<u>Hotel Occupancy Rate Volatility and its Determinants</u>

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Doctor of Philosophy

April, 2011

Abstract

In the hotel industry, the occupancy rate, which is the number of rooms occupied by inbound tourists in proportion to the total number of rooms available for occupation, is an indicator of a hotel's availability. For planning purposes, it is useful for hotel management to know well in advance the expected occupancy rates. However, since the hotel industry is among the most volatile and is influenced by local and international economic and political factors, it is difficult to predict exact occupancy rates. To manage risks associated with this volatility and uncertainty, the hotel industry considers it sufficient to be able to know in advance the turning points in occupancy rates, which are the periods in time when increasing occupancy rates change to decreasing occupancy rates and, subsequently, decreasing occupancy rates change to increasing occupancy rates.

The present study aims to develop models that could predict the turning points of the upward and downward trends in hotel occupancy rates so that hoteliers would know in advance when the current trend would change for the better or worse. These models are developed not for individual hotels but for groups of hotels that have similar tariffs or pricing levels, as occupancy rates vary according to prices charged. Given that there is no evidence of past research using non-linear models for predicting occupancy rates in the hotel industry, the present study predicts the turning points that indicate the directional change in the hotel occupancy rate by estimating logistic and probit regression models with a composite leading indicator and hotel demand determinants.

The present study uses secondary data from Hong Kong's hotel industry and the occupancy rates of tourists for each hotel tariff level to predict the turning points. The

occupancy rates have been obtained for each hotel tariff level from the Hong Kong Tourism Board (HKTB) for the period 1972 (quarter 1) to 2010 (quarter 3).

The results of the forecast performance has shown that the regression logistic and probit models estimated with the hotel demand determinants have higher accuracy outcomes in predicting the turning points of the hotel occupancy growth rate compared to the composite leading indicator models.

Declaration

"I, Candy Mei Fung, TANG, declare that the PhD thesis titled, *Hotel Occupancy Rate Volatility and ItsDeterminants*, is not more than 100,000 words in length, including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work."

Signature:

Date:

Acknowledgement

I would like to thank Dr. Nada Kulendran for giving me a chance to learn from him and for guiding me though my study in the past three years. I am so fortunate to have Dr. Kulendran as my supervisor. His expert advicece, invaluable support, encouragement, professional supervision, and critical suggestions make me confident about finishing my study steadily and smoothly at Victoria University.

I also wish to thank Dr. Hubert Fernando for taking up the role of thesis co-supervisor. The kind man has supported me in the writing and editing of my thesis, which made my work easier, especially in the last stages of my study.

I dedicate my thesis to my parents, Ping Kwan TANG (鄧炳坤) and Lau Cheun YEUNG (楊流川). They have always given me their boundless love. Their happiness, caring, support, hard work, trust, and guidance have made me set my goals toward becoming a better person. They are my role models, and I am so glad and feel blessed to be part of the TANG family.

I also thank all my siblings, in-laws, and the children in my family who have given me support and encouragement for my study, namely, Peter, Berra, Yee, Ling, Kam Fung, Ken, Alice, Siu, Leung, Steve, Joyce, Jimmy, Cheryl, Coby, Jacky, and my special Regan.

Publications Associated with this Thesis

Tang, M.F. C. and Kulendran, N (2011), *A composite leading indicator for the hotel industry*, Tourism Economics, June, 2011 (due to be published)

Tang, M.F. C. and Kulendran, N (2009), *Constructing composite leading indicator for Hotel Industry***,** 2nd Conference of the International Association for Tourism Economics (IATE), Chiang Mai, Thailand

Tang, M.F. C. and Kulendran, N (2009), *Predicting directions and turning points in Hong Kong Hotel Occupancy Growth Rate*, 8th Asia Pacific Forum for Graduate Students Research in Tourism, Sejong University, Seoul, Korea

Tang, M.F. C. and Kulendran, N (2009), *Predicting Turns in Hotel Occupancy Growth Rate,* 29th International Symposiums on Forecasting, Hong Kong Polytechnic University, Hong Kong

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Chapter 1

INTRODUCTION

1.1 Introduction

The financial viability of hotels depends on the demand for hotel rooms, which is usually measured by the hotel occupancy rate. Local and international economic and political factors influence tourism demand, which are key factors that determine the highly volatile hotel occupancy rates. During positive tourism demand growth periods, resources required to meet the expected increase in occupancy are in relatively high demand, whereas in contraction periods, these resources are in less demand. It is important for hotel managements to know well in advance the expected hotel occupancy rates so they can better manage their resources.

Law (1998) addressed the importance of having an accurate forecasting tool for hotel occupancy to help hotel managers tackle the challenges of unstable economic conditions and strong competition from nearby tourist destinations. For the purpose of capital investment, strategic planning, minimizing marketing risks, and resources allocation, hotel managements need an early warning system that predicts the occupancy rate to efficiently manage their resources and reduce the risk to their financial viability from the volatility of hotel occupancy rates.

