MODELLING AND FORECASTING INTERNATIONAL TOURISM DEMAND TO CHINA

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ABSTRACT

China has experienced a massive growth in international tourism over the past two decades. To date, there have been few attempts to analyse this massive increase in the demand for international tourism to China.

This study, therefore, employs modern econometric techniques to identify the important determinants of tourism demand to China and thus determine the best forecasting models of tourism demand applied to China. This thesis has set three objectives for itself. First, it aims to undertake the first application of modern time-series econometric techniques to modelling international tourism flows to China. Second, it provides the first application of the Vector Autoregression (VAR) approach to modelling the demand for tourism. Third, this thesis compares relative forecasting performance of the two econometric techniques — the time-series approach and the VAR approach, in order to provide 'best possible' forecasts of international tourism flows to China. The thesis models demand from three of China's most important markets for international travelers: Australia, the USA and Japan.

The thesis is organised into nine chapters. Chapter One is the Introduction. Chapter Two provides an overview of some important aspects of tourism development in China since 1978. Chapter Three analyses the changes in, and current characteristics of, China's inbound tourism market. Chapter Four sets up the theoretical framework of modelling and forecasting international tourism to China while Chapter Five reviews previous studies of international tourism demand. Chapter Six performs modern time-series testing of the important variables identified for inclusion in the demand modelling. Chapter Seven develops a VAR system for international tourism to China. Chapter

Eight undertakes forecasting and forecast comparison of the VAR systems against ARIMA and no-change models. The thesis closes with a concluding Chapter Nine.

The major findings from the thesis may be summarised as follows:

- The VAR system approach provides a very promising framework to analyse international tourism demand to China from the three identified market sources and therefore may have more general application for analysing tourism demand in other market contexts.
- Two-way trade between China and these tourist source countries is one of the most important determinants of tourism demand to China and may be a variable of more general significance in international tourism demand studies.
- When using the diagnostic test of directional change, the VAR models generally outperform ARIMA and naïve models for forecasting demand one and two years ahead.

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CHAPTER 1: **INTRODUCTION**

1.1 RESEARCH ISSUE

During the last two decades China has experienced a massive growth in international tourism. From 1980 to 1998 China's inbound visitor arrivals and international tourism receipts grew respectively at 14.3% and 18.2% per annum.[1] According to the World Tourism Organization (WTO, 1999), China became the 5th most important tourist destination in the world in 1998, whereas it was ranked as the 19th destination in terms of tourist arrivals in 1980.[2]

Accompanying China's "Open Door" policy in international relations and its economic reform program since 1978, tourism in China has transformed from being initially a political policy tool, which was centrally controlled to an economic force driven by a more decentralized, deregulated market approach. The development of tourism infrastructure in China has resulted from changes in tourism policy and the liberalization of tourism operations in China.

The development of tourism infrastructure at the supply side is one of the key factors in international tourism arrivals to China, which has been analyzed by several researchers (e.g., Tisdell and Wen 1991, Choy 1993, Zhang 1995, Zhang *et al.* 2000). These studies provide a better understanding of the significant development of tourism sectors in China. However, as international tourism in China is also part of the international tourism market, demand factors in its tourist source countries push or constrain international travel to China and thus determine the level or scale of tourism flows to China.

Over the past three decades, a large number of empirical studies of international tourism demand (see Crouch 1994a, Crouch 1994b, Witt and Witt 1995, Lim 1997,

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[1] Figures are calculated based on statistics provided by China Yearbook of Tourism Statistics (1999).
[2] WTO statistics only include overnight visitors.

Morley 2000) have been conducted focusing on the European and American tourism experiences. Other world regions, such as, Asia, the Middle East and Africa, have been ignored by researchers despite a rapid tourism growth in these countries since the 1980's (see Witt and Witt 1995). Studies on tourism in China are limited. In particular, empirical assessments of international travel flows in China using econometric methods are rarely found.

Previous studies on China's tourism are mainly focused on a descriptive introduction to China's tourism policy and infrastructure developments since 1978 (e.g.: Zhao 1989, Hall 1994, Lew and Yu 1995, Go and Jenkins 1996, and Zhang *et al.* 1999). One exception is the study by Wen and Tisdell (1996) on the spatial distribution of tourism in China, and another is Zhou, King and Turner (1998) on the reasons for China's outbound tourism. Many previous studies in international tourism demand forecasting have employed both causal and non-causal methods and compared the accuracy of forecasting. These studies suggest that the accuracy of different modeling methods vary for data from country to country over different periods. Therefore, neither a single model nor a single method will necessarily be appropriate for all origin-destination pairs. For the econometric models, certain explanatory variables influence tourism demand for some origin-destination pairs but not others, and the coefficients also vary considerably across tourist flows (see Witt and Witt 1995, p.469). It should be noted that these results are based on the case studies of established tourism countries. The results may differ in developing destination countries in Asia, such as China.

Tourism in Asian countries have special characteristics which are different from that in "western countries" (see Richter 1983, 1993, Sinclair and Vokes 1993, and Jenkins and Liu 1994). These special characteristics, in particular, its demand side characteristics, such as travel purposes (or motivations), travel abilities and constraints, require further theoretical and empirical investigations and assessments. Although relatively sophisticated measures have been used in tourism demand modeling and forecasting, the use of econometric techniques in many previous tourism studies is subject to some criticism (see Crouch 1994a, Crouch 1994b, Witt and Witt 1995, Kulendran 1996, Lim 1997, Morley 2000). These criticisms may be summarized as follows:

- As indicated by Witt and Witt (1995) and Crouch (1994a, 1994b), the lack of diagnostic checking for the econometric issues, such as stationarity, multicollinearity and serial correlation, in the econometric studies of many authors clearly limits the usefulness of much of the empirical results.
- Although regression analysis deals with the dependence of one variable on other variables, it does not necessarily imply causation. It assumes that the explanatory variables are not affected by the dependent variable, ignoring the feedback effects of dependent variables.
- In many previous causal studies (see Witt and Witt 1995), income, relative prices, exchange rates and substitute prices were most commonly used as the important determinants in tourism demand functions. Economic theories on tourism demand suggest that factors influencing tourism demand are wide-ranging and the determinants of tourism demand are complex and varied. Some of the variables which are assumed to be closely associated with changes of tourism demand are generally ignored in these studies, such as supply variables; for example the availability of natural tourism attractions, infrastructure at destinations, and trade and investment flows between tourist generation and destination countries. The omission of important variables and the inadequate use of determinants in tourism demand functions often leads to biased estimates.

1.2 RESEARCH AIM

This thesis uses modern econometric methods in attempt to identify the important determinants of tourism demand to China and determine the best forecasting models of tourism demand to China.

This thesis has three objectives:

- It aims to undertake the first application of modern time-series econometric techniques to the modeling of international tourism flows to China.
- It provides the first use of the Vector Autoregression (VAR) approach to modeling the demand for tourism.
- It undertakes comprehensive forecast comparison of the time-series approach to the VAR econometric approach in order to provide "best possible" forecasts of international tourism flows to China.

1.3 RESEARCH APPROACH

In order to achieve these objectives, this thesis is organized as follows.

Chapter 2 provides an overview of some important aspects of tourism development in China since 1978. This includes the policy changes and the process of tourism decentralization since 1978 and the ongoing development of tourism sectors, i.e., hotels, airlines and travel services in China. International tourism flows to China did not occur in a policy vacuum. Therefore, this chapter provides an insight into the extent of the growth of inbound international tourism to China over the past 20 years, and an appreciation of the policy context that helped lead to this growth.

Chapter 3 analyses the changes in, and the current characteristics of China's inbound tourism market, by examining its major generation countries, tourist compositions, spatial distribution and seasonality of tourist arrivals. This chapter examines important characteristics of the inbound tourism market and identifies important factors influencing international tourism demand to China. Based on this analysis and relevant economic theories, variables used to model and forecast the tourism demand can be determined and selected.

Chapter 4 sets up the theoretical framework of modeling and forecasting international tourism to China, by reviewing theories on the determinants of international tourism, including macroeconomic considerations and microeconomic formulations. This chapter identifies theoretical factors influencing international tourism demand and the range of determinants of international tourism demand.

Chapter 5 further builds up the theoretical framework to analyze and forecast international tourism demand to China, by critically reviewing previous empirical studies of international tourism demand. This chapter presents a comprehensive review of the developed modeling methodologies applied in traditional regression models, time series models, and error correction models and vector autoregression models. It also discusses measures of forecasting accuracy employed in previous empirical studies of international tourism demand.

Chapter 6 selects variables to model and forecast international tourism to China. This chapter identifies the most important determinants of tourism demand to China, and defines appropriate economic indicators to measure these determinants. In addition, a range of statistical analyses is conducted to examine the time series properties (i.e., the trends and seasonalties) of the selected data for each variable.

Chapter 7 develops a VAR process developed by Sims (1980) to analyze and forecast the quarterly tourist flows to China from its three tourist source countries. The VAR systems permit the feedback effects between economic variables, which are ignored by the single-equation approach. The interactions (feedback effects) between the variables can be further analyzed and forecasting can be conducted in the VAR systems. In addition, in the VAR systems, we are able to deal with the issues of cointegration and causality. The cointegration test developed by Johansen and Juselius (1990) is applied to test if there are "long-run equilibrium" relationships among the selected variables and further estimates the "long-run" tourism demand to China from the three selected countries. The Granger causality test developed by Ganger (1978) is used to examine if there are "causal" relationships between the selected variables.

In order to evaluate the forecasting performance of the VAR models developed in this research, in Chapter 8, we employ time series methods (i.e., seasonal ARIMA models) to generate forecasts of the quarterly tourist flows to China from Australia, the

USA and Japan. No-change models are used as the benchmark to assess the forecasting performance of the VAR Models and the ARIMA models. The forecasting performance is compared in terms of forecasting error magnitude and directional change accuracy.

The thesis concludes in Chapter 9 with discussions of the outcomes of the research reported in this thesis and insights from lessons learned.

CHAPTER 2: **INTERNATIONAL TOURISM IN CHINA: THE POLICY AND INSTITUTIONAL CONTEXT**

2.1 INTRODUCTION

We begin our analysis of China's inbound tourism with two related chapters dealing with the important contextual setting. In this chapter we look explicitly at policy and institutional changes that have led to the massive growth in inbound tourism to China over the past two decades. Chapter 3 further undertakes a contextual analysis by discussing important market characteristics of inbound tourism in China.

International tourism in China has experienced dramatically rapid growth since China commenced its "Open Door Policy" in international relations and the reform of its economic system in 1978. According to the Chinese National Tourism Administration (CNTA), during the last two decades (1978-1998), international tourist arrivals to China increased 35 times from 1.8 million persons up to 63.4 million;[3] the revenue from international tourism expanded over 48 fold from US$ 262.9 million to US$ 12.6 billion during the same period (CNTA, 1999). Such a rapid advance in China's international inbound tourism has been accompanied by the on-going economic reform and policy changes in tourism administration and operation, and arguably, tourism growth has resulted in significant benefits to the Chinese economy.

This chapter, therefore, provides an overview of some important aspects of tourism development in China since 1978. The following section, section 2 reviews the policy changes and the process of tourism decentralization since 1978, which play an important role in international tourism development in China. Further, the ongoing development of tourism sectors, i.e., hotels, airlines and travel services in China, is briefly illustrated in section 3. Section 4 discusses the contributions of international

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[3] These statistics include both overnight and same day visitors.

tourism development in China to the country as a whole. A summary and conclusion is presented in section 5.

2.2 POLICY SHIFT

2.2.1 Political Objective To Economic Objective

Before 1978, tourism in China was considered as a part of diplomatic activity, rather than a part of its economic activity, as the government's main objectives on international tourism were political rather than commercial. There was hardly any inbound tourism from western countries between 1949 and 1978 except diplomatic receptions as a result of the "cold war" and China's isolation from the "capitalist world" (see Usal *et al.* 1986, and Jenkins and Liu 1996). The limited "foreign tourists" were mainly diplomatic visitors from the socialist-bloc countries. Later, following the establishment of diplomatic relationships with more western countries, China began to receive western guests in the 1960's. However, tourism in China still served political purposes: to introduce the achievements of socialist China, to expanding China's political influence, and to promote international understanding and friendship from the western countries through receiving international guests and tourists (Han, 1994). Holiday travel to China was discouraged by the Chinese government through the imposition of strict visa requirements.

After 1978 when the Chinese government started to shift to its "Open Door Policy" and the reform of its economic system, China began to emphasize the economic benefits of international tourism and tourism has been regarded as a key element in economic development and an important avenue to gain foreign exchange income, to improve the balance of payments, and to provide employment opportunities. "These fundamental changes in the concept of tourism and the corresponding change in policy served as the basis for the development of the modern Chinese tourism industry " (Zhang, 1989, p.58).

Early in 1978, Mr. Zhao Ziyang, the Chinese Prime Minister, addressed the Thirteenth National Congress of the Communist Party of China and stated that

> More should be done to expand export-oriented industries, especially the tourism sectors catering for foreigners so as to increase foreign exchange earnings". [see Zhao 1987, p. 28]

In 1986, for the first time, tourism development was included in the National Social-Economic Development Plan — the Seventh Five-Year Plan (1986-1990). In this Plan, seven key tourist cities and provinces were given priority for tourism investment: Beijing, Shanghai, Xi'an, Guilin, Hangzhou, Jiangsu, and Guangdong provinces (including Hainan Island until 1988 when the latter was upgraded to province level). Targets were set to receive 3 million foreign tourists in 1990 and 7-8 million foreign tourists in 2000, making China one of the top tourist destinations in the world (Jenkins and Liu, 1996, p.105). Further, in the Ninth (1996-2000) Five-year Plan, tourism sectors were expected to earn US$ 10 billion from international tourists and US$ 120 billion from domestic tourists (CNTA, 1996a).

The above changes in the concept of international tourism and the corresponding changes in the government policy has led to a decentralizing process in the system of international tourism administration and operation in China.

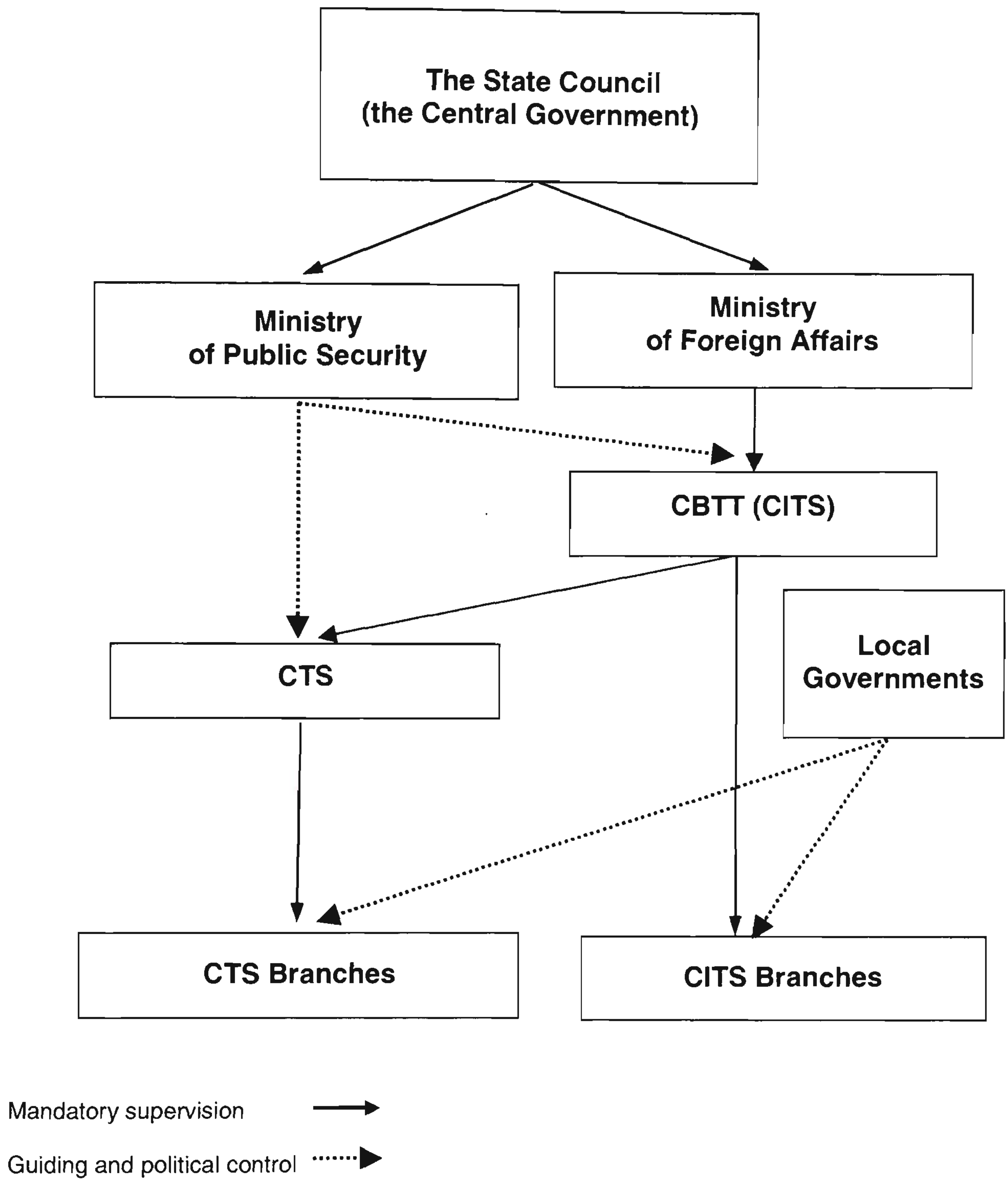
2.2.2. Centralization To Decentralization

Decentralization is a concept here embracing two important changes in the administration and operation of the system of international tourism in China: first, the movement away from central government control to the dual administration system with local governments; second, the movement from government monopoly ownership to collective and private ownership.

For a long time in China, the administrative and operating system of tourism featured significant state monopoly and centralization prior to 1978. All travel businesses, including travel agencies, hotels and transport services, were operated by state-owned enterprises, and hence were under the strict control of the central government. Its two ministries under the State Council,[4] Ministry of Foreign Affairs and Ministry of Public Security, are responsible for the mandatory supervision and guiding and political control to international tourism in China. The China Bureau of Travel and Tourism (CBTT), also known as China International Travel Services (CITS) head office, was a government body supervising two state-owned and central-controlled travel services: the CITS local branches and the China Travel services (CTS) head office; on the other hand, it was also involved in travel operations because the head or deputy head of the CBTT was also the general manager of the CITS. The CITS and CTS together oligopolized the operation of international tourism and domestic tourism including tourism operation at the local level. Local governments were only involved in the policies and organizations of the China Communist Party within these local branches (see Figure 2.1A).

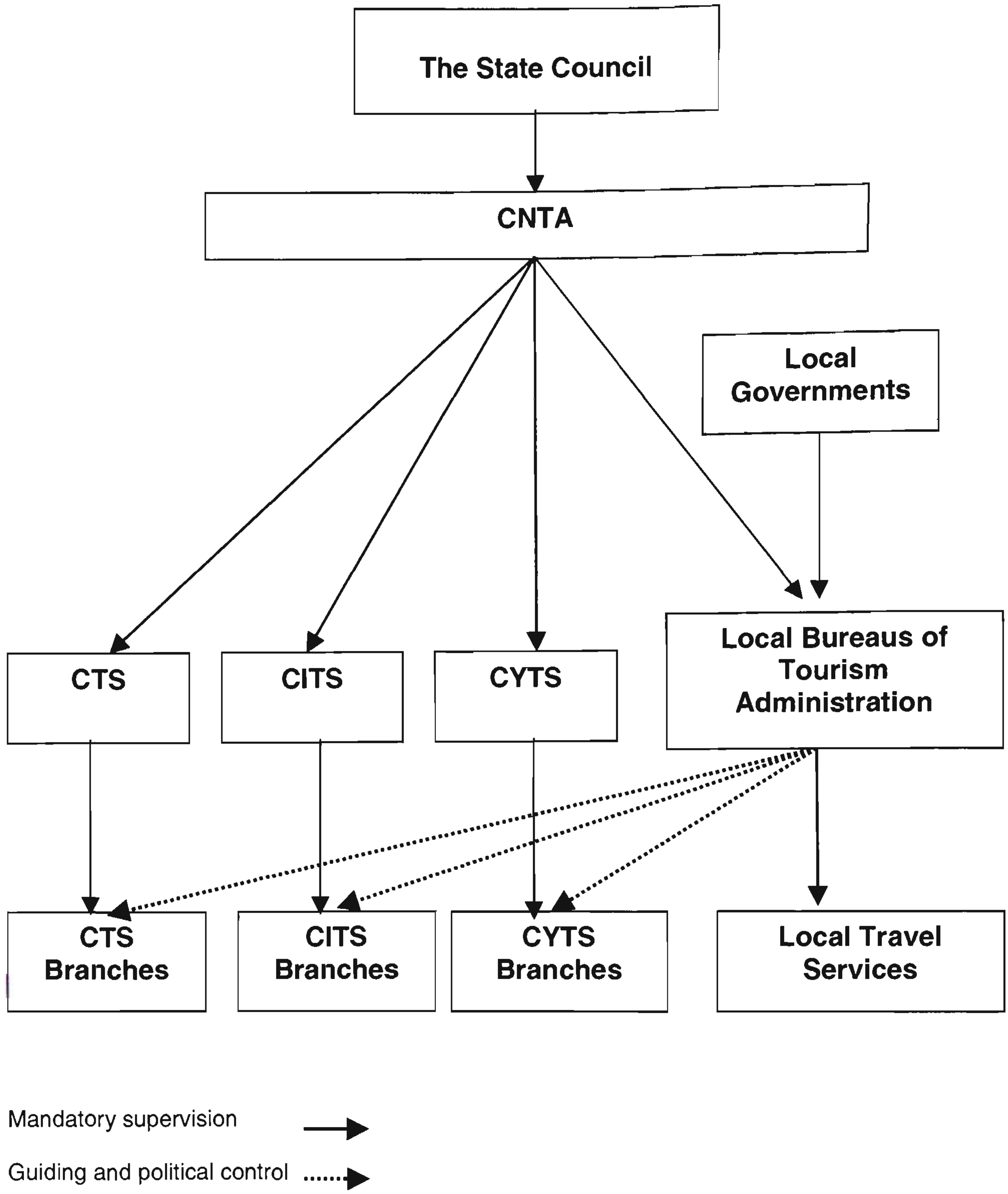
[4] The State Council is the highest organ of China's state administration, which is composed of the Premier, vice Premiers, State Councilors and the Ministers in charge of ministries and commissions. The Premier has overall responsibility for the State Council.

Figure 2.1A: System of Tourism Administration Before 1978



After 1978, as part of the economic reform and decentralization process, tourism management has been gradually decentralized (see Figure 2.1B).

Figure 2.1B: System of Tourism Administration After Decentralization



Early in 1978, the former CBTT was separated from the Ministry of Foreign Affairs and became the sole government body responsible for tourism administration as an independent government body directly under State Council. In 1982, it was renamed as the China National Tourism Administration (CNTA) responsible for national tourism development planning, international tourism promotion and policy formation. To increase competition and efficiency, provincial tourism bureaus were established in the middle of the 1980's. Local branch offices were allowed to establish contact directly with foreign tour operators and were also granted authority for visa distribution. In 1988, provinces, autonomous regions and municipalities, directly under the jurisdiction of the central government, including municipalities under separate plans, were granted the authority to set up their own travel agencies including "Category 1" Travel agencies.[5] Later on, complete authority was granted to local travel bureaus to process visa applications, develop packaged tours, determine prices and independently finance their operations.

Further, to meet the tourism demand stemming from both international and domestic travel growths, the Civil Aviation Administration of China (CAAC) initiated airline liberalization policies to enable the airlines industry to react more efficiently to changes in the tourism market. Among these policies was the separation of the regulator functions of the CAAC from its airline and airports administrative operations. These structural reforms started in 1984 and were completed on June 30, 1988. Therefore, by 1988, the CAAC had become a regulatory body concentrating on regulating civil aviation standards and supervising the airline industry. The responsibility for operating both the airlines and airports was given to its regional branch offices. In addition, the CAAC has granted permission to certain provincial and municipal governments to establish commercial airlines. The airline industry in China has been dramatically transformed from a single, government-owned airline to an estimated over 40 regional provincial and local airlines (see Yu and Lew, 1997).

In July 1984, the State Council approved the suggestion from the CNTA to break the monopolization of the state ownership in tourism sectors and to use collective and

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[5] These agencies are completely independent from the CITS, and can engage in international travel business including processing visa applications.

private capital in the construction of tourism infrastructure. According to CNTA (1995), tourism sectors, in particular the hotel sector, has become the sector with the highest proportion of foreign investment. By the end of April 1994, foreign companies invested over 10 billion dollars in China's tourism sectors (while the total foreign investment in China was 76.6 billion), including hotels, tourist transportation, tourist commodity developments, scenic spot constructions, tourist entertainment, restaurants and food services (CBS, 1995). Since 1992, foreign aviation investors were allowed to operate any aviation business jointly with China except for those related to aviation control. Based on this policy, foreign investors could operate joint venture airlines with China and also could invest in commercial airports (TTG, 1994). By 1994, China had also set up 15 aircraft maintenance and ground service corporations with foreign investors from Hong Kong, the USA, Singapore and Indonesia, with Hainan Airline the first airline in China to receive foreign investment (Zhang *et al.*, 1999).

Although local tourism bureaus and branches of three major travel agencies, the CITS, CTS and China Youth Travel Services (CYTS), are still under the dual control of both local governments and their higher tourist administration, complete decentralization of authority was granted to local government at the end of 1980. Comparing the administrative system controlling tourism prior to 1980, tourism has been decentralized by the following three steps. First, the CITS was separated from the government body (the CNTA) so that it is financially independent, in an effort to achieve the commercialization of public enterprises. Second, provincial governments were allowed to operate or control tourism sectors in their own regions, and their branch offices can engage in both domestic and international travel businesses. Third, private or collective ownership providers, and foreign companies were allowed to invest and operate in the domestic tourism sectors, and later, in international tourism. By the end of the 1980's, an open and multi-channel operating system came into being with a dozen national key tour operators.

Some problems arising from the decentralization may be noted (see Han 1994a, Hall 1996, Zhang 1995, Jenkins and Liu 1996, Wen and Tisdell 1997, Zhang and Lew 1997, Zhang *et al.* 1999). In general, these problems mainly arise from the following areas: firstly, the confusion created by the proliferation of travel organizations, such as in the standards of service qualities, levels of prices and abuses of visa processing, which have caused concerns for the reputation of tourism in China. Secondly, decentralization has also made it difficult to coordinate tourism planning and development for the country as whole, particularly when China's tourism market and hotel construction are still in a "dual system" of both government planning and market-based private investment. For instance, hotels, especially luxury hotels, became over-supplied in the middle of the 1980's (see Zhao 1989 and EIU 1989). Finally, decentralization and competition in tourism sectors may worsen the negative effects of tourism on the social-biological environment in China. Tourism growth in China has been blamed for the increase in venereal disease, prostitution, drug addiction and drug trafficking (see Jenkins and Liu 1996).

As a consequence of the decentralization process of tourism management, an "open multi-channel" tourist operating system seems to have played an important role in the development of tourism infrastructure.

2.3 THE DEVELOPMENT OF TOURISM INFRASTRUCTURE

Tourism decentralization in China appears to have had a remarkable impact on the tourism sectors in China. Hotels, transportation and travel agencies, which are usually regarded as the three basic elements of tourism sectors, have experienced significant growth under the decentralization policy.

2.3.1 Hotels

The boom of hotel construction since 1978 may be the best example to demonstrate the development of tourism in China after the decentralization policy. Hotel shortage was one major obstacle to the expansion of tourism in China at the beginning of the 1980's, as China did not have hotels of an international standard before 1978 (see Zhang, 1995a). There a few accommodation units of international standard not called hotels but "Bin Guan" (guesthouse), which were used by the Chinese government to host invited foreign guests. Only a few cities in China had "Bin Guan" before 1978 and they were not commercially used.

After implementation of sets of investment policies for tourist hotels, which had been set up focusing on the construction of hotels using collective, private capital, and foreign investments, the shortage situation had been overcome by the end of 1980's. There was a boom in hotel building by joint ventures, collective and private enterprises within the main tourist cities (see Zhao 1989, Zhang 1995a, EIU 1989). By the end of 1998, there were 5,782 hotels with 764,800 rooms (1.5 million beds) available for overseas visitors (see Figure 2.2).

Figure 2.2: Breakdown of Hotels by Economic Type and Star-Rating

1998	Number of Hotels	% of Total
Total	5,782	100
By Economic Type		
State-owned	3639	62.9
Collective	859	14.9
Private	153	2.6
Alliance	155	2.7
Stock	282	4.9
Foreign Invested	458	7.9
H.K. Macau, Taiwan Invested	236	4.1
By Star-Rating*		
5 Star	64	1.1
4 Star	176	3.0
3 Star	1,085	18.8
2 Star	1,610	27.8
1 Star	313	5.4
No Star	2,534	43.8

Data Source: China Yearbook of Tourism Statistics (CNTA, 1999).
* For the hotel star-rating system in China, please refer to Yu (1992).

Therefore, the number of hotel rooms available had increased over 18 fold since 1980 with an annual growth rate of 20%. This exceeds the annual growth in overseas arrivals (15%) during the same period (CNTA, 1999). Moreover, the number of state-owned hotels has decreased to 62% of the total number of hotels for overseas visitors, with the rapid growth of other economic types of hotels.

2.3.2 Transportation

The development of a modern transport network has not only been a major priority in the development of China's economy, but also has catered for the growth of both domestic and international tourism. Although transport still remains a bottleneck for further tourism development (as well as the entire economy) in China, the growth has been tremendous during the last two decades. Accompanying the boom of the economy and tourism, the provision of tour buses, taxi cabs, trains, and air networks has experienced a considerable growth since 1979. In particular, the expansion of the aviation industry, which is an important international travel mode into China, has increased dramatically. There were only 167 routes in 1978, but by the end of 1997, the Civil Aviation Administration of China (CAAC) had increased its capacity to 967 routes including 109 international routes connecting 31 countries and 57 cities. In the 20 year period from 1978 to 1998, the number of total passengers using air traffic grew from 2.3 million to 56.3 million (CNTA, 1998). Moreover, in order to introduce an element of competition and improve air services, the CAAC has been separated from the state airline, Air China. The CAAC formerly operated the sole airline, Air China, in the country. Beginning in 1985, it has been divided into six state-owned regional airlines with Air China as the national carrier. These airlines provide both international and domestic services and would be responsible for their own profits and losses. In addition, some 20 local, allied and even private airlines have been founded in recent years. Airport operations were also transferred to local and regional governments, with the airports in Shanghai and Beijing the first to be taken over by local government authorities (Han, 1994b).

2.3.2 Travel Agencies

Travel to China had been oligopolized by three government travel agencies before 1987. The CITS was established in 1954 to handle foreign travelers. It worked as one government body responsible to the foreign ministry, and served as both a government tour operator and tourism organization before the establishment of the CNTA. The CTS was established in 1953 to handle primarily overseas Chinese tourists residing abroad. The China Youth Travel Service (CYTS) was set up in 1980 to promote the link between Chinese youth and the youth from other countries.

With the strategic shift in Chinese tourism policy, greater authority was granted to local travel agencies to operate domestic and international tourism business. By the end of 1998, there are altogether 6,222 travel agencies, including 1,312 international travel agencies and 4,910 domestic travel agencies.

In summary, it can be seen that international tourism in China has undergone a policy shift since 1978, which has played an important role in the development of tourism infrastructure. Consequently these developments of international tourism in China have made significant contributions to the national economy.

2.4 CONTRIBUTIONS OF INTERNATIONAL TOURISM DEVELOPMENT TO CHINA

Tourism development contributes significantly to the economic and social environments in destination areas. Tourism has a wide market linkage in a national economy and the influences of tourism extend to several fields of the economy, such as, employment, foreign trade, regional development, and the balance of payments. Moreover, tourism development also affects the social-cultural and ecological environments of tourism destinations.

Mathieson and Wall (1982) point out that the rapid injection of tourist expenditures and foreign investment into developing countries often has rather different and more significant effects than if equivalent sums were expended in developed countries, as developing countries usually have the characteristics of low levels of income, labor-intensive employment, high levels of unemployment, and deficit of foreign trade. Thus, the impact of tourism development on China is substantial and diverse.

This section, therefore, explores contributions of international tourism to employment, foreign trade, the national economy, and development of domestic tourism in China. It also examines the impact of tourism on China's social-cultural and ecological environment.

2.4.1 International Tourism And Employment

Numerous industries are directly linked to tourism (hospitality, transport, accommodation, entertainment, travel agencies and related services, administration, finance, health etc.), and moreover, tourism is also indirectly supplied by several other industries: construction, agriculture, manufacturing and processing. Therefore, the growth of tourism in both industrialized and developing countries has created many direct and indirect job opportunities.

Moreover, "in developing countries employment created in export industries is far inferior to employment created by tourism, as the employment features low level of technical expertise and are labor-intensive" (Vellas and Becherel, 1995, p. 218). Therefore, China benefits more from the development of its tourism sectors, as a developing country with a big population.

First of all, tourism sectors directly provide significant employment in China. For example, in 1998 alone, there were 9 million people employed indirectly in the industries related to tourism, and 1.8 million directly employed in international tourism sectors, including hotels, travel services, transportation (coach and cruise companies), tourism administrations and tourism trading and service companies (CNTA, 1999). The hotel industry contributed the most by absorbing the majority of the total tourism employees which made up 60% of the total number of employees in tourism sectors (see Figure 2.3).

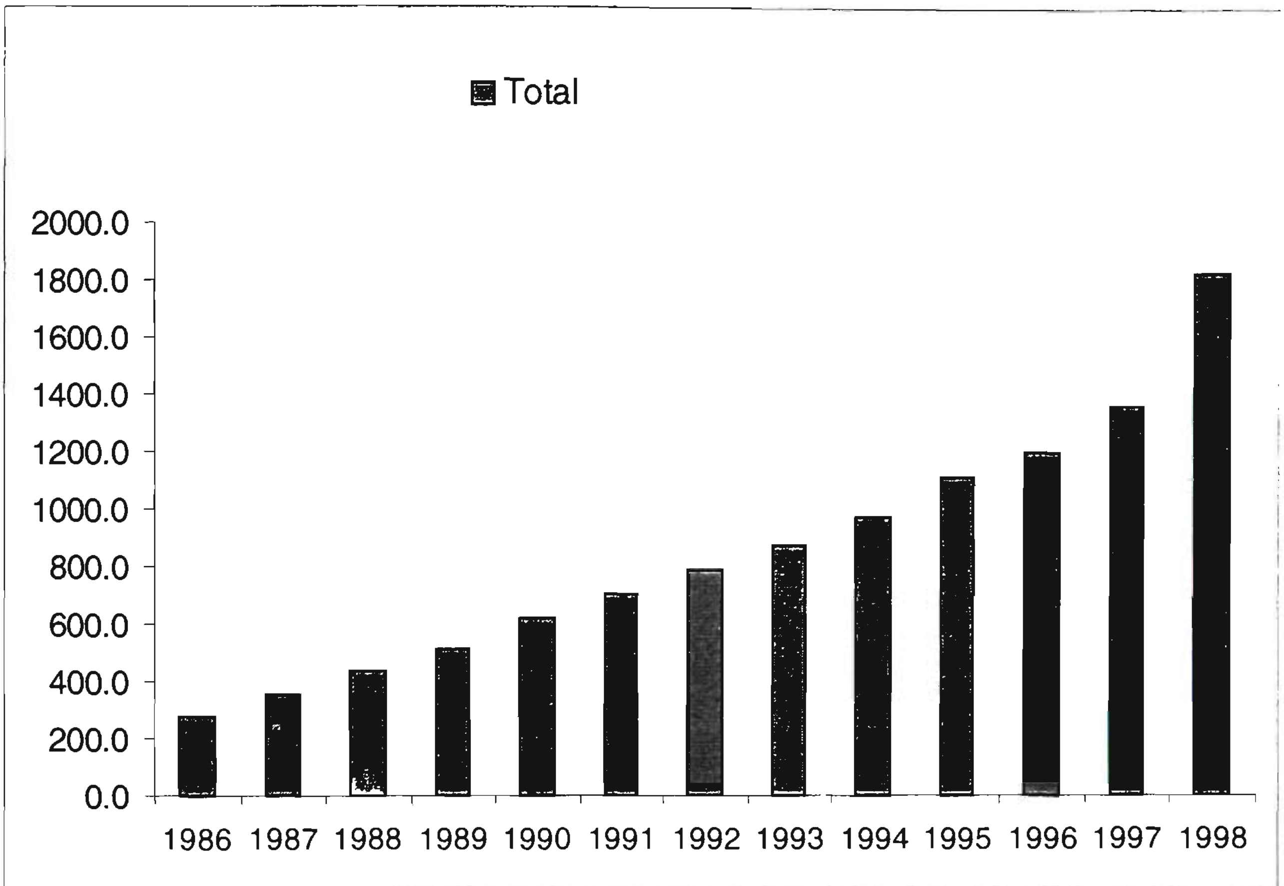
Figure 2.3: Number of Employees in International Tourism sectors (1998)

	Total	% of Total
Hotels	1,098,923	60.0
Travel Agencies	100,448	5.4
Coach and Cruise Companies	84,253	4.5
Tourism Trading and Services Companies	9,411	0.5
Tourism Administrative Institutions	19,732	1.0
Others	517,233	28.6
Total	1,830,000	100

Data Source: China Yearbook of Tourism Statistics (CNTA, 1999)
Note: statistics in the table are for equivalent full-time employees.

Secondly, the number of employees in international tourism sectors has increased significantly since the middle of the 1980's. From 1986 to 1998, the total number of people employed directly in tourism sectors averaged at 17% annually, and reached up to 1.8 million in 1998 from the 0.27 million persons in 1986. The figure increased more than 6 times in a decade (see Figure 2.4).

Figure 2.4: Total Number of Employees in International Tourism Sectors



Data Source: China Yearbook of Tourism Statistics (CNTA, 1998).
Note: statistics in the figure are for equivalent full-time employees.

Thirdly, in spite of technological advances, the skill level necessary for many jobs in tourism industry, particularly in hotels, is low whilst the number of jobs created is very high. The International Labor Office (ILO) has calculated an average " bed to employees" ratio in industrialized countries as follows:

Number of hotel employees / Number of beds = 0.5,

which means that two hotel-beds need one employee in industrialized countries (Vellas and Becherel, 1995, p. 218). Calculating this ratio for China, we obtain more than three times higher "bed to employee" ratio (i.e., 1.6), by measuring its 942,459 hotel employees against 593,696 beds in its hotel industry in 1996, which means two beds employ about three persons in China's hotel management due to its relatively lower efficiency of hotel management.

Finally, the effects of tourism on employment must be analyzed not only from the quantitative angle but also from the qualitative perspective by appraising job skills. Foreign or domestic investment in the tourism-related industries has not only allowed for the construction of tourist facilities, but has also led to the adoption of technological innovations, improvement of skill levels of employees, and application of modern hospitality management skills.

In summary, compared to the industrialized countries, the proportion of tourism employment from the total employment number is not significant.[6] However, the potential of tourism in employment for the Chinese economy is substantial. The employment contribution of tourism in China can hardly be entirely comprehended because of the large and rapidly growing number of related private and informal occupations. There are, for example, hot food stands on street corners, mobile souvenir traders, photographers at the viewpoints, and many small private workshops producing a variety of arts and crafts for tourists. The ability of tourism to create employment, commonly in urban areas, has not only provided job opportunities for the urban residents, but also facilitated the drift of people from the rural to urban locations, which has promoted the urbanization in China.

2.4.2 International Tourism And Foreign Trade

Gray (1970) defines international tourism as an 'invisible trade', which gives rise to flows of international money payment without directly or primarily resulting in the international transfer of ownership of tangible goods. Therefore, international tourism, as a part of international service transactions, plays a major role in a country's balance of payment. International tourism, like the exchange of the commodities, is part of foreign trade, in view of its ability to raise the flow of foreign exchanges. The purchase of commodities by a foreign tourist at a destination is equivalent to exports of products and

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[6] The number of employees in international tourism made up 0.8% of total working population in China in 1996, while tourism employment took up 5% of the total employment in some industrialized countries (see Vellas and Becherell, 1995, p.218).

the services from the destination country to the tourist source country, which will effect its trade balance.

Moreover, as argued by many researchers (e.g., Peters 1969, Vellas and Becherell 1995, and Kulendran and Wilson 2000b), there are close links between the growth of international tourism and trade.

On one hand, international travel may lead to a subsequent increase in international trade between a tourist destination and its source country. International tourism does involve transactions in commodities to some degree, as development in international tourism sectors in a host country will inevitably increase its import demand for foreign goods and services (e.g., foreign investments in tourism facilities and demand for imported materials). For instance:

- The construction of tourism superstructures and the requirements of tourism consumption necessitate importing goods and services that can not be produced by the country. Therefore, inbound tourism in a country may offer a major opportunity for stimulating investment in the destination countries (see Peters, 1969, p.22).
- Countries which have acquired a reputation for expertise in tourism tend to export tourism equipment, goods and services (Vellas and Becherell, 1995, p.239).
- More foreign tourists to a host country generally increase the image of this country for its goods and services around the world and hence create good opportunities for foreign trade (Kulendran and Wilson, 2000b).

On the other hand, international trade is quite often the generator of international travel flows, as:

- An important component of international travel is business travel. Business deals including foreign trade and investment often generate subsequent travels on business to the destination country.

- Increased business travel may also lead to increased holiday and other travel seeking adventure and recreation. "Greater trade between countries will increase awareness of each country... and hence increase holiday travel based on consumer interest." (Kulendran and Wilson, 1997, P.5).

Therefore, there exist interactions between international travel and international trade, which constitutes a possible source of future economic expansion.

In the case of China, the role of international tourism receipts in gaining total foreign exchange income has significantly increased during the last decade or so. For instance, in terms of the proportion of the total foreign exchange receipts, income from international tourism grew from 3.4% of total foreign exchange receipts in 1980 to 6.8% in 1996.[7] There is no doubt that revenue from the international tourism will take on a more important role of total foreign exchange income in the near future, with the rapid growth of international tourism in China.

Further, a comparison of the trends in international trade and international tourism in China reveals a rapid growth in both the volume of tourist arrivals and the value of total imports and exports since 1978 (see Figure 2.5).

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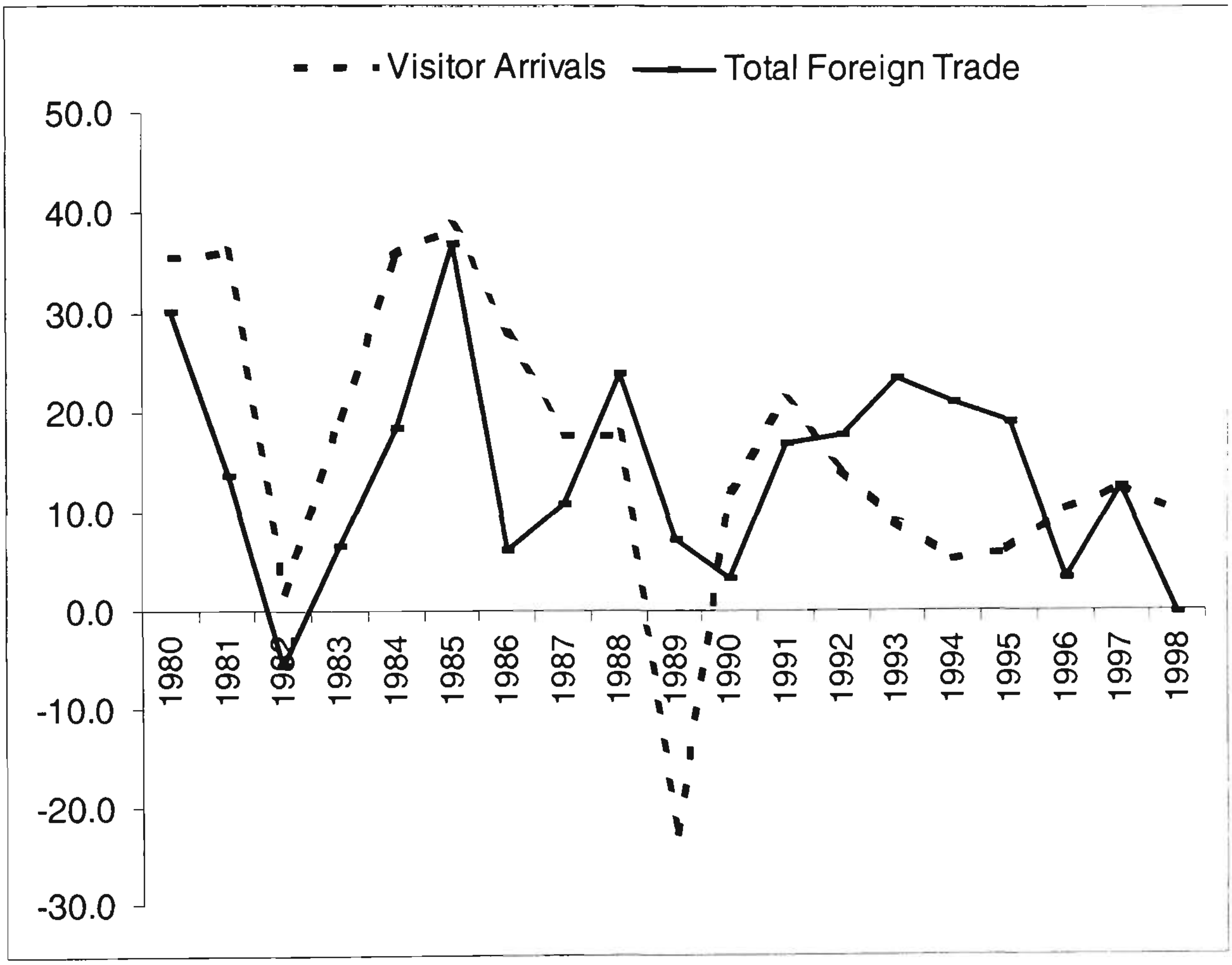
[7] Figures are calculated from the statistics provided by the Yearbook of China Statistics (CBS,1981, 1997).

Figure 2.5: Annual Increases of International Tourism and Trade (1980-1998)



Data Source: China Yearbook of Tourism Statistics (CNTA, 1998).

Furthermore, over the 1980-1998 period, international arrivals and international trade followed a very similar pattern (see Figure 2.5). In terms of the annual growth rate, the total foreign trade volume (exports + imports) in China grew by an average 12.6% each year from 1980 to 1998, while the annual growth of international arrivals averaged at 14.3% during the same period. It provides some indication of the close relationship between international travel and international trade in China, which needs further investigation.

2.4.3 International Tourism And Income

The activities comprising tourism are so diverse that its economic impact is substantial. Tourist expenditure can be divided into different categories. Vellas and Brecherel (1995, p.231) classify tourist expenditure into the following three categories:

- **Direct tourism expenditure:** this category consists of expenditure by tourists on goods and services in hotels, restaurants, shops and other tourism services. It also includes expenditure on goods exported because of tourism or investments related to tourism in the region.
- **Indirect tourism expenditure:** this corresponds to transactions between businesses caused by the direct tourism expenditure. For instance, it includes purchases made by hotels from local suppliers and goods bought by suppliers from the wholesalers.
- **Induced tourism expenditure:** this consists of increased consumption expenditure. For example, hotel staff use their salaries to buy goods and services.

To analyze the secondary expenditures (including the indirect expenditure and the induced expenditure), different multipliers have to be explored by Input-Output modeling or general models of economic interdependence. In the case of China, it is difficult to calculate the international tourism multipliers because of lack of suitable data. However, the CNTA has generated estimates of the direct expenditure by foreign tourists. China's accumulated foreign exchange earnings from international tourism between 1978 and 1998 was estimated as US$ 78.3 billion (CNTA, 1999). From Figure 2.6, we can see the breakdown of the international Tourism expenditure in 1998. Visitors to China contributed directly 28.8% of their expenditure to China's transportation industries, 20.6% to the retails and 13.8% to accommodation.

Figure 2.6: Breakdown of International Tourism Receipts 1998

	Receipts (Mn. US $)	% of Total
Total	12,602	100
Transportation	3,627	28.8
-------long-distance transportation	3,185	25.3
-------Local Transportation	442	3.5
Shopping	2,591	20.6
Accommodation	1,734	13.8
Food and Beverage	1,548	12.3
Entertainment	810	6.4
Sightseeing	548	4.3
Communication	502	4.0
Others	1,239	9.8

Data Source: China Yearbook of Tourism Statistics (CNTA, 1999).
*Long-distance Transaction includes Air, Rail, Motor and Sea.

The economic importance of the direct expenditure from foreign tourists can also be assessed simply by calculating it as a proportion of GDP. The proportion of international tourism income in GDP has expanded by 6 fold from the 0.2 per cent in 1980 to 1.2 per cent in 1996 (see Table 2.1).

For China's national economy, in addition to the considerable income from the international tourism, tourism growth has helped to diversify the national economy and promoted the development of industries related to tourism, such as transportation, communication, commerce, and public utilities. Therefore, "its interaction with other sectors has stimulated development far beyond the industry itself " (Jenkins and Liu, 1996, p. 113).

2.4.4 The Ecological And Social-Cultural Effects Of International Tourism

As experienced in many other developing countries, tourism development in China has also brought in both positive and negative results to the ecological and social-cultural environment.

The rapid development of international and domestic tourism has contributed significantly to the social-cultural development in China, which has been well addressed by Jenkins and Liu (1996). To summarize, first of all, it has served to preserve and reinforce local culture and contributed to reviving ancient traditions. International tourism development in particular provides a much-needed boost to the restoration and the renovation of the cultural heritage; furthermore, it has expanded international social-cultural cooperation and exchange, promoted friendship and understanding between Chinese people and people in the rest of the world.

On the other hand, tourism development in China has also upset the social and cultural equilibrium. It has inevitably caused some negative effects to the social-cultural environment. The face-to-face encounters with foreign tourists have caused changes not only in social values but more importantly in lifestyles. Tourism growth in China has particularly been blamed for the increase in venereal disease, prostitution, pornography, drug addiction and drug trafficking (see Jenkins and Liu, 1996).

There is no doubt that tourism development brings damage to the natural environment, notably by the urbanization of natural sites, the development of access infrastructures (roads and motorways), and the contamination of rivers and beaches. On the other hand, however, international tourism also finances land development programs which help to combine visits by tourists with the preservation and even improvement of tourism sites and attractions.

2.5 SUMMARY AND CONCLUSION

Tourism in China has undergone a structural shift in its policy which coincides with a dramatic change in the Chinese economy. The role and the nature of tourism have changed significantly. Tourism in China has transferred from being initially a political policy tool, which was centrally controlled, to a significant economic force which is driven by a more decentralized and deregulated market system. Although a complete assessment of the impact of tourism development requires more empirical evidence through a more rigorous quantitative study, our analysis in this chapter suggests that decentralization of tourism operations in China has brought with it a significant positive impact on tourism development and hence has promoted economic development in China as a whole.

International tourism in China has undergone rapid growth and significant changes in the tourism sectors, which has played and will continue to play an important role in China's social-economic development. It has been and will be working as a key element in the social-cultural reformation and a means to gain foreign exchange income, improve the balance of payment situation, and provide employment opportunities. The rapid development of international and domestic tourism has contributed to the economic, social and cultural development in China by exchanging economic, social cultural information among domestic regions and different countries. International tourism will continue to promote more understanding of the economic, social and cultural conditions between China and other countries in the world, and increase opportunities for cooperation in different fields, especially for foreign trade and direct foreign investment.

On the other hand, however, although the government involvement and control have been important features of international tourism development in China, the social-economic development, improvement of tourism services and implementation of promotional policies may be strong incentives for international and domestic travel.

Therefore, it should be noted that there exist varied interactions and intersections between tourism growth and many aspects of economic development, for instant, the interrelation between international tourist arrivals and foreign trade and foreign direct investment flows. Factors influencing international tourism in China may be from the supply side, such as the development of tourism infrastructure and the improvement of travel conditions in China, as well as the demand side, such as the attraction of cheap tourism price and the growth of income at the tourist origin countries.

A more complete picture of the contextual setting which will help explain the rapid growth in inbound travel to China can be formed by examining in more detail of the important structure and characteristics of the inbound travel market. We, therefore, further undertake such an analysis in Chapter 3.

Table 2.1: Contribution of international Tourism to GDP (1980-1996)

Year	Tourism Receipts (mn. US $)	GDP at Current Price (mn. US $)	% Contribution to GDP
1980	617	301508.275	0.20
1981	785	285238.246	0.28
1982	843	279782.726	0.30
1983	941	300404.420	0.31
1984	1131	309089.498	0.37
1985	1250	305258.355	0.41
1986	1531	295476.991	0.52
1987	1862	321391.150	0.58
1988	2247	401071.975	0.56
1989	1860	449102.417	0.41
1990	2218	387770.974	0.57
1991	2845	406090.856	0.70
1992	3947	483047.697	0.82
1993	4683	601087.130	0.78
1994	7323	540941.019	1.35
1995	8733	697611.903	1.25
1996	10200	815415.129	1.25

Data Source: World Bank Tables, DX Database

CHAPTER 3: **CHINA INBOUND TOURISM MARKET: STRUCTURE AND CHARACTERISTICS**

3.1 INTRODUCTION

As discussed in chapter 2, accompanying the rapid economic growth and development of tourism infrastructure in China, the international tourism inbound market has been seen remarkable changes during the last two decades. This chapter further provides some analyses of these changes and the current properties of China's inbound tourism market, by examining its major generation countries, tourist compositions, spatial distribution and seasonality of tourist arrivals.

3.2 COMPOSITION OF TOURISTS: FROM WHERE DO THE TOURISTS COME?

3.2.1 "Foreigners" And Ethnic Chinese

Consistent with the administration system of international travel in China before 1978, the Chinese government catalogues international visitors to China into three basic groups: "Foreigners", "Overseas Chinese" and "Compatriots". Foreigners of non-Chinese origin and ethnic Chinese holding foreign passports are grouped into one category: "foreigners". Chinese travelers from abroad are separated into two categories: "Overseas Chinese" and "Compatriots". Overseas Chinese are those who reside in other countries, but hold Chinese passports; Compatriots (or H-M-T visitors) are Chinese visitors from Hong Kong, Macau, and Taiwan.[8] Statistics on annual tourist arrivals to China in Table 3.1 show that compatriots from Hong Kong and Macau are a major source of travelers to China. The total number of annual compatriots visited China has been consistently more than 20 millions since 1986, and reached 56 million in 1998. In terms of composition of total tourist arrivals, visitors from Hong Kong and Macau

[8] With the relaxation of tensions between Taiwan and mainland China in 1988, the Taiwan government opened up an "Unofficial Connection Channel" with mainland China and permitted tourists for Visiting Friends and Relatives (VFRs) to visit mainland China for the first time since 1949. Therefore, Statistics on visitors from Taiwan to mainland China only started in 1988.

made up over 90% and 80% of the inbound tourists in the 1980's and 1990's respectively; visitors from Taiwan increased from 1.4% of the total "compatriots" in 1988 to 3.8% in 1998. The number of "foreign visitors" accounted for less than 10% of the total tourist arrivals to China in the 1980's, and increased to over 10% in the 1990's. On the whole, therefore, ethnic Chinese visitors from Hong Kong and Macau form the overwhelming majority of the total tourist arrivals to China.

We also see from Table 3.1 that foreigners have also been visiting China in significantly increasing numbers from the 1980's to the 1990's. For instance, whereas just 1.3 million foreigners visited China in 1985, the number of foreign visitors had grown to 7.1 million by 1998. It is this tremendous growth in foreign visits to China that we are particularly interested in.

3.2.2 Major Source Countries Of "Foreign Tourists"

Table 3.2 further shows data on the top four countries that provided "foreign" tourists to China from 1979 to 1998. Japan has been consistently the number one tourist source country since 1979. However, there have been considerable changes in the rankings of other countries in terms of annual tourist arrivals to China between the 1980's and the 1990's.

In the 1980's, Japan, USA, UK, Australia and the Philippines were the five major origin countries of foreign tourists to China, whose tourist arrivals made up two thirds of the total "foreigner arrivals" in China. Japan and the USA had dominated the top two places on the list respectively, providing half of the total foreign tourists to China, while the UK and Australia had ranked alternatively the third and fourth for most of the period.

Since the beginning of the 1990's, some neighboring countries, such as South Korea, the CIS (the former USSR), and Singapore, have taken the place of the UK and Australia and emerged as the top tourist generation countries other than Japan and the USA. Tourist arrivals from Japan, South Korea, the CIS and USA make up 50% of the total number of foreign tourist arrivals to China in current years.

The CIS has become one of the new major sources of visitors to China since after the visit to China of Mikhail Gorbachev in 1989 (the leader of the USSR). After 1989, the previous tense relationship between China and the USSR has been softened and border crossings and border trade between these two countries developed rapidly thereafter. In 1991, the CIS became the fourth most important origin country of international tourist arrivals to China with its 285 thousand tourists visiting China after the abolition of visa requirements and the opening of more border stations. The number of visitors grew by 77 fold in the ten-year period of 1981-1991. However, most of these visitors were actually day-trippers. It is confirmed by a survey (Gormsen, 1995) indicating that "285 thousand Russian citizens entered China in 1991, whereas only 86.3 thousand arrived in hotels in the major selected cities" (p.72), i.e., only about 30% of the total visitors from the CIS are over-night visitors.

