbin Watson(1)	1.75
Mean	2.75
Standard Deviation	0.30
Auto-Correlation	0.64
Auto-Covariance	0.05
Ljung-Box	7.01

Table 5A.1.6
ARMA results for Australian tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-9.61
BIC	-9.12
Mean Absolute Percentage Error (MAPE)	3.02%
R-Square	60.15%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.52

Forecast Statistics	**Value**
Durbin Watson(1)	1.74
Mean	3.51
Standard Deviation	0.25
Auto-Correlation	0.59
Auto-Covariance	0.03
Ljung-Box	6.66

Table 5A.1.7
ARMA results for Australian tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	4.13
BIC	4.62
Mean Absolute Percentage Error (MAPE)	5.95%
R-Square	45.71%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.92

Forecast Statistics	**Value**
Durbin Watson(1)	1.62
Mean	2.78
Standard Deviation	0.37
Auto-Correlation	0.50
Auto-Covariance	0.06
Ljung-Box	3.56

Table 5A.1.8
ARMA results for Australian tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	2.85
BIC	3.33
Mean Absolute Percentage Error (MAPE)	6.55%
R-Square	24.47%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.62

Forecast Statistics	**Value**
Durbin Watson(1)	1.60
Mean	2.96
Standard Deviation	0.30
Auto-Correlation	0.20
Auto-Covariance	0.02
Ljung-Box	4.12

Table 5A.1.9
ARMA results for Australian tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-14.47
BIC	-13.98
Mean Absolute Percentage Error (MAPE)	1.94%
R-Square	79.02%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	1.17

Forecast Statistics	**Value**
Durbin Watson(1)	2.26
Mean	4.50
Standard Deviation	0.28
Auto-Correlation	0.61
Auto-Covariance	0.04
Ljung-Box	9.07

Table 5A.1.10
ARMA results for Australian tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-11.16
BIC	-10.19
Mean Absolute Percentage Error (MAPE)	2.19%
R-Square	83.62%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.73
T-Test For Constant	1.09

Forecast Statistics	Value
Durbin Watson(1)	2.12
Mean	4.24
Standard Deviation	0.33
Auto-Correlation	0.73
Auto-Covariance	0.07
Ljung-Box	5.49

Table 5A.1.11
ARMA results for Australian tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.08
BIC	-5.11
Mean Absolute Percentage Error (MAPE)	3.23%
R-Square	74.35%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.32
T-Test For Constant	0.97

Forecast Statistics	Value
Durbin Watson(1)	2.16
Mean	4.08
Standard Deviation	0.33
Auto-Correlation	0.61
Auto-Covariance	0.06
Ljung-Box	4.99

Table 5A.1.12
ARMA results for Australian tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-7.51
BIC	-7.03
Mean Absolute Percentage Error (MAPE)	3.35%
R-Square	71.39%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.34

Forecast Statistics	Value
Durbin Watson(1)	1.77
Mean	3.44
Standard Deviation	0.32
Auto-Correlation	0.67
Auto-Covariance	0.06
Ljung-Box	7.38

Table 5A.1.13
ARMA results for Australian tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.86
BIC	2.34
Mean Absolute Percentage Error (MAPE)	4.80%
R-Square	34.97%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.20

Forecast Statistics	Value
Durbin Watson(1)	1.96
Mean	3.65
Standard Deviation	0.31
Auto-Correlation	0.50
Auto-Covariance	0.04
Ljung-Box	7.43

Table 5A.1.14
ARMA results for Australian tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.06
BIC	2.54
Mean Absolute Percentage Error (MAPE)	5.91%
R-Square	58.90%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.91

Forecast Statistics	Value
Durbin Watson(1)	1.78
Mean	2.95
Standard Deviation	0.40
Auto-Correlation	0.60
Auto-Covariance	0.09
Ljung-Box	7.67

Table 5A.1.15
ARMA results for Australian tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.18
BIC	-11.69
Mean Absolute Percentage Error (MAPE)	2.90%
R-Square	60.52%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.87

Forecast Statistics	Value
Durbin Watson(1)	1.45
Mean	3.70
Standard Deviation	0.22
Auto-Correlation	0.52
Auto-Covariance	0.02
Ljung-Box	7.73

Table 5A.1.16
ARMA results for Australian tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	16.10
BIC	16.58
Mean Absolute Percentage Error (MAPE)	8.88%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.47

Forecast Statistics	Value
Durbin Watson(1)	1.96
Mean	3.46
Standard Deviation	0.45
Auto-Correlation	0.16
Auto-Covariance	0.03
Ljung-Box	7.89

Table 5A.1.17
ARMA results for Australian tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.39
BIC	1.88
Mean Absolute Percentage Error (MAPE)	5.31%
R-Square	51.80%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.02

Forecast Statistics	Value
Durbin Watson(1)	1.77
Mean	3.68
Standard Deviation	0.35
Auto-Correlation	0.45
Auto-Covariance	0.05
Ljung-Box	4.18

Table 5A.1.18
ARMA results for Australian tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	9.05
BIC	10.02
Mean Absolute Percentage Error (MAPE)	7.41%
R-Square	18.71%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.39
T-Test For Constant	0.30

Forecast Statistics	Value
Durbin Watson(1)	1.88
Mean	3.39
Standard Deviation	0.35
Auto-Correlation	0.39
Auto-Covariance	0.04
Ljung-Box	5.71

Table 5A.1.19
ARMA results for Australian tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-13.27
BIC	-12.78
Mean Absolute Percentage Error (MAPE)	1.87%
R-Square	9.94%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.17

Forecast Statistics	Value
Durbin Watson(1)	1.51
Mean	4.51
Standard Deviation	0.14
Auto-Correlation	0.17
Auto-Covariance	0.00
Ljung-Box	5.28

Table 5A.1.20
ARMA results for Australian tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-8.97
BIC	-8.49
Mean Absolute Percentage Error (MAPE)	2.84%
R-Square	15.54%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.55

Forecast Statistics	Value
Durbin Watson(1)	1.59
Mean	3.89
Standard Deviation	0.17
Auto-Correlation	0.17
Auto-Covariance	0.00
Ljung-Box	3.42

Table 5A.1.21
ARMA results for Australian tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.07
BIC	-5.58
Mean Absolute Percentage Error (MAPE)	3.73%
R-Square	52.14%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.41

Forecast Statistics	Value
Durbin Watson(1)	1.23
Mean	3.10
Standard Deviation	0.26
Auto-Correlation	0.46
Auto-Covariance	0.03
Ljung-Box	8.17

Table 5A.1.22
ARMA results for Australian tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-2.51
BIC	-2.02
Mean Absolute Percentage Error (MAPE)	3.42%
R-Square	70.12%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.02

Forecast Statistics	**Value**
Durbin Watson(1)	1.57
Mean	3.53
Standard Deviation	0.38
Auto-Correlation	0.64
Auto-Covariance	0.09
Ljung-Box	7.12

Table 5A.1.23
ARMA results for Australian tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-9.02
BIC	-8.54
Mean Absolute Percentage Error (MAPE)	3.55%
R-Square	18.20%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.52

Forecast Statistics	**Value**
Durbin Watson(1)	1.89
Mean	3.65
Standard Deviation	0.18
Auto-Correlation	0.30
Auto-Covariance	0.01
Ljung-Box	9.94

Table 5A.1.24
ARMA results for Australian tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	14.38
BIC	14.87
Mean Absolute Percentage Error (MAPE)	10.26%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.87

Forecast Statistics	**Value**
Durbin Watson(1)	1.60
Mean	2.93
Standard Deviation	0.42
Auto-Correlation	0.07
Auto-Covariance	0.01
Ljung-Box	4.21

Table 5A.1.25
ARMA results for Australian tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-7.12
BIC	-6.63
Mean Absolute Percentage Error (MAPE)	2.98%
R-Square	35.44%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.00

Forecast Statistics	**Value**
Durbin Watson(1)	1.69
Mean	3.93
Standard Deviation	0.22
Auto-Correlation	0.39
Auto-Covariance	0.02
Ljung-Box	5.90

Table 5A.1.26
ARMA results for Australian tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-3.38
BIC	-2.41
Mean Absolute Percentage Error (MAPE)	4.81%
R-Square	8.83%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.31
T-Test For Non Seasonal MA	-0.13

Forecast Statistics	**Value**
Durbin Watson(1)	1.95
Mean	3.36
Standard Deviation	0.19
Auto-Correlation	0.24
Auto-Covariance	0.01
Ljung-Box	8.66

Table 5A.1.27
ARMA results for Australian tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	21.07
BIC	21.56
Mean Absolute Percentage Error (MAPE)	11.07%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.74

Forecast Statistics	**Value**
Durbin Watson(1)	1.88
Mean	3.92
Standard Deviation	0.53
Auto-Correlation	-0.06
Auto-Covariance	-0.02
Ljung-Box	2.95

Table 5A.1.28
ARMA results for Australian tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-6.88
BIC	-6.39
Mean Absolute Percentage Error (MAPE)	3.04%
R-Square	72.21%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.15

Forecast Statistics	**Value**
Durbin Watson(1)	1.97
Mean	3.37
Standard Deviation	0.33
Auto-Correlation	0.69
Auto-Covariance	0.07
Ljung-Box	7.80

Table 5A.1.29
ARMA results for Australian tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-9.10
BIC	-8.61
Mean Absolute Percentage Error (MAPE)	5.34%
R-Square	32.25%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.75

Forecast Statistics	**Value**
Durbin Watson(1)	1.82
Mean	2.37
Standard Deviation	0.19
Auto-Correlation	0.52
Auto-Covariance	0.02
Ljung-Box	9.50

Table 5A.1.30
ARMA results for Australian tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-8.52
BIC	-8.03
Mean Absolute Percentage Error (MAPE)	6.24%
R-Square	28.41%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-0.33

Forecast Statistics	**Value**
Durbin Watson(1)	1.99
Mean	1.87
Standard Deviation	0.19
Auto-Correlation	0.50
Auto-Covariance	0.02
Ljung-Box	3.90

Table 5A.1.31
ARMA results for Australian tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.52
BIC	-6.03
Mean Absolute Percentage Error (MAPE)	3.48%
R-Square	24.50%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.52

Forecast Statistics	Value
Durbin Watson(1)	1.76
Mean	3.32
Standard Deviation	0.20
Auto-Correlation	0.49
Auto-Covariance	0.02
Ljung-Box	2.46

Table 5A.2.1
ARMA results for Canadan tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-20.87
BIC	-20.39
Mean Absolute Percentage Error (MAPE)	1.61%
R-Square	17.37%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.14

Forecast Statistics	Value
Durbin Watson(1)	1.75
Mean	4.68
Standard Deviation	0.11
Auto-Correlation	0.26
Auto-Covariance	0.00
Ljung-Box	4.17

Table 5A.2.2
ARMA results for Canadan tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.41
BIC	7.89
Mean Absolute Percentage Error (MAPE)	4.69%
R-Square	53.24%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.70

Forecast Statistics	Value
Durbin Watson(1)	1.83
Mean	3.58
Standard Deviation	0.46
Auto-Correlation	0.61
Auto-Covariance	0.12
Ljung-Box	5.08

Table 5A.2.3
ARMA results for Canadan tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	17.46
BIC	18.43
Mean Absolute Percentage Error (MAPE)	10.05%
R-Square	0.03%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	26.46
T-Test For Non Seasonal MA	-0.07

Forecast Statistics	Value
Durbin Watson(1)	1.71
Mean	3.56
Standard Deviation	0.44
Auto-Correlation	0.02
Auto-Covariance	0.00
Ljung-Box	6.65

Table 5A.2.4
ARMA results for Canadan tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	6.96
BIC	7.45
Mean Absolute Percentage Error (MAPE)	7.49%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.27

Forecast Statistics	Value
Durbin Watson(1)	2.21
Mean	3.13
Standard Deviation	0.29
Auto-Correlation	-0.01
Auto-Covariance	0.00
Ljung-Box	4.60

Table 5A.2.5
ARMA results for Canadan tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	6.10
BIC	7.07
Mean Absolute Percentage Error (MAPE)	7.07%
R-Square	36.51%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.54
T-Test For Non Seasonal MA	-1.45

Forecast Statistics	Value
Durbin Watson(1)	1.70
Mean	2.69
Standard Deviation	0.35
Auto-Correlation	0.28
Auto-Covariance	0.03
Ljung-Box	8.16

Table 5A.2.6
ARMA results for Canadan tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.63
BIC	-10.15
Mean Absolute Percentage Error (MAPE)	3.13%
R-Square	65.51%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.01

Forecast Statistics	Value
Durbin Watson(1)	1.74
Mean	3.53
Standard Deviation	0.25
Auto-Correlation	0.64
Auto-Covariance	0.04
Ljung-Box	6.86

Table 5A.2.7
ARMA results for Canadan tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-3.64
BIC	-3.15
Mean Absolute Percentage Error (MAPE)	3.43%
R-Square	61.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.31

Forecast Statistics	**Value**
Durbin Watson(1)	2.04
Mean	2.84
Standard Deviation	0.32
Auto-Correlation	0.57
Auto-Covariance	0.05
Ljung-Box	5.91

Table 5A.2.8
ARMA results for Canadan tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	8.38
BIC	8.87
Mean Absolute Percentage Error (MAPE)	7.86%
R-Square	32.18%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-2.24

Forecast Statistics	**Value**
Durbin Watson(1)	1.86
Mean	3.19
Standard Deviation	0.40
Auto-Correlation	0.48
Auto-Covariance	0.07
Ljung-Box	6.19

Table 5A.2.9
ARMA results for Canadan tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-19.88
BIC	-18.91
Mean Absolute Percentage Error (MAPE)	1.44%
R-Square	82.13%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.00
T-Test For Constant	0.77

Forecast Statistics	**Value**
Durbin Watson(1)	2.25
Mean	4.40
Standard Deviation	0.22
Auto-Correlation	0.67
Auto-Covariance	0.03
Ljung-Box	6.21

Table 5A.2.10
ARMA results for Canadan tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-18.01
BIC	-17.53
Mean Absolute Percentage Error (MAPE)	1.75%
R-Square	86.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.75

Forecast Statistics	Value
Durbin Watson(1)	2.09
Mean	4.19
Standard Deviation	0.29
Auto-Correlation	0.73
Auto-Covariance	0.06
Ljung-Box	6.90

Table 5A.2.11
ARMA results for Canadan tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.54
BIC	-6.06
Mean Absolute Percentage Error (MAPE)	3.22%
R-Square	61.52%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.70

Forecast Statistics	Value
Durbin Watson(1)	2.03
Mean	4.09
Standard Deviation	0.29
Auto-Correlation	0.56
Auto-Covariance	0.04
Ljung-Box	6.07

Table 5A.2.12
ARMA results for Canadan tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-4.18
BIC	-3.70
Mean Absolute Percentage Error (MAPE)	4.57%
R-Square	65.41%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.84

Forecast Statistics	Value
Durbin Watson(1)	1.78
Mean	3.38
Standard Deviation	0.33
Auto-Correlation	0.57
Auto-Covariance	0.06
Ljung-Box	7.78

Table 5A.2.13
ARMA results for Canadan tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-1.35
BIC	-0.87
Mean Absolute Percentage Error (MAPE)	4.51%
R-Square	40.79%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.98

Forecast Statistics	**Value**
Durbin Watson(1)	1.92
Mean	3.61
Standard Deviation	0.29
Auto-Correlation	0.53
Auto-Covariance	0.04
Ljung-Box	5.99

Table 5A.2.14
ARMA results for Canadan tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-18.37
BIC	-17.40
Mean Absolute Percentage Error (MAPE)	2.27%
R-Square	87.58%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	2.15
T-Test For Non Seasonal MA	0.19

Forecast Statistics	**Value**
Durbin Watson(1)	2.21
Mean	3.03
Standard Deviation	0.28
Auto-Correlation	0.53
Auto-Covariance	0.04
Ljung-Box	4.23

Table 5A.2.15
ARMA results for Canadan tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-11.01
BIC	-10.53
Mean Absolute Percentage Error (MAPE)	2.86%
R-Square	39.29%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.72

Forecast Statistics	**Value**
Durbin Watson(1)	1.69
Mean	3.83
Standard Deviation	0.19
Auto-Correlation	0.36
Auto-Covariance	0.01
Ljung-Box	3.14

Table 5A.2.16
ARMA results for Canadan tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	11.62
BIC	12.11
Mean Absolute Percentage Error (MAPE)	8.07%
R-Square	25.72%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.85

Forecast Statistics	Value
Durbin Watson(1)	1.98
Mean	3.44
Standard Deviation	0.44
Auto-Correlation	0.42
Auto-Covariance	0.07
Ljung-Box	7.46

Table 5A.2.17
ARMA results for Canadan tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.70
BIC	8.19
Mean Absolute Percentage Error (MAPE)	5.87%
R-Square	27.46%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.81

Forecast Statistics	Value
Durbin Watson(1)	2.48
Mean	3.81
Standard Deviation	0.38
Auto-Correlation	0.25
Auto-Covariance	0.03
Ljung-Box	7.65

Table 5A.2.18
ARMA results for Canadan tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	8.65
BIC	9.62
Mean Absolute Percentage Error (MAPE)	5.77%
R-Square	33.54%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-1.69
T-Test For Non Seasonal MA	0.60

Forecast Statistics	Value
Durbin Watson(1)	2.05
Mean	3.81
Standard Deviation	0.38
Auto-Correlation	0.25
Auto-Covariance	0.03
Ljung-Box	5.08

Table 5A.2.19
ARMA results for Canadan tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-13.33
BIC	-12.84
Mean Absolute Percentage Error (MAPE)	2.22%
R-Square	0.80%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.59

Forecast Statistics	**Value**
Durbin Watson(1)	1.86
Mean	4.55
Standard Deviation	0.13
Auto-Correlation	0.11
Auto-Covariance	0.00
Ljung-Box	7.25

Table 5A.2.20
ARMA results for Canadan tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-8.85
BIC	-8.37
Mean Absolute Percentage Error (MAPE)	2.48%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.65

Forecast Statistics	**Value**
Durbin Watson(1)	1.91
Mean	3.85
Standard Deviation	0.16
Auto-Correlation	-0.05
Auto-Covariance	0.00
Ljung-Box	5.59

Table 5A.2.21
ARMA results for Canadan tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-14.83
BIC	-14.35
Mean Absolute Percentage Error (MAPE)	2.55%
R-Square	60.35%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.73

Forecast Statistics	**Value**
Durbin Watson(1)	1.29
Mean	3.15
Standard Deviation	0.20
Auto-Correlation	0.53
Auto-Covariance	0.02
Ljung-Box	4.59

Table 5A.2.22
ARMA results for Canadan tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-5.15
BIC	-4.66
Mean Absolute Percentage Error (MAPE)	3.25%
R-Square	50.33%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.93

Forecast Statistics	Value
Durbin Watson(1)	1.71
Mean	3.58
Standard Deviation	0.27
Auto-Correlation	0.43
Auto-Covariance	0.03
Ljung-Box	3.12

Table 5A.2.23
ARMA results for Canadan tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.78
BIC	-10.29
Mean Absolute Percentage Error (MAPE)	2.76%
R-Square	37.44%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.93

Forecast Statistics	Value
Durbin Watson(1)	1.69
Mean	3.70
Standard Deviation	0.19
Auto-Correlation	0.50
Auto-Covariance	0.02
Ljung-Box	6.13

Table 5A.2.24
ARMA results for Canadan tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	9.42
BIC	9.90
Mean Absolute Percentage Error (MAPE)	8.60%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.92

Forecast Statistics	Value
Durbin Watson(1)	1.41
Mean	3.24
Standard Deviation	0.34
Auto-Correlation	0.21
Auto-Covariance	0.02
Ljung-Box	8.14

Table 5A.2.25
ARMA results for Canadan tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.13
BIC	-5.65
Mean Absolute Percentage Error (MAPE)	3.41%
R-Square	19.34%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.31