Compared with other cities, Hong Kong maintains a relatively high occupancy rate of over 80% overall. However, due to the dynamic nature of the tourist-origin countries and intense competition with nearby tourist destinations, the growth rate of the Hong Kong hotel occupancy is volatile, making it difficult for hoteliers to manage their resources and the hotel revenue. This makes the Hong Kong hotel industry a most appropriate area for analysis in the present study. Furthermore, Hong Kong has maintained reliable historical hotel occupancy rates and, according to the Hong Kong Tourism Board (HKTB, 2009), these are classified according to hotel prices for high tariff A, high tariff B, and medium tariff hotels. This classification is based not only on the hotel room rate but also on the staff ratio and other important factors, such as location, facilities, and the business mix of the hotels.

The high volatility of the hotel industry makes it difficult to predict exact occupancy rates ahead, and hotel managements often have sufficient data to know in advance the turning points in occupancy rates, which are the periods in time when increasing occupancy rates change to decreasing occupancy rates and subsequently decreasing occupancy rates change to increasing occupancy rates. Chan, Lim, and McAleer, (2005) stated that if managers knew the volatility pattern of the market, they could easily evaluate their business strengths and weaknesses from time to time and identify attractive opportunities; however, management also needs to understand the adverse consequences of volatility in tourism demand on the organization. However, not many studies have discussed the volatility patterns in hotel occupancy or even the tourism sector. Shareef and McAleer (2005) worked on models for predicting volatility patterns for the Small Island Tourism Economies. Kim and Wong (2006) used a similar approach to capture the volatility pattern of the inbound tourist demand in Korea. These researchers found that there were very few studies that focused on the occurrence of such volatility patterns and how to recover after such a crisis.

The present study aims to develop models that could predict the turning points of the upward and downward trends in hotel occupancy rates of tourists so that hoteliers would know in advance when the current trend would change for the better or worse. Given that there is no evidence of past research using non-linear models for predicting occupancy rates in the hotel industry, the present study predicts the turning points that indicate the directional change in the hotel occupancy rate by estimating logistic and probit regression models with a composite leading indicator and hotel demand determinants. The accuracy of each regression model will be assessed by the quadratic probability score (QPS).

A composite leading indicator is a basket of economic time series, combined using different weights that can track the turns in the hotel occupancy rate. It is useful for hotel managements to identify early warning signals that indicate turns in hotel occupancy. Niemira and Klein (1994) stated that "composite leading indicators can provide a more reliable gauge of economic activity." Past tourism forecasting studies have demonstrated the usefulness of leading indicators in predicting turning points. Choi (2003) stated that leading indicators can provide signals in advance for the basic performance of the hotel industry as a whole. Two types of weighting methods, the coefficient of cross-correlation analysis and the market share of the overnight-stay tourist arrival, will be used to combine the economic time series.

Hotel demand determinants are economic indicators such as tourist income, cost of a room in the destination, substitute destination pricing, nominal exchange rate, and cost of travelling, which may have a leading correlation with the turning points of hotel occupancy rates.

Figure 1.1 shows the occupancy rate for inbound tourists in all tariff categories of Hong Kong hotels for the period 1972 to 2010 (HKTB, 2011). This graph shows the volatility and cyclical pattern of the hotel occupancy rate. However, this pattern is easier to identify as a positive or negative growth when it is converted into the occupancy growth rate.

Figure 1.1 Occupancy rate for inbound tourists in all tariff categories of Hong Kong hotels for the period 1972 to 2010 (Hong Kong Tourism Board, 2011)