In conjunction with the development of tourism services and improvement of diplomatic relationship between China and some Southeast Asian countries, more tourists visited China for business opportunities or visiting friends and relatives (VFRs). The annual visitors from South Korea, Mongolia, Malaysia and Indonesia have increased steadily in the current 4-5 years (CNTA, 1996a). In particular, the number of visitors from South Korea has soared in recent years since the government of South Korea lifted the ban on its citizens visiting China in 1994. The total Korean visitors to China increased annually by 79.2% between 1993 and 1994. Before 1992, South Korea was a relatively unimportant source of tourist generation for China ranked as the ninth tourist generation country in terms of tourist arrivals (CNTA, 1993). However, since 1993 South Korea has become a major source of foreign tourists and surpassed the number of visitors from Singapore and the USA, and has stepped into the top four tourist-generation countries, with Japan, the CIS and USA (see Table 3.2). Many Korean visitors to China come to visit their relatives and friends in the northeast provinces of China, where about 2 million Korean Chinese reside (see Zhang and Lew, 1997). Business opportunities have also brought many wealthy Koreans to China.

Cities, such as Weihai, Qingdao, and Yantai in Shandong province, across the Yellow Sea from South Korea, have become the most important bases for Korean investment in China (see Li and Hou 1993, Zhang and Yin 1993).

3.3 PURPOSE OF VISIT: WHY DO TOURISTS COME TO CHINA?

As statistics on the purpose of visits are not provided in China's official publications, some researchers have estimated tourist motivations based on the type of the travel agencies/organizations that handle visitors. Gormsen (1995, p.66) classifies the tourist motivations by the following categories:

- **Package tours (tourists organized by travel agencies**) can reflect the **tourists on holiday and leisure**. Most foreign holiday tourists come under this category, as this is a practical way to receive a visa.
- **Official trips (in the "other organizations**" category) are those that fall under the auspices of government authorities and institutions, scientific and other organizations, or economic enterprises. Most foreign visitors under this category are primarily **business travelers** instead of vacationing tourists.
- **Private visits** to relatives or friends are typically conducted without the involvement of any of the aforementioned offices. Many compatriots' business trips as well as some-day visits are also parts of the number.

Accordingly, the number of holiday trips by "foreigners" to China can be estimated by the number of visitors under the "Organized Tourists by Travel Agencies" category; the number of business trips by "foreigners" can be estimated by the number of visitors under the category of " Tourists Organized by Other Organizations" (see Figure 3.1).

Figure 3.1: Proportions of Tourists to China by Organizations (%)

Category	1985		1990		1995	
	Foreign Visitors	H-M-T Visitors*	Foreign Visitors	H-M-T Visitors	Foreign Visitors	H-M-T Visitors
Organized Tourists	85.8	9.0	100.0	9.7	98.3	5.5
• by Travel agencies	68.1	8.7	38.2	8.3	27.0	3.6
• by Other Organizations	17.7	0.4	61.8	1.4	71.3	1.9
Individual Visitors	14.2	91.0	NA	90.3	1.7	94.5

Data source: China Yearbook of Tourism Statistics (CNTA, 1986, 1996a).
*Ethnic Chinese visitors from Hong Kong, Macau and Taiwan.

Figure 3.1 shows that there are marked differences between foreigners and H-M-T visitors in the way they are travelling to China.

The holiday trips of foreign tourists (i.e., the tourists organized by travel agencies) to China made up 68.1% of the total foreign tourists to China in 1985. Business travels by "foreigners" which were organized by other organization category accounted for 17.7% of the total trips.

Comparing the statistics in 1985 and 1995 in Figure 3.1, the relative significance of holiday vacation trips by foreigners, which are mostly organized tours by travel agencies, has decreased steadily to 27% in 1995. Business trips, which are normally organized by governments and institutions, increased to 71.3% in 1995. The recent increase in foreign travel to China can, therefore, be attributed mainly to the growth of business travelers, who make up some 61.8% and 71.3% of the foreign trips to China in 1990 and 1995 respectively (see "tourist arrival by other organizations" in Figure 3.1). This seemingly indicates that much of the growth in the foreign tourists to China is driven by business opportunities, and consequently, will be sensitive to the changes of economic conditions, foreign trade, and foreign investment flows between China and its tourist source countries.

In contrast, most of the ethnic Chinese visitors are to see friends and relatives or for leisure travel, but they prefer to travel individually. An increasing number of compatriot business trips are also part of the total individual visitor arrivals. "The desire to visit China stems from a history of well maintained familial and culture ties, despite many years of separation" (Lew, 1995, p. 155). This provides strong motives for travelling from Hong Kong to mainland China for holiday and visiting friends and relatives in 1980's. The growing economic and business connections between mainland China and Hong Kong have also been expanding helping to increase business trips to China from Hong Kong, Macau and Taiwan since the late 1980's. In total, individual travelers from H-M-T including holiday, and VFR trips accounted for 91% and 94.5% of the total ethnic Chinese visitors in 1985 and 1995 respectively (see Figure 3.1), given that many compatriot business trips fall under the category of individual visitors, as well as day visits (Gormsen, 1995).

The pattern and structure of international trips to China have undergone some changes in current years. The CNTA provides annual sample survey data of travel purposes by the category of "organized tourists" and "individual tourists" to China respectively since 1990, in which "organized tourists" include tourists organized by travel agencies, government organizations and other institutions. According to the sample survey of 16308 international tourists conducted by the CNTA in 1997, 46.1% of the international tourists to China are on business, followed by holiday (33.2%) and VFRs (10.7%) (see Table 3.3).

Importantly, the survey results indicate that more business tourists travel to China individually rather than travel under "organizations", whereas most of the holiday travelers still prefer "package" travel or other forms of travel organized by travel agencies. Table 3.3 shows 61.4% of the surveyed individual foreign tourists are business tourists, while 62.9% of the surveyed holiday tourists are "organized tourists" or packaged tourists. For the tourists from Hong Kong and Macau, 53.4% of the business visitors travel individually while 74.9% of the "organized tourists" are holiday visitors.

These statistics indicate a significant change of travel patterns of international tourists to China from the 1980's to 1990's. Whereas in the1980's most of the foreign business travelers were visitors organized through government organizations or scientific and economic institutions, by the 1990's more business people travel individually.

The sample survey conducted by the CNTA since 1990 further provides additional information on purposes of visiting China by selected countries. Figure 3.2 provides surveyed information of travel purposes of visits to China from Japan, the USA, Australia, the UK, South Korea and the CIS in 1995.

Figure 3.2: Purposes of Visits to China by Tourists from Major Generation Countries (1995)

	Sample Number	Holiday	Business	VFRs	Others*
Japan	1653	35.2%	56.5%	2.3%	6.0%
USA	873	44.0%	43.1%	3.1%	9.2%
Australia	263	54.0%	33.1%	2.3%	10.6%
UK	226	39.3%	54.1%	2.8%	6.5%
South Korea	860	34.6%	45.7%	0.0%	19.7%
CIS	603	15.6%	58.5%	1.3%	24.6%

Data Source: Sample Survey of International Tourists 1995 (CNTA, 1996b).
* Including visits for health treatment, religious pilgrimages, cultural and sports exchanges, and other purposes.

From Figure 3.2 we can see that over 50% of the visitors from the CIS, Japan and the UK are travelling to China on business, while more than 40% of the total tourists from the USA and South Korea are business travelers, and above 30% of tourists from Australia travel to China for business. In general, from the surveyed information, business trips make up approximately 40%-50% of the total trips of foreign tourists to China.

3.4 TOURIST EXPENDITURE AND LENGTH OF STAY: HOW MUCH DO TOURISTS SPEND?

In 1996 China received US$ 10.2 billion of international tourist receipts from 51.1 million international visitors, of which, there were 22.8 million overnight visitors and 28.4 million day-trippers (CNTA, 1997a). The overnight visitors expended 9.2 billion US$ in China, which accounts for 90% of the total expenditure, while the expenditure from the majority number of same-day visitors makes up 10% of the total (see Figure 3.3).

Figure 3.3: Compositions of Tourist Expenditure in 1996 (%)

	Total	Overnight Visitors	Same-day Visitors
Foreign Visitors	47.8	46.8	1.4
Overseas Chinese	1.5	1.5	0.02
Compatriot	50.3	41.7	8.6
Total	100	90	10

Source: Sample Survey of International Tourists 1996 (CNTA, 1997b).

Further statistics on the proportions of expenditure from foreign visitors and ethnic Chinese visitors in Figure 3.3 shows that foreign visitors, who account for about 10% of the tourist arrivals, contribute 47.8% of the total tourist expenditure; ethnic Chinese visitors, who account for 90% of the total arrivals, contribute 50% of the total expenditure. Therefore, in terms of tourism receipts, foreign visitors are equally as important as the compatriots. This is important for it highlights the fact that foreign visitors to China spend, on average, many times more Yuan per night than do the H-M-T visitors.

Figure 3.4 further provides information of the average expenditure and average length of stay by foreign tourists from the six major generation countries.

Figure 3.4: The Average Expenditure and Length of Stay in China by Tourists from Major Generation Countries (1996)

	Average Day Expenditure (US $)	**Average Length of Stay** (days)	**Average Trip Expenditure** (US$)
Japan	175.70	6.1	1071.8
USA	139.33	9.1	1267.9
Australia	147.85	8.6	1271.5
UK	139.62	8.9	1242.6
South Korea	174.44	7.7	1343.2
CIS	205.89	4.7	967.7

Source: Sample Survey of International Tourists 1996 (CNTA, 1997b).

In general, the average length of stay of travelers to China is short-term, with an overall average of 7.5 days, which could be attributed to the following reasons: first of all, tourist arrivals from the major source countries include a large share of business travelers who tend to stay for a shorter period of time than holiday tourists and VFRs; secondly, most of the holiday travelers still prefer "package" travel or other forms of travel organized by travel agencies (refer to section 3.3), which makes them stay for a shorter term than individual travelers; finally, some of these major source countries are neighboring countries, only a short distance from China, such as Japan, South Korea and the CIS, which also encourages short stays. For instance, tourists from the USA, UK, Australia usually have longer trips (about 9 days) in China, while visitors from the CIS have the shortest average stay (4.7 days) in China, about half the time of these countries as most of the visitors from CIS are same-day visitors.

In terms of average expenditure, tourists from the CIS make the highest day expenditure (US $ 205.89), followed by Japanese tourists (US $ 175.70) and Korean tourists (US $ 174.44). Tourists from the CIS are very big spenders because of their high level of shopping which is their major purpose in visiting. Visitor arrivals from Japan and South Korea tend to have high daily expenditure on other activities than shopping, such as accommodation, transport and entertainment. However, by total expenditure per trip, tourists from South Korea, followed by Australia, the USA and Japan are seen as the highest spenders in China (see Figure 3.4). Therefore, South Korea, Australia, the USA and Japan are the top four most important tourist source countries in terms of international tourism income to China.

3.5 SPATIAL DISTRIBUTION: WHERE DO TOURISTS VISIT?

Despite the overall size of the country, international tourists to China are, on the whole, concentrated in a dozen large cities and the noted tourist areas, particularly in the coastal area (see Zhang 1995a, 1995b, Tisdell and Wen 1996, and Wen and Tisdell 1997). For instance, in 1992, 12 coastal regions obtained most of the China's tourism receipts (90%) and attracted most tourist arrivals (84%) and tourist nights (83%) (Wen and Tisdell, 1997).

China's coastal area covers three municipalities and nine provinces, namely, Beijing, Tianjing, Shanghai, Liaoning, Hebei, Shandong, Jiangsu (including Hanzhou and Suzhuo City), Zhejiang, Fujian, Guangdong (including Guangzhuo, Zhuhai, Shenzhen and Zhongshan City), Guangxi (inlcuding Guilin City), and Hainan. This area is considered as China's relatively developed area as it produces about 60.6% of its GDP on 14% of the nation's land area (CBS, 1999).

This considerable spatial inequality in the distribution of the inbound tourism in China is mainly owing to the unequal development of the Chinese economy and tourism infrastructure as well as the pattern and purpose of visits to China.

- The tourism infrastructure was first developed in the big cities and coastal areas in China, such as the booming of construction of international standard hotels in Beijing and Shanghai in the early 1980's (see Zhao1989, EIU 1989, Zhang 1995a). The coast, for example, accounts for 71.5% of total hotel rooms in China (see Wen and Tisdell 1997). Some cities, such as Beijing, Shanghai, Guanzhuo, Xi'an and Tianjing, are also where the main international airway entries and major tourist attractions are located.

Therefore, holiday travelers to China flow to the areas which could provide standard tourism accommodation, transport (mainly international airlines), and travel services.

- The concentration of tourists in the coastal area is also a result of ethnic, culture and emigration linkages. Guangdong province has an over 1000 year history of emigration and has generated more than 10 million Chinese descendants abroad with roots in this province (Anon, 1989); Taiwanese visitors have close family connections in Fujian, Shandong, and Zhejiang. In 1994, for instance, Guangdong received 71.1% of tourists from Hong Kong and Macao; Fujian hosted 23.2% of the total tourist nights spent by Taiwanese travelers (CNTA, 1995). Therefore, VFR's from Hong Kong, Macau and Taiwan mainly come to the coastal areas where their friends and relatives reside.
- For the business travelers, business opportunities or activities, such as foreign trade and investments, are located in the economically developed areas. The economic growth rate in the coastal area has been faster than the national average and more than 90% out of the 17,000 enterprises with foreign investment are located on the coastal regions (see Tisdell and Wen 1996). This attracts business travelers to the coast, who constitute a stable source of tourists in the area.

In short, the heavy concentration of inbound tourist arrivals along the coast is results of favorable conditions from both the demand and supply sides of international tourism in China. Factors, such as greater international business connections on the coast, strong family/ ethnic links between overseas Chinese and the coastal provinces, location of tourism infrastructures and attractions, and the predominance of international entries in the coastal provinces, may help to explain the spatial distribution of international tourist arrivals to China.

According to CNTA (1997a), there has been some slight improvement in the inequality of international tourism distribution in China by the 1990's. Figure 3.5 provides statistics on the top 10 cities in overseas tourist arrivals in 1986 and 1996 respectively. In the1980's, the top ten cities absorbed the most tourists from overseas (e.g. 33.5% of the total tourist arrivals in 1986), and the rank order of these ten cities has remained unchanged for several years; whereas in 1996 tourist arrivals to the top 10 cities reduced to 21.8% of total tourist arrivals. Moreover, some new cities are emerging and entering into the top 10 list every year, e.g., Kunming and Quanzhuo, which have stepped into the list of top ten cities since 1994 mainly benefiting from the establishment of some new international and national airlines (CNTA, 1995, p.39).

Figure 3.5: Top 10 Cities in Overseas Tourist Arrivals

Rank	1986 City	1986 Arrivals (1000)	1996 City	1996 Arrivals (1000)
1	Guangzhou	2512	Guanzhou	2592
2	Shenzhen	1072	Shezhen	2338
3	Beijing	990	Beijing	2189
4	Zhuhai	680	Shanghai	1432
5	Shanghai	659	Hangzhou	462
6	Zhongshan	650	Zhuhai	462
7	Guilin	357	Xian	459
8	Hangzhou	266	Kunming	451
9	Xi'an	258	Guilin	409
10	Suzhou	192	Quanzhou	401
	% of total arrivals	33.5	% of total arrivals	21.9

Source: China Yearbook of Tourism Statistics (CNTA, 1987, 1997a).

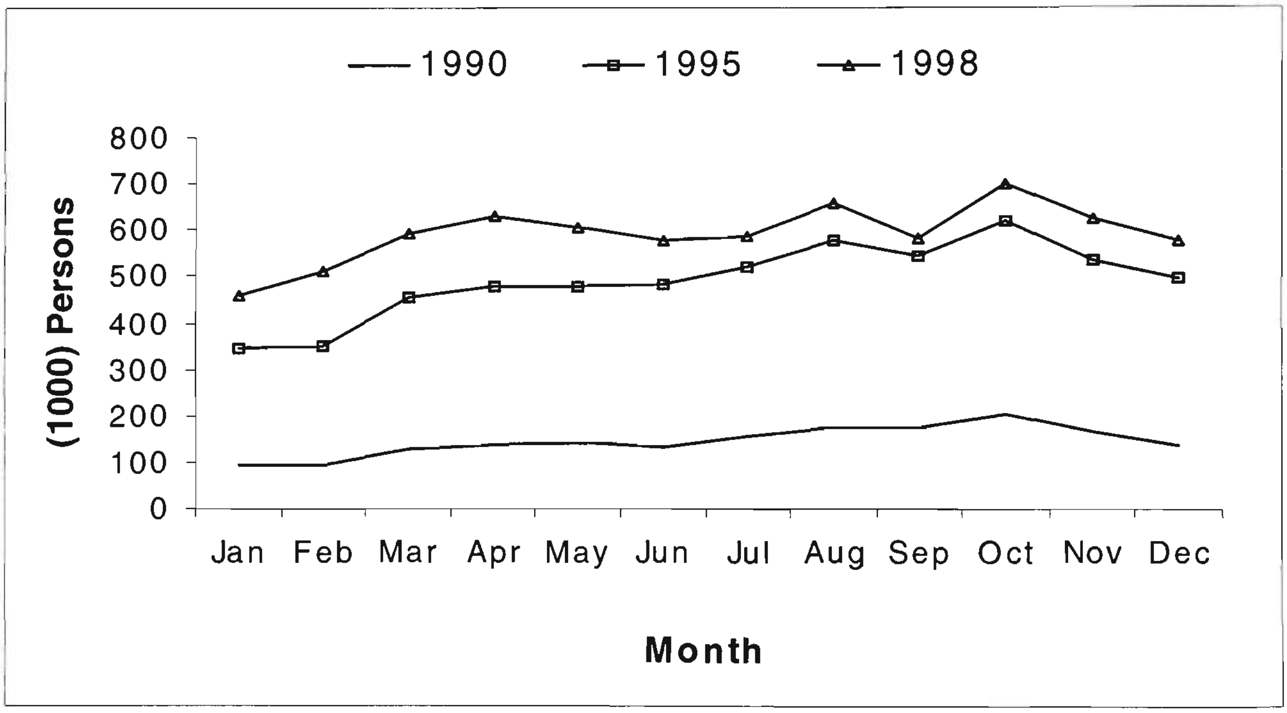
Whether this inequality of tourist distribution in China is likely to be moderated in the future remains a question, as this inequality is determined by China's regional economic inequality as well as the structure and characteristics of the tourism demand. Economic development and improvement of tourism infrastructure in interior regions in China will work as a "pull" factor for more tourist arrivals to the regions. At the same time, there are many other factors from the demand side determining whether, how, and to what extent, the tourism demand responds to the "pulling" power, such as the visiting purposes and travel budgets of international tourists to China.

3.6 SEASONALITY: WHEN DO TOURISTS VISIT CHINA?

Seasonal patterns of international tourism to China vary with the different source countries, though China as a whole has a relatively constant volume of arrivals throughout the year.

To avoid the weather extremes in some tourist resorts, "foreign tourists" prefer to visit China between May and October when the weather conditions around the country are pleasant for travel, with the reduced demand between November and February (see Figure 3.6A).

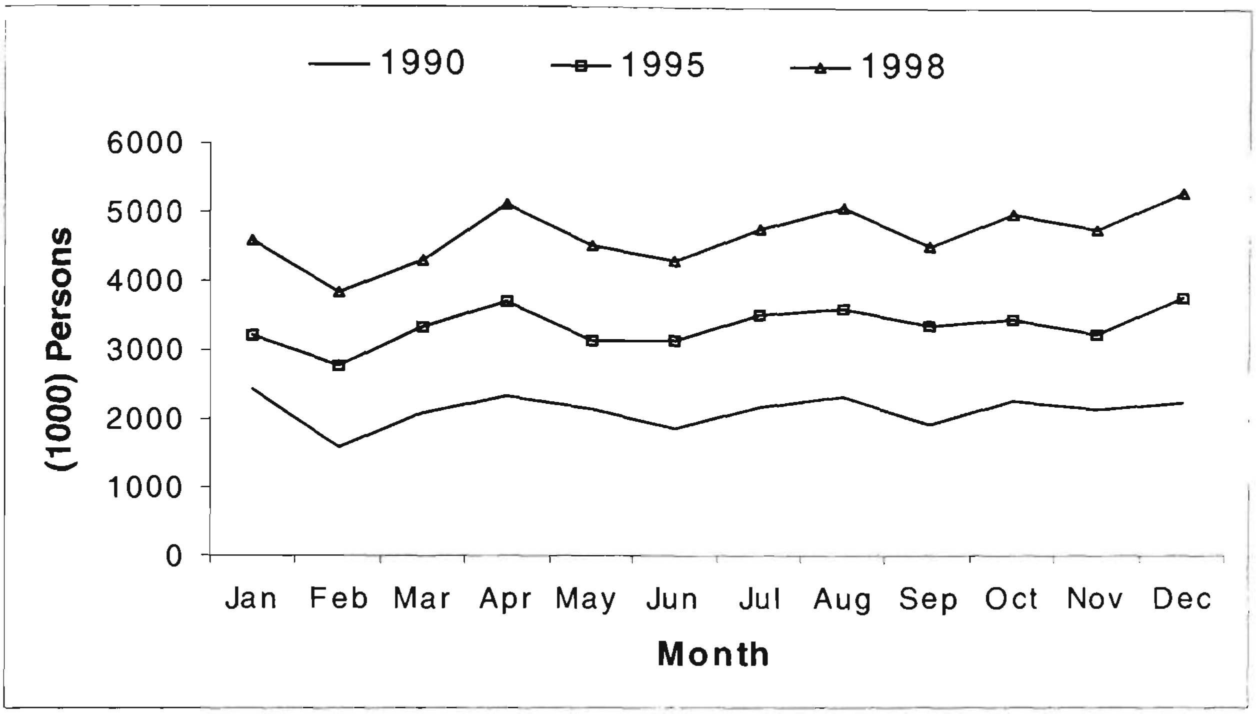
Figure 3.6A: Monthly Foreign Tourist Arrivals



Data Source: China Yearbook of Tourism Statistics (CNTA, 1991, 1996,1999).

The majority of visitors from H-M-T and the overseas Chinese usually visit the mainland during the period between December and January in order to meet their friends and relatives during the Chinese New Year and the Spring Festival Holidays (see Figure 3.6B).

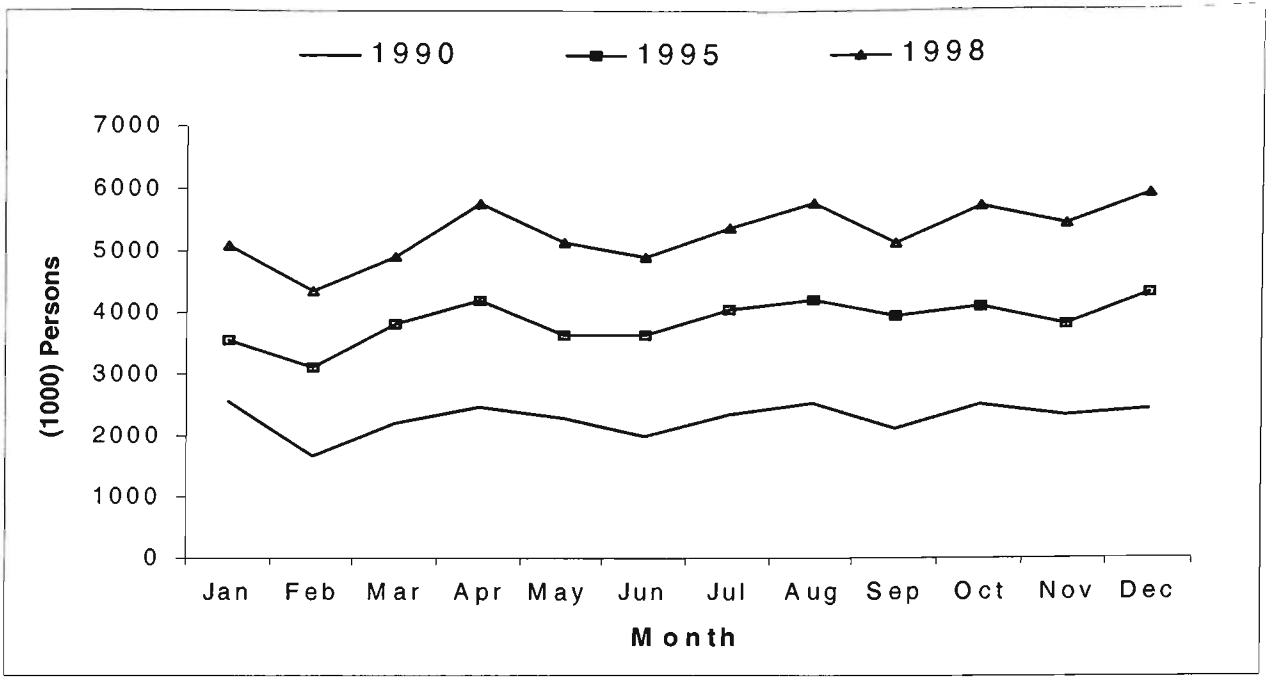
Figure 3.6B: Monthly Compatriot Arrivals



Data Source: China Yearbook of Tourism Statistics (CNTA, 1991, 1996,1999).

Therefore, the different timing of visits by tourists for different purposes, to some extent, evens out the seasonality of total tourist arrivals to China. For China as a whole, the seasonality of tourist arrivals is not seen to be significant (see Figure 3.6C). However, if the interest is in particular source markets, additional analyses should be carried out in order to distinguish the different seasonal patterns of tourist arrivals from these source countries.

Figure 3.6C: Monthly Total Tourist Arrivals to China



Data Source: China Yearbook of Tourism Statistics (CNTA, 1991, 1996,1999).

3.7 SUMMARY AND CONCLUSION

This chapter sets out to identify the structure and characteristics of the international tourist arrivals to China in order to provide a complete contextual discussion of the China inbound travel market.

In terms of the number of tourist arrivals to China, the "compatriots" (ethnic Chinese) from Hong Kong and Macau form the majority of overall tourists arrivals (about 90%) since 1979. The number of "foreign tourists" who made up about 10% of the total arrivals has also been seen to be steadily growing since the early 1990's. The major source countries of "foreign tourists" to China are Japan, the USA, the UK and Australia in the 1980's. However, South Korea and the CIS took the place of Australia and the UK and emerged as the top two source countries other than Japan and the USA in the 1990s.

In terms of the tourism expenditure, " foreign tourists" who only account for 10% of total tourist arrivals contribute far more on a percentage basis as compared to "compatriots". For instance, in 1996 the expenditure from foreign tourists was estimated as 47.8% of total tourist expenditure, while the expenditure from "compatriots" contributed about 50% of total tourist expenditure (see Section 3.4). Tourists from South Korea, followed by Australia, the USA, Japan and the UK, make the highest contribution in China's international tourism income, and hence become most important tourism source markets of China.

Although the separate statistics on tourists according to travel purpose are not available, we could estimate the main purpose of travelling to China by different "categories" of tourists. The "compatriots" visitors, who are ethnic Chinese from Hong Kong, Macau and Taiwan, are mainly to see friends and relatives or for leisure travel, while the majority of "foreign tourists" are travelling to China on business. The data from the sample survey conducted by the CNTA also further confirm that about 40-50% of the tourists from South Korea, Australia, the USA, and Japan are travelling to China on business.

In spite of the size of the country, tourists to China mainly concentrate in the economically developed areas, i.e., the top ten big cities and coastal areas. The spatial inequality in the distribution of the inbound tourists is reducing also marginally with the development of the overall Chinese economy and the improvement of tourism infrastructure in China.

In general, seasonality does not seem to be a significant problem for China as a whole as international tourists to China for different purposes are travelling in various seasonal patterns, and, to some extent, even out the peak demand pressure on the transport, accommodation and other tourist facilities. However, tourists from different sources of markets do have different seasonal patterns. In particular, if the interest is in particular source markets, additional analysis is required in order to identify the seasonal patterns of tourist arrivals from these source countries.

Chapter 2 provides an insight into the extent of the growth of inbound international tourism to China over the past 20 years or so, and an appreciation of the policy context that helped lead to this growth. Chapter 3 has further identified some important characteristics of the inbound tourism market. These two chapters together provide very useful insights into policy, institutional and economic factors which have facilitated the rapid growth in China inbound travel. This contextual setting plays an important role in informing the applied demand analysis that follows below. However, as China competes with all other countries for international travelers, an analysis of inbound international tourism to China must also be undertaken using the appropriate economic framework where demand for travel to China is part of the global market for international travel. Therefore, prior to undertaking an applied demand analysis, we undertake a review of the relevant theoretical as well as empirical international demand literature in the following two chapters, in which Chapter 4 introduces the relevant theoretical tourism demand literature while chapter 5 introduces the related applied demand literature. To this end the following two chapters provide an appropriate survey of the relevant tourism demand literature.

Table 3.1: Annual Tourist Arrivals to China* (1000 Persons)

Year	Foreign Tourists		Overseas Chinese		Compatriots		
	Total	(%)	Total	(%)	H & M	Taiwan	(%)
1978	229	12.7	18	1.0	1561		86.3
1979	362	8.6	20	0.5	3820		90.9
1980	529	9.3	34	0.6	5138		90.1
1981	675	8.7	38	0.5	7053		90.8
1982	764	9.6	42	0.5	7117		89.8
1983	872	9.2	40	0.4	8564		90.4
1984	1134	8.8	47	0.4	11670		90.8
1985	1370	7.7	84	0.5	16377		91.8
1986	1482	6.5	68	0.3	21269		93.2
1987	1727	6.4	87	0.3	25087		93.3
1988	1842	5.8	79	0.2	29773	437.7	93.9
1989	1460	6.0	68	0.3	22971	541.0	93.8
1990	1747	6.4	91	0.3	25623	948.0	93.3
1991	2710	8.1	133	0.4	30506	946.6	91.5
1992	4006	10.5	165	0.4	33943	1317.8	89.1
1993	4655	11.2	166	0.4	36704	1527.0	88.4
1994	5182	11.9	115	0.3	38387	1390.2	87.8
1995	5886	12.2	115	0.2	40383	1532.3	87.6
1996	6744	13.2	155	0.3	44229	1733.9	86.5
1997	7428	12.9	99	0.2	50060	2117.6	86.9
1998	7108	11.2	121	0.2	56250	2174.6	88.6

Source: China Yearbook of Tourism Statistics (CNTA, 1999).
* Note: these Statistics including same-day visitors. The separate statistics of overnight visitors are only available from 1996; H & M are compatriot visitors from Hong Kong and Macau.

Table 3.2: Top Four Origin Countries of Foreign Tourists (1979-1998)

Rank	1		2		3		4		
Year	Country	%	Country	%	Country	%	Country	%	% of Total
1979	Japan	29.4	USA	18.7	Philippine	4.8	UK	4.5	57.4
1980	Japan	32.0	USA	19.2	UK	5.4	Australia	5.4	62.0
1981	Japan	33.1	USA	19.3	UK	6.2	Australia	6.0	64.6
1982	Japan	32.1	USA	19.0	Italy	10.0	Australia	7.0	68.1
1983	Japan	30.4	USA	19.3	Australia	6.2	UK	5.8	61.7
1984	Japan	32.5	USA	18.7	Australia	6.4	UK	5.5	63.1
1985	Japan	34.3	USA	17.5	Australia	5.7	UK	5.2	62.7
1986	Japan	32.6	USA	19.7	UK	5.4	Australia	4.9	62.6
1987	Japan	33.4	USA	18.3	UK	4.8	Singapore	3.7	60.2
1988	Japan	23.1	USA	16.3	UK	5.2	Germany	3.9	48.5
1989	Japan	24.6	USA	14.7	Russia	5.6	Philippine	5.0	49.9
1990	Japan	26.5	USA	13.3	CIS	6.3	UK	4.5	50.6
1991	Japan	23.6	USA	11.6	UK	4.2	Philippine	3.9	43.3
1992	Japan	19.8	USA	8.6	Singapore	3.8	Thailand	3.7	35.9
1993	Japan	19.6	USA	8.6	Singapore	4.3	Korea	4.1	36.6
1994	Japan	22.0	USA	9.1	CTS	7.7	Korea	6.5	45.3
1995	Japan	22.2	Korea	9.0	USA	8.7	CIS	8.3	48.2
1996	Japan	30.0	Korea	10.3	USA	8.5	CIS	8.2	59.7
1997	Japan	21.3	CIS	11.0	Korea	10.5	USA	8.3	51.1
1998	Japan	22.1	CIS	9.7	USA	9.5	Korea	8.9	50.2

Data Source: China Yearbook of Tourism Statistics (CNTA, 1998).

Table 3.3: Purposes of Visiting China (1996)

	Sample Number	Holiday (%)	VFR (%)	Business (%)	Others[2] (%)
Total	16308	33.2	10.7	46.1	10.3
Organized Tourists[1]	4860	64.8	4.3	18.9	12.7
Individual Tourists	11448	19.9	13.4	57.6	9.1
Foreign Tourists	9069	38.0	6.2	43.6	12.2
Organized	3988	62.9	3.7	20.9	12.5
Individual	5081	18.5	8.1	61.4	12.0
Overseas Chinese	153	33.3	26.1	30.8	9.8
Organized	30	66.7	10.0	13.4	9.9
Individual	123	25.2	30.1	34.9	9.8
H-M Visitors	5613	25.2	17.5	50.4	6.6
Organized	390	74.9	8.2	10.8	6.1
Individual	5223	21.5	18.2	53.4	6.9
Taiwan Visitor	1473	34.4	11.4	46.2	8.0
Organized	452	72.8	6.2	9.3	11.7
Individual	1021	17.3	13.7	62.6	6.4

Source: Sample Survey of International Tourists 1996 (CNTA, 1997b).

Note:

(1) Tourists organized by travel agencies and government organizations and other institutions.

(2) Including visits for health treatment, religious pilgrimages, cultural and sports exchanges, and other purposes.

CHAPTER 4: **THE DETERMINANTS OF INTERNATIONAL TOURISM DEMAND: A SURVEY**

4.1 INTRODUCTION

The previous two chapters provide an analysis of the important policy, institutional and economic settings that influence inbound tourism demand to China. However, before undertaking an appropriate demand analysis of inbound tourism in China, a theoretical framework for the analysis needs to be established by undertaking a relevant literature review. Therefore, Chapter 4 and Chapter 5 are structured to introduce the theoretical tourism demand literature and the applied tourism demand literature, respectively. Important insights from previous studies of tourism demand are used in the subsequent analysis for later chapters.

Although with considerable social and environmental impact, essentially tourism is an economic activity, the result of various market forces. Wilson (1998) has defined tourism conceptually into a "market" category rather than an "industry" by distinguishing the basic concepts of an "industry" and a "market". Wilson (1998) states that

> the tourism event contains three elements: the consumer, the product, and the supplier, with the consumer determining whether economic activity is tourism. In this sense market activity determines firm or supplier activity. Although there is no monolithic single tourism market, there are literally thousands of tourism markets influencing the supply decision of firms in a range of industries related to tourism. A tourism-related industry is one where a considerable percentage of supply is generated by tourism demand. [p.814]

Accordingly, there exists no tourism "industry", but "tourism related industries" which are elements of tourism consumption under various industry classifications. First of all, tourists consume a variety of goods and services, which are generated in different industries, such as hotel, transport, retail and communication. Moreover, for many of these industries, tourist spending will only generate part of the total output of the industry. For instance, accommodation consumption can be measured through night stays or occupancy rates, but not all the consumers of hotel accommodation are tourists. Accordingly, from the supply side, tourism cannot be analyzed as one and a supply-side analysis of tourism must be studied by each industry separately. Therefore, the principal measurement of tourism must be related to the demand side.

This chapter, from the demand perspective, firstly provides a discussion of measurements of international tourism demand and then reviews theories on the determinants of international tourism, including macroeconomic considerations and microeconomic formulations. Further it discusses theoretical factors influencing international tourism demand and identifies the range of determinants of international tourism demand. A summary and conclusion are presented in the final section.

4.2 MEASURING INTERNATIONAL TOURISM DEMAND

Economists mostly focus on the effective demand, which can be defined as "the quantities of a product that buyers collectively are willing and able to buy at any potential price over some specified period" (Bull 1995, p25). There are three commonly used measures of the effective tourism demand:

- visitor arrivals;
- visitor-days or nights;
- visitor expenditures.

Visitor arrivals are the number of people who arrive at a destination by air, sea, road and ferries. In measuring tourism demand, visitor arrivals are the easiest type of data to obtain, which can measure broad changes and variation in demand. According to the UN definition of "visitors" (WTO, 1993), visitors coming through seaports, including "tourists" staying 24 hours or longer and "excursionists" not staying overnight, should be classified, but travelers who do not leave the airport transit area and those who illegally enter the country should not be included.

The number of days or nights which visitors stay at the destination is another important type of measures of tourism demand. The longer that visitors stay at the destination, the bigger is the tourism demand. This measure is especially valuable to tourism planners, more so than the number of visitor arrivals. Data on visitor days and nights are of great benefit to planners who are working on public facilities for tourists, such as, utility systems, parking and recreation areas. Likewise, private developers planning new hotels or other accommodation or services want and need information on visitor nights of stay.

Tourism expenditure can be defined as the total consumption expenditure made by a visitor or on behalf of a visitor for and during his/her trip and stay at the destination. The WTO (1993) offers separate definitions of international tourism payments for inbound and outbound tourism. "International tourist receipts" is used to measure the expenditure of international inbound visitors, including their payments to national carriers for international transport. It also includes any other payments made for goods/services received in the destination country. "International tourism expenditure" is used to measure the expenditure of outbound visitors in other countries including their payments to foreign carriers for international transport. Tourism expenditure is the most meaningful measure of demand, if accurately determined. However, it is the most difficult measure to obtain. Statistics of this type tend to be hidden or partially forgotten by visitors, thus not as accurate as desired.

Due to its importance to an economy, tourism has been closely examined by economists who focus on descriptions of structure and operation of tourism sectors (e.g., Cleverdon and Edwards 1982, Lundberg1995, Bull 1991,1995). There are also many empirical tourism demand studies which concentrate on modeling and estimating tourism demand in different countries and time periods (e.g., Archer 1976, Witt and Martin 1989, Witt and Witt 1995, Kulendran and King 1997). However, most of the studies lack the explicit theories, which can provide frameworks for analyzing causes of international tourism flows and lead to a better understanding of tourism demand. Therefore, the following two sections discuss some important economic theories which are the foundations of modeling tourism demand and thus can be used to suggest variables included in tourism demand models.

4.3 INTERNATIONAL TRADE THEORIES

Based on the theorem that international tourism is a segment of international trade, some economists (e.g., Gray 1970) have applied the theories of international exchange to explain the determinants of international tourism at the macroeconomic level. Vellas and Becherel (1995) and Sinclair and Stabler (1995) reviewed the following four main schools of "macroeconomic" theories:

- The theory of absolute advantage and technology;
- The theory of comparative costs;
- The theory of factor endowments;
- The theory of conditions of demand.

These theories explain the position of a country in international tourism exchanges at the aggregate level, by analyzing the causes of international tourism and how they influence economic and social growth and development. Although most of them explain tourism flows from the supply perspective, to some extent, they help us understand the distribution and trends of international tourism flows.

4.3.1 Supply-Side Economic Theories

The theory of absolute advantage and technological advance developed by Adam Smith is widely used to explain the export monopolies of certain countries, which either arise from unique natural advantages or from technological advances. In terms of international tourism, it explains: (i) countries that have unique tourism resources (such as exceptional natural sites and architectural resources) are known worldwide and monopolize some international tourists. For instance, as a country with abundant sunshine and beautiful beaches, Australia attracts holiday travelers from all over the world; (ii) technical innovation can reinforce a country's absolute advantages. Technical innovation in the tourism sector mainly involves infrastructure, information, product development and marketing. Particularly, innovation can not only bring down costs (new materials, energy savings, electronic data transmission, new management, reservations and payment techniques), but also create new tourism products (e.g., leisure and holiday centres). Thus, the theory of absolute advantages adequately explains the monopoly position of some tourist destinations which possess unique natural resources or tourism services with high levels of technology.

Another well-known explanation of international trade is the theory of comparative costs expounded by David Ricardo in 1817. This theory demonstrates that short term gains from trade can be obtained if each country specializes in the production and exports of the goods which it produces relatively efficiently, i.e., in which it holds a comparative advantage. The pattern of trade is determined by differences in the relative production efficiencies of different countries, and hence trade gains can result from specialization in production. Nevertheless, comparative costs can be considered as one of the determining factors in the distribution and trends of international tourism. A country that provides tourism services with relatively lower prices will gain more tourists than will its competing destinations with higher prices for similar tourism products, all other things held equal.

For international tourism, although there are wide fluctuations in the costs, it is difficult to determine what a country specializes in by price alone. Tourism products are generally services and have great diversity. The costs of tourism products, include the costs of transport, accommodation and other services which are related to hospitality, catering and various leisure services. Moreover, variations in exchange rates and economic policies (such as, labor policy, price policy and credit policy) will directly or indirectly influence the cost of tourism products. Finally, while analyzing the components of costs in transport, accommodation and other tourism-associated services, the quality-prices of these products and technological advances must also be taken into account.

The theory of absolute advantage was further developed into the theory of factor endowments which was first formulated by Hechscher (1919) and further developed by Ohlin (1933). The orthodox Hechscher-Ohlin (H-O) theorem asserts that the differences in factor endowments are the basic determinants of trade flows. Countries with an abundance of certain resources (labor, capital and land/natural resources), rather than relative efficiencies of production will benefit from a comparative advantage for the production and export of products requiring these resources. A country will tend to specialize in the production and sale of goods and services, which it has in abundance and which are cheap. On the other hand, it will tend to purchase goods and services, which are unavailable in the country. Thus, countries, which have a large supply of labor and land as well as plentiful natural resources, would appear to have comparative advantages in tourism. There is a greater likelihood that they will export their international tourism services, which results in a positive balance in their travel accounts.

The H-O theory is useful so far as it points to the role which the supply-side can play in determining patterns of international production and trade. However, the relationship between tourism production and factor endowments is complicated in terms of measuring factor abundance and quality. For instance, abundance can be measured by quality of tourism products; it can also be measured by the value of tourism products, in which case demand also enters into play as higher demand for the product results in higher price.

To summarise, the theory of absolute advantage and technological advance and theory of factor endowments emphases the role of a country's different tourism resources, which helps to explain the position of a country in international tourism exchanges. The theory of comparative costs is useful in indicating the gains which countries can make from international tourism if they are relatively efficient in tourism production, and hence it points to the importance of increasing production efficiency. However, these theories cannot be simply applied to explain international tourism flows as international tourism is a different activity from international trade, with its own features and complexity in terms of demand. Moreover, these theories are all supply-side oriented theorems and hence pose some difficulties in understanding the nature of trade and tourism flows as the essence of tourism is more a demand than supply side phenomenon. The existence of two-way trade and tourism indicates that variations in supply factors are not the sole cause of trade and tourism flows. In most cases, it is not the conditions of supply which explain the causes of international tourism, but the conditions of demand. For instance, tourists from neighboring countries with similar resources are more likely travelling across borders with various needs and motives. Therefore, these supply-oriented theories have certain limitations in understanding the nature of tourist flows; whereas economic theories from the demand perspective provide more reasonable explanations for tourism flows.

4.3.2. The Theory Of Demand

Tourism demand represents the quantity of goods and services that tourists require at some specific time period. One of the interesting features about international tourism is that it tends to be two-way. That is, international travelers leave country A to visit country B, whist at the same time international travelers are leaving country B to visit country A. Thus international travel is best described by a theory of intra-industry trade. The theory of demand, which was formulated by Linder (1961), provides an explanation for intra-industry trade, i.e., two-way trade in products supplied by the same industry.

Linder's intra-industry trade theory suggests International exchanges depend on both the volume of demand and the demand for differentiation of products in structure, quality and brand. The "demand for difference" is particularly significant in international tourism. It is often the geographical, cultural and linguistic differences that induce two-way tourism between neighboring countries with similar levels of economic development. For instance, a tourist may travel across the border simply to experience these differences in the neighbouring country.

This theory also highlights consumers' similarity in tastes as a cause of such trade. According to Linder, the more similar the demand for the products supplied by different countries, the greater the likelihood of trade between them. The explanation is based on the argument that the nature of demand by consumers is determined by the level of per capita income within a country. Residents of developed countries with relatively high per capita income demand a range of higher quality products, while those in developing countries are more likely to purchase a lower quality good. Hence there is greater potential for trade between countries with similar levels of income than between those with dissimilar levels. Accordingly, the volume of the international exchange in tourism will be greater between countries with similar economic structures and levels of income.

Linder's theory helps to explain the higher level of tourism movements between countries which, in contrast to the postulates of the H-O theorem, have relative similar factor endowments. However, the determinants of international tourism demand are complicated and wide- ranged. Factors which can influence the demand for tourism may range from personal psychological motivations to economic, social and political factors. Human behaviours are influenced by other factors in conjunction with motivation. No matter how motivated a person is to travel, it is not enough to complete the task if he/she lacks the necessary abilities, such as information, experience, money, health and time. Therefore, distinguishing of international tourism from international trade and further differentiating tourism demand by its travel motivation, destination and source market are very important in analyzing and modeling tourism demand.

4.3.3 Gray's Simple And General Model

Under the argument that tourism can be treated much like any other commodities or services in international trade, with some minor differences of degree, Gray (1970) has attempted to develop a coherent theory of tourism. Gray's theory makes contributions to theories of international tourism through the following points:

- Gray argues that:

> international trade in travel services will conform generally, to the orthodox theory of the causation of international trade flows and any differences which do exist between trade in travel and trade in commodities (or other services), will be differences of degree rather than of kind. .... However, the orthodox H-

O model may be only a partial explanation of trade in travel services. The existence of two-way trade in a single trade category necessarily indicates that variation in factor productions alone is not the sole cause of trade. [p.16]

Therefore, trade in travel is a differentiated good and its demand-oriented characteristics should be considered as determinants of trade in travel flows.

- Gray further differentiates pleasure travel into two categories in terms of tourist motivation: "wanderlust" and "sunlust". The "wanderlust" tourists are some individuals who want to leave things with which they are familiar and to go to see different cultures and places, or the relics of past cultures in places famous for their historical associations, ruins, and monuments. The "sunlust" tourists are looking for the existence elsewhere of different or better amenities for a special purpose than are available locally. The crucial difference between the two types of travel relates to the degree to which they are likely to be international (as opposed to domestic), and in the type of travel facilities required by the destination. The "wanderlust" travelers may be expected to be more international in character than the "sunlust" travelers. The "sunlust" tourism demand focuses on natural resource attractions and is characterised by a high degree of substitutability between products, and strong competitive forces. The "wanderlust" tourism demand focuses on human resources as attractions and is characterized by pronounced heterogeneity of destination in perceived quality - hence less substitutability and less price sensitivity.
- Gray also indicates that the actual volume of foreign travel imports will always be subject to general economic constraints that determine the actual expenditure on any individual goods or services. These constraints include a large number of forces which operate on individual demand schedules but which are too small to allow their effects to be discerned by analysis of the aggregated, national demand function for travel imports. Forces that will exert some effect upon the aggregate volume of travel imports include: changes in income distribution in the importing country, fluctuations in relative prices both

internationally and domestically, the addition of new direct services routes to international transportation and the development of new facilities at different rates in different supply areas.

Nevertheless, Gray's foreign trade theory and his theoretical model is not fully developed and integrated into a systematic economic theory of tourism demand as argued by Smeral (1989) and Morley (1992). Firstly, Gray's generalization neglects major tourist motivations, such as "VFRs" and business motivation categories, and important distinctions between different tourist types which play important roles in analyzing international tourism demand. Moreover, the traditional view of the foreign trade theory, such as the factor proportion theory of the H-O model, is basically a supply-side oriented analysis and hence ignores demand, an important factor in international travel.

In summary, the macroeconomic theories discussed in this section have, to some extent, explained international tourism flows at the aggregated level. On the other hand, these trade theories are not fully developed into a theoretical framework or foundation for modeling tourism demand as most of these theories are supply-oriented theorems and hence misunderstand tourism activity conceptually by confusing it with trade flows. Therefore, the development of theories of tourism demand appear to lag behind empirical work, as indicated by Morley (1995a) and Sinclair and Stabler (1997).

However, although the development of macroeconomic theories of tourism demand appear to lag behind empirical work, as indicated by Morley (1995a) and Sinclair and Stabler (1997), the theoretical framework of modeling tourism demand at individual level is well established based on some principles of microeconomics.

4.4 MICROECONOMIC FORMALUTIONS

Microeconomic formulations of tourism demand are theoretical models of tourism demand, which are derived from economic theories and work as foundations of modeling tourism demand at the disaggregated level.

The attempt to develop theoretical models of tourism demand begins with the microeconomic formulation of economic variables (such as price, income and demand) by Rugg (1973), who develops the basic theoretical model of tourism demand at the individual level.

The consumer theory, among others, represents the main school of microeconomic theories of tourism demand, which have been developed since the 1960's. At an individual level, consumer theory attempts to integrate the Marshallian Utility concept with the psychological and sociological influences in consumer behaviours. In the framework of the microeconomic consumption theory, tourism demand can be explained by the utility maximization of an individual or household under constraints, given complete information.

Generally, the theoretical models of tourism demand based on the consumption theory can be classified into three groups: the neoclassical model, the consumer reference model, and the single utility model.

4.4.1 The Neoclassical Model

In neoclassical theory, consumers allocate their money over the available goods and services in order to achieve the maximum total utility. It is assumed that an individual consumer has complete information on all relevant prices and the availability of goods and services and can assess and rank the various possible combinations in an order of attractiveness or utility. Consequently, the individual demand for tourism originates from a budget allocation process, which maximizes utility. The demand for each good or each specific tourism service is a function of all prices and the consumer budget; leisure time is assumed to be constant and given.

In applying such a theory to tourism demand, it is assumed that individuals' decisions are made in a two-stage process (see Smeral 1988, 1989). In the first stage, the amount of consumption of tourism goods is decided upon in conjunction with other goods and services. Prices of all goods and services and the individual's income are relevant to the decision in this stage. Moreover, changes in the prices of non-tourism goods may affect the amount spent on tourism. The level of income of an individual and the amount required for meeting basic needs would jointly determine the level of discretionary income needed to realize the consumption of luxury goods including foreign travel. When the decision to consume travel goods and services has been made, the next stage involves the choice of which travel good or service. Therefore, in the second stage, the travel destination is chosen. Only the tourism prices of the various destinations are relevant to the choice of destination decision making, all other things held constant. Thus, two-demand functions are derived based on each stage of this process: one for the total tourism demand from a source and another for the destination given the total tourism demand from the source. Empirical modeling based on the standard two-stage theory usually concentrates on the second stage. Effectively, it is the market share of a destination for a given total market size that is modeled.

Through time, complete demand systems have been developed (e.g., Stone, 1954; O'Hagan and Harrison, 1984; Smeral, 1988). Smeral (1989) integrated the neoclassical approach into the framework of tourism demand in the following model:

$D_{ij} = \mathbf{f}\,(P_{ij} \ldots P_{nj}, Y_j),$

.

.

$D_{nj} = \mathbf{f}\,(P_{ij} \ldots P_{nj}, Y_j),$

where

$D_{ij} \ldots D_{(n-2)j}$ = demand for non-tourism consumer goods in country j

$D_{(n-1)j}$ = domestic consumption of tourism services by country j

D_{nj} = tourism consumption abroad by country j

$P_{ij} \ldots P_{(n-2)j}$ = prices of non-tourism consumer goods in country j (expressed as units of homogeneous currency)

$P_{(n-1)j}$ = prices of domestic tourism goods and services in units of a homogeneous international currency in country j

P_{nj} = prices of foreign tourism goods and services in units of a homogeneous currency for country j

Y_j = disposable income in units of a homogeneous international currency in country j

$\sum P_{ij}D_{ij} = Y_j$ (i=1…n)

n = number of consumer goods, i=1…n

m = number of countries of origin, j = 1…m

l = number of destination countries, k = 1…l.

With a neoclassical model, the demand for each consumer good is a function of prices and disposable income. Savings can be thought of as a future consumption good and thus finds a place within the model. Therefore, the demand for tourism goods and services is a function of (1) prices of non-tourism consumer goods and services, domestic tourism and foreign tourism goods and services; and (2) of disposable income in the tourist-origin country.

Under the assumption of a two-stage decision process separable for each country, two separate equations can be derived: one for the first step--to determine the volume of demand for domestic and foreign tourism goods and services from the consumer in the origin countries; one for the second step--to determine the country of destination according to prices of tourism goods in all possible destinations and the foreign travel budget restriction (see Smeral, 1988).

4.4.2 Lancaster's Consumer Reference Model

The explanation of tourism demand in the framework of consumption theory further progressed through the contribution of Lancaster (1966, 1971). In Lancaster's development of theory, goods and services are not assessed as their direct utility objectives, but according to their characteristics. Lancaster (1971) formulates a basic consumer reference model (utility maximization model): Let z be a vector whose characteristics are the quantities of various attributes; let x be a vector of the elements of which are quantities of various commodities; let p be a vector of corresponding prices, and y the level of income (U = utility). Thus, the consumer desire to maximize:

U = U (z),

$$z = f(x) = Bx,$$

$$p'x \leq y,$$

$$x,z \geq 0.$$

The function **f**(x) describes the "production" of attributes by commodities. A simplification is provided by replacing it by the linear approximation **B**x, where B is a matrix with as many rows as there are attributes and as many columns as there are commodities. The matrix B is then the 'consumption technology'.

The special application of this theory is based on the assumption that under certain conditions, it is possible to separate a set of activities and characteristics. Therefore, a vacation trip is independent of non-tourism consumption. Consequently, changes in prices of non-tourism goods or services cause no reaction in the travel behavior.

Following Lancaster's (1966) theory of Utility, Rugg (1973) has developed a microeconomic theory of tourism destination choice by building a model of an individual maximizing utility dependent upon destination characteristics, subject to time constraints. Rugg's model is only concerned with the choice of destination assuming that the consumer has decided to take a tourist trip and made a budget allocation of time and money. The destination characteristics are expressed as a function of the time spent at the destinations, and this production function is incorporated as another constraint. The consumer is assumed to maximize

$$U= U(z),$$

$$Z= b(d),$$

$$Y \geq P_d \,.\, d + p_t \,.\, m,$$

where z is a vector of the elements which are quantities of the various commodities of destination characteristics; d is a vector of the elements which are quantities of the various commodities (days spent visiting each country); p_d is a vector of corresponding prices; p_t is a vector of the elements which are transportation fares between all pairs of countries within the transport network; m is a permutation column vector whose elements are either one or zero, depending upon whether the traveler does or does not travel between the defined country pair; Y is a scalar representing the budgeted income of the consumer. The budget constraint in this modified model differs considerably from the one suggested by Lancaster by including the constraint term $\boldsymbol{p_t} \cdot \boldsymbol{m}$, representing the total cost of transportation.

4.2.3 Morley's Single Utility Model

More recent developments of the utility function can be seen in the work of Morley (1992, 1994a, 1995a). Applying the discrete choice theory (see Ben-Akiva and Lerman 1985), Morley (1992) puts forward a micro-economic utility model which has a single-stage decision-making process. Morley's models incorporate both tourism characteristics and non-tourism goods into a single utility function. The model is also developed to incorporate the concomitant decision to tour or not and the choice of tour. It is thus a hybrid of Lancaster's model of demand in which utility is derived from characteristics of goods, and the classical model in which the goods are directly the source of utility. The general form of the model is expressed as:

$$\text{Max } U_r(t_r, q_r),$$

$$t_r + t^{\wedge} \leq T,$$

$$p' \cdot q_r + c_0 t_r + f \leq Y_r,$$

where tourism decisions by economic agents can be considered as the results of utility maximization subject to constraints: the time spent in tourism T and the quantities of n other goods consumed q constrained by the individual's income Y. In which, r is denoted as an agent's utility dependent on their tastes; t_r the time spent in transit; $t^{\wedge}$ time spent at the destination(s); T the time individual has available for potential tourism purpose; p' a vector of prices of other goods; q_r the quantities of other goods consumed; c_0 the price per unit of time of the tour; and f the fare.

In this model, the choice of tour to be taken depends on the individual's income, the time available for touring and the prices of non-tourism goods and services in addition to tourism prices and tour characteristics. The theory of the one-stage decision-making process is argued to be more realistic and practical than the restriction in the two-stage process as it simplifies the theoretical model and avoids unnecessary complications (see Morley 1995a).

In summary, the economic analysis of tourism demand begins with the microeconomic formulation of the rational maximizing utility subject to an individual's budget and time constraints (see Rugg, 1973). The direct utility is a function of characteristics of tours available to the individual and quantities of other goods and services that the individual might consume. Maximizing this utility yields the indirect utility function for that individual. The indirect utility is a function of an individual's income, time available for touring, the fare for the tour, transit time for the tour, attributes of the tour characteristics, the cost of the tour, and prices of other goods and services. Therefore, the microeconomic formulations theoretically define that economic factors, such as time available for touring, the level of income and price of travelling, determine tourism demand at the individual level.

Many aspects of economic theories can be applied in developing a tourism-demand model. The challenge of tourism-demand modeling is how to go beyond the theoretically-defined economic factors (i.e., income and price) and to reflect changes in all influencing factors. This discussion of the microeconomic theories of tourism demand is a necessary first step to undertaking an applied demand study. In the next section, we move to discuss all possible factors influencing tourism demand in general.

4.5 DETERMINANTS OF TOURISM DEMAND

4.5.1 Factors Influencing Demand For International Tourism

A number of descriptive analyses have been done concerning determinants of international tourism demand (e.g., Bull 1995, Vellas and Becherel 1995, Lickorish and

Jenkins 1997, Sinclair and Stabler 1997). As travel behaviors depend on personal motivations for travel and the ability to travel, a tourist's choice of destination is related to economic, social, psychological, political and other factors. Therefore, factors influencing tourism demand are generally classified into the following categories:

4.5.1.1 Economic Factors

From an economic perspective, what is important is the derived demand for tourism, i.e., the desire and ability to travel supported by a sufficient income level to facilitate this desire.