Forecast Statistics	Value
Durbin Watson(1)	1.93
Mean	3.86
Standard Deviation	0.20
Auto-Correlation	0.35
Auto-Covariance	0.01
Ljung-Box	4.32

Table 5A.2.26
ARMA results for Canadan tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.33
BIC	-1.36
Mean Absolute Percentage Error (MAPE)	4.72%
R-Square	15.90%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	54.79
T-Test For Non Seasonal MA	1.53

Forecast Statistics	Value
Durbin Watson(1)	1.70
Mean	3.29
Standard Deviation	0.21
Auto-Correlation	-0.38
Auto-Covariance	-0.02
Ljung-Box	7.92

Table 5A.2.27
ARMA results for Canadan tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	14.87
BIC	15.84
Mean Absolute Percentage Error (MAPE)	7.73%
R-Square	33.64%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	31.13
T-Test For Non Seasonal MA	2.89

Forecast Statistics	Value
Durbin Watson(1)	1.52
Mean	3.85
Standard Deviation	0.49
Auto-Correlation	-0.25
Auto-Covariance	-0.06
Ljung-Box	7.54

Table 5A.2.28
ARMA results for Canadan tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	6.29
BIC	6.78
Mean Absolute Percentage Error (MAPE)	6.37%
R-Square	30.30%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.27

Forecast Statistics	Value
Durbin Watson(1)	1.81
Mean	3.25
Standard Deviation	0.36
Auto-Correlation	0.34
Auto-Covariance	0.04
Ljung-Box	2.98

Table 5A.2.29
ARMA results for Canadan tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.41
BIC	2.38
Mean Absolute Percentage Error (MAPE)	7.13%
R-Square	61.31%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	1.83
T-Test For Non Seasonal MA	-2.30

Forecast Statistics	Value
Durbin Watson(1)	1.11
Mean	2.43
Standard Deviation	0.36
Auto-Correlation	0.57
Auto-Covariance	0.07
Ljung-Box	10.08

Table 5A.2.30
ARMA results for Canadan tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.98
BIC	-3.49
Mean Absolute Percentage Error (MAPE)	7.47%
R-Square	27.95%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-0.15

Forecast Statistics	Value
Durbin Watson(1)	1.92
Mean	2.14
Standard Deviation	0.23
Auto-Correlation	0.46
Auto-Covariance	0.02
Ljung-Box	7.55

Table 5A.2.31
ARMA results for Canadian tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-5.65
BIC	-5.17
Mean Absolute Percentage Error (MAPE)	3.74%
R-Square	4.86%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.11

Forecast Statistics	Value
Durbin Watson(1)	2.28
Mean	3.22
Standard Deviation	0.19
Auto-Correlation	0.19
Auto-Covariance	0.01
Ljung-Box	2.90

Table 5A.3.1
ARMA results for French tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-15.69
BIC	-15.20
Mean Absolute Percentage Error (MAPE)	1.80%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.81

Forecast Statistics	Value
Durbin Watson(1)	1.84
Mean	4.92
Standard Deviation	0.12
Auto-Correlation	0.13
Auto-Covariance	0.00
Ljung-Box	2.93

Table 5A.3.2
ARMA results for French tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-1.00
BIC	-0.52
Mean Absolute Percentage Error (MAPE)	4.78%
R-Square	36.26%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.76

Forecast Statistics	Value
Durbin Watson(1)	1.64
Mean	3.50
Standard Deviation	0.28
Auto-Correlation	0.47
Auto-Covariance	0.03
Ljung-Box	12.32

Table 5A.3.3
ARMA results for French tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	18.64
BIC	19.61
Mean Absolute Percentage Error (MAPE)	9.21%
R-Square	2.61%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.55
T-Test For Constant	3.10

Forecast Statistics	Value
Durbin Watson(1)	1.76
Mean	3.93
Standard Deviation	0.47
Auto-Correlation	-0.14
Auto-Covariance	-0.03
Ljung-Box	6.75

Table 5A.3.4
ARMA results for French tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	0.73
BIC	1.21
Mean Absolute Percentage Error (MAPE)	3.72%
R-Square	25.67%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.35

Forecast Statistics	Value
Durbin Watson(1)	2.07
Mean	3.78
Standard Deviation	0.28
Auto-Correlation	0.17
Auto-Covariance	0.01
Ljung-Box	2.66

Table 5A.3.5
ARMA results for French tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	6.87
BIC	7.36
Mean Absolute Percentage Error (MAPE)	6.20%
R-Square	20.40%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.96

Forecast Statistics	Value
Durbin Watson(1)	1.85
Mean	2.87
Standard Deviation	0.35
Auto-Correlation	0.44
Auto-Covariance	0.05
Ljung-Box	2.44

Table 5A.3.6
ARMA results for French tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.23
BIC	-9.74
Mean Absolute Percentage Error (MAPE)	3.54%
R-Square	43.44%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.06

Forecast Statistics	Value
Durbin Watson(1)	1.79
Mean	3.49
Standard Deviation	0.20
Auto-Correlation	0.47
Auto-Covariance	0.02
Ljung-Box	5.46

Table 5A.3.7
ARMA results for French tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.22
BIC	7.70
Mean Absolute Percentage Error (MAPE)	6.67%
R-Square	44.60%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.75

Forecast Statistics	Value
Durbin Watson(1)	1.71
Mean	2.88
Standard Deviation	0.42
Auto-Correlation	0.45
Auto-Covariance	0.07
Ljung-Box	5.13

Table 5A.3.8
ARMA results for French tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	4.68
BIC	5.16
Mean Absolute Percentage Error (MAPE)	6.64%
R-Square	11.60%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.75

Forecast Statistics	Value
Durbin Watson(1)	1.72
Mean	3.20
Standard Deviation	0.30
Auto-Correlation	0.18
Auto-Covariance	0.01
Ljung-Box	3.89

Table 5A.3.9
ARMA results for French tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-1.91
BIC	-1.43
Mean Absolute Percentage Error (MAPE)	3.28%
R-Square	13.36%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.41

Forecast Statistics	Value
Durbin Watson(1)	1.94
Mean	4.67
Standard Deviation	0.23
Auto-Correlation	0.30
Auto-Covariance	0.01
Ljung-Box	3.95

Table 5A.3.10
ARMA results for French tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-13.44
BIC	-12.95
Mean Absolute Percentage Error (MAPE)	2.18%
R-Square	54.20%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.43

Forecast Statistics	**Value**
Durbin Watson(1)	1.84
Mean	4.48
Standard Deviation	0.20
Auto-Correlation	0.57
Auto-Covariance	0.02
Ljung-Box	2.92

Table 5A.3.11
ARMA results for French tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-9.90
BIC	-9.42
Mean Absolute Percentage Error (MAPE)	2.25%
R-Square	62.55%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.96

Forecast Statistics	**Value**
Durbin Watson(1)	1.59
Mean	4.22
Standard Deviation	0.25
Auto-Correlation	0.58
Auto-Covariance	0.03
Ljung-Box	5.19

Table 5A.3.12
ARMA results for French tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-5.80
BIC	-5.32
Mean Absolute Percentage Error (MAPE)	3.60%
R-Square	61.38%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.00

Forecast Statistics	**Value**
Durbin Watson(1)	1.76
Mean	3.57
Standard Deviation	0.29
Auto-Correlation	0.57
Auto-Covariance	0.05
Ljung-Box	4.23

Table 5A.3.13
ARMA results for French tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.53
BIC	-0.05
Mean Absolute Percentage Error (MAPE)	4.77%
R-Square	43.72%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.14

Forecast Statistics	Value
Durbin Watson(1)	1.79
Mean	3.48
Standard Deviation	0.30
Auto-Correlation	0.49
Auto-Covariance	0.04
Ljung-Box	6.14

Table 5A.3.14
ARMA results for French tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	6.63
BIC	7.12
Mean Absolute Percentage Error (MAPE)	6.32%
R-Square	30.68%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.32

Forecast Statistics	Value
Durbin Watson(1)	1.44
Mean	3.05
Standard Deviation	0.37
Auto-Correlation	0.34
Auto-Covariance	0.04
Ljung-Box	7.72

Table 5A.3.15
ARMA results for French tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-9.83
BIC	-9.35
Mean Absolute Percentage Error (MAPE)	2.84%
R-Square	53.38%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.73

Forecast Statistics	Value
Durbin Watson(1)	1.35
Mean	3.75
Standard Deviation	0.23
Auto-Correlation	0.46
Auto-Covariance	0.02
Ljung-Box	4.03

Table 5A.3.16
ARMA results for French tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-2.54
BIC	-2.05
Mean Absolute Percentage Error (MAPE)	4.13%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.77

Forecast Statistics	**Value**
Durbin Watson(1)	1.86
Mean	3.86
Standard Deviation	0.21
Auto-Correlation	0.08
Auto-Covariance	0.00
Ljung-Box	7.24

Table 5A.3.17
ARMA results for French tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	9.98
BIC	10.47
Mean Absolute Percentage Error (MAPE)	5.76%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.02

Forecast Statistics	**Value**
Durbin Watson(1)	1.98
Mean	4.24
Standard Deviation	0.35
Auto-Correlation	-0.11
Auto-Covariance	-0.01
Ljung-Box	6.19

Table 5A.3.18
ARMA results for French tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	6.19
BIC	7.16
Mean Absolute Percentage Error (MAPE)	7.07%
R-Square	16.84%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	39.04
T-Test For Non Seasonal MA	1.68

Forecast Statistics	**Value**
Durbin Watson(1)	1.68
Mean	3.34
Standard Deviation	0.30
Auto-Correlation	-0.38
Auto-Covariance	-0.03
Ljung-Box	6.26

Table 5A.3.19
ARMA results for French tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-4.09
BIC	-3.12
Mean Absolute Percentage Error (MAPE)	2.77%
R-Square	3.99%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.18
T-Test For Non Seasonal MA	-0.07

Forecast Statistics	Value
Durbin Watson(1)	1.74
Mean	4.61
Standard Deviation	0.18
Auto-Correlation	0.15
Auto-Covariance	0.00
Ljung-Box	1.57

Table 5A.3.20
ARMA results for French tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.11
BIC	-5.14
Mean Absolute Percentage Error (MAPE)	3.34%
R-Square	27.57%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	86.68
T-Test For Non Seasonal MA	2.43

Forecast Statistics	Value
Durbin Watson(1)	1.61
Mean	4.36
Standard Deviation	0.19
Auto-Correlation	-0.31
Auto-Covariance	-0.01
Ljung-Box	6.37

Table 5A.3.21
ARMA results for French tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-4.53
BIC	-4.05
Mean Absolute Percentage Error (MAPE)	4.15%
R-Square	40.92%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.05

Forecast Statistics	Value
Durbin Watson(1)	1.06
Mean	3.06
Standard Deviation	0.25
Auto-Correlation	0.32
Auto-Covariance	0.02
Ljung-Box	5.07

Table 5A.3.22
ARMA results for French tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.66
BIC	-6.17
Mean Absolute Percentage Error (MAPE)	3.39%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.92

Forecast Statistics	Value
Durbin Watson(1)	2.03
Mean	3.84
Standard Deviation	0.17
Auto-Correlation	-0.06
Auto-Covariance	0.00
Ljung-Box	7.97

Table 5A.3.23
ARMA results for French tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.40
BIC	-2.92
Mean Absolute Percentage Error (MAPE)	3.81%
R-Square	14.03%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.37

Forecast Statistics	Value
Durbin Watson(1)	1.47
Mean	3.94
Standard Deviation	0.22
Auto-Correlation	0.32
Auto-Covariance	0.01
Ljung-Box	9.05

Table 5A.3.24
ARMA results for French tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-8.71
BIC	-7.74
Mean Absolute Percentage Error (MAPE)	3.30%
R-Square	37.86%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	79.38
T-Test For Non Seasonal MA	3.29

Forecast Statistics	Value
Durbin Watson(1)	1.55
Mean	3.57
Standard Deviation	0.19
Auto-Correlation	-0.35
Auto-Covariance	-0.01
Ljung-Box	6.06

Table 5A.3.25
ARMA results for French tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-2.28
BIC	-1.79
Mean Absolute Percentage Error (MAPE)	3.89%
R-Square	12.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.85

Forecast Statistics	**Value**
Durbin Watson(1)	1.70
Mean	4.17
Standard Deviation	0.23
Auto-Correlation	0.35
Auto-Covariance	0.02
Ljung-Box	1.76

Table 5A.3.26
ARMA results for French tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-7.00
BIC	-6.51
Mean Absolute Percentage Error (MAPE)	3.33%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.15

Forecast Statistics	**Value**
Durbin Watson(1)	2.44
Mean	3.74
Standard Deviation	0.17
Auto-Correlation	-0.27
Auto-Covariance	-0.01
Ljung-Box	5.44

Table 5A.3.27
ARMA results for French tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	23.14
BIC	24.11
Mean Absolute Percentage Error (MAPE)	10.05%
R-Square	7.21%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.95
T-Test For Constant	3.34

Forecast Statistics	**Value**
Durbin Watson(1)	1.88
Mean	4.30
Standard Deviation	0.58
Auto-Correlation	-0.25
Auto-Covariance	-0.08
Ljung-Box	2.46

Table 5A.3.28
ARMA results for French tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-12.95
BIC	-12.47
Mean Absolute Percentage Error (MAPE)	2.55%
R-Square	41.50%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.80

Forecast Statistics	**Value**
Durbin Watson(1)	1.81
Mean	3.74
Standard Deviation	0.18
Auto-Correlation	0.44
Auto-Covariance	0.01
Ljung-Box	4.47

Table 5A.3.29
ARMA results for French tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-6.56
BIC	-6.08
Mean Absolute Percentage Error (MAPE)	5.05%
R-Square	34.63%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.69

Forecast Statistics	**Value**
Durbin Watson(1)	2.15
Mean	2.95
Standard Deviation	0.22
Auto-Correlation	0.32
Auto-Covariance	0.01
Ljung-Box	7.29

Table 5A.3.30
ARMA results for French tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	7.46
BIC	7.95
Mean Absolute Percentage Error (MAPE)	11.01%
R-Square	11.64%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.36

Forecast Statistics	**Value**
Durbin Watson(1)	1.82
Mean	2.20
Standard Deviation	0.34
Auto-Correlation	0.31
Auto-Covariance	0.03
Ljung-Box	8.25

Table 5A.3.31
ARMA results for French tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.33
BIC	-9.36
Mean Absolute Percentage Error (MAPE)	2.86%
R-Square	36.13%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.12
T-Test For Non Seasonal MA	1.16

Forecast Statistics	Value
Durbin Watson(1)	1.47
Mean	3.64
Standard Deviation	0.17
Auto-Correlation	-0.34
Auto-Covariance	-0.01
Ljung-Box	6.00

Table 5A.4.1
ARMA results for German tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-21.06
BIC	-20.58
Mean Absolute Percentage Error (MAPE)	1.42%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.57

Forecast Statistics	Value
Durbin Watson(1)	1.72
Mean	5.02
Standard Deviation	0.09
Auto-Correlation	-0.06
Auto-Covariance	0.00

Table 5A.4.2
ARMA results for German tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.99
BIC	-0.02
Mean Absolute Percentage Error (MAPE)	3.70%
R-Square	30.35%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-2.91
T-Test For Non Seasonal MA	-0.98

Forecast Statistics	Value
Durbin Watson(1)	1.89
Mean	3.69
Standard Deviation	0.25
Auto-Correlation	0.00
Auto-Covariance	0.00
Ljung-Box	6.30

Table 5A.4.3
ARMA results for German tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	18.65
BIC	19.62
Mean Absolute Percentage Error (MAPE)	9.30%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.54
T-Test For Non Seasonal MA	0.88

Forecast Statistics	Value
Durbin Watson(1)	1.87
Mean	3.82
Standard Deviation	0.45
Auto-Correlation	0.06
Auto-Covariance	0.01
Ljung-Box	0.95

Table 5A.4.4
ARMA results for German tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-6.24
BIC	-5.75
Mean Absolute Percentage Error (MAPE)	3.95%
R-Square	58.09%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-4.55

Forecast Statistics	**Value**
Durbin Watson(1)	1.55
Mean	3.60
Standard Deviation	0.28
Auto-Correlation	0.22
Auto-Covariance	0.02
Ljung-Box	5.89

Table 5A.4.5
ARMA results for German tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	1.14
BIC	1.62
Mean Absolute Percentage Error (MAPE)	4.90%
R-Square	47.13%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.30

Forecast Statistics	**Value**
Durbin Watson(1)	1.75
Mean	3.09
Standard Deviation	0.34
Auto-Correlation	0.43
Auto-Covariance	0.04
Ljung-Box	4.06

Table 5A.4.6
ARMA results for German tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-10.14
BIC	-9.65
Mean Absolute Percentage Error (MAPE)	2.56%
R-Square	67.87%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.70

Forecast Statistics	**Value**
Durbin Watson(1)	1.75
Mean	3.80
Standard Deviation	0.27
Auto-Correlation	0.67
Auto-Covariance	0.04
Ljung-Box	7.45

Table 5A.4.7
ARMA results for German tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.98
BIC	8.46
Mean Absolute Percentage Error (MAPE)	5.64%
R-Square	21.76%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.15

Forecast Statistics	Value
Durbin Watson(1)	1.95
Mean	3.70
Standard Deviation	0.37
Auto-Correlation	0.45
Auto-Covariance	0.06
Ljung-Box	5.70

Table 5A.4.8
ARMA results for German tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.79
BIC	2.76
Mean Absolute Percentage Error (MAPE)	4.54%
R-Square	5.51%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.22
T-Test For Constant	0.20

Forecast Statistics	Value
Durbin Watson(1)	2.05
Mean	3.20
Standard Deviation	0.24
Auto-Correlation	0.16
Auto-Covariance	0.01
Ljung-Box	2.21

Table 5A.4.9
ARMA results for German tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-18.54
BIC	-17.57
Mean Absolute Percentage Error (MAPE)	1.34%
R-Square	83.46%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	1.91
T-Test For Constant	0.71

Forecast Statistics	Value
Durbin Watson(1)	1.97
Mean	4.85
Standard Deviation	0.24
Auto-Covariance	0.04
Ljung-Box	3.29

Table 5A.4.10
ARMA results for German tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-24.15
BIC	-23.67
Mean Absolute Percentage Error (MAPE)	1.10%
R-Square	83.09%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	1.41

Forecast Statistics	Value
Durbin Watson(1)	2.15
Mean	4.57
Standard Deviation	0.21
Auto-Correlation	0.68
Auto-Covariance	0.03
Ljung-Box	4.73

Table 5A.4.11
ARMA results for German tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-9.84
BIC	-9.35
Mean Absolute Percentage Error (MAPE)	2.44%
R-Square	63.55%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.93

Forecast Statistics	Value
Durbin Watson(1)	1.57
Mean	4.35
Standard Deviation	0.26
Auto-Correlation	0.57
Auto-Covariance	0.03
Ljung-Box	6.20

Table 5A.4.12
ARMA results for German tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.86
BIC	-6.37
Mean Absolute Percentage Error (MAPE)	3.17%
R-Square	72.83%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.54

Forecast Statistics	Value
Durbin Watson(1)	1.88
Mean	3.74
Standard Deviation	0.34
Auto-Correlation	0.68
Auto-Covariance	0.07
Ljung-Box	11.85

Table 5A.4.13
ARMA results for German tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	2.12
BIC	2.60
Mean Absolute Percentage Error (MAPE)	4.49%
R-Square	33.94%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.01

Forecast Statistics	**Value**
Durbin Watson(1)	1.96
Mean	3.71
Standard Deviation	0.31
Auto-Correlation	0.47
Auto-Covariance	0.04
Ljung-Box	4.57

Table 5A.4.14
ARMA results for German tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	7.69
BIC	8.18
Mean Absolute Percentage Error (MAPE)	7.08%
R-Square	22.06%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.95

Forecast Statistics	**Value**
Durbin Watson(1)	1.91
Mean	3.23
Standard Deviation	0.36
Auto-Correlation	0.28
Auto-Covariance	0.03
Ljung-Box	10.70