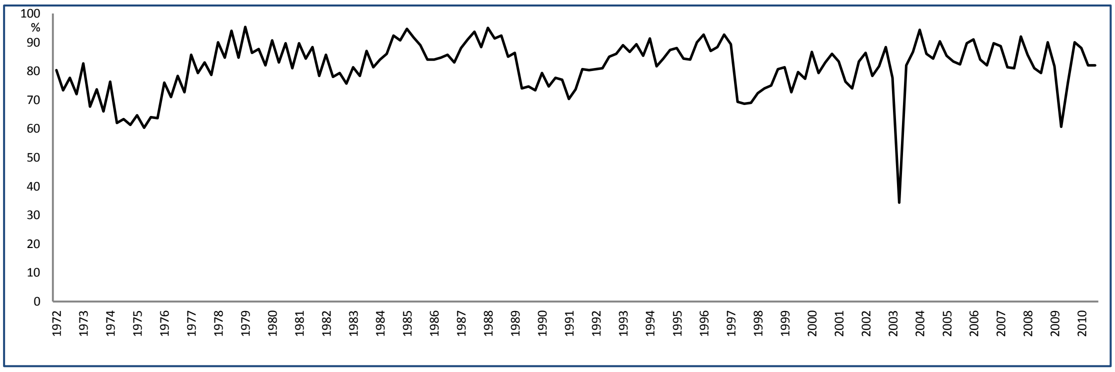

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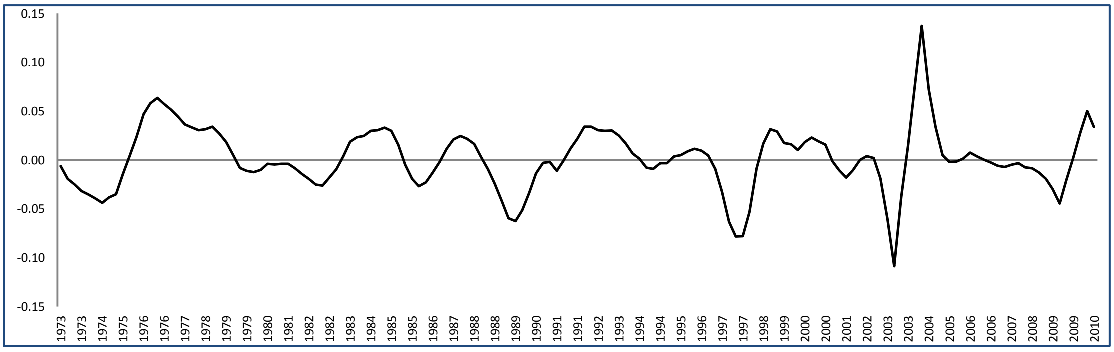
Figure 1.2 Occupancy growth rate cycle for inbound tourists in all tariff categories of Hong Kong hotels for the period 1972 to 2010 (Hong Kong Tourism Board, 2011)



1.2 Research Problem

1.2.1 Problem Statements

One of the main problems faced by the hotel industry is the unavailability of information on the possible downturns and upturns in hotel occupancy rates of inbound tourists. In the recent past, international economic conditions have created much adversity in the hotel sector due to unexpected changes in international travel. In turn, these sudden changes in the travel patterns of international tourists affect the ability to manage the operations of each individual hotel and maintain their profitability. Although good forecasts of demand for hotel occupancy would be ideal, the hotel industry is so volatile that such accurate forecasts are difficult to obtain. The industry would still benefit immensely from forecasts of the expected growth or decay in hotel occupancy rates, as any prior indication of upturns or downturns would assist in effectively managing their resources.

The problem to be researched in the present study is that of developing forecasting models using appropriate mathematical forecasting methodology to predict the turning points in the hotel occupancy growth rates in Hong Kong. As the hotel occupancy growth rate varies according to the quality of services provided and the associated price levels, occupancy data are required separately for each of the different hotel rating levels, High Tariff A Hotels, High Tariff B Hotels, and Medium Tariff Hotels, as defined by the HKTB.

Short-term forecasts in hotel occupancy growth rates are important in the management of the operations and resources of individual hotels; on the other hand, long-term forecasts are required by investors, governments, and other stakeholders for long-term investment and strategic planning. This study will make medium- to long-term predictions of turning points in hotel occupancy growth rates using demand determinants and a constructed composite leading indicator for the Hong Kong hotel sector.

1.2.2 Benefits of the Research

The predictions of the turns in occupancy growth rates that are made by the models developed in detail in the present study for different tariff levels will assist hotel managers in developing their operational plans more precisely to minimize their operating cost and maximize their returns. The potential savings would be extremely high. Information on future turning points in the hotel occupancy growth rate will assist investors and the hotel industry in general in long-term investment and strategic planning. Potential savings in resources in the hotels sector would be extremely high as a result of improved planning.

Econometric models with hotel demand determinants and composite leading indicators developed for the hotel industry will have a very significant impact on the way hotels would be managed not only in Hong Kong but worldwide as well. The present study will identify which demand determinants will contribute to the turns in the hotel occupancy growth rate. Furthermore, the composite leading indicators will predict the directional changes that would provide advance signals of impending changes of occupancy for hotel managements and policy makers. Hotel chains and tourist organizations would be inclined to place greater emphasis on collecting reliable occupancy data to be used recurrently in the new models. Further research would be stimulated to refine the models and redesign them to facilitate short-run and long-run volatility risk management. Both industry and academia would significantly benefit from the present study, which will enhance the confidence of hoteliers in academic work. Furthermore, there will be greater incentive for hoteliers to examine and commission academic work in re-engineering their operations.

1.2.3 Contribution to Knowledge

A preliminary review of the literature shows no previous research on predicting turning points in the hotel occupancy growth rate using composite leading indicators and hotel demand determinants, despite the methodology and the conceptual knowledge being available for some time. Moreover, there has been no attempt in past research to construct composite leading indicators and OECD indicators for the hotel industry based on the market share of tourist arrivals. Furthermore, no past study has used logistic and probit regression models to predict turns in the hotel occupancy growth rate. Linking this knowledge to hotel occupancy, where turning points are predicted for hotel occupancy growth rates, is new and is a very significant contribution to knowledge and the literature on hotel management worldwide.

1.2.4 Statement of Significance

The present study is significant in providing a solution to a major problem in the hotel sector in relation to changes in hotel occupancy, which directly affects medium- and long-term investment and strategic planning in the hotel industry. The development of an econometric model and an approach to predict the turning points of the hotel occupancy growth rate will potentially save millions of dollars per annum in operating costs, staffing, and investment. Such forecasting will also provide significant assistance to industry organizations to develop plans to even out occupancy rates by adjusting the timing of attractions and events in a city.

Potential cost savings and higher returns that may result from better forecasting and management of the changes in hotel occupancy rates, particularly in its growth, may prompt an extensive change in yield management in the hotel sector. Moreover, when such models are developed for the Hong Kong hotel industry, the findings would have extensive relevance to other major hotel groups at significant tourist arrival destinations.