Smeral (1988) states that

> (in long run) the demand for tourism services depends greatly on the level and growth of gross national product. In short run, only the economic expectations regarding the real income and the labor-market situation are important. [p.38]

Smeral (1988) further explain that economic levels and growth directly and indirectly influence tourism demand through: (i) the Level of disposable income; (ii) growing importance of business travel as international trade increases and becomes more complex; (iii) the development of tourism infrastructure; (iv) development of and the level of relative prices of tourism goods and services and consumer goods in an economy, and relative prices between the country of origin and the country of destination; (v) increases in industrialization and urbanization, which lead to a growing need for holiday travel; (vi) demographics, such as the income and age structures and educational background of a society, as well as the political situation and the availability of leisure time.

In the short term, however, the economic determinants of tourism demand are basically income and prices.

As standards of living have risen and levels of income have increased, more people have become able to afford to travel. Real income in a generation country, which is usually measured by either real GDP per capita, or disposable income and discretionary income, is regarded as the most important economic determinant of international tourism. From the disposable income the person will meet basic living expenses, such as, mortgage or rent payments, heating, food, clothes and other similar expenditures. After these necessary expenditures have been met, the remaining income is termed as discretionary income. It is that proportion of a consumer's disposable income which is free to be spent (or saved) as the consumer wishes. As vacation travel is regarded as "luxury consumption", travelling overseas for a vacation is actually determined by the level of disposable income and discretionary income or more effectively by the discretionary income.

There is, however, some evidence that holidays are becoming part of the household budget, not just discretionary items (see Guitart 1982, Boerjan and Vanhove 1984).

Business travel may be more affected by economic circumstance in the tourist-origin country. Cleverdon (1985) indicates that

> the rate of growth of the economy determines the level of business travel and the speed of change of that level. Business travel activity (i.e., trips and expenditures) matches the growth of the economy when economic performance is weak but moves ahead of the rate of increase in economy during periods of economic stability and expansion. [pp.199-200]

Therefore, in general, business travel is set by economic performance which can be measured by the level of gross national product, i.e., GDP or GNP. However, as an important segment of business travel, conference travel is not as predetermined as other forms of business travel, in that the conference organizers can choose the location for the conference on the basis of facilities, price, and so on. Thus "conference destinations are in strong competition with each other to attract conferences" (Witt *et al.* 1991, p.42). In another words, conference travel also depends on the decision-making processes of all the organizations involved, both in terms of site selection and attendance policies.

Tourism demand and prices are usually negatively related with income held constant. The price level in the generation country determines the basic living expenditure, and consequently affects the level of discretionary income, and finally determines the ability to travel. Consumers have to decide to purchase tourism among other non-tourism goods and services, and then to choose between a range of tourism products and destinations. Tourism demand depends not only on its own price but also on the prices of other goods and services and the relative prices of different types of tourism and destinations. Therefore, tourism demand should incorporate relative prices of alternative goods and services and substitute prices of alternative tourism products and destinations.

In regard to international tourism, the exchange rates between the origin country and a range of other destinations are likely to be one of the important factors influencing the choice of destination. With international travel, many of the costs of a trip are *ex ante* and therefore consumers, because they are often paying for air travel and accommodation up front, are aware of the exchange-rate-affected price shifts. In the short term, tourists take account of relative prices and exchange rates separately and are more aware of the changes of exchange rates than the inflation rates in the destination countries (see Sinclair and Stabler, 1997). However, in long run, most tourists pay for their tourism consumption in their own currency and the prices which they are charged take account of both differences in relative prices and exchange rates. Therefore, the "effective exchange rate" (normal exchange rate adjusted by relative inflation rates), in addition to other relative prices, is taken into account in many studies of international tourism demand (e.g., Kulendran1995, 1996, Witt and Witt 1992, Kulendran and Wilson 2000a).

The price of transport is another element of the tourism price. The price of transport is considered as a separate factor influencing tourism demand based on the following two reasons: (1) the retail price indices, which have usually been used as measurements of price levels at both tourist origin and destination countries, do not take explicit account of the price of transport between the origin and the destination; and (2) the cost of transport is such a significant proportion of the total cost of travel (especially overseas travel) that changes in it may induce a change of travel mode. However, the cost of transport influences travel decision differently on tourists with different travel motivations. For instance, travel for business purposes is less elastic (or more inelastic) to the cost of transport compared to holiday and VFR's travel.

4.5.1.2 Social Factors

Population and leisure time in the origin country are two important factors influencing tourist behaviors socially. Although population is the original source of tourism, the absolute population numbers have very little relevance to the tourism demand. In fact, "the population structure changes is one of the long-term factors effecting demand" (Lickorish and Jenkins, 1997, p58). "The availability of free time is a primary condition of tourism demand" (Vellas and Becherel, 1995, p92). The 'long weekend', increases of holiday time and the fall in retirement age have contributed greatly to the recent development of international tourism demand.

4.5.1.3 Personal Factors

Personal factors are individual's tastes and preferences which influence tourism demand. These factors are very important forces which operate on individual demand schedules and affect a tourist's choice of travel destinations. These factors are often ignored in the analysis of the aggregate, national demand function, as they are too small or difficult to be discerned.

The factors vary according to individual countries but the following are sufficiently important to be regarded as generally applicable: education, urbanization, marketing, the level of travel agency support, and destination attractions (see Lickorish and Jenkins 1997, Mehmet 1981).

Lickorish and Jenkins (1997) explain that there is a correlation between the level of education and a person's cultural curiosity as well as income levels. People with a higher level of education tend to be more curious, and more importantly, have greater financial ability to travel. Therefore, many long-haul travelers, perhaps because of the expenses of the journey, are relatively wealthy people, often with a high level of education.

It is noticeable that most international tourists live in urban areas. Compared to people living in rural areas, people living in urban areas tend to enjoy higher income and are more exposed to public media information, which includes travel data.

Travel services, including tour operators and travel agents, exert considerable influence on holiday decisions, as more potential travelers seek travel information and advice from travel services. Travel services and tourism promotion can influence and often change the initial perceptions of a proposed destination.

4. 5.1.4 Other Factors Effecting Demand In International Tourism

International tourism demand is further influenced by international political conflicts, administrative issues, and other important events, such as the relationships between the generation and destination countries, and border-crossing facilitation. For instance, a government may seek to control both inbound and outbound tourists through passport and visa requirements, foreign exchange controls and other regulations. The growth of Japanese travel in the 1970's can be attributed to the liberalization of Japanese currency exchange regulations in 1964 and to the easing of procedures to obtain passports in 1970 (see Pearce 1995, p.25). Similarly, the increase in Taiwanese outbound travel to mainland China in the 1980's reflects the relaxation of travel restrictions between the destination and the origin country.

4.5.2 Other Classifications Of Determinants Of Tourism Demand

As discussed above, the determinants of international tourism demand are widely ranging from economic to social, cultural and personal factors. However, these factors can be further classified into different criteria from different aspects.

In terms of location, economic factors influencing international travel generate widely from the destination area, generation area, and even from competition between substitute destinations and competition between destination and generation countries (see Bull, 1995).

Based upon the consumer theory, factors affecting foreign travel may work in different stages of decision making. There are some factors influencing the decision to travel or not (i.e., the first stage of decision making), and those influencing the choice of destinations (i.e., the second stage of decision making), and those generally affecting both procedures. For example, the level or magnitude of discretionary income is a major determinant of international travel in the first stage of decision making, as discretionary income determines the amount required for the consumption of luxury goods and services including foreign travel. Travel costs and attributes in substitute destinations usually affect the choice of destinations. Other economic factors, such as prices and exchange rates, together with non-economic factors mentioned above will certainly play different roles in travel-decision making procedures.

4.6 SUMMARY AND CONCLUSION

Tourism as a human activity is very complex and hence can neither simply be defined as an "industry" nor be analyzed in the same way as trade flows. Many researchers (e.g., Goodall 1988, Morley 1992, Witt and Witt 1991, and Wilson 1998) emphasize that tourism is a form of complementary demand, which is significantly different from an "industry" or international trade flows. Firstly, there exists no tourism "industry", but "tourism related industries" as tourists consume a variety of goods and services, which are elements of tourism catalogued into various industry classifications. Secondly, unlike the traded goods, most tourism activities are private consumption. The share of income spent on tourism has a high-income elasticity; tourism is influenced by business cycles in the economy rather than determining them as trade flows do. Finally, there are a number of characteristics that further distinguish tourism from other consumption behaviors: (i) much of tourism supply cannot be stored or transported. Consumers move to tourism products rather than vice versa. Thus, the roles of distance and transportation should not be ignored; (ii) as tourism demand is primarily private consumption of services, inventory cycles are not important and investment is capital intensive and long term. Therefore, in marking up a description of individual and segment group utility, it is vital to appreciate the differences in tourist's motivations and characteristics. It is also important to interrelate economics with the sociology, psychology and geography of tourism.

Each group of macroeconomic theories on the economic determinants of international tourism is essential and can explain, to some extent, international tourism flows. Thus, even if the theory of demand is the main theory on the determinants of international tourism, it must be in conjunction with conditions of supply (such as factor endowments and comparative costs), in order to explain the international tourism demand comprehensively. Although personal motivations and the real discretionary income are the main determinants of demand for tourism, there are also supply factors which pull tourists to specific destinations, such as the price level, the quality of amenities, accommodation and transport at a destination, the ease of access to the destination, and even more the social, economic and political environments in the destination. Therefore, factors influencing international tourism demand must be examined from both demand and supply sides (or from both a tourism generator and the receptor) as well as from the perspective of personal psychological motivations, economics, social and political backgrounds.

In terms of microeconomic theories of tourism demand, the standard model assumes a two-stage decision-making process. It involves two separate "utility" calculations and demand functions. The volume of tourism demand and a travel budget are determined in the first stage and the travel destination chosen subsequently constrained in the second stage. However, as argued by many researchers (e.g., Um and Crompton 1990, 1995, Crompton 1992, Pearce 1995, and Sinclair and Stabler 1997), consumers are imperfectly aware about information of income and the travel market. Most potential tourists lack perfect knowledge in the decision making process and will not be aware of all possible destinations which might be able to fulfil their motivations or satisfy their needs. On the contrary, many tourists are selecting from a relatively small number of destinations which they are likely to visit in any given year. Moreover, economists are mostly interested in aggregate demand, or effective demand which can be defined as the quantities of a product that buyers collectively are willing and able to buy at any potential price over the same specified period of time. Strategic policies in tourism require information on the aggregated level rather than individual level. Therefore, most applications of the utility approach to tourism are concentrating on the destination-based models, though there is no doubt that a very large of proportion of demand is latent, or potential. Consequently, the aggregation issue arises in building from the individual, microeconomic theory to an aggregate level model (for example, national level of tourism demand model), in a form suitable for estimating and using aggregated data and measures (see Morley 1992, 1995a).

Many economic theories may be applied in the development of models for tourism demand. The challenge for the future research remains the question of how to go beyond the theoretically-defined economic factors (i.e., prices and income) in modeling tourism demand and how to reflect not only changes in purely economic variables but also possible changes in other influencing factors as well.

Tourism demand can be analyzed for groups of countries, individual countries, regions or local areas. Demand can also be disaggregated by categories as types of visits (for example, holiday, business and VFR etc), and types of tourists (covering nationality, age, gender and social-economic groups etc). Factors influencing tourism demand vary among different pairs of countries, different types of tourist groups, and even different time periods. Therefore, in modeling and forecasting tourism demand, it is very important to segment the tourism demand in order to identify the appropriate determinants of tourism demand and to chose appropriate variables for a demand function. Before forecasting any tourism flow between different pairs of countries, further analyses supported by the empirical studies is needed in order to examine specific determinants of tourism demand between certain generation and destination countries during different time periods.

Having gained important insights from the theoretical tourism demand literature, in the following chapter we further review the applied tourism demand literature.

CHAPTER 5: **MODELING AND FORECASTING INTERNATIONAL TOURISM DEMAND: A LITERATURE REVIEW**

5.1 INTRODUCTION

In the previous chapter we surveyed the relevant theories for international tourism demand. In this chapter we further build up the theoretical framework to analyze and forecast international tourism demand to China, by critically reviewing previous empirical studies of international tourism demand.

Empirical modeling of tourism demand is important for two reasons. First, we can learn which economic factors are more important in influencing tourism demand in China's circumstances. Secondly, demand modeling provides us with an entry to consider another important topic, tourism forecasting.

The empirical modeling of international tourism demand has proved popular and recent surveys of this literature have been provided by Crouch (1994a, 1994b), Witt and Witt (1995), Lim (1997), and Morley (2000). Crouch (1994a, 1994b) surveys the determinants of international tourism demand covered in 85 empirical studies of international tourism demand, and also outlines the nature of different approaches applied in each study. Lim (1997) provides an econometric classification and evaluation of 100 published papers which model international tourism demand. Witt and Witt (1995) provide a broader review of 48 empirical studies on tourism forecasting methods. Morley (2000) discusses the methodologies of tourism demand modeling commonly used in previous empirical research of tourism demand, including such issues as functional forms, estimation methods, and some newly developed modeling techniques.

This chapter attempts to present a comprehensive review of the developed modeling methodologies applied in traditional regression models, time series models, error correction models and vector autoregression models. It also discusses measures of forecasting accuracy employed in previous empirical studies of international tourism demand. The plan of this chapter is as follows: section 2 provides a review of the regression models; section 3 presents the methods of time series models; section 4 discusses the concept of cointegration and error correction models based on the cointegration concept; section 5 introduces vector autoregression models; section 6 examines measures of forecasting accuracy generated from different forecasting models. An overall summary is provided in the final section.

Although methodologies employed in modeling international tourism demand differ in a number of ways in terms of different modeling methods, generally, empirical studies in modeling international tourism demand are categorized into two broad groups: causal methods and non-causal methods (see Frechtling 1996, Witt and Wiit 1987, 1995). Causal methods (also called regression methods or econometric methods) attempt to statistically capture cause-effect relationships between tourism demand and factors influencing tourism growth and decline. Determining the causal variables that effect tourism demand and an appropriate mathematical expression of the relationship is the central objective of these methods. Non-causal methods (also called time-series methods) assume that a variable's past course is the key to predicting its future. Past patterns in tourism demand are used to project or extrapolate the future, while the effects of the causal factors are ignored.

Therefore, in the following two sections, we discuss, respectively, the two groups of methodologies applied in tourism modeling and forecasting.

5.2 REGRESSION MODELS

Studies of international tourism demand using regression (or econometric) methods attempt to mathematically simulate cause-effect relationships between international tourism demand and its influential co-determining factors. Witt and Witt (1995), who have reviewed 48 empirical tourism studies conducted from 1975 to 1992, find that the majority of empirical studies of tourism demand have applied regression analysis methods.

Early pioneering contributions in the field of regression analysis of tourism demand can be found in Gray (1966), Smith and Toms (1967), Artus (1972), Jud (1974), and Jud and Joseph (1974). Since the 1980's, Edwards (1985), Martin and Witt (1989), Usal (1985), among others, have led the way in this field. More recently, we have seen contributions by Divisekera (1995) and Kulendran (1996), Witt and Witt (1991,1992,1995), Morley (1991, 1996, 1998, 2000), and Song and Witt (2000).

The tourism demand functions in the regression methods embody the relationships between tourism demand for international tourism and those factors that influence tourism demand.

In terms of tourism demand, the vast majority of empirical studies of tourism demand examine either total tourist trips (i.e. travel trips for all purposes), or just holiday trips. Only a few studies (e.g.: Smith and Toms 1967, Witt *et al.* 1992, and Kulendran and Wilson 2000a) are concerned with business tourism, although tourist visits may be generated from various motives: holiday, business, visiting friends and/or relatives (VFR's), and pilgrimages. Only one study (Turner and Kulendran 1996) disaggregates tourism demand into several types for modeling and forecasting purposes.

Although there is a broad range of explanatory factors affecting international tourism demand, most studies focus only on the major economic factors (see Lim 1997). The general form of these regression models may be expressed as:

$$Q_{ijt} = \alpha_0 + \alpha_1 GDP_{it} + \alpha_2 TC_{ijt} + \alpha_3 RP_{ijt} + \alpha_4 ER_{ijt} + \alpha_5 DM_{ijt} + \mu_{t,} \qquad (5.1)$$

where

Q_{ijt} = the demand for international tourism to destination country j from origin country i at time t;

GDP_{it} = income of origin country i at time t;

TC_{ijt} = transportation costs between country i and country j at time t;

RP_{ijt} = relative prices (the ratio of prices in country j to prices in country i and/or in alternative destinations) at time t;

ER_{ijt} =currency exchange rate, measured as units of destination j's currency per unit of origin i's currency at time t;

DM_{ijt} = qualitative factors in destination j and/or in origin country i at time t;

μ_t = random error terms at time t; and

α_n = parameters to be estimated (n= 0, 1, 2,...5).

We now turn to further consider the alternative variables that have been included in the demand function and review the regressing procedures employed in regression models.

5.2.1 Selection Of Variables

In regard to causal studies, selection of dependent and independent variables has largely been determined.

The dependent variable, tourism demand, is generally measured either by: (1) the number of tourist arrivals/departures from an origin country to a destination country; (2) tourist expenditures/receipts in the destination country; or (3) tourist nights/days spent in the destination country. The number of tourist arrivals/ departures is most frequently used as the measure of demand, followed by tourist expenditure/receipts (see Witt and Witt 1995, Lim 1997, Crouch 1994b).

The number of potential demand determinants is very large and complex (as discussed in Chapter 4). An selection of appropriate variables depends on a number of factors, such as the country examined, the time-period investigated, the data source, the types of models and the type of tourism involved.

Witt and Witt (1992) have defined seven commonly used determinant variables for holiday demand functions in the previous empirical studies. They are, namely, population, income, own price, substitute price, dummy variable, trend, and promotional activities.

Further investigation of the explanatory variables (e.g., Crouch 1994b, Witt and Witt 1995) finds measures of income, prices (both own-price and relative price), and exchange rates have been dominant variables in previous studies. Other additional factors include measures of marketing effort, population, ethnic attraction/culture ties and distance/travel time, dummy variables, trend terms and lagged dependent variables.

Therefore, the literature states that although the range of factors affecting demand for international tourism is undoubtedly very large, variables measuring income levels, prices, exchange rates, and transportation costs are the most prominent and hence are considered as the most important independent variables for international tourism demand models.

Income

A growing economy generates more sales, jobs and personal income than a stagnant one, and can therefore be expected to generate more travel, including holiday, VFR's and business travel (refer to section 4.5.1, chapter 4).

The level of income in the origin country, or more specifically the discretionary income or disposable income, will affect the ability of holiday and VFR's tourists to pay for overseas travel, as overseas travel is generally regarded as luxury consumption. The level of economic activity in a destination and/or an origin country is likely to influence the demand for business travel. Therefore, international travel for different purposes may respond to changes in income differently.

Witt and Witt (1995) suggest that

> If (mainly) holiday visits or visits to friends and relatives are under consideration then the appropriate form of the variable is private consumption or personal disposable income, but if attention focuses on business visits (or they form an important part of the total), then a more general income variable (such as national income) should be used. [p. 453]

Accordingly, national income or real GDP is a reasonable income variable for business demand or total tourism demand with a high proportion of business travel, for instance, international tourism demand to China. On the other hand, if attention focuses on the holiday visits or visits to friends and relatives, then private consumption or personal disposable income will be an appropriate choice. As the vast majority of empirical studies of tourism demand focus either on holiday trips or total tourist trips, the national income (measured by GDP or aggregate expenditure) or private consumption (measured by personal disposable income or discretional income) in the origin countries is commonly included as an explanatory variable in tourism demand functions.

Although income is commonly included in the demand function as a main push factor of travel, there are certainly some other important factors for international travel which should be considered in the functions, such as travel prices or costs.

Relative Prices

Prices are included in tourism demand functions as resistance variables because most potential travelers have limited income for travel in their day to day needs. The higher prices are, the fewer items this income can finance. Price variables are the second most frequently used explanatory variable in the previous studies (see Lim 1997, Crouch 1994b). For international tourism, there are two elements of price: the cost of transportation (i.e., the cost of travel in reaching a destination from an origin country); and the cost of living for tourists in the destination, which is a complex of prices for accommodation, food, entertainment and recreation and transportation.

Selection of an appropriate form of price measures is very complicated, because of the following factors:

- Even though, theoretically, variables for the cost of transport should be included in demand functions of international tourism (refer to section 4.5.1.1, Chapter 4), it is far more complicated to put it into practice. Witt *et al.* (1991) suggest that transport costs can be measured by using representative air fares for air travel and representative ferry fares and or petrol costs for surface travel in real terms in origin-country currency. However, many previous studies exclude these variables on the grounds of a potential multicollinearity problem and the lack of sufficient data (see Witt and Witt 1995, and Lim 1997). A further issue in inclusion of a transport cost variable arises due to the transport pricing system. Within as well between most forms of transport, there are different fares, which also vary according to such criteria as the pre-booking time, times of travel and length of stay. Among these various fares, an appropriate candidate representing the transport cost is not clearly defined theoretically and practically in tourism demand modeling. Morley (1995b) in particular addresses the issue of measurement bias in airfares. Empirically, some studies of tourism demand find transport cost variables have been insignificant (see Little 1980, Strong and Redman 1982). Other studies (e.g., Kliman 1981 and Tremblay 1989) find a significant negative relationship between the tourism demand and the transport cost.

- It is very difficult to directly measure tourist cost of living because often there is no suitable data on the basket of goods and services purchased by tourists, which includes prices for accommodation, food, transportation, entertainment and recreation.
- There are some arguments that tourists are more aware of exchange rates than destination costs of living (Artus 1970 and Gray 1966). Therefore, exchange rates are often included as another price factor in the tourism demand models in addition to the relative price variables. Such studies specifically examine the influence of nominal exchange rates on international tourism demand.

The microeconomic theories of tourism demand discussed in Chapter 4 (see section 4.4) demonstrate that international tourism demand depends not only on its own price but also that of other goods and services. Therefore, tourism can be either a substitute for, or a complement to, other goods and services. Morley (1994b) analyses 13 country cases and finds that the three selected components of tourist spending (i.e., hotel price, restaurant price and travel price) are all highly correlated with their CPI ratios. Therefore this empirically confirms that tourism can be either a substitute for or a complement to other goods and services, and hence the CPI ratios measuring the overall price levels in the tourist origin country and destination country can be reasonable proxies to present the tourist cost of living, on the grounds of lacking more suitable data on the basket of goods and services purchased by tourists. However, it is noted that justification via correlation does not rule out the possibility of a bias in the coefficient of CPI if used as a tourism price elasticity.

As for the debate on exchange rates as a separate price factor in tourism demand, although tourists are more aware of exchange rates than destination costs of living, most tourists pay their tourism consumption in their own currency, and the prices which they are charged take account of both differences in relative prices and exchange rates. Considering the prevailing methods of pricing and paying for tourism consumption, exchange rate between the origin currency and the destination currency should be included as one of the price factors of tourism. In practice, the exchange-rate-adjusted CPI ratio is commonly used as a proxy for the cost of tourism. Some researchers (see Kulendran 1996, Kulendran and King 1997, Song and Witt 2000, and Kulendran and Wilson 2000b) have composed the "relative price" variable using exchange-rate-adjusted CPI ratios between the destination and origin country in econometric forecasting models.

Finally, due to the unavailability or insufficiency of data, consideration of transport cost as a possible determinant of tourism demand should be treated with caution and be the subject to more detailed theoretical and empirical investigations on the tourism demand of interest.

Substitute Price

Economic theories suggest that international tourists may compare prices of a holiday in a particular foreign destination with prices of a domestic holiday as well as an overseas holiday in alternative foreign destinations. Thus, substitute travel costs and substitute living costs should be considered as important variables for the international tourism demand to a given destination from a particular origin. Substitute prices in previous studies are usually accommodated in a model through the inclusion of: (1) a weighted average substitute transport cost variable, and (2) a weighted average substitute tourists' cost of living variable. The weight is usually determined to reflect the relative attractiveness of the various destinations to residents of the origin country under consideration, and are often based on previous market shares (see Gray 1966, Artus 1970, Barry and O'Hagan 1972, Jud and Joseph 1974, Martin and Witt 1987, and Witt *et al.* 1991).

It should be noted that the consideration of substitute price varies for different pairs of tourism destination and origin countries. It also may depend on the purpose of travel or the type of tourists. Some tourists may have other overseas destinations as alternatives and therefore higher than expected prices in one country may result in a change to a domestic destination or an alternative overseas destination. However, some tourists may compare the cost of a holiday overseas with the price of a domestic holiday or purchase of some other goods. In this case, the cost of a domestic holiday and changes of price level in the origin country should be related to the travel costs to and in overseas destinations, and thus the cost for a domestic holiday is considered as a substitute price for the overseas holiday. Nevertheless, when the tourists have substitute destination or destinations, the travel costs to and in the substitute destination/destinations should also be considered. Therefore, different strategies and methods to compose the relative price and substitute price should be applied in modeling tourist flows between different pairs of destination and origin countries.

Population

The level of foreign tourism from a generation country is expected to depend upon the population (the higher the number of people resident in the country, the greater the number of trips taken abroad, *ceteris paribus*). However, only a few of the previous studies have considered population as a separate explanatory variable, but often, the effect of population is accommodated by modifying the variables in per capita form, such as per capita expenditure/ receipt, per capita income etc, in order to remove the effect of natural increase in arrivals due merely to population growth.

Other Variables

It is evident that non-economic factors are also important in determining travel growth. Gray (1970), Edwards (1979) and Lim (1997) have stated that there is a large number of forces affecting demand that are too small to detect at the aggregate level, and that, in combination, they are likely to be as important as prices and income in determining travel growth. Many empirical studies (e.g., O'Hagan and Harrison 1984, Witt and witt 1989, Turner *et al.* 1995) find non-economic factors to be highly significant in their international tourism demand models.

Some non-economic variables, such as dummy variables, trends, and lagged dependent variables, were usually included in tourism demand functions in past empirical studies.

Time trend variables are usually used to capture some changes in tourist preferences. Social-cultural and personal factors, such as, changes in the age structure of population, advances in the level of education, and increases of length of paid holidays, will affect the demand for foreign travel by giving people greater interest in travelling abroad. A trend term, if included in a model, mainly captures a steady change in the popularity of a destination country over the period considered as a result of changing travel preferences. It also captures the time dependent effects of all other explanatory variables not explicitly included in the equation, such as changes in air service frequencies and demographic changes in the origins (Witt *et al.* 1991). Therefore, the time trend variable tends to be a theoretical catch of all variables aimed at increasing the explanatory power of a model.

Dummy variables are used to capture seasonal variations in tourism demand and to account for a number of qualitative factors. There are a variety of qualitative factors which influence the decision to travel, for example, tourists' attributes (gender, age, education and employment/profession), destination attractiveness (climate, culture, history, and natural environment), and political, social, and sporting events in a destination. Qualitative factors are typically accommodated with the use of dummy variables (see Lim 1997).

Dynamics (or lagged variables) may be used to account for lagged effects. The inclusion of lagged independent variables, for instance, the previous values of income and relative prices, reflects the pattern that consumption behaviors do not change immediately with the income, price and other influencing factors in a short time due to "some psychological, technical and institutional reasons" (see Gujarati 1995, pp589-590). The lagged dependent variables are usually included in tourism demand functions to allow for the effects for habit persistence, friends and relatives' recommendations, institutional relationships (see Kulendran 1996, Frechtling 1995).

In summary, in previous causal studies, income, relative price, exchange rate and substitute price variables were most commonly included in tourism demand functions. Economic theories on tourism demand suggest that factors influencing tourism demand are wide-ranging and the determinants of tourism demand are complex and varied. Ghali *et al.* (1976) point out that existing forecasting models generally consider only demand variables, while supply variables are ignored. There is an implicit assumption that the supply of tourism services is perfectly elastic. For example, the availability of natural resources, infrastructure, superstructure, and transportation facilities, are assumed to expand in response to increases in demand. Crouch (1994a) finds that some variables, such as weather and climate, tourist appeal, barriers to travel, and demographic factors, are subject to less interest in previous studies. Kulendran and Wilson (2000b) are concerned that very little research (e.g., Turner and Kulendran, 1997) has been undertaken which examines the relationship between international tourism and trade flows, and the role of trade in forecasting tourism demand. This issue has fundamental implications for forecasting tourist demand/flows as a failure to consider this issue may be a factor influencing the accuracy of current tourism demand functions. Lim (1997) finds very few studies attempt to measure business travel using proxies such as trade and direct foreign investment or capital outflows. Needless to say, the omission of relevant explanatory variables yields biased estimates in tourism demand modeling and forecasting.

In regard to previous causal studies, not only major economic factors for tourism demand, but also regressing procedures to estimate the quantitative relationship between tourism demand and its determinants, have largely been determined. In the following section, the regressing procedures used in the previous causal studies of tourism demand are discussed.

5.2.2 Regression Procedures

These regression models accommodate a wide range of relationships, such as linear and non-linear associations, as well as lagged effects of explanatory variables over several periods. The regression methods used in tourism demand modeling are virtually all linear in their coefficients, because these can be estimated through the powerful and well-understood techniques of least square regression.

The general form of linear regression model is:

$$Y = \alpha + \beta_1 X_1 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon, \qquad (5.2)$$

where Y is the dependent variable (tourism demand); α is the intercept; β_n are coefficients; X_n are explanatory variables; n is number of explanatory variables; ε is residual term.

In terms of the number of coefficient estimated in the models, the multivariable regression analysis using Ordinary Least-Squares (OLS) has been the most widely used approach in modeling tourism demand. In terms of the functional form of the models, there is a universal agreement that the log-linear form is superior to the linear form, as the former often fits the data better and conveniently provides demand elasticity measures (see Martin and Witt 1989; Crouch 1994b).

Traditional econometric studies are performed under the hypothesis that economic data is stationary (at least around a deterministic time trend). However, recent developments in econometric methodology (e.g., Engle and Granger 1987, Phillips

1987, Davidson and Mackinnon 1993, Maddala and Kim 1998) demonstrate that economic data is often non-stationary, so identification of dynamic structures of time series data and application of updated measures to test for stationarity are important for tourism studies. Therefore, recent developments in econometric methodology which focus on the specification of dynamic structures of time series have been applied to tourism demand studies (e.g., Divisekera 1995, Kulendran 1996, and Turner *et al.* 1997). Moreover, a small number of studies have applied different approaches in tourism demand studies. Kulendran and King (1997) and Song *et al.* (1999) have employed the cointegration concept to analyze international tourism demand. In particular, Kulendran and Wilson (2000b) have utilized the Granger-Causality test procedure to examine the relationship between international trade and international travel between Australia and four of its major trading partners: the USA, Japan, UK and New Zealand.

Econometric tourism-demand models are usually developed to empirically examine the causal relationships between tourism demand and its determinants, more precisely, to address the effects of causal variables included in the models. Whereas historic data is used to estimate the causal relationships embodied in these models, future values of tourism demand can be forecasted in conjunction with the estimated causal relationships. In the next section, therefore, a discussion of the forecasting procedures used in econometric models is provided.

5.2.3 Forecasting With Regression Models

Forecasting future tourism demand using the estimated models involves substituting values for the explanatory variables in the models. If lagged explanatory variables appear in a regression model, and then the actual values can be used for forecasts since they are known. More often, however, forecast values for the explanatory variables have to be resorted in order to forecast the dependent variable (i.e., the tourism demand). Thus, this requirement necessarily increases forecast errors.

The less reliable the forecast explanatory variables, the less reliable will be the forecast of the dependent variable. Nevertheless, this method has its advantages over other forecasting methods in portraying the "cause and effect" relationship and hence addressing explicitly what factors affect tourism demand and how these factors affect tourism demand. This will be very beneficial to tourism marketing plans and government policies.

In a thorough comparative study of various international tourism forecasting methods, Witt and Witt (1995) find that regression models are less accurate than no-change models which assume the next period's value equals the last period's in forecasting the level of tourism demand. Regression models are, however, the most accurate among seven other methods examined in terms of directional changes of tourism demand, i.e., whether next year's value would be higher or lower than this year's. In short, we may not expect a great deal of accuracy in forecasting levels of tourism demand from such models, but should demand that they perform well in predicting directional changes of tourism demand in the future.

In summary, regression analysis is a powerful and popular method of estimating the quantitative relationship between tourism demand and variables associated with that demand. However, the use of regression analysis has attracted some critics (see Usal 1983, Summary 1987, Witt and Martin 1989, Frechtling 1996). One of its limitations is that it does not prove that the cause-effect relationship exists between a dependent variable and its explanatory variables. Rather, "it indicates variations in the former are associated with certain variations in the latter variables" (Frechtling 1996, p.168). Crouch *et al.* (1992) also notes that "regression analysis results should therefore be treated as prima facie evidence of cause-effect relationship and not as conclusive proof" (p.206). Another problem is that it assumes that the explanatory variables are not effected by the dependent variable, ignoring the feedback effects of dependent variables. Thus, most studies have applied single-equation models to estimate the causal relationships between tourism demand and its explanatory variables. However, there may be occasions where there is a feedback of the dependent variables on one of the explanatory variables, such as tourism expenditures abroad on tourism price, in which case rising visitor volumes causes an increase in prices at a destination.

Therefore, the forecasting accuracy of tourism demand using single-equation regression models may suffer from its ignorance of feedback effects between tourism demand and its influential factors as well as its complexity in forecasting other related explanatory variables.

In recent years statistical time series models have been developed to generate forecasts that compare favorably in terms of accuracy with those generated by regression models. In the next section, the methods used in time series models are discussed.

5.3 TIME SERIES MODELS

Time series models focus primarily on the statistical models themselves rather than economic outlook. A time series forecasting model of tourism demand relates the values of tourism demand to its previous values. Time series analysis enables a model to be developed to extrapolate the horizontal, trend and seasonal patterns of the historical data and predict the future values of the data. It is appreciated by many researchers (see Armstrong 1972, Gujarati 1995, Turner and Kulendran 1996, 1997) also because of the advantage that it is, for the most part, relatively simple to apply, requiring no more than a data series, except the Box-Jenkins approach (see Frechtling 1996).

Early time-series studies can be found at Greurts *et al.* (1975), who have employed an exponential smoothing model and univariate Box-Jenkins forecasting approach to forecast tourist visits to Hawaii using monthly data and assessed the accuracy of 24 one-month-ahead forecasts in terms of percentage error. Gapiniski and Tuckman (1976) have applied naïve models (i.e., no-change models) using quarterly time series data to forecast the inbound tourism to Florida.[9] Decomposition methods also attracted some attention during the 1970's. Baron (1972, 1973, and 1975) has used Census X11 to forecast a range of time series: inbound, outbound tourists, international tourism receipts and hotel bed-nights. There are a number of tourism studies which compute multiple models and compare the accuracy of different time-series forecasting techniques in different country cases, e.g., Van Doorn (1984), Martin and Witt (1989), Witt and Witt (1989, 1991), Witt *et al.* (1994), Morley (1996), Turner *et al.* (1995) and Kulendran and King (1997).

In general, the naïve models, moving average, exponential smoothing and autoregression models are the basic and simple time series models, which are only applicable for time series data with simple patterns. The Box-Jenkins approach (the ARIMA model) is a more sophisticated time-series method, which allows for a wide range of models to be applied to various time-series data.

5.3.1 The Box-Jenkins Approach

The Box-Jenkins approach searches for the combination of two forecasting methods, autoregression and moving average, and their parameters that minimize the error in simulating the past series. There are two general components for the Box-Jenkins approach: autoregressive moving average model (ARMA) and autoregressive, integrated, moving average model (ARIMA).

With stationary time series, ARMA (p, q) is applied. The equation follows as:

$$Y_t = \theta + \alpha_0 Y_{t-1} + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots \alpha_p Y_{t-p} + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \beta_2 \varepsilon_{t-2} - \ldots - \beta_q \varepsilon_{t-q} \qquad (5.3)$$

where Y_t is a stationary time series with a white noise error term ε_t (i.e., $E(\varepsilon_t) = 0$, $Var(\varepsilon_t) = \delta^2$); p is the order of autoregression (or the number of lags of the Y's); q is the order of the moving average of the white noise stochastic error term μ.

[9] A no-change model is a simple time series forecasting method which uses the most recent actual value as the forecast for the next period. This method is often used as a basis in evaluating other forecasting methods.

If a time series is not stationary and integrated at order d (i.e., by making *dth* differences, the data becomes stationary), then an ARIMA (p, d, q) is applied. Therefore, after differencing the data series d times, we have a stationary time series and then we can apply the ARMA (p, q) model to the differenced data.

5.3.2 Forecasting With Time Series Models

Apart from its relative simplicity in model regression, the most important advantage of a time series model is that, unlike the regression methods, it requires no more than a data series (i.e., the tourism demand data itself) to generate forecasts. Actual values of tourism demand can be used to generate at least one-period ahead forecast, and more than one-period forecasts of tourism demand can be performed using forecasting values generated by the model itself. This avoids the forecasting variations from other variables, which occurs in the regression models.

The Box-Jenkins approach is an advanced, complex approach to building a forecasting model for time series data. However, previous studies of tourism forecasting using ARIMA models together with other forecasting methods find that ARIMA models are not more accurate than other models in some circumstances. Witt *et al.* (1994) find that ARIMA models outperformed five other methods in forecasting, but are not much more accurate than naïve, no-change models; Turner *et al.* (1995) have compared the accuracy of ARIMA models to an exponential smoothing method in forecasting tourist arrivals to New Zealand from five countries. They conclude that where the series showed a regular trend and highly variable seasonality, the exponential smoothing method performed better; but when the trend and seasonality were not marked, the ARIMA model produced more accurate forecasts. Di Benedetto and Bojanic (1993) have used the Box-Jenkins approach to model visits to Cypress Gardens, Florida. They find that the ARIMA model produced the best forecasts over periods not characterized by "rejuvenation efforts", but it was not quite as good as a regression model for the whole period. This indicates that the ARIMA model is a powerful time-series forecasting method when the pattern of the tourism demand during the forecasting periods is relatively stable.

Recently some researchers have applied the error correction model (ECM) (e.g., Kulendran, 1996, Kulendran and King 1997) in tourism forecasting, and the vector autoregressive (VAR) model (see Song and Witt 2000), which are models combining both regression and time series methods. These models are used to attempt to capture the effects of tourism determinants, which are ignored by sole time series methods, and the trends of tourism demand over past periods, which are ignored by sole regression analysis models.

5.4 COINTEGRATION AND ERROR CORRECTION MODELS

Most previous regression models implicitly assume that the underlying time series are stationary (i.e., its mean, variance, and autocovariance are constant over time). When a regression model is used to estimate tourism demand, it is further assumed that the model error terms are normally distributed with zero mean, constant error variance and uncorrelated with each other. In practice most time series are non-stationary. If non-stationary time series are employed in a regression analysis model then the asymptotic distribution of the ordinary least square (OLS) coefficient estimators do not generally follow a normal distribution and the validity of the statistical inferences using t test and F test may be in doubt. Therefore, the estimated equation will be open to the criticism of "spurious regression"(see Granger and Newbold 1974, and Phillips 1986). However, if the regressors are non-stationary, the regression analysis may be applied after differencing the data series, which will satisfy the conditions of stationarity and white noise residuals. One drawback of the differencing approach is that it will eliminate the "long run information" among the variables. Most economic theories are stated as long term relationships among variables in their original levels rather than differenced forms (see Gujarati, 1995).

In recent years, the concept of a cointegrated series, which was introduced by Granger and Weiss (1983), has been suggested as one solution to the "spurious regression" problem. If an economic theory is correct, the specific set of variables suggested by the theory may diverge in the short run, but converge to a common trend in the long run because of market forces or government policy decisions. The existence of common trends (referred to as common stochastic trends) in economic time series data has motivated the notion of cointegration which is related to long-run equilibrium. The existence of cointegration between a set of economic variables provides a statistical foundation for the usage of the ECM models. To employ the ECM approach, variables must have a common trend and must move together in the long run (i.e., the data series of all variables are integrated). If not, there is no long-run relationship between the economic variables, and the ECM cannot be applied. The existence or otherwise of a common trend among the economic variables will be identified by unit root tests, such as the DF, ADF (see Dickey and Fuller 1979,1981), Durbin Watson (CRWE) test (see Sargan and Bhargava 1983), and the Johansen ML test (see Johansen and Juselius 1990).

There are many applications of the cointegration methodology and ECM models in economic studies. Sargan (1964), among others (e.g., Hendry and Anderson 1977, and Davidson *et al.* 1978), uses the ECM method in estimating the relationship between wages and prices in the UK. Later, Engle and Granger (1987) popularize this methodology by introducing the "long run error correction term" and the two-step regression procedure of the ECM models. More recent research papers on cointegration and the ECM methodology can be found in Hall (1986), Jenkinson (1986), Nymoen (1989), Osborn *et al.* (1988), Johansen and Juselius (1990), and Banerjee *et al.* (1994). Particularly, Kulendran (1996), Kulendran and Wilson (2000a), and Song and Witt (2000) have applied this methodology in tourism demand modeling and forecasting.

As a simple example of the ECM method, consider the following model:

$$Y_t = \beta_0 + \beta_1 X_t + \mu_t, \tag{5.4}$$

$$\Delta Y_t = \alpha_0 + \alpha_1 \Delta X_{t-1} + \alpha_2 \mu_{t-1} + \varepsilon_t, \tag{5.5}$$

where equation (5.4) represents the long run relationship between variable Y and X, and equation (5.5) is the short-term dynamic model which is used for forecasting; Δ denotes the first difference of the data; ε_t is the white noise error term for the ECM; μ_{t-1} is the one-period lagged value of the residual from the long-run relationship model (5.4), which captures the adjustments to disequilibrium deviated from the long run equilibrium; the coefficient α_2 measures how much the changes in X_t and Y_t (i.e., ΔX_t and ΔY_t) respond to the departures from the long run equilibrium.

The estimation of the ECM involves two steps: first, to estimate the long run relationship model (5.4) and obtain the long run equilibrium error term μ_{t-1}; second, to estimate the short-term dynamic model (5.5) with μ_{t-1} as one of the explanatory variables. The short-term dynamic model is developed to forecast the future values of tourism demand by substituting the actual values for the explanatory variables (as they are lagged variables). Therefore, the error correction mechanism will be of particular value where the extent of an adjustment to a deviation from equilibrium is especially interesting.

As a combined method of regression and time series methodologies, the ECM forecasting model has advantages over both regression and time series models. First, the ECM captures the effects from tourism demand determinants, by including explanatory variables in the model. Secondly, it captures the trend of tourism demand over the past periods, by including some lagged values of both the dependent and independent variables as explanatory variables. Some studies of tourism demand forecasting have found that, in most of the cases, the ECM models outperform the time series models, and in some of the cases, the ECM's even outperform the no-change models (see Kulendran 1996, Kulendran and Wilson 2000a).

As a form of regression analyses, however, most of the ECM models apply the single-model approach, which only deals with the dependence of one variable on other variables assuming there are no interactions between the dependent and independent variables. Economic indicators and even non-economic indicators are, in most of the cases, interrelated. Changes occurring in one economic indicator may result from interactions with others, and may further result in changes in other indicators. Therefore, studies of tourism demand functions using the ECM suffer from the ignorance of interrelated relationships or feedback effects between economic or even non-economic indicators, if there are any.

More recently, the feedback effects among economic variables have been considered in some applications of simultaneous equations (e.g., White 1985, Smeral 1988, Turner *et al.* 1995, 1997,1998). However, few tourism studies have applied the approach of simultaneous equations due to its technical complication in model estimation procedures, particularly, the identification of the endogeneity of all variables included in the model.

Sims (1980) has first developed a vector autoregression process to analyze and forecast interrelated economic variables. The vector autoregression approach is further applied and developed by Litterman (1986a), Terrell (1988), Penm and Terrell (1982), and Lutkepohi (1991). The forecasts obtained by vector autoregression systems have in many cases proved better than those obtained from the more complex simultaneous equation models (see Mahmoud 1984), or at least can "present a strong challenge to conventional practice and serve as a powerful standard of comparison for other forecasts" (McNee 1986, p.15).

5.5 THE VECTOR AUTOREGRESSION MODEL

The vector autoregression (VAR) models are general unrestricted vector autoregressive time-series models. The term for "autoregressive" is due to the inclusion of lagged values of the dependent variable in the right-hand side of the models, and the term of vector is due to the fact that we are dealing with a vector of variables. The general form of VAR models can be described as:

$$Y_t = A_0X + A_1Y_{t-1} + A_2Y_{t-2} + \ldots + A_pY_{t-p} \quad (5.6)$$

where Y_t is a $(k \times 1)$ vector of variables generated by a *pth* order of vector autoregressive process; k is the dimension of the VAR system (i.e., the number of time series data included in the process, or the number of the sub-systems), p is the number of lags of each time series included in the system; A_0 is a vector of coefficients and X represents the net deterministic component of Y_t, which may include seasonal dummies, trend and constant terms; A_p are $(k \times k)$ matrices of coefficients; and ε_t is a $(k \times 1)$ vector of multivariate white noise residuals at time t, which satisfies the following assumption:

$$E(\varepsilon_t)=0,$$

$$Cov(\varepsilon_t, \varepsilon_{t+k})=0, k\neq 0,$$

$$Var(\varepsilon_t)=\Sigma_\delta,$$

where Σ_δ is a $k \times k$ positive-definite matrix.

Compared with the simultaneous equation method, the distinctive feature of VAR models is that there is not *à priori* distinction between endogenous and exogenous variables.

Sims (1980) developed his VAR model based on the following economic and econometric arguments:

- First, most economic variables are interrelated, and the fluctuation of time series data is the result of interactions among many economic variables. Therefore, a VAR model is a useful forecasting model for a set of inter-related economic time series, where single equation models are subject to criticism.
- Second, business and economic behaviors are dynamic. Some economic activities are effected by expectations of future economic conditions, while others are sluggish in responding to changes of economic conditions. Therefore, it would ordinarily be reasonable to include lagged dependent variables and more reasonable to assume lag lengths and shapes of lag distribution are not known *à priori*.

- Third, the individual equations of econometric models, which were derived from economic theory, are not products of any distinct exercise in economic theory. In practice, we usually fail to identify the original parameter space, which implies equivalent behavior, and have to use a reduced form of a parameterization. Instead of using a reduced form, however, we could normalize the parameter space by requiring the residuals to be orthogonal across equations and the coefficient matrix of current endogenous variables to be triangular. Therefore, it should be feasible to estimate economic models as unrestricted reduced forms, treating all variables as endogenous.

Technically, the VAR models are also advocated by the following virtues of the method:

- First, the method is simpler than structural models as one does not have to worry about determining which variables are endogenous and which ones are exogenous.
- Secondly, the estimation is simple as the usual OLS method can be applied to each equation separately.
- Thirdly, although the individual coefficients in the estimated VAR models are often difficult to interpret, the method of variance decomposition and the use of Impulse Response Function (IRF) can trace out the response of the dependent variable in the VAR system to shocks in the error terms. Thus a VAR model can be used for analyzing tourism policy simulations in the destination country.

Forecasting using the VAR approach has been applied in macroeconomic areas (e.g., Mahmoud 1984, Trevor and Thorp 1988, Poirier 1995, Pagan and Dungey 1996), but few studies of tourism demand modeling and forecasting have attempted to employ this method, except one recent study by Song and Witt (2000).

5.6. MEASURES OF FORECASTING ACCURACY

Tourism demand forecasting is very important to tourism management, as more accurate forecasts reduce the risks of tourism management decisions and government policies. There are numerous studies which purport to compare the accuracy of different forecasting techniques. However, until the late 1980s there were relatively few comparative studies of forecasting accuracy which examined outside sample forecasting performance. There are two measures of accuracy which are commonly used to compare forecasting performance, error magnitude accuracy and directional change accuracy.

5.6.1 Error Magnitude Accuracy

The basic form of measures of forecasting accuracy is called "error magnitude accuracy" (EMA), which is defined as:

$$e_t = A_t - F_t, \quad (5.7)$$

where t is the time period; e_t is the forecast error at time t; A_t is an actual value at time t; F_t is the forecast value at time t.

For more than one-step forecasts, the mean absolute error (MAE) and the mean squared error (MSE) are commonly used to measure the forecasting performance of a model, which are defined as:

$$MAE = \frac{1}{n} * \Sigma|e_t|, \quad (5.8)$$

$$MSE = \frac{1}{n} * \Sigma e_t^2, \quad (5.9)$$

where n is the number of forecasting periods; e_t is the forecasting error at time t.

As the MAE and MSE are subject to the magnitude of forecasting units and time period over which forecasting values are tested, it is often difficult to interpret and compare the MAE and MSE across different country cases and studies using different methods and data. Therefore, relative measures are preferred to use in the accuracy comparison.

Mean Absolute Percentage Error (MAPE) is one simple and intuitive measure of forecasting accuracy, which is defined as:

$$MAPE = \frac{1}{n} * \sum \left(\frac{|e_t|}{A_t} \right) * 100. \qquad (5.10)$$

where t is the time period; e_t is the forecast error at time t; A_t is an actual value at time t; F_t is the forecast value at time t; n is the number of forecasting periods.

The MAPE is a simple measure permitting comparison across different forecasting models with different time periods and numbers of observations, and weighting all percentage error magnitudes the same. Lower MAPE values are preferred to higher ones because they indicate a forecasting model is producing smaller percentage errors. Moreover, its interpretation is intuitive. The MAPE indicates, on average, the percentage error that a given forecasting model produces for a specific period.

Another measure of error magnitude accuracy, which is useful over all time series and quantitative forecasting methods, is the root mean square percentage error (RMSPE). It is calculated as:

$$RMSPE = \sqrt{\frac{\sum \left(\frac{e_t}{A_t} \right)^2}{n}} * 100. \qquad (5.11)$$

where t, e_t, A_t, F_t, n are the same as the definitions for equation 5.10. This measure also computes an average error in terms of percentages and can be compared to actual rates of change in the past data series. The RMSPE measure is more affected by the extreme forecasting errors.

Therefore, the MAPE measure is the better indicator of forecasting accuracy, if we are interested in capturing the overall trend of the data series; while the RMSPE measure will be a better choice if we are concerned with the large forecasting errors at a specific time period.

Frechtling (1995, p. 23) further suggests that a better set of standards for assessing the accuracy of a forecasting model is simulating its time series based on the naïve forecasting model. To set the standards for evaluating the MAPE of a forecasting model, compute the MAPE from the naïve model, and compare the MAPEs from the two models.

5.6.2 Directional Change Accuracy

Sometimes, the most important information we wish to know in tourism forecasting is whether there will be more or fewer visitors in the forecasting period than the previous period. This will help tourism businesses in deciding whether or not to increase tourism facilities. A directional change error occurs when a forecasting model fails to predict the actual direction of change for a period. There is a measure of directional change accuracy, which is defined as:

$$PDA = \frac{\sum FD}{\sum AD} * 100 , \qquad (5.12)$$

where PDA denotes percentage directional change accuracy; FD denotes number of accurate forecasts in directional changes; AD denotes number of directional changes actually occurring. This measure indicates how much percentage accuracy the model forecasts successfully in the directional changes of the data. Witt and Witt (1995) suggest that "in order to outperform this model (naïve 1), a forecasting method must, therefore, forecast over 50% of the directions of movement correctly" (p.466).

Similar to the measure of directional change accuracy, the turning point accuracy is also measured by the percentage accuracy of turning points, which is calculated by the number of accurate turning points in forecasts over the total number of turning point in the actual values. However, theoretically and empirically, there is not a clear definition of a trend change or a turning point in tourism flows. The identification of a turning point may be subject to data frequency and span as well as the observer's point of views. This makes it difficult or often impossible to compare the turning point accuracy from forecasting methods using different data sources and country cases.

5.7 SUMMARY AND CONCLUSION

Despite an increasing number of empirical studies on international tourism demand, several areas remain incomplete and hence require further study. Although relatively sophisticated measures have been used and developed in the methodologies of tourism demand forecasting, all of these approaches have limitations and can only produce short-term forecasts.

The causal methods (regression analyses) quantify the relationships between tourism demand and its influencing factors. A major advantage of regression analysis models over time series models is that it will help tourism companies and governments to understand what factors affect tourism and to explore the consequence of alternative future policies on tourism demand. This is not possible with non-causal methods, though regression models are found to be less accurate than time series models in tourism forecasting (see Witt and Witt 1995). However, the use of econometric techniques in many previous tourism studies is poor and hence subject to some debates (see Crouch 1994a, 1994b, Witt and Witt 1995, Lim 1997, and Morley 2000).

- As indicated by Witt and Witt (1995) and Crouch (1994a, 1994b), the lack of diagnostic checking for the econometric issues, such as stationarity, multicollinearity and serial correlation, in the econometric studies clearly limits the usefulness of the empirical results.
- Although regression analysis deals with the dependence of one variable on other variables, it does not necessarily imply causation. Moreover, it assumes

that the explanatory variables are not affected by the dependent variable, ignoring feedback effects of dependent variables. Therefore, previous econometrics studies of tourism demand function suffer from the ignorance of endogeneity test of variables in the demand functions.

- In previous causal studies, income, relative price, exchange rate and substitute prices were most commonly used as the important determinants in the tourism demand functions. Economic theories on tourism demand suggest that factors influencing tourism demand are wide-ranging and the determinants of tourism demand are complex and varied. Some variables which are assumed to be closely associated with changes of tourism demand are generally ignored in these studies, such as trade and investment flows between the tourist generation country and destination country. Needless to say, the omission of variables and the inadequate use of determinants in tourism demand functions often lead to biased estimates.

With regard to the time series methods, the basic time series methods have broad applications in tourism, as they are simple and cheap to operate if the data fit the requirements of the models. In a thorough comparative study of various international tourism forecasting methods, Witt and Witt (1995) find that time series methods are more accurate than regression models. However, one major disadvantage of these methods is that they cannot take account of factors affecting the series other than its past values. Thus these methods do not explain the relationship between tourism demand and the influencing factors at work, though they can indicate the values that should have been achieved in the situation where the other determinants of tourism demand remain the same. The ARIMA model is a powerful method in the class of time series forecasting methods, when some "simple and cheap" time series methods can only be applied in the specific data series. However, it has the same disadvantage as the other time series methods. Moreover, the comparisons of some previous tourism forecasting models show that more complicated methods (e.g., ARIMA models) do not outperform the basic time series models, such as exponential smoothing models (see Witt and Witt 1995).

In terms of the different measures of forecasting accuracy, the performance of different forecasting methods varies considerably. Martin and Witt (1989) find that econometric models and time series models, including the naïve, autoregressive, and exponential smoothing models, perform differently for different origin countries in terms of MAPE. Witt and Witt (1989b) have also assessed the forecasting performance in terms of directional change accuracy for the same group of origin countries. They find that the econometric models yield the most accurate forecasting of directional changes, followed by the exponential smoothing, autoregrssive and the no change models. Therefore, theoretically and empirically, it appears that the econometric models perform better in capturing the trend changes and directional changes of data, while some basic time series models, such as the naïve1 and exponential smoothing models, are the better choices to catch the overall trends of the time series data.

Therefore, an attempt at applying different methodologies mentioned above is necessary in the study of international tourism demand. Different criteria of measures of forecasting accuracy should also be applied in order to choose the best forecasting method for international tourism demand, which may also be applied to other tourism developing countries.

The objective of this chapter was to review relevant applied modeling and forecasting techniques in common use, particularly in tourism demand modeling and forecasting. As discussed in this literature review, the VAR approach has several advantages that make its use in tourism demand modeling and forecasting an appealing and encouraging proposition. However, before undertaking an application of the VAR approach, we first determine and select the variables for the demand function, and then undertake a suitable investigation and analysis of the time series properties of the data. Therefore, the next chapter comes to identify the determinants of international tourism demand to China and the time series properties of the selected data. The development of the appropriate VAR models based on the time series properties of the selected variables is undertaken in Chapter 7. The forecasting performance of the VAR models will be compared in Chapter 8.

CHAPTER 6: VARIABLE SELECTION, DATA DEFINITIONS AND TIME SERIES PROPERTIES

6.1 INTRODUCTION

In the last two chapters we have surveyed the theoretical determinants of international tourism demand and reviewed the empirical methodologies of international tourism modelling and forecasting used in many previous studies.

Economic theories on tourism demand suggest that factors influencing tourism demand are wide-ranging and the determinants of tourism demand are complex and varied. Factors influencing tourism demand vary for different pairs of tourist origin-destination countries, different types of visit, and even different time periods. The selection of appropriate variables to measure these factors depends on a number of factors, such as the country examined, the time-period investigated, the data sources used, the models applied and the type of travel studied. Therefore, selection of variables to model and forecast international tourism to China should work within the framework of general economic theories as well as the specific features of China tourism demand and the properties of data employed.

Until fairly recently, econometric studies of tourism demand that used time series data assumed that economic time-series data were stationary, however, recent developments in econometric methodology (e.g., Engle and Granger 1987, Phillips 1987, Davidson and Mackinnon 1993, Maddala and Kim 1998) demonstrate that economic data are often non-stationary, which could result in the problem of "spurious regression" (see Granger and Newbold 1974, and Phillips 1986). Therefore, when regression methods are applied to analyse tourism demand, investigations on the time series properties of data must be carried out.

This chapter, based on economic theories and in accordance with the structures and characteristics of international tourist flows to China, first identifies the most important determinants of tourism demand to China, and then defines appropriate economic indicators to measure these determinants. Further, a range of statistical analyses is conducted to examine the time series properties of the selected data for each variable.