Table 5A.4.15
ARMA results for German tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-13.18
BIC	-12.70
Mean Absolute Percentage Error (MAPE)	2.09%
R-Square	46.79%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.28

Forecast Statistics	**Value**
Durbin Watson(1)	1.48
Mean	4.00
Standard Deviation	0.18
Auto-Correlation	0.46
Auto-Covariance	0.01
Ljung-Box	4.02

Table 5A.4.16
ARMA results for German tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.34
BIC	-2.85
Mean Absolute Percentage Error (MAPE)	3.74%
R-Square	24.32%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-4.03

Forecast Statistics	Value
Durbin Watson(1)	1.71
Mean	3.92
Standard Deviation	0.23
Auto-Correlation	-0.29
Auto-Covariance	-0.01
Ljung-Box	4.08

Table 5A.4.17
ARMA results for German tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-1.31
BIC	-0.34
Mean Absolute Percentage Error (MAPE)	4.31%
R-Square	37.25%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	57.15
T-Test For Non Seasonal MA	3.28

Forecast Statistics	Value
Durbin Watson(1)	1.55
Mean	3.50
Standard Deviation	0.26
Auto-Correlation	-0.29
Auto-Covariance	-0.02
Ljung-Box	7.91

Table 5A.4.18
ARMA results for German tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	219.98
BIC	220.95
Mean Absolute Percentage Error (MAPE)	48.77%
R-Square	11.83%
Adjusted R-Square	3.02%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.35
T-Test For Constant	0.00

Forecast Statistics	Value
Durbin Watson(1)	1.66
Mean	3,681.42
Standard Deviation	2,179.35
Auto-Correlation	-0.23
Ljung-Box	5.59

Table 5A.4.19
ARMA results for German tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-8.79
BIC	-8.31
Mean Absolute Percentage Error (MAPE)	2.44%
R-Square	1.50%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.71

Forecast Statistics	**Value**
Durbin Watson(1)	1.79
Mean	4.62
Standard Deviation	0.16
Auto-Correlation	0.19
Auto-Covariance	0.00
Ljung-Box	2.88

Table 5A.4.20
ARMA results for German tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-16.65
BIC	-15.68
Mean Absolute Percentage Error (MAPE)	1.86%
R-Square	44.99%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	134.19
T-Test For Non Seasonal MA	3.29

Forecast Statistics	**Value**
Durbin Watson(1)	1.80
Mean	4.36
Standard Deviation	0.14
Auto-Correlation	-0.20
Auto-Covariance	0.00
Ljung-Box	7.92

Table 5A.4.21
ARMA results for German tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-3.53
BIC	-3.05
Mean Absolute Percentage Error (MAPE)	4.07%
R-Square	17.58%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.03

Forecast Statistics	**Value**
Durbin Watson(1)	1.52
Mean	3.44
Standard Deviation	0.22
Auto-Correlation	0.17
Auto-Covariance	0.01
Ljung-Box	6.90

Table 5A.4.22
ARMA results for German tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	5.44
BIC	5.93
Mean Absolute Percentage Error (MAPE)	4.95%
R-Square	50.36%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.76

Forecast Statistics	Value
Durbin Watson(1)	2.00
Mean	4.00
Standard Deviation	0.41
Auto-Correlation	0.54
Auto-Covariance	0.09
Ljung-Box	4.23

Table 5A.4.23
ARMA results for German tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.98
BIC	-3.50
Mean Absolute Percentage Error (MAPE)	3.54%
R-Square	10.94%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.18

Forecast Statistics	Value
Durbin Watson(1)	1.72
Mean	4.02
Standard Deviation	0.21
Auto-Correlation	0.36
Auto-Covariance	0.01
Ljung-Box	6.54

Table 5A.4.24
ARMA results for German tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.05
BIC	-2.08
Mean Absolute Percentage Error (MAPE)	4.73%
R-Square	20.06%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	56.11
T-Test For Non Seasonal MA	1.90

Forecast Statistics	Value
Durbin Watson(1)	1.60
Mean	3.31
Standard Deviation	0.21
Auto-Correlation	-0.31
Auto-Covariance	-0.01
Ljung-Box	2.69

Table 5A.4.25
ARMA results for German tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-12.69
BIC	-12.20
Mean Absolute Percentage Error (MAPE)	2.51%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.43

Forecast Statistics	**Value**
Durbin Watson(1)	1.58
Mean	4.20
Standard Deviation	0.13
Auto-Correlation	0.14
Auto-Covariance	0.00
Ljung-Box	5.17

Table 5A.4.26
ARMA results for German tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-8.58
BIC	-7.61
Mean Absolute Percentage Error (MAPE)	2.51%
R-Square	17.34%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.52
T-Test For Constant	3.64

Forecast Statistics	**Value**
Durbin Watson(1)	1.87
Mean	3.97
Standard Deviation	0.16
Auto-Correlation	-0.42
Auto-Covariance	-0.01
Ljung-Box	5.54

Table 5A.4.27
ARMA results for German tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	24.35
BIC	25.32
Mean Absolute Percentage Error (MAPE)	11.30%
R-Square	12.77%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	24.05
T-Test For Non Seasonal MA	1.41

Forecast Statistics	**Value**
Durbin Watson(1)	1.89
Mean	4.30
Standard Deviation	0.63
Auto-Correlation	-0.32
Auto-Covariance	-0.12
Ljung-Box	1.89

Table 5A.4.28
ARMA results for German tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.80
BIC	-11.83
Mean Absolute Percentage Error (MAPE)	2.62%
R-Square	1.29%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.09
T-Test For Non Seasonal MA	0.05

Forecast Statistics	Value
Durbin Watson(1)	1.66
Mean	3.83
Standard Deviation	0.13
Auto-Correlation	-0.06
Auto-Covariance	0.00
Ljung-Box	3.32

Table 5A.4.29
ARMA results for German tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.87
BIC	-9.90
Mean Absolute Percentage Error (MAPE)	3.80%
R-Square	30.59%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	71.55
T-Test For Non Seasonal MA	3.31

Forecast Statistics	Value
Durbin Watson(1)	1.44
Mean	2.94
Standard Deviation	0.16
Auto-Correlation	-0.03
Auto-Covariance	0.00
Ljung-Box	17.17

Table 5A.4.30
ARMA results for German tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.59
BIC	-1.62
Mean Absolute Percentage Error (MAPE)	6.76%
R-Square	22.66%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.27
T-Test For Constant	3.76

Forecast Statistics	Value
Durbin Watson(1)	2.00
Mean	2.34
Standard Deviation	0.22
Auto-Correlation	0.29
Auto-Covariance	0.01
Ljung-Box	11.57

Table 5A.4.31
ARMA results for German tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-9.15
BIC	-8.18
Mean Absolute Percentage Error (MAPE)	3.11%
R-Square	12.76%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	83.14
T-Test For Non Seasonal MA	1.58

Forecast Statistics	**Value**
Durbin Watson(1)	1.68
Mean	3.70
Standard Deviation	0.16
Auto-Correlation	-0.23
Auto-Covariance	-0.01
Ljung-Box	2.40

Table 5A.5.1
ARMA results for Japanese tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.74
BIC	4.22
Mean Absolute Percentage Error (MAPE)	3.56%
R-Square	25.04%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.01

Forecast Statistics	Value
Durbin Watson(1)	1.74
Mean	4.81
Standard Deviation	0.31
Auto-Correlation	0.58
Auto-Covariance	0.05
Ljung-Box	9.63

Table 5A.5.2
ARMA results for Japanese tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	5.64
BIC	6.61
Mean Absolute Percentage Error (MAPE)	3.61%
R-Square	25.62%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.22
T-Test For Non Seasonal MA	-0.06

Forecast Statistics	Value
Durbin Watson(1)	1.80
Mean	4.81
Standard Deviation	0.31
Auto-Correlation	0.58
Auto-Covariance	0.05
Ljung-Box	9.63

Table 5A.5.3
ARMA results for Japanese tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	18.23
BIC	19.20
Mean Absolute Percentage Error (MAPE)	5.94%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	0.11
T-Test For Non Seasonal MA	0.11

Forecast Statistics	Value
Durbin Watson(1)	3.01
Mean	4.54
Standard Deviation	0.35
Auto-Correlation	0.04
Auto-Covariance	0.00
Ljung-Box	5.67

Table 5A.5.4
ARMA results for Japanese tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.28
BIC	-1.80
Mean Absolute Percentage Error (MAPE)	3.29%
R-Square	1.22%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.89

Forecast Statistics	Value
Durbin Watson(1)	1.97
Mean	4.48
Standard Deviation	0.21
Auto-Correlation	-0.37
Auto-Covariance	-0.02
Ljung-Box	1.99

Table 5A.5.5
ARMA results for Japanese tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.00
BIC	1.97
Mean Absolute Percentage Error (MAPE)	3.79%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.98
T-Test For Non Seasonal MA	-0.10

Forecast Statistics	Value
Durbin Watson(1)	1.81
Mean	4.14
Standard Deviation	0.22
Auto-Correlation	-0.15
Auto-Covariance	-0.01
Ljung-Box	3.08

Table 5A.5.6
ARMA results for Japanese tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-13.17
BIC	-12.20
Mean Absolute Percentage Error (MAPE)	1.63%
R-Square	77.29%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.52
T-Test For Non Seasonal MA	-0.18

Forecast Statistics	Value
Durbin Watson(1)	1.72
Mean	5.25
Standard Deviation	0.26
Auto-Correlation	0.69
Auto-Covariance	0.04
Ljung-Box	10.34

Table 5A.5.7
ARMA results for Japanese tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-15.70
BIC	-14.73
Mean Absolute Percentage Error (MAPE)	1.90%
R-Square	61.34%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.47
T-Test For Non Seasonal MA	-0.16

Forecast Statistics	Value
Durbin Watson(1)	1.58
Mean	4.29
Standard Deviation	0.18
Auto-Correlation	0.55
Auto-Covariance	0.02
Ljung-Box	9.13

Table 5A.5.8
ARMA results for Japanese tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.57
BIC	-3.09
Mean Absolute Percentage Error (MAPE)	3.24%
R-Square	29.44%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.53

Forecast Statistics	Value
Durbin Watson(1)	1.72
Mean	4.45
Standard Deviation	0.24
Auto-Correlation	0.28
Auto-Covariance	0.01
Ljung-Box	8.19

Table 5A.5.9
ARMA results for Japanese tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-21.15
BIC	-20.18
Mean Absolute Percentage Error (MAPE)	0.94%
R-Square	58.86%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.24
T-Test For Non Seasonal MA	-0.08

Forecast Statistics	Value
Durbin Watson(1)	1.89
Mean	5.81
Standard Deviation	0.14
Auto-Correlation	0.60
Auto-Covariance	0.01
Ljung-Box	3.75

Table 5A.5.10
ARMA results for Japanese tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-26.96
BIC	-25.99
Mean Absolute Percentage Error (MAPE)	0.83%
R-Square	86.26%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	0.34
T-Test For Non Seasonal MA	0.13

Forecast Statistics	Value
Durbin Watson(1)	2.15
Mean	5.48
Standard Deviation	0.19
Auto-Correlation	0.70
Auto-Covariance	0.02
Ljung-Box	7.37

Table 5A.5.11
ARMA results for Japanese tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.70
BIC	-12.22
Mean Absolute Percentage Error (MAPE)	1.55%
R-Square	62.04%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.71

Forecast Statistics	Value
Durbin Watson(1)	2.19
Mean	5.23
Standard Deviation	0.22
Auto-Correlation	0.61
Auto-Covariance	0.03
Ljung-Box	9.27

Table 5A.5.12
ARMA results for Japanese tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-15.85
BIC	-14.88
Mean Absolute Percentage Error (MAPE)	1.88%
R-Square	66.32%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-1.48
T-Test For Non Seasonal MA	-0.38

Forecast Statistics	Value
Durbin Watson(1)	1.82
Mean	4.52
Standard Deviation	0.19
Auto-Correlation	0.57
Auto-Covariance	0.02
Ljung-Box	6.69

Table 5A.5.13
ARMA results for Japanese tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	39.57
BIC	40.05
Mean Absolute Percentage Error (MAPE)	9.79%
R-Square	4.76%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-0.03

Forecast Statistics	Value
Durbin Watson(1)	2.00
Mean	4.51
Standard Deviation	1.24
Auto-Correlation	0.07
Auto-Covariance	0.10
Ljung-Box	1.52

Table 5A.5.14
ARMA results for Japanese tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-13.30
BIC	-12.81
Mean Absolute Percentage Error (MAPE)	2.32%
R-Square	3.53%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.90

Forecast Statistics	Value
Durbin Watson(1)	1.58
Mean	4.06
Standard Deviation	0.14
Auto-Correlation	0.20
Auto-Covariance	0.00
Ljung-Box	5.29

Table 5A.5.15
ARMA results for Japanese tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.79
BIC	-11.82
Mean Absolute Percentage Error (MAPE)	1.82%
R-Square	71.80%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.93
T-Test For Non Seasonal MA	-0.26

Forecast Statistics	Value
Durbin Watson(1)	1.58
Mean	5.09
Standard Deviation	0.24
Auto-Correlation	0.58
Auto-Covariance	0.03
Ljung-Box	9.85

Table 5A.5.16
ARMA results for Japanese tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-6.56
BIC	-5.59
Mean Absolute Percentage Error (MAPE)	2.69%
R-Square	13.83%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-1.12
T-Test For Non Seasonal MA	0.37

Forecast Statistics	**Value**
Durbin Watson(1)	1.47
Mean	4.56
Standard Deviation	0.18
Auto-Correlation	0.08
Auto-Covariance	0.00
Ljung-Box	4.61

Table 5A.5.17
ARMA results for Japanese tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	4.69
BIC	5.66
Mean Absolute Percentage Error (MAPE)	4.08%
R-Square	0.61%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	60.72
T-Test For Non Seasonal MA	-0.27

Forecast Statistics	**Value**
Durbin Watson(1)	1.76
Mean	4.76
Standard Deviation	0.26
Auto-Correlation	0.07
Auto-Covariance	0.00
Ljung-Box	7.73

Table 5A.5.18
ARMA results for Japanese tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-3.53
BIC	-2.56
Mean Absolute Percentage Error (MAPE)	3.86%
R-Square	1.21%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	76.48
T-Test For Non Seasonal MA	0.35

Forecast Statistics	**Value**
Durbin Watson(1)	1.83
Mean	4.27
Standard Deviation	0.19
Auto-Correlation	-0.11
Auto-Covariance	0.00
Ljung-Box	5.72

Table 5A.5.19
ARMA results for Japanese tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-13.18
BIC	-12.70
Mean Absolute Percentage Error (MAPE)	1.61%
R-Square	65.06%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.24

Forecast Statistics	**Value**
Durbin Watson(1)	1.80
Mean	5.60
Standard Deviation	0.23
Auto-Correlation	0.62
Auto-Covariance	0.03
Ljung-Box	7.68

Table 5A.5.20
ARMA results for Japanese tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-24.28
BIC	-23.80
Mean Absolute Percentage Error (MAPE)	1.23%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.12

Forecast Statistics	**Value**
Durbin Watson(1)	1.92
Mean	4.92
Standard Deviation	0.08
Auto-Correlation	0.02
Auto-Covariance	0.00
Ljung-Box	7.25

Table 5A.5.21
ARMA results for Japanese tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-9.79
BIC	-8.82
Mean Absolute Percentage Error (MAPE)	2.81%
R-Square	42.75%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	3.15
T-Test For Constant	4.30

Forecast Statistics	**Value**
Durbin Watson(1)	1.82
Mean	4.29
Standard Deviation	0.19
Auto-Correlation	0.46
Auto-Covariance	0.01
Ljung-Box	4.35

Table 5A.5.22
ARMA results for Japanese tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-7.16
BIC	-6.19
Mean Absolute Percentage Error (MAPE)	2.24%
R-Square	6.69%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-1.97
T-Test For Non Seasonal MA	0.31

Forecast Statistics	Value
Durbin Watson(1)	1.92
Mean	4.65
Standard Deviation	0.16
Auto-Correlation	-0.09
Auto-Covariance	0.00
Ljung-Box	4.05

Table 5A.5.23
ARMA results for Japanese tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	0.40
BIC	1.37
Mean Absolute Percentage Error (MAPE)	3.39%
R-Square	25.85%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	1.95
T-Test For Constant	3.49

Forecast Statistics	Value
Durbin Watson(1)	2.04
Mean	4.83
Standard Deviation	0.25
Auto-Correlation	0.46
Auto-Covariance	0.03
Ljung-Box	6.34

Table 5A.5.24
ARMA results for Japanese tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.34
BIC	-11.37
Mean Absolute Percentage Error (MAPE)	2.41%
R-Square	20.08%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	103.00
T-Test For Non Seasonal MA	3.28

Forecast Statistics	Value
Durbin Watson(1)	1.24
Mean	4.02
Standard Deviation	0.14
Auto-Correlation	-0.29
Auto-Covariance	-0.01
Ljung-Box	9.29

Table 5A.5.25
ARMA results for Japanese tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-7.28
BIC	-6.79
Mean Absolute Percentage Error (MAPE)	2.43%
R-Square	29.81%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.00

Forecast Statistics	Value
Durbin Watson(1)	2.15
Mean	4.85
Standard Deviation	0.20
Auto-Correlation	0.49
Auto-Covariance	0.02
Ljung-Box	6.41

Table 5A.5.26
ARMA results for Japanese tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.67
BIC	-2.70
Mean Absolute Percentage Error (MAPE)	3.34%
R-Square	38.06%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.11
T-Test For Constant	0.06

Forecast Statistics	Value
Durbin Watson(1)	1.70
Mean	3.93
Standard Deviation	0.23
Auto-Correlation	-0.57
Auto-Covariance	-0.03
Ljung-Box	5.71

Table 5A.5.27
ARMA results for Japanese tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	15.58
BIC	16.55
Mean Absolute Percentage Error (MAPE)	5.22%
R-Square	7.89%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-1.20
T-Test For Non Seasonal MA	2.42

Forecast Statistics	Value
Durbin Watson(1)	1.97
Mean	5.03
Standard Deviation	0.43
Auto-Correlation	-0.29
Auto-Covariance	-0.05
Ljung-Box	1.26

Table 5A.5.28
ARMA results for Japanese tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-9.40
BIC	-8.43
Mean Absolute Percentage Error (MAPE)	2.09%
R-Square	4.09%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.70
T-Test For Constant	3.37

Forecast Statistics	Value
Durbin Watson(1)	1.97
Mean	4.55
Standard Deviation	0.15
Auto-Correlation	-0.20
Auto-Covariance	0.00
Ljung-Box	2.42

Table 5A.5.29
ARMA results for Japanese tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-7.31
BIC	-6.83
Mean Absolute Percentage Error (MAPE)	3.55%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.75

Forecast Statistics	Value
Durbin Watson(1)	1.97
Mean	3.42
Standard Deviation	0.17
Auto-Correlation	0.37
Auto-Covariance	0.01
Ljung-Box	3.69

Table 5A.5.30
ARMA results for Japanese tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-16.95
BIC	-15.98
Mean Absolute Percentage Error (MAPE)	2.38%
R-Square	2.62%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	100.46
T-Test For Non Seasonal MA	-0.81

Forecast Statistics	Value
Durbin Watson(1)	1.95
Mean	3.20
Standard Deviation	0.11
Auto-Correlation	0.10
Auto-Covariance	0.00
Ljung-Box	2.65

Table 5A.5.31
ARMA results for Japanese tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-14.76
BIC	-13.79
Mean Absolute Percentage Error (MAPE)	1.97%
R-Square	39.99%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	129.52
T-Test For Non Seasonal MA	3.18

Forecast Statistics	Value
Durbin Watson(1)	1.67
Mean	4.58
Standard Deviation	0.15
Auto-Correlation	-0.19
Auto-Covariance	0.00
Ljung-Box	5.68

Table 5A.6.1
ARMA results for Korean tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-4.56
BIC	-3.59
Mean Absolute Percentage Error (MAPE)	2.56%
R-Square	31.59%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.41
T-Test For Constant	3.63