The present study will significantly contribute to a new direction in hotel management that could enhance efficiency and returns in this global industry and lead to new practices in the management of hotel resources that are more closely linked to changing demand.

1.2.5 Aims of the Research

The Hong Kong Special Administrative Region, as a major tourism destination in its own right and a major gateway to mainland China, has an extensive and varied hotel accommodation sector. This hotel industry sector caters to 17 million overnight tourists per year (HKTB, 2011). However, the hotel occupancy growth rate is volatile, caused by the dynamic nature of the tourist-origin countries and the intense competition with nearby tourist destinations, making it difficult for hoteliers to manage their resources. Such volatile patterns of hotel occupancy growth rates necessitate the application of modern forecasting techniques and the latest technology to provide a comprehensive decision-making environment for hotel managements to boost their revenue. Therefore, the aim of the present study is to predict the turning points in hotel occupancy growth rates in Hong Kong using demand determinants and composite leading indicators for the three main hotel categories classified according to pricing tariff levels as High Tariff A hotels, High Tariff B hotels, and Medium Tariff hotels. A hotel occupancy growth rate cycle will be constructed as the indicator of variation in hotel occupancy rates to assist management in long-term strategic planning, new project development, and capital investment. The short-term volatility in the occupancy growth rate cycle that the present study would identify will provide a change-in-demand signal to hotel managements to assist in staffing and resource allocation in the short term.

The specific objectives of the present study are:

- Extract the growth cycle of the hotel occupancy rate for different hotel categories.
- Identify the turning points in the growth cycle of occupancy rates.
- Construct a composite leading indicator using selected economic variables of the top five markets of Hong Kong overnight-stay tourists.
- Construct a composite leading indicator using the existing composite leading indicator or indexes, such as OECD composite leading indicator, OECD business survey index, and OECD consumer confidence index.
- Combine the composite leading indicators using two different weighting methods, the market share of the top five overnight-stay tourist hotels of Hong Kong, and the cross-correlation coefficient of the series.

- Estimate the logistic and probit regression models with the constructed composite leading indicator and the existing OECD composite leading indicators or indexes.

- Estimate the logistic and probit models with hotel demand determinants.

- Assess the forecasting performance of logistic and probit regression models that are estimated by the composite leading indicators and hotel demand determinants using the QPS method.

1.3 International Tourism

Tourism is travel for different purposes, such as recreation, vacation, or commerce. The World Tourism Organization (UNWTO) defines tourists as people who "travel to and stay in places outside their usual environment for more than twenty-four (24) hours and not more than one consecutive year for leisure, business, and other purposes not related to the exercise of an activity remunerated from within the place visited."

The UNWTO is an association in the United Nations that provides guidelines and information on tourism, and is a global forum for tourism policy issues that promotes global tourism. UNWTO also implements the Global Code of Ethics for Tourism to maximize the positive economic, social, and cultural effects of tourism as well as to minimize its negative social and environmental impacts.

According to UNWTO, over the past years, the dramatic economic growth of tourism has made this sector one of the fastest-growing economic sectors in the world. The business volume of tourism equals or even exceeds that of oil exports, food products, or automobiles. Tourism has become one of the main invisible earnings for many developing countries. The UNWTO identifies three forms of tourism, namely, (1) domestic tourism, which involves residents of the given country traveling only within that country; (2) inbound tourism, which involves nonresidents traveling in a given country; and (3) outbound tourism, which involves residents traveling in another country.

1.4 The Four Key Industries in the Hong Kong Economy

Hong Kong has a total land area of 1,074 square kilometers, and a population of nearly seven million. It is located just south of the Tropic of Cancer at about the same latitude as Hawaii. Hong Kong has no natural resources; it has thus become known as Asia's service-oriented city. Hong Kong was a British territory in 1841. Under a joint declaration in 1984, the territory's sovereignty was given back to China on July 1, 1997. Hong Kong has since become a special administrative region of China, and China has since highly contributed to Hong Kong's economy, including the tourism sector. China is well aware of the economic importance of Hong Kong, and to maintain the prosperity of Hong Kong, China granted the latter independent status and a high degree of autonomy. It is unlikely that China will directly rule Hong Kong and treat it as a mainland province.

Tourism is one of the four key sectors of the Hong Kong economy, the other three being financial services, trading and logistics, and producer and professional services.

These four key economic sectors are the driving force of Hong Kong's economy and the basis for employment generation.

According to the Hong Kong Government (2008), in 2008, tourism generated HK$43.8 billion (Figure 1.3), or 2.8% of GDP (Figure 1.4), whereas the tourism sector employed 197,400 (Figure 1.5), or 5.6% of total employment (Figure 1.6). These statistics show that the tourism industry contributes significantly to the Hong Kong economy.