This chapter is organised into five sections including this section. The following section, Section 2, first provides a discussion of the main determinants of the inbound tourism demand to China from its three major generation countries: Australia, Japan and the USA. Section 3 selects and defines economic indicators to measure these determinants. Section 4 examines time series properties of the selected data using a range of statistical analyses. In the section, first, a visual inspection on whether the data are stationary is carried out, by plotting the level data and their sample autocorrelation functions (ACFs); further, two standard statistical tests for stationarity (i.e., unit root tests), namely the ADF test (Dickey-Fuller 1979,1981) and Phillips-Perron (PP) test (Phillips and Perron 1988), are used to confirm the information from the visual observation; finally, the HEGY seasonal unit-root test (HEGY 1990) is applied to detect both stochastic trends and seasonal patterns in quarterly data used in this study. A summary and conclusion of this chapter is presented in the final section.

6.2 VARIABLE SELECTION

As discussed in the previous two chapters, many parts and aspects of economic theory may be applied to explain international tourism flows, and hence can be used in developing tourism demand models.

The review of macroeconomic theories of tourism demand in Chapter 4 (see Section 4.3) shows that factors influencing international tourism demand are generated from both demand and supply sides, and they also vary in accordance with different tourist motivations and different economic, social and political backgrounds.

In terms of microeconomic theories of tourism demand discussed in Chapter 4 (see Section 4.4), the standard model assumes a two-stage decision-making process.

The volume of tourism demand and a travel budget are determined in the first stage, and the travel destination is chosen in the second stage. Therefore, the microeconomic formulations theoretically define that economic factors, such as the time available for touring, the level of income and price paid for travel, determine tourism demand at the individual level.

The review of empirical studies of tourism demand in Chapter 5 indicates that, although there is a broad range of explanatory factors affecting international tourism demand, most tourism demand studies using regression methods focus on the major economic factors. Witt and Witt (1992) have identified seven commonly used determinant variables for the holiday demand function in the previous empirical studies of international tourism demand. They are: population, income, own price, substitute prices, dummy variables, trend, and promotional activities. Further investigations of the explanatory variables (e.g., Crouch 1994b, Witt and Witt 1995) find that measures of income, prices (both the own-price and relative price), and exchange rate have been dominant variables in previous studies of tourism demand modelling. Therefore, the literature states that although the range of factors affecting the demand for international tourism is undoubtedly very large, the most prominent variables, including income, prices (own-price and relative price), exchange rate, and transportation cost, are the most important independent variables for international tourism demand models.

Factors influencing tourism demand vary with different pairs of tourist origin-destination countries and different types of tourist groups with specific travel motives. Therefore, in order to identify the appropriate determinants of tourism demand to China and hence to select appropriate variables for the demand function, it is very important to incorporate the general model of tourism demand with the specific features of tourism demand between China and its certain generation countries.

As discussed in Chapter 3, international tourists to China comprise mainly two statistical categories: ethnic Chinese visitors from Hong Kong, Macau and Taiwan (i.e., H-M-T visitors) and foreign tourists. The H-M-T visitors are mainly holiday and VFR travelers which make up an overwhelming majority of the total tourists arrivals. However, separate statistics on visitors from Hong Kong and Macau are not available and statistics on tourists from Taiwan only started at 1988. Moreover, after the "Hong Kong Handover" in 1997, the nature of tourists from Hong Kong is not clear so that whether they are still counted as international tourists or domestic tourists is arguable. All these circumstances make a separate study of the H-M-T tourists very difficult or impossible.

Moreover, although "foreign tourists" to China only make up about 10% of the total tourist arrivals, they contribute about 50% of total tourism receipts to China and hence are equally important with the H-M-T tourists in terms of tourist expenditures (see Section 3.4, Chapter 3). Among all origin countries of "foreign tourists", Australia, Japan and the USA are the three most important origin countries in terms of number of tourists arrivals and tourist expenditures. In addition, this group of foreign tourists is potentially a more interesting group to study since generally speaking they lack the close cultural and geographical ties of H-M-T tourists and their travel behaviours may be more accurately captured with a standard demand model.

Therefore, we set our focus on a study of the "foreign tourist" to China from its three major tourist-generation countries, Australia, Japan and the USA.

As statistics of "foreign tourist" arrivals to China are not classified by travel purposes in the available publications provided by the CNTA, it is not possible to disaggregate international tourists to China by travel purposes. Therefore, the aggregated tourism demand at national level from the three tourist-source countries, rather than the disaggregated tourism demand, is used in this study.

According to Gormsen (1995), some 60-70% of "foreign tourists" to China since 1990 are travelling for business purposes (see Chapter 3, Figure 3.1). A sample survey by the CNTA in 1995 further provides some information on the composition of foreign tourists from individual countries (see Chapter 3, Table 3.3). Accordingly, business travel from Australia, Japan and the USA makes up, respectively, 33.1%, 56.5% and

43.1% of their total number of tourist arrivals to China. Therefore, tourism demand to China from these three countries is believed to be a combination of business travel and holiday travel together, with a large proportion of business travel.

In accordance with both the characteristics of tourism demand to China and standard economic theories, we identify three economic variables, namely, income, trade, relative price as important determinants of tourism demand to China from the three tourist-source countries. The general form of the tourism demand may be represented as:

$$Q_{it} = \alpha_0 + \alpha_1 GDP_{it} + \alpha_2 TA_{it} + \alpha_3 TP_{it} + \varepsilon_{it}, \qquad (6.1)$$

where

Q_{it} = the demand for international tourism to China from origin country i at time t;

GDP_{It} = income of origin country i at time t;

TA_{it} = volume of international trade between China and its tourist origin country i at time t;

TP_{It} = relative "tourism price" between China and its tourist origin country i at time t;

ε_{it} = random error term at time t; and

α_n = parameters to be estimated (n= 0, 1, 2,...5).

Discussions of variable selection and definitions are as follows:

6.2.1 Income Variable

A growing economy generates more sales, jobs and personal income than a stagnant one, and can be expected to generate travel, including holiday, VFR's and business travel (refer to section 4.5.1, Chapter 4). However, income determinants of tourism demand vary from holiday travel to business travel. The level of income in a tourist-origin country affects the ability to pay for overseas holiday travel. Therefore, private consumption or personal disposable income is considered as an income explanatory-variable of holiday tourism demand. Business travel, however, is more related to business activities and general economic growth rather than the level of private consumption or personal disposable income in the tourist-origin country. As the tourism demand under this study is a combination of business travel and holiday travel together, with a large proportion of business travel, we choose real GDP in the three tourist-origin countries to represent the overall levels of income in these three countries.

6.2.2 Relative Price Variable

Two components of price, the cost of travel from a generation country to a destination and the cost of living in the destination, are often considered in tourism demand functions in previous studies.

In the case of China, the majority of "foreign tourists" visiting China on business, are attracted by the business opportunities resulted from China's political-economic changes after 1978; some 30% of the holiday tourists come to China for recreation in an Asian cultural context and dramatically changing economic environment. We expect, in this study, that there are no foreign destinations, as substitutes for China, which can offer an exact or closely similar environment or sets of opportunities. Therefore, substitute prices of alternative international destinations are not considered as an important determinant of tourism demand from the three origin countries.

Consequently the cost of living component is defined as a "relative price" as International tourism demand depends not only on its own price but also other goods and services. According to the microeconomic theories of tourism demand (see Section 4.4, Chapter 4), travel can be either a substitute for, or a complement to, other goods and services. That is, a potential tourist has to first make a decision on travel or not, by comparing the cost of travel and the price level of other goods and services; after having decided to travel, the tourist also has to make a choice between different types of travel, for instance, domestic travel and overseas travel. Therefore, if there are no sufficient data on the basket of goods and services purchased by tourists, the CPI ratios both in the destination and origin country are reasonable proxies to present the tourist cost of living. Moreover, most tourists pay their tourism consumption in their own currencies and the prices which they are charged take account of both differences in relative prices and exchange rates. Thus, the exchange rates between currencies of the tourism destination and the origin country should also be considered as one important price determinant. Therefore, the exchange-rate-adjust CPI ratio between the destination and origin country is a more appropriate proxy for the "relative price" of tourism. Recently, some researchers (e.g., Kulendran 1996, Kulendran and King 1997, Song *et al.* 1999, and Kulendran and Wilson 2000b) have composed the "relative price" variable using exchange-rate-adjusted CPI ratios in tourism demand models. We therefore follow this recent practice.

International airfares are most commonly used as the proxy of the cost of travel in international tourism demand modelling. In an ideal world with accurate international travel price data, information on this variable might be included. However, there is no such thing as a single simple airline price as each airline, through its sales networks, offers a wide range of prices and discounts for the same seat on the same sector. In this study, therefore, the variable for transport cost is excluded mainly due to the lack of sufficient accurate data for international airfares. In addition, because a large proportion of travellers to China from these three countries are business travelers and business travel is considered to be less or not elastic to travel cost, then omission of this variable is not so important.

6.2.3 Trade Variable

As discussed before, there is a high proportion of business travel to China from Australia, Japan and the USA. Considering the close linkage between international travel (particularly business travel) and trade flows (see the theoretical discussions in Chapter 2, Section 2.4.2 and the empirical study by Kulendran and Wilson 2000a, 2000b), a trade variable is considered as an important determinant of tourism demand from these three countries. Therefore, two-way real trade volumes between China and the three tourist-source countries are included as proxy variables to measure scale of business activities between China and the three countries.

6.2.4 Tourism Demand Variable

In regard to the measurement of tourism demand, although theoretically tourism demand can be measured by three indicators (i.e., number of tourist arrivals, tourist expenditure and tourist nights in the destination country), most previous studies of tourism demand used the number of tourist arrivals as the measure of tourism demand because of the unavailability of the other two indicators (see Crouch 1994b, Witt and Witt 1995, Lim 1997). In this study the number of tourist arrivals is chosen to measure tourism demand to China from its three generation countries, as data for the other two indicators are not available in relevant references and sources (i.e., the China Statistics Monthly and OECD Main Indicators).

6.3 DATA DEFINITION

6.3.1 Data Source

Quarterly data from 1983 (1) to 1999 (4) are collected from various data sources, in which 60 observations from 1983 (1) to 1997 (4) will be used in the statistical analysis and model estimation, and 8 quarter data from 1998 (1) to 1999 (4) will be used for out of sample forecasts and forecasting comparison. The data for China are mainly collected from *China Statistic Monthly* published by China Bureau of Statistics, and *Monthly International Monetary and Finance Statistics* published by IMF. Data for Australia, Japan and the USA are from the *OECD Main Indicators* (Econ Data DX Database), *Monthly Statistics of Japan*, and *Monthly Labour Statistics* (the USA). Both seasonally adjusted and unadjusted data series are used because of the lack of consistent seasonal unadjusted data. Details of the data sources are listed in Table 6.1. Data are seasonally unadjusted unless indicated.

Main economic indicators were selected and named as follows:

- **TU:** number of tourist arrivals to China from, respectively, Australia, Japan and the USA;
- **EXP**: total current value of exports between China and Australia, Japan and the USA respectively;
- **IMP**: total current value of imports between China and Australia, Japan and the USA, respectively;
- **EPI**: export price index between China and Australia, Japan and the USA, respectively;
- **IPI**: import price index between China and Australia, Japan and the USA, respectively;
- **GDP:** GDP at constant price in Australia, Japan and the USA, respectively, seasonally adjusted;
- **CPI**: Consumer Price Index of China, Australia, Japan and the USA, respectively;
- **EX**: exchange rate between China Yuan and Australia dollar, Japanese Yen, and US dollar, respectively.

6.3.2 Variable Composition

For tourism demand from Australia, Japan and the USA, we define the following variables:

- **Tourism Demand Variable TU_{tj}** : number of tourist arrivals to China at time t from origin country j;
- **Two-way Trade Variable TA_{tj}** : total real volume of foreign trade between China and origin country j at time t, defined as $TA_{tj} = EXP_{tj}/EPI_{tj}+IMP_{tj}/IPI_{tj}$, where EXP_{tj} is total current volume of exports between China and origin country j at time t; IMP_{tj} is total current volume of imports between China and origin country j at time t; EPI_{tj} and IPI_{tj} are, respectively, export price index and import price index between China and origin country j at time t;

- **Income Variable GDP_{tj}**: GDP at constant price in origin country j at time t;
- **Tourism Price Variable TP_{tj}**: Cost of living in China for a tourist from origin country j at time t, which is calculated as $TP_{tj} = (CPI_{tch} / CPI_{tj,})^{*} EX_{tj}$, where CPI_{tch} is Consumer Price Index in China at time t (1978=100); EX_{tj} is an index of currency in country j per unit China Yuan at time t; CPI_{tj} is Consumer Price Index of country j at time t (1978=100).

As 60 quarterly observations are used to compose each variables defined above, we need to examine the time series properties of the data in order to determine the modelling and forecasting methods used in the following chapters.

6.4 TIME SERIES PROPERTIES OF VARIABLES

An analysis of time series properties of the selected data provides us with information on the structure and pattern of trends and seasonalities of each defined variable, which are important in determining the modelling and forecasting methods used in the following chapters.

6.4.1 The Issue Of Stationarity

Theoretically a stochastic time series is a collection of random variables $\{Y_t\}$. Such a collection of random variables ordered in time is also called a stochastic process. Generally "a stochastic process is said to be stationary if its mean and variance are constant over time and the value of covariance between two time periods depends only on the distance or lag between the two time periods and not on the actual time at which the covariance is computed" (Gujarati 1995, p713). To explain the statement, let Y_t be a stochastic time series with these properties:

$$\text{Mean } E(Y_t) = \mu,$$

$$\text{Variance } var(Y_t) = \sigma^2,$$

$$\text{Covariance } cov(Y_t, Y_{t+k}) = \theta_k.$$

In short, if a time series is stationary, its mean, and variance remain the same no matter at what time we measure them, and covariance (at various lags k) depends only on the lag number k not time t. If a time series is not stationary in the sense defined above, it is called a non-stationary time series.

In traditional regression analysis, all regressors are assumed to be deterministic variables and the model errors are white noise and uncorrelated with the variables in the model. Practically, many time series are non-stationary i.e., they are stochastic variables, which means that either their means, or variances, or covariances may be changing with the time, so that models which assume these values are all constant may be misleading. If non-stationary time series are employed in a regression model of tourism demand, then the asymptotic distribution of the OLS coefficient estimators do not generally follow a normal distribution and the validity of the statistical inferences using the standard t test may be in doubt (see Phillips 1986). The F-test will not follow the F distribution under the null hypothesis (see Granger and Newbold 1974). Therefore, the estimated equation may be open to the criticism of "spurious regression".

A non-stationary time series can often be made stationary by differencing the data set. If a time series has to be differenced *d* times and the differenced series is stationary, the original series is integrated at order *d*, i.e., the time series is an I(*d*) process. If $d = 0$, the resulting I(0) process represents a stationary time series. If $d = 1$, the time series is integrated at order 1, and is said to have a unit root. Thus, any time we have an integrated time series of order 1 or greater, we have non-stationary time series.

A visual plot of data is usually the first step in analysing time series data. For this study, the original data were transformed into the natural logarithms (LN), because a priori we do not know whether the true economic relationships between the variables are linear or non-linear, and also it is easy to interpret the coefficients as elasticities of tourism demand in regression models using logarithm data. Therefore, data plotted graphically and analysed in this study are all in LN forms. The LN data plots are presented in Figure 6.1(A-C), which provide visual plots of both the level and first differenced data respectively for Australia, Japan and the USA. The first impression that we have from the data plots in the Figures is that these time series seem to be either trending upwards or downwards, and hence the means of the individual series do not seem to be time-invariant. Therefore, a series of formal tests are carried out to examine the stationarity of the data, including the plot of sample correlation functions (ACFs), the Augmented Dickey-Fuller (1979, 1981) test, the Phillips-Perron (1988) test, and the Hylleberg, Engle, Granger and Yoo (HEGY) (1990) seasonal unit-root test.

6.4.2 The Sample Correlation Functions (ACF)

The correlations between values of a time series Y_t and Y_{t-k} separated by k time periods are called the autocorrelation process. A stochastic process is stationary if its autocorrelation at any lag depends only on the number of lags k not time t. Therefore, the sample autocorrelation functions between values of a time series Y_t and Y_{t-k} can be used to examine the relationship between observations separated by various amount of time. The sample correlation function at lag k is defined as:

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0} \tag{6.2}$$

In time series modelling, coefficients of sample autocorrelation function (ACF's) are used to identify the relationship between variable Y_t and Y_{t-k}. If the ACFs are significantly different from zero or do not die off quickly, it is an indication of non-stationary and hence a need for differencing transformations.

The ACFs at lag 1-25 for each set of data are presented in Table 6.2A, Table 6.2B, and Table 6.2C, which provide the ACFs of data, respectively, for Australia, Japan and the USA. The ACF plots show that the ACF's for each set of data start at a very high value and taper off gradually. This pattern is generally an indication that all tested time series are non-stationary. Therefore, the plots of ACF in Figure 6.2(A-C) confirm the evidence from the visual plots in Figure 6.1(A-C).

For certainty, however, the subjective visual inspection from the graphical plots of original data and the ACFs should be further confirmed by a formal test of null hypothesis for the number of unit roots, i.e., the parameter *d*. The simplest and widely used test for unit roots is the standard Dickey-Fuller (1979) (DF) test, which is based on the assumption of independent and identically distributed errors of the regression models. Later the DF test is further modified to avoid serial correlation in error terms by two approaches: the Augmented Dickey-Fuller (1979, 1981) Test and Phillips-Perron (1988) test. These tests are applied to many macroeconomic time series (see Nelson and Plosser 1982), and the results show that most macroeconomic variables are characterised by one unit root.

6.4.3 Unit Root Tests

The Augmented Dickey-Fuller (ADF) test is based on the OLS estimation results from two regression equations. For a time series Y_t, the ADF test is applied to run in the following two forms of regression equations:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \varepsilon_t, \tag{6.3}$$

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 t + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \varepsilon_t, \tag{6.4}$$

where ΔY_t represents the time series data is transformed into first differencing data. Equation (6.3) includes a constant term, and equation (6.4) include a constant term and a time trend as well. The number of lagged terms p is chosen to ensure the error terms ε_t in the estimated equation are not correlated.

The null hypothesis α_1=0 (*d* =1) for unit root in equation (6.3) and equation (6.4) can be tested respectively. If the null hypothesis can be rejected by the τ critical statistics, it suggests the time series data are stationary, i.e., they are an I(0) time series; If the null hypothesis can not be rejected by the τ critical statistics, it suggests the data series are not stationary and integrated at order one, or higher, which requires a differencing transformation to make the data stationary.

To further confirm that the non-stationary data are integrated at order one, i.e., I(1), the test using first differenced data should also be carried out to indicate that the non-stationary data are stationary after the first differencing transformation. If the null hypothesis for unit root of the differenced data can be rejected at the 5% significance level, it further confirms that the data are integrated at I(1); if the test statistics are not significant at the 5% level, it may suggest that the tested data are integrated at order two (i.e., I(2)), or a higher order.

An alternative test to inclusion of lag terms to allow for serial correlation is the Phillips-Perron (PP) method (Phillips 1987, Phillips and Perron 1988) which uses a non-parametric correction for serial correlation. The approach is to first calculate the above unit root tests for the regression equations (6.3 and 6.4) with lag p=0. The statistics are then transformed to remove the effects of serial correlation on the asymptotic distribution of the test statistics. The critical values are the same as those used in the ADF test. The formula for the transformed tests statistics are listed in Perron (1988, Table1, pp.308-309).

For the following tests, we use the equation (6.4) and report the test results from a model with an intercept and a time trend, as all selected data exhibit time trends. The results of tests for I(1) data using the ADF test are reported in Table 6.3. The results of tests for I(1) data using the PP test are reported in Table 6.4. The overall results of the ADF and PP tests are reported in Table 6.5.

From the tables we can see that the results from the ADF and PP tests are not consistent. The ADF test results suggest that all variables tested are not stationary, but integrated at different orders. For the case of Australia, all four variables are integrated at order one; for the case of Japan, variable TU and TA are integrated at order one, and GDP and TP are integrated at order two or higher; for the case of the USA, variable TU is integrated at order one, and variable TA, GDP and TP are integrated at order two or higher. In the PP test, the results suggest that some of the variables are stationary and some of them are I(1) data. For the case of Australia, variable TA is stationary, and variable TU, GDP and TP are I(1) data; for the case of Japan, all four variables are I(1) data; for the case of the USA, variable TU and TA are I(0) data, i.e., stationary data, and GDP and TP are I(1) data.

The results from the ADF and PP tests are not consistent, as both tests are very sensitive to the choice of different lag number p in the equations. Selecting different lag number p often results in different τ values and hence may reach contradictory conclusions. Davidson and Mackinnon (1993, Chapter 10, Section 5) also indicate that statistics from the ADF and PP tests are severely biased against rejecting the null hypothesis when they are used with data that have been seasonally adjusted by means of a linear filter or by the methods used by government statistical agencies. The test statistics using seasonal adjusted data will reject the null hypothesis substantially less often than they should according to the critical values. Therefore, the ADF and PP tests have a low power in testing unit roots of seasonal adjusted data.

Moreover, HEGY (1990) argues that seasonal data including quarterly data and monthly data may have two components: a trend and seasonalities. A time series data may be not stationary in both its trend and seasonality. Therefore, in the next section we further apply the HEGY seasonal unit-root test to confirm the stationarity of the data and also to further examine the seasonal patterns in the quarterly time series data.

6.4.4 Seasonality And HEGY Seasonal Unit-root Test

HEGY (1990) propose a test strategy that looks at unit roots at all the seasonal frequencies. For a given quarterly integrated series $\{X_t\}$, HEGY test involves t and F tests of the coefficients of the following regression:

$$Y_{4t} = \mu_t + \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-2} + \pi_4 y_{3,t-1} + \varepsilon_t , \qquad (6.5)$$

where $Y_{4t} = (1-B^4)\chi_t$, $Y_{1t} = (1+B+B^2+B^3)\chi_t$, $Y_{2t} = -(1-B+B^2-B^3)\chi_t$, $Y_{3t} = -(1-B^2)\chi_t$; B is the backward shift operator which is defined as $Y_{t-1} = BY_t$, $Y_{t-2} = B^2Y_t$, $Y_{t-3} = B^3Y_t$, $Y_{t-4} = B^4Y_t$; ε_t is white noise, and μ_t is a deterministic component which may include seasonal dummies, a trend and a constant term according to the pattern of the data set.

The null hypothesis is H_0: $\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0$, denoted by I(1, 1, 1) implying that there is a unit root at the zero frequency (i.e., $\pi_1 = 0$), at biannual frequency (i.e., $\pi_2 = 0$), and at the annual frequency ($\pi_3 = \pi_4 = 0$) respectively. The null hypothesises H_0: $\pi_1 = 0$, H_0: $\pi_2 = 0$, and H_0: $\pi_3 = \pi_4 = 0$, are tested separately by using t statistics and F statistics, respectively, to detect the stochastic seasonalities at different frequencies. If individual *t* statistics (for H_0: $\pi_1 = 0$, and H_0: $\pi_2 = 0$), and F statistics (for H_0: $\pi_3 = \pi_4 = 0$) are significantly different from zero, the order of integration of the series is I (0, 0, 0) such that it is stationary. If π_1 is not significant from zero, but π_2, and both π_3 and π_4 are significantly different from zero, then the order of integration of the data series is I (1, 0, 0). This implies there are unit roots at zero frequency and first difference is required to make the data stationary. If π_1 and π_2 and are not significant from zero, but both π_3 and π_4 are significantly different from zero, then the order of integration of the data series is I(1,1,0), which implies there are unit roots at zero frequency and seasonal unit root at biannual frequency. First and/or fourth differencing is required to make the data stationary.[9] If either π_1 and π_2, or π_3 and π_4 are not significant from zero, then the order of integration of the data series is I(1,1,1), which implies there are unit roots at zero frequency, biannual frequency and annual frequency. First and fourth differencing may be required to make the data stationary.

The t and F test statistics from HEGY seasonal unit-root tests for each data set are reported in Table 6.6. In the auxiliary regression models for the HEGY test, intercepts, time trends and seasonal dummy variables are included. $\chi^2(4)$ statistics for

[9] As by making fourth difference the zero frequency unit root in the data may also be removed (see HEGY 1990, and Kulendran 1995).

the information of serial error correlations in each regression model are also computed and reported in the table, which indicate that, in all regression models, there are no error correlation problems at the 5% significance level after choosing the appropriate number of lagged terms for each model.

The statistic results of HEGY test suggest that all variables tested are with unit roots at zero frequency (i.e., all data tested have stochastic trends) as all the null hypothesis's H_0: $\pi_1 = 0$ in the tables are not significant at the 5% significance level. However, the seasonal patterns vary between different sets of data and different country cases (see Table 6.6).

For simplicity, the test results in Table 6.6 are summarised and presented in Table 6.7. For two origin countries, Australia and Japan, all tested variables are integrated at order I(1, 0, 0), which implies there are stochastic trends (unit roots at zero frequency) in these data series, but no significant sign of stochastic seasonal trends. Therefore, data are stationary after the first differencing transformation. In the case of the USA, however, TU variable is integrated at order I(1, 1, 1), which implies that there are unit roots at zero frequency (i.e., stochastic trend), biannual frequency and annual frequency (i.e., biannual and annual stochastic seasonalities). Therefore, TU data need to be made a maximum fourth difference to achieve stationarity. Variables TA, GDP and TP are integrated at I(1, 0, 0) which implies there are only stochastic trends (unit roots at zero frequency) in these data series, and stationary data can be achieved after first differencing.

In summary, unit root tests conducted in this section are used to determine if the selected variables are stationary in order to avoid the "spurious regression" problem. The plots of sample ACFs, the ADF test and the PP test suggest consistently that the data tested are not stationary, although the results from the ADF test and the PP test are not consistent in the order of integration of the non-stationary data. The results of the HEGY test indicate all variables tested are with unit roots at zero frequency (i.e., all data tested have stochastic trends), while TU variable in the case of the USA also has seasonal unit roots at biannual frequency and annual frequency (i.e., biannual and annual stochastic seasonalities). Therefore, except TU data in the case of the USA, which needs a fourth differencing transformation, all data require first differencing transformation to achieve stationarity

6.5. SUMMARY AND CONCLUSION

In this chapter we have identified and defined variables which will be included in regression models in the next chapter. In addition, we have also analysed the time series properties of the selected variables, which determine the forms of models we will employ to forecast the tourism demand in the following two chapters. The main findings in this chapter may be summarised as follows.

In accordance with the structure and characteristics of tourism demand to China from its three major tourist-generation countries (Australia, Japan and the USA), four variables, TU, GDP, TA and TP, are selected and defined respectively as: (1) the tourism demand measured by the number of tourist arrivals to China from the three touirist-generation countries; (2) income levels measured by real GDP in the three countries; (3) China's two-way trade scales with the three countries; and the relative "tourism prices" measured by the exchanged-rate-adjusted CPI ratios between China and the three countries.

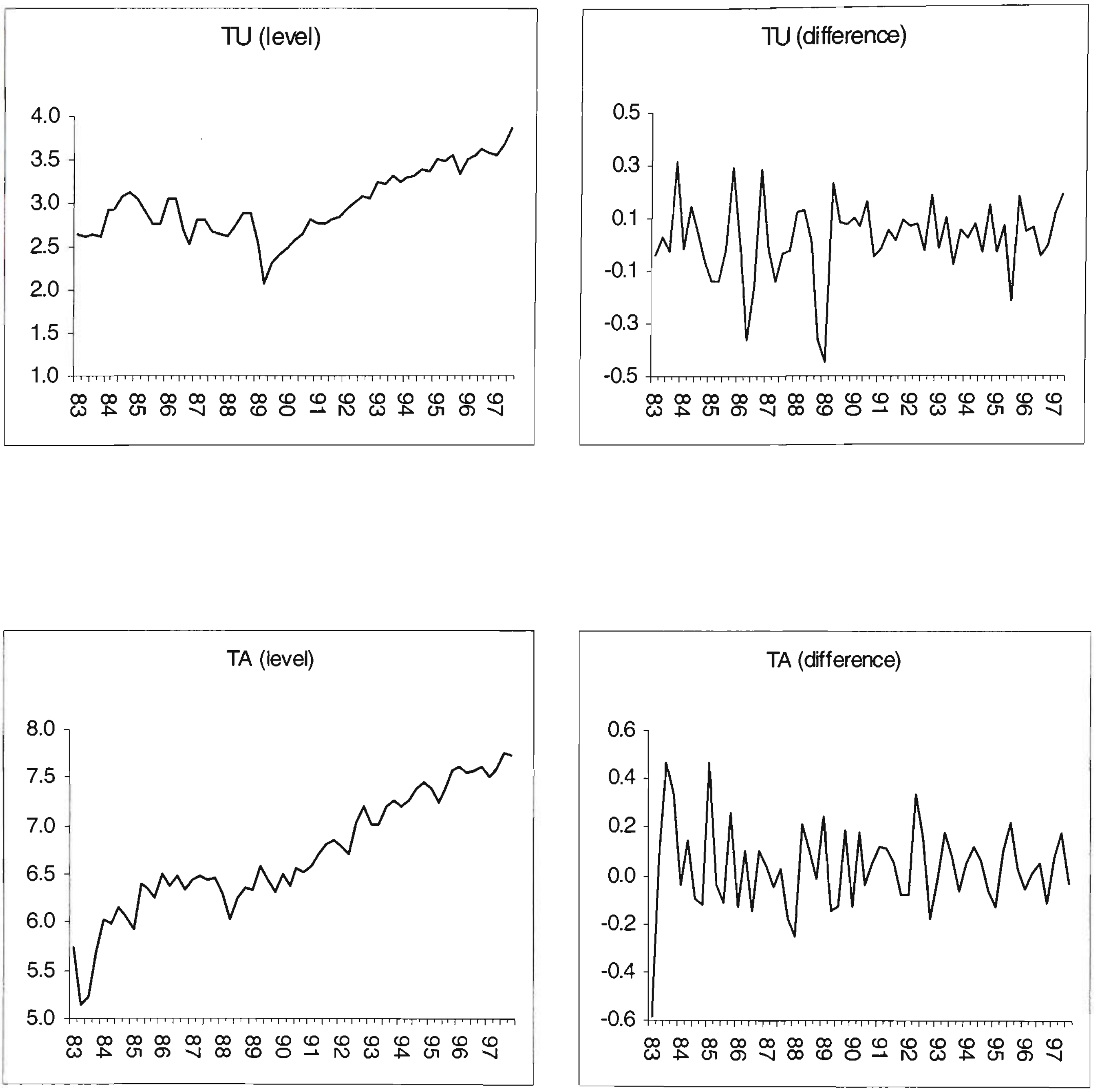
The ACFs, ADF and PP tests used in this chapter suggest that the time-series variables selected are not stationary; the HEGY test further confirms that the data are integrated at order one. Variable TU in the case of the USA also has stochastic seasonal trends. To conclude, the non-stationary data detected in this chapter indicate that the selected variables need to be adjusted with first or even fourth differencing transformations to meet the stationarity assumption in regression models in order to avoid the "spurious regression" problem.

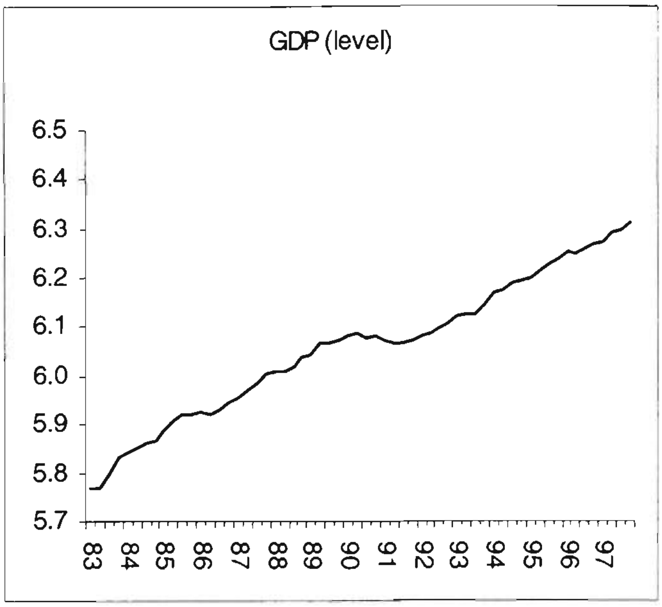
Yet further cointegration tests will need to be conducted to see if the non-stationary variables satisfy certain conditions. When non-stationary variables are "cointegrated", there presents a direction where a meaningful long-run relationship among the non-stationary variables exists. Hence, the cointegrating relationships, if any, should be considered where difference data are used for modelling.

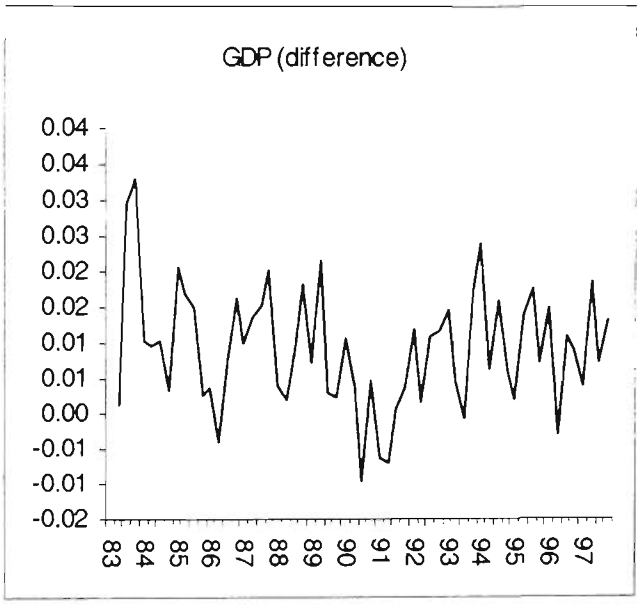
Moreover, the "causal" relationships between the four selected variables should be further examined. Some theoretical "explanatory variables" do not necessarily "cause" the "dependent" variable—tourism demand; on the contrary, tourism demand may "cause" these "independent " variables. Therefore, there may be "feedback effects" between tourism demand and other three "independent" variables, such as tourism arrivals and two-way trade. Consequently, it is possible that regression models using the single-equation approach may suffer from the problem of ignoring endogeneity of the variables and the consequent forecasting will not be able to consider "feedback effects" between those interrelated variables.

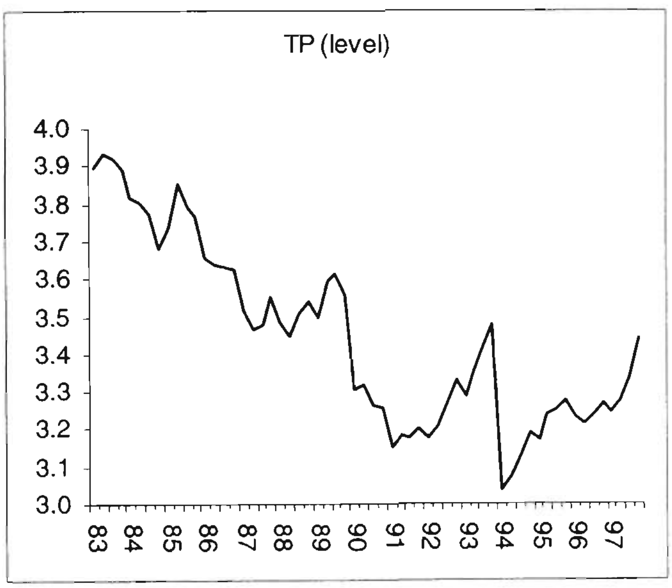
Therefore, in the following chapter, we develop vector autoregressive (VAR) models to further examine if there are cointegrating relationships between the non-stationary variables and also perform the causality tests to identify the causal relationships between the four selected variables. The appropriate VAR regression models of tourism demand to China from its three major tourist-source countries will be developed and forecasts of tourist arrivals will be generated by the optimal models.

Figure 6.1A: Levels and First Differences of Logarithm Data for the Australia Model




GDP (level)
6.5
6.4
6.3
6.2
6.1
6.0
5.9
5.8
5.7
83
84
85
86
87
88
89
90
91
92
93
94
95
96
97


GDP (difference)
0.04
0.04
0.03
0.03
0.02
0.02
0.01
0.01
0.00
-0.01
-0.01
-0.02
83
84
85
86
87
88
89
90
91
92
93
94
95
96
97


TP (level)
4.0
3.9
3.8
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3.0
83
84
85
86
87
88
89
90
91
92
93
94
95
96
97

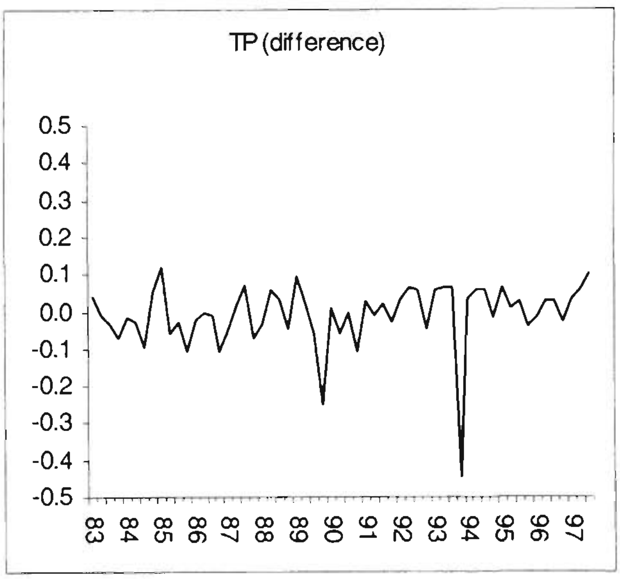
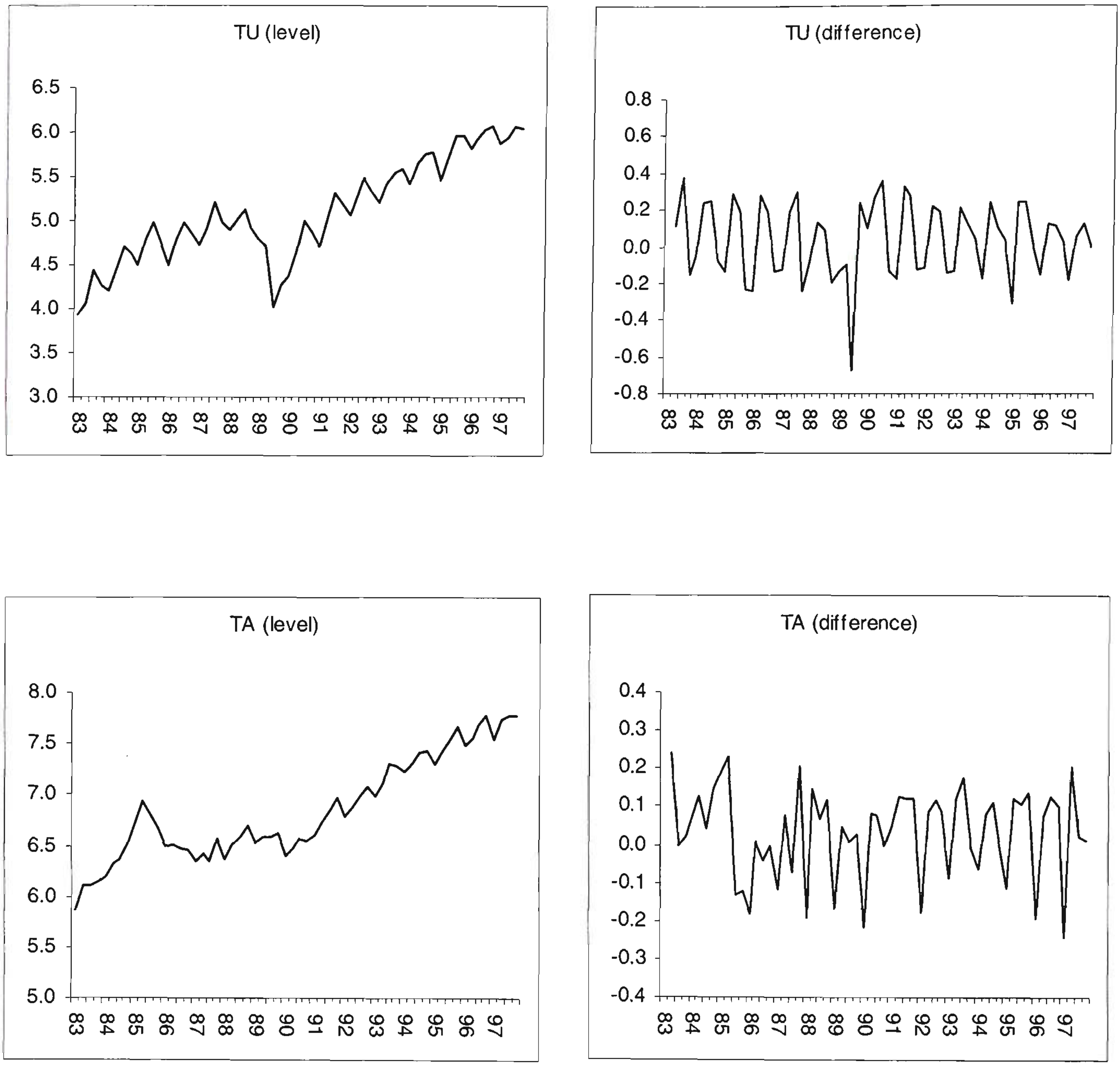
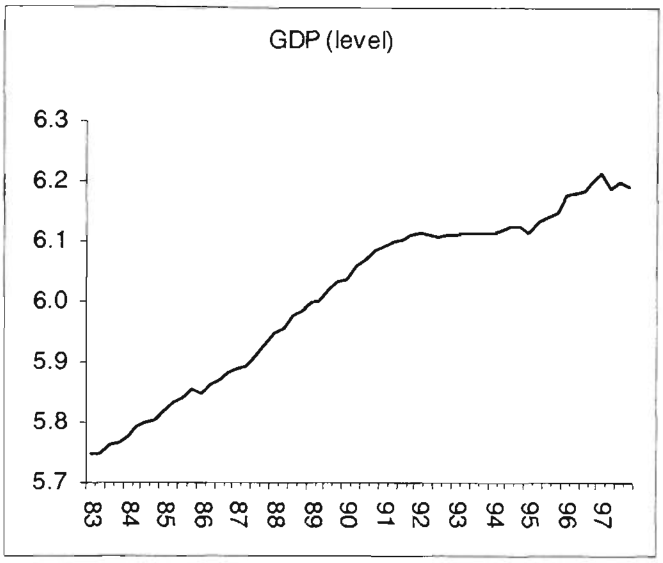
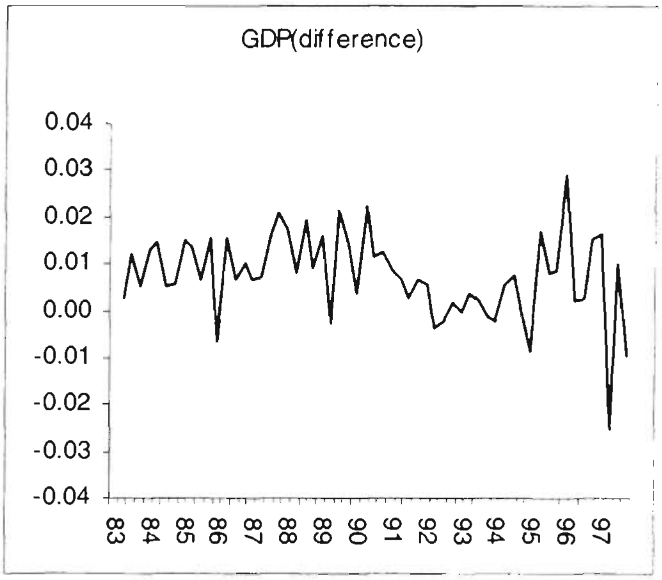
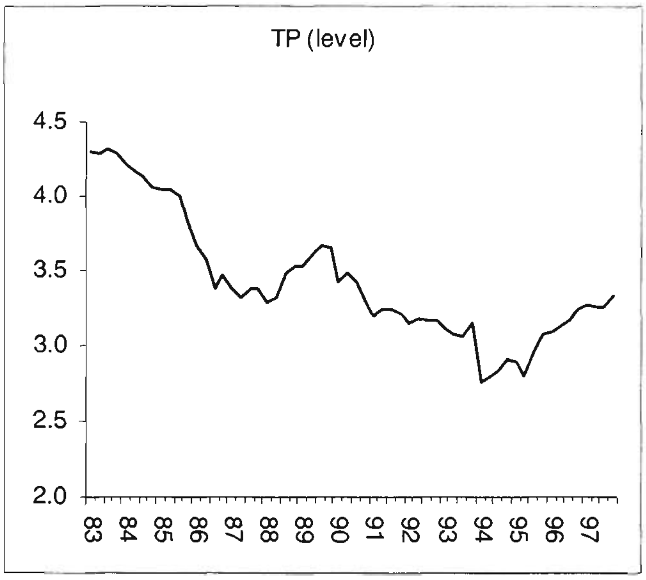

TP (difference)
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
83
84
85
86
87
88
89
90
91
92
93
94
95
96
97

Figure 6.1B: Levels and First Differences of Logarithm Data for the Japan Model




GDP (level)
6.3
6.2
6.1
6.0
5.9
5.8
5.7
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97


GDP(difference)
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
-0.03
-0.04
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97


TP (level)
4.5
4.0
3.5
3.0
2.5
2.0
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97

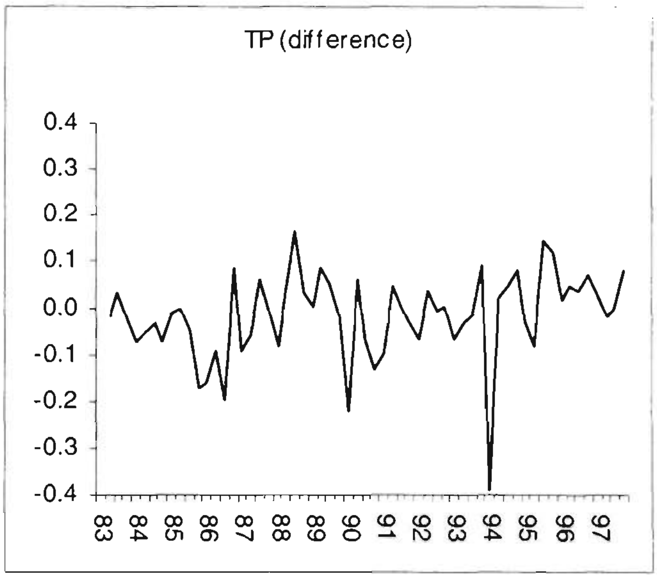
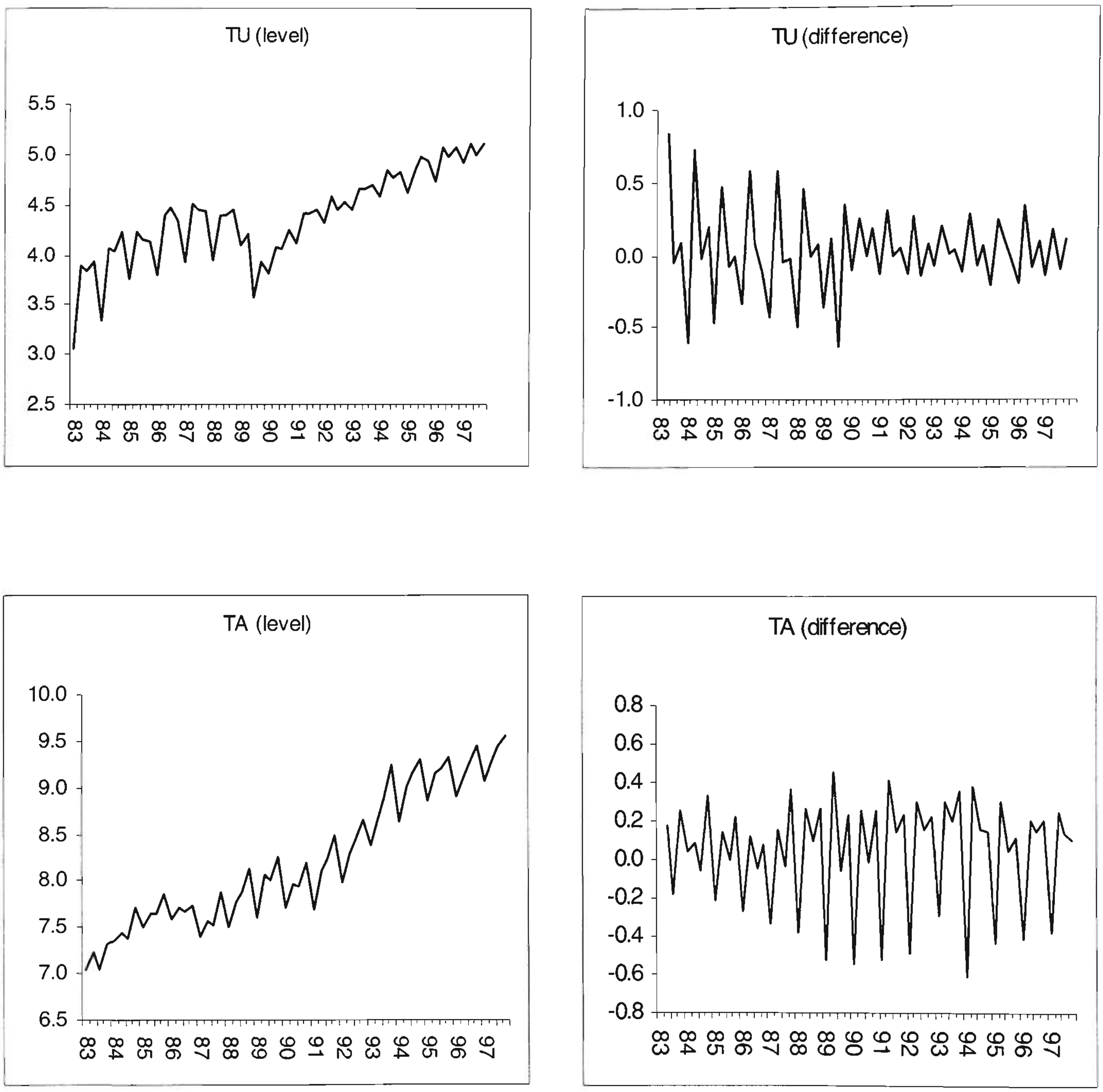
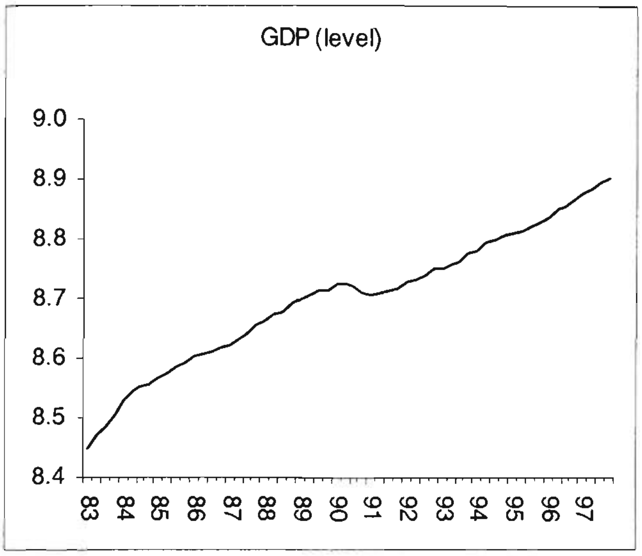
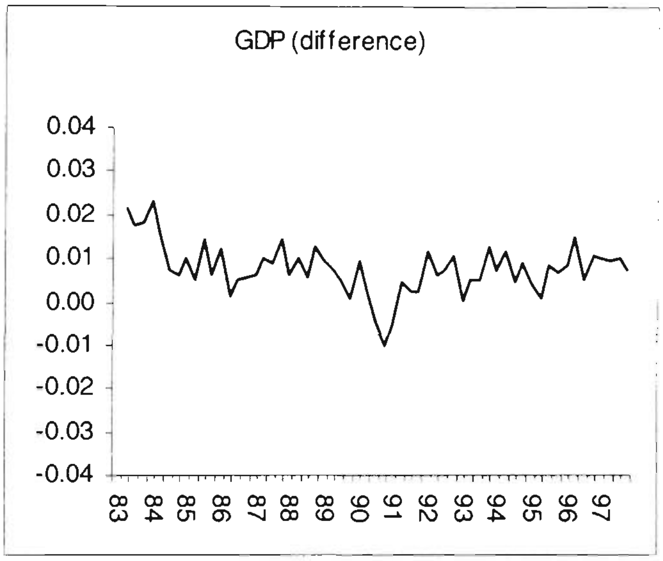
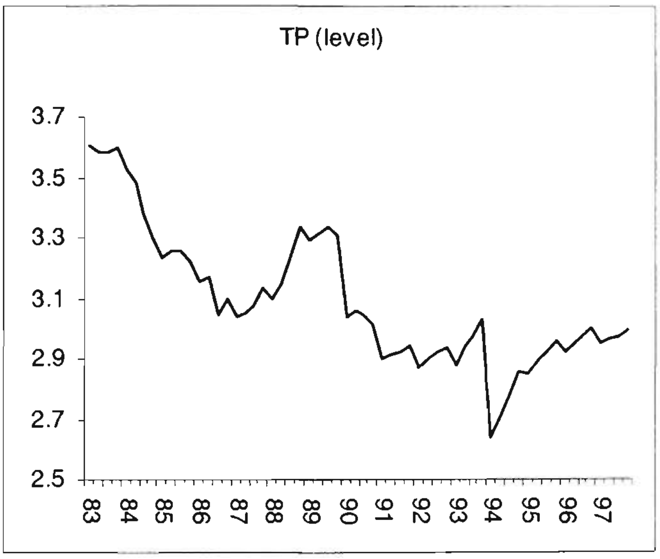

TP (difference)
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97

Figure 6.1C: Levels and First Differences of logarithm Data for the USA Model




GDP (level)
9.0
8.9
8.8
8.7
8.6
8.5
8.4
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97


GDP (difference)
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
-0.03
-0.04
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97


TP (level)
3.7
3.5
3.3
3.1
2.9
2.7
2.5
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97

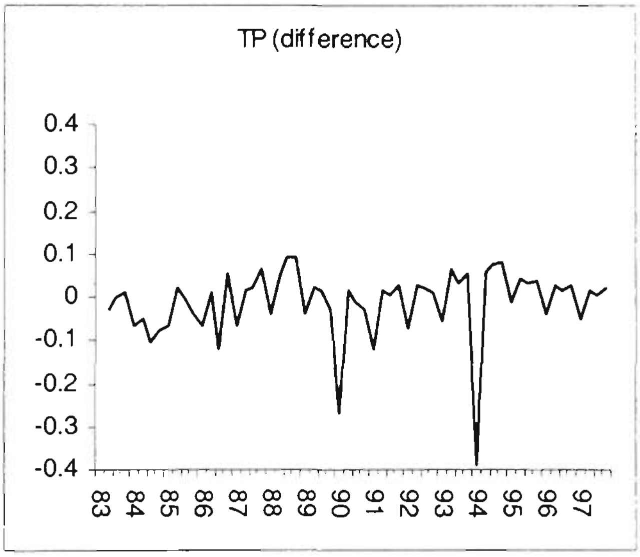

TP (difference)
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97

Table 6.1: Sources of Quarterly data (1983Q1-1999Q4)

ECONOMIC INDICATORS	DATA SOURCES
TU Tourist Arrivals to China from Australia, Japan and the USA	***China Statistics Monthly,*** China Bureau of Statistics, Beijing (1984-)
EXP Total current exports of goods and services between China and Australia, the USA, and Japan **IMP** Total current imports of goods and services between China and Australia, the USA, and Japan **EPI** Export Price Index between China and Australia, USA, and Japan respectively **IPI** Import Price Index between China and Australia, the USA, and Japan (89, 90 and 95 base period respectively)	• ***China Statistics Monthly,*** China Bureau of Statistics, Beijing (1984-) • ***Monthly Labor Statistics***, Bureau of Labor Statistics, the USA (1999). • ***Monthly Statistics of Japan***, Statistics Bureau, Management and Coordination Agency, Japan (1984-) • ***Exports and Imports Australia***, Australian Bureau of Statistics, Canberra (1984)
GDP GDP for Australia Japan and the USA, at constant price (89, 90 and 92 price level respectively, seasonally adjusted)	***OECD Main Indicators,*** Econ Data DX Database
CPI CPI ratios in China, Australia, Japan and the USA (1990=100) **EX** Exchange Rates between China Yuan and A$, US $, and Japanese Yen (market rates, period average)	***International Monetary and Finance Statistics***, IMF (1984-)

Table 6.2A: ACF's of Data for the Australia Model

Lag k	TU	TA	GDP	TP
1	0.87	0.92	0.94	0.91
2	0.76	0.81	0.87	0.82
3	0.69	0.74	0.81	0.74
4	0.65	0.68	0.75	0.69
5	0.59	0.64	0.70	0.62
6	0.53	0.60	0.65	0.56
7	0.47	0.55	0.59	0.52
8	0.45	0.49	0.54	0.51
9	0.40	0.43	0.49	0.46
10	0.37	0.40	0.44	0.41
11	0.28	0.36	0.39	0.37
12	0.20	0.32	0.35	0.34
13	0.13	0.30	0.31	0.30
14	0.11	0.26	0.26	0.26
15	0.08	0.22	0.22	0.22
16	0.03	0.20	0.18	0.21
17	-0.05	0.15	0.14	0.16
18	-0.01	0.13	0.11	0.11
19	-0.15	0.12	0.08	0.06
20	-0.20	0.10	0.05	0.02
21	-0.23	0.05	0.02	-0.02
22	-0.24	0.00	0.00	-0.05
23	-0.25	-0.03	-0.03	-0.08
24	-0.24	-0.06	-0.05	-0.11
25	-0.23	-0.09	-0.06	-0.17

Note: ACFs at lag order 1-25 start at high levels (close to 1) and tape off gradually.