Forecast Statistics	Value
Durbin Watson(1)	2.23
Mean	5.35
Standard Deviation	0.21
Auto-Correlation	0.44
Auto-Covariance	0.02
Ljung-Box	3.99

Table 5A.6.2
ARMA results for Korean tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.81
BIC	-3.32
Mean Absolute Percentage Error (MAPE)	3.07%
R-Square	51.68%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.41

Forecast Statistics	Value
Durbin Watson(1)	1.39
Mean	4.66
Standard Deviation	0.29
Auto-Correlation	0.67
Auto-Covariance	0.05
Ljung-Box	7.38

Table 5A.6.3
ARMA results for Korean tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	17.47
BIC	17.95
Mean Absolute Percentage Error (MAPE)	8.88%
R-Square	11.52%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.98

Forecast Statistics	Value
Durbin Watson(1)	2.22
Mean	4.14
Standard Deviation	0.51
Auto-Correlation	0.20
Auto-Covariance	0.05
Ljung-Box	4.94

Table 5A.6.4
ARMA results for Korean tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	4.65
BIC	5.62
Mean Absolute Percentage Error (MAPE)	5.32%
R-Square	41.53%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.90
T-Test For Non Seasonal MA	-0.32

Forecast Statistics	Value
Durbin Watson(1)	1.57
Mean	3.58
Standard Deviation	0.34
Auto-Correlation	0.50
Auto-Covariance	0.05
Ljung-Box	6.53

Table 5A.6.5
ARMA results for Korean tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	9.41
BIC	9.90
Mean Absolute Percentage Error (MAPE)	8.01%
R-Square	6.08%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.19

Forecast Statistics	Value
Durbin Watson(1)	1.89
Mean	3.23
Standard Deviation	0.36
Auto-Correlation	0.26
Auto-Covariance	0.03
Ljung-Box	2.83

Table 5A.6.6
ARMA results for Korean tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.91
BIC	3.88
Mean Absolute Percentage Error (MAPE)	3.59%
R-Square	37.52%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.82
T-Test For Constant	3.81

Forecast Statistics	Value
Durbin Watson(1)	2.66
Mean	5.11
Standard Deviation	0.31
Auto-Correlation	0.34
Auto-Covariance	0.03
Ljung-Box	10.72

Table 5A.6.7
ARMA results for Korean tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-3.81
BIC	-2.84
Mean Absolute Percentage Error (MAPE)	2.82%
R-Square	23.52%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	87.98
T-Test For Non Seasonal MA	3.21

Forecast Statistics	**Value**
Durbin Watson(1)	1.25
Mean	4.91
Standard Deviation	0.21
Auto-Correlation	-0.01
Auto-Covariance	0.00
Ljung-Box	21.24

Table 5A.6.8
ARMA results for Korean tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	7.48
BIC	8.45
Mean Absolute Percentage Error (MAPE)	5.46%
R-Square	18.17%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.06
T-Test For Constant	3.59

Forecast Statistics	**Value**
Durbin Watson(1)	2.58
Mean	4.10
Standard Deviation	0.32
Auto-Correlation	0.24
Auto-Covariance	0.02
Ljung-Box	10.03

Table 5A.6.9
ARMA results for Korean tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-7.83
BIC	-7.35
Mean Absolute Percentage Error (MAPE)	2.31%
R-Square	57.56%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.67

Forecast Statistics	**Value**
Durbin Watson(1)	1.91
Mean	5.12
Standard Deviation	0.26
Auto-Correlation	0.58
Auto-Covariance	0.04
Ljung-Box	10.76

Table 5A.6.10
ARMA results for Korean tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.20
BIC	-5.71
Mean Absolute Percentage Error (MAPE)	2.28%
R-Square	86.32%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.98

Forecast Statistics	Value
Mean	4.85
Standard Deviation	0.49
Auto-Correlation	0.74
Auto-Covariance	0.16
Ljung-Box	5.37

Table 5A.6.11
ARMA results for Korean tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	0.86
BIC	1.83
Mean Absolute Percentage Error (MAPE)	3.44%
R-Square	76.82%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	5.46
T-Test For Constant	6.89

Forecast Statistics	Value
Mean	4.91
Standard Deviation	0.46
Auto-Correlation	0.67
Auto-Covariance	0.13
Ljung-Box	4.75

Table 5A.6.12
ARMA results for Korean tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	10.93
BIC	11.90
Mean Absolute Percentage Error (MAPE)	6.20%
R-Square	53.05%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	1.67
T-Test For Constant	0.74

Forecast Statistics	Value
Durbin Watson(1)	2.07
Mean	4.23
Standard Deviation	0.49
Auto-Correlation	0.43
Auto-Covariance	0.10
Ljung-Box	5.77

Table 5A.6.13
ARMA results for Korean tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.11
BIC	3.59
Mean Absolute Percentage Error (MAPE)	4.66%
R-Square	69.20%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.41

Forecast Statistics	Value
Durbin Watson(1)	1.97
Mean	4.02
Standard Deviation	0.48
Auto-Correlation	0.63
Auto-Covariance	0.13
Ljung-Box	7.49

Table 5A.6.14
ARMA results for Korean tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.18
BIC	4.15
Mean Absolute Percentage Error (MAPE)	5.64%
R-Square	63.01%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.16
T-Test For Non Seasonal MA	-0.09

Forecast Statistics	Value
Durbin Watson(1)	1.45
Mean	3.25
Standard Deviation	0.40
Auto-Correlation	0.56
Auto-Covariance	0.08
Ljung-Box	4.98

Table 5A.6.15
ARMA results for Korean tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.22
BIC	0.75
Mean Absolute Percentage Error (MAPE)	3.14%
R-Square	61.73%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	3.91
T-Test For Constant	4.95

Forecast Statistics	Value
Durbin Watson(1)	2.50
Mean	5.20
Standard Deviation	0.34
Auto-Correlation	0.44
Auto-Covariance	0.05
Ljung-Box	12.30

Table 5A.6.16
ARMA results for Korean tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	5.79
BIC	6.28
Mean Absolute Percentage Error (MAPE)	6.08%
R-Square	34.73%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.88

Forecast Statistics	Value
Durbin Watson(1)	1.65
Mean	3.82
Standard Deviation	0.37
Auto-Correlation	0.31
Auto-Covariance	0.04
Ljung-Box	4.98

Table 5A.6.17
ARMA results for Korean tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.42
BIC	8.39
Mean Absolute Percentage Error (MAPE)	5.40%
R-Square	68.53%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.90
T-Test For Constant	1.30

Forecast Statistics	Value
Durbin Watson(1)	2.34
Mean	3.76
Standard Deviation	0.52
Auto-Correlation	0.66
Auto-Covariance	0.16
Ljung-Box	4.16

Table 5A.6.18
ARMA results for Korean tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	13.08
BIC	13.56
Mean Absolute Percentage Error (MAPE)	6.98%
R-Square	71.77%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.44

Forecast Statistics	Value
Durbin Watson(1)	2.19
Mean	4.27
Standard Deviation	0.75
Auto-Correlation	0.59
Auto-Covariance	0.31
Ljung-Box	4.63

Table 5A.6.19
ARMA results for Korean tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-6.72
BIC	-6.24
Mean Absolute Percentage Error (MAPE)	2.61%
R-Square	67.83%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.19

Forecast Statistics	**Value**
Durbin Watson(1)	1.88
Mean	4.84
Standard Deviation	0.31
Auto-Correlation	0.62
Auto-Covariance	0.05
Ljung-Box	12.88

Table 5A.6.20
ARMA results for Korean tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	8.37
BIC	9.34
Mean Absolute Percentage Error (MAPE)	5.34%
R-Square	36.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.65
T-Test For Constant	4.12

Forecast Statistics	**Value**
Durbin Watson(1)	2.00
Mean	4.57
Standard Deviation	0.38
Auto-Correlation	0.52
Auto-Covariance	0.07
Ljung-Box	2.31

Table 5A.6.21
ARMA results for Korean tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	21.15
BIC	21.63
Mean Absolute Percentage Error (MAPE)	10.36%
R-Square	56.89%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.66

Forecast Statistics	**Value**
Durbin Watson(1)	1.92
Mean	3.84
Standard Deviation	0.85
Auto-Correlation	0.63
Auto-Covariance	0.42
Ljung-Box	7.18

Table 5A.6.22
ARMA results for Korean tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.84
BIC	8.81
Mean Absolute Percentage Error (MAPE)	5.97%
R-Square	68.92%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.30
T-Test For Non Seasonal MA	-0.04

Forecast Statistics	Value
Durbin Watson(1)	1.82
Mean	3.69
Standard Deviation	0.53
Auto-Correlation	0.74
Auto-Covariance	0.19
Ljung-Box	7.78

Table 5A.6.23
ARMA results for Korean tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.87
BIC	-0.39
Mean Absolute Percentage Error (MAPE)	4.09%
R-Square	75.32%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-1.29

Forecast Statistics	Value
Durbin Watson(1)	2.19
Mean	3.96
Standard Deviation	0.45
Auto-Correlation	0.65
Auto-Covariance	0.12
Ljung-Box	5.48

Table 5A.6.24
ARMA results for Korean tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	12.71
BIC	13.19
Mean Absolute Percentage Error (MAPE)	8.50%
R-Square	7.58%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.44

Forecast Statistics	Value
Durbin Watson(1)	1.33
Mean	2.90
Standard Deviation	0.41
Auto-Correlation	0.15
Auto-Covariance	0.02
Ljung-Box	0.97

Table 5A.6.25
ARMA results for Korean tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.78
BIC	0.19
Mean Absolute Percentage Error (MAPE)	3.61%
R-Square	82.27%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	3.29
T-Test For Constant	1.40

Forecast Statistics	Value
Durbin Watson(1)	2.07
Mean	4.13
Standard Deviation	0.49
Auto-Correlation	0.70
Auto-Covariance	0.15
Ljung-Box	5.45

Table 5A.6.26
ARMA results for Korean tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	14.48
BIC	15.45
Mean Absolute Percentage Error (MAPE)	8.91%
R-Square	31.38%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-1.66
T-Test For Non Seasonal MA	-0.54

Forecast Statistics	Value
Durbin Watson(1)	1.83
Mean	3.10
Standard Deviation	0.47
Auto-Correlation	0.27
Auto-Covariance	0.05
Ljung-Box	3.37

Table 5A.6.27
ARMA results for Korean tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	17.11
BIC	18.08
Mean Absolute Percentage Error (MAPE)	7.37%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.86
T-Test For Non Seasonal MA	2.10

Forecast Statistics	Value
Durbin Watson(1)	1.48
Mean	4.48
Standard Deviation	0.43
Auto-Correlation	-0.07
Ljung-Box	3.65

Table 5A.6.28
Two year ahead forecast
ARMA results for Korean tourists to Gansu

Audit trail – statistics

Accuracy Measures	**Value**
AIC	3.19
BIC	3.68
Mean Absolute Percentage Error (MAPE)	4.98%
R-Square	43.89%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.51

Forecast Statistics	**Value**
Durbin Watson(1)	1.88
Mean	3.47
Standard Deviation	0.35
Auto-Correlation	0.48
Auto-Covariance	0.06
Ljung-Box	6.64

Table 5A.6.29
ARMA results for Korean tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	1.08
BIC	1.57
Mean Absolute Percentage Error (MAPE)	5.85%
R-Square	47.43%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.04

Forecast Statistics	**Value**
Durbin Watson(1)	1.98
Mean	2.56
Standard Deviation	0.34
Auto-Correlation	0.41
Auto-Covariance	0.04
Ljung-Box	8.52

Table 5A.6.30
ARMA results for Korean tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	4.27
BIC	4.76
Mean Absolute Percentage Error (MAPE)	8.18%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.03

Forecast Statistics	**Value**
Durbin Watson(1)	1.80
Mean	2.17
Standard Deviation	0.25
Auto-Correlation	0.08
Auto-Covariance	0.00
Ljung-Box	12.57

Table 5A.6.31
Two year ahead forecast
ARMA results for Korean tourists to Xinjiang

Audit trail – statistics

Accuracy Measures	Value
AIC	-0.75
BIC	0.22
Mean Absolute Percentage Error (MAPE)	4.41%
R-Square	59.20%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-0.36
T-Test For Non Seasonal MA	-0.08

Forecast Statistics	Value
Durbin Watson(1)	2.00
Mean	3.47
Standard Deviation	0.32
Auto-Correlation	0.60
Auto-Covariance	0.06
Ljung-Box	6.41

Table 5A.7.1
ARMA results for Malayan tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-13.50
BIC	-12.53
Mean Absolute Percentage Error (MAPE)	1.96%
R-Square	2.79%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.64
T-Test For Constant	3.33

Forecast Statistics	Value
Durbin Watson(1)	1.93
Mean	4.89
Standard Deviation	0.12
Auto-Correlation	0.14
Auto-Covariance	0.00
Ljung-Box	3.34

Table 5A.7.2
ARMA results for Malayan tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	12.81
BIC	13.78
Mean Absolute Percentage Error (MAPE)	7.52%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.27
T-Test For Non Seasonal MA	-0.03

Forecast Statistics	Value
Durbin Watson(1)	1.96
Mean	3.77
Standard Deviation	0.36
Auto-Correlation	0.03
Auto-Covariance	0.00
Ljung-Box	8.52

Table 5A.7.3
ARMA results for Malayan tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	22.25
BIC	23.22
Mean Absolute Percentage Error (MAPE)	9.87%
R-Square	20.48%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	27.21
T-Test For Non Seasonal MA	3.27

Forecast Statistics	Value
Durbin Watson(1)	1.26
Mean	4.50
Standard Deviation	0.61
Auto-Correlation	-0.28
Auto-Covariance	-0.10
Ljung-Box	7.74

Table 5A.7.4
ARMA results for Malayan tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	1.08
BIC	1.56
Mean Absolute Percentage Error (MAPE)	3.78%
R-Square	12.45%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.28

Forecast Statistics	**Value**
Durbin Watson(1)	1.50
Mean	3.36
Standard Deviation	0.26
Auto-Correlation	0.26
Auto-Covariance	0.02
Ljung-Box	4.57

Table 5A.7.5
ARMA results for Malayan tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	2.27
BIC	2.75
Mean Absolute Percentage Error (MAPE)	6.40%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.64

Forecast Statistics	**Value**
Durbin Watson(1)	2.04
Mean	2.98
Standard Deviation	0.25
Auto-Correlation	-0.18
Auto-Covariance	-0.01
Ljung-Box	2.85

Table 5A.7.6
ARMA results for Malayan tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-4.14
BIC	-3.65
Mean Absolute Percentage Error (MAPE)	3.62%
R-Square	55.41%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.95

Forecast Statistics	**Value**
Durbin Watson(1)	1.98
Mean	3.67
Standard Deviation	0.29
Auto-Correlation	0.58
Auto-Covariance	0.05
Ljung-Box	2.95

Table 5A.7.7
ARMA results for Malayan tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	14.11
BIC	14.60
Mean Absolute Percentage Error (MAPE)	5.69%
R-Square	28.04%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.37

Forecast Statistics	**Value**
Durbin Watson(1)	1.74
Mean	3.40
Standard Deviation	0.49
Auto-Correlation	0.37
Auto-Covariance	0.08
Ljung-Box	1.83

Table 5A.7.8
ARMA results for Malayan tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-0.16
BIC	0.81
Mean Absolute Percentage Error (MAPE)	5.05%
R-Square	14.28%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.16
T-Test For Non Seasonal MA	0.79

Forecast Statistics	**Value**
Durbin Watson(1)	1.40
Mean	3.31
Standard Deviation	0.23
Auto-Correlation	-0.19
Auto-Covariance	-0.01
Ljung-Box	5.85

Table 5A.7.9
ARMA results for Malayan tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-16.20
BIC	-15.72
Mean Absolute Percentage Error (MAPE)	1.95%
R-Square	70.94%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.99

Forecast Statistics	**Value**
Durbin Watson(1)	1.62
Mean	4.69
Standard Deviation	0.22
Auto-Correlation	0.60
Auto-Covariance	0.03
Ljung-Box	12.49

Table 5A.7.10
ARMA results for Malayan tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.17
BIC	-9.69
Mean Absolute Percentage Error (MAPE)	2.24%
R-Square	76.60%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.69

Forecast Statistics	Value
Durbin Watson(1)	1.79
Mean	4.94
Standard Deviation	0.31
Auto-Correlation	0.68
Auto-Covariance	0.06
Ljung-Box	14.37

Table 5A.7.11
ARMA results for Malayan tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.74
BIC	-3.26
Mean Absolute Percentage Error (MAPE)	2.88%
R-Square	57.54%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.78

Forecast Statistics	Value
Durbin Watson(1)	1.83
Mean	4.69
Standard Deviation	0.31
Auto-Correlation	0.54
Auto-Covariance	0.05
Ljung-Box	5.37

Table 5A.7.12
ARMA results for Malayan tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.50
BIC	-10.01
Mean Absolute Percentage Error (MAPE)	2.78%
R-Square	53.91%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.98

Forecast Statistics	Value
Durbin Watson(1)	1.89
Mean	4.00
Standard Deviation	0.22
Auto-Correlation	0.41
Auto-Covariance	0.02
Ljung-Box	8.67

Table 5A.7.13
ARMA results for Malayan tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	277.29
BIC	278.26
Mean Absolute Percentage Error (MAPE)	44.06%
R-Square	0.00%
Adjusted R-Square	0.00%

Forecast Statistics	Value
Durbin Watson(1)	2.10
Mean	53,993.83
Standard Deviation	22,118.41
Auto-Correlation	0.15
Ljung-Box	6.03

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.79
T-Test For Constant	3.31

Table 5A.7.14
ARMA results for Malayan tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.18
BIC	-5.70
Mean Absolute Percentage Error (MAPE)	4.20%
R-Square	63.67%

Forecast Statistics	Value
Durbin Watson(1)	1.56
Mean	3.05
Standard Deviation	0.30
Auto-Correlation	0.54
Auto-Covariance	0.04
Ljung-Box	6.56

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.55

Table 5A.7.15
ARMA results for Malayan tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-9.16
BIC	-8.68
Mean Absolute Percentage Error (MAPE)	2.88%
R-Square	59.66%

Forecast Statistics	Value
Durbin Watson(1)	1.88
Mean	4.03
Standard Deviation	0.25
Auto-Correlation	0.50
Auto-Covariance	0.03
Ljung-Box	9.12

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.41

Table 5A.7.16
ARMA results for Malayan tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	4.78
BIC	5.26
Mean Absolute Percentage Error (MAPE)	5.25%
R-Square	41.45%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.08

Forecast Statistics	Value
Durbin Watson(1)	1.90
Mean	3.91
Standard Deviation	0.37
Auto-Correlation	0.33
Auto-Covariance	0.04
Ljung-Box	9.31

Table 5A.7.17
ARMA results for Malayan tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.29
BIC	4.26
Mean Absolute Percentage Error (MAPE)	4.91%
R-Square	61.16%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	51.75
T-Test For Non Seasonal MA	-3.29

Forecast Statistics	Value
Durbin Watson(1)	1.32
Mean	3.81
Standard Deviation	0.39
Auto-Correlation	0.65
Auto-Covariance	0.09
Ljung-Box	14.86

Table 5A.7.18
ARMA results for Malayan tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.92
BIC	4.89
Mean Absolute Percentage Error (MAPE)	5.97%
R-Square	34.22%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.15
T-Test For Non Seasonal MA	0.96

Forecast Statistics	Value
Durbin Watson(1)	1.76
Mean	3.50
Standard Deviation	0.31
Auto-Correlation	-0.36
Auto-Covariance	-0.03
Ljung-Box	4.73

Table 5A.7.19
ARMA results for Malayan tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-9.93
BIC	-9.44
Mean Absolute Percentage Error (MAPE)	1.98%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.95

Forecast Statistics	Value
Durbin Watson(1)	1.79
Mean	5.03
Standard Deviation	0.15
Auto-Correlation	-0.07
Auto-Covariance	0.00
Ljung-Box	4.12