Figure 1.3 Contribution of the tourism sector to Hong Kong gross domestic product ($ million) (Hong Kong Government, 2008)

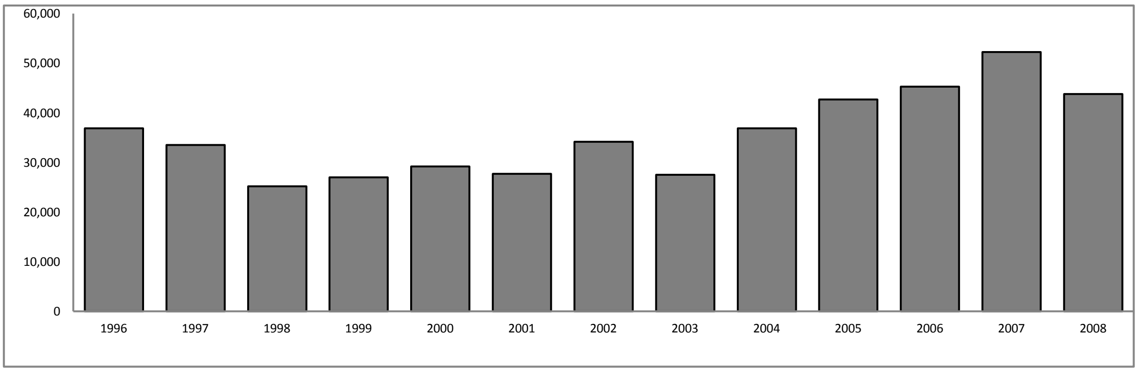


Figure 1.4 Contribution of the tourism sector to Hong Kong gross domestic product (percentage) (Hong Kong Government, 2008)

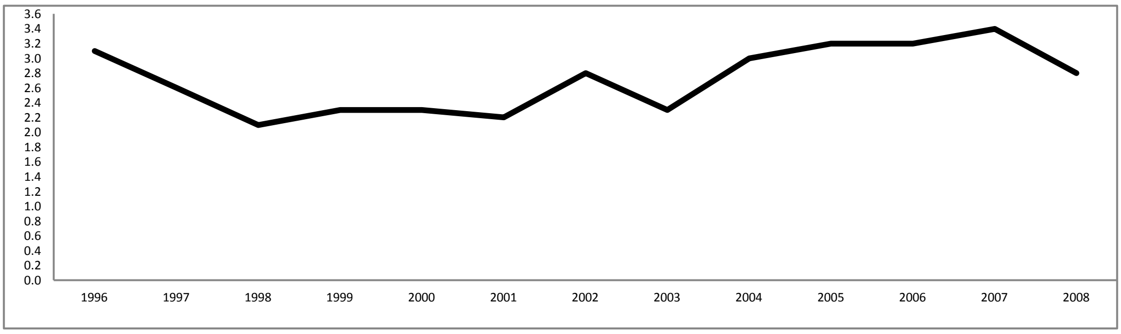


Figure 1.5 Contribution of the tourism sector to Hong Kong total employment (Hong Kong Government, 2008)

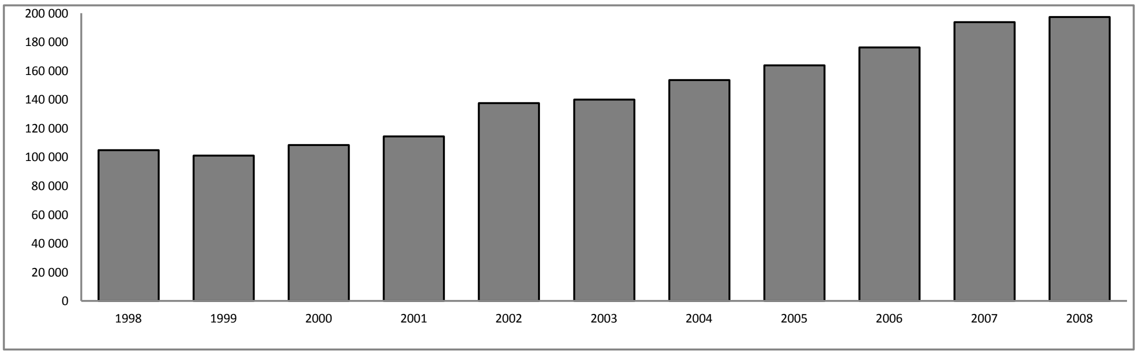
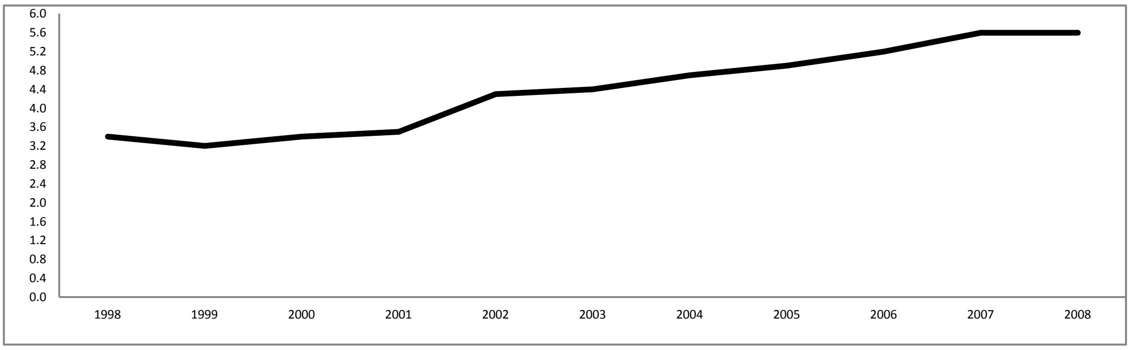


Figure 1.6 Contribution of the tourism sector to Hong Kong total employment (percentage) (Hong Kong Government, 2008)



1.5 Hong Kong Tourism Sector

The Hong Kong tourism sector covers both inbound and outbound tourism. According to the Hong Kong Census and Statistics Department, inbound tourism covers retail trade, hotels and boarding houses, restaurants, personal services, travel and airline ticketing, and passenger transport services, pertaining only to that segment of services provided to visitors to Hong Kong. Outbound tourism covers travel and airline ticketing as well as cross-boundary passenger transport services, pertaining only to that segment of services provided to Hong Kong residents travelling abroad. The present study deals with the hotel occupancy rate relevant to inbound tourists.