Table 6.2B: ACF's of Data for the Japan Model

Lag k	TU	TA	GDP	TP
1	0.88	0.91	0.95	0.94
2	0.76	0.84	0.91	0.87
3	0.73	0.77	0.86	0.80
4	0.69	0.72	0.80	0.73
5	0.59	0.63	0.75	0.64
6	0.50	0.57	0.70	0.56
7	0.47	0.51	0.65	0.48
8	0.45	0.49	0.59	0.42
9	0.37	0.43	0.55	0.34
10	0.30	0.41	0.50	0.27
11	0.30	0.39	0.46	0.20
12	0.30	0.38	0.41	0.16
13	0.23	0.33	0.37	0.13
14	0.17	0.28	0.32	0.10
15	0.15	0.24	0.27	0.09
16	0.14	0.21	0.23	0.08
17	0.07	0.14	0.81	0.07
18	0.02	0.08	0.14	0.06
19	0.03	0.03	0.09	0.05
20	0.04	0.01	0.05	0.04
21	0.01	-0.05	0.01	0.04
22	-0.02	-0.08	-0.03	0.03
23	-0.02	-0.10	-0.06	0.01
24	-0.01	-0.10	-0.10	0.00
25	-0.04	-0.10	-0.14	-0.02

Note: ACFs at lag order 1-25 start at high levels (close to 1) and tape off gradually.

Table 6.2C: ACF's of Data for the USA Model

Lag k	TU	TA	GDP	TP
1	0.69	0.87	0.93	0.89
2	0.68	0.84	0.86	0.80
3	0.56	0.77	0.79	0.70
4	0.69	0.79	0.73	0.61
5	0.44	0.67	0.67	0.50
6	0.44	0.64	0.62	0.41
7	0.33	0.58	0.57	0.34
8	0.44	0.62	0.52	0.31
9	0.24	0.50	0.48	0.25
10	0.26	0.47	0.43	0.21
11	0.18	0.42	0.39	0.18
12	0.27	0.45	0.34	0.18
13	0.09	0.33	0.30	0.14
14	0.12	0.30	0.26	0.12
15	0.06	0.25	0.22	0.12
16	0.16	0.26	0.18	0.13
17	0.00	0.14	0.15	0.12
18	0.04	0.10	0.11	0.12
19	-0.02	0.05	0.08	0.12
20	0.08	0.06	0.05	0.12
21	-0.04	-0.03	0.02	0.10
22	0.03	-0.06	-0.01	0.09
23	-0.04	-0.10	-0.03	0.07
24	0.04	-0.07	-0.05	0.03
25	-0.05	-0.15	-0.06	-0.03

Note: ACFs at lag order 1-25 start at high level (close to 1) and tape off gradually.

Table 6.3: Results of the ADF Test for Unit Roots

Variable	Lag p	H_0: I(1) τ Statistics	Lag p	H_0: I(2) τ Statistics
Australia Data				
TU	0	-7.3307	3	-4.1056*
TA	4	-1.7147	2	-5.6680*
GDP	0	-6.6458	2	-3.9095*
TP	0	-10.1150	4	-4.0064*
Japan Data				
TU	6	-1.9920	4	-3.2581*
TA	4	-2.7693	7	-3.4313*
GDP	0	-0.9559	2	-2.7488
TP	4	-2.2117	3	-2.7814
The USA Data				
TU	4	-2.6007	5	-3.1280*
TA	7	-1.9615	5	-2.5265
GDP	2	-2.6885	1	-3.0855
TP	4	-3.1818	7	-2.5914

Note:

(1) * indicates τ Statistics are significant at the 5% significance level; Critical values are sourced from Fuller (1996, p.642) for the sample size 50.

(2) Lag number p is chosen automatically by Shazam program at the highest significant level of ACF's of the data.

Table 6.4: Results of Phillips-Perron Test for Unit Roots

Variable	Lag p	H_0: I(1) τ Statistics	H_0: I(2) τ Statistics
Australia Data			
TU	1	-8.2217	-55.432
TA	1	23.707*	-62.095
GDP	1	-7.4196	-47.311
TP	1	-10.4930	-61.044
Japan Data			
TU	1	-19.4660	-58.457
TA	1	-10.1540	-66.402
GDP	1	-0.7484	-64.498
TP	1	-3.0559	-58.106
The USA Data			
TU	1	-43.183*	-84.412
TA	1	-40.104*	-88.260
GDP	1	-8.3966	-26.623
TP	1	-9.7958	-63.990

Note:

(1) * indicates τ Statistics are significant at the 5% significance level; Critical values are sourced from Fuller (1996, p.642) for the sample size 50.

(2) Lag number p is chosen automatically by Shazam program at the highest significant level of ACF's of the data.

Table 6.5: Summary of Test Results from the ADF and PP tests

Origin Country	Variable	ADF	PP
Australia	TU	I (1)	I (1)
	TA	I (1)	I (0)
	GDP	I (1)	I (1)
	TP	I (1)	I (1)
Japan	TU	I (1)	I (1)
	TA	I (1)	I (1)
	GDP	I (2)+	I (1)
	TP	I (2)+	I (1)
USA	TU	I (1)	I (0)
	TA	I (2)+	I (0)
	GDP	I (2)+	I (1)
	TP	I (2)+	I (1)

Note: + indicates data are integrated at order two or higher.

Table 6.6: Test Statistics for HEGY Unit Root Tests

Origin Country	Variable	τ: π_1=0	τ: π_2=0	F: π_3 =π_4=0	Lags	LM χ^2 (4)
Australia	TU	-1.0488	-4.6237*	11.9407*	0	0.5065
	TA	-0.41998	-5.8014*	26.8356*	1	3.1044
	GDP	-0.0049	-4.3978*	30.9176*	0	1.6626
	TP	-1.9233	-4.2971*	18.4899*	0	2.0366
Japan	TU	-0.9778	-4.7445*	17.8283*	0	0.8430
	TA	-0.7259	-4.6025*	21.6845*	0	5.8936
	GDP	-0.0049	-4.4155*	35.7744*	0	2.0290
	TP	-2.2733	-4.7789*	28.4367*	0	3.1258
USA	TU	-1.2473	-2.5348	5.4799	1	5.9228
	TA	-0.2951	-4.3648*	21.0951*	0	6.1554
	GDP	-0.3529	-3.4150*	42.3030*	0	5.0296
	TP	-2.4367	-4.3205*	23.0244*	0	3.4178
Critical 5%	Value	-3.08	-3.04	6.60		

Notes:

(1) Intercept terms, time trends and seasonal dummy variables are included in the auxiliary regression models;
(2) Critical values are from HEGY (1990, Table 1a and Table 1b, pp.226-227);
(3) * indicates that statistics are significant at the 5% level;
(4) Lagged terms are chosen to ensure there is no error correlation in the regression models;
(5) The LM statistics χ^2 (4) test for error correlation of the regression models. χ^2 (4) = 9.49 at the 5% significance level;

Table 6.7: Results of HEGY Unit Root Tests

Variable	Australia	Japan	USA
TU	(1, 0, 0)	(1, 0, 0)	(1, 1, 1)
TA	(1, 0, 0)	(1, 0, 0)	(1, 0, 0)
GDP	(1, 0, 0)	(1, 0, 0)	(1, 0, 0)
TP	(1, 0, 0)	(1, 0, 0)	(1, 0, 0)

CHAPTER 7: **MODELING AND FORECASTING INTERNATIONAL TOURISM DEMAND TO CHINA USING VAR SYSTEMS**

7.1 INTRODUCTION

In chapter 6 we have defined four important economic variables related to international tourism demand to China from its three major tourist-source countries Australia, Japan and the USA, and we have also identified the time series properties of the selected data. In accordance with the structure and pattern of the time series data, this chapter aims to develop a vector autoregressive (VAR) process to analyze and forecast the quarterly tourist flows to China from the three countries.

Although all regression analyzes in the previous studies of tourism demand modeling deal with the dependence of the tourism demand variable on the theoretical "explanatory" variables, this does not necessarily imply causation between tourism demand and these "explanatory" variables. Moreover, most regression methods have employed the single-equation approach which only deals with the dependence of tourism demand on the selected "independent variables", assuming that there are no interactions or feedback effects between the dependent and independent variables. However, according to economic theory, these economic variables are often interrelated. For the four variables defined in Chapter 6, on one hand, China's two-way trade with its tourist-source countries, GDP in the tourist-source countries, and the relative "tourism price" between China and the tourist-source countries may "cause" or influence the increase and decline of tourist arrivals to China. On the other hand, changes in tourist arrivals may affect the two-way trade, GDP and "tourism price". For instance, the growth of tourist arrivals to China from an origin country may result in an increase of two-way trade between these two countries, and also may lead to a higher "tourism price" level. Therefore, regression models using the single-equation approach are subject to the criticism of ignoring the feedback effects between the dependent and independent variables. Hence forecasting, in particular, long-term forecasting using the single-equation regression models is subject to errors due to ignoring these feedback effects.

This chapter therefore attempts to apply a VAR process developed by Sims (1980), which is used to analyze and forecast interrelated economic variables. As discussed in Chapter 5 (see Section 5.2.3), the distinctive feature of a VAR model is that there is no *à priori* distinction between endogenous and exogenous variables, and all variables included in the model are treated as endogenous variables; each equation in a VAR process includes the same number of lags on each and every variable, and each equation thus has coefficients on lagged variables.

Compared with single–equation regression models and system equation models, the application of the VAR approach in tourism demand modeling and forecasting features a range of advantages, relating to its ability to deal with the endogeneity of the variables, its simplicity in model estimation and its forecasting power.

First of all, as the interrelations (or feedback effects) between all variables are considered and further can be analyzed in a VAR system, the VAR model can be used for analysis of tourism policy simulations via the impulse response analysis. For instance, we could analyze how much and how long a policy change (or an exogenous shock) in the two-way trade between China and its tourist-source countries, will affect the tourist arrivals, and vice versa.

Secondly, the VAR method is technically simpler than the system (or simultaneous) equation method in the following ways:

- All variables included in the model are treated as endogenous variables. We do not have to worry about determining which variables are endogenous and which variables are exogenous. The endogeneity issue in the system equation models makes an application of the system equation method specially difficult and complicated.

- For the regression procedure of a VAR model, although the structure of the model looks complex, the usual OLS method can be applied to estimate each sub-equation separately.

Thirdly, in a VAR system, using the formal causality test developed by Granger (1978), we are able to further deal with the endogeneity issue by examining the "causal" relationships between the variables.

Fourthly, the more sophisticated cointegration test developed by Johansen and Juselius (1990), which concerns the long run relationships between the variables, is developed and conducted in a VAR context.

Finally, a VAR model is a powerful forecasting model as it has three significant advantages in forecasting compared to single-equation regression models.

- In the single-equation approach, in order to forecast the dependent variable we need to forecast the exogenous variables (i.e., the explanatory variables) first. This can be very difficult due to limitations of the data and the understanding of the data generating processes for the forecasted exogenous variables. Moreover, in some studies of tourism demand modeling and forecasting (e.g., Kulendran and King 1997), the actual values of the explanatory variables are used to generate more than one-step forecasts of tourism demand, which makes it lose the comparability with other models, such as time series models and naïve models which use forecasting values to generate time-lead forecasts. In a VAR system, however, the forecasts of all explanatory variables are automatically generated from the system and can be pre-determined for the forecasts of a "dependent" variable of interest. This makes the VAR models comparable to other forecasting models using the forecasting values to generate more than one period forecasts.

- Furthermore, in a VAR system, we are able to analyze the composition of the forecasting errors which are generated from the forecasting process of all variables including the forecasted variable itself.

Therefore, in order to analyze the interrelationships between the selected variables and also to compare the accuracy of different forecasting models of international tourism demand to China, regression models in VAR systems are further developed in this chapter to analyze and forecast the quarterly tourist flows.

The plan of this chapter is as follows. Section 2 introduces the model specifications and then identifies the orders of the VAR models, in which we build up the appropriate models for the following analyzes and forecasting.

In Section 3 we perform the Granger causality test to examine if there are "causal" relationships between the four endogenous variables. By conducting this test, on one hand, we are able to identify if there are "causal" relationships between two variables, and what direction the "causal' relationships are. On the other hand, we are also able to test if the specified model is the efficient model for forecasting, i.e., if a variable Granger-causes tourist arrivals, the inclusion of this variable in the tourism demand function will improve the forecasting of the tourist arrivals.

In Section 4, we further apply the cointegration test developed by Johansen and Juselius (1990) to detect if there are "long-run equilibrium" relationships among the four variables. Based on the cointegration results, we are able to estimate the "long run" tourism demand to China from the three selected countries.

In Section 5, we first present the estimation results and the diagnostic checking of the estimated VAR models in order to confirm that the estimated models are specified properly, and further, if the estimated models pass the tests of diagnostic checking, we carry out eight-quarter forecasts of quarterly tourist arrivals generated by the estimated VAR models. By comparing the forecasting errors, we are able to identify the optimal VAR model for each country case. Finally, The impulse response analysis based on the optimal model for each country case is also provided in this section, which allows us to analyze China's tourism policy simulations with respect to two-way trade and "tourism price".

The final section (Section 6) draws out the conclusions from the empirical results of this chapter.

7.2 MODEL SPECIFICATION AND SELECTION OF VAR ORDERS

7.2.1 Model Specification

For international tourism demand to China from Australia, Japan and the USA respectively, we establish a VAR(p) system (p=lag number of each endogenous variable) with a set of four variables TU, TA, GDP and TP, which are defined (in Chapter 6) as tourism arrivals, two-way trade, GDP and relative "tourism price" respectively.

$$\begin{bmatrix} \Delta TU_t \\ \Delta TA_t \\ \Delta GDP_t \\ \Delta TP_t \end{bmatrix} = A_0 X + A_1 \begin{bmatrix} \Delta TU_{t-1} \\ \Delta TA_{t-1} \\ \Delta GDP_{t-1} \\ \Delta TP_{t-1} \end{bmatrix} + A_2 \begin{bmatrix} \Delta TU_{t-2} \\ \Delta TA_{t-2} \\ \Delta GDP_{t-2} \\ \Delta TP_{t-2} \end{bmatrix} + \ldots + A_p \begin{bmatrix} \Delta TU_{t-p} \\ \Delta TA_{t-p} \\ \Delta GDP_{t-p} \\ \Delta TP_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{TU,t} \\ \varepsilon_{TA,t} \\ \varepsilon_{GDP,t} \\ \varepsilon_{T,tP} \end{bmatrix} \quad (7.1)$$

$$A_p = \begin{bmatrix} a_{11}^{(i)} & a_{12}^{(i)} & a_{13}^{(i)} & a_{14}^{(i)} \\ a_{21}^{(i)} & a_{22}^{(i)} & a_{23}^{(i)} & a_{24}^{(i)} \\ a_{31}^{(i)} & a_{32}^{(i)} & a_{33}^{(i)} & a_{34}^{(i)} \\ a_{41}^{(i)} & a_{42}^{(i)} & a_{43}^{(i)} & a_{44}^{(i)} \end{bmatrix}; \quad A_0 = \begin{bmatrix} a_{10} \\ a_{20} \\ a_{30} \\ a_{40} \end{bmatrix}$$

i=1,2,..p

A_p is a 4×4 matrix of coefficients; A_0 is a (4×1) parameter vector; $\varepsilon_t = (\varepsilon_{TU,t}, \varepsilon_{TA,t}, \varepsilon_{GDP,t}, \varepsilon_{TP,t})'$ is (4×1) vector of white noise residuals; X is the deterministic component in each VAR system, including intercepts, seasonal dummy variables capturing the seasonality of the quarterly data, and dummy variables capturing the shocks from unusual events, such as the Tiananmen Square event which caused a significant decrease in tourist arrivals and foreign trade to China between 1989 and 1990, and policy changes of foreign exchanges in 1990 and 1994 in China which resulted in a sudden decrease in the "tourism price" to China.

Δ represents the differenced data. According to the results of unit root tests in Chapter 6, variables TU, TA, GDP and TP are not time invariant and have unit roots at zero frequency; moreover, TU in the case of the USA also has seasonal unit roots. Therefore, to achieve the white noise disturbances ε_{TU}, ε_{TA}, ε_{GDP}, and ε_{TP} respectively, we need to make the fourth differencing transformation of the TU data in the USA model and undertake first differencing transformations for the rest of data.

P lagged terms of TA, GDP and TP are considered in the models as tourists do not adjust their patterns of consumption to the changes of two-way trade, "tourism price" and GDP in the short run due to "some psychological, technical and institutional reasons"(see Gujarati 1995, pp589-590). The lagged variable of TU is included in the model to allow for the possibility of tourist habit persistence and supply rigidities (see Kulendran 1996).

In the VAR system (7.1), the four-dimensional multiple time series (i.e., TU, TA, GDP and TP) are summarized as a VAR(p) process. However, in practice the order of a VAR process p will usually be unknown, and obviously there is not just one correct VAR order for a process. As forecasting is the objective in our VAR process, we use relevant criteria to choose the VAR order such that a measure of forecast precision is minimized.

7.2.2 Selection Of VAR Orders

To ensure no serial error correlation in the VAR system, we first select the number of lagged terms p using the Akaike Information Criteria (AIC) and the Schwarz Bayesian Criteria (SBC) (see Akiake 1973, 1974 and Schwarz 1978) which are widely used in selecting the order of estimated VAR process. Considering the relatively small sample size used for the estimation, we set the maximum order of the VARs at p=5. The VAR order p is chosen according to the maximum values of AIC and SBC which minimize the forecast variance MSE (Mean Squared Error) of the VAR systems. However, the results from the AIC and the SBC may not be consistent when selecting the order of a VAR model. As discussed by Lütkepohi (1991, section 4.3), the SBC selects the most parsimonious model (a model with the least number of freely estimated parameters), and the AIC selects the least parsimonious model. In another words, the AIC criterion tends to select a higher order model compared to the SBC. In a VAR system, forecasts from lower order models are usually preferred to higher order models because the forecast variance matrix of the 1-step predictor will increase with the order p. Unfortunately, in practice we do not often know the finite order of a VAR system. We are mostly dealing with a VAR system with infinite order and we may just approximate an infinite order VAR scheme by a finite order model. In this case, for a VAR model with moderate sample size, some less parsimonious criteria like AIC may give superior results in terms of forecast precision. Therefore, it may be a good strategy to compare the order estimates obtained by different criteria, and choose the optimal model in terms of forecast errors.

Test statistics against the null hypothesis p=1, 2, ..., 5 for VAR systems are reported in Table 7.1. For the three VAR models, both AIC and SBC consistently suggest the VAR order p=1 for the Australia model. For the Japan and the USA models, the SBC reaches maximum at p=1, while the AIC reaches maximum at p=3 and p=5 respectively. By comparing the forecasting errors (the mean absolute errors) for each model with different p values, we find that the VAR model with p=3 produces better forecasts (i.e., a smaller mean absolute error) for the Japan model and the VAR model with p=1 produces better forecasts (i.e., a smaller mean absolute error) for the USA model. Therefore, we select VAR order p=1 for the Australia and the USA VAR systems, and p=3 for the case of Japan. The following analyzes will be conducted in a VAR(1) system for the cases of Australia and the USA, and a VAR(3) system for the case of Japan.

7.3 THE TEST FOR GRANGER CAUSALITY AND EXOGENEITY

We have mentioned previously the likelihood of endoneneity in the underlying economic relationships of this tourism demand model. Fortunately, the VAR approach enables us to deal specifically with this possibility. One possible form of the endogeneity is the causality that may go from the "dependent variable" (i.e., tourism demand) to the theoretically defined independent variables (e.g., GDP and tourism prices).

Granger (1969) has defined a concept of causality based on the idea that a cause cannot come after the effect. Thus, if a variable X affects a variable Y, the former should help improve the predictions of the latter variable. In other words, since the future cannot predict the past, if a variable X (Granger) causes variable Y, then changes in X should precede changes in Y. Therefore, in a regression model of Y on other variables (including its own past values) if we include past or lagged values of X and it significantly improves the prediction of Y, then we can say that X (Granger) causes Y. A similar definition applies for Y (Granger) causing X.

Although the "cause-effect" relations between individual variables identified solely by the Granger causality, are arguable,[10] the Ganger causality test is very useful in building up a better forecasting model to produce more accurate forecasts.

Granger (1969) first proposed a causality test by using a lead-lag relationship between two variables in econometric modeling. Later several alternative procedures have been developed in an attempt to improve the size and power of the Granger no-causality test (e.g., Johansen and Juselius 1990, Toda and Phillips 1993, and Toda and Yamamoto 1995). Because of the simplicity of its application in VAR systems, in this study we apply the Block Granger Causality procedure to test the bi-directional causal relationships (i.e., "feedback" effects) among the four variables TU, TA, GDP and TP in the selected VAR(1) system for the cases of Australia and the USA, and the VAR(3) for the case of Japan.

The Granger causality test, which is known as the "Block Granger Causality Test" examines whether a lagged variable X would Granger-cause other variables in the system, by first imposing restrictions that all of the coefficients of X's lagged variables in

[10] Maddala and Kim (1998) argue that a better term for Granger causality is "Precedence" since it does not exactly mean "causality" between variables (p.188).

the system are zero, and then computing the likelihood ratio (LR) statistics. The null hypothesis that the joint coefficients of lagged X terms are equal to zero (i.e., lagged X terms do not belong in the regression) is tested by the above LR statistics. The Block Granger Causality test can also be used to test whether several variables jointly Granger-cause a single variable.

The statistical results are reported in Table 7.2. If the statistics of the null hypothesis of non-causality from variable A to variable B are statistically significant, it implies that variable A Granger-causes variable B. Like wise, if the statistics of the null hypothesis of no-causality from variable A to variable B are not statistically significant, it implies that variable A does not Granger-cause variable B.

In the Australia VAR(1) process, the test statistic for the null hypothesis of non-causality from TU to TA, GDP and TP is significant at the 5% level of significance; the test for the null hypothesis that TA, GDP and TP do not jointly Granger cause TU is significant at the 5% level while the test statistics for the null hypothesis of non-causality, respectively, from TA to TU, from GDP to TU, and from TP to TU are not significant at the 5% level. Therefore, the test results suggest that TU Granger-causes TA, GDP and TP; TA, GDP and TP jointly Granger-cause TU while the causality, respectively, from TA to TU, from GDP to TU, and from TP to TU is not statistically significant at the 5% significance level.

In the Japan VAR(3) process, the test statistic for the null hypothesis of non-causality from TU to TA, GDP and TP is significant at the 5% level; the statistics for the null hypothesis of non-causality from both TA and TP to TU are significant at the 5% level; the statistic for the null hypothesis that TA, GDP and TP do not jointly Granger-cause TU is significant at the 5% level. The results of the statistical tests suggest that there are two-way causalities between TU and TP, and between TU and TA, while there is one-way causality from TU to TP at the 5% significance level.

In the VAR(1) system for the case of the USA, the test statistic for the null hypothesis of non-causality from TU to TA, GDP and TP is significant at the 5% level;

the statistic testing for the null hypothesis of non-causality from TP to TU is significant at the 5% level, whereas statistics testing for the null hypothesis that TA, GDP and TP do not jointly Granger-cause TU is also significant at the 5% level. This suggests that there is two-way causality between TU and TP, whereas there is one-way causality both from TU to TA and from TU to GDP at the 5% significance level.

The results of causality tests can be summarized as follows: in the case where the tourist origin country is Australia, two-way trade, GDP and relative "tourism price" jointly Granger-cause tourist arrivals to China, while tourist arrivals also Granger-cause two-way trade, GDP and the relative "tourism price". In the case where the origin country is Japan, two-way trade and the relative "tourism price" Granger-cause tourist arrivals to China; while tourist arrivals also Granger-cause two-way trade, GDP and the relative "tourism price. In the case where the tourist origin country is the USA, the relative "tourism price" Granger-cause tourist arrivals, while tourist arrivals also Granger-cause two-way trade, GDP and the relative "tourism price". Therefore, there is a two-way causality between two-way trade and tourist arrivals, and between the relative "tourism price" and tourist arrivals respectively in the case of Japan, whereas there is a two-way causality between the relative "tourism price" and tourist arrivals in the case of the USA.

The causality from tourist arrivals to two-way trade, GDP and the relative "tourism price" detected by the Granger causality test above suggests that the theoretically defined "dependent variable"—tourism demand also "causes" the "explanatory" variables defined in the single-equation models. Moreover, the two-way (or bi-directional) causalities detected by the Granger causality test suggest there are interactions or feedback effects between the theoretical dependent variable and independent variables defined in the single-equation models. Forecasting of tourism demand using the single-equation models may suffer from biases by ignoring these interrelations between the variables, which the following VAR systems compromise.

In the VAR system 7.1, to achieve the white noise disturbances ε_{TU}, ε_{TA}, ε_{GDP}, and ε_{TP} respectively, we need to first make stationary transformations of the data, to achieve the zero mean for each set of the data TU, TA GDP and TP. However, by taking the first (or higher order) differencing transformation, we may lose valuable information on the links among the variables in the level form, which is a concern based on the "cointegration" theorem. Therefore, in the next section, we undertake the cointegration test to help settle this issue.

7.4 TEST OF COINTEGRATION AND ESTIMATION OF LONG-RUN TOURISM DEMAND

7.4.1. Cointegration Test

In recent years, the concept of cointegrated time-series, which was introduced by Granger (1981) and Granger and Weiss (1983), has attracted much attention in the applied econometrics literature (e.g., Johansen 1988, Phillips and Ouliaris 1988, Stock and Watson 1988, Johansen and Juselius 1990, Hansen and Phillips 1990, Banerjee *et al.* 1994, and Harris 1997). The concept of cointegration is based on the idea that some economic variables converge and reach a "long-run equilibrium" relationship although the variables may drift away from the equilibrium at some specific periods because of exogenous shocks.[11] In other words, a long-run relationship entails a systematic co-movement among economic variables except for some deviations in the short term. Most of the I(1) variables tend to diverge as their means and variances are changing with time and thus might seem never to be expected to obey any sort of long-run equilibrium relationship. But in fact it is possible for two or more variables to be I(1) and yet for certain linear combinations of those variables to be I(0). If that is the case, the variables are said to be cointegrated. Statistically, components of time series data,

[11] For a detailed interpretation of the concept of "long-run equilibrium" please see Banerjee *et al.* (1994), p.2.

namely means, variances, and covariances, may have movements varying with time, but some linear combinations of these series may have time-invariant linear properties.

A number of methods for testing cointegration based on the residual terms of single equation models have been proposed in the literature, such as Engle and Granger (1987), Phillips and Hansen (1990), Phillips and Loreton (1991), and Stock and Watson (1993). These residual-based tests first estimate the static regression by OLS and then test if the estimated error correction terms (the residual terms from the regression) are stationary. If the residual term from the OLS regression is I(0), i.e., stationary, the variables regressed are cointegrated, even though the individual variables are I(1). The efficiency of the residual-based tests is questionable considering the following aspects: First of all, these single equation methods have only considered two variables and are interested in estimating only one particular cointegrating vector. Therefore, these methods do not carry over to models with more than two variables, where more than one stable linear combination may exist. Moreover, under the OLS regression method, asymptotic distribution of the estimators depends on endogeneity of the regressor and serial correlation in the errors. Only in the case where there is no endogeneity and serial correlation problems, will the t statistics for testing the null hypothesis have the standard normal distribution asymptotically (see Maddala and Kim 1998, Chapter 5, Section 3).

Johansen and Juselius (1990) propose a Maximum Likelihood (ML) procedure and provide a framework for testing all possible stationary linear combinations – the cointegrating relations between two more variables in the context of a vector of autoregressive error-correction model (VARECM), in which the number of cointegrating vectors is not fixed but determined in the course of estimation.

Johansen's ML approach assumes following a vector autoregression model of order k, VAR(k), in which a vector time-series Y_t which contains N variables, all **I(1).**

$$Y_t = \mu_t + \sum_{i=1}^{k} A_i Y_{t-i} + \varepsilon_t, \qquad (7.2)$$

where μ_t contains a constant term, seasonal dummies and a deterministic trend; A_i is an n×n matrix; the maximum lag of the system k is chosen so as to ensure that the residual ε_t is while noise.

This VAR system can be transferred to following an error correction model (ECM) representation:

$$\Delta Y_t = \mu_t + \sum_{i=1}^{k-1} \Gamma_j \Delta Y_{t-i} + \Pi Y_{t-k} + \varepsilon_t, \qquad (7.3)$$

$$\Gamma_i = -(\mathrm{I} - \Pi_1 - \ldots - \Pi_i); \quad \Pi = -(\mathrm{I} - \Pi_1 \ldots - \Pi_k),$$

where I is the identity matrix and Π is an N×N matrix (N is the number of variables tested); the variables ΔY_t and ΔY_{t-i} are I(0) variables and Y_{t-k} are I(1) variables; the level terms (Π) capture the long-run steady relationships among the N variables, while the difference terms (Γ_j) estimate short-run dynamics.

The rank of Π, *r* determines whether or not, and to what extent, the system 7.2 is cointegrated. If $r = 0$, there is no long-run relationship between the variables; if $r = N$, then the process Y_t is stationary; if $r = 1$ then N variables are cointegrated and there is a unique long-run relationship between the set of variables; if $1 < r < N$, there are multiple cointegrating vectors and multiple long-run relationships which need further external information to identify (see Johansen and Juselius 1990).

The objective of the Johansen and Juselius (1990) cointegration test is to test whether the eigenvalues of the estimated Π are significantly different from zero by using the Maximum Likelihood Method. There are two statistical tests involved in the cointegration test. The first statistic $\Lambda(q, T)$ tests the null hypothesis that H_0: *$r \leq q$ against* the alternative H_a: $r \geq T$ ($q < T < N$). The second statistic $\Lambda(q, q+1)$ tests the null hypothesis H_0: $r \leq q$ against the alternative H_a: $r = q+1$. The null hypothesis $r = 0$ tests the hypothesis that there is no long-run relationship between the dependent and independent variables.

To test the cointergrated relationship between the four variables (i.e., TU, TA, GDP and TP) we defined in the last section, we transfer the VAR system 7.1 to the following VARECM form:

$$\begin{bmatrix} \Delta TU_t \\ \Delta TA_t \\ \Delta GDP_t \\ \Delta TP_t \end{bmatrix} = \mu_t + \sum_{i=1}^{k-1} \Gamma_i \begin{bmatrix} \Delta TU_{t-i} \\ \Delta TP_{t-i} \\ \Delta GDP_{t-i} \\ \Delta TP_{t-i} \end{bmatrix} + \Pi \begin{bmatrix} TU_{t-1} \\ TA_{t-1} \\ GDP_{t-1} \\ TP_{t-1} \end{bmatrix} + \varepsilon_t, \quad (7.4)$$

where Γ_i and Π are (4×4) matrices; ΔTU_t, ΔTA_t, ΔGDP_t and ΔTP_t are I(0) variables after the first differencing, and TU_{t-1}, TA_{t-1}, GDP_{t-1} and TP_{t-1} are I(1) variables.

We test the rank of Π in order to see if the level data of variable TU, TA, GDP and TP are cointegrated, i.e., some linear combinations of these four variables are stationary even though the individual variables are not stationary.

The results of cointegration tests $\Lambda(q, T)$ and $\Lambda(q, q+1)$ for variable vectors of TU, TA, GDP and TP in the three country cases are presented in Table 7.3A and Table 7.3B respectively. For the cases of Australia and Japan, the null hypothesis $r = 0$ can be rejected in favor of $r = 2$ for both tests. The results suggest that the four time-series variables are cointegrated and there are two cointergrating vectors in the case of Australia and Japan. In the case of the USA, both the $\Lambda(q, T)$ and $\Lambda(q, q+1)$ tests suggest that there are three cointegrating vectors. Therefore, the results of the cointegration test suggest that in the case of Australia and Japan there are two "long-run" relationships among the four selected variables, and there are three "long-run" relationships among the four selected variables in the case of the USA.

By using the Johansen Maximum Likelihood (ML) procedure (see Johansen and Juselius 1990), the long-run relationships among selected variables (TU, TA, GDP and TP) can be identified and the elasticities of the "long-run" tourism demand from the three origin countries can be further estimated respectively.

7.4.2 Estimation Of Long-Run Tourism Demand

The estimated long-run relationships between variable TU, TA, GDP and TP are further estimated by using the Johansen ML procedure in this section. Exogenous I(0) variables (such as seasonal dummy variables and time trends) are not included in the long-run tourism demand models as we assume that in the long-run the equilibrium relation between the variables is not caused by the exogenous variables, and it is unlikely there exists a time trend in the cointegrating relation between the variables. Intercepts and dummy variables are not included in the long-run models as they will be incorporated in short term dynamic forecasting models at a later stage together with the error correction terms from the long-run models.[12]

The estimated long-run equilibrium relationships between these four variables are reported in Table 7.4. Although the test results indicate statistically that there are multiple "long-run" relationships among the variables, we still need to further confirm these long-run relations by checking if the long-run estimates coincide with economic theory. Following economic theory, one of the estimated long-run demand models in the case of Australia and Japan is excluded as the estimated coefficients have the wrong sign for the GDP and TA variables. For the case of the USA, two estimated models are not valid because of the wrong sign of variables TA, GDP and TP respectively. Therefore, a unique long-run relationship between tourist arrivals (TU), two-way trade (TA), income (GDP), and the relative "tourism price" to China (TP) is obtained for all three country cases.

[12] Moreover, the error correction terms in an ECM model are not affected by the incorporation of any constant terms (please refer to Banerjee *et at*, 1994, p. 52).

Holding other variables constant and assuming there are no interactions between the four variables, the elasticities of long-run tourism demand can be obtained:

Long-run tourism demand from Australia

$$\mathbf{TU} = \mathbf{0.15\ TA} + \mathbf{0.55\ GDP} - \mathbf{0.72\ TP}$$
$$(17.9753)^{*} \quad (18.1270)^{*} \quad (18.7572)^{*}$$

Long-run tourism demand from Japan

$$\mathbf{TU} = \mathbf{0.84\ TA} + \mathbf{0.04\ GDP} - \mathbf{0.25\ TP}$$
$$(15.4601)^{*} \quad (2.7344) \quad (6.5486)^{*}$$

Long-run tourism demand from the USA

$$\mathbf{TU} = \mathbf{0.28\ TA} + \mathbf{0.38\ GDP} - \mathbf{0.43\ TP}$$
$$(16.5417)^{*} \quad (29.1901)^{*} \quad (33.0950)^{*}$$

Figures in brackets are values of χ^2 test statistics for zero restrictions on the estimated coefficients. * indicates statistics are significant at the 5% significance level. In all cases the estimated coefficients are statistically significant at the 5% significance level, except for the GDP variable in the Japan model.

We can interpret the estimated coefficients as follows. In the case where Australia is the tourist source country, a one per cent increase in the relative "tourism price" to China is associated with a 0.72% decrease in tourist arrivals to China; a one per cent increase in Australian GDP is associated with a 0.55% increase in tourist arrivals from Australia to China; a one per cent increase in two-way trade between these two countries is associated with a 0.15% increase in tourist arrivals to China. The results suggest that travel to China from Australia is relatively more responsive to the changes of the relative "tourism price" to China and GDP level in Australia, but less responsive to two-way trade volumes between these two countries if all other things are held constant. Therefore, these results indicate that income growth in Australia and the relatively cheaper "tourism price" to China are important variables to explain tourist flows from Australia to China. However, given the long-term trend of increasing trade volumes between China and Australia, any increase in trade between these two countries will lead to some increase in international travel flows to China, even if the increase is slight.

For the case of tourist arrivals from Japan, a one per cent increase in the relative "tourism price" to China is associated with a 0.25% decrease in tourist arrivals to China; a one per cent increase in Japan's GDP is associated with a 0.04% increase in tourist arrivals to China; a one per cent increase in two-way trade between the two countries is associated with a 0.84% increase in tourist arrivals to China. Therefore, the results suggest that travel to China from Japan is the most elastic to the changes of two-way trade, followed by the change of the relative "tourism price" to China, whist there is a negligible income elasticity. This indicates that, two-way trade volumes between China and Japan, followed by the cheaper "tourism price" to China, are important variables to explain tourist flows from Japan to China.

In the case of the USA as the tourist source country, a one per cent increase in the relative "tourism price" to China is associated with a 0.44% decrease in tourist arrivals to China; a one per cent increase in GDP in the USA is associated with a 0.39% increase in tourist arrivals to China; a one per cent increase in two-way trade between the two countries is associated with a 0.29% increase in tourist arrivals to China. Therefore, the results suggest that travel to China from the USA is relatively more elastic to the changes of the relative "tourism price" to China, followed by the GDP in the USA and two-way trade between these two countries. This indicates that the cheaper "tourism price" to China is the most important variable in explaining tourist flows from the USA to China.

We see that it is interesting that the results for the USA and Australia are quite similar. The tourism demand from Australia and the USA is characterized by relatively higher elasticities of "tourism price" and GDP, suggesting that the relative "tourism price" to China and the income level in the origin countries are the most important determinants of international travel to China from these two origin countries. In the case of tourism demand from Japan, however, tourist arrivals from Japan are more responsive to the two-way trade volumes with China, and relatively less responsive to the changes of the relative "tourism price" to China. It is quite interesting to note that tourism demand from Japan is characterized by an almost negligible income elasticity whereas there is a much stronger two-way trade elasticity between China and Japan. This suggests that the two-way trade between China and Japan is a very important determinant of international tourism demand to China. It may reflect that, compared with tourists from Japan, relatively more visitors from Australia and the USA are on holiday rather than travelling for business purposes, while by contrast most of the visitors from Japan may be on business trips.

The above estimations of long-run tourism demand examine the long-run relationships between the four selected variables and provide an analysis of the elasticities of tourism demand from the three tourist-source countries. The estimated elasticities of tourism demand suggest that tourist arrivals from the three countries respond differently to the changes from two-way trade, GDP and the relative "tourism price" variables. This may indicate some important differentiation of the tourism demand to China from these three origin countries as discussed above.

However, the estimation of the long-run tourism demand only provides a static analysis under long-run equilibrium assumptions. In the short-term, tourism demand may be affected by other factors outside the equilibrium system and may experience its own dynamic patterns. Moreover, there may be also feedback effects between the "assumed" "dependent" and "independent" variables. Therefore, in next section we further estimate the short-term dynamic demand models in VAR systems, which is further used for forecasting.

7.5 ESTIMATION OF TOURISM DEMAND USING VAR MODELS

7.5.1 Model Estimation

The cointegration tests conducted in the last section indicate that, although each individual variable is integrated at order one, some linear combinations of the four variables (i.e., TU, TA, GDP and TP) are integrated at order zero. Therefore, there are some long-run relationships between the variables in the level form even though individual variables are diverse from each other in the short term. This suggests that the "long-run" equilibrium relationships between the variables should be considered in regression models.

For international tourism demand from Australia, Japan and the USA, we establish a VAR system (p=lag number of each variables) incorporating a set of error correction terms from the long-run equilibrium relationships as endogenous variables in the system, namely a vector of autoregressive error correction model (VARECM):

$$\begin{bmatrix} \Delta TU_t \\ \Delta TA_t \\ \Delta GDP_t \\ \Delta TP_t \end{bmatrix} = A_0 X + A_1 \begin{bmatrix} \Delta TU_{t-1} \\ \Delta TA_{t-1} \\ \Delta GDP_{t-1} \\ \Delta TP_{t-1} \end{bmatrix} + A_2 \begin{bmatrix} \Delta TU_{t-2} \\ \Delta TA_{t-2} \\ \Delta GDP_{t-2} \\ \Delta TP_{t-2} \end{bmatrix} + \ldots + A_p \begin{bmatrix} \Delta TU_{t-p} \\ \Delta TA_{t-p} \\ \Delta GDP_{t-p} \\ \Delta TP_{t-p} \end{bmatrix} + \begin{bmatrix} u_{TU,t-1} \\ u_{TA,t-1} \\ u_{GDP,t-1} \\ u_{TP,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{TU,t} \\ \varepsilon_{TA,t} \\ \varepsilon_{GDP,t} \\ \varepsilon_{T,tP} \end{bmatrix},$$

$$A_p = \begin{bmatrix} a_{11}^{(i)} & a_{12}^{(i)} & a_{13}^{(i)} & a_{14}^{(i)} \\ a_{21}^{(i)} & a_{22}^{(i)} & a_{23}^{(i)} & a_{24}^{(i)} \\ a_{31}^{(i)} & a_{32}^{(i)} & a_{33}^{(i)} & a_{34}^{(i)} \\ a_{41}^{(i)} & a_{42}^{(i)} & a_{43}^{(i)} & a_{44}^{(i)} \end{bmatrix}; A_0 = \begin{bmatrix} a_{10} \\ a_{20} \\ a_{30} \\ a_{40} \end{bmatrix}, \quad (7.5)$$

i=1,2,..p,

where $\varepsilon_t = (\varepsilon_{TU,t}, \varepsilon_{TA,t}, \varepsilon_{GDP,t}, \varepsilon_{TP,t})'$ is a (4×1) vector of white noise residuals; u_{t-1}'s are the error correction terms generated from the "long-run" relationships to capture the long-run equilibrium relations between the variables which are lost because of differencing the data.

Although we have only accepted one cointegrating vector based on the economic interpretations of the coefficients of the long-run tourism demand models in section 7.4.2, in order to perform better forecasting, however, we include all cointegrating vectors in the VARECM models for each county case (i.e., two for the Australia and Japan models and three for the USA model).

The deterministic component X in each VAR system includes exogenous variables: intercepts, seasonal dummy variables and dummy variables for unusual events. Four dummy variables, representing the special events, i.e., the Tiananmen Square Event in China between 1989 and 1990, and policy changes in foreign exchanges in 1990 and 1994 in China, are included in the three models; and two more dummy variables to capture the shocks from the Asian Financial Crisis in 1997 to the outbound Japanese tourist flows are also included in the Japan model.

Δ represents the first difference data as variables TU, TA GDP and TP are not time invariant and have unit roots at zero frequency.

P lagged terms of TU, GDP and TP are considered in the models, as tourists do not adjust their patterns of consumption to changes of two-way trade, "tourism prices" and GDP in the short term. The lagged variable of TU is included in the model to allow for tourist habit persistence and supply rigidities.

By comparing the forecasting errors (mean absolute errors) for each model with p=1,2,...5 respectively for each model, we select p=1 for the Australia and Japan models, and p=4 for the USA VAR system.

To further confirm the results from the cointegration test and to select better VAR models for forecasting, we also estimate the VAR models without the error correction terms (i.e., the system 7.1) respectively for the three country cases. The forecasts of quarterly tourist flows from the three selected countries will be generated respectively by the VARECM (system 7.5) and VAR (system 7.1) models, so the forecasting accuracy from both systems can be compared and the models with better forecasting performance can be identified.

In a VAR system, the system-covariance matrix of errors is assumed to be diagonal, i.e., the estimated error terms from each sub-equation are independent. Therefore, we could estimate each sub-equation in a VAR system separately using the

OLS method. Since we are interested in forecasts of tourist arrivals, only the estimation results for tourist arrivals (TU) equation are presented in this chapter, and the estimation results for the other three sub-equations for each country cases are provided in the appendix.

The estimated coefficients of the TU equations from the three VARECM systems are presented in Table 7.5(A-C), respectively, for the cases of Australia, Japan and the USA. The estimated coefficients of the TU equations from three VAR systems are presented in Table 7.6(A-C), respectively, for the cases of Australia, Japan and the USA.

If results of the cointegration tests in Section 7.4 are correct, we would normally expect that, in each estimated ECM equation of TU, at least one error correction term (u_{t-1}) experiences a negative sign and is statistically significant. In the estimated Japan model (see Table 7.5B) and in the USA model (see Table 7.5C) respectively, there is one long-run error correction term ($u_{1,\ t-1}$) that is negative and also statistically significant. In the Australia model (Table 7.5A), however, both long-run error correction terms ($u_{1,\ t-1}$ and $u_{2,\ t-1}$) have the wrong sign and not statistically significant.

In all six estimated tourism demand models, many of the coefficient estimators are not significantly different from zero. This observation may be interpreted in two ways. First, some of the coefficients may actually be zero and this may be reflected in the estimation results. For instance, if some variables are not Ganger-causal for the remaining variables, zero coefficients are encountered. Second, insignificant coefficient estimates are found if the information in the data is not rich enough to provide sufficiently precise estimates.

However, as argued by Litterman (1986a), many economic variables behave like a random walk; hence the systematic variation in the data is relatively small compared with the random variation. As it is generally impossible to perform randomized experiments to test hypotheses about those economic structures, economic modeling has to set à priori information or restrictions for a variety of variables, and economic forecasting has essentially two choices: to exclude a variable, which is to specify that a coefficient is exactly zero, or to include the variable, which is the case if nothing is known about its likely value. In the case of VAR systems, we include the variables with non-significant coefficients.

As the estimated VAR models are further used for forecasting of tourism demand from these three countries respectively, the diagnostic checking of the estimated models need to be carried out before the forecasting.

7.5.2 Diagnostic Checking

Diagnostic test statistics for the residuals from each sub-equation are also presented together with the estimation results (see Table7.5 and Table 7.6). The diagnostic statistics for each OLS regression sub-model are included in order to test for residual serial correlation, normality and heteroscedasticity. The Lagrange multiplier (LM) (see Godfrey 1978) statistics are computed to test for the hypothesis of no fourth order of residual correlation; JB statistics (see Jarque and Bera, 1981) are provided to test the hypothesis of normality of residuals; The LM statistics (see Koenker 1981) are used to test the hypothesis of the homoskedasticity assumption. For the hypotheses testing for residual serial correlation and heteroscedasticity, the Microfit computer program computes two types of test statistics: the Lagrange multiplier (LM) statistics and F statistics. The LM statistic is asymptotically distributed as a chi-squared (χ^2) variate. The F statistic, which is also known as the "modified LM", is found to have the same distribution and have higher power in small sample data (see Harvey 1981, and Kiviet 1986). All F test statistics from the estimated VAR and VARECM models are not significant at the 5% level except for the Heteroscedasticity test in the USA VAR(1) model.

Furthermore, we perform the diagnostic test for the assumption of uncorrelated error terms in each VAR system: $\delta_{ij}=0$ ($i \neq j$; $i=1,2,\ldots 4$; $j=1,2,\ldots 4$), i.e., the estimated system covariance matrix of errors is diagonal and thus the estimated error terms from each sub-equation are independent.

In all VAR systems we test the following hypothesis:

$$H_0: \sigma_{12} = \sigma_{21} = \sigma_{13} = = \sigma_{31} = \sigma_{14} = \sigma_{41} = \sigma_{23} = \sigma_{32} = \sigma_{42} = \sigma_{24} = 0,$$

by computing Log-Likelihood ratio (LR) statistics:

$$LR = 2\,(LR_u - LR_r) \sim \chi^2,\ k(k-1)/2,$$

where LR_u is the ML log-likelihood ratio estimator of the residual from the estimated VAR system, and LR_r is the log-likelihood statistics of the *kth* equation computed at the OLS estimators (k=1, 2, ...4). Under the null hypothesis, LR is asymptotically distributed as a χ^2 with k(k-1)/2 degrees of freedom.

Test results are reported in Table 7.7. The test statistics are not significant at the 5% level, i.e., the assumption of uncorrelated error terms in each estimated VAR system can not be rejected at the 5% significance level. Therefore, the statistics suggest that the system-covariance matrix of errors from each VAR system is diagonal and thus the estimated error terms from each sub-equation are independent. The estimated covaraince matrix of each VAR system (see Table 7.8A-B) further confirms the test results as the covariance ratios ($\delta_{ij}=0$, $i \neq j$) are very small and close to zero compared with system covariance ratios (δ_{ij}, for i=j).

The results of the diagnostic tests indicate there is no significant evidence of model misspecification in all the VAR systems. Therefore, we further perform forecasts of tourist arrivals using the six estimated VAR models and conduct the analysis of the interrelations between the variables using the VAR systems which produce better forecasts.

7.5.3 Forecasting And Error Variance Decomposition

Four and eight step forecasts of tourist arrivals from Australia, Japan and USA using VARECM models are provided in Table 7.9(A-B), and forecasts of tourist arrivals from Australia, Japan and USA using VAR models are presented in Table 7.10(A-B) respectively. The measurement of forecasting accuracy, mean absolute error (MAE) (for definition for the MAE, please see section 5.6.1 in Chapter 5 and Equation 5.8) for each model, is also reported in the tables. As the magnitude of the number of tourist arrivals is the same for each country, we simply compare the MAEs from the forecasts generated by the three selected ARIMA models.

By comparing the MAEs of from the VAR and VARECM models respectively for each country case, we find that the VARECM models and the VAR models perform differently in terms of different forecasting periods. For four-step forecasts, the VARECM models outperform the VAR models in the cases of Japan and the USA tourist arrivals, while the VAR model outperforms the VARECM model in the case of the Australian tourist arrivals (see Table 7.9A and Table 7.10A). For the eight-step forecasts, the VARECM models outperform the VAR models in the cases of Australia and Japan tourist arrivals, while the VAR model outperforms the VARECM model in the case of USA tourist arrivals (see Table 7.9B and Table 7.10B). This suggests that the inclusion of the long-run error-correction terms based on the cointegration test improves the forecasting performance of the Australia and Japan VAR models, whereas it does not improve the forecasting performance in the case of tourist arrivals from the USA.

In a VAR system more than one step forecasts of tourist arrivals are based on the forecast values of other variables (TA, GDP and TP) in the system, which are generated from the TA, GDP and TP equations respectively. Therefore, the forecasting error of tourist arrivals is influenced by all other variables and tourist arrivals itself. The forecast error variance can be decomposed into components accounted for innovations in all variables of the system.

The forecast errors from equation (7.5) can be presented as a VAR process with a (4×1) vector of white noise residuals $\Sigma_{\omega}=I_k$, which is (4×1) unit matrix:

$$\varepsilon_t = \mu + \sum_{i=1}^{\infty} \Theta_j v_{t-i}, \tag{7.6}$$

where the contributions of innovations in variable k to the h-step forecast of variable j, ω^2_{jk} are given by

$$\omega_{ijk,h} = \sum_{i=0}^{h-1} (e_j' \Theta_i e_k) / MSE \quad [Y_{j,t}(h)], \tag{7.7}$$

where e_j is the ith column of I_k.

For the estimated four dimension VAR systems, j=1, 2, 3, 4 represents variable TU, TA, GDP and TP respectively. Therefore ω^2_{1k} (k=1, 2, 3, 4) measures the proportion of innovations in TU, TA, GDP and TP to the forecast error variance of the h-step forecast of TU.

For the analysis of forecast error variance decomposition in this section, we analyze the optimal forecasting models, namely the Australia VARECM(1), the Japan VARECM(1) and the USA VAR(1) models respectively. The forecast error variance decomposition of all four variables (i.e, proportions of ω^2_{11}, ω^2_{12}, ω^2_{13} and ω^2_{14}) are given in Table 7.11A-C, respectively, for the Australia model, Japan model and the USA model. The forecasting error variance decomposition shows the share of the variation in tourist arrivals that is due to it own shocks and also the shocks from the other variables, we are able to interpret the results as follows:

- For the Australia VARECM(1), about 94.7% of forecast error variance of tourist arrivals (TU) is accounted by its own innovations, about 2.4% by two-way trade (TA) innovations, 2.8% by GDP, and 0.1% by the relative "tourism price" (TP). This suggests that the innovations from tourist arrivals itself contribute significantly in the forecast errors of tourist arrivals, followed by TA and GDP. The effects of innovations from TP are relatively negligible.

- In the case of Japan VARECM(1) model, about 58.7% of 4-step forecast error variance of tourist arrivals is accounted by its own innovations, about 40.8% by TA, 0.4% by TP and 0.1% by GDP. For 8-step forecasts, about 48.0% of forecast error variance of tourist arrivals is contributed by own innovations, about 51.3% by TA, 0.5% by TP and 0.3% by GDP. This indicates that the innovations from two-way trade between China and Japan contribute significantly in the forecast errors of tourist arrivals. In particular, for long-term forecasts, forecasting variation in two-way trade between China and Japan impact more significantly on the forecast accuracy of tourist arrivals.
- From the USA VAR(1) model, the 4-step forecast errors are mainly attributed to innovations from tourist arrivals itself (about 83.2%), followed by GDP (8.8%), TP (7.4%) and TA (0.6%). This suggests that the innovations from tourist arrivals itself contribute significantly to the forecast errors of tourist arrivals, followed by GDP and TP. The effects of innovations from two-way trade are relatively negligible.

To summarize the decomposition analysis of forecast error variance in the three optimal VAR models, forecast error variance for tourists arrivals from Australia is mainly attributed to the variations from the tourist arrivals itself; whereas in the Japan model, variations from two-way trade contribute significantly in the forecast error variance besides the tourist arrivals itself; whist for the case of the USA, variations in GDP and TP affect the forecast error of tourist arrivals significantly in addition to the contribution from tourist arrivals itself. Therefore, the decomposition analysis of forecast error variance in the three VAR models demonstrates that variations from both the forecasted variable itself and other related variables included in the demand function influence forecasting error of tourist arrivals and the extent of the effects vary from each variable in each model. This shows the difference of forecasting features using causal methods from that using time series methods, where the forecasting errors are affected by one variable, the forecasted variable itself.

In this chapter, we summarize the interrelationship between tourism arrivals, two-way trade, GDP and the relative "tourism price" in a VAR system, which treats all four variables as endogenous variables. The Granger causality test conducted in section 7.3 also further confirms that there are interactions or feedback effects between the four variables. Therefore, an exogenous shock or innovation in one of the variables has effects on some or all of the other variables. For instance, a decrease of the tourist arrivals to China induced by political turbulence (e.g., the Tiananmen Square event in 1989), may also affect two-way trade between China and its tourist-source countries. An exogenous shock in a variable has effects on other variables if there is a causal relationship between the "shocked" variable and the remaining variables. In practice, we would like to know how long and how much an exogenous shock in a variable affects on other variables, so we could determine what is the efficient policy, say, to stimulate international tourist arrivals. Therefore, in the next section, we carry out the impulse response analysis in the three optimal VAR systems.

7.5.4 Impulse Response Analysis

In the VAR system consisting of four endogenous variables (i.e., TU TA, GDP and TP), a reaction/response of one variable to an exogenous shock may involve a number of other variables as well. An exogenous shock in a variable has effects on other variables if there is a causal relationship between the "shocked" variable and the remaining variables. Therefore, from the estimated VAR models, we can trace out the effect of an exogenous shock or innovation in one of the variables on some or all of the other variables, which is called the impulse response analysis or multiplier analysis.

Under the assumption that shocks in different variables are independent, we may assume that shocks occur only in one variable at a time. In the contemporaneous correlation test in section 7.5.2, we could not reject the null hypothesis that the system-variance matrix of the errors in the VAR model is diagonal (i.e., the autocorrelation covariances $\delta_{ij}=0$, $i \neq j$, in the system are expected to be zero). Therefore, we expect the estimated error terms in the VAR systems are independent and a shock occurs only in one variable at a time.

To isolate such an effect between TU to TA, GDP and TP in all three VAR systems, we use the simplest VAR system—VAR(1) as an example:

$$Y_t = \begin{bmatrix} TU_t \\ TA_t \\ GDP_t \\ TP_t \end{bmatrix} = A_0 X + A_1 \begin{bmatrix} TU_{t-1} \\ TA_{t-1} \\ GDP_{t-1} \\ TP_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{TU,t} \\ \varepsilon_{TA,t} \\ \varepsilon_{GDP,t} \\ \varepsilon_{TP,t} \end{bmatrix}, \tag{7.8}$$

where A_1 is a 4×4 matrices of coefficients; A_0 is a parameter matrix.

We assume that the mean of three variables (TA, GDP and TP) priori to t is zero. With $A_0=0$, $Y_t=A_1Y_{t-1} + \varepsilon_t$, to trace a unit shock in TU in time period t=0 in the system, we obtain:

$$Y_0 = A_0 Y_{-t} + \varepsilon_0 = \varepsilon_0 = \begin{bmatrix} \varepsilon_{TU,0} \\ \varepsilon_{TA,0} \\ \varepsilon_{GDP,0} \\ \varepsilon_{TP,0} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \tag{7.9}$$

$$Y_1 = A_1 Y_0, \qquad Y_2 = A_1 Y_1 = A_1^2 Y_0, \ldots, \qquad Y_t = A_1^t Y_0,$$

$$A_1 = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}.$$

By computing vector Y_t, we can trace out the responses of variables (TA, GDP, and TP) to one unit shock from TU as well as the responses of TU to shocks from TA, GDP and TP at time t (t=0, 1, 2, ...). In practice, we use a one standard deviation of forecast error as a unit shock to measure the response of variable j to a unit shock in variable k in the VAR system.

Impulse responses of three optimal VAR systems are depicted and graphed in Figure 7.1A-C, respectively, for the case of Australia, Japan and the USA. The X axis of the graphs represents the duration (quarters) of the response of one variable to one unit shocks from another variable, while the Y axis measures the level or degree of the response. The maximum horizon duration t is chosen at 25 quarters and the measuring unit of degree of response is one standard deviation. In the figures we depicted both the impulse responses of variable TU to shocks from TA, GDP and TP and the impulse responses of variable TA, GDP and TP to shocks from TU. The observations from the figures may be summarized as follows:

- First, exogenous shocks in two-way trade and the relative "tourism price" are seen to induce significant shocks in tourist arrivals in all three country cases, whereas there is no significant response to the shocks from the GDP except for the case of Australia. On the other hand, exogenous shocks in tourist arrivals are seen to induce changes in two-way trade and the relative cost of living in all three country cases, but no significant sign of shocks on GDP except for the case of the USA.
- In terms of the duration of response, the shocks last longer (over 25 quarters) in the case of Japan (see Figure 7.2A-B), followed by the case of the USA, where the shocks last up to 6 quarters (see Figure 7.3A-B). The duration of response in the case of Australia ranges from 2-3 quarters (see Figure 7.1A-B).