Table 5A.7.20
ARMA results for Malayan tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.55
BIC	4.04
Mean Absolute Percentage Error (MAPE)	4.48%
R-Square	67.60%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.16

Forecast Statistics	Value
Durbin Watson(1)	1.95
Mean	4.24
Standard Deviation	0.47
Auto-Correlation	0.64
Auto-Covariance	0.13
Ljung-Box	5.50

Table 5A.7.21
ARMA results for Malayan tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-1.22
BIC	-0.73
Mean Absolute Percentage Error (MAPE)	3.93%
R-Square	33.25%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	0.23

Forecast Statistics	Value
Durbin Watson(1)	1.79
Mean	3.91
Standard Deviation	0.27
Auto-Correlation	0.35
Auto-Covariance	0.02
Ljung-Box	7.88

Table 5A.7.22
ARMA results for Malayan tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	11.72
BIC	12.20
Mean Absolute Percentage Error (MAPE)	8.49%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.89

Forecast Statistics	Value
Durbin Watson(1)	1.01
Mean	3.57
Standard Deviation	0.38
Auto-Correlation	0.42
Auto-Covariance	0.05
Ljung-Box	14.35

Table 5A.7.23
ARMA results for Malayan tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	9.47
BIC	9.95
Mean Absolute Percentage Error (MAPE)	6.62%
R-Square	12.03%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.77

Forecast Statistics	Value
Durbin Watson(1)	1.92
Mean	4.17
Standard Deviation	0.37
Auto-Correlation	0.38
Auto-Covariance	0.05
Ljung-Box	3.90

Table 5A.7.24
ARMA results for Malayan tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.24
BIC	-2.27
Mean Absolute Percentage Error (MAPE)	3.82%
R-Square	54.21%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	69.85
T-Test For Non Seasonal MA	-3.27

Forecast Statistics	Value
Durbin Watson(1)	1.68
Mean	3.94
Standard Deviation	0.28
Auto-Correlation	0.68
Auto-Covariance	0.05
Ljung-Box	11.43

Table 5A.7.25
ARMA results for Malayan tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.70
BIC	-10.21
Mean Absolute Percentage Error (MAPE)	2.36%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.56

Forecast Statistics	Value
Durbin Watson(1)	1.73
Mean	4.79
Standard Deviation	0.15
Auto-Correlation	0.10
Auto-Covariance	0.00
Ljung-Box	5.99

Table 5A.7.26
ARMA results for Malayan tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	4.56
BIC	5.53
Mean Absolute Percentage Error (MAPE)	7.60%
R-Square	27.36%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.10
T-Test For Constant	3.76

Forecast Statistics	Value
Durbin Watson(1)	1.53
Mean	2.79
Standard Deviation	0.30
Auto-Correlation	-0.48
Auto-Covariance	-0.04
Ljung-Box	3.15

Table 5A.7.27
ARMA results for Malayan tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	15.95
BIC	16.43
Mean Absolute Percentage Error (MAPE)	9.45%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.12

Forecast Statistics	Value
Durbin Watson(1)	1.83
Mean	3.71
Standard Deviation	0.44
Auto-Correlation	0.20
Auto-Covariance	0.04
Ljung-Box	3.27

Table 5A.7.28
ARMA results for Malayan tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-1.27
BIC	-0.78
Mean Absolute Percentage Error (MAPE)	4.37%
R-Square	10.84%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.58

Forecast Statistics	Value
Durbin Watson(1)	1.59
Mean	3.53
Standard Deviation	0.23
Auto-Correlation	-0.15
Auto-Covariance	-0.01
Ljung-Box	3.51

Table 5A.7.29
ARMA results for Malayan tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	22.12
BIC	23.09
Mean Absolute Percentage Error (MAPE)	24.38%
R-Square	17.68%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	1.83
T-Test For Constant	3.44

Forecast Statistics	Value
Durbin Watson(1)	2.05
Mean	1.99
Standard Deviation	0.59
Auto-Correlation	0.29
Auto-Covariance	0.09
Ljung-Box	2.68

Table 5A.7.30
ARMA results for Malayan tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.21
BIC	4.18
Mean Absolute Percentage Error (MAPE)	7.89%
R-Square	24.86%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	1.45
T-Test For Non Seasonal MA	-2.22

Forecast Statistics	Value
Durbin Watson(1)	2.67
Mean	1.97
Standard Deviation	0.28
Auto-Correlation	0.20
Auto-Covariance	0.01
Ljung-Box	6.06

Table 5A.7.31
ARMA results for Malayan tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-10.22
BIC	-9.73
Mean Absolute Percentage Error (MAPE)	3.52%
R-Square	22.62%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.29

Forecast Statistics	**Value**
Durbin Watson(1)	2.01
Mean	3.34
Standard Deviation	0.17
Auto-Correlation	0.36
Auto-Covariance	0.01
Ljung-Box	9.31

Table 5A.8.1
ARMA results for Philippine tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-24.46
BIC	-23.49
Mean Absolute Percentage Error (MAPE)	1.40%
R-Square	50.96%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	170.62
T-Test For Non Seasonal MA	3.23

Forecast Statistics	Value
Durbin Watson(1)	2.04
Mean	4.01
Standard Deviation	0.11
Auto-Correlation	-0.37
Auto-Covariance	0.00
Ljung-Box	3.62

Table 5A.8.2
ARMA results for Philippine tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	25.87
BIC	26.84
Mean Absolute Percentage Error (MAPE)	15.46%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.53
T-Test For Non Seasonal MA	-0.08

Forecast Statistics	Value
Durbin Watson(1)	1.90
Mean	3.31
Standard Deviation	0.63
Auto-Correlation	0.06
Auto-Covariance	0.02
Ljung-Box	7.02

Table 5A.8.3
ARMA results for Philippine tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	19.46
BIC	20.43
Mean Absolute Percentage Error (MAPE)	11.33%
R-Square	21.51%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	23.90
T-Test For Non Seasonal MA	3.31

Forecast Statistics	Value
Durbin Watson(1)	1.25
Mean	3.48
Standard Deviation	0.54
Auto-Correlation	-0.17
Auto-Covariance	-0.04
Ljung-Box	11.74

Table 5A.8.4
ARMA results for Philippine tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	9.49
BIC	10.46
Mean Absolute Percentage Error (MAPE)	9.20%
R-Square	12.57%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.43
T-Test For Constant	3.45

Forecast Statistics	Value
Durbin Watson(1)	1.69
Mean	2.94
Standard Deviation	0.34
Auto-Correlation	-0.30
Auto-Covariance	-0.03
Ljung-Box	7.33

Table 5A.8.5
ARMA results for Philippine tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	15.55
BIC	16.52
Mean Absolute Percentage Error (MAPE)	34.67%
R-Square	60.33%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	16.28
T-Test For Non Seasonal MA	3.31

Forecast Statistics	Value
Durbin Watson(1)	2.52
Mean	2.01
Standard Deviation	0.65
Auto-Correlation	-0.56
Auto-Covariance	-0.22
Ljung-Box	4.97

Table 5A.8.6
ARMA results for Philippine tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.94
BIC	3.43
Mean Absolute Percentage Error (MAPE)	5.14%
R-Square	47.65%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.05

Forecast Statistics	Value
Durbin Watson(1)	2.01
Mean	3.26
Standard Deviation	0.36
Auto-Correlation	0.54
Auto-Covariance	0.07
Ljung-Box	5.52

Table 5A.8.7
ARMA results for Philippine tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	6.57
BIC	7.05
Mean Absolute Percentage Error (MAPE)	9.10%
R-Square	20.13%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.97

Forecast Statistics	**Value**
Durbin Watson(1)	1.65
Mean	2.50
Standard Deviation	0.34
Auto-Correlation	0.29
Auto-Covariance	0.03
Ljung-Box	6.75

Table 5A.8.8
ARMA results for Philippine tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	4.80
BIC	5.77
Mean Absolute Percentage Error (MAPE)	9.00%
R-Square	0.48%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.07
T-Test For Constant	0.21

Forecast Statistics	**Value**
Durbin Watson(1)	1.79
Mean	2.52
Standard Deviation	0.26
Auto-Correlation	0.07
Auto-Covariance	0.00
Ljung-Box	5.66

Table 5A.8.9
ARMA results for Philippine tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-6.50
BIC	-6.01
Mean Absolute Percentage Error (MAPE)	2.53%
R-Square	27.03%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.67

Forecast Statistics	**Value**
Durbin Watson(1)	2.22
Mean	4.65
Standard Deviation	0.21
Auto-Correlation	-0.16
Auto-Covariance	-0.01
Ljung-Box	2.36

Table 5A.8.10
ARMA results for Philippine tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-8.51
BIC	-8.02
Mean Absolute Percentage Error (MAPE)	3.05%
R-Square	63.39%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-0.81

Forecast Statistics	Value
Durbin Watson(1)	1.88
Mean	3.79
Standard Deviation	0.27
Auto-Correlation	0.58
Auto-Covariance	0.04
Ljung-Box	6.58

Table 5A.8.11
ARMA results for Philippine tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-9.36
BIC	-8.88
Mean Absolute Percentage Error (MAPE)	2.69%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.76

Forecast Statistics	Value
Durbin Watson(1)	1.89
Mean	4.15
Standard Deviation	0.15
Auto-Correlation	0.13
Auto-Covariance	0.00
Ljung-Box	6.51

Table 5A.8.12
ARMA results for Philippine tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.62
BIC	-11.65
Mean Absolute Percentage Error (MAPE)	2.83%
R-Square	31.45%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	76.05
T-Test For Non Seasonal MA	2.57

Forecast Statistics	Value
Durbin Watson(1)	1.41
Mean	3.16
Standard Deviation	0.15
Auto-Correlation	-0.36
Auto-Covariance	-0.01
Ljung-Box	10.59

Table 5A.8.13
ARMA results for Philippine tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-4.87
BIC	-4.38
Mean Absolute Percentage Error (MAPE)	3.04%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.04

Forecast Statistics	**Value**
Durbin Watson(1)	2.05
Mean	4.30
Standard Deviation	0.19
Auto-Correlation	-0.07
Auto-Covariance	0.00
Ljung-Box	2.97

Table 5A.8.14
ARMA results for Philippine tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	1.98
BIC	2.46
Mean Absolute Percentage Error (MAPE)	5.77%
R-Square	29.45%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.63

Forecast Statistics	**Value**
Durbin Watson(1)	1.63
Mean	2.59
Standard Deviation	0.30
Auto-Correlation	0.17
Auto-Covariance	0.01
Ljung-Box	6.12

Table 5A.8.15
ARMA results for Philippine tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	10.69
BIC	11.66
Mean Absolute Percentage Error (MAPE)	7.83%
R-Square	30.73%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.68
T-Test For Constant	3.91

Forecast Statistics	**Value**
Durbin Watson(1)	1.50
Mean	3.90
Standard Deviation	0.40
Auto-Correlation	-0.26
Auto-Covariance	-0.04
Ljung-Box	9.04

Table 5A.8.16
ARMA results for Philippine tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	11.69
BIC	12.17
Mean Absolute Percentage Error (MAPE)	9.05%
R-Square	35.14%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.10

Forecast Statistics	**Value**
Durbin Watson(1)	1.80
Mean	3.29
Standard Deviation	0.47
Auto-Correlation	0.47
Auto-Covariance	0.10
Ljung-Box	6.77

Table 5A.8.17
ARMA results for Philippine tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	9.85
BIC	10.82
Mean Absolute Percentage Error (MAPE)	7.91%
R-Square	10.67%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.25
T-Test For Constant	0.27

Forecast Statistics	**Value**
Durbin Watson(1)	1.93
Mean	3.09
Standard Deviation	0.34
Auto-Correlation	0.29
Auto-Covariance	0.03
Ljung-Box	6.44

Table 5A.8.18
ARMA results for Philippine tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	12.88
BIC	13.85
Mean Absolute Percentage Error (MAPE)	9.58%
R-Square	0.11%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.11
T-Test For Constant	3.29

Forecast Statistics	**Value**
Durbin Watson(1)	1.93
Mean	3.02
Standard Deviation	0.37
Auto-Correlation	0.03
Auto-Covariance	0.00
Ljung-Box	6.15

Table 5A.8.19
ARMA results for Philippine tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.89
BIC	-9.92
Mean Absolute Percentage Error (MAPE)	2.49%
R-Square	24.08%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	1.58
T-Test For Non Seasonal MA	-2.26

Forecast Statistics	Value
Durbin Watson(1)	2.56
Mean	4.21
Standard Deviation	0.16
Auto-Correlation	0.15
Auto-Covariance	0.00
Ljung-Box	6.00

Table 5A.8.20
ARMA results for Philippine tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-9.76
BIC	-9.28
Mean Absolute Percentage Error (MAPE)	3.61%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.55

Forecast Statistics	Value
Durbin Watson(1)	1.80
Mean	3.25
Standard Deviation	0.15
Auto-Correlation	0.08
Auto-Covariance	0.00
Ljung-Box	7.80

Table 5A.8.21
ARMA results for Philippine tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	0.07
BIC	0.55
Mean Absolute Percentage Error (MAPE)	6.00%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.92

Forecast Statistics	Value
Durbin Watson(1)	1.77
Mean	2.79
Standard Deviation	0.22
Auto-Correlation	0.04
Auto-Covariance	0.00
Ljung-Box	3.64

Table 5A.8.22
ARMA results for Philippine tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.56
BIC	3.04
Mean Absolute Percentage Error (MAPE)	5.88%
R-Square	6.43%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.72

Forecast Statistics	Value
Durbin Watson(1)	1.54
Mean	2.86
Standard Deviation	0.27
Auto-Correlation	0.23
Auto-Covariance	0.02
Ljung-Box	6.64

Table 5A.8.23
ARMA results for Philippine tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	0.44
BIC	0.92
Mean Absolute Percentage Error (MAPE)	5.08%
R-Square	1.56%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.32

Forecast Statistics	Value
Durbin Watson(1)	1.54
Mean	3.23
Standard Deviation	0.24
Auto-Correlation	0.23
Auto-Covariance	0.01
Ljung-Box	7.24

Table 5A.8.24
ARMA results for Philippine tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	12.56
BIC	13.53
Mean Absolute Percentage Error (MAPE)	9.21%
R-Square	20.10%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	28.51
T-Test For Non Seasonal MA	-3.28

Forecast Statistics	Value
Durbin Watson(1)	2.70
Mean	3.09
Standard Deviation	0.40
Auto-Correlation	0.27
Auto-Covariance	0.04
Ljung-Box	7.66

Table 5A.8.25
ARMA results for Philippine tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.00
BIC	1.97
Mean Absolute Percentage Error (MAPE)	4.75%
R-Square	22.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.14
T-Test For Constant	3.73

Forecast Statistics	Value
Durbin Watson(1)	1.86
Mean	3.50
Standard Deviation	0.25
Auto-Correlation	0.33
Auto-Covariance	0.02
Ljung-Box	7.33

Table 5A.8.26
ARMA results for Philippine tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	17.52
BIC	18.49
Mean Absolute Percentage Error (MAPE)	20.71%
R-Square	13.11%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	13.88
T-Test For Non Seasonal MA	1.76

Forecast Statistics	Value
Durbin Watson(1)	1.63
Mean	1.90
Standard Deviation	0.48
Auto-Correlation	-0.30
Auto-Covariance	-0.06
Ljung-Box	6.36

Table 5A.8.27
ARMA results for Philippine tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	20.91
BIC	21.88
Mean Absolute Percentage Error (MAPE)	15.81%
R-Square	31.16%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	19.07
T-Test For Non Seasonal MA	3.16

Forecast Statistics	Value
Durbin Watson(1)	1.46
Mean	2.98
Standard Deviation	0.62
Auto-Correlation	-0.22
Auto-Covariance	-0.08
Ljung-Box	8.20

Table 5A.8.28
ARMA results for Philippine tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	14.84
BIC	15.33
Mean Absolute Percentage Error (MAPE)	13.84%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.98

Forecast Statistics	Value
Durbin Watson(1)	2.26
Mean	2.59
Standard Deviation	0.43
Auto-Correlation	-0.21
Auto-Covariance	-0.04
Ljung-Box	8.29

Table 5A.8.29
ARMA results for Philippine tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	27.52
BIC	28.49
Mean Absolute Percentage Error (MAPE)	83.32%
R-Square	4.33%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	6.10
T-Test For Non Seasonal MA	-1.35

Forecast Statistics	Value
Durbin Watson(1)	2.08
Mean	1.26
Standard Deviation	0.69
Auto-Correlation	0.09
Auto-Covariance	0.04
Ljung-Box	7.53

Table 5A.8.30
ARMA results for Philippine tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	13.27
BIC	13.75
Mean Absolute Percentage Error (MAPE)	38.24%
R-Square	26.22%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.56

Forecast Statistics	Value
Durbin Watson(1)	2.05
Mean	0.99
Standard Deviation	0.47
Auto-Correlation	0.41
Auto-Covariance	0.08
Ljung-Box	9.98

Table 5A.8.31
ARMA results for Philippine tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.09
BIC	-5.60
Mean Absolute Percentage Error (MAPE)	5.90%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.15

Forecast Statistics	Value
Durbin Watson(1)	1.50
Mean	2.37
Standard Deviation	0.18
Auto-Correlation	0.23
Auto-Covariance	0.01
Ljung-Box	3.14

Table 5A.9.1
ARMA results for Russian tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-16.73
BIC	-15.76
Mean Absolute Percentage Error (MAPE)	1.68%
R-Square	9.78%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.30
T-Test For Non Seasonal MA	-0.20

Forecast Statistics	**Value**
Durbin Watson(1)	1.47
Mean	4.76
Standard Deviation	0.11
Auto-Correlation	0.18
Auto-Covariance	0.00
Ljung-Box	6.15

Table 5A.9.2
ARMA results for Russian tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	13.37
BIC	14.34
Mean Absolute Percentage Error (MAPE)	8.85%
R-Square	47.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.11
T-Test For Non Seasonal MA	1.40

Forecast Statistics	**Value**
Durbin Watson(1)	1.74
Mean	3.65
Standard Deviation	0.51
Auto-Correlation	-0.42
Auto-Covariance	-0.10
Ljung-Box	3.98

Table 5A.9.3
ARMA results for Russian tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	16.45
BIC	17.42
Mean Absolute Percentage Error (MAPE)	8.44%
R-Square	52.04%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-2.06
T-Test For Non Seasonal MA	-1.41

Forecast Statistics	**Value**
Durbin Watson(1)	1.44
Mean	4.12
Standard Deviation	0.61
Auto-Correlation	0.36
Auto-Covariance	0.13
Ljung-Box	4.58

Table 5A.9.4
ARMA results for Russian tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.58
BIC	0.39
Mean Absolute Percentage Error (MAPE)	4.97%
R-Square	73.95%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-3.40
T-Test For Non Seasonal MA	-1.40

Forecast Statistics	Value
Durbin Watson(1)	1.78
Mean	3.04
Standard Deviation	0.41
Auto-Correlation	0.43
Auto-Covariance	0.07
Ljung-Box	5.41

Table 5A.9.5
ARMA results for Russian tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.24
BIC	1.73
Mean Absolute Percentage Error (MAPE)	2.69%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.36

Forecast Statistics	Value
Durbin Watson(1)	1.20
Mean	5.09
Standard Deviation	0.24
Auto-Correlation	0.17
Auto-Covariance	0.01
Ljung-Box	10.59

Table 5A.9.6
ARMA results for Russian tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.88
BIC	2.85
Mean Absolute Percentage Error (MAPE)	3.27%
R-Square	12.53%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-2.03
T-Test For Non Seasonal MA	-0.75

Forecast Statistics	Value
Durbin Watson(1)	1.43
Mean	4.32
Standard Deviation	0.25
Auto-Correlation	-0.19
Auto-Covariance	-0.01
Ljung-Box	5.57

Table 5A.9.7
ARMA results for Russian tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	32.42
BIC	32.91
Mean Absolute Percentage Error (MAPE)	17.36%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.97