Tse (2001) pointed out that international tourism became one of the booming industries after the Second World War, with a consistent and significant growth rate that has continued to date. Hong Kong has also had a similar growth in tourist arrivals. In 2009, total visitor arrivals to Hong Kong from all countries reached 29.59 million, compared with the yearend total of 29.506 million visitors in 2008. The total visitor arrivals in 2009 represented a 400% increase compared to the number of arrivals 20 years earlier. Figure 1.7 shows the total number of tourist arrivals in Hong Kong from 1961 to 2009. Figure 1.8 shows the yearly percentage growth in the number of arrivals. The growth appears to be very cyclical.

Figure 1.7 Total number of tourist arrivals in Hong Kong from 1961 to 2009 (HKTB)

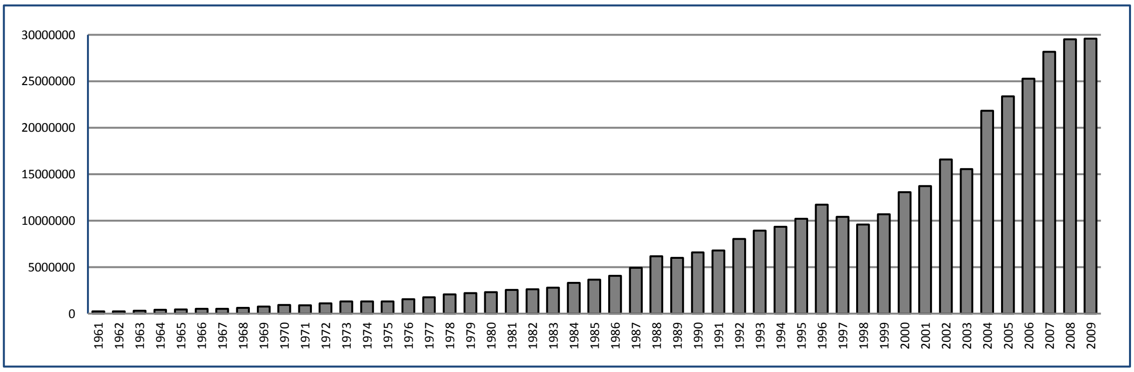
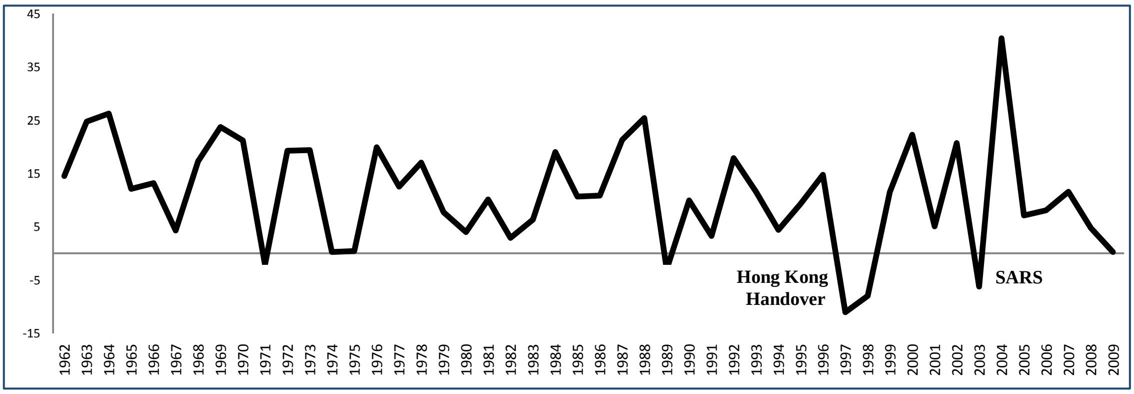


Figure 1.8 Yearly percentage growth in the number of arrivals (HKTB)



1.5.1 Hong Kong Visitor Arrivals

According to the UNWTO (2010), there were 880 million tourists in the world in 2009. In 2008, Hong Kong was ranked as the city that attracted the second-highest number of visitors (next to London), or 17.2 million tourists for the year (Bremner, 2008). Lloyd, La Lopa, and Braunlich (2000) stated that the growth of tourism not only helps Hong Kong earn foreign exchange, but also directly helps Hong Kong become a world-renowned international centre. In a review of Hong Kong tourism in 2007, the HKTB executive director refers to Hong Kong as "Asia's World City."