- In terms of the degree of response, the level of responses to one unit exogenous shocks vary from different pairs of variables in each system. For instance, one unit exogenous shock in the relative "tourism price" induces 0.06 unit shock in tourist arrivals from Japan, 0.03 unit shock in tourist arrivals from Australia, and 0.01 unit shock in tourist arrivals from the USA; one unit exogenous shock in two-way trade induces 0.04 unit shock in tourist arrivals from Japan, 0.01 unit shock in tourist arrivals from Australia and the USA.

Exogenous shocks in one variable will affect other variables which are interrelated with the shocked variable. The results of the impulse analysis indicate that: (1) in all three country cases there are feedback effects between tourist arrivals and two-way trade, and between tourists arrivals and the relative cost of living; (2) there are one-way effects from GDP to tourist arrivals in the case of Australia and the USA, but there are no interactions between tourist arrivals and GDP in the case of Japan. The results are generally consistent with the Causality test in section 7.3.

Therefore, the above results have significant implications to government policy in international tourism as well as international trade.

- For the Chinese government, the implementation of a policy in stimulating two-way trade with its tourist-source countries may induce an increase in tourist arrivals from Japan, followed by the USA and Australia; a policy change related to the reduction of the relative "tourism price" to China may induce an increase in tourist arrivals from Japan, followed by Australia and the USA. In comparison, tourist arrivals from Japan are more responsive to the trade stimulation and the response is also longer lasting; tourist arrivals from Australia are more responsive to the price promotion policy, but the response lasts for a shorter period; tourist arrivals from the USA are responsive to both the trade stimulation and the price impact and the response is of relatively medium duration compared with that in the cases of Japan and Australia. Therefore, different government policies in stimulating international tourism will have different effects to these three tourist-source countries. The government has to set its policy with different emphases according to different tourist-source country in order to achieve significant results.

- An innovation in international tourism is also seen to induce increases in the two-way trade between China and its tourist-source countries. Therefore, the implementation of a policy to promote tourist flows to China from these three countries may also stimulate the two-way trade flows. Tourism promotions are seen to induce the most significant and longest lasting two-way trade increases between China and Japan, followed by the USA and Australia. Therefore, the international tourism policies or regulations between the Chinese and Japanese governments are very important factors influencing the two-way trade growth between these two-countries.

7.6 SUMMARY AND CONCLUSION

Based on theoretical interrelationships between the four variables: tourist arrivals, the two-way trade, GDP and relative "tourism price", we have analyzed and forecasted tourism demand to China from Australia, Japan and the USA using VAR systems.

The Granger Causality test indicates that: there is a two-way causality between the two-way trade and tourist arrivals, and a two-way causality between the relative "tourism price" and tourist arrivals respectively in the case of Japan; there is a two-way causality between the relative "tourism price" and tourist arrivals in the case of the USA. The results of the Granger causality test suggests that the theoretically defined "dependent variable"—tourism demand also "causes" the "explanatory" variables defined in the single-equation models. Moreover, the two-way (or bi-directional) causalities detected by the Granger causality test suggest there are feedback effects between the theoretical dependent variables and independent variables defined in the single-equation models.

The cointegration test using the Johansen's ML procedure suggests that in all three country cases the four selected variables are cointegrated at the 5% significance level, and there are two cointegrating vectors in the case of Australia and Japan, and three in the case of the USA. Based on economic theories, one unique long-run relationship between the four variables is selected for each county case. The estimated coefficients of the "long-run" tourism demand suggest that tourism demand from Australia and the USA, is relatively more elastic to changes in the "tourism price" and GDP, whereas tourist arrivals from Japan are more responsive to the two-way trade volume with China, and are less responsive to changes in the relative "tourism price". Interestingly, the tourism demand from Japan is almost income inelastic, whereas there is a considerable two-way trade elasticity between China and Japan. This suggests that the income level in the tourist origin country and the relatively cheap "tourism price" to China are important variables to explain tourist flows to China from Australia and the USA, whereas the two-way trade volumes between China and Japan is the most important determinant of international tourism demand from Japan to China. It may reflect that, compared with tourists from Japan, relatively more visitors from Australia and the USA are on holiday than those for business purposes, while most of the visitors from Japan may be on business trips.

In accordance with the Ganger Causality test and the cointegration test, the VARECM and VAR systems for each country case were estimated respectively, and further eight-step forecasts were generated from these 6 VAR regression models. By comparing the forecasting errors from the VAR and VARECM models respectively for each country case, we find that the inclusion of the long-run error-correction term, based on the cointegration test, improves the forecasting performance of the Australia and Japan VAR models, but not in the case of tourist arrivals from the USA. This confirms the results of the cointegration test in the two of three country cases, while the long-run relationships in the case of the USA model suggested by the cointegration test are questionable.

Three optimal VAR models were selected in terms of forecasting accuracy and the impulse response analysis and the decomposition of forecast error varainces are performed in the three optimal VAR systems.

The decomposition analysis of forecast error variance demonstrates that the variations from both the forecasted variable itself and the other related variables included in the demand function influence the forecasting error of tourist arrivals; the extent of the effects vary from each variable in each model. This shows the different forecasting feature of causal methods from that of time series methods, where the forecasting errors are affected by one variable, the forecasted variable itself. The decomposition analysis of forecast error variance in the three VAR models suggests that forecast error variance for tourists arrivals from Australia is mainly attributed to the variations from the tourist arrivals itself; whereas in the Japan model, the variations from the two-way trade contribute significantly in the forecast error variance besides the tourist arrivals itself; whist for the case of the USA, variations in GDP and TP affect the forecast error of tourist arrivals significantly in addition to the contribution from tourist arrivals itself.

The impulse response analysis provides useful implications to evaluate government policy with respect to international tourism and trade stimulation. For the Chinese government, the implementation of a policy in stimulating the two-way trade with its tourist-source countries may induce a significant increase in tourist arrivals from Japan, followed by the USA and Australia; a policy change in relation to a decrease in the relative "tourism price" to China will induce a significant increase in the tourist arrivals from Japan, followed by Australia and the USA. However, as the duration and degree of the response are seen to vary from different country cases, the government stimulation policy related to trade and the relative "tourism price" respectively may have different effects on these three tourist-source countries. Therefore, the government has to set its target tourist source country in order to achieve significant results in tourism stimulation policy. On the other hand, the implementation of a policy to promote tourist flows to China from these three countries will also stimulate their two-way trade flows. Tourism promotion are seen to induce the most significant and longest lasting two-way trade increases between China and Japan, followed by the USA and Australia. Therefore, the international tourism policies or regulations between Chinese and Japanese government are very important factors influencing the two-way trade growth between these two-countries. It is worth noting that a policy of either trade promotion or tourism promotion may create a "virtuous circle" whereby the endogeneity from one to the other provides a further feedback stimulus from trade to travel and vice versa.

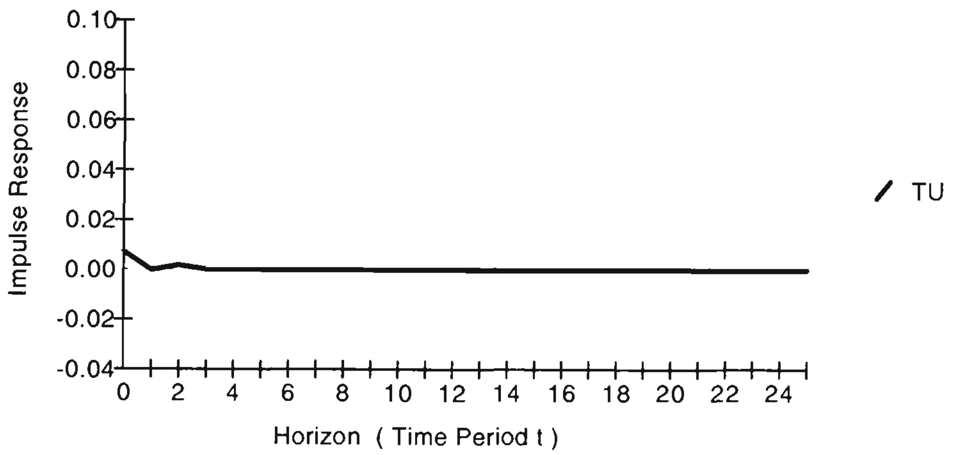
To conclude, the empirical results from the estimated long-run demand functions suggest that the two-way trade between China and its tourist-source countries is one of the most important determinants of tourism demand to China from origin countries with a high proportion of business travel. It provides further support to the idea that trade volumes between a tourist source country and a destination country may be an important independent variable, which should be considered in the international tourism demand modeling, especially for the modeling of international business travel. The results reported here provide further support to the recent study by Kulendran and Wilson (2000b) who argue that the role of international trade as a determinant of international travel has been neglected in the research of international travel and this should no longer be acceptable.

The analysis of the three VAR systems, including the causality test and the impulse response analysis, indicates that the four selected variables, namely tourism demand, two-way trade, GDP and the relative "tourism price", are interrelated in most of the cases. There are feedback effects between tourist arrivals and two-way trade volumes, tourist arrivals and the relative "tourism price". More explicitly, two-way trade volumes, GDP at the three tourist-source countries, and the relative "tourism price" are important determinants of tourism demand and hence influence tourism growth and decline in China. On the other hand, however, changes in tourist arrivals will also result in changes in the relative "tourism price" and two-way trade. Therefore, tourism demand modeling and forecasting using single-equation models suffers from the biases by ignoring of these feedback effects between these variables.

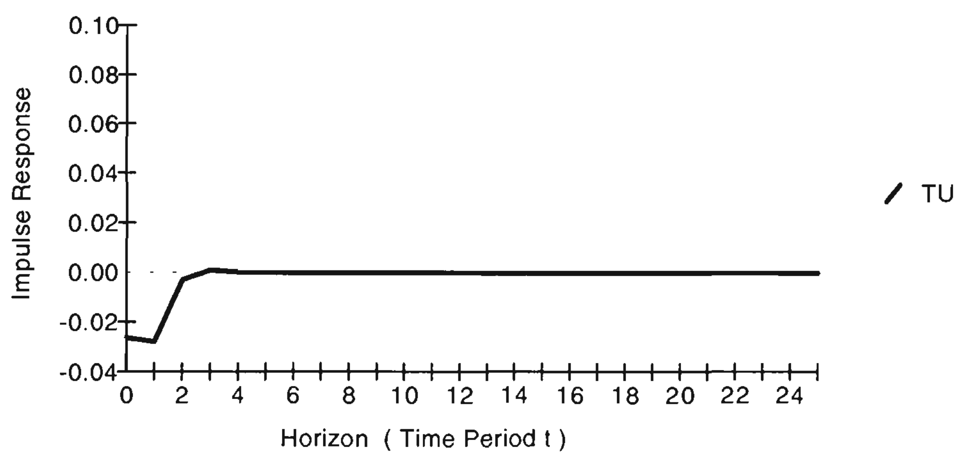
There are some limitations in the analysis of VAR models. Although in real economic systems economic indicators are mostly interrelated, we have to work on low-dimensional VAR systems, as it is impossible to include all the related variables in our VAR systems. All effects of omitted variables are assumed to be in the innovations. If some important variables are omitted from the system this may lead to major distortions in the impulse responses. Moreover, the forecasting performance of the VAR models need to be further evaluated by comparison with other forecasting methods, such as time series and naive models. Therefore, in the next chapter we will undertake a more detailed forecast comparison analysis by using a range of measures of forecasting accuracy.

Figure 7.1 A: Impulse Responses of TU to One Unit Shocks from TA, GDP and TP: the Australia VARECM(1)

Impulse Responses to Shocks from TA



Impulse Response to Shocks from GDP



Impulse Responses to Shocks from TP

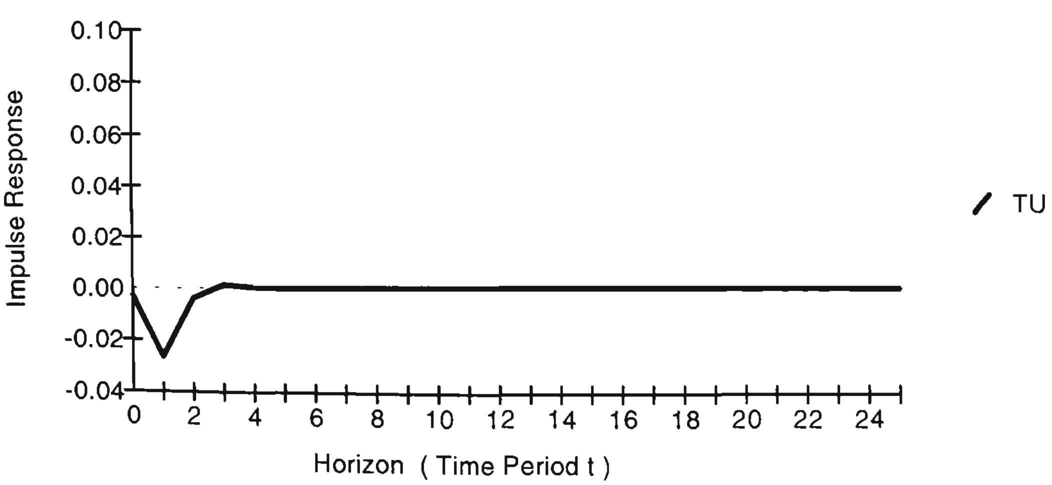


Figure 7.1B: Impulse Responses of TA, GDP and TP to One Unit Shocks from TU: the Australia VARECM(1)

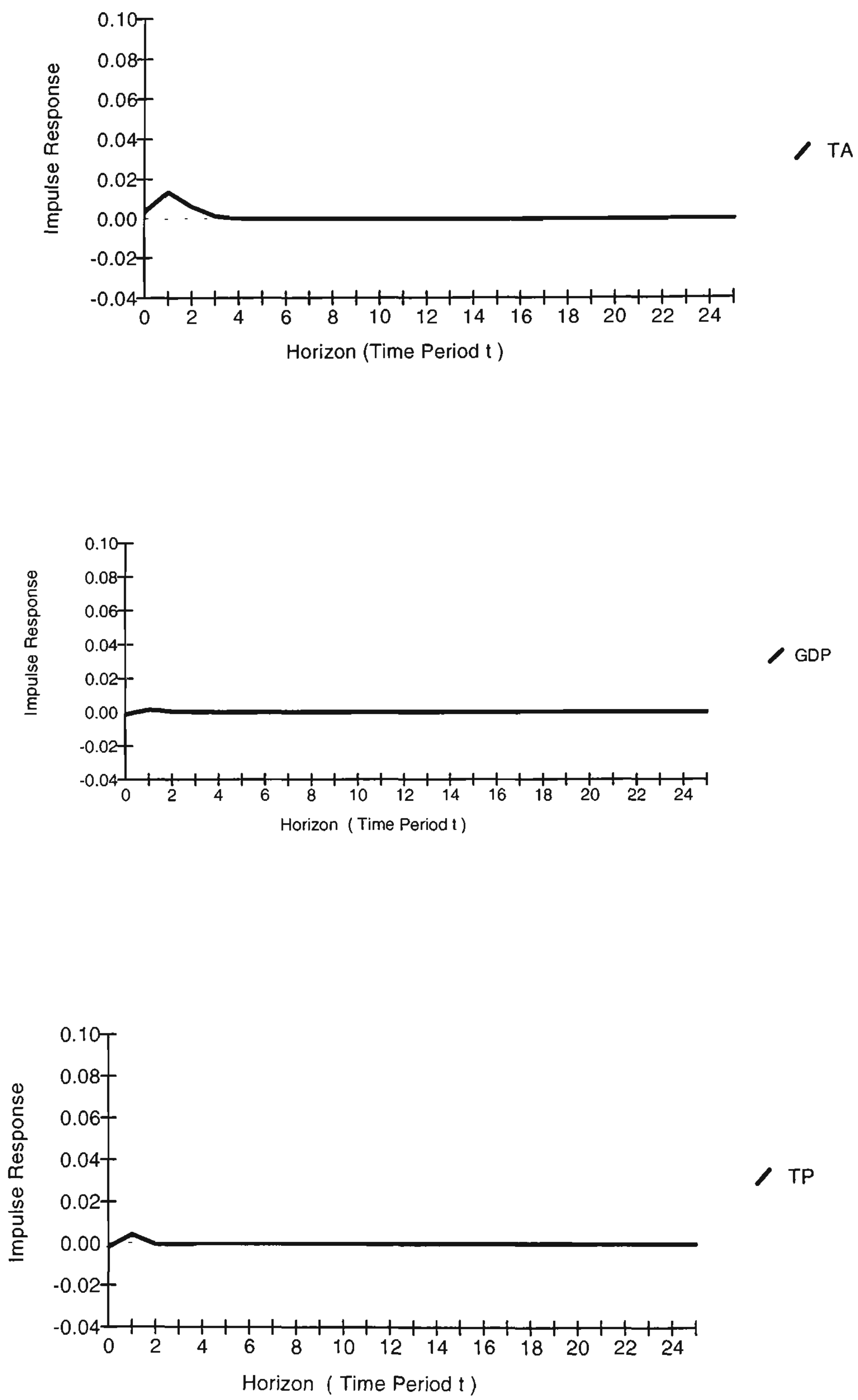
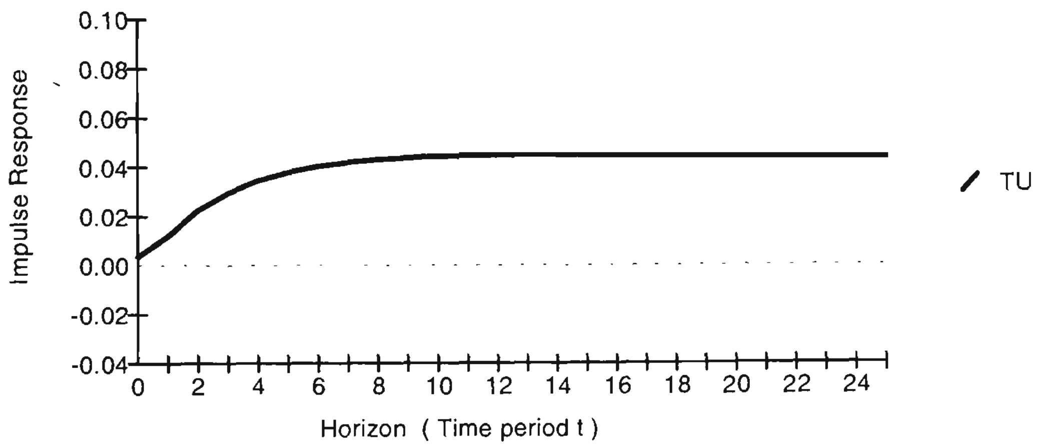
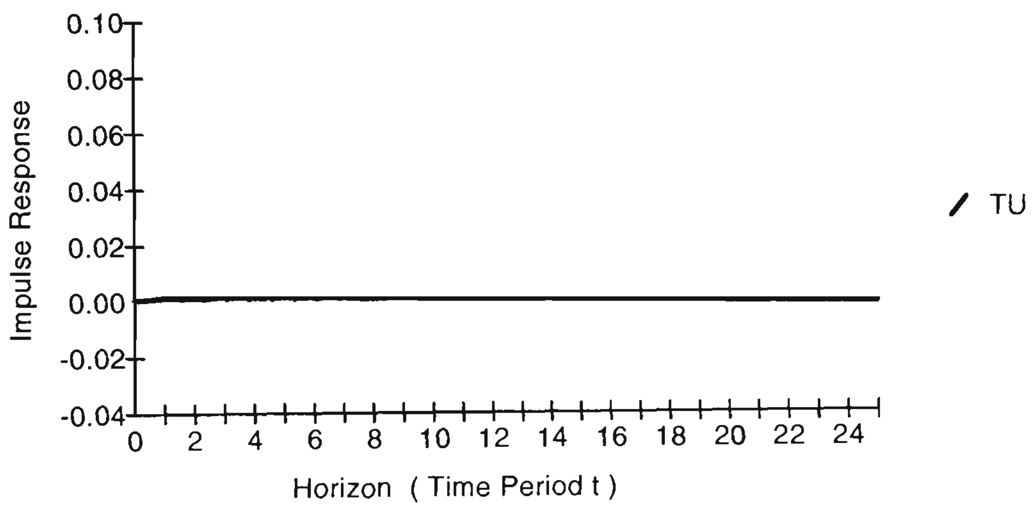


Figure 7.2A: Impulse Response of TU to One Unit Shocks from TA, GDP and TP: the Japan VARECM(1)

Impulse Responses to Shocks from TA



Impulse Responses to Shocks from GDP



Impulse Responses to Shocks from TP

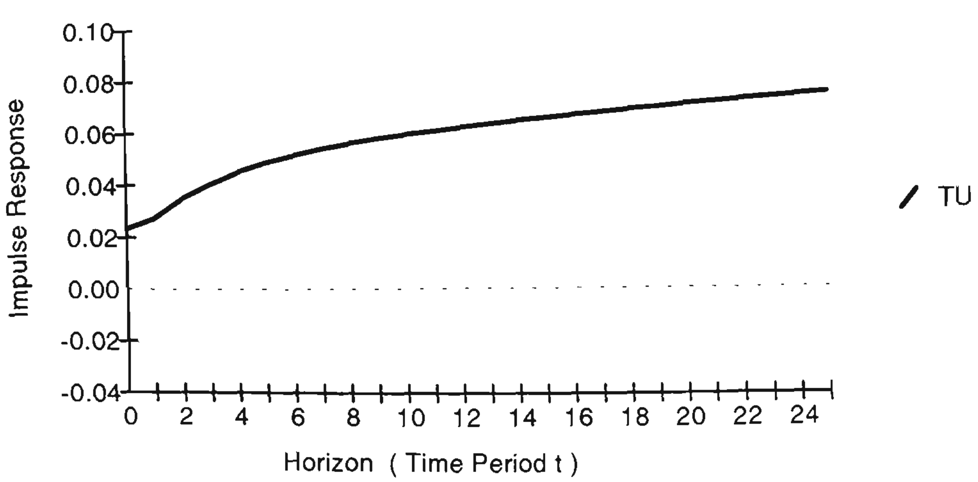


Figure 7.2B: Impulse Response of TA, GDP and TP to One Unit Shocks from TU: the Japan VARECM(1)

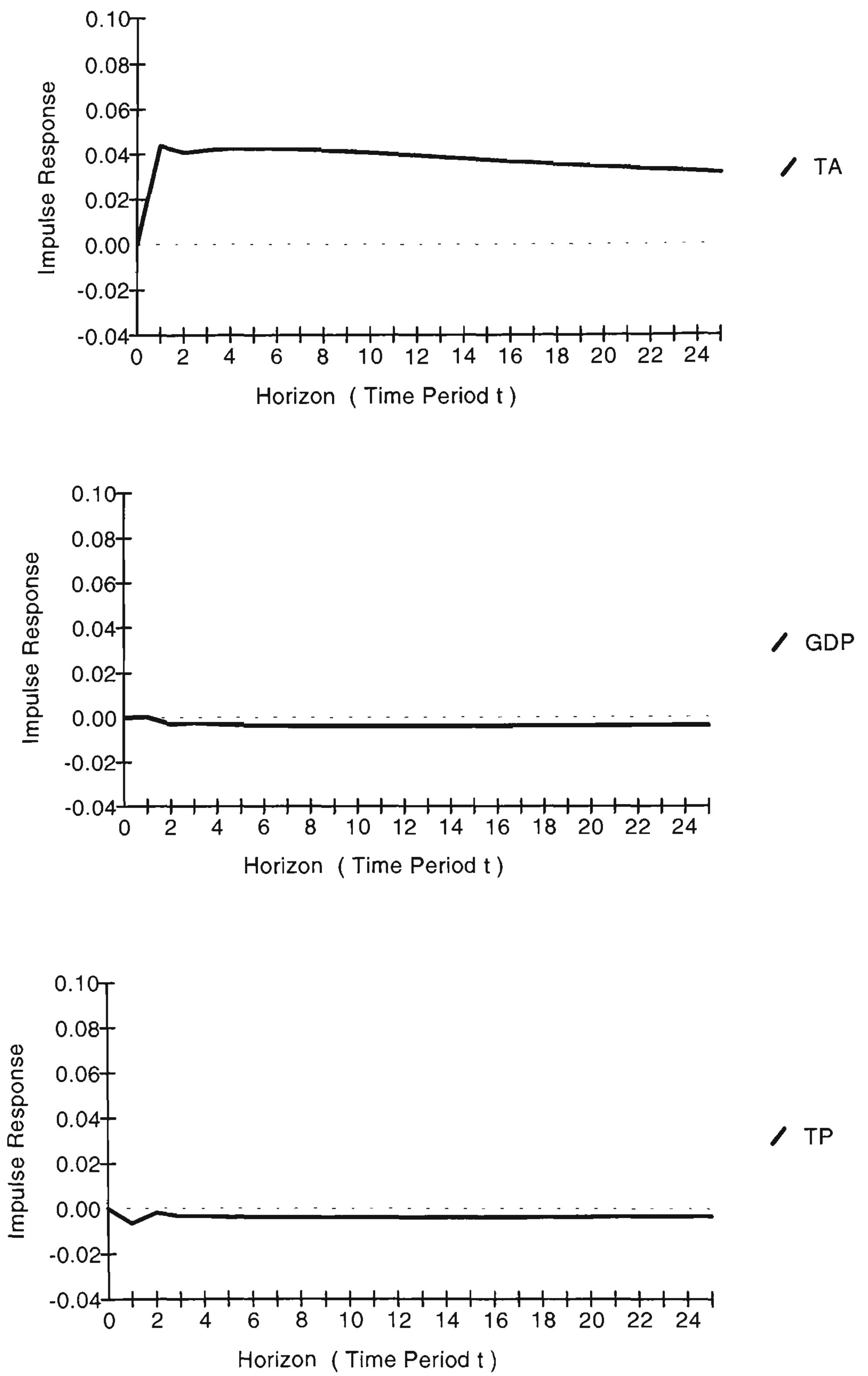
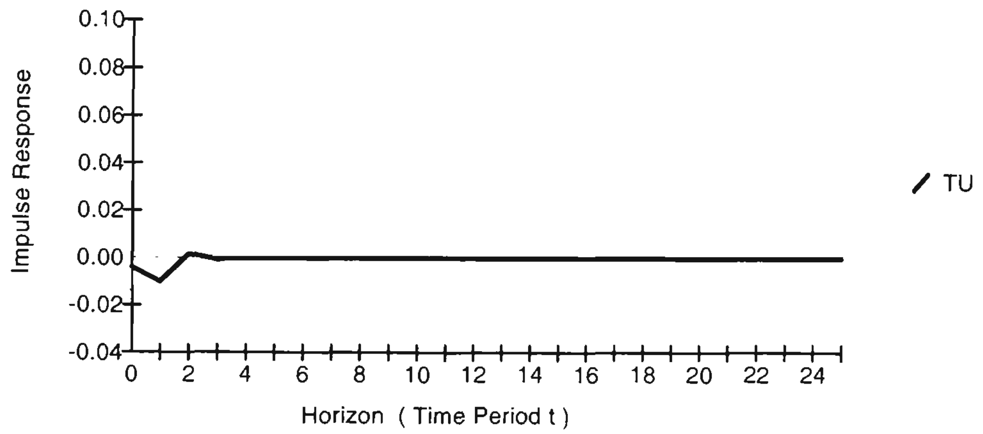
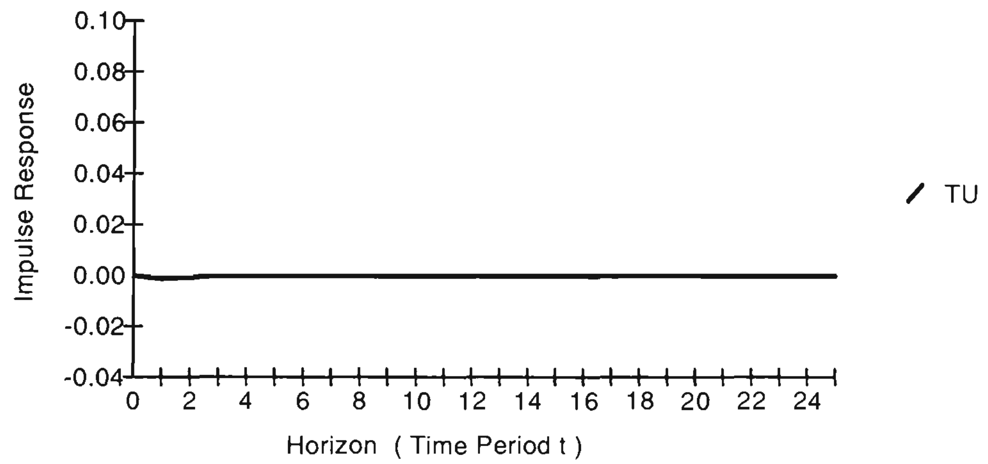


Figure 7.3A: Impulse Response of TA, GDP and TP to One Unit Shocks from TU: the USA VAR(1)

Impulse Responses to Shocks from TA



Impulse Responses to Shocks from GDP



Impulse Responses to Shocks from TP

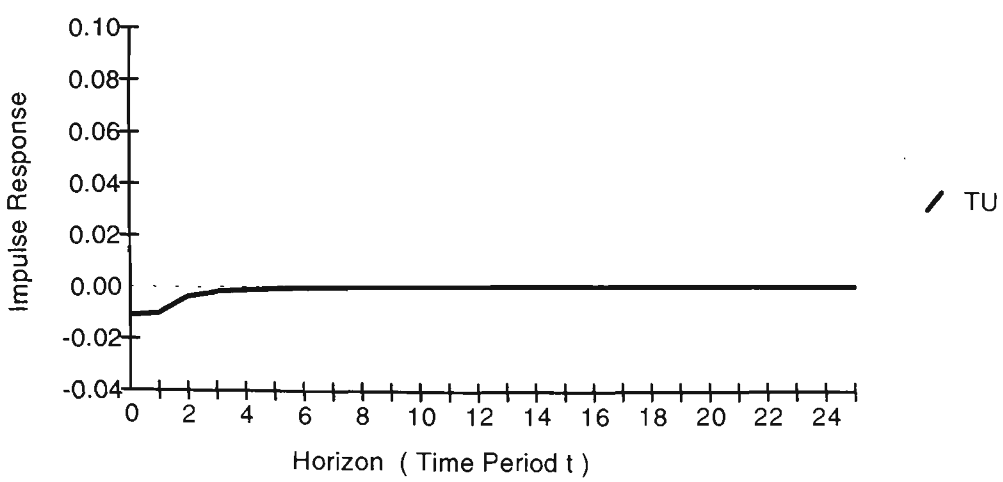


Figure 7.3B: Impulse Response of TA, GDP and TP to One Unit Shocks from TU: the USA VAR(1)

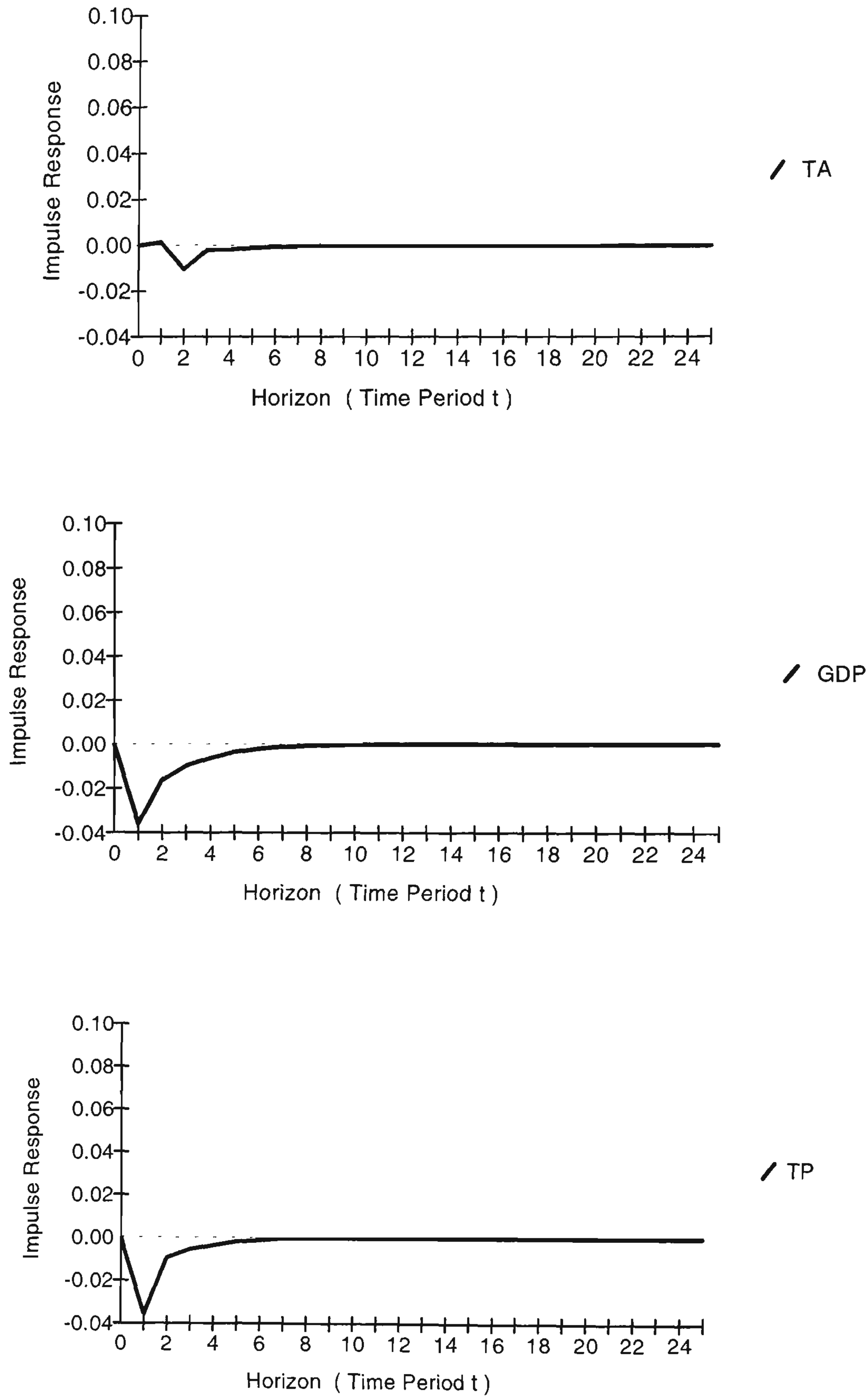


Table 7.1: Statistics Testing for the Order of VAR Models

Origin County	Order P	AIC	SBC
Australia	1	332.6537*	281.4261*
	2	330.0222	263.0323
	3	319.4486	236.6963
	4	316.4810	217.9664
	5	313.8797	199.6027
Japan	1	327.9654	272.7972*
	2	321.2423	250.3118
	3	330.6343	243.9415
	4	326.7033	224.2841
	5	331.7953*	213.5778
USA	1	359.5497	313.6612*
	2	369.7992	308.6145
	3	372.2478*	295.7669
	4	368.5325	276.7554
	5	361.3906	254.3173

Note: * are the maximum values of AIC and SBC indicating the number of lagged terms where there is no serial error correlation in the regression model.

Table 7.2: LR Statistics Testing for the Block Granger Causality

H_0: Non-Causality	TA TU → GDP TP	TU TA → GDP TP	TU GDP→ TA TP	TU TP → GDP TA	TA GDP →TU TP
Australia VAR(1) $\chi^2(3)$	10.9799*	6.7744	6.3405	1.7382	11.0395*
Japan VAR(3) $\chi^2(9)$	20.1026*	41.1743*	6.1552	20.7277*	35.2401*
USA VAR(1) $\chi^2(3)$	9.1715*	3.1883	7.4134	13.4441*	16.1619*

Notes: * indicates statistics are significant at the 5% significance level.

Table 7.3A: Cointegration Test $\Lambda_1(q, T)$

Origin Country	VAR Order k	H_o	H_a	LR Statistics
Australia	1	$r=0$	$r\geq1$	100.4392*
		$r\leq1$	$r\geq2$	33.1081*
		$r\leq2$	$r\geq3$	6.3825
Japan	1	$r=0$	$r\geq1$	76.9814*
		$r\leq1$	$r\geq2$	24.0680*
		$r\leq2$	$r\geq3$	4.0650
US	1	$r=0$	$r\geq1$	124.6564*
		$r\leq1$	$r\geq2$	52.6387*
		$r\leq2$	$r\geq3$	13.7532*
		$r\leq3$	$r\geq4$	0.68674
Critical Values (5%)		$r=0$	$r\geq1$	***39.8100***
		$r\leq1$	$r\geq2$	***24.0500***
		$r\leq2$	$r\geq3$	***12.3600***
		$r\leq3$	$r\geq4$	***4.1600***

Note: * indicates statistics testing r (number of cointegration vectors) are significant at the 5% significance level.

Table 7.3B: Cointegration Test $\Lambda_1(q, q+1)$

Origin Country	VAR Order	H_o	H_a	LR Statistics
Australia	1	$r=0$	$r=1$	67.3310*
		$r\leq1$	$r=2$	26.7257*
		$r\leq2$	$r=3$	4.0552
Japan	1	$r=0$	$r=1$	52.9133*
		$r\leq1$	$r=2$	20.0031*
		$r\leq2$	$r=3$	2.8619
US	1	$r=0$	$r\geq1$	72.0177*
		$r\leq1$	$r\geq2$	38.8855*
		$r\leq2$	$r\geq3$	13.0665*
		$r\leq3$	$r\geq4$	0.6874
Critical Values (5%)		$r=0$	$r\geq1$	***23.9200***
		$r\leq1$	$r\geq2$	***17.6800***
		$r\leq2$	$r\geq3$	***11.0300***
		$r\leq3$	$r\geq4$	***4.1600***

Note: * indicates statistics testing r (number of cointegration vectors) are significant at the 5% significance level.

Table 7.4: Estimated Long-Run Equilibrium of Tourism Demand

Origin Country	Tourism Demand Function
Australia	-1.1257 *TU + 1.3236*TA – 1.6115*GDP + 1.2185*TP =0
	-0.2726 *TU + 0.0394*TA + 0.1499*GDP – 0.1971*TP = 0
Japan	0.1176 *TU – 0.2576*TA + 0.1612*GDP + 0.1114*TP = 0
	-0.7800 *TU + 0.6516*TA + 0.0321*GDP – 0.1911*TP = 0
USA	0.1035 *TU + 0.0369*TA – 0.2051*GDP + 0.3698*TP =0
	0.5680 *TU – 0.1641*TA – 0.2207*GDP + 0.2472*TP = 0
	0.1223 *TU – 0.3251*TA + 0.4575*GDP – 0.5826*TP = 0

Table 7.5A: Estimation of ECM for Variable TU based on 2 Cointegrating Vectors: Tourist Arrivals from Australia

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	-0.5360	0.5771	-.92875[.358]
ΔTU_{t-1}	0.1209	0.1357	.89054[.378]
ΔTA_{t-1}	0.0366	0.1011	.36195[.719]
ΔGDP_{t-1}	-1.5218	1.8648	-.81610[.419]
ΔTP_{t-1}	-0.0335	0.1964	-.17047[.865]
$U_{1,t-1}$	0.1039	0.0998	1.0408[.304]
$U_{2,t-1}$	0.0941	0.0998	.94277[.351]
S1	-0.0841	0.0408	-2.0626[.045]
S2	0.0603	0.0455	1.3238[.193]
S3	-0.0403	0.0419	-.96349[.341]
D1	-0.4249	0.1039	-4.0889[.000]
D2	-0.4672	0.0798	-5.8557[.000]
D3	0.1060	0.1353	.78351[.438]
D4	0.0195	0.1265	.15425[.878]
D5	-0.0707	0.1103	-.64136[.525]
R-Squared			0.6491
R-Bar-Squared			0.5349
F(14, 43)			5.6826(.000)
Equation Log-likelihood			60.0173
System Log-likelihood			430.9437

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 5.8314[.212]	F(4, 39) = 1.0898[.375]
B: Normality	CHSQ (2) = 1.2443[.537]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 1.0801[.299]	F(1, 56) = 1.0627[.307]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 7.5B: Estimation of ECM for Variable TU based on 2 Cointegrating Vectors: Tourist Arrivals from Japan

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	1.0008	0.3553	2.8171[.007]
ΔTU_{t-1}	-0.1276	0.0824	-1.5480[.129]
ΔTA_{t-1}	0.3204	0.1111	2.8850[.006]
ΔGDP_{t-1}	0.2060	1.0741	.19178[.849]
ΔTP_{t-1}	-0.0238	0.1290	-.18417[.855]
$U_{1,t-1}$	-0.2191	0.0669	-3.2751[.002]
$U_{2,t-1}$	0.0940	0.0669	1.4051[.167]
S1	-0.1418	0.0326	-4.3498[.000]
S2	0.2458	0.0359	6.8540[.000]
S3	0.2258	0.0284	7.9397[.000]
D1	-0.2572	0.0718	-3.5803[.001]
D2	-0.9032	0.0747	-12.0941[.000]
D3	0.1900	0.0925	2.0538[.046]
D4	0.1574	0.0727	2.1645[.036]
D5	0.0429	0.0747	.57437[.569]
D6	-0.0246	0.0720	-.34094[.735]
R-Squared			.9235
R-Bar-Squared			0.8962
F(15, 42)			33.8021[.000]
Equation Log-likelihood			83.9408
System Log-likelihood			437.9246

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 2.4034[.662]	F(4, 38) = 0.4107[.800]
B: Normality	CHSQ (2) = 0.22991[.861]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.3907[.532]	F(1, 56) = 0.3798[.540]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C: Based on the regression of squared residuals on squared fitted values

Table 7.5C: Estimation of ECM for Variable TU based on 3 Cointegrating Vectors: Tourist Arrivals from the USA

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	0.8487	3.2783	.25890[.798]
ΔTU_{t-1}	-0.0949	0.1452	-.65377[.519]
ΔTA_{t-1}	0.0658	0.1654	.39791[.694]
ΔGDP_{t-1}	0.3789	2.2401	.16913[.867]
ΔTP_{t-1}	-0.1415	0.2370	-.59684[.555]
ΔTU_{t-2}	-0.1481	0.1455	-1.0180[.317]
ΔTA_{t-2}	-0.2324	0.1602	-1.4505[.158]
ΔGDP_{t-2}	-1.5767	2.2079	-.71414[.481]
ΔTP_{t-2}	0.1889	0.2401	.78673[.438]
ΔTU_{t-3}	-0.1670	0.1272	-1.3129[.200]
ΔTA_{t-3}	0.0669	0.1333	.50201[.620]
ΔGDP_{t-3}	-0.7399	2.1669	-.34144[.735]
ΔTP_{t-3}	-0.2302	0.2370	-.97129[.340]
ΔTU_{t-4}	0.2238	0.1105	2.0260[.052]
ΔTA_{t-4}	-0.4299	0.1260	-3.4110[.002]
ΔGDP_{t-4}	2.4023	2.1350	1.1252[.270]
ΔTP_{t-4}	0.4525	0.2323	1.9482[.061]
$U_{1,t-1}$	-0.2259	0.0790	-2.8601[.008]
$U_{2,t-1}$	-0.0666	0.0790	-.84327[.406]
$U_{3,t-1}$	0.1189	0.0790	1.5055[.143]
S1	-0.4432	0.1354	-3.2726[.003]
S2	0.1733	0.1157	1.4979[.145]
S3	-0.2267	0.1554	-1.4588[.156]
D1	-0.2021	0.0997	-2.0262[.052]
D2	-0.8102	0.1024	-7.9133[.000]
D3	-0.2835	0.1475	-1.9224[.065]
D4	0.0519	0.0997	.52048[.607]
R-Squared			0.9556
R-Bar-Squared			0.9144
F(26, 28)			23.1887[.000]
Equation Log-likelihood			80.1418
System Log-likelihood			517.2455

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 16.1542[.003]	F(4, 24) = 2.4951[.070]
B: Normality	CHSQ (2) = 0.9822[.612]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.2365[.627]	F(1, 53) = 0.2289[.634]

A: Lagrange multiplier test of residual serial correlation
B: Based on a test of skewness and kurtosis of residuals
C: Based on the regression of squared residuals on squared fitted values.

Table 7.6A: OLS Estimation of the TU Equation in VAR(1): Tourist Arrivals from Australia

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	-0.0041	0.1213	-.0339[.973]
ΔTA_{t-1}	0.1243	0.0840	1.4797[.146]
ΔGDP_{t-1}	-2.0573	1.7323	-1.1876[.241]
ΔTP_{t-1}	-0.0625	0.1942	-.3218[.749]
A	0.0620	0.0338	1.8342[.073]
S1	-0.0709	0.0404	-1.7546[.086]
S2	0.0645	0.0454	1.4206[.162]
S3	-0.0267	0.0415	-.6441[.523]
D1	-0.4239	0.1041	-4.0718[.000]
D2	-0.4700	0.0791	-5.9396[.000]
D3	0.1949	0.1215	1.6036[.116]
D4	0.1124	0.1092	1.0298[.309]
D5	-0.0387	0.1064	-.3640[.718]
R-Squared			0.6281
R-Bar-Squared			0.5289
F(12, 45)			6.3330[.000]
Equation Log-likelihood			58.5259
System Log-likelihood			403.1156

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 6.8305[.145]	F(4, 41) = 1.3682[.262]
B: Normality	CHSQ (2) = 1.5969[.450]	Not applicable
C: Heteroscedasticity	CHSQ (1) = .77562[.378]	F(1, 56) = .75903[.387]

A: Lagrange multiplier test of residual serial correlation
B: Based on a test of skewness and kurtosis of residuals
C: Based on the regression of squared residuals on squared fitted values

Table 7.6B: OLS Estimation of The TU Equation in VAR(3): Tourist Arrivals from Japan

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	-0.3812	0.0851	-4.4750[.000]
ΔTU_{t-2}	-0.0617	0.1463	-.42208[.676]
ΔTU_{t-3}	-0.2231	0.0800	-2.7868[.009]
ΔTA_{t-1}	0.4794	0.1169	4.0992[.000]
ΔTA_{t-2}	0.1690	0.1365	1.2381[.224]
ΔTA_{t-3}	-0.1506	0.1324	-1.1370[.263]
ΔGDP_{t-1}	0.2400	1.2323	.1947[.847]
ΔGDP_{t-2}	-0.6216	1.1847	-.5247[.603]
ΔGDP_{t-3}	-0.0547	1.2945	-.0423[.966]
ΔTP_{t-1}	-0.2087	0.1267	-1.6467[.109]
ΔTP_{t-2}	-0.1642	0.1230	-1.3349[.191]
ΔTP_{t-3}	-0.1437	0.1229	-1.1687[.251]
A	-0.1005	0.0399	-2.5150[.017]
S1	-0.0477	0.0466	-1.0233[.313]
S2	0.3252	0.0535	6.0745[.000]
S3	0.2891	0.0842	3.4323[.002]
D1	-0.2556	0.0768	-3.3274[.002]
D2	-0.8942	0.0770	-11.6096[.000]
D3	0.3029	0.1767	1.7136[.096]
D4	0.3039	0.0976	3.1116[.004]
D5	0.0534	0.0773	.6911[.494]
D6	-0.0321	0.0729	-.4410[.662]
R-Squared			0.9338
R-Bar-Squared			0.8930
F(21, 34)			22.8571[.000]
Equation Log-likelihood			85.5524
System Log-likelihood			437.7543

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 4.9517[.292]	F(4, 30) = .72750[.580]
B: Normality	CHSQ (2) = .20685[.902]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 1.1297[.288]	F(1, 54) = 1.1118[.296]

A: Lagrange multiplier test of residual serial correlation
B: Based on a test of skewness and kurtosis of residuals
C: Based on the regression of squared residuals on squared fitted value.

Table 7.6C: OLS Estimation of the TU Equation in VAR (1): Tourist Arrivals from the USA

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	0.2489	0.1310	1.8996[.064]
ΔTA_{t-1}	0.1174	0.1608	.72992[.469]
ΔGDP_{t-1}	-7.0206	3.2396	-2.1671[.036]
ΔTP_{t-1}	-0.9089	0.2953	-3.0774[.004]
A	0.1405	0.0415	3.3787[.002]
S1	0.0278	0.0516	.5383[.593]
S2	-0.0351	0.0806	-.4358[.665]
S3	-0.0266	0.0521	-.5099[.613]
D1	-0.5205	0.1070	-4.8627[.000]
D2	0.4134	0.1290	3.2034[.003]
D3	0.1600	0.1429	1.1191[.269]
D4	0.0158	0.1239	.1277[.899]
R-Squared			0.7564
R-Bar-Squared			0.6941
F(11, 43)			12.1393[.000]
Equation Log-likelihood			47.1368
System Log-likelihood			435.9012

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ(4) = 5.6992[.223]	F(4, 39) = 1.1271[.358]
B: Normality	CHSQ(2) = 5.8532[.054]	Not applicable
C: Heteroscedasticity	CHSQ(1) = 6.1093[.013]	F(1, 53) = 6.6228[.013]

A: Lagrange multiplier test of residual serial correlation
B: Based on a test of skewness and kurtosis of residuals
C: Based on the regression of squared residuals on squared fitted values.

Table 7.7:Tests for Contemporaneous Correlation of Residuals

LR Statistics	Australia Model	Japan Model	USA Model
	VARECM(1)	VARECM(1)	VARECM(4)
$\chi^2(6)$	3.9864	11.5222	11.7202
	VAR(1)	VAR(3)	VAR(1)
$\chi^2(6)$	6.1478	4.238	9.2934

Note: $\chi^2(6)$=12.59 at the 5% significance level.

Table 7.8A: Estimated Covariance Matrix of VARECM Residuals

VAR System	Sub-Model	TU	TA	GDP	TP
Australia VARECM(1)	TU	0.0118	0.0008	0.0002	0.0003
	TA		0.0191	-0.0002	0.0004
	GDP			0.0001	0.0001
	TP				0.0014
Japan VARECM(1)	TU	0.0047	0.0002	0.0000	0.0015
	TA		0.0072	-0.0001	0.0007
	GDP			0.0001	0.0001
	TP				0.0049
USA VARECM(4)	TU	0.0069	-0.0008	-0.0000	-0.0005
	TA		0.0061	0.0001	0.0005
	GDP			0.0000	0.0000
	TP				0.0013

Table 7.8B: Estimated Covariance Matrix of VAR Residuals

VAR System	Sub-Model	TU	TA	GDP	TP
Australia VAR(1)	TU	0.0100	-0.0001	-0.0001	-0.0000
	TA		0.0240	0.0002	0.0009
	GDP			0.0001	0.0001
	TP				0.0020
Japan VAR(3)	TU	0.0045	-0.0000	-0.0000	0.0003
	TA		0.0076	-0.0001	0.0007
	GDP			0.0001	-0.0001
	TP				0.0050
USA VAR(1)	TU	0.0135	-0.0006	-0.0000	-0.0012
	TA		0.0102	0.0000	0.0011
	GDP			0.0000	0.0000
	TP				0.0018

Table 7.9A: Four-Step Forecasts of Tourist arrivals (1000 Persons) by VARECM Models

Period	Australia		Japan		USA	
	Actual Values	Forecasts	Actual Values	Forecasts	Actual Values	Forecasts
1998Q1	41.3	46.1	344	334	138	132
1998Q2	48.4	51.5	361	402	187	177
1998Q3	46.5	52.7	435	476	167	156
1998Q4	49.9	53.0	433	425	174	171
MAE*		4.31		25.26		7.61

Note: * for Mean Absolute Errors

Table 7.9B: Eight-Step Forecasts of Tourist Arrivals (1000 Persons) by VARECM Models

Period	Australia		Japan		USA	
	Actual Values	Forecasts	Actual Values	Forecasts	Actual Values	Forecasts
1998Q1	41.3	46.1	344	334	138	132
1998Q2	48.4	51.5	361	402	187	177
1998Q3	46.5	52.7	435	476	167	156
1998Q4	49.9	53.0	433	425	174	171
1999Q1	45.6	52.0	403	355	158	137
1999Q2	49.4	58.3	426	424	196	190
1999Q3	50.8	59.3	502	504	187	165
1999Q4	57.8	59.6	524	450	196	182
MAE		5.33		27.96		11.62

Table 7.10A: Four-Step Forecasts of Tourist Arrivals (1000 Persons) by VAR Models

Period	Australia		Japan		USA	
	Actual Values	Forecasts	Actual Values	Forecasts	Actual Values	Forecasts
1998Q1	41.3	45.0	344	345	138	155
1998Q2	48.4	50.0	361	418	187	180
1998Q3	46.5	51.0	435	501	167	161
1998Q4	49.9	53.9	433	466	174	181
MAPE		3.43		40.20		9.20

Table 7.10B: Eight-Step Forecasts of Tourist Arrivals (1000 Persons) by VAR Models

Period	Australia		Japan		USA	
	Actual Values	Forecasts	Actual Values	Forecasts	Actual Values	Forecasts
1998Q1	41.3	45.0	344	345	138	155
1998Q2	48.4	50.0	361	418	187	180
1998Q3	46.5	51.0	435	501	167	161
1998Q4	49.9	53.9	433	466	174	181
1999Q1	45.6	52.6	403	392	158	179
1999Q2	49.4	58.8	426	469	196	197
1999Q3	50.8	60.0	502	552	187	175
1999Q4	57.8	63.4	524	515	196	201
MAE		5.57		34.29		9.41

Table 7.11A: Decomposition of Forecast Error Variance for the Australia VARECM(1)

Horizon (Quarter)	TU	TA	GDP	TP
0	1.0000	0.0000	0.0000	0.0000
1	0.9473	0.0242	0.0278	0.0007
2	0.9470	0.0243	0.0278	0.0009
3	0.9470	0.0243	0.0279	0.0009
4	0.9470	0.0243	0.0279	0.0009
5	0.9470	0.0243	0.0279	0.0009
6	0.9470	0.0243	0.0279	0.0009
7	0.9470	0.0243	0.0279	0.0009
8	0.9470	0.0243	0.0279	0.0009
9	0.9470	0.0243	0.0279	0.0009
10	0.9470	0.0243	0.0279	0.0009
11	0.9470	0.0243	0.0279	0.0009
12	0.9470	0.0243	0.0279	0.0009
13	0.9470	0.0243	0.0279	0.0009
14	0.9470	0.0243	0.0279	0.0009
15	0.9470	0.0243	0.0279	0.0009
16	0.9470	0.0243	0.0279	0.0009
17	0.9470	0.0243	0.0279	0.0009
18	0.9470	0.0243	0.0279	0.0009
19	0.9470	0.0243	0.0279	0.0009
20	0.9470	0.0243	0.0279	0.0009

Table 7.11B: Decomposition of Forecast Error Variance for the Japan VARECM(1)

Horizon (Quarter)	TU	TA	GDP	TP
0	1.0000	0.0000	0.0000	0.0000
1	0.7679	0.2268	0.0000	0.0053
2	0.6875	0.3075	0.0008	0.0042
3	0.6308	0.3642	0.0010	0.0040
4	0.5867	0.4079	0.0013	0.0041
5	0.5517	0.4424	0.0017	0.0042
6	0.5232	0.4704	0.0021	0.0043
7	0.4996	0.4935	0.0024	0.0045
8	0.4799	0.5127	0.0027	0.0046
9	0.4633	0.5290	0.0030	0.0048
10	0.4490	0.5428	0.0033	0.0049
11	0.4367	0.5547	0.0035	0.0050
12	0.4261	0.5651	0.0037	0.0051
13	0.4167	0.5741	0.0040	0.0052
14	0.4085	0.5820	0.0042	0.0053
15	0.4013	0.5890	0.0043	0.0054
16	0.3948	0.5952	0.0045	0.0055
17	0.3890	0.6008	0.0047	0.0056
18	0.3837	0.6058	0.0048	0.0057
19	0.3790	0.6103	0.0050	0.0057
20	0.3747	0.6144	0.0051	0.0058

Table 7.11C: Decomposition of Forecast Error Variance for the USA VAR(1)

Horizon (Quarter)	TU	TA	GDP	TP
0	1.0000	0.0000	0.0000	0.0000
1	0.8534	0.0001	0.0732	0.0733
2	0.8379	0.0057	0.0829	0.0735
3	0.8341	0.0058	0.0863	0.0737
4	0.8324	0.0059	0.0878	0.0739
5	0.8318	0.0060	0.0883	0.0739
6	0.8316	0.0060	0.0884	0.0739
7	0.8316	0.0060	0.0885	0.0739
8	0.8315	0.0060	0.0885	0.0739
9	0.8315	0.0060	0.0885	0.0739
10	0.8315	0.0060	0.0885	0.0739
11	0.8315	0.0060	0.0885	0.0739
12	0.8315	0.0060	0.0885	0.0739
13	0.8315	0.0060	0.0885	0.0739
14	0.8315	0.0060	0.0885	0.0739
15	0.8315	0.0060	0.0885	0.0739
16	0.8315	0.0060	0.0885	0.0739
17	0.8315	0.0060	0.0885	0.0739
18	0.8315	0.0060	0.0885	0.0739
19	0.8315	0.0060	0.0885	0.0739
20	0.8315	0.0060	0.0885	0.0739

CHAPTER 8: FORECASTING COMPARISON

8.1. INTRODUCTION

In order to evaluate the forecasting performance of the VAR models developed in Chapter 7, in this chapter, we employ time series methods including naïve models to generate forecasts of the quarterly tourist flows to China from Australia, Japan and the USA.