Forecast Statistics	**Value**
Durbin Watson(1)	1.97
Mean	3.68
Standard Deviation	0.89
Auto-Correlation	0.15
Auto-Covariance	0.11
Ljung-Box	2.31

Table 5A.9.8
ARMA results for Russian tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	18.66
BIC	19.63
Mean Absolute Percentage Error (MAPE)	6.94%
R-Square	3.52%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	37.66
T-Test For Non Seasonal MA	0.97

Forecast Statistics	**Value**
Durbin Watson(1)	1.69
Mean	5.34
Standard Deviation	0.47
Auto-Correlation	-0.15
Auto-Covariance	-0.03
Ljung-Box	4.67

Table 5A.9.9
ARMA results for Russian tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	3.88
BIC	4.36
Mean Absolute Percentage Error (MAPE)	5.49%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.50

Forecast Statistics	**Value**
Durbin Watson(1)	1.47
Mean	3.99
Standard Deviation	0.27
Auto-Correlation	0.06
Auto-Covariance	0.00
Ljung-Box	9.16

Table 5A.9.10
ARMA results for Russian tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	11.89
BIC	12.37
Mean Absolute Percentage Error (MAPE)	6.49%
R-Square	13.78%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.22

Forecast Statistics	**Value**
Durbin Watson(1)	1.64
Mean	3.62
Standard Deviation	0.41
Auto-Correlation	0.29
Auto-Covariance	0.04
Ljung-Box	6.70

Table 5A.9.11
ARMA results for Russian tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	11.04
BIC	11.52
Mean Absolute Percentage Error (MAPE)	6.16%
R-Square	34.64%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.04

Forecast Statistics	**Value**
Durbin Watson(1)	1.51
Mean	3.66
Standard Deviation	0.46
Auto-Correlation	0.43
Auto-Covariance	0.08
Ljung-Box	9.37

Table 5A.9.12
ARMA results for Russian tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	12.21
BIC	12.70
Mean Absolute Percentage Error (MAPE)	8.98%
R-Square	10.51%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.18

Forecast Statistics	**Value**
Durbin Watson(1)	1.76
Mean	2.82
Standard Deviation	0.41
Auto-Correlation	0.41
Auto-Covariance	0.06
Ljung-Box	5.72

Table 5A.9.13
ARMA results for Russian tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	11.08
BIC	12.05
Mean Absolute Percentage Error (MAPE)	8.28%
R-Square	27.94%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.95
T-Test For Constant	0.55

Forecast Statistics	Value
Durbin Watson(1)	1.78
Mean	2.92
Standard Deviation	0.40
Auto-Correlation	0.43
Auto-Covariance	0.06
Ljung-Box	7.36

Table 5A.9.14
ARMA results for Russian tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.56
BIC	8.05
Mean Absolute Percentage Error (MAPE)	8.16%
R-Square	30.34%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.22

Forecast Statistics	Value
Durbin Watson(1)	1.61
Mean	2.69
Standard Deviation	0.38
Auto-Correlation	0.29
Auto-Covariance	0.04
Ljung-Box	11.32

Table 5A.9.15
ARMA results for Russian tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	4.87
BIC	5.84
Mean Absolute Percentage Error (MAPE)	5.39%
R-Square	38.59%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.90
T-Test For Constant	3.87

Forecast Statistics	Value
Durbin Watson(1)	1.51
Mean	3.83
Standard Deviation	0.33
Auto-Correlation	-0.23
Auto-Covariance	-0.02
Ljung-Box	6.12

Table 5A.9.16
ARMA results for Russian tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	16.32
BIC	17.29
Mean Absolute Percentage Error (MAPE)	9.37%
R-Square	51.25%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-1.66
T-Test For Non Seasonal MA	-1.31

Forecast Statistics	Value
Durbin Watson(1)	1.68
Mean	3.27
Standard Deviation	0.60
Auto-Correlation	0.44
Auto-Covariance	0.15
Ljung-Box	8.46

Table 5A.9.17
ARMA results for Russian tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.73
BIC	4.21
Mean Absolute Percentage Error (MAPE)	6.45%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.52

Forecast Statistics	Value
Durbin Watson(1)	1.82
Mean	2.84
Standard Deviation	0.27
Auto-Correlation	0.07
Auto-Covariance	0.00
Ljung-Box	7.53

Table 5A.9.18
ARMA results for Russian tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	20.23
BIC	20.71
Mean Absolute Percentage Error (MAPE)	14.65%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.07

Forecast Statistics	Value
Durbin Watson(1)	1.56
Mean	2.99
Standard Deviation	0.53
Auto-Correlation	0.18
Auto-Covariance	0.05
Ljung-Box	8.05

Table 5A.9.19
ARMA results for Russian tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.15
BIC	7.63
Mean Absolute Percentage Error (MAPE)	5.80%
R-Square	12.80%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.33

Forecast Statistics	Value
Durbin Watson(1)	1.54
Mean	3.87
Standard Deviation	0.34
Auto-Correlation	0.14
Auto-Covariance	0.01
Ljung-Box	7.84

Table 5A.9.20
ARMA results for Russian tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.92
BIC	2.89
Mean Absolute Percentage Error (MAPE)	7.19%
R-Square	34.24%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	2.82
T-Test For Constant	3.98

Forecast Statistics	Value
Durbin Watson(1)	2.06
Mean	2.67
Standard Deviation	0.29
Auto-Correlation	0.27
Auto-Covariance	0.02
Ljung-Box	6.54

Table 5A.9.21
ARMA results for Russian tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	24.97
BIC	25.45
Mean Absolute Percentage Error (MAPE)	13.00%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.49

Forecast Statistics	Value
Durbin Watson(1)	1.45
Mean	3.29
Standard Deviation	0.65
Auto-Correlation	0.21
Auto-Covariance	0.08
Ljung-Box	6.48

Table 5A.9.22
ARMA results for Russian tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	17.53
BIC	18.50
Mean Absolute Percentage Error (MAPE)	13.63%
R-Square	36.35%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	1.92
T-Test For Constant	0.99

Forecast Statistics	Value
Durbin Watson(1)	1.90
Mean	2.34
Standard Deviation	0.56
Auto-Correlation	0.51
Auto-Covariance	0.14
Ljung-Box	4.41

Table 5A.9.23
ARMA results for Russian tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.29
BIC	3.26
Mean Absolute Percentage Error (MAPE)	5.29%
R-Square	0.81%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.08
T-Test For Constant	0.14

Forecast Statistics	Value
Durbin Watson(1)	1.48
Mean	2.98
Standard Deviation	0.24
Auto-Correlation	0.06
Auto-Covariance	0.00
Ljung-Box	6.60

Table 5A.9.24
ARMA results for Russian tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	17.68
BIC	18.16
Mean Absolute Percentage Error (MAPE)	18.17%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.35

Forecast Statistics	Value
Durbin Watson(1)	1.53
Mean	2.02
Standard Deviation	0.48
Auto-Correlation	0.16
Auto-Covariance	0.03
Ljung-Box	7.82

Table 5A.9.25
ARMA results for Russian tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	16.56
BIC	17.04
Mean Absolute Percentage Error (MAPE)	9.64%
R-Square	14.81%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-0.85

Forecast Statistics	Value
Durbin Watson(1)	1.70
Mean	2.94
Standard Deviation	0.50
Auto-Correlation	0.37
Auto-Covariance	0.09
Ljung-Box	5.75

Table 5A.9.26
ARMA results for Russian tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	11.72
BIC	12.21
Mean Absolute Percentage Error (MAPE)	9.58%
R-Square	4.74%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.33

Forecast Statistics	Value
Durbin Watson(1)	1.45
Mean	2.68
Standard Deviation	0.39
Auto-Correlation	0.10
Auto-Covariance	0.01
Ljung-Box	5.74

Table 5A.9.27
ARMA results for Russian tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	23.14
BIC	24.11
Mean Absolute Percentage Error (MAPE)	16.53%
R-Square	11.99%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	17.79
T-Test For Non Seasonal MA	3.16

Forecast Statistics	Value
Durbin Watson(1)	1.08
Mean	3.13
Standard Deviation	0.60
Auto-Correlation	-0.14
Auto-Covariance	-0.05
Ljung-Box	7.56

Table 5A.9.28
ARMA results for Russian tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	28.14
BIC	28.63
Mean Absolute Percentage Error (MAPE)	26.59%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.09

Forecast Statistics	Value
Durbin Watson(1)	1.81
Mean	2.24
Standard Deviation	0.71
Auto-Correlation	-0.02
Auto-Covariance	-0.01
Ljung-Box	7.76

Table 5A.9.29
ARMA results for Russian tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	25.06
BIC	25.54
Mean Absolute Percentage Error (MAPE)	29.76%
R-Square	10.52%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.11

Forecast Statistics	Value
Durbin Watson(1)	2.02
Mean	1.47
Standard Deviation	0.70
Auto-Correlation	0.16
Auto-Covariance	0.07
Ljung-Box	8.89

Table 5A.9.30
ARMA results for Russian tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	14.29
BIC	15.26
Mean Absolute Percentage Error (MAPE)	30.83%
R-Square	63.15%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-2.29
T-Test For Non Seasonal MA	-1.48

Forecast Statistics	Value
Durbin Watson(1)	1.99
Mean	1.25
Standard Deviation	0.64
Auto-Correlation	0.59
Auto-Covariance	0.22
Ljung-Box	8.29

Table 5A.9.31
ARMA results for Russian tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-14.59
BIC	-13.62
Mean Absolute Percentage Error (MAPE)	1.54%
R-Square	47.89%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	137.67
T-Test For Non Seasonal MA	3.30

Forecast Statistics	Value
Durbin Watson(1)	1.88
Mean	4.85
Standard Deviation	0.16
Auto-Correlation	-0.34
Auto-Covariance	-0.01
Ljung-Box	5.82

Table 5A.10.1
ARMA results for Singaporean tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-25.99
BIC	-25.50
Mean Absolute Percentage Error (MAPE)	1.08%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.16

Forecast Statistics	**Value**
Durbin Watson(1)	1.88
Mean	4.84
Standard Deviation	0.08
Auto-Correlation	0.06
Auto-Covariance	0.00
Ljung-Box	5.68

Table 5A.10.2
ARMA results for Singaporean tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	0.17
BIC	0.65
Mean Absolute Percentage Error (MAPE)	4.63%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.68

Forecast Statistics	**Value**
Durbin Watson(1)	1.95
Mean	3.86
Standard Deviation	0.22
Auto-Correlation	0.06
Auto-Covariance	0.00
Ljung-Box	10.53

Table 5A.10.3
ARMA results for Singaporean tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	18.78
BIC	19.27
Mean Absolute Percentage Error (MAPE)	8.51%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.08

Forecast Statistics	**Value**
Durbin Watson(1)	2.32
Mean	4.18
Standard Deviation	0.51
Auto-Correlation	-0.19
Auto-Covariance	-0.04
Ljung-Box	2.44

Table 5A.10.4
ARMA results for Singaporean tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.21
BIC	2.70
Mean Absolute Percentage Error (MAPE)	5.08%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.42

Forecast Statistics	Value
Durbin Watson(1)	1.61
Mean	3.54
Standard Deviation	0.24
Auto-Correlation	-0.01
Auto-Covariance	0.00
Ljung-Box	6.07

Table 5A.10.5
ARMA results for Singaporean tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.01
BIC	-1.04
Mean Absolute Percentage Error (MAPE)	4.95%
R-Square	19.97%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.11
T-Test For Non Seasonal MA	1.34

Forecast Statistics	Value
Durbin Watson(1)	1.15
Mean	3.01
Standard Deviation	0.22
Auto-Correlation	-0.20
Auto-Covariance	-0.01
Ljung-Box	9.98

Table 5A.10.6
ARMA results for Singaporean tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.32
BIC	-11.83
Mean Absolute Percentage Error (MAPE)	2.54%
R-Square	65.06%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.27

Forecast Statistics	Value
Durbin Watson(1)	1.69
Mean	3.90
Standard Deviation	0.24
Auto-Correlation	0.64
Auto-Covariance	0.03
Ljung-Box	7.16

Table 5A.10.7
ARMA results for Singaporean tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	4.75
BIC	5.24
Mean Absolute Percentage Error (MAPE)	3.40%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.42

Forecast Statistics	Value
Durbin Watson(1)	1.89
Mean	3.60
Standard Deviation	0.27
Auto-Correlation	0.16
Auto-Covariance	0.01
Ljung-Box	2.75

Table 5A.10.8
ARMA results for Singaporean tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.09
BIC	4.06
Mean Absolute Percentage Error (MAPE)	4.33%
R-Square	0.62%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.03
T-Test For Constant	0.11

Forecast Statistics	Value
Durbin Watson(1)	1.73
Mean	3.47
Standard Deviation	0.24
Auto-Correlation	-0.06
Auto-Covariance	0.00
Ljung-Box	4.60

Table 5A.10.9
ARMA results for Singaporean tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-18.19
BIC	-17.71
Mean Absolute Percentage Error (MAPE)	1.49%
R-Square	67.28%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.72

Forecast Statistics	Value
Durbin Watson(1)	1.78
Mean	4.76
Standard Deviation	0.19
Auto-Correlation	0.60
Auto-Covariance	0.02
Ljung-Box	6.15

Table 5A.10.10
ARMA results for Singaporean tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-15.77
BIC	-15.29
Mean Absolute Percentage Error (MAPE)	1.67%
R-Square	66.22%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.53

Forecast Statistics	Value
Durbin Watson(1)	1.63
Mean	4.73
Standard Deviation	0.21
Auto-Correlation	0.60
Auto-Covariance	0.02
Ljung-Box	5.51

Table 5A.10.11
ARMA results for Singaporean tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.17
BIC	-2.69
Mean Absolute Percentage Error (MAPE)	2.92%
R-Square	2.60%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.45

Forecast Statistics	Value
Durbin Watson(1)	2.03
Mean	4.63
Standard Deviation	0.21
Auto-Correlation	0.22
Auto-Covariance	0.01
Ljung-Box	5.83

Table 5A.10.12
ARMA results for Singaporean tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-15.05
BIC	-14.08
Mean Absolute Percentage Error (MAPE)	2.03%
R-Square	18.93%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.05
T-Test For Constant	0.03

Forecast Statistics	Value
Durbin Watson(1)	1.73
Mean	4.16
Standard Deviation	0.13
Auto-Correlation	-0.36
Auto-Covariance	-0.01
Ljung-Box	7.35

Table 5A.10.13
ARMA results for Singaporean tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-1.04
BIC	-0.07
Mean Absolute Percentage Error (MAPE)	3.27%
R-Square	0.90%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	76.80
T-Test For Non Seasonal MA	-0.39

Forecast Statistics	Value
Durbin Watson(1)	1.97
Mean	4.75
Standard Deviation	0.21
Auto-Correlation	0.07
Auto-Covariance	0.00
Ljung-Box	5.37

Table 5A.10.14
ARMA results for Singaporean tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.19
BIC	-1.70
Mean Absolute Percentage Error (MAPE)	4.55%
R-Square	46.30%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.86

Forecast Statistics	Value
Durbin Watson(1)	2.10
Mean	3.37
Standard Deviation	0.29
Auto-Correlation	0.41
Auto-Covariance	0.03
Ljung-Box	12.72

Table 5A.10.15
ARMA results for Singaporean tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-5.62
BIC	-5.14
Mean Absolute Percentage Error (MAPE)	3.59%
R-Square	26.60%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.65

Forecast Statistics	Value
Durbin Watson(1)	1.58
Mean	4.21
Standard Deviation	0.21
Auto-Correlation	0.31
Auto-Covariance	0.01
Ljung-Box	6.77

Table 5A.10.16
ARMA results for Singaporean tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	1.29
BIC	1.78
Mean Absolute Percentage Error (MAPE)	5.31%
R-Square	32.13%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.78

Forecast Statistics	Value
Durbin Watson(1)	1.21
Mean	3.78
Standard Deviation	0.30
Auto-Correlation	0.24
Auto-Covariance	0.02
Ljung-Box	7.38

Table 5A.10.17
ARMA results for Singaporean tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	5.00
BIC	5.96
Mean Absolute Percentage Error (MAPE)	5.57%
R-Square	25.76%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.53
T-Test For Non Seasonal MA	-0.39

Forecast Statistics	Value
Durbin Watson(1)	1.81
Mean	3.76
Standard Deviation	0.31
Auto-Correlation	0.39
Auto-Covariance	0.03
Ljung-Box	7.35

Table 5A.10.18
ARMA results for Singaporean tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	9.77
BIC	10.74
Mean Absolute Percentage Error (MAPE)	7.53%
R-Square	0.08%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.10
T-Test For Constant	3.18

Forecast Statistics	Value
Durbin Watson(1)	1.86
Mean	3.69
Standard Deviation	0.32
Auto-Correlation	-0.02
Auto-Covariance	0.00
Ljung-Box	3.89

Table 5A.10.19
ARMA results for Singaporean tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.54
BIC	-12.05
Mean Absolute Percentage Error (MAPE)	1.82%
R-Square	24.25%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.28

Forecast Statistics	Value
Durbin Watson(1)	1.87
Mean	4.91
Standard Deviation	0.16
Auto-Correlation	0.29
Auto-Covariance	0.01
Ljung-Box	3.00

Table 5A.10.20
ARMA results for Singaporean tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.61
BIC	-6.12
Mean Absolute Percentage Error (MAPE)	3.56%
R-Square	0.95%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.88

Forecast Statistics	Value
Durbin Watson(1)	1.57
Mean	3.79
Standard Deviation	0.18
Auto-Correlation	0.22
Auto-Covariance	0.01
Ljung-Box	4.40

Table 5A.10.21
ARMA results for Singaporean tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-18.96
BIC	-17.99
Mean Absolute Percentage Error (MAPE)	1.99%
R-Square	32.19%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	133.94
T-Test For Non Seasonal MA	3.14

Forecast Statistics	Value
Durbin Watson(1)	1.35
Mean	4.05
Standard Deviation	0.12
Auto-Correlation	-0.12
Auto-Covariance	0.00
Ljung-Box	6.72

Table 5A.10.22
ARMA results for Singaporean tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	5.89
BIC	6.86
Mean Absolute Percentage Error (MAPE)	5.29%
R-Square	18.31%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	1.57
T-Test For Constant	3.48

Forecast Statistics	Value
Durbin Watson(1)	1.96
Mean	3.60
Standard Deviation	0.30
Auto-Correlation	0.40
Auto-Covariance	0.03
Ljung-Box	6.05

Table 5A.10.23
ARMA results for Singaporean tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.52
BIC	0.45
Mean Absolute Percentage Error (MAPE)	3.68%
R-Square	25.05%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	69.75
T-Test For Non Seasonal MA	-1.82

Forecast Statistics	Value
Durbin Watson(1)	1.85
Mean	4.41
Standard Deviation	0.24
Auto-Correlation	0.39
Auto-Covariance	0.02
Ljung-Box	4.26

Table 5A.10.24
ARMA results for Singaporean tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-1.48
BIC	-0.99
Mean Absolute Percentage Error (MAPE)	4.29%
R-Square	34.76%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.18

Forecast Statistics	Value
Durbin Watson(1)	2.14
Mean	3.95
Standard Deviation	0.27
Auto-Correlation	0.37
Auto-Covariance	0.02
Ljung-Box	9.47

Table 5A.10.25
ARMA results for Singaporean tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-21.31
BIC	-20.34
Mean Absolute Percentage Error (MAPE)	1.48%
R-Square	0.80%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.31
T-Test For Constant	3.32

Forecast Statistics	Value
Durbin Watson(1)	1.95
Mean	4.77
Standard Deviation	0.09
Auto-Correlation	-0.09
Auto-Covariance	0.00
Ljung-Box	8.73

Table 5A.10.26
ARMA results for Singaporean tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-13.51
BIC	-12.54
Mean Absolute Percentage Error (MAPE)	2.55%
R-Square	56.94%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-6.89
T-Test For Non Seasonal MA	2.57