Inbound tourism is classified generally as domestic or international. Given its border-control structures, Hong Kong has the unique situation of having the bulk of domestic tourism from mainland China designated as international. For both domestic and international visitors, a tourist is defined as a person who is staying away from his usual place of residence. In presenting the 2010 Hong Kong Tourism overview, the HKTB executive director projected that tourist arrivals would increase in 2010 by 5.2% to reach 31.14 million. His projection had been more than half achieved by June 2010, with the arrival of 16.9 million tourists.

The proximity of mainland China leads to heavy cross-border traffic, which increased international tourist arrivals by 0.3% in 2009 compared to 2008 (HKTB, 2011). Table 1.1 shows the top five source markets of tourist arrivals to Hong Kong in 2008 and 2009 (HKTB, 2011).

Table 1.1 Top Five Source Markets of Tourist Arrivals to Hong Kong in 2008 and 2009 (Hong Kong Tourism Board, 2011)

Ranking	Markets (2008)	No of Arrivals (million)	Share of total (%)	Markets (2009)	No of Arrivals (million)	Share of total (%)
1	China	16.862	57.1	China	17.956	60.7
2	Taiwan	2.240	7.6	Taiwan	2.009	6.8
3	Japan	1.325	4.5	Japan	1.204	4.1
4	USA	1.146	3.9	USA	1.070	3.6
5	South Korea	0.904	3.1	Macau	0.671	2.3
	Total	22.477	76.2	Total	22.910	77.5

Figure 1.9 Top 5 source markets of Visitor Arrivals to Hong Kong in 2008 (Hong Kong Tourism Board, 2011)

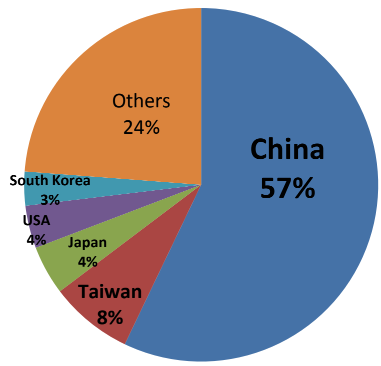
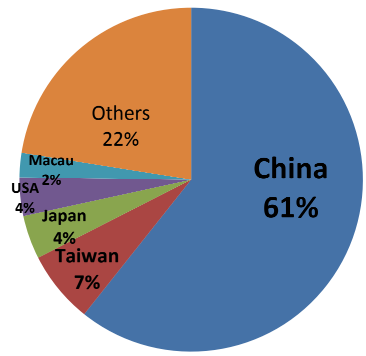


Figure 1.10 Top 5 source markets of Visitor Arrivals to Hong Kong in 2009 (Hong Kong Tourism Board, 2011)



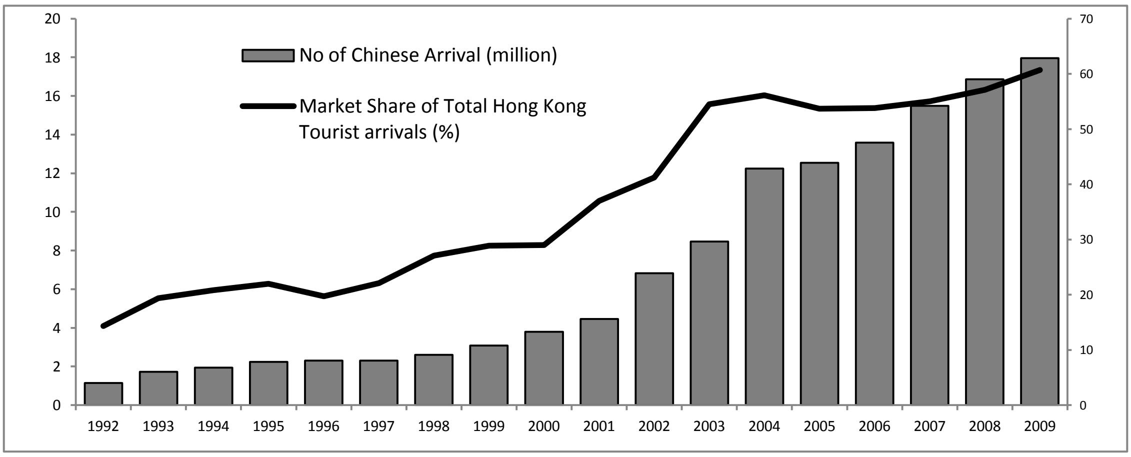
1.5.2 Individual Visit Scheme for the China Market

In 2003, China introduced the Individual Visit Scheme (IVS) for Chinese citizens to visit Hong Kong in their individual capacity. The IVS was first introduced in four Guangdong cities, namely, Dongguan, Zhongshan, Jiangmen, and Foshan. Today, 49 cities in China have implemented this scheme, paving the way for around 270 million mainland citizens to come to Hong Kong on their own travel arrangements.

Chinese residents living in the cities that have implemented the IVS and with permanent household registration are eligible to apply for the relevant exit endorsement from the relevant mainland authorities. The endorsement is valid for three months or one year, and may be used for one or two visits to Hong Kong. The endorsement holder can stay in Hong Kong for not more than seven days on each visit. Eligible candidates may apply for a new endorsement once the current one has expired or has been used up. There is no quota on the number of endorsements for a particular period of time.