Unlike a regression model that is usually generated based on economic theories, a time series forecasting model relates the values of tourism demand to its past values; forecasts of tourism demand are generated based solely on the historical pattern of the data, assuming that the pattern will continue in the future. In recent years, time series models have been developed to generate forecasts that compare favourably in terms of accuracy with those generated by regression models in many contexts (e.g., Armstrong 1978, Arora and Smyth 1990, and Ash *et al.* 1990). Many studies of tourism demand forecasting (e.g., Witt and Wiit 1995, and Kulendran and King 1997) have also found that the time series models and naïve models outperform the econometric models in short-term forecasting. For more than two decades, the Box-Jenkins approach (see Box and Jenkins 1976) has been the most sophisticated time-series method used in tourism modeling and forecasting. It allows for a wide range of possible models which can be applied for various types of data and provides an intensive strategy for selecting a model which best represents the data. In this study, we therefore further apply the Box-Jenkins approach to identify appropriate time-series models to forecast tourist arrivals to China from Australia, Japan and the USA, and further compare their forecasting performance with that generated by the regression models developed in chapter 7 (i.e., the VAR and VARECM models).

This chapter is organised as follows. Section 2 discusses the structure of a seasonal time series model and the modelling and forecasting techniques. Section 3 applies seasonal time series models to forecast tourist arrivals to China from Australia, Japan and the USA. In this section, we first identify the patterns of the time series data so that we are able to select appropriate models to represent the data; further we estimate the selected time series models and carry out the diagnostic checking on the adequacy of the estimated models. Models that survive the diagnostic checking are used to generate forecasts of tourist arrivals from the three tourist-origin countries. Finally one model with the smallest forecasting error, for each country case, will be chosen as the optimal time series model and used for overall forecasting comparison with other forecasting methods. Section 4 provides an overall comparison of the forecasting performance generated by the VAR, time series and no-change models, in terms of the error magnitude and directional changes. Section 5 draws conclusions of this chapter.

8.2. THE ARIMA MODELLING

For a stationary time series Y_t, the Box-Jenkins approach incorporates two processes: the autoregressive (AR) process and the moving average (MA) process in a model, i.e., an ARMA (p, q) model, which can be expressed as:

$$Y_t = C + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}, \qquad (8.1)$$

where C is the constant term; p is the order of the autoregressive process (or the number of lags of the Y's); q is the order of the moving average process; ε_t are white noise error terms, which are independent and normally distributed with zero mean and constant variance.

By using the backshift operation notation B, the model can be transferred into the following form:

$$Y_t (1- \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p) Y_t = C + (1- \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^p) \varepsilon_t. \qquad (8.2)$$

where $B(Y_t) = Y_{t-1}$, $B^p(Y_t) = Y_{t-p}$.

If a time series is not stationary and integrated at order *d* (i.e., the order of differences of the data to achieve stationarity), then an ARIMA (p, d, q) is applied, and equation 8.3 can be further expressed as follows

$$\mathbf{\Phi_p (B)}\ \nabla^d Y_t = \mathbf{C} + \ \mathbf{\Theta_q (B)}\ \varepsilon_t, \qquad (8.3)$$

where $\mathbf{\Phi_p (B)} = (1- \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p)$; $\mathbf{\Theta_q (B)} = (1- \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q)$; $\nabla^d Y_t = (1\text{-}B)^d Y_t$.

For seasonal time-series data (e.g., quarterly and monthly data), Box and Jenkins (1976) propose a seasonal ARIMA model which consists of the seasonal and non-seasonal patterns of the data. In general, a seasonal model is denoted by ARIMA (p, d, q)(P, D, Q), in which p, d, q are the orders for non-seasonal autoregression, integration, and moving average respectively, and P, D, Q are orders for seasonal autoregression, integration, and moving average respectively. Therefore, a multiplicative seasonal ARIMA can be written as:

$$\mathbf{\Phi_p (B)}\ \ \mathbf{\varphi_P (B^s)}\ \ \nabla^d\ \nabla_s^D\ \mathbf{Y_t} = \ \mathbf{C} + \mathbf{\Theta_q (B)}\ \ \mathbf{\theta_Q (B^s)}\ \ \varepsilon_t, \qquad (8.4)$$

where s is the number of periods per season (e.g., s = 4 for quarterly data); $\mathbf{\Phi_p (B)}$ and $\mathbf{\Theta_q (B)}$ are polynomial in B of no-seasonal orders defined in equation 8.3; $\mathbf{\varphi_P(B^s)} = (1 - \phi_1 B^s - \phi_2 B^{s+1} - \ldots - \phi_p B^{s+P})$, and $\mathbf{\theta_Q (B^s)} = (1- \theta_1 B^s - \theta_2 B^{s+1} - \ldots - \theta_q B^{s+Q})$ are polynomial in B of seasonal orders; $\nabla^D Y_t = (1\text{-}B^s)^D Y_t$.

The seasonal ARIMA modelling and forecasting consists of four steps:

- Identification. The first step of ARIMA modelling is to select appropriate models for fitting to the time series data, i.e., to find out the appropriate values of *p, d, q* and *P, D, Q* for an ARIMA model. That is to determine the order of differencing (d and D) for the data to achieve stationary and the lag number of autoregression ϕ's (p and P), and the lag number of moving average terms θ's (q and Q). The Box-Jenkins approach emphasizes the important principle of "parsimony" in selecting a "best" ARIMA model. According to this principle, we have to find the simplest adequate model—one that contains the fewest coefficients needed to explain the behaviour of the observed data. A parsimonious model makes a good use of a limited sample and tends to give more accurate forecasts (see Ledolter and Abraham 1981).

- Estimation. That is to estimate the parameters of the autoregression ϕ's and the moving average terms θ's for the identified ARIMA model. Models with estimated coefficients statistically significant at 5% level will be selected and used for forecasting if the models pass the diagnostic tests in the next step.
- Diagnostic checking. The estimated ARIMA (p, d, q) (P, D, Q) model will be further examined by diagnostic tests of residuals. For a good forecasting model, the error terms should be simply white noise (i.e., they are independent and normally distributed with zero mean and constant variance). Therefore, the diagnostic checking is carried out to see if the residuals of the selected model satisfy the assumption of a white noise process. Models that pass diagnostic tests can be further used for forecasting.
- Forecasting. The final phase of the ARIMA modelling is to use the best model or models which pass the diagnostic checking to forecast future values of the time series. The best forecasting model should forecast the future satisfactorily, with the smallest possible or acceptable forecasting errors.

Following the above four steps, in the next section, we estimate the appropriate ARIMA models to forecast tourist arrivals from Australia, Japan and the USA respectively.

8.3 MODELLING AND FORECASTING TOURISM DEMAND USING ARIMA MODELS

8.3.1 Identification Of The Time Series Patterns

Economic time series data usually consist of four basic sub-patterns, namely: the trend, seasonal, horizontal and cyclical components (see O'Donovan 1983, p.7). ARIMA models are in particular developed to extrapolate the horizontal, trend and seasonal patterns of the historical data and thus predict the future values of the data.

Therefore, the selection of an appropriate ARIMA model depends on the systematic pattern of the time-series data of interest.

The first step in analysing a time series is to plot the data against time. This will often show up the most important properties of a time series, such as trend, and seasonality. As discussed in Chapter 6, The plot of quarterly tourist arrivals to China from Australia, Japan and the USA exhibits a trend and seasonalities. Therefore, to select an appropriate seasonal ARIMA model, first we need to identify its no-seasonal and seasonal orders of integration (d and D), i.e., to determine the order of differencing required to achieve stationarity.

8.3.1.1 Order Of Integration

An ARIMA model based on the Box-Jenkins approach can be applied directly to stationary data, i.e., the data has a time invariant mean and constant variance (the concept of stationarity of time series data has been addressed in detail in Chapter 6, section 3). A seasonal time series may be non-stationary in mean due to a trend or a seasonal pattern. If a time series has a stochastic trend as well as a stochastic seasonality, both non-seasonal differencing (i.e., *dth* differencing) transformation and seasonal differencing (i.e., *Dth* differencing) transformation need to be considered in the ARIMA model, i.e., we need to estimate a seasonal ARIMA (p, d, q) (P, D, Q) model.

The stationarity test for the level data of tourist arrivals from Australia, Japan and the USA, respectively, has been carried out in Chapter 6 by using the sample autocorrelation function (ACF) and partial autocorrelation function (PACF), and Q statistics (see Table 6.1A-C in Chapter 6).[13] The statistics suggest that the three sets of time-series data are non-stationary as the sample ACFs and PACFs start at high values and do not "decay quickly" even at higher lag numbers, which suggests the time series data of interest are integrated at order one (i.e., d=1).

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[13] To keep consistency with other models in the previous chapter as well as for the purpose of variance modification of the data, data for ARIMA models are kept in natural logarithm from.

Apart from the stochastic trend, quarterly time series data may also have stochastic seasonalities, which require seasonal differencing (i.e., fourth differencing) to make the data stationary. The plot of ACFs can be used to visually investigate seasonal patterns. If time series data have significant ACFs at seasonal lags, 4, 8, 12 etc, it may indicate a strong seasonal pattern in the data. Significant autocorrelation at seasonal lags can be removed by taking a seasonal differencing, i.e., using the operator $\nabla_4 Y_t = (y_t - y_{t-4})$. Therefore, if a quarterly time series exhibits a trend as well as a seasonality, the traditional seasonal ARIMA modelling approach uses non-seasonal and seasonal differencing, i.e., it uses the operator $\nabla_1\nabla_4$ = (1-B) (1-B^4), in which the first differencing ∇_1 is used to remove the trend and the four difference ∇_4 to remove the seasonality.

The formal seasonal unit-root test (i.e., the HEGY test) applied in Chapter 6 suggests that: quarterly tourist arrivals from Australia and Japan are seasonally stationary; and quarterly tourist arrivals from the USA are seasonally non-stationary and exhibit biannual and annual seasonalities (refer to Chapter 6, section 6.3). Therefore, the HEGY test results suggest that, to achieve stationarity, the time series data for the Australia and Japan models require ∇_1 transformation, and data for the USA model requires $\nabla_1\nabla_4$ transformation.

The reliance on only the sample autocorrelations for the degree of differencing and even the HEGY test can sometimes lead to the problem of overdifferencing (Mills 1991, p.121). Osborn (1990) and Kulendran (1995) also show concern with this issue. Kulendran (1995, p.37) demonstrates that $\nabla_1\nabla_4$ may overdifference the series. For a quarterly time series, the $\nabla_1\nabla_4$ operator can be written as $\nabla_1\nabla_4$ = (1-B) (1-B^4) = (1-B) (1-B) (1 + B + B^2 + B^3), in which (1-B) (1-B) operator indicates the potential danger of double first differencing (1-B). Osborn (1990) also points out that if seasonal dummies can be incorporated in the ARIMA models, many time series do not require seasonal differencing and have stationary stochastic seasonality.

Therefore, to avoid the problem of "overdifferencing", we use three types of differencing data to estimate the ARIMA models respectively for each country case. First, we use ∇_1 data with seasonal dummy variables in the ARIMA models to select the best fitting model. Further, we use ∇_4 data to estimate ARIMA models and then select the best fitting model for each country case. Finally, we also use $\nabla_1\nabla_4$ data to estimate ARIMA models and select the best fitting model for each country case. Therefore, for each country case, we will have three selected ARIMA models using three types of differencing data respectively, and by comparing the forecasting errors, we will be able to choose the optimal model for forecasting for each country case.

After transferring the three data sets to stationary data by the above three type of differencing respectively, we further identify the non-seasonal and seasonal orders of autoregression (p and P) and moving average (q and Q).

8.1.1.2 Order Of Autoregression And Moving Average

The basic technique in the identification stage of ARIMA modelling is to observe the patterns of ACF and PACF of the differenced data in Section 8.1.1. A decision matrix for identifying the appropriate no-seasonal orders p and q of an ARMA model is presented as follows:

Order	ACF	PACF
Autoregression (p)	Tail off	Cut off after lag p
Moving Average (q)	Cut off after lag q	Tail off
ARMA (p, q)	Tail off	Tail off

Source: Frechtling, 1996, p.109.

"Cut off' in the table means to drop immediately to statistical insignificance, while to "tail off" is to decline over time into insignificance. The significant values of ACF and PACF are usually determined by two standard errors $2/\sqrt{n}$ (where n is the number of sample data). The value of p is identified from the statistically significant PACF (i.e, greater than two standard errors), and the q value is identified from the statistically significant ACF (i.e, greater than the two standard errors).

Seasonality may suggest that autocorrelations and partial autocorrelations at seasonal lags (e.g., lag 4, 8, 16...for quarterly data) are large and significantly different from zero. Thus we could also apply the above rule to identify the seasonal order of autoregression and moving average (i.e., P and Q respectively) by the patterns of the ACF and the PACF.

The plot of ACF and PACF for the ARIMA models with the ∇_1 data of tourist arrivals, respectively from Australia, Japan and the USA, is reported in Figure 8.1(A-F). The plot of ACF and PACF for the seasonal ARIMA models with the ∇_4 data of tourist arrivals, respectively from Australia, Japan and the USA, is provided in Figure 8.2(A-F). The plot of ACF and PACF for the ARIMA models with the ∇_1 ∇_4 data of tourist arrivals, respectively from Australia, Japan and the USA, is presented in Figure 8.3(A-F). However, information from the above visual plots of ACF's and PACF's does not clearly indicate a unique order of p, q, P and Q for these three sets of data.

Therefore, in accordance with the parsimony principle, we set the maximum non-seasonal order p = 0, 1, ..., 4, q = 0, 1, ...,4, and the maximum seasonal order P=4, Q=4 respectively. Therefore, for each country case, 75 ARIMA models are estimated, with p = 0, 1, ..., 4, q = 0, 1, ...,4, P=4, and Q=4 respectively, and with ∇_1 , ∇_4 and ∇_1 ∇_4 data respectively. Models with insignificant coefficients are dropped and models with coefficients significant at the 5% level are selected for each country case. The diagnostic checking of the selected models will be carried out next to examine the adequacy of these models. Models that pass the diagnostic checking will be further used for forecasting.

8.3.2 Estimation And Diagnostic Tests

Considering the seasonality of the quarterly data and the "overdifferencing" issue, for each country case, we estimate three ARIMA models with the ∇_1, ∇_4 and $\nabla_1\nabla_4$ data respectively, i.e., $ARIMA^1$, $ARIMA^4$, and $ARIMA^{1,4}$. Constant terms and dummy variables which reflect the circumstance flowing from the Tiananmen Square incident in 1989 and 1990 are also included in all the estimated ARIMA models. Sixty observations (from 1983Q1 to 1997Q4) are used to estimate the ARIMA models for quarterly tourist arrivals to China from Australia, Japan and the USA respectively. The Maximum Likelihood Method is applied to estimate the models.

Models with statistically significant coefficients φ's and θ's are selected for each origin country of tourist arrivals, i.e., Australia, Japan and the USA respectively. The estimation of selected $ARIMA^1$, $ARIMA^4$, and $ARIMA^{1,4}$ models of tourist arrivals from these three countries are reported in Table 8.1. For all selected models, the estimated coefficients φ's and/or θ's are statistically significant at the 5% level of significance except for the Japan $ARIMA^1$; the dummy variables for the Tiananmen Square impact in all estimated models are significant at the 5% level and have the expected negative sign.

Further, the diagnostic checking based on residuals of the estimated models is carried out to assess the validity of the selected models, i.e., to see if the error terms of the estimated models are white noise. The outstanding feature of a white noise model is that its error terms are independent or uncorrelated. Since the error terms are independent, all the theoretical ACF and PACF of the error terms will be zero. Thus an obvious check on the adequacy of the fitted models is to calculate the sample ACF and PACF of the residuals, and also to examine the ACF and PACF visually and statistically.

The plot of correlogram of the estimated residuals gives some visual evidence for the existence of autocorrelations. If the error terms are independent (uncorrelated), we would expect to find that the sample ACF and PACF of the residuals from the estimated ARIMA models should be close to zero. Therefore, for the estimated ARIMA models, we first compute the ACF and the PACF of the residuals with lag = 1, 2,...14 and plot the ACFs and PACFs with two standard error bars. The ACF's and PACF's of the residuals from the estimated $ARIMA^1$ models are reported in Figure 8.4(A-C) respectively for Australia, Japan and the USA models. The ACF's and PACF's of the residuals from the estimated $ARIMA^4$ models are provided in Figure 8.5(A-C) respectively for Australia, Japan and the USA models. The ACF's and PACF's of the residuals from the estimated $ARIMA^{1,4}$ models are presented in Figure 8.6(A-C) respectively for Australia, Japan and the USA models.

Through visual examination of the plot of the ACF's and the PACF,'s we can see that the ACF's and PACF's of the residuals from the selected ARIMA models are very close to zero, and all the values of ACF and PACF fall below 2 standard errors by lag 6. Therefore, the visual plots of the ACF and PACF suggest that the residuals from the selected ARIMA models are uncorrelated.

A formal test of error correlation using the Q statistics, developed by Ljung and Box (1978), is further applied to test if the sample ACF and PACF of the residuals are statistically significant from zero. If the calculated Q statistics exceed the critical chi-squared value $\chi^2(p\text{-}m)$ (where p is the number of lags, and m is the number of parameters in the model), then the Q value is "too big" and the fitted model is judged inadequate. The Q statistics for the null hypothesis of non-error-correlation of the estimated ARIMA models are reported in Table 8.2. The Q statistics at all selected lags are not significant at the 5% level, which further confirms that residuals from the estimated models appear uncorrelated, except for the USA model at lag 6.

Therefore, all three models (i.e., $ARIMA^1$, $ARIMA^4$ $ARIMA^{1,4}$) for each of the three tourist-origin countries are selected at this stage to generate forecasts, and one optimal ARIMA model for each country will be determined by comparing the forecasting error generated from each of the three selected models in next section.

8.3.3 Forecasts With ARIMA Models

Four-step and eight-step forecasts of quarterly tourist arrivals are generated by three ARIMA models, i.e., $ARIMA^1$, $ARIMA^4$ $ARIMA^{1,4}$, for each of the three countries

(Australia, Japan and the USA) respectively. To select the best ARIMA model for each country, we need to examine the forecasting error generated from each of the three ARIMA models. As the magnitude of the number of tourist arrivals is the same for each country, we simply compare the mean absolute errors (MAEs) (see Equation 5.8) from the forecasts generated by the three selected ARIMA models.

The results of MAEs generated from the three selected ARIMA models for the three tourist-origin countries are provided in Table 8.3. Further, for each country case, we rank the ARIMA^{1}, ARIMA^{4}, and ARIMA^{1,4} models based on their MAEs and provide the ranking in Table 8.4.

For four-step forecasting, we find the ARIMA^{1} model generates the best forecasts of tourist arrivals from Australia, and the ARIMA^{1,4} model provides the best forecasts of tourist arrivals from Japan and the USA. For eight-step forecasts, the ARIMA^{1,4} model produces the best forecasts of tourist arrivals from Australia and Japan, while the ARIMA^{4} model produces the best forecasts of tourist arrivals from the USA.

This may further imply that, for four-step forecasts, the Australia ARIMA^{1,4} model has been overdifferenced and thus produce less accurate forecasts in comparison with the model using first differenced data; whereas for the eight-step forecasts, the USA ARIMA^{1,4} model has been overdifferenced and thus produce less accurate forecasts in comparison with the model using fourth differenced data.

Therefore, for one-year ahead forecasts, the Australia ARIMA^{1}, Japan ARIMA^{1,4} and USA ARIMA^{1,4} are chosen as the optimal forecasting models; for two-year ahead forecasts, the Australia ARIMA^{1,4}, Japan ARIMA^{1,4} and USA ARIMA^{4} are chosen as the optimal forecasting models. The optimal models with the smallest forecasting errors will be used to compare with other forecasting models, i.e., VAR, VARECM and no-change models in the next section.

8.4 FORECASTING COMPARISON

In section 8.3, ARIMA models using time series methods have been estimated and one optimal forecasting model has been selected to generate forecasts of tourist arrivals to China, respectively, from Australia, Japan and the USA. Therefore, in this section, we assess the forecasting performance of four types of models, including:

- Three optimal VAR models selected in Chapter 7, which are the VAR(1) for tourist arrivals from Australia, the VAR(3) for tourist arrivals from Japan, and the VAR (1) for tourist arrivals from the USA;
- Three optimal VARECM models (i.e. VAR model with error correction terms) selected in Chapter 7, which are the VARECM(1) for tourist arrivals from Australia, the VARECM(1) for tourist arrivals from Japan, and the VARECM (4) for tourist arrivals from the USA;
- Three optimal ARIMA models selected for one-year ahead forecasting, which are the ARIMA(0, 1, 2)(0, 0, 0) for tourist arrivals from Australia, the ARIMA(1, 1, 0)(1, 1, 0) for tourist arrivals from Japan, and the ARIMA(0, 1, 1)(0, 1, 1) for tourist arrivals from the USA; Three optimal ARIMA models selected for two-year ahead forecasting, which are the ARIMA(2, 1, 0)(1, 1, 0) for tourist arrivals from Australia, the ARIMA(1, 1, 0)(1, 1, 0) for tourist arrivals from Japan, and the ARIMA(0, 0, 1)(0, 1, 1) for tourist arrivals from the USA (see Table 8.1).
- No-change models, which are defined as $F_t=Y_{t-4}$, which assumes that the forecasting number of a quarterly tourist arrivals F_t is equal to the actual number of tourist arrivals in the same quarter in the previous year Y_{t-4}. Forecasts of tourist arrivals from the three tourist-origin countries generated by the no-change models are used as benchmarks of the forecasting evaluation of the regression and time series models.

The accuracy of ex post (i.e., outside sample) forecasts of tourist arrivals from the VAR and VARECM regression methods and the time series method are measured and assessed by relative forecasting errors and percentage directional change accuracy.

8.4.1 Relative Forecasting Accuracy

The forecasting errors of tourist arrivals from three tourist-origin countries (i.e., Australia, Japan, and the USA) generated from these models are first assessed by the relative measurements of forecasting accuracy, the MAPE and RMSPE which have been defined in section 5.6.1 in Chapter 5. They are the simplest measures permitting comparison across different forecasting models with different time periods and numbers of observations.

As the MAPE and RMSPE do not depend on the magnitude of the demand variables (i.e., the number of tourist arrivals from different tourist-origin countries), both measurements are commonly used to compare the overall forecasting performance of different models generated for cross country cases. Lower MAPE and RMSPE values are preferred to higher ones because they indicate that a forecasting model is producing smaller percentage errors. However, the RMSPE penalizes large errors more than small ones as it captures efficiently the extreme forecast errors. Therefore, the MAPE is the better indicator of forecasting accuracy if we are interested in capturing the overall trend of the data series.

The MAPE and RMSPE of the selected models for one-year ahead forecasts are calculated and provided in Table 8.5A, and the MAPE and RMSPE of the selected models for two-year ahead forecasts are calculated and provided in Table 8.5B. To set the standards for evaluating the MAPE and the RMSPE of a forecasting model, we have also calculated the MAPE and the RMSPE from naïve models—no-change models.

The overall forecasting performance of all models is further assessed based on the MAPE and the ranking of the estimated models in terms of the MAPE is presented in Table 8.6. The reports of relative forecast error measures in Table 8.5 and Table 8.6 can be summarized as follows:

- For one-year-ahead forecasts, the ARIMA model ranks first among the three models for all three country cases, whereas the performance of the VAR and VARECM models varies from different country cases. The VAR and VARECM models outperform the no-change models in the cases of Australia and the USA, and no-change outperforms the VAR and VARECM models in the case of Japan.
- For two-year-ahead forecasts of tourist arrivals from the three countries, all three models (i.e., the VAR, VARECM and ARIMA models) outperform the no-change models, but rank differently in different country cases. In the case of Australia, the ARIMA model ranks first, followed by the VARECM, VAR and no-change models; for the case of tourist arrivals from Japan, the VARECM model generates the best forecasts, followed by the VAR, no-change, and ARIMA models; in the case of tourist arrivals from the USA, the ARIMA model produces the best forecasts, followed by the VAR, VARECM and no-change models

The overall forecasting performance of all models across the three country cases is further assessed, in terms of the frequency that each model appears as the best model in the three country cases, as follows:

	One-Year Forecasts		Two-Year Forecasts	
Models	Frequency	Percentage	Frequency	Percentage
ARIMA	3	100%	2	67%
VARECM	0	0	1	33%
VAR	0	0	0	0
No-change	0	0	0	0
Total	3	100%	3	100%

In terms of one-year-ahead forecasts, the ARIMA performs the best forecasting for the three countries, i.e. 100% of the three country cases. For the two-year-ahead forecasts, the ARIMA performs the best forecasting in two of the three cases (i.e. 67% of the three cases), followed by the VARECM model which performs the best forecasting in one of the three cases (i.e., 33% of the three cases).

For the long-term (two-year-ahead) forecasts, the ARIMA model performs the best, followed by VARECM model, while the no-change model provides the relatively poor forecasts in the three cases. Overall, in forecasting tourist demand to China from three major tourist-origin countries, the time series model outperforms the regression model, and the regression model outperforms the no-change model.

This finding is consistent with the study by Witt and Witt (1995) who find that regression models are found to be less accurate than time series models, and the study by Kim and Song (1998) which find that the ECM models generate more accurate forecasts than no-change models. However, the findings from this study conflict with the studies by Witt and Wilson (1994) and Song and Witt (2000) which show that the no-change model outperforms the regression and time series models.

8.4.2 Accuracy Of Directional Change

In tourism forecasting, the most important information we wish to know is whether there will be more or fewer visitors in the forecasting period than the previous period. A directional error occurs when a forecasting model fails to predict actual changes of direction for a period. Therefore, accurate prediction of directional change is often the most important indicator of forecast accuracy. The measure of directional change accuracy is defined as:

$$PDA = \frac{\sum FD}{\sum AD} * 100 \qquad (8.5)$$

where PDA denotes percentage directional change accuracy; FD denotes number of accurate forecasts in directional changes; AD denotes number of directional changes actually occurring. This measure indicates how much percentage accuracy the model forecasts successfully in the directional changes of the data.

For quarterly time series data, however, to identify the cyclical patterns or the trend of directional changes, we need to remove seasonal patterns of the data. Therefore, for the two-year forecasts of tourist arrivals, we calculate the two-year (eight-quarter) percentage changes of the actual and forecasting tourist arrivals as follows:

$$\frac{y_t - y_{t-i4}}{y_t} * 100 \qquad (8.6)$$

where Y_t is the number of tourist arrivals, t is the forecasting period (t = 1, 2,...8 quarter), I=1,2 respectively for one and two year forecasts.

The visual plots of percentage changes of actual and forecasting values of tourist arrivals between 1998Q1 and 1999Q4 are provided in Figure 8.7(A-C), respectively, for the tourist-origin country Australia, Japan and the USA. In accordance with equation 8.7, the number of accurate forecasts in directional changes FD is calculated as the number of forecasting points with the same sign as the actual changes from each model; the number of directional changes actually occurring AD=8, i.e., eight directional changes actually occurring for the two-year forecasts. The percentage directional change accuracy (PDA) from three forecasting models, the VARECM, VAR and ARIMA models, are calculated as follows:

	Australia	Japan	USA	Average
ARIMA	100%	50%	87.5%	79.2%
VAR	100%	87.5%	87.5%	91.7%
VARECM	100%	75%	75%	83.3%

All three models predict the eight direction changes correctly in the case of Australia, thus the PDA is calculated as 100%, whereas the PDA varies for the cases of Japan and the USA. The ARIMA model predicts correctly four of the eight points in the case of Japan tourist arrivals (i.e., PDA = 50%), and seven in the case of the USA (i.e., PDA = 87.5%). The VAR model forecasts correctly seven of the eight directional changes of tourist arrivals from both Japan and the USA (i.e., PDA = 87.5%). The VARECM achieves six FD points for both country cases, which makes a 75% PDA.

In terms of country cases, all three models produce the best forecasts of directional changes in the case of Australia, and followed by the USA, whereas all three models perform the poorest forecasts in the case of Japan, in particular, the ARIMA model predicts the worst forecasts of directional changes of tourist arrivals from Japan, which had significant directional changes during the Asian crisis between 1998 and 1999.

On average, among these three models, the VAR model provides the best forecasts in terms of directional change accuracy, followed by VARECM, whereas the ARIMA model performs the poorest forecasts. Therefore, overall, the regression method outperforms the time series method in terms of directional change accuracy. Given the importance of being able to predict directional changes in tourism demand, the VAR model is superior in predicting directional changes for these time periods examined.

8.5 CONCLUSION

This chapter developed time series forecasting models to generate two-year-ahead forecasts of tourist arrivals to China from Australia, Japan and the USA, which were further compared with those generated by the VAR and VARECM models in Chapter 7. The main findings in this chapter may be summarised as follows.

ARIMA models using first differrenced data ($ARIMA^1$), fourth differenced data ($ARIMA^4$), and first and fourth differenced data ($ARIMA^{1,4}$) were estimated for each of the three tourist-origin countries, i.e., Australia, Japan and the USA. All selected ARIMA models, including ARIMA^{1}, ARIMA^{4} and ARIMA^{1,4}, have passed the diagnostic checking for error correlations of the models. This suggests that residuals of the selected models satisfy the assumption of white noise. The evidence also provides support for the observation by Osborn (1990) that if seasonal dummies can be incorporated in the ARIMA models, many time series do not require seasonal differencing and have stationary stochastic seasonality.

In terms of forecasting error magnitude, one optimal ARIMA model was selected for each country case, and was further used for forecasting comparison with the VAR and VARECM models. For one-year ahead forecasts, the Australia ARIMA^{1}, Japan ARIMA^{1,4} and USA ARIMA^{1,4} models were chosen as the optimal forecasting models; for two-year ahead forecasts, the Australia ARIMA^{1,4}, Japan ARIMA^{1,4} and USA ARIMA^{4} are chosen as the optimal forecasting models.

The model selection based on forecasting accuracy is not consistent with the results of the HEGY (1990) seasonal unit-root test. This suggests that the Australia and Japan data need the first differencing transformation only, whereas the USA data require the seasonal differencing (fourth differencing) transformation. This may imply that the reliance only on the HEGY test may cause overdifferencing problems in some cases (e.g., the USA data), and moreover, models with good sample fit do not necessarily generate the best forecasts. Therefore, it may a good strategy to examine all possible types of models with different data transformations when applying ARIMA modelling techniques in forecasting.

By comparing the measures of relative forecasting accuracy, the MAPE's, of the estimated the VAR, VARECM, ARIMA and no-change models, we find that, in the three country cases, the ARIMA model provides best two-year forecasts, followed by the VARECM model. However, in the case of Japan, the VARECM model provides the best forecasts of tourist arrivals from Japan, followed by the no-change model, whereas the ARIMA model generates the poorest forecasts due to its failure to capture the sudden decrease in tourist arrivals from Japan during the Asian Financial Crisis from 1998 to 1999.

The relative performance of the different forecasting methods, however, differed when we used the criterion of directional change accuracy. In terms of the directional change accuracy, the VAR regression model provides the best forecasts of the eight directional changes of tourist arrivals among the three country cases, followed by the VARECM model, whereas the ARIMA model produces the poorest forecasts. In terms of country cases, all three models produce the best forecasts of directional changes in the case of Australia, followed by the USA, whereas all three models provide the poorest forecasts in the case of Japan, in particular, the ARIMA model generates the worst forecast accuracy in directional changes for tourist arrivals from Japan, which had significant directional changes during the Asian crisis between 1998 and 1999.

This indicates that the ARIMA models perform better when forecasting for the country from which tourist arrivals have a stable trend and seasonal pattern (e.g., Australia and the USA), but fail under any structural or level changes of tourist arrivals which may be caused by unexpected events, for instance, tourist arrivals from Japan. However, the regression models are better able to capture these changes by including related variables, which impact upon the tourism demand. In particular, in the VAR models, we treat all variables as endogenous variables, and the "feedback" effects are considered in the models.

Therefore, in the case of tourism demand to China, we find that: although the regression models may not necessarily generate more accurate forecasts than the time series models in terms of the forecasting error magnitude, these VAR regression models developed in this study show better performance as compared to the time series models in forecasting directional changes. Moreover, the VAR regression approach allows us to examine the short-term and long-term causal relationships between tourist demand and its determinants, and to evaluate the impact of government policies related to tourism (as discussed in Chapter 7).

Forecasting of tourism flows, particularly international tourism flows, is one of the most important challenges faced by both government policy makers and investors alike. Failure to anticipate increases in demand may lead to considerable shortfalls in the supply of tourism infrastructure, because of the lead times involved in building and providing the infrastructure. The cost of developing tourism infrastructure may lead to price increases and foregone opportunities that may feedback into demand resulting in unfortunate negative impact upon demand. Therefore, the ability to forecast accurately both the volumes of international visitor arrivals and any directional changes is extremely important.

In this chapter we have compared several forecasting techniques that take very different approaches. We have used the VAR and VARECM models which come from the econometric school of forecasting. The advantage of these approaches is that they are modeling approaches based on economic causal relationships and it allows for endogeneity and feedback effects, a very important real world economic phenomena. The VAR and VARECM models were compared to the ARIMA models, which in many other studies have proved to be comparatively good forecasting tools (see Witt and Witt, 1995) and on the criterion of directional changes they compare most favorably.

Given the popularity and success of the ARIMA approach, if the VAR and VARECM models are able to compare favorably with these techniques, then the VAR and VARECM approaches may well be worth applying in many more tourism forecasting studies.

It is therefore pleasing to report the success of the VAR and VARECM models, particularly in their ability to forecast directional changes. Although there are differences between the one-year and two-year forecast comparison, as well as differences between the three country cases, overall there is sufficient evidence from this study to support for the VAR and VARECM approaches to be used in the future analysis of international tourism demand.

Figure 8.1A: ACF Plot of Tourist Arrivals from Australia (∇_1)

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1       -0.01312    |              .    |    .              |
  2       -0.00166    |              .    |    .              |
  3        0.06221    |              .    |*   .              |
  4        0.00310    |              .    |    .              |
  5       -0.14022    |              . ***|    .              |
  6       -0.02409    |              .    |    .              |
  7       -0.14713    |              . ***|    .              |
  8       -0.00896    |              .    |    .              |
  9        0.04710    |              .    |*   .              |
 10       -0.01949    |              .    |    .              |
 11       -0.06970    |              .   *|    .              |
 12        0.14528    |              .    |*** .              |
 13        0.07436    |              .    |*   .              |
 14        0.05599    |              .    |*   .              |

"." marks two standard errors
```

Figure 8.1B: PACF Plot of Tourist Arrivals from Australia (∇_1)

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1        0.04459    |              .    |*   .              |
  2       -0.01942    |              .    |    .              |
  3       -0.07990    |              .  **|    .              |
  4        0.00755    |              .    |    .              |
  5        0.14552    |              .    |*** .              |
  6        0.03575    |              .    |*   .              |
  7        0.09145    |              .    |**  .              |
  8       -0.03387    |              .   *|    .              |
  9       -0.04514    |              .   *|    .              |
 10        0.04061    |              .    |*   .              |
 11        0.07469    |              .    |*   .              |
 12       -0.16460    |              . ***|    .              |
 13       -0.08471    |              .  **|    .              |
 14       -0.06093    |              .   *|    .              |
```

Figure 8.1C: ACF Plot of Tourist Arrivals from Japan (∇_1)

```
Lag    Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1     -0.03712     |               .   *|    .               |
  2      0.11034     |               .    |**  .               |
  3      0.03365     |               .    |*   .               |
  4      0.15175     |               .    |*** .               |
  5      0.05104     |               .    |*   .               |
  6      0.13351     |               .    |*** .               |
  7     -0.12698     |               . ***|    .               |
  8      0.15818     |               .    |*** .               |
  9     -0.04152     |               .   *|    .               |
 10      0.03895     |               .    |*   .               |
 11     -0.02639     |               .   *|    .               |
 12      0.02232     |               .    |    .               |
 13     -0.03283     |               .   *|    .               |
 14     -0.03188     |               .   *|    .               |
```

Figure 8.1D: PACF Plot of Tourist Arrivals from Japan (∇_1)

```
Lag    Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1     -0.00708     |               .    |    .               |
  2     -0.01895     |               .    |    .               |
  3     -0.06008     |               .   *|    .               |
  4     -0.10906     |               .  **|    .               |
  5     -0.07632     |               .  **|    .               |
  6     -0.12331     |               .  **|    .               |
  7      0.14012     |               .    |*** .               |
  8     -0.17784     |               .****|    .               |
  9      0.02928     |               .    |*   .               |
 10     -0.05199     |               .   *|    .               |
 11      0.01978     |               .    |    .               |
 12     -0.02791     |               .   *|    .               |
 13      0.03751     |               .    |*   .               |
 14      0.03517     |               .    |*   .               |
```

Figure 8.1E: ACF Plot of Tourist Arrivals from the USA (∇_1)

```
Lag   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1     -0.25957      |               *****|    .               |
 2      0.19471      |               .    |****.               |
 3     -0.02253      |               .    |    .               |
 4     -0.07037      |               .   *|    .               |
 5      0.10900      |               .    |**  .               |
 6     -0.37495      |             *******|    .               |
 7      0.12419      |               .    |**  .               |
 8     -0.18971      |               .****|    .               |
 9      0.03133      |               .    |*   .               |
10      0.07803      |               .    |**  .               |
11     -0.05376      |               .   *|    .               |
12      0.07978      |               .    |**  .               |
13     -0.00874      |               .    |    .               |
14      0.08956      |               .    |**  .               |
```

Figure 8.1F: PACF Plot of Tourist Arrivals from the USA (∇_1)

```
Lag   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1      0.18412      |               .    |****.               |
 2     -0.13284      |               . ***|    .               |
 3      0.00459      |               .    |    .               |
 4     -0.08087      |               .  **|    .               |
 5      0.10175      |               .    |**  .               |
 6      0.30780      |               .    |******              |
 7     -0.06381      |               .   *|    .               |
 8      0.15612      |               .    |*** .               |
 9     -0.08961      |               .  **|    .               |
10     -0.05349      |               .   *|    .               |
11      0.03542      |               .    |*   .               |
12     -0.07813      |               .  **|    .               |
13     -0.04114      |               .   *|    .               |
14     -0.11718      |               .  **|    .               |
```

Figure 8.2A: ACF Plot of Tourist Arrivals from Australia (∇_4)

```
Lag   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1     -0.15055     |              . ***|    .              |
 2     -0.07635     |              .  **|    .              |
 3     -0.07547     |              .  **|    .              |
 4      0.31051     |              .    |******             |
 5     -0.16242     |              . ***|    .              |
 6     -0.07391     |              .   *|    .              |
 7     -0.16347     |              . ***|    .              |
 8      0.26394     |              .    |*****              |
 9      0.01241     |              .    |    .              |
10     -0.09233     |              .  **|    .              |
11     -0.04984     |              .   *|    .              |
12      0.15790     |              .    |*** .              |
13      0.01086     |              .    |    .              |
14     -0.02673     |              .   *|    .              |
```

Figure 8.2B: PACF Plot of Tourist Arrivals from Australia (∇_4)

```
Lag   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1      0.11354     |              .    |**  .              |
 2     -0.07407     |              .   *|    .              |
 3     -0.12299     |              .  **|    .              |
 4     -0.10597     |              .  **|    .              |
 5      0.25956     |              .    |*****              |
 6      0.04287     |              .    |*   .              |
 7      0.04433     |              .    |*   .              |
 8     -0.25165     |              *****|    .              |
 9      0.04268     |              .    |*   .              |
10      0.10668     |              .    |**  .              |
11      0.00890     |              .    |    .              |
12     -0.20271     |              .****|    .              |
13     -0.00489     |              .    |    .              |
14      0.03419     |              .    |*   .              |
```

Figure 8.2C: ACF Plot of Tourist Arrivals from Japan (∇_4)

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1      -0.20497      |                .****|    .                |
 2      -0.02291      |                .    |    .                |
 3      -0.16583      |                . ***|    .                |
 4       0.37837      |                .    |********             |
 5      -0.14085      |                . ***|    .                |
 6       0.03802      |                .    |*   .                |
 7      -0.17897      |                .****|    .                |
 8       0.34029      |                .    |*******              |
 9      -0.12690      |                . ***|    .                |
10      -0.01188      |                .    |    .                |
11      -0.05556      |                .   *|    .                |
12       0.10430      |                .    |**  .                |
13      -0.08398      |                .  **|    .                |
14       0.01745      |                .    |    .                |
```

Figure 8.2D: PACF Plot of Tourist Arrivals from Japan (∇_4)

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1      -0.02462      |                .    |    .                |
 2       0.09356      |                .    |**  .                |
 3       0.04240      |                .    |*   .                |
 4      -0.16590      |                . ***|    .                |
 5      -0.03736      |                .   *|    .                |
 6      -0.04453      |                .   *|    .                |
 7       0.18172      |                .    |****.                |
 8      -0.35127      |             *******|    .                |
 9       0.10402      |                .    |**  .                |
10       0.03883      |                .    |*   .                |
11       0.06768      |                .    |*   .                |
12      -0.12491      |                .  **|    .                |
13       0.10910      |                .    |**  .                |
14      -0.02363      |                .    |    .                |
```

Figure 8.2E: ACF Plot of Tourist Arrivals from the USA (∇_4)

```
Lag   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1     -0.17882     |               .****|    .               |
 2      0.27565     |               .    |******              |
 3     -0.00355     |               .    |    .               |
 4     -0.13904     |               . ***|    .               |
 5      0.14263     |               .    |*** .               |
 6     -0.43517     |           *********|    .               |
 7      0.11143     |               .    |**  .               |
 8     -0.21714     |               .****|    .               |
 9      0.00504     |               .    |    .               |
10      0.07096     |               .    |*   .               |
11     -0.07641     |               .  **|    .               |
12      0.17124     |               .    |*** .               |
13     -0.00377     |               .    |    .               |
14      0.15694     |               .    |*** .               |
```

Figure 8.2F: PACF Plot of Tourist Arrivals from the USA (∇_4)

```
Lag   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1      0.07130     |               .    |*   .               |
 2     -0.17753     |               .****|    .               |
 3     -0.00982     |               .    |    .               |
 4     -0.03726     |               .   *|    .               |
 5      0.00313     |               .    |    .               |
 6      0.30578     |               .    |******              |
 7     -0.06690     |               .   *|    .               |
 8      0.13654     |               .    |*** .               |
 9     -0.02957     |               .   *|    .               |
10     -0.02139     |               .    |    .               |
11      0.08196     |               .    |**  .               |
12     -0.14745     |               . ***|    .               |
13     -0.04577     |               .   *|    .               |
14     -0.21995     |               .****|    .               |
```

Figure 8.3A: ACF Plot of Tourist Arrivals from Australia ($\nabla_1\nabla_4$)

```
Lag     Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1        -0.04485      |                .   *|   .                 |
 2        -0.03127      |                .   *|   .                 |
 3         0.01041      |                .    |   .                 |
 4         0.30527      |                .    |******               |
 5        -0.10834      |                .  **|   .                 |
 6        -0.03244      |                .   *|   .                 |
 7        -0.12908      |                . ***|   .                 |
 8         0.27580      |                .    |******               |
 9         0.04207      |                .    |*  .                 |
10        -0.06963      |                .   *|   .                 |
11        -0.01831      |                .    |   .                 |
12         0.16206      |                .    |*** .                |
13         0.01469      |                .    |   .                 |
```

Figure 8.3B: PACF Plot of Tourist Arrivals from Australia ($\nabla_1\nabla_4$)

```
Lag     Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1         0.02544      |                .    |*  .                 |
 2        -0.09958      |                .  **|   .                 |
 3        -0.19514      |                .****|   .                 |
 4        -0.17141      |                . ***|   .                 |
 5         0.21986      |                .    |****.                |
 6         0.02217      |                .    |   .                 |
 7         0.05958      |                .    |*  .                 |
 8        -0.27477      |               *****|   .                 |
 9        -0.00096      |                .    |   .                 |
10         0.10482      |                .    |** .                 |
11         0.01528      |                .    |   .                 |
12        -0.20490      |                .****|   .                 |
13        -0.01849      |                .    |   .                 |
```

Figure 8.3C: ACF Plot of Tourist Arrivals from Japan ($\nabla_1\nabla_4$)

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1       0.00631      |               .    |    .               |
 2       0.29066      |               .    |******              |
 3       0.07030      |               .    |*   .               |
 4       0.43872      |               .    |*********           |
 5       0.02798      |               .    |*   .               |
 6       0.18390      |               .    |****.               |
 7      -0.04485      |               .   *|    .               |
 8       0.35759      |               .    |*******             |
 9      -0.06181      |               .   *|    .               |
10       0.06020      |               .    |*   .               |
11      -0.01938      |               .    |    .               |
12       0.09512      |               .    |**  .               |
13      -0.05901      |               .   *|    .               |
```

Figure 8.3D: PACF Plot of Tourist Arrivals from Japan ($\nabla_1\nabla_4$)

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1      -0.03008      |               .   *|    .               |
 2      -0.09897      |               .  **|    .               |
 3      -0.06442      |               .   *|    .               |
 4      -0.21149      |               .****|    .               |
 5      -0.11512      |               .  **|    .               |
 6      -0.05967      |               .   *|    .               |
 7       0.09219      |               .    |**  .               |
 8      -0.42735      |           *********|    .               |
 9       0.05391      |               .    |*   .               |
10      -0.05340      |               .   *|    .               |
11      -0.00199      |               .    |    .               |
12      -0.14075      |               . ***|    .               |
13       0.08648      |               .    |**  .               |
```

Figure 8.3E: ACF Plot of Tourist Arrivals from the USA ($\nabla_1\nabla_4$)

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1      -0.12640      |               . ***|    .               |
 2       0.22740      |               .    |*****               |
 3       0.04365      |               .    |*   .               |
 4      -0.09736      |               .  **|    .               |
 5       0.11667      |               .    |**  .               |
 6      -0.38170      |            ********|    .               |
 7       0.02780      |               .    |*   .               |
 8      -0.11738      |               .  **|    .               |
 9      -0.05916      |               .   *|    .               |
10       0.03992      |               .    |*   .               |
11      -0.11671      |               .  **|    .               |
12       0.08198      |               .    |**  .               |
13       0.00585      |               .    |    .               |
```

Figure 8.3F: PACF Plot of Tourist Arrivals from the USA ($\nabla_1\nabla_4$)

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 1       0.08510      |               .    |**  .               |
 2      -0.18724      |               .****|    .               |
 3      -0.02214      |               .    |    .               |
 4      -0.07416      |               .   *|    .               |
 5       0.03720      |               .    |*   .               |
 6       0.33557      |               .    |*******             |
 7      -0.01927      |               .    |    .               |
 8       0.15140      |               .    |*** .               |
 9       0.02139      |               .    |    .               |
10       0.02394      |               .    |    .               |
11       0.13312      |               .    |*** .               |
12      -0.10680      |               .  **|    .               |
13      -0.00751      |               .    |    .               |
```

Figure 8.4A: Autocorrelation Plot of Residuals: Australia ARIMA[1]

```
Lag  Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

0      0.014225       1.00000   |                    |********************|           0
1      0.000634       0.04459   |               .    |*   .               |    0.130189
2     -0.000247      -0.01740   |               .    |    .               |    0.130447
3     -0.001157      -0.08137   |               .  **|    .               |    0.130487
4      0.000008       0.00063   |               .    |    .               |    0.131344
5      0.002095       0.14728   |               .    |*** .               |    0.131344
6      0.000766       0.05389   |               .    |*   .               |    0.134114
7      0.001266       0.08903   |               .    |**  .               |    0.134480
8     -0.000706      -0.04967   |               .   *|    .               |    0.135475
9     -0.000779      -0.05482   |               .   *|    .               |    0.135784
10     0.000628       0.04417   |               .    |*   .               |    0.136158
11     0.001354       0.09523   |               .    |**  .               |    0.136401
12    -0.001662      -0.11685   |              .   **|     .              |    0.137523
13    -0.001456      -0.10239   |              .   **|     .              |    0.139196
14    -0.001181      -0.08308   |              .   **|     .              |    0.140467

"." marks two standard errors
```

Figure 8.4B: Autocorrelation Plot of Residuals: Japan ARIMA[1]

```
Lag  Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

0      0.022414       1.00000   |                    |********************|           0
1     -0.000158      -0.00708   |               .    |    .               |    0.130189
2     -0.000423      -0.01890   |               .    |    .               |    0.130195
3     -0.001340      -0.05979   |               .   *|    .               |    0.130242
4     -0.002405      -0.10733   |               .  **|    .               |    0.130706
5     -0.001575      -0.07030   |               .   *|    .               |    0.132192
6     -0.002462      -0.10984   |               .  **|    .               |    0.132824
7      0.003543       0.15809   |               .    |*** .               |    0.134355
8     -0.003287      -0.14667   |               . ***|    .               |    0.137471
9      0.001087       0.04852   |              .     |*    .              |    0.140098
10    -0.000500      -0.02235   |              .     |     .              |    0.140383
11     0.000388       0.01731   |              .     |     .              |    0.140443
12     0.000048       0.00217   |              .     |     .              |    0.140479
13     0.000367       0.01640   |              .     |     .              |    0.140480
14     0.002124       0.09478   |              .     |**   .              |    0.140512
```

Figure 8.4C: Autocorrelation Plot of Residuals: the USA ARIMA[1]

```
Lag  Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

0      0.019340       1.00000   |                    |********************|           0
1      0.003560       0.18412   |               .    |****.               |    0.130189
2     -0.001826      -0.09444   |               .  **|    .               |    0.134530
3     -0.000769      -0.03980   |               .   *|    .               |    0.135649
4     -0.001384      -0.07159   |               .   *|    .               |    0.135847
5      0.001349       0.06977   |               .    |*   .               |    0.136485
6      0.006572       0.33985   |               .    |*******             |    0.137088
7      0.001069       0.05529   |              .     |*    .              |    0.150692
8      0.001290       0.06671   |              .     |*    .              |    0.151036
9     -0.000829      -0.04291   |              .    *|     .              |    0.151534
10    -0.002494      -0.12895   |              .  ***|     .              |    0.151740
11     0.000717       0.03712   |              .     |*    .              |    0.153586
12     0.001414       0.07313   |              .     |*    .              |    0.153738
13    -0.000815      -0.04216   |              .    *|     .              |    0.154327
14    -0.000806      -0.04171   |              .    *|     .              |    0.154522
```

Figure 8.5A: Autocorrelation Plot of Residuals: Australia ARIMA[4]

```
Lag    Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1   Std Error

  0      0.021296      1.00000  |                    |********************|   0
  1     0.0024180      0.11354  |              .     |**   .              |   0.133631
  2    -0.0012826     -0.06023  |              .    *|     .              |   0.135342
  3    -0.0029068     -0.13650  |              .  ***|     .              |   0.135820
  4    -0.0027315     -0.12827  |              .  ***|     .              |   0.138248
  5     0.0050877      0.23891  |              .     |*****.              |   0.140357
  6     0.0026316      0.12357  |              .     |**   .              |   0.147440
  7     0.0013914      0.06534  |              .     |*    .              |   0.149278
  8    -0.0054792     -0.25729  |              .*****|     .              |   0.149788
  9    -0.0022544     -0.10586  |             .    **|      .             |   0.157482
 10     0.0026699      0.12537  |             .      |***   .             |   0.158748
 11     0.0019955      0.09370  |             .      |**    .             |   0.160506
 12    -0.0009964     -0.04679  |             .     *|      .             |   0.161480
 13    -0.0029755     -0.13972  |             .   ***|      .             |   0.161722
 14    -0.0018904     -0.08877  |             .    **|      .             |   0.163863

"." marks two standard errors
```

Figure 8.5B: Autocorrelation Plot of Residuals: Japan ARIMA[4]

```
Lag    Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1   Std Error

  0      0.031758      1.00000  |                    |********************|   0
  1     -0.000781     -0.02462  |              .     |     .              |   0.133631
  2      0.002988      0.09411  |              .     |**   .              |   0.133712
  3      0.001194      0.03760  |              .     |*    .              |   0.134889
  4     -0.004991     -0.15719  |              .  ***|     .              |   0.135076
  5     -0.000669     -0.02110  |              .     |     .              |   0.138304
  6     -0.002316     -0.07294  |              .    *|     .              |   0.138361
  7      0.005030      0.15842  |              .     |***  .              |   0.139046
  8     -0.010223     -0.32190  |              ******|     .              |   0.142233
  9      0.003700      0.11651  |             .      |**    .             |   0.154696
 10      0.000362      0.01142  |             .      |      .             |   0.156255
 11     -0.000473     -0.01491  |             .      |      .             |   0.156270
 12      0.001313      0.04137  |             .      |*     .             |   0.156296
 13      0.001362      0.04292  |             .      |*     .             |   0.156491
 14      0.001014      0.03196  |             .      |*     .             |   0.156701
```

Figure 8.5C: Autocorrelation Plot of Residuals: the USA ARIMA[4]

```
Lag    Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1   Std Error

  0      0.019270      1.00000  |                    |********************|   0
  1      0.001373      0.07130  |              .     |*    .              |   0.133631
  2     -0.003305     -0.17155  |              .  ***|     .              |   0.134308
  3     -0.000703     -0.03652  |              .    *|     .              |   0.138165
  4     -0.000178     -0.00928  |              .     |     .              |   0.138338
  5      0.000143      0.00745  |              .     |     .              |   0.138349
  6      0.005846      0.30339  |              .     |******              |   0.138356
  7     -0.000195     -0.01012  |             .      |      .             |   0.149766
  8      0.000150      0.00784  |             .      |      .             |   0.149778
  9     -0.000190     -0.00990  |             .      |      .             |   0.149785
 10     -0.000827     -0.04295  |             .     *|      .             |   0.149797
 11      0.001122      0.05824  |             .      |*     .             |   0.150016
 12      0.000080      0.00420  |             .      |      .             |   0.150420
 13     -0.002092     -0.10856  |             .    **|      .             |   0.150422
 14     -0.002584     -0.13412  |             .   ***|      .             |   0.151814
```

Figure 8.6A: Autocorrelation Plot of Residuals: Australia ARIMA[1,4]

```
Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

0      0.022997      1.00000    |                    |********************|           0
1      0.000585      0.02544    |               .    |*   .               |    0.134840
2     -0.002273     -0.09887    |               .  **|    .               |    0.134927
3     -0.004562     -0.19838    |               .****|    .               |    0.136238
4     -0.003690     -0.16049    |              .  ***|     .              |    0.141393
5      0.005606      0.24377    |              .     |*****.              |    0.144667
6      0.002048      0.08908    |              .     |**   .              |    0.151952
7      0.001736      0.07552    |              .     |**   .              |    0.152898
8     -0.007016     -0.30510    |              ******|     .              |    0.153575
9     -0.002569     -0.11174    |             .    **|      .             |    0.164226
10     0.003178      0.13820    |             .      |***   .             |    0.165603
11     0.002302      0.10013    |             .      |**    .             |    0.167686
12    -0.000720     -0.03131    |             .     *|      .             |    0.168770
13    -0.003266     -0.14205    |             .   ***|      .             |    0.168876

"." marks two standard errors
```

Figure 8.6B: Autocorrelation Plot of Residuals: Japan ARIMA[1,4]

```
Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

0      0.037636      1.00000    |                    |********************|           0
1     -0.001132     -0.03008    |               .   *|    .               |    0.134840
2     -0.003687     -0.09797    |               .  **|    .               |    0.134962
3     -0.002164     -0.05751    |               .   *|    .               |    0.136249
4     -0.007310     -0.19425    |               .****|    .               |    0.136690
5     -0.002916     -0.07750    |              .   **|     .              |    0.141620
6      0.000217      0.00578    |              .     |     .              |    0.142389
7      0.005281      0.14034    |              .     |***  .              |    0.142393
8     -0.013090     -0.34781    |             *******|     .              |    0.144886
9      0.003600      0.09566    |              .     |**   .              |    0.159346
10     0.002317      0.06159    |              .     |*    .              |    0.160386
11    -0.000282     -0.00750    |              .     |     .              |    0.160816
12     0.001657      0.04403    |              .     |*    .              |    0.160822
13     0.003154      0.08381    |              .     |**   .              |    0.161041
```

Figure 8.6C: Autocorrelation Plot of Residuals: the USA ARIMA[1,4]

```
Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

0      0.019714      1.00000    |                    |********************|           0
1      0.001677      0.08510    |               .    |**  .               |    0.134840
2     -0.003521     -0.17864    |               .****|    .               |    0.135813
3     -0.001088     -0.05519    |               .   *|    .               |    0.140020
4     -0.000890     -0.04519    |              .    *|     .              |    0.140415
5      0.000757      0.03844    |              .     |*    .              |    0.140679
6      0.006885      0.34928    |              .     |*******             |    0.140870
7      0.000702      0.03563    |              .     |*    .              |    0.155822
8      0.000182      0.00928    |              .     |     .              |    0.155970
9      0.000137      0.00700    |              .     |     .              |    0.155980
10    -0.000496     -0.02517    |              .    *|     .              |    0.155986
11     0.002187      0.11096    |              .     |**   .              |    0.156060
12     0.001034      0.05247    |              .     |*    .              |    0.157487
13    -0.001023     -0.05193    |              .    *|     .              |    0.157805
```