Forecast Statistics	Value
Durbin Watson(1)	2.04
Mean	3.11
Standard Deviation	0.19
Auto-Correlation	-0.78
Auto-Covariance	-0.02
Ljung-Box	5.44

Table 5A.10.27
ARMA results for Singaporean tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	14.09
BIC	15.06
Mean Absolute Percentage Error (MAPE)	7.23%
R-Square	3.26%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.64
T-Test For Constant	3.30

Forecast Statistics	Value
Durbin Watson(1)	1.88
Mean	3.69
Standard Deviation	0.39
Auto-Correlation	-0.17
Auto-Covariance	-0.02
Ljung-Box	2.81

Table 5A.10.28
ARMA results for Singaporean tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	1.65
BIC	2.13
Mean Absolute Percentage Error (MAPE)	4.88%
R-Square	8.88%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.29

Forecast Statistics	**Value**
Durbin Watson(1)	2.09
Mean	3.59
Standard Deviation	0.26
Auto-Correlation	-0.03
Auto-Covariance	0.00
Ljung-Box	6.43

Table 5A.10.29
ARMA results for Singaporean tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	9.75
BIC	10.72
Mean Absolute Percentage Error (MAPE)	9.54%
R-Square	15.53%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.59
T-Test For Non Seasonal MA	-0.33

Forecast Statistics	**Value**
Durbin Watson(1)	1.92
Mean	2.88
Standard Deviation	0.35
Auto-Correlation	0.36
Auto-Covariance	0.04
Ljung-Box	6.53

Table 5A.10.30
ARMA results for Singaporean tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-0.37
BIC	0.60
Mean Absolute Percentage Error (MAPE)	7.27%
R-Square	52.11%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	1.59
T-Test For Non Seasonal MA	-2.19

Forecast Statistics	**Value**
Durbin Watson(1)	1.00
Mean	2.06
Standard Deviation	0.30
Auto-Correlation	0.36
Auto-Covariance	0.03
Ljung-Box	5.31

Table 5A.10.31
ARMA results for Singaporean tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	2.32
BIC	3.29
Mean Absolute Percentage Error (MAPE)	5.77%
R-Square	0.05%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.07
T-Test For Constant	3.29

Forecast Statistics	**Value**
Durbin Watson(1)	1.99
Mean	3.44
Standard Deviation	0.24
Auto-Correlation	0.02
Auto-Covariance	0.00
Ljung-Box	2.06

Table 5A.11.1
ARMA results for Thailand tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-16.44
BIC	-15.47
Mean Absolute Percentage Error (MAPE)	1.87%
R-Square	11.93%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	133.77
T-Test For Non Seasonal MA	1.52

Forecast Statistics	Value
Durbin Watson(1)	1.47
Mean	4.54
Standard Deviation	0.11
Auto-Correlation	-0.13
Auto-Covariance	0.00
Ljung-Box	8.48

Table 5A.11.2
ARMA results for Thailand tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	7.30
BIC	8.27
Mean Absolute Percentage Error (MAPE)	7.12%
R-Square	21.37%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.11
T-Test For Non Seasonal MA	1.36

Forecast Statistics	Value
Durbin Watson(1)	1.32
Mean	3.08
Standard Deviation	0.33
Auto-Correlation	-0.15
Auto-Covariance	-0.02
Ljung-Box	10.57

Table 5A.11.3
ARMA results for Thailand tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	20.23
BIC	21.20
Mean Absolute Percentage Error (MAPE)	11.82%
R-Square	25.37%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	23.04
T-Test For Non Seasonal MA	3.29

Forecast Statistics	Value
Durbin Watson(1)	1.27
Mean	3.48
Standard Deviation	0.58
Auto-Correlation	-0.21
Auto-Covariance	-0.06
Ljung-Box	10.20

Table 5A.11.4
ARMA results for Thailand tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.38
BIC	0.11
Mean Absolute Percentage Error (MAPE)	5.35%
R-Square	8.93%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.67

Forecast Statistics	Value
Durbin Watson(1)	1.62
Mean	3.14
Standard Deviation	0.24
Auto-Correlation	-0.01
Auto-Covariance	0.00
Ljung-Box	4.39

Table 5A.11.5
ARMA results for Thailand tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	19.01
BIC	19.50
Mean Absolute Percentage Error (MAPE)	13.80%
R-Square	0.64%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.45

Forecast Statistics	Value
Durbin Watson(1)	1.06
Mean	2.68
Standard Deviation	0.52
Auto-Correlation	0.04
Auto-Covariance	0.01
Ljung-Box	11.75

Table 5A.11.6
ARMA results for Thailand tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.19
BIC	-2.70
Mean Absolute Percentage Error (MAPE)	4.41%
R-Square	56.04%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.52

Forecast Statistics	Value
Durbin Watson(1)	2.00
Mean	3.25
Standard Deviation	0.31
Auto-Correlation	0.50
Auto-Covariance	0.04
Ljung-Box	6.17

Table 5A.11.7
ARMA results for Thailand tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-0.06
BIC	0.43
Mean Absolute Percentage Error (MAPE)	6.39%
R-Square	12.58%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.23

Forecast Statistics	**Value**
Durbin Watson(1)	1.91
Mean	2.87
Standard Deviation	0.25
Auto-Correlation	0.34
Auto-Covariance	0.02
Ljung-Box	3.12

Table 5A.11.8
ARMA results for Thailand tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	6.91
BIC	7.88
Mean Absolute Percentage Error (MAPE)	7.26%
R-Square	0.81%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.51
T-Test For Constant	3.05

Forecast Statistics	**Value**
Durbin Watson(1)	1.70
Mean	3.06
Standard Deviation	0.29
Auto-Correlation	0.05
Auto-Covariance	0.00
Ljung-Box	3.38

Table 5A.11.9
ARMA results for Thailand tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-12.54
BIC	-12.05
Mean Absolute Percentage Error (MAPE)	2.53%
R-Square	52.03%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.81

Forecast Statistics	**Value**
Durbin Watson(1)	1.70
Mean	4.33
Standard Deviation	0.20
Auto-Correlation	0.54
Auto-Covariance	0.02
Ljung-Box	7.16

Table 5A.11.10
ARMA results for Thailand tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-18.54
BIC	-18.05
Mean Absolute Percentage Error (MAPE)	2.08%
R-Square	91.51%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-3.13

Forecast Statistics	**Value**
Durbin Watson(1)	2.15
Mean	4.20
Standard Deviation	0.37
Auto-Correlation	0.74
Auto-Covariance	0.09
Ljung-Box	18.54

Table 5A.11.11
ARMA results for Thailand tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-3.39
BIC	-2.90
Mean Absolute Percentage Error (MAPE)	3.32%
R-Square	45.59%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.88

Forecast Statistics	**Value**
Durbin Watson(1)	2.09
Mean	4.41
Standard Deviation	0.27
Auto-Correlation	0.52
Auto-Covariance	0.04
Ljung-Box	4.11

Table 5A.11.12
ARMA results for Thailand tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-5.85
BIC	-5.37
Mean Absolute Percentage Error (MAPE)	3.91%
R-Square	13.29%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.51

Forecast Statistics	**Value**
Durbin Watson(1)	2.08
Mean	3.71
Standard Deviation	0.20
Auto-Correlation	0.30
Auto-Covariance	0.01
Ljung-Box	10.81

Table 5A.11.13
ARMA results for Thailand tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-3.85
BIC	-3.36
Mean Absolute Percentage Error (MAPE)	3.96%
R-Square	60.07%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.24

Forecast Statistics	**Value**
Durbin Watson(1)	1.75
Mean	3.67
Standard Deviation	0.31
Auto-Correlation	0.56
Auto-Covariance	0.05
Ljung-Box	14.31

Table 5A.11.14
ARMA results for Thailand tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	3.48
BIC	3.96
Mean Absolute Percentage Error (MAPE)	5.90%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.99

Forecast Statistics	**Value**
Durbin Watson(1)	2.05
Mean	2.97
Standard Deviation	0.25
Auto-Correlation	0.02
Auto-Covariance	0.00
Ljung-Box	12.31

Table 5A.11.15
ARMA results for Thailand tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	19.01
BIC	19.50
Mean Absolute Percentage Error (MAPE)	13.80%
R-Square	0.64%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.45

Forecast Statistics	**Value**
Durbin Watson(1)	1.06
Mean	2.68
Standard Deviation	0.52
Auto-Correlation	0.04
Auto-Covariance	0.01
Ljung-Box	11.75

Table 5A.11.16
ARMA results for Thailand tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	10.22
BIC	10.70
Mean Absolute Percentage Error (MAPE)	7.58%
R-Square	41.69%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.12

Forecast Statistics	**Value**
Durbin Watson(1)	1.88
Mean	3.60
Standard Deviation	0.47
Auto-Correlation	0.39
Auto-Covariance	0.08
Ljung-Box	8.29

Table 5A.11.17
ARMA results for Thailand tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	4.23
BIC	5.20
Mean Absolute Percentage Error (MAPE)	6.16%
R-Square	35.80%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	44.38
T-Test For Non Seasonal MA	-3.08

Forecast Statistics	**Value**
Durbin Watson(1)	2.10
Mean	3.44
Standard Deviation	0.32
Auto-Correlation	0.23
Auto-Covariance	0.02
Ljung-Box	6.85

Table 5A.11.18
ARMA results for Thailand tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	13.96
BIC	14.93
Mean Absolute Percentage Error (MAPE)	9.29%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.00
T-Test For Constant	0.18

Forecast Statistics	**Value**
Durbin Watson(1)	1.64
Mean	3.19
Standard Deviation	0.38
Auto-Correlation	0.01
Auto-Covariance	0.00
Ljung-Box	7.92

Table 5A.11.19
ARMA results for Thailand tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.63
BIC	-2.14
Mean Absolute Percentage Error (MAPE)	3.37%
R-Square	15.82%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.23

Forecast Statistics	Value
Durbin Watson(1)	1.86
Mean	4.72
Standard Deviation	0.23
Auto-Correlation	0.34
Auto-Covariance	0.02
Ljung-Box	10.55

Table 5A.11.20
ARMA results for Thailand tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	5.35
BIC	5.84
Mean Absolute Percentage Error (MAPE)	5.61%
R-Square	47.16%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.52

Forecast Statistics	Value
Durbin Watson(1)	1.91
Mean	3.88
Standard Deviation	0.40
Auto-Correlation	0.54
Auto-Covariance	0.08
Ljung-Box	4.89

Table 5A.11.21
ARMA results for Thailand tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.07
BIC	-5.58
Mean Absolute Percentage Error (MAPE)	4.08%
R-Square	9.37%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.34

Forecast Statistics	Value
Durbin Watson(1)	1.75
Mean	3.53
Standard Deviation	0.19
Auto-Correlation	0.33
Auto-Covariance	0.01
Ljung-Box	6.52

Table 5A.11.22
ARMA results for Thailand tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.55
BIC	3.04
Mean Absolute Percentage Error (MAPE)	5.07%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.98

Forecast Statistics	Value
Durbin Watson(1)	1.69
Mean	3.31
Standard Deviation	0.26
Auto-Correlation	0.06
Auto-Covariance	0.00
Ljung-Box	4.21

Table 5A.11.23
ARMA results for Thailand tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.14
BIC	0.34
Mean Absolute Percentage Error (MAPE)	3.99%
R-Square	54.06%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.62

Forecast Statistics	Value
Durbin Watson(1)	1.99
Mean	4.29
Standard Deviation	0.34
Auto-Correlation	0.51
Auto-Covariance	0.05
Ljung-Box	7.98

Table 5A.11.24
ARMA results for Thailand tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	8.37
BIC	8.85
Mean Absolute Percentage Error (MAPE)	7.28%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.15

Forecast Statistics	Value
Durbin Watson(1)	1.58
Mean	3.47
Standard Deviation	0.33
Auto-Correlation	0.21
Auto-Covariance	0.02
Ljung-Box	7.37

Table 5A.11.25
ARMA results for Thailand tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-7.56
BIC	-6.59
Mean Absolute Percentage Error (MAPE)	2.61%
R-Square	35.05%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	101.77
T-Test For Non Seasonal MA	-3.08

Forecast Statistics	Value
Durbin Watson(1)	2.21
Mean	4.82
Standard Deviation	0.19
Auto-Correlation	0.33
Auto-Covariance	0.01
Ljung-Box	7.47

Table 5A.11.26
ARMA results for Thailand tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.87
BIC	4.84
Mean Absolute Percentage Error (MAPE)	7.97%
R-Square	27.35%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.08
T-Test For Constant	3.74

Forecast Statistics	Value
Durbin Watson(1)	1.73
Mean	2.60
Standard Deviation	0.29
Auto-Correlation	-0.48
Auto-Covariance	-0.04
Ljung-Box	3.53

Table 5A.11.27
ARMA results for Thailand tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	22.29
BIC	22.77
Mean Absolute Percentage Error (MAPE)	12.74%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.09

Forecast Statistics	Value
Durbin Watson(1)	2.11
Mean	3.43
Standard Deviation	0.59
Auto-Correlation	-0.09
Auto-Covariance	-0.03
Ljung-Box	1.60

Table 5A.11.28
ARMA results for Thailand tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.18
BIC	2.67
Mean Absolute Percentage Error (MAPE)	6.05%
R-Square	9.26%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.54

Forecast Statistics	Value
Durbin Watson(1)	1.66
Mean	2.97
Standard Deviation	0.27
Auto-Correlation	0.29
Auto-Covariance	0.02
Ljung-Box	2.94

Table 5A.11.29
ARMA results for Thailand tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	24.71
BIC	25.20
Mean Absolute Percentage Error (MAPE)	35.19%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.01

Forecast Statistics	Value
Durbin Watson(1)	1.99
Mean	1.62
Standard Deviation	0.61
Auto-Correlation	-0.02
Auto-Covariance	-0.01
Ljung-Box	7.73

Table 5A.11.30
ARMA results for Thailand tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	16.67
BIC	17.15
Mean Absolute Percentage Error (MAPE)	36.71%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.04

Forecast Statistics	Value
Durbin Watson(1)	2.04
Mean	1.10
Standard Deviation	0.44
Auto-Correlation	-0.14
Auto-Covariance	-0.02
Ljung-Box	4.14

Table 5A.11.31
ARMA results for Thailand tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	0.98
BIC	1.46
Mean Absolute Percentage Error (MAPE)	6.82%
R-Square	22.50%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.45

Forecast Statistics	**Value**
Durbin Watson(1)	1.73
Mean	2.84
Standard Deviation	0.28
Auto-Correlation	0.53
Auto-Covariance	0.04
Ljung-Box	5.74

Table 5A.12.1
ARMA results for British tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-21.79
BIC	-21.30
Mean Absolute Percentage Error (MAPE)	1.43%
R-Square	42.16%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.61

Forecast Statistics	Value
Durbin Watson(1)	1.79
Mean	4.95
Standard Deviation	0.12
Auto-Correlation	0.45
Auto-Covariance	0.01
Ljung-Box	6.54

Table 5A.12.2
ARMA results for British tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.38
BIC	-1.90
Mean Absolute Percentage Error (MAPE)	4.16%
R-Square	19.81%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.60

Forecast Statistics	Value
Durbin Watson(1)	1.76
Mean	3.65
Standard Deviation	0.24
Auto-Correlation	0.42
Auto-Covariance	0.02
Ljung-Box	5.50

Table 5A.12.3
ARMA results for British tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	12.77
BIC	13.74
Mean Absolute Percentage Error (MAPE)	7.53%
R-Square	28.56%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	35.68
T-Test For Non Seasonal MA	2.93

Forecast Statistics	Value
Durbin Watson(1)	1.39
Mean	4.13
Standard Deviation	0.43
Auto-Correlation	-0.13
Auto-Covariance	-0.02
Ljung-Box	12.33

Table 5A.12.4
ARMA results for British tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	2.13
BIC	2.61
Mean Absolute Percentage Error (MAPE)	5.43%
R-Square	5.15%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.92

Forecast Statistics	**Value**
Durbin Watson(1)	2.02
Mean	3.44
Standard Deviation	0.26
Auto-Correlation	0.07
Auto-Covariance	0.00
Ljung-Box	5.92

Table 5A.12.5
ARMA results for British tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	6.12
BIC	6.60
Mean Absolute Percentage Error (MAPE)	5.77%
R-Square	41.71%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.59

Forecast Statistics	**Value**
Durbin Watson(1)	1.83
Mean	3.03
Standard Deviation	0.39
Auto-Correlation	0.54
Auto-Covariance	0.08
Ljung-Box	2.84

Table 5A.12.6
ARMA results for British tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-10.00
BIC	-9.52
Mean Absolute Percentage Error (MAPE)	2.69%
R-Square	62.45%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.48

Forecast Statistics	**Value**
Durbin Watson(1)	1.91
Mean	3.60
Standard Deviation	0.25
Auto-Correlation	0.65
Auto-Covariance	0.04
Ljung-Box	4.44

Table 5A.12.7
ARMA results for British tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-10.50
BIC	-10.01
Mean Absolute Percentage Error (MAPE)	3.71%
R-Square	57.19%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	1.22

Forecast Statistics	**Value**
Durbin Watson(1)	2.22
Mean	2.96
Standard Deviation	0.23
Auto-Correlation	0.47
Auto-Covariance	0.02

Table 5A.12.8
ARMA results for British tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	9.46
BIC	10.43
Mean Absolute Percentage Error (MAPE)	6.00%
R-Square	7.10%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.39
T-Test For Constant	0.31

Forecast Statistics	**Value**
Durbin Watson(1)	2.18
Mean	3.13
Standard Deviation	0.33
Auto-Correlation	0.18
Auto-Covariance	0.02
Ljung-Box	3.06

Table 5A.12.9
ARMA results for British tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	7.09
BIC	8.06
Mean Absolute Percentage Error (MAPE)	3.98%
R-Square	19.81%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	1.53
T-Test For Non Seasonal MA	-2.28

Forecast Statistics	**Value**
Durbin Watson(1)	2.64
Mean	4.47
Standard Deviation	0.32
Auto-Correlation	0.22
Auto-Covariance	0.02
Ljung-Box	4.64

Table 5A.12.10
ARMA results for British tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-19.50
BIC	-19.02
Mean Absolute Percentage Error (MAPE)	1.76%
R-Square	72.16%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.51

Forecast Statistics	Value
Durbin Watson(1)	1.61
Mean	4.48
Standard Deviation	0.20
Auto-Correlation	0.66
Auto-Covariance	0.02
Ljung-Box	13.26

Table 5A.12.11
ARMA results for British tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-8.49
BIC	-8.01
Mean Absolute Percentage Error (MAPE)	3.08%
R-Square	67.49%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.24

Forecast Statistics	Value
Durbin Watson(1)	1.45
Mean	4.11
Standard Deviation	0.29
Auto-Correlation	0.59
Auto-Covariance	0.04
Ljung-Box	6.70

Table 5A.12.12
ARMA results for British tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.91
BIC	-11.94
Mean Absolute Percentage Error (MAPE)	2.98%
R-Square	81.20%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	6.16
T-Test For Constant	7.61

Forecast Statistics	Value
Durbin Watson(1)	2.07
Mean	3.44
Standard Deviation	0.29
Auto-Correlation	0.70
Auto-Covariance	0.05
Ljung-Box	2.36

Table 5A.12.13
ARMA results for British tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-1.37
BIC	-0.89
Mean Absolute Percentage Error (MAPE)	4.16%
R-Square	32.05%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.72

Forecast Statistics	Value
Durbin Watson(1)	1.96
Mean	3.65
Standard Deviation	0.27
Auto-Correlation	0.48
Auto-Covariance	0.03
Ljung-Box	2.43

Table 5A.12.14
ARMA results for British tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.18
BIC	-2.69
Mean Absolute Percentage Error (MAPE)	4.59%
R-Square	57.48%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	-0.43

Forecast Statistics	Value
Durbin Watson(1)	1.76
Mean	3.33
Standard Deviation	0.31
Auto-Correlation	0.52
Auto-Covariance	0.05
Ljung-Box	2.44