Figure 8.7A: Directional Changes (%) of Tourist Arrivals from Australia

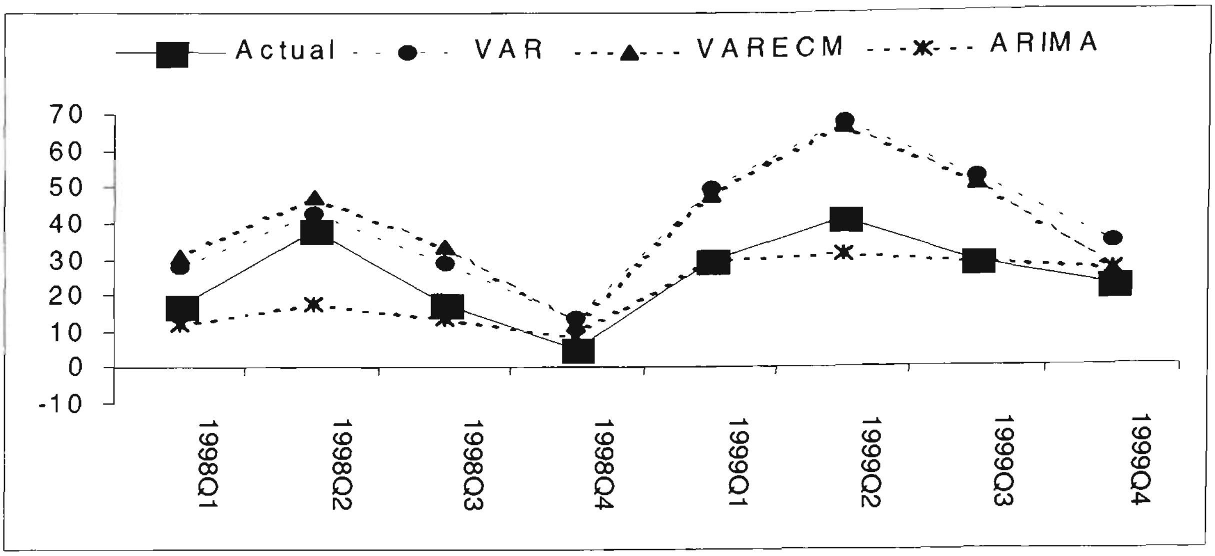

Figure 8.7B: Directional Changes (%) of Tourist Arrivals from Japan

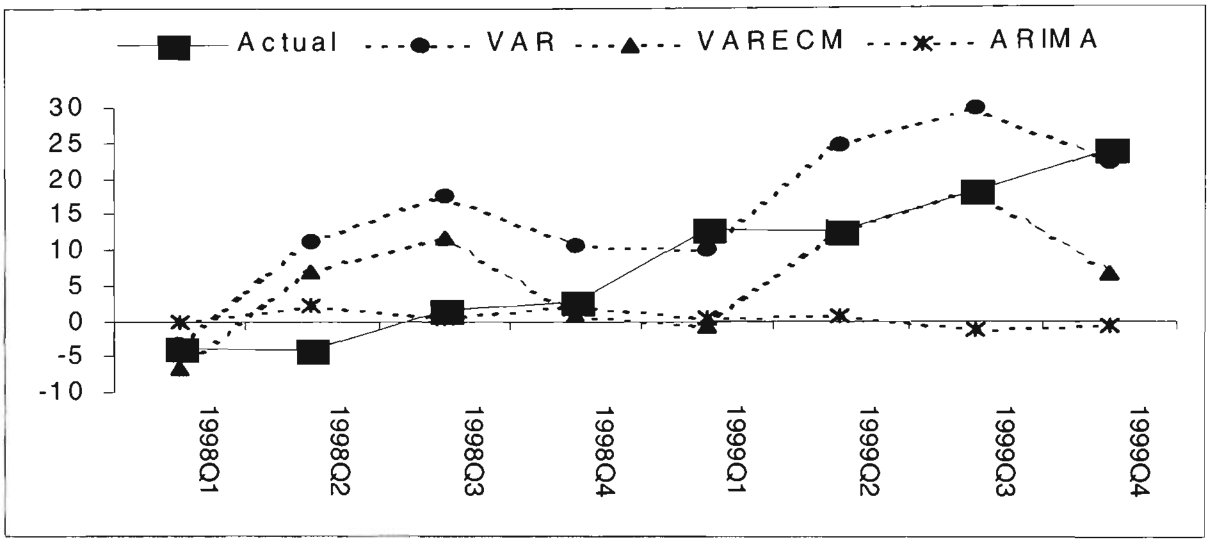

Figure 8.7C: Directional Changes (%) of Tourist Arrivals from the USA

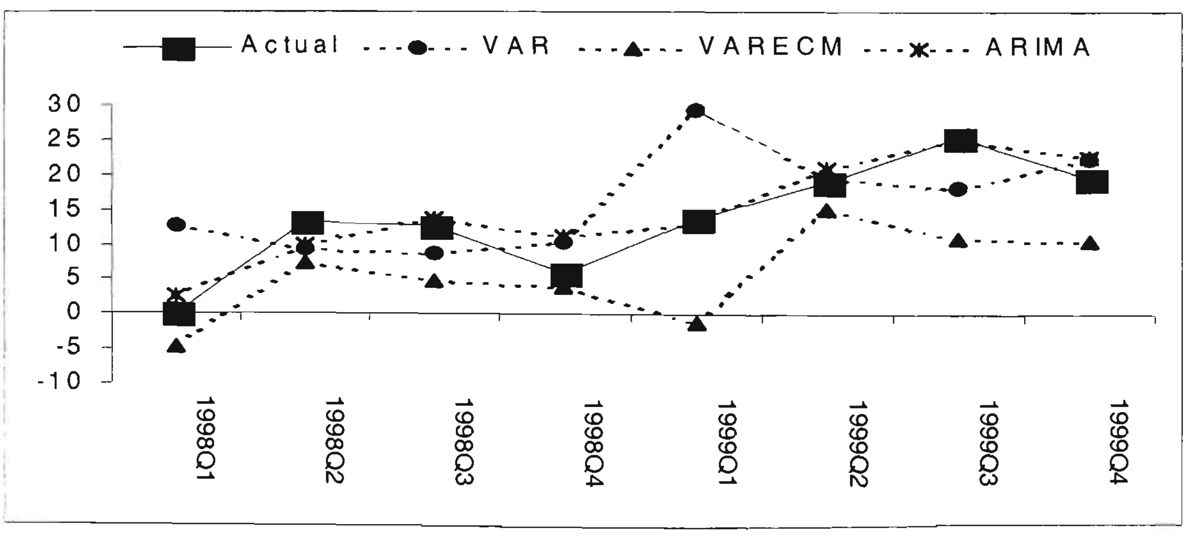

Table 8.1: Estimation of Selected Seasonal ARIMA Models

ARIMA[1]	**Australia ARIMA (0, 1, 2) (0, 0, 0)** $(1-B)Y_t = (1 - 0.4324B^2)\,\varepsilon_t + 0.0194 - 0.0686S_1 + 0.0176S_2 - 0.0185S_3 - 0.3364D$ (3.38) (2.15) (2.06) (0.40) (0.58) (4.16) **Japan ARIMA (2, 1, 0) (0, 0, 0)** $(1 + 0.2672B + 0.1820B^2)(1-B)Y_t = \varepsilon_t$ (1.93) (1.28) $+ 0.0325 - 0.1700S_1 - 0.0133S_2 + 0.1032S_3 - 0.3177D$ (2.48) (4.26) (0.29) (2.64) (3.14) **USA ARIMA (0, 1, 1) (1, 0, 0)** $(1 - 0.3595B^4)(1-B)Y_t = (1 - 0.7366B)\,\varepsilon_t$ (2.65) (7.35) $+ 0.0249 - 0.3468S_1 + 0.0469S_2 - 0.0521S_3 - 0.3632D$ (3.34) (5.18) (0.70) (0.79) (5.19)
ARIMA[4]	**Australia ARIMA (2, 0, 0) (1, 1, 0)** $(1 - 0.8066B + 0.3350B^2)(1 + 0.5034B^4)(1-B^4)Y_t = \varepsilon_t + 0.0826 - 0.2896D$ (8.41) (2.02) (3.67) (1.73) (3.56) **Japan ARIMA (1, 0, 0) (1, 1, 0)** $(1 - 0.5433B)(1 + 0.3879B^4)(1-B^4)Y_t = \varepsilon_t + 0.1276 - 0.3508D$ (4.45) (3.01) (3.43) (3.71) **USA ARIMA (0, 0, 1) (0, 1, 1)** $(1-B^4)Y_t = (1 - 0.5942B)(1 + 0.5573B^4)\,\varepsilon_t + 0.0265 - 0.3631D$ (2.83) (3.84) (3.71) (5.07)
ARIMA[1,4]	**Australia ARIMA (2, 1, 0) (1, 1, 0)** $(1 - 0.4001B^2)(1 - 0.5520B^4)(1-B)(1-B^4)Y_t = \varepsilon_t - 0.0017 - 0.2695D$ (2.87) (4.37) (0.18) (3.34) **Japan ARIMA (1, 1, 0) (1, 1, 0)** $(1 + 0.26601B)(1 + 0.4414B^4)(1-B)(1-B^4)Y_t = \varepsilon_t - 0.0052 - 0.3175D$ (1.98) (3.50) (0.36) (3.29) **USA ARIMA (0, 1, 1) (0, 1, 1)** $(1-B)(1-B^4)Y_t = (1 - 0.6799B)(1 - 0.5572B^4)\,\varepsilon_t - 0.0022 - 0.3710D$ (5.96) (4.43) (0.72) (5.69)

Note:

- Figures in brackets are *t* statistics of estimated coefficients;
- S_1, S_2, S_3, are seasonal dummy variables;
- D is the dummy variable for the exogenous effect from the Tiananmen Square Event during 1989 and 1990 in China.

Table 8.2: χ^2 Statistics Checking Autocorrelation Residuals from the Estimated ARIMA Models

Origin Country	Lag p	$ARIMA^1$	$ARIMA^4$	$ARIMA^{1,4}$
	6	2.21	7.78	8.81
Australia	**12**	5.02	15.22	18.35
	18	7.75	20.56	24.32
	14	10.52	23.01	27.33
	6	2.16	2.57	3.52
Japan	**12**	5.63	12.34	13.91
	18	11.19	18.52	19.05
	14	16.53	22.17	22.63
	6	11.27*	8.14*	10.52*
USA	**12**	13.66	5.53	11.73
	18	18.58	17.91	19.12
	14	33.69	24.03	26.82

Note: * indicates that statistics are significant at 5% level.

Table 8.3: MAE's of Forecasts of Tourist Arrivals Using ARIMA Models

	Model	Australia	Japan	USA
Four-Step Forecasting	$ARIMA^1$	2.62	55.09	5.08
	$ARIMA^4$	3.42	58.44	4.95
	$ARIMA^{1,4}$	3.07	10.74	4.15
Eight-Step Forecasting	$ARIMA^1$	2.94	51.09	7.44
	$ARIMA^4$	3.38	52.56	3.72
	$ARIMA^{1,4}$	2.23	39.81	6.98

Table 8.4: Ranking of Forecasting Accuracy of ARIMA Models

	Model	Australia	Japan	USA
Four-Step Forecasting	$ARIMA^1$	1	2	3
	$ARIMA^4$	2	3	2
	$ARIMA^{1,4}$	3	1	1
Eight-Step Forecasting	$ARIMA^1$	3	2	3
	$ARIMA^4$	2	3	1
	$ARIMA^{1,4}$	1	1	2

Table 8.5A: Comparison of One-Year-Ahead Forecasting Errors

	Australia		Japan		USA	
	MAPE	RMSPE	MAPE	RMSPE	MAPE	RMSPE
VAR	0.074	0.078	0.099	0.118	0.059	0.071
VECM	0.094	0.099	0.064	0.077	0.045	0.048
ARIMA	0.055	0.057	0.029	0.037	0.029	0.023
No-Change	0.159	0.178	0.032	0.033	0.074	0.088

Table 8.5B: Comparison of Two-Year-Ahead Forecasting Errors

	Australia		Japan		USA	
	MAPE	RMSPE	MAPE	RMSPE	MAPE	RMSPE
VAR	0.114	0.124	0.081	0.099	0.058	0.073
VECM	0.111	0.122	0.065	0.085	0.067	0.076
ARIMA	0.046	0.063	0.087	0.109	0.021	0.025
No-Change	0.121	0.142	0.091	0.110	0.089	0.100

Table 8.6: Ranking of Forecasting Accuracy

Forecast Period	Model	Australia	Japan	USA
One Year	VAR	2	4	3
	VARECM	3	3	2
	ARIMA	1	1	1
	No-Change	4	2	4
Two Year	VAR	3	2	2
	VARECM	2	1	3
	ARIMA	1	4	1
	No-Change	4	3	4

CHAPTER 9: **SUMMARY AND CONCLUSION**

9.1 SUMMARY

This thesis has applied recently developed econometric methods to identify the important determinants of tourism demand to China and the best forecasting models of tourist flows to China. It has set three objectives:

- undertaking the first application of modern time-series econometric techniques to the modeling of international tourism flows to China;
- providing first use of the VAR approach to modeling the demand for tourism;
- performing comprehensive forecast comparison of the time-series approach against the VAR econometric approach in order to provide "best possible" forecasts of international tourism flows to China.

The thesis began with an analysis of China's inbound tourism with two related chapters (i.e., Chapter 2 and Chapter 3), which deal with the important contextual setting.

In Chapter 2 we looked explicitly at policy and institutional changes which led to the massive growth in inbound tourism to China over the past two decades. We have learnt that international tourism in China has experienced rapid growth since China commenced its "Open Door" policy in international relations and the reform of its economic system since 1978. We have learnt that tourism in China underwent a structural shift in its policy, which coincided with a dramatic change in the Chinese economy. The role and the nature of tourism have changed significantly. Tourism in China has been transformed from being initially a political policy tool, which was centrally controlled, to a significant economic force, which is driven by a more decentralized and deregulated market system.

The rapid development of international and domestic tourism has contributed to the economic, social and cultural development in China by exchanging economic, social cultural information among domestic regions and different countries. It has been noted that there exist varied interactions and intersections between tourism growth and many aspects of economic development. For instance, the interrelation between international tourist arrivals and foreign trade and foreign direct investment flows. An important observation is the shift away from a centralized to decentralized administrative and policy framework for managing tourism.

In Chapter 3 we have learnt about the structure and characteristics of international tourist arrivals to China in order to provide a complete contextual discussion of the China inbound travel market.

The comparison between tourist arrival figures and tourist expenditure figures provided an important justification for why this thesis had concentrated on an analysis of "foreign tourists". Even a small increase in "foreign tourist" arrivals to China has a relatively much greater impact upon foreign exchange earnings as compared to the "compatriots". It has been found that tourists from Korea, followed by Australia, the USA, Japan and the UK, make the highest contribution in China's international tourism income, and hence become the most important tourism source markets of China. Therefore, from a policy perspective it is important to understand and evaluate the demand characteristics of "foreign tourists" from these major tourist source countries.

Although the separate statistics on tourists according to travel purpose are not available, we have been able to estimate the main purpose of travelling to China by different "categories" of tourists. For instance, the "compatriots" visitors who are ethnic Chinese from Hong Kong, Macao and Taiwan, visit China mainly to see friends and relatives or for leisure travel, while the majority of "foreign tourists" are travelling to China on business.

Chapters 2 and 3 together provided useful insights into policy, institutional and economic factors, which facilitated the rapid growth in China, inbound travel. This contextual setting played an important role in informing the applied demand analysis that follows. However, since China competes with all other countries for international travelers, an analysis of inbound international tourism to China must also be undertaken using the appropriate economic framework where demand for travel to China is part of the global market for international travel. Therefore, prior to undertaking an applied demand analysis, a review of the relevant theoretical as well as empirical international demand literature was undertaken in Chapter 4 and Chapter 5.

It has been known that tourism as a human activity is very complex and hence can neither simply be analyzed as an "industry" nor be defined in the same way as traded goods flows. It has been further noted that each of the so-called macroeconomic theories on the economic determinants of international tourism is able to explain, to some extent, international tourism flows. Thus, even if the theory of demand is the main theory on the determinants of international tourism, it must be used in conjunction with conditions of supply (factor endowments and comparative costs), in order to explain the international tourism demand comprehensively. Although personal motivations and the level of real discretionary income are the main determinants of demand for tourism, there are also supply factors which pull tourists to specific destinations, such as the price level in the destination, the quality of amenities, accommodation and transport at a destination, the ease of access to the destination, and even more the social, economic and political changes in the destination. Factors influencing international tourism demand must be examined from both demand supply sides (or from both tourism generator and the receptor) as well as from the perspective of personal psychological motivations, economics, social and political backgrounds.

Tourism demand can be analyzed for groups of countries, individual countries, regions or local areas. Demand can also be disaggregated by categories as types of visits (for example, holiday, business, VFR and etc), and the types of tourists (covering nationality, age, gender and social-economic group). Factors influencing tourism demand vary with different pairs of origin-destination countries and different types of tourist groups. Therefore, in modeling and forecasting tourism demand, it is very important to segment the tourism demand in order to identify the appropriate determinants of tourism demand and to chose appropriate variables for a demand function. Before forecasting any tourism flow between different pairs of countries, further analyses supported by the empirical studies also need to examine specific determinants of tourism demand between certain generation and destination countries during different periods.

Although methodologies employed in modeling international tourism demand vary in a number of ways in terms of different modeling methods, in general, empirical studies in modeling international tourism demand are catalogued into two broad groups, causal methods and non-causal methods. Despite an increasing number of empirical studies on international tourism demand, several areas remain incomplete and hence require further study. Although relatively sophisticated measures have been used and developed in the methodologies of tourism demand forecasting, all of these approaches have limitations and can only produce short-term forecasts.

The causal methods (regression analyses) quantify the relationships between tourism demand and its influencing factors. A major advantage of regression analysis models over time series models is that it will help tourism companies or governments to understand what factors affect tourism and to explore the consequence of alternative future policies on tourism demand. This is not possible with non-causal methods, though regression models are found to be less accurate than time series models in tourism forecasting. Therefore, a practitioner can benefit from the regression models with the respect to the identification of the size of the effects that changes in the explanatory variables upon tourism demand, and not as a direct forecasting tool. However, the use of econometric techniques in many previous tourism studies was inadequate and suffers from one or more of the following problems:

- the lack of diagnostic checking for the econometric issues, such as stationarity, multicolinearity and serial correlation;
- the ignoring of potential feedback effects on dependent and independent variables and the failure to undertake any endogeneity test of variables in the demand function.

- the omission of potentially important variables or the inadequate use of the determinants in the tourism demand function.

With regard to the time series methods, the basic time series methods have broad applications in tourism, as they are simple to operate if the data fit the requirements for the models. However, one major disadvantage of these methods is that they cannot take account of factors affecting the series other than its past values. Thus these methods do not explain the relationship between tourism demand and the influencing factors at work, though they can indicate the values that should have been achieved in the situation where the other determinants of tourism demand remain the same or without much change. The ARIMA model is an advanced method in the class of time series forecasting methods, when some simple time series methods can only be applied in the specific data series. However, it has the same disadvantage as the other time series methods.

In terms of the different measures of forecasting accuracy, the performance of different forecasting methods has been found to vary considerably. Therefore, an attempt at applying different methodologies mentioned above is necessary in the study of international tourism demand; different criteria of measures of forecasting accuracy should also be applied in order to choose the best forecasting method for international tourism demand, which may also be applied to other tourism developing countries.

The next challenge faced in this thesis was the need to select variables to model and forecast international tourism to China. In Chapter 6 we first identified the most important determinants of tourism demand to China, and further defined appropriate economic indicators to measure these determinants. In addition, a range of statistical analyses was conducted to examine the time series properties (i.e., the trends and seasonalities) of the selected data for each variable.

In accordance with the structure and characteristics of tourism demand to China from its three major generation countries (Australia, Japan and the USA), four variables using 60 quarterly observations were selected and defined as TU, GDP, TA and TP, namely: the tourism demand measured by the number of tourist arrivals to China from the three generation countries; income levels measured by GDP in the countries; business activities between China and the three countries measured by China's two-way trade scales with the three countries; and the relative "tourism prices" measured by the exchanged-rate-adjusted CPI ratios between China and the three countries.

The ACFs, ADF and PP tests suggest that the time-series variables selected are not stationary; the HEGY test further confirms that the data are integrated at order one (i.e., they are I(1) variables). Variable TU in the case of the USA also has stochastic seasonal trends. The non-stationary data need to be adjusted with first or even fourth differencing transformations to meet the stationarity assumption in regression models in order to avoid the "spurious regression" problem.

As an outcome of Chapter 6 it has been noted that the "causal" relationships between the four selected variables should be further examined. Some theoretical "explanatory variables" do not necessarily "cause" the "dependent" variable—tourism demand; on the contrary, tourism demand may "cause" these "independent " variables. Therefore, there might be feedback effects between tourism demand and the other three "independent" variables. Consequently, it is possible that regression models using the single equation approach may suffer the problem of ignoring endogeneity of the variables and the consequent forecasting models may not consider feedback effects between those interrelated variables.

In Chapter 7, based on theoretical interrelationships between the four variables: tourist arrivals, two-way trade, GDP and the relative "tourism price", we analysed and forecasted tourism demand to China from Australia, Japan and the USA using VAR systems.

The cointegration test using the Johansen's ML procedure suggests that there are "long-run" relationships between the four variables: tourist arrivals, two-way trade, GDP and the relative "tourism price". The estimated coefficients of "long-run" tourism demand suggest that the income level in the tourist origin country and the relatively cheap cost of living in China are important variables to explain tourist flows to China from Australia and the USA, whereas the two-way trade volumes between China and Japan is the most important determinant of international tourism demand from Japan to China. It may reflect that, compared with tourists from Japan, relatively more visitors from Australia and the USA are on holiday than for business purpose, while most of the visitors from Japan may be on business trips. The empirical results from the estimated long-run demand functions suggest that two-way trade between China and its tourist source countries is one of the most important determinants of tourism demand to China from origin countries with a high proportion of business travel. It provides further support for the idea that trade volumes between a pair of tourist origin-destination countries may be an important independent variable, which should be considered in the international tourism demand modeling, especially for the modeling of international business travel. The results reported in this thesis provide further support for the role of international trade as a determinant of international travel.

The analysis of the three VAR systems, including the causality test and the impulse response analysis, indicates that the four selected variables (i.e., tourism demand, two-way trade, GDP and the relative "tourism price") are interrelated in most cases. There are feedback effects between tourist arrivals and two-way trade volumes, tourist arrivals and the relative "tourism price". More explicitly, two-way trade volumes, GDP at the three tourist source countries, and the relative "tourism price" are important determinants of tourism demand and hence influence tourism growth in China. However, changes in tourist arrivals may also result in changes in the relative "tourism price" and two-way trade. Therefore, tourism demand modeling and forecasting using single-equation models suffers from biases by ignoring feedback effects between these variables.

The impulse response analyses in the three VAR systems have provided useful implications to evaluate government policy with respect to international tourism and trade stimulation. For the Chinese government, the implementation of a policy in stimulating two-way trade with its tourist source countries may induce increases in tourist arrivals from these countries; a policy change in relation to a decrease of the relative cost of living in China may induce a significant increase in the tourist arrivals from these countries. However, as the duration and degree of the response were seen to vary from different country cases, the government stimulation policy related to trade and the relative "tourism price" respectively will have different effects to these three tourist-source countries. Therefore, different government policies in stimulating international tourism will have different effects to these three tourist-source countries. The government has to set its policy with different emphases according to different tourist-source country in order to achieve significant results. On the other hand, the implementation of a policy to promote tourist flows to China from these three countries will also stimulate their two-way trade flows. The international tourism policies or regulations between Chinese and Japanese government were found to be very important factors influencing the two-way trade growth and decline between these two-countries. It is worth noting that a policy of either trade promotion or tourism promotion may create a "virtuous circle" whereby the endogeneity from one to the other provides a further feedback stimulus from trade to travel and vice versa.

In accordance with the Ganger Causality test and the cointegration test, the VARECM and VAR systems for each country case were estimated respectively, and further eight-step forecasts were generated from these 6 VAR regression models. By comparing the forecasting errors from the VAR and VARECM models respectively for each country case, we found that the inclusion of the long-run error-correction term, based on the cointegration test, improved the forecasting performance of the Australia and Japan VAR models, but not in the case of tourist arrivals from the USA. Three optimal VAR models were selected in terms of forecasting accuracy and the forecasting performance of the VAR models were further evaluated by comparison with other forecasting methods (i.e., ARIMA models and no-changes models) in Chapter 8.

ARIMA models using first differenced data (ARIMA^{1}), fourth differenced data (ARIMA^{4}), and first and fourth differenced data (ARIMA^{1,4}) were estimated for each of the three origin countries, i.e., Australia, Japan and the USA. All selected ARIMA models, including ARIMA^{1}, ARIMA^{4} and ARIMA^{1,4}, past the diagnostic checking of error correlations of the models, which suggests that residuals of the selected models satisfy the assumption of white noise.

In terms of forecasting error magnitude, one optimal ARIMA model was selected for each country case, which was further used for forecasting comparison with the VAR and VARECM models. For one-year ahead forecasts, the Australia ARIMA^{1}, Japan ARIMA^{1,4} and USA ARIMA^{1,4} models were chosen as the optimal forecasting models; for two-year ahead forecasts, the Australia ARIMA^{1,4}, Japan ARIMA^{1,4} and USA ARIMA^{4} were chosen as the optimal forecasting models.

By comparing the measures of relative forecasting accuracy (i.e., MAPE's) of the estimated the VAR, VARECM, ARIMA and no-change models, we found that, in the three country cases, the ARIMA model provided best long-term (two-year) forecasts, followed by the VARECM model. However, in the case of Japan, the VARECM model provided the best forecasts of tourist arrivals from Japan, followed by the no-change model, whereas the ARIMA model generated the poorest forecasts due to its failure to catch the sudden decrease of tourist arrivals from Japan during the Asian Financial Crisis from 1998 to 1999.

In terms of the directional change accuracy, the VAR regression model provided the best forecasts of the eight directional changes of tourist arrivals among the three country cases, followed by the VARECM model, whereas the ARIMA model produced the poorest forecasts. In terms of origin country, all three models produced the best forecasts of directional changes in the case of Australia, followed by the USA, whereas all three models provided the poorest forecasts in the case of Japan, in particular, the ARIMA model generated the worst forecast accuracy in directional changes for tourist arrivals from Japan, which had significant directional changes during the Asian crisis between 1998 and 1999.

This indicates that the ARIMA models perform better when forecasting for the origin country from which tourist arrivals have a stable trend and seasonal pattern (e.g., Australia and Japan), but perform less well under any structural or level changes of tourist arrivals which may be caused by unexpected events, for instance, tourist arrivals from Japan. However, regression models are better able to capture these changes by including related variables, which impact upon the tourism demand. In particular, in a VAR system, all variables are treated as endogenous variables, and the feedback effects are considered in the model. In the three optimal VAR models employed in Chapter 7, tourist arrivals were also treated as an explanatory variable in other sub-equations (i.e., two-way trade, GDP, and the "tourism price") and were further used, as explanatory variables, for the forecasts of tourist arrivals. Therefore, changes in tourist arrivals were also captured in the forecasts of other variables.

Therefore, in the case of tourism demand to China, we find that although regression models may not necessarily generate more accurate forecasts than time series models in terms of the forecasting error magnitude, these VAR regression models developed in this thesis showed better performance as compared to the time series models in forecasting directional changes. Moreover, The VAR regression approach allowed us to examine the short-term and long-term causal relationships between tourist demand and its determinants, and to evaluate the impact of government policies related to tourism.

9.2 IMPLICATIONS

The forecasting of tourism flows, particularly international tourism flows, is one of the most important challenges faced by both government policy makers and investors alike. Failure to anticipate increases in demand may lead to considerable shortfalls in the supply of tourism infrastructure, because of the lead times involved in building and providing this infrastructure. The necessary tourism infrastructure may lead to price increases and foregone opportunities that may feedback into demand resulting in unfortunate negative impact upon demand. Therefore, the ability to forecast accurately both the volumes of international visitor arrivals and any directional changes is extremely important.

This thesis has used the VAR and VARECM models, which come from the econometric school of forecasting. The advantage of these approaches is that they are modeling approaches that include economic causal relationships and also allow for endogeneity and feedback effects, a very important real world economic phenomenon. The VAR and VARECM models were compared to the ARIMA models, which in many other studies have proved to be comparatively good forecasting tools and on the criterion of directional change they compare most favorably.

Given the popularity and success of the ARIMA approach, if the VAR and VARECM models are able to compare favorably with these techniques, then the VAR and VARECM approaches may well be worth applying in many more tourism forecasting studies.

It is therefore pleasing to report the success of the VAR and VARECM models, particularly in their ability to forecast directional changes. Although there are differences between the one-year and two-year forecast comparison, as well as differences between the three country cases, overall there is sufficient support for the VAR and VARECM approach to encourage further use of this approach.

This thesis has provided a detailed analysis of international tourism demand to China of 'foreign tourists' from three of China's important source countries. There are important implications from the results of the research reported here for both the China market alone but for analysis of international tourism demand and forecasting more generally. First of all it is clear that international trade between any two counties is an important influential variable in affecting international travel between the two countries and should therefore be included in any 'causal' or regression modeling approach.

Second, more general use of the VAR approach should be made in international tourism demand modeling and forecasting.

APPENDIX

Table 1.1: Estimation of ECM for Variable TA Based on Two Cointegrating Vectors: the Australia VARECM (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	1.3766	0.7588	1.8141[.077]
ΔTU_{t-1}	-0.2897	0.1784	-1.6238[.112]
ΔTA_{t-1}	0.2024	0.1329	1.5231[.135]
ΔGDP_{t-1}	0.8455	2.4519	.34481[.732]
ΔTP_{t-1}	0.1093	0.2582	.42347[.674]
$U_{1,t-1}$	-0.5708	0.1313	-4.3476[.000]
$U_{2,t-1}$	-0.1739	0.1313	-1.3244[.192]
S1	-0.0500	0.0536	-.93322[.356]
S2	-0.0267	0.0599	-.44661[.657]
S3	0.0361	0.0551	.65591[.515]
D1	-0.2338	0.1366	-1.7114[.094]
D2	-0.0156	0.1049	-.14874[.882]
D3	0.1536	0.1779	.86321[.393]
D4	0.5043	0.1663	3.0329[.004]
D5	0.0564	0.1450	.38931[.699]
R-Squared			0.4680
R-Bar-Squared			0.2948
F(14, 43)			2.7021(.006)
Equation Log-likelihood			44.1401
System Log-likelihood			430.9437

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 14.9852[.005]	F(4, 39) = 3.3966[.018]
B: Normality	CHSQ (2) = 0.4418[.802]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.5835[.445]	F(1, 56) = 0.5691[.454]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 1.2: Estimation of ECM for Variable GDP Based on Two Cointegrating Vectors: the Australia VARECM (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
	0.0047	0.0467	.10035[.921]
ΔTU_{t-1}	-0.0037	0.0110	-.34160[.734]
ΔTA_{t-1}	0.0013	0.0082	.15815[.875]
ΔGDP_{t-1}	0.0970	0.1508	.64343[.523]
ΔTP_{t-1}	0.0122	0.0159	.77062[.445]
$U_{1,t-1}$	-0.0219	0.0081	-2.7122[.010]
$U_{2,t-1}$	0.0031	0.0081	.38936[.699]
S1	-0.0037	0.0033	-1.1231[.268]
S2	-0.0011	0.0037	-.29447[.770]
S3	-0.0030	0.0034	-.88955[.379]
D1	-0.0025	0.0084	-.29264[.771]
D2	0.0001	0.0065	.020468[.984]
D3	-0.0016	0.0109	-.14457[.886]
D4	0.0094	0.0102	.91435[.366]
D5	0.0144	0.0089	1.6174[.113]

R-Squared	0.2941
R-Bar-Squared	0.0643
F(14, 43)	1.2800(.259)
Equation Log-likelihood	205.8799
System Log-likelihood	430.9437

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 4.8718[.301]	F(4, 39) = 0.8940[.477]
B: Normality	CHSQ (2) = 1.7806[.411]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.0566[.812]	F(1, 56) = 0.0547[.816]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table1.3: Estimation of ECM for Variable TP Based on Two Cointegrating Vectors: the Australia VARECM (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	0.9889	0.2121	4.6626[.000]
ΔTU_{t-1}	0.0722	0.0499	1.4469[.155]
ΔTA_{t-1}	-0.0160	0.0371	-.43027[.669]
ΔGDP_{t-1}	0.6790	0.6853	.99078[.327]
ΔTP_{t-1}	0.1223	0.0722	1.6948[.097]
$U_{1,t-1}$	0.0153	0.0367	.41578[.680]
$U_{2,t-1}$	-0.1704	0.0367	-4.6440[.000]
S1	-0.0653	0.0150	-4.3577[.000]
S2	0.0105	0.0167	.62800[.533]
S3	-0.0240	0.0154	-1.5571[.127]
D1	-0.0219	0.0382	-.57355[.569]
D2	0.0802	0.0293	2.7368[.009]
D3	0.0613	0.0497	1.2335[.224]
D4	-0.1485	0.0465	-3.1958[.003]
D5	-0.4033	0.0405	-9.9507[.000]
R-Squared			0.8592
R-Bar-Squared			0.8134
F(14, 43)			18.7481(.000)
Equation Log-likelihood			118.0739
System Log-likelihood			430.9437

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 4.7802[.311]	F(4, 39) = 0.8757[.487]
B: Normality	CHSQ (2) = 2.2274[.328]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.7492[.387]	F(1, 56) = 0.7331[.396]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 2.1: Estimation of ECM for Variable TA Based on Two Cointegrating Vectors: the Japan VARECM (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	-1.0121	0.4337	-2.3335[.024]
ΔTU_{t-1}	-0.1211	0.1007	-1.2028[.236]
ΔTA_{t-1}	0.1029	0.1356	.75877[.452]
ΔGDP_{t-1}	-0.1755	1.3113	-.13383[.894]
ΔTP_{t-1}	0.1106	0.1575	.70260[.486]
$U_{1,t-1}$	0.0932	0.0817	1.1415[.260]
$U_{2,t-1}$	-0.1783	0.0817	-2.1830[.035]
S1	-0.1886	0.0398	-4.7395[.000]
S2	0.0913	0.0438	2.0842[.043]
S3	0.0184	0.0347	.52937[.599]
D1	-0.1022	0.0877	-1.1645[.251]
D2	-0.0731	0.0912	-.80135[.427]
D3	0.0560	0.1129	.49555[.623]
D4	0.0306	0.0888	.34442[.732]
D5	0.0759	0.0912	.83266[.410]
D6	0.3292	0.0879	3.7449[.001]

R-Squared	0.6454
R-Bar-Squared	0.5188
F(15, 42)	5.0972[.000]
Equation Log-likelihood	72.3668
System Log-likelihood	437.9246

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 5.5019[.240]	F(4, 38) = 0.9956[.422]
B: Normality	CHSQ (2) = 1.1087[.574]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 1.4942[.222]	F(1, 56) = 1.4808[.229]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 2.2: Estimation of ECM for Variable GDP Based on Two Cointegrating Vectors: the Japan VARECM (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	0.0273	0.0538	.50733[.615]
ΔTU_{t-1}	0.0126	0.0125	1.0105[.318]
ΔTA_{t-1}	0.0177	0.0168	1.0528[.298]
ΔGDP_{t-1}	-0.0363	0.1625	-.22318[.824]
ΔTP_{t-1}	-0.0005	0.0195	-.024614[.980]
$U_{1,t-1}$	-0.0141	0.0101	-1.3932[.171]
$U_{2,t-1}$	-0.0043	0.0101	-.42139[.676]
S1	0.0044	0.0049	.88224[.383]
S2	0.0016	0.0054	.28846[.774]
S3	-0.0011	0.0043	-.26117[.795]
D1	-0.0034	0.0109	-.31575[.754]
D2	0.0136	0.0113	1.2039[.235]
D3	-0.0085	0.0140	-.60912[.546]
D4	-0.0008	0.0110	-.075810[.940]
D5	-0.0187	0.0113	-1.6576[.105]
D6	0.0063	0.0109	.57890[.566]

R-Squared	0.2401
R-Bar-Squared	0.0312
F(15, 42)	0.8847[.585]
Equation Log-likelihood	193.4620
System Log-likelihood	437.9246

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 7.0935[.131]	F(4, 38) = 1.3238[.279]
B: Normality	CHSQ (2) = 1.8535[.396	Not applicable
C: Heteroscedasticity	CHSQ (1) = 3.3477[.067]	F(1, 56) = 3.4303[.069]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 2.3: Estimation of ECM for Variable TP Based on Two Cointegrating Vectors: the Japan VARECM (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	-0.1376	0.3635	-.37846[.707]
ΔTU_{t-1}	-0.0404	0.0844	-.47859[.635]
ΔTA_{t-1}	0.2282	0.1136	2.0084[.051]
ΔGDP_{t-1}	1.3601	1.0990	1.2375[.223]
ΔTP_{t-1}	-0.0364	0.1320	-.27613[.784]
$U_{1,t-1}$	0.1973	0.0684	2.8827[.006]
$U_{2,t-1}$	0.1007	0.0684	1.4719[.149]
S1	-0.0679	0.0334	-2.0372[.048]
S2	0.0227	0.0367	.61929[.539]
S3	0.0057	0.0291	.19456[.847]
D1	0.1182	0.0735	1.6076[.115]
D2	0.0910	0.0764	1.1909[.240]
D3	-0.0784	0.0947	-.82874[.412]
D4	-0.0554	0.0744	-.74476[.461]
D5	-0.3360	0.0764	-4.3947[.000]
D6	0.0701	0.0737	.95190[.347]
R-Squared			0.6151
R-Bar-Squared			0.4778
F(15, 42)			4.4759[.000]
Equation Log-likelihood			82.6089
System Log-likelihood			437.9246

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 4.3504[.361]	F(4, 38) = 0.7703[.551]
B: Normality	CHSQ (2) = 3.2470[.197]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.5901[.442]	F(1, 56) = 0.5756[.451]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 3.1: Estimation of ECM for Variable TA Based on Three Cointegrating Vectors: the USA VARECM (4) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	-5.0060	3.1666	-1.5809[.125]
ΔTU_{t-1}	-0.1280	0.1402	-.91293[.369]
ΔTA_{t-1}	0.1611	0.1598	1.0085[.322]
ΔGDP_{t-1}	-0.5028	2.1638	-.23236[.818]
ΔTP_{t-1}	-0.1445	0.2290	-.63112[.533]
ΔTU_{t-2}	0.0484	0.1405	.34405[.733]
ΔTA_{t-2}	0.1520	0.1547	.98239[.334]
ΔGDP_{t-2}	1.6042	2.1326	.75224[.458]
ΔTP_{t-2}	-0.1323	0.2319	-.57051[.573]
ΔTU_{t-3}	0.1033	0.1228	.84077[.408]
ΔTA_{t-3}	0.3211	0.1288	2.4943[.019]
ΔGDP_{t-3}	-3.8940	2.0931	-1.8604[.073]
ΔTP_{t-3}	0.3514	0.2289	1.5353[.136]
ΔTU_{t-4}	0.0702	0.1067	.65765[.516]
ΔTA_{t-4}	0.3917	0.1217	3.2174[.003]
ΔGDP_{t-4}	3.8820	2.0623	1.8824[.070]
ΔTP_{t-4}	-0.0574	0.2244	-.25565[.800]
$U_{1,t-1}$	0.0369	0.0763	.48377[.632]
$U_{2,t-1}$	0.1699	0.0763	2.2268[.034]
$U_{3,t-1}$	-0.0761	0.0763	-.99757[.327]
S1	-0.5811	0.1308	-4.4420[.000]
S2	-0.1742	0.1117	-1.5590[.130]
S3	-0.1797	0.1501	-1.1976[.241]
D1	0.1621	0.0963	1.6829[.104]
D2	-0.1934	0.0989	-1.9555[.061]
D3	-0.0112	0.1425	-.078871[.938]
D4	-0.2163	0.0963	-2.2459[.033]
R-Squared			0.9625
R-Bar-Squared			0.9276
F(26, 28)			27.6186[.000]
Equation Log-likelihood			82.0482
System Log-likelihood			517.2455

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 14.3471[.006]	F(4, 24) = 2.1175[.110]
B: Normality	CHSQ (2) = 0.6680[.716]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.2186[.640]	F(1, 53) = 0.2115[.647]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 3.2: Estimation of ECM for Variable GDP Based on Three Cointegrating Vectors: the USA VARECM (4) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	0.6908	0.2390	2.8904[.007]
ΔTU_{t-1}	-0.0308	0.0106	-2.9140[.007]
ΔTA_{t-1}	0.0270	0.0121	2.2425[.033]
ΔGDP_{t-1}	-0.4314	0.1633	-2.6414[.013]
ΔTP_{t-1}	-0.0332	0.0173	-1.9233[.065]
ΔTU_{t-2}	-0.0263	0.0106	-2.4796[.019]
ΔTA_{t-2}	0.0139	0.0117	1.1923[.243]
ΔGDP_{t-2}	-0.0211	0.1610	-.13088[.897]
ΔTP_{t-2}	-0.0178	0.0175	-1.0163[.318]
ΔTU_{t-3}	-0.0315	0.0093	-3.3928[.002]
ΔTA_{t-3}	0.0006	0.0097	.063178[.950]
ΔGDP_{t-3}	-0.1347	0.1580	-.85254[.401]
ΔTP_{t-3}	-0.0077	0.0173	-.44809[.658]
ΔTU_{t-4}	-0.0195	0.0081	-2.4159[.022]
ΔTA_{t-4}	-0.0005	0.0092	-.052898[.958]
ΔGDP_{t-4}	-0.1467	0.1557	-.94271[.354]
ΔTP_{t-4}	0.0082	0.0169	.48705[.630]
$U_{1,t-1}$	0.0237	0.0058	4.1111[.000]
$U_{2,t-1}$	-0.0121	0.0058	-2.0982[.045]
$U_{3,t-1}$	-0.0010	0.0058	-.17660[.861]
S1	0.0023	0.0099	.23513[.816]
S2	0.0155	0.0084	1.8409[.076]
S3	0.0033	0.0113	.28905[.775]
D1	0.0119	0.0073	1.6356[.113]
D2	-0.0100	0.0075	-1.3364[.192]
D3	-0.0053	0.0108	-.49404[.625]
D4	-0.0083	0.0073	-1.1410[.264]

R-Squared	0.6149
R-Bar-Squared	0.2573
F(26, 28)	1.7197[.081]
Equation Log-likelihood	78.0488
System Log-likelihood	517.2455

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 7.3235[.120]	F(4, 24) = 0.9216[.468]
B: Normality	CHSQ (2) = 1.9066[.385]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.8455[.358]	F(1, 53) = 0.82755[.367]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 3.3: Estimation of ECM for Variable TP Based on Three Cointegrating Vectors: the USA VARVECM (4) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
A	1.148	1.467	.78219[.441]
ΔTU_{t-1}	-0.140	0.065	-2.1587[.040]
ΔTA_{t-1}	0.148	0.074	2.0025[.055]
ΔGDP_{t-1}	-0.492	1.003	-.49091[.627]
ΔTP_{t-1}	0.073	0.106	.69004[.496]
ΔTU_{t-2}	-0.073	0.065	-1.1214[.272]
ΔTA_{t-2}	0.113	0.072	1.5819[.125]
ΔGDP_{t-2}	-0.414	0.988	-.41882[.679]
ΔTP_{t-2}	-0.023	0.107	-.21703[.830]
ΔTU_{t-3}	-0.098	0.057	-1.7281[.095]
ΔTA_{t-3}	-0.003	0.060	-.05724[.955]
ΔGDP_{t-3}	0.745	0.970	.76776[.449]
ΔTP_{t-3}	-0.013	0.106	-.11789[.907]
ΔTU_{t-4}	-0.104	0.049	-2.1031[.045]
ΔTA_{t-4}	0.042	0.056	.73758[.467]
ΔGDP_{t-4}	-0.255	0.956	-.26683[.792]
ΔTP_{t-4}	-0.027	0.104	-.26174[.795]
$U_{1,t-1}$	0.139	0.035	3.9222[.001]
$U_{2,t-1}$	0.105	0.035	2.9774[.006]
$U_{3,t-1}$	0.027	0.035	.75773[.455]
S1	-0.039	0.061	-.64883[.522]
S2	0.096	0.052	1.8563[.074]
S3	0.044	0.070	.62887[.535]
D1	0.039	0.045	.86523[.394]
D2	0.038	0.046	.83892[.409]
D3	-0.127	0.066	-1.9296[.064]
D4	-0.349	0.045	-7.8285[.000]
R-Squared			0.9037
R-Bar-Squared			0.8143
F(26, 28)			10.1080[.000]
Equation Log-likelihood			124.3521
System Log-likelihood			517.2455

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 5.7250[.221]	F(4, 24) = 0.6971[.601]
B: Normality	CHSQ (2) = 9.0216[.011]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.5409[.462]	F(1, 53) = 0.5264[.471]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 4.1: Estimation of TA Equation: the Australia VAR (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	0.1752	0.1878	.93265[.356]
ΔTA_{t-1}	-0.1487	0.1301	-1.1436[.259]
ΔGDP_{t-1}	5.2323	2.6820	1.9509[.057]
ΔTP_{t-1}	0.1263	0.3007	.42009[.676]
A	0.0338	0.0524	.64446[.523]
S1	-0.0818	0.0626	-1.3064[.198]
S2	-0.0531	0.0704	-.75525[.454]
S3	0.0112	0.0643	.17362[.863]
D1	-0.1998	0.1612	-1.2393[.222]
D2	0.0040	0.1225	.032776[.974]
D3	-0.1272	0.1882	-.67596[.503]
D4	0.1735	0.1691	1.0258[.310]
D5	-0.1175	0.1648	-.71325[.479]

R-Squared	0.2182
R-Bar-Squared	0.0097
F(12, 45)	1.0467[.425]
Equation Log-likelihood	33.1712
System Log-likelihood	403.1156

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 12.8222[.012]	F(4, 41) = 2.9091[.033]
B: Normality	CHSQ (2) = 2.7191[.257]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.0663[.797]	F(1, 56) = 0.0640[.801]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 4.2: Estimation of GDP Equation: the Australia VAR (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	0.0179	0.0100	1.7814[.082]
ΔTA_{t-1}	-0.0125	0.0069	-1.7967[.079]
ΔGDP_{t-1}	0.3341	0.1431	2.3342[.024]
ΔTP_{t-1}	0.0182	0.0160	1.1334[.263]
A	0.0091	0.0028	3.2571[.002]
S1	-0.0043	0.0033	-1.2840[.206]
S2	-0.0034	0.0038	-.91474[.365]
S3	-0.0045	0.0034	-1.3236[.192]
D1	0.0059	0.0086	.68147[.499]
D2	0.0065	0.0065	1.0007[.322]
D3	-0.0022	0.0100	-.21665[.829]
D4	0.0004	0.0090	.043705[.965]
D5	0.0114	0.0088	1.2997[.200]
R-Squared			0.2707
R-Bar-Squared			0.0762
F(12, 45)			1.3921[.205]
Equation Log-likelihood			203.1459
System Log-likelihood			403.1156

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 3.6872[.450]	F(4, 41) = 0.6958[.599]
B: Normality	CHSQ (2) = 0.2903[.865]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.0002[.988]	F(1, 56) = 0.0002[.989]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 4.3: Estimation of TP Equation: the Australia VAR (1) System Table

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	0.1512	0.0543	2.7874[.008]
ΔTA_{t-1}	-0.0464	0.0376	-1.2341[.224]
ΔGDP_{t-1}	0.3334	0.7747	.43041[.669]
ΔTP_{t-1}	0.1248	0.0869	1.4367[.158]
A	0.0212	0.0151	1.4009[.168]
S1	-0.0740	0.0181	-4.0879[.000]
S2	0.0106	0.0203	.52356[.603]
S3	-0.0313	0.0186	-1.6867[.099]
D1	-0.0296	0.0466	-.63615[.528]
D2	0.0717	0.0354	2.0245[.049]
D3	-0.0214	0.0544	-.39325[.696]
D4	-0.2301	0.0489	-4.7109[.000]
D5	-0.4177	0.0476	-8.7750[.000]

R-Squared	0.7864
R-Bar-Squared	0.7295
F(12, 45)	13.8104[.000]
Equation Log-likelihood	105.1989
System Log-likelihood	403.1156

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 10.9042[.028]	F(4, 41) = 2.3732[.068]
B: Normality	CHSQ (2) = 0.0942[.954]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.9851[.321]	F(1, 56) = 0.9676[.329]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values

Table 5.1: Estimation of TA Equation: the Japan VAR(3) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	0.0271	0.1106	.24476[.808]
ΔTU_{t-2}	0.2916	0.1900	1.5353[.134]
ΔTU_{t-3}	0.0975	0.1039	.93829[.355]
ΔTA_{t-1}	0.0300	0.1518	.19778[.844]
ΔTA_{t-2}	-0.2032	0.1772	-1.1468[.259]
ΔTA_{t-3}	-0.0265	0.1720	-.15398[.879]
ΔGDP_{t-1}	0.3596	1.5999	.22474[.824]
ΔGDP_{t-2}	-0.8887	1.5381	-.57779[.567]
ΔGDP_{t-3}	-0.3041	1.6807	-.18093[.857]
ΔTP_{t-1}	0.3387	0.1646	2.0580[.047]
ΔTP_{t-2}	-0.1395	0.1597	-.87318[.389]
ΔTP_{t-3}	0.2006	0.1596	1.2563[.218]
A	0.0486	0.0519	.93700[.355]
S1	-0.2364	0.0606	-3.9018[.000]
S2	0.1295	0.0695	1.8621[.071]
S3	0.0331	0.1094	.30234[.764]
D1	-0.0702	0.0998	-.70332[.487]
D2	-0.0651	0.1000	-.65095[.519]
D3	0.1812	0.2295	.78960[.435]
D4	-0.1602	0.1268	-1.2632[.215]
D5	0.0851	0.1004	.84805[.402]
D6	0.3303	0.0948	3.4849[.001]

R-Squared	0.6741
R-Bar-Squared	0.4729
F(21, 34)	3.3499[.001]
Equation Log-likelihood	70.9304
System Log-likelihood	437.7543

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 12.8907[.012]	F(4, 30) = 2.2427[.088]
B: Normality	CHSQ (2) = 0.1714[.918]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.7515[.386]	F(1, 54) = 0.73460[.395]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted value.

Table 5.2: Estimation of GDP Equation: the Japan VAR(3) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	0.0041	0.0118	.35065[.728]
ΔTU_{t-2}	-0.0072	0.0202	-.35587[.724]
ΔTU_{t-3}	-0.0163	0.0111	-1.4773[.149]
ΔTA_{t-1}	0.0391	0.0162	2.4207[.021]
ΔTA_{t-2}	-0.0183	0.0189	-.96841[.340]
ΔTA_{t-3}	-0.0055	0.0183	-.29876[.767]
ΔGDP_{t-1}	0.1034	0.1702	.60745[.548]
ΔGDP_{t-2}	0.2524	0.1636	1.5428[.132]
ΔGDP_{t-3}	0.3220	0.1788	1.8014[.081]
ΔTP_{t-1}	-0.0102	0.0175	-.58078[.565]
ΔTP_{t-2}	-0.0040	0.0170	-.23620[.815]
ΔTP_{t-3}	0.0105	0.0170	.62107[.539]
A	0.0018	0.0055	.32954[.744]
S1	0.0059	0.0064	.91419[.367]
S2	0.0061	0.0074	.82571[.415]
S3	-0.0097	0.0116	-.83686[.409]
D1	-0.0126	0.0106	-1.1869[.244]
D2	0.0155	0.0106	1.4525[.156]
D3	-0.0189	0.0244	-.77322[.445]
D4	0.0078	0.0135	.57991[.566]
D5	-0.0020	0.0107	-.18955[.851]
D6	0.0022	0.0101	.21348[.832]
R-Squared			0.3748
R-Bar-Squared			0.0112
F(21, 34)			0.9708[.517]
Equation Log-likelihood			196.4206
System Log-likelihood			437.7543

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 10.9245[.027]	F(4, 30) = 1.8214[.151]
B: Normality	CHSQ (2) = 10.7542[.005]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 3.2243[.073]	F(1, 54) = 3.2991[.075]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted value.

Table 5.3: Estimation of TP Equation: the Japan VAR(3) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	0.0833	0.0896	.92955[.359]
ΔTU_{t-2}	-0.1674	0.1539	-1.0881[.284]
ΔTU_{t-3}	-0.2002	0.0842	-2.3783[.023]
ΔTA_{t-1}	0.2864	0.1230	2.3284[.026]
ΔTA_{t-2}	-0.1372	0.1436	-.95558[.346]
ΔTA_{t-3}	0.0101	0.1393	.072393[.943]
ΔGDP_{t-1}	1.1526	1.2959	.88943[.380]
ΔGDP_{t-2}	0.3303	1.2459	.26512[.793]
ΔGDP_{t-3}	-2.1672	1.3614	-1.5920[.121]
ΔTP_{t-1}	0.1297	0.1333	.97325[.337]
ΔTP_{t-2}	0.0292	0.1294	.22536[.823]
ΔTP_{t-3}	0.3279	0.1293	2.5362[.016]
A	0.0383	0.0420	.91188[.368]
S1	-0.0112	0.0491	-.22922[.820]
S2	0.0391	0.0563	.69399[.492]
S3	-0.1210	0.0886	-1.3655[.181]
D1	0.0321	0.0808	.39741[.694]
D2	0.0407	0.0810	.50236[.619]
D3	-0.4638	0.1859	-2.4948[.018]
D4	0.0155	0.1027	.15091[.881]
D5	-0.3244	0.0813	-3.9904[.000]
D6	0.0720	0.0768	.93788[.355]

R-Squared	0.6596
R-Bar-Squared	0.4494
F(21, 34)	3.1380[.001]
Equation Log-likelihood	82.7319
System Log-likelihood	437.7543

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ (4) = 6.3107[.177]	F(4, 30) = 0.9525[.448]
B: Normality	CHSQ (2) = 0.8409[.657]	Not applicable
C: Heteroscedasticity	CHSQ (1) = 0.8889[.346]	F(1, 54) = 0.8710[.355]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted value.

Table 6.1: Estimation of TA Equation: the USA VAR (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	-0.1145	0.1141	-1.0031[.321]
ΔTA_{t-1}	-0.1044	0.1401	-.74514[.460]
ΔGDP_{t-1}	-2.1663	2.8209	-.76796[.447]
ΔTP_{t-1}	-0.2203	0.2572	-.85669[.396]
A	0.2584	0.0362	7.1359[.000]
S1	-0.5825	0.0450	-12.9406[.000]
S2	-0.0223	0.0703	-.31715[.753]
S3	-0.1168	0.0454	-2.5701[.014]
D1	-0.1167	0.0932	-1.2517[.217]
D2	-0.1297	0.1124	-1.1544[.255]
D3	-0.1495	0.1245	-1.2005[.237]
D4	-0.1985	0.1080	-1.8382[.073]
R-Squared			0.8987
R-Bar-Squared			0.8728
F(11, 43)			34.6915[.000]
Equation Log-likelihood			54.7497
System Log-likelihood			435.9012

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ(4) = 5.4915[.240]	F(4, 39) = 1.0815[.379]
B: Normality	CHSQ(2) = 1.0269[.598]	Not applicable
C: Heteroscedasticity	CHSQ(1) = 0.6854[.408]	F(1, 53) = 0.6688[.417]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values.

Table 6.2: Estimation of GDP Equation: the USA VAR (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	-0.0119	0.0049	-2.4066[.020]
ΔTA_{t-1}	0.0065	0.0061	1.0710[.290]
ΔGDP_{t-1}	0.2803	0.1219	2.2993[.026]
ΔTP_{t-1}	-0.0126	0.0111	-1.1325[.264]
A	0.0066	0.0016	4.2028[.000]
S1	-0.0012	0.0019	-.63990[.526]
S2	0.0023	0.0030	.76787[.447]
S3	-0.0011	0.0020	-.53672[.594]
D1	-0.0116	0.0040	-2.8915[.006]
D2	-0.0143	0.0049	-2.9443[.005]
D3	0.0074	0.0054	1.3789[.175]
D4	-0.0013	0.0047	-.27728[.783]

R-Squared	0.3821
R-Bar-Squared	0.2241
F(11, 43)	2.4183[.019]
Equation Log-likelihood	227.5442
System Log-likelihood	435.9012

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ(4) = 10.7737[.029]	F(4, 39) = 2.3751[.069]
B: Normality	CHSQ(2) = 2.0685[.355]	Not applicable
C: Heteroscedasticity	CHSQ(1) = 0.0993[.753]	F(1, 53) = 0.0958[.758]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values.

Table 6.3: Estimation of TP Equation: the USA VAR (1) System

Regressor	Coefficient	Standard Error	T-Ratio[P Value]
ΔTU_{t-1}	-0.0768	0.0485	-1.5849[.120]
ΔTA_{t-1}	0.0499	0.0595	.83926[.406]
ΔGDP_{t-1}	-0.5895	1.1986	-.49178[.625]
ΔTP_{t-1}	0.0834	0.1093	.76302[.450]
A	0.0316	0.0154	2.0505[.046]
S1	-0.0856	0.0191	-4.4750[.000]
S2	0.0394	0.0299	1.3188[.194]
S3	-0.0221	0.0193	-1.1470[.258]
D1	-0.0542	0.0396	-1.3682[.178]
D2	-0.0464	0.0478	-.97108[.337]
D3	-0.2101	0.0529	-3.9712[.000]
D4	-0.3370	0.0459	-7.3461[.000]

R-Squared	0.7787
R-Bar-Squared	0.7221
F(11, 43)	13.7557[.000]
Equation Log-likelihood	101.8238
System Log-likelihood	435.9012

Diagnostic Tests

Test Statistics	LM Version	F Version
A: Serial Correlation	CHSQ(4) = 11.9376[.018]	F(4, 39) = 2.7029[.044]
B: Normality	CHSQ(2) = 12.0811[.002]	Not applicable
C: Heteroscedasticity	CHSQ(1) = 0.6702[.413]	F(1, 53) = 0.6538[.422]

A:Lagrange multiplier test of residual serial correlation
B:Based on a test of skewness and kurtosis of residuals
C:Based on the regression of squared residuals on squared fitted values.

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Publications and Presentations Associated With This Thesis

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