Table 5A.12.15
ARMA results for British tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-13.32
BIC	-12.35
Mean Absolute Percentage Error (MAPE)	2.20%
R-Square	71.15%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	1.82
T-Test For Constant	0.76

Forecast Statistics	Value
Durbin Watson(1)	2.65
Mean	3.84
Standard Deviation	0.23
Auto-Correlation	0.56
Auto-Covariance	0.03
Ljung-Box	5.82

Table 5A.12.16
ARMA results for British tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.55
BIC	3.04
Mean Absolute Percentage Error (MAPE)	5.45%
R-Square	41.91%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.37

Forecast Statistics	Value
Durbin Watson(1)	1.73
Mean	3.67
Standard Deviation	0.34
Auto-Correlation	0.34
Auto-Covariance	0.04
Ljung-Box	5.35

Table 5A.12.17
ARMA results for British tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	13.32
BIC	13.81
Mean Absolute Percentage Error (MAPE)	7.52%
R-Square	47.46%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.38

Forecast Statistics	Value
Durbin Watson(1)	2.10
Mean	4.21
Standard Deviation	0.56
Auto-Correlation	0.40
Auto-Covariance	0.12
Ljung-Box	6.60

Table 5A.12.18
ARMA results for British tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	8.90
BIC	9.87
Mean Absolute Percentage Error (MAPE)	7.67%
R-Square	0.57%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.26
T-Test For Constant	3.02

Forecast Statistics	Value
Durbin Watson(1)	1.80
Mean	3.42
Standard Deviation	0.31
Auto-Correlation	-0.07
Auto-Covariance	-0.01
Ljung-Box	7.80

Table 5A.12.19
ARMA results for British tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-13.85
BIC	-13.36
Mean Absolute Percentage Error (MAPE)	1.55%
R-Square	38.43%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.51

Forecast Statistics	Value
Durbin Watson(1)	1.75
Mean	4.71
Standard Deviation	0.17
Auto-Correlation	0.45
Auto-Covariance	0.01
Ljung-Box	3.02

Table 5A.12.20
ARMA results for British tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-25.88
BIC	-24.91
Mean Absolute Percentage Error (MAPE)	1.33%
R-Square	57.32%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	0.10
T-Test For Non Seasonal MA	1.36

Forecast Statistics	Value
Durbin Watson(1)	2.34
Mean	4.17
Standard Deviation	0.11
Auto-Correlation	-0.43
Auto-Covariance	0.00
Ljung-Box	6.78

Table 5A.12.21
ARMA results for British tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.81
BIC	-3.33
Mean Absolute Percentage Error (MAPE)	4.91%
R-Square	51.91%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.48

Forecast Statistics	Value
Durbin Watson(1)	1.41
Mean	3.19
Standard Deviation	0.29
Auto-Correlation	0.55
Auto-Covariance	0.04
Ljung-Box	9.07

Table 5A.12.22
ARMA results for British tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-0.54
BIC	-0.05
Mean Absolute Percentage Error (MAPE)	3.62%
R-Square	79.04%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.62

Forecast Statistics	**Value**
Durbin Watson(1)	1.82
Mean	3.84
Standard Deviation	0.50
Auto-Correlation	0.76
Auto-Covariance	0.17
Ljung-Box	7.16

Table 5A.12.23
ARMA results for British tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-9.80
BIC	-9.31
Mean Absolute Percentage Error (MAPE)	2.63%
R-Square	21.25%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.67

Forecast Statistics	**Value**
Durbin Watson(1)	1.46
Mean	3.92
Standard Deviation	0.17
Auto-Correlation	0.31
Auto-Covariance	0.01
Ljung-Box	9.99

Table 5A.12.24
ARMA results for British tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	1.07
BIC	2.04
Mean Absolute Percentage Error (MAPE)	4.93%
R-Square	11.31%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	48.87
T-Test For Non Seasonal MA	1.71

Forecast Statistics	**Value**
Durbin Watson(1)	1.41
Mean	3.51
Standard Deviation	0.24
Auto-Correlation	-0.17
Auto-Covariance	-0.01
Ljung-Box	2.51

Table 5A.12.25
ARMA results for British tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.00
BIC	-9.04
Mean Absolute Percentage Error (MAPE)	2.72%
R-Square	20.11%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	97.13
T-Test For Non Seasonal MA	-1.69

Forecast Statistics	Value
Durbin Watson(1)	1.99
Mean	4.13
Standard Deviation	0.16
Auto-Correlation	0.37
Auto-Covariance	0.01
Ljung-Box	4.31

Table 5A.12.26
ARMA results for British tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.25
BIC	-11.29
Mean Absolute Percentage Error (MAPE)	2.90%
R-Square	47.02%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	91.92
T-Test For Non Seasonal MA	2.83

Forecast Statistics	Value
Durbin Watson(1)	2.00
Mean	3.70
Standard Deviation	0.18
Auto-Correlation	-0.56
Auto-Covariance	-0.02
Ljung-Box	3.25

Table 5A.12.27
ARMA results for British tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	17.27
BIC	18.24
Mean Absolute Percentage Error (MAPE)	8.37%
R-Square	20.96%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	31.67
T-Test For Non Seasonal MA	3.22

Forecast Statistics	Value
Durbin Watson(1)	1.26
Mean	4.32
Standard Deviation	0.49
Auto-Correlation	-0.33
Auto-Covariance	-0.07
Ljung-Box	7.09

Table 5A.12.28
ARMA results for British tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-7.24
BIC	-6.76
Mean Absolute Percentage Error (MAPE)	3.98%
R-Square	43.46%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.10

Forecast Statistics	Value
Durbin Watson(1)	1.86
Mean	3.62
Standard Deviation	0.23
Auto-Correlation	0.35
Auto-Covariance	0.02
Ljung-Box	5.17

Table 5A.12.29
ARMA results for British tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.17
BIC	4.14
Mean Absolute Percentage Error (MAPE)	7.78%
R-Square	38.44%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.94
T-Test For Constant	0.53

Forecast Statistics	Value
Durbin Watson(1)	1.78
Mean	2.70
Standard Deviation	0.31
Auto-Correlation	0.55
Auto-Covariance	0.05
Ljung-Box	14.80

Table 5A.12.30
ARMA results for British tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	2.61
BIC	3.10
Mean Absolute Percentage Error (MAPE)	9.55%
R-Square	5.17%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.63

Forecast Statistics	Value
Durbin Watson(1)	1.56
Mean	2.21
Standard Deviation	0.27
Auto-Correlation	0.39
Auto-Covariance	0.03
Ljung-Box	8.20

Table 5A.12.31
ARMA results for British tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-13.97
BIC	-13.49
Mean Absolute Percentage Error (MAPE)	2.32%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.15

Forecast Statistics	**Value**
Durbin Watson(1)	2.22
Mean	3.51
Standard Deviation	0.13
Auto-Correlation	-0.17
Auto-Covariance	0.00
Ljung-Box	5.50

Table 5A.13.1
ARMA results for American tourists to Beijing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-15.23
BIC	-14.74
Mean Absolute Percentage Error (MAPE)	1.76%
R-Square	29.92%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.12

Forecast Statistics	Value
Durbin Watson(1)	1.87
Mean	5.40
Standard Deviation	0.15
Auto-Correlation	0.35
Auto-Covariance	0.01
Ljung-Box	2.70

Table 5A.13.2
ARMA results for American tourists to Tianjin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-7.91
BIC	-6.94
Mean Absolute Percentage Error (MAPE)	2.71%
R-Square	47.15%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,1) * (0,0,0)
T-Test For Non Seasonal AR	-3.62
T-Test For Non Seasonal MA	-1.33

Forecast Statistics	Value
Durbin Watson(1)	1.79
Mean	4.24
Standard Deviation	0.21
Auto-Correlation	0.02
Auto-Covariance	0.00
Ljung-Box	7.24

Table 5A.13.3
ARMA results for American tourists to Hebei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	11.24
BIC	12.21
Mean Absolute Percentage Error (MAPE)	6.14%
R-Square	0.73%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	39.42
T-Test For Non Seasonal MA	0.30

Forecast Statistics	Value
Durbin Watson(1)	1.80
Mean	4.09
Standard Deviation	0.34
Auto-Correlation	-0.08
Auto-Covariance	-0.01
Ljung-Box	7.50

Table 5A.13.4
ARMA results for American tourists to Shanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.34
BIC	-2.85
Mean Absolute Percentage Error (MAPE)	3.65%
R-Square	7.33%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.14

Forecast Statistics	Value
Durbin Watson(1)	1.86
Mean	3.82
Standard Deviation	0.21
Auto-Correlation	0.01
Auto-Covariance	0.00
Ljung-Box	6.67

Table 5A.13.5
ARMA results for American tourists to Inner Mongolia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-11.78
BIC	-11.30
Mean Absolute Percentage Error (MAPE)	2.45%
R-Square	58.72%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.69

Forecast Statistics	Value
Durbin Watson(1)	2.16
Mean	3.34
Standard Deviation	0.22
Auto-Correlation	0.61
Auto-Covariance	0.03
Ljung-Box	5.12

Table 5A.13.6
ARMA results for American tourists to Liaoning
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-17.24
BIC	-16.76
Mean Absolute Percentage Error (MAPE)	1.94%
R-Square	66.07%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.90

Forecast Statistics	Value
Durbin Watson(1)	1.38
Mean	4.17
Standard Deviation	0.19
Auto-Correlation	0.59
Auto-Covariance	0.02
Ljung-Box	5.96

Table 5A.13.7
ARMA results for American tourists to Jilin
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.93
BIC	-2.44
Mean Absolute Percentage Error (MAPE)	2.73%
R-Square	15.38%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-3.53

Forecast Statistics	Value
Durbin Watson(1)	1.61
Mean	3.51
Standard Deviation	0.22
Auto-Correlation	0.01
Auto-Covariance	0.00
Ljung-Box	1.79

Table 5A.13.8
ARMA results for American tourists to Heilongjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	9.03
BIC	10.00
Mean Absolute Percentage Error (MAPE)	5.60%
R-Square	3.25%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	0.16
T-Test For Constant	0.20

Forecast Statistics	Value
Durbin Watson(1)	1.99
Mean	3.63
Standard Deviation	0.32
Auto-Correlation	0.14
Auto-Covariance	0.01
Ljung-Box	7.06

Table 5A.13.9
ARMA results for American tourists to Shanghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-15.85
BIC	-15.37
Mean Absolute Percentage Error (MAPE)	1.42%
R-Square	73.04%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.08

Forecast Statistics	Value
Durbin Watson(1)	1.93
Mean	5.19
Standard Deviation	0.23
Auto-Correlation	0.64
Auto-Covariance	0.03
Ljung-Box	3.84

Table 5A.13.10
ARMA results for American tourists to Jiangsu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-14.05
BIC	-13.57
Mean Absolute Percentage Error (MAPE)	1.63%
R-Square	78.29%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.33

Forecast Statistics	Value
Durbin Watson(1)	1.85
Mean	4.93
Standard Deviation	0.28
Auto-Correlation	0.71
Auto-Covariance	0.05
Ljung-Box	5.83

Table 5A.13.11
ARMA results for American tourists to Zhejiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-10.26
BIC	-9.77
Mean Absolute Percentage Error (MAPE)	2.30%
R-Square	67.58%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	0.55

Forecast Statistics	Value
Durbin Watson(1)	2.10
Mean	4.75
Standard Deviation	0.27
Auto-Correlation	0.60
Auto-Covariance	0.04
Ljung-Box	10.16

Table 5A.13.12
ARMA results for American tourists to Anhui
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-8.06
BIC	-7.57
Mean Absolute Percentage Error (MAPE)	3.10%
R-Square	62.94%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.52

Forecast Statistics	Value
Durbin Watson(1)	1.63
Mean	4.19
Standard Deviation	0.27
Auto-Correlation	0.50
Auto-Covariance	0.03
Ljung-Box	5.78

Table 5A.13.13
ARMA results for American tourists to Fujian
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	8.56
BIC	9.04
Mean Absolute Percentage Error (MAPE)	4.91%
R-Square	31.29%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.06

Forecast Statistics	Value
Durbin Watson(1)	1.79
Mean	4.47
Standard Deviation	0.40
Auto-Correlation	0.45
Auto-Covariance	0.07
Ljung-Box	7.72

Table 5A.13.14
ARMA results for American tourists to Jiangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.94
BIC	4.43
Mean Absolute Percentage Error (MAPE)	5.57%
R-Square	26.73%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.89

Forecast Statistics	Value
Durbin Watson(1)	1.56
Mean	3.79
Standard Deviation	0.32
Auto-Correlation	0.30
Auto-Covariance	0.03
Ljung-Box	3.50

Table 5A.13.15
ARMA results for American tourists to Shandong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.08
BIC	-11.60
Mean Absolute Percentage Error (MAPE)	2.30%
R-Square	42.62%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.40

Forecast Statistics	Value
Durbin Watson(1)	1.80
Mean	4.44
Standard Deviation	0.19
Auto-Correlation	0.41
Auto-Covariance	0.01
Ljung-Box	4.57

Table 5A.13.16
ARMA results for American tourists to Henan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-0.71
BIC	-0.22
Mean Absolute Percentage Error (MAPE)	4.72%
R-Square	21.57%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.04

Forecast Statistics	Value
Durbin Watson(1)	1.65
Mean	3.98
Standard Deviation	0.25
Auto-Correlation	0.18
Auto-Covariance	0.01
Ljung-Box	3.41

Table 5A.13.17
ARMA results for American tourists to Hubei
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	13.89
BIC	14.37
Mean Absolute Percentage Error (MAPE)	6.69%
R-Square	1.33%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.17

Forecast Statistics	Value
Durbin Watson(1)	2.41
Mean	4.68
Standard Deviation	0.42
Auto-Correlation	0.10
Auto-Covariance	0.02
Ljung-Box	9.54

Table 5A.13.18
ARMA results for American tourists to Hunan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	6.27
BIC	7.24
Mean Absolute Percentage Error (MAPE)	5.07%
R-Square	10.17%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.10
T-Test For Constant	0.06

Forecast Statistics	Value
Durbin Watson(1)	1.28
Mean	4.26
Standard Deviation	0.29
Auto-Correlation	-0.17
Auto-Covariance	-0.01
Ljung-Box	6.65

Table 5A.13.19
ARMA results for American tourists to Guangdong
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-18.06
BIC	-17.57
Mean Absolute Percentage Error (MAPE)	1.41%
R-Square	57.63%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.34

Forecast Statistics	**Value**
Durbin Watson(1)	1.85
Mean	5.25
Standard Deviation	0.17
Auto-Correlation	0.56
Auto-Covariance	0.01
Ljung-Box	6.33

Table 5A.13.20
ARMA results for American tourists to Guangxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-10.26
BIC	-9.78
Mean Absolute Percentage Error (MAPE)	2.34%
R-Square	0.00%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.24

Forecast Statistics	**Value**
Durbin Watson(1)	1.98
Mean	4.66
Standard Deviation	0.14
Auto-Correlation	-0.08
Auto-Covariance	0.00
Ljung-Box	2.35

Table 5A.13.21
ARMA results for American tourists to Hainan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	**Value**
AIC	-16.78
BIC	-16.29
Mean Absolute Percentage Error (MAPE)	2.24%
R-Square	56.19%

Method Statistics	**Value**
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.70

Forecast Statistics	**Value**
Durbin Watson(1)	1.37
Mean	3.76
Standard Deviation	0.17
Auto-Correlation	0.50
Auto-Covariance	0.01
Ljung-Box	6.74

Table 5A.13.22
ARMA results for American tourists to Chongqing
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-2.26
BIC	-1.78
Mean Absolute Percentage Error (MAPE)	4.17%
R-Square	54.17%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	2.98

Forecast Statistics	Value
Durbin Watson(1)	2.42
Mean	3.84
Standard Deviation	0.31
Auto-Correlation	0.14
Auto-Covariance	0.01
Ljung-Box	6.50

Table 5A.13.23
ARMA results for American tourists to Sichuan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-3.37
BIC	-2.89
Mean Absolute Percentage Error (MAPE)	3.59%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	2.76

Forecast Statistics	Value
Durbin Watson(1)	1.36
Mean	4.51
Standard Deviation	0.20
Auto-Correlation	0.19
Auto-Covariance	0.01
Ljung-Box	8.20

Table 5A.13.24
ARMA results for American tourists to Guizhou
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	0.77
BIC	1.74
Mean Absolute Percentage Error (MAPE)	4.18%
R-Square	2.91%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,0,0) * (0,0,0)
T-Test For Non Seasonal AR	-0.57
T-Test For Constant	2.98

Forecast Statistics	Value
Durbin Watson(1)	1.77
Mean	3.76
Standard Deviation	0.22
Auto-Correlation	-0.15
Auto-Covariance	-0.01
Ljung-Box	5.11

Table 5A.13.25
ARMA results for American tourists to Yunnan
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-12.20
BIC	-11.71
Mean Absolute Percentage Error (MAPE)	2.25%
R-Square	11.07%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.73

Forecast Statistics	Value
Durbin Watson(1)	1.80
Mean	4.55
Standard Deviation	0.15
Auto-Correlation	0.24
Auto-Covariance	0.00
Ljung-Box	5.74

Table 5A.13.26
ARMA results for American tourists to Tibet
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	3.67
BIC	4.15
Mean Absolute Percentage Error (MAPE)	4.70%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.86

Forecast Statistics	Value
Durbin Watson(1)	1.84
Mean	4.14
Standard Deviation	0.25
Auto-Correlation	-0.08
Auto-Covariance	0.00
Ljung-Box	7.43

Table 5A.13.27
ARMA results for American tourists to Shaanxi
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	16.61
BIC	17.58
Mean Absolute Percentage Error (MAPE)	7.32%
R-Square	31.38%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,0,1) * (0,0,0)
T-Test For Constant	36.14
T-Test For Non Seasonal MA	3.24

Forecast Statistics	Value
Durbin Watson(1)	1.46
Mean	4.69
Standard Deviation	0.52
Auto-Correlation	-0.29
Auto-Covariance	-0.07
Ljung-Box	6.01

Table 5A.13.28
ARMA results for American tourists to Gansu
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-5.27
BIC	-4.78
Mean Absolute Percentage Error (MAPE)	3.53%
R-Square	40.22%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-2.22

Forecast Statistics	Value
Durbin Watson(1)	1.60
Mean	3.95
Standard Deviation	0.24
Auto-Correlation	0.45
Auto-Covariance	0.02
Ljung-Box	7.16

Table 5A.13.29
ARMA results for American tourists to Qinghai
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-7.28
BIC	-6.80
Mean Absolute Percentage Error (MAPE)	4.14%
R-Square	48.74%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(1,1,0) * (0,0,0)
T-Test For Non Seasonal AR	-1.10

Forecast Statistics	Value
Durbin Watson(1)	2.10
Mean	3.00
Standard Deviation	0.24
Auto-Correlation	0.55
Auto-Covariance	0.03
Ljung-Box	3.98

Table 5A.13.30
ARMA results for American tourists to Ningxia
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-8.53
BIC	-8.05
Mean Absolute Percentage Error (MAPE)	4.68%
R-Square	13.14%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	1.45

Forecast Statistics	Value
Durbin Watson(1)	1.96
Mean	2.52
Standard Deviation	0.17
Auto-Correlation	0.27
Auto-Covariance	0.01
Ljung-Box	8.52

Table 5A.13.31
ARMA results for American tourists to Xinjiang
Two year ahead forecast
Audit trail – statistics

Accuracy Measures	Value
AIC	-6.56
BIC	-6.08
Mean Absolute Percentage Error (MAPE)	3.18%
R-Square	0.00%

Method Statistics	Value
Method Selected	Box Jenkins
Model Selected	ARIMA(0,1,1) * (0,0,0)
T-Test For Non Seasonal MA	3.16

Forecast Statistics	Value
Durbin Watson(1)	2.06
Mean	3.94
Standard Deviation	0.18
Auto-Correlation	-0.04
Auto-Covariance	0.00
Ljung-Box	2.88