Another new measure introduced in 2009 allows non-Guangdong residents in Shenzhen to apply for endorsement under the IVS. Considering that Shenzhen is the nearest city to Hong Kong, the new measure enables non-Guangdong residents who work and live in Shenzhen to visit Hong Kong during their spare time. As a result of this policy, non-Guangdong residents living and working in Shenzhen do not need to go back to their original province to apply for an endorsement to visit Hong Kong. The IVS is the main reason for the sharp increase in visitor-tourist arrivals from China, which was only 6.83 million in 2002, increasing to 17.96 million in 2009 (Figure 1.11).

Figure 1.11 Number of tourist arrivals from China and the market share of total arrivals to Hong Kong (HKTB)



1.5.3 Overnight Visitors in Hong Kong

The HKTB has two categories for total tourist arrivals, namely, overnight visitors and same-day in-town visitors. Same-day in-town visitors, also known as transit visitors, with special interests in visiting Hong Kong such as shopping without staying overnight, still contribute to the Hong Kong tourism economy. However, same-day in-town visitors do not use any accommodation facilities in Hong Kong; therefore, the present study will use data based on overnight visitors.

According to HKTB (2011), the total tourism expenditure by tourists in Hong Kong in 2009 was HK$162.89 billion. Within the total tourism expenditure, the same-day in-town visitor spending was HK$22.69 billion and the overnight visitor spending was HK$97.66 billion. The spending pattern of the overnight visitors in Hong Kong indicates that HK$16.30 billion or 16.7% of the total expenditure by tourists was on hotel bills (HKTB, 2011). Of this tourist expenditure on hotel bills, 64.4% was payment for rooms (HKTB, 2011). Compared to other cities, Hong Kong maintains a relatively high room occupancy rate at 80% overall. As a result, Hong Kong attracts many international hotel chains to establish facilities (Law, 1998). Following are the top five overnight-visitor arrival markets to Hong Kong. Table 1.2 illustrates the top five source markets of overnight-tourist arrivals to Hong Kong in 2008 and 2009 (HKTB, 2011).

Table 1.2 Top five source markets of overnight-visitor arrivals to Hong Kong in 2008 and 2009 (HKTB, 2011)

Ranking	Markets (2008)	No of Arrivals (million)	Share of total (%)	Markets (2009)	No of Arrivals (million)	Share of total (%)
1	China	9.380	56.2	China	9.663	59.5
2	USA	0.838	5.0	Japan	0.780	4.8
3	Japan	0.817	4.9	USA	0.756	4.7
4	Taiwan	0.649	3.9	Taiwan	0.614	3.8
5	South Korea	0.638	3.8	Australia	0.463	2.9
Total		12.322	73.8		12.276	75.7

Figure 1.12 Top 5 Source Markets of Overnight Arrivals to Hong Kong 2008 (Hong Kong Tourism Board, 2011)

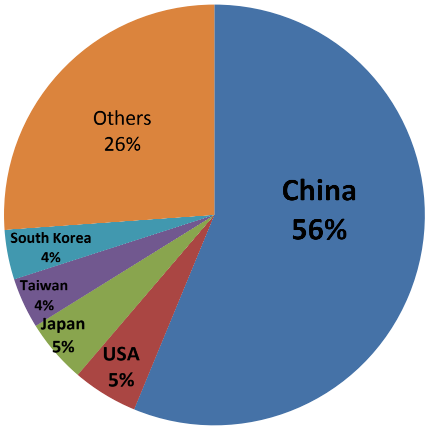
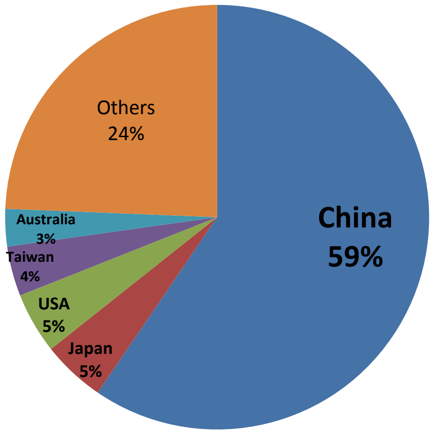


Figure 1.13 Top 5 Source Markets of Overnight Arrivals to Hong Kong 2009 (Hong Kong Tourism Board, 2011)



1.5.4 Hong Kong Tourism Board (HKTB)

The Hong Kong Tourism board (HKTB) is a government-subsidized body founded in 2001 under the HKTB Ordinance. HKTB replaced the Hong Kong Tourist Association (HKTA), which had been established by Hong Kong Government Ordinance in 1957. The most critical difference between HKTB and its predecessor HKTA is that HKTB has no affiliation to any specific sector or organization within the industry, which means that there is no conflict of interest and HKTB can support the interests of Hong Kong tourism in their entirety.

The chief task of HKTB is to market and promote Hong Kong as a travel destination worldwide and to enhance visitor experience once they arrive. The mission of HKTB is to maximize the social and economic contribution that tourism makes to the community of Hong Kong, and to consolidate Hong Kong’s position as a unique, world-class, and most-desired destination.

Working closely with the Tourism Commission, a department under the Commerce and Economic Development Bureau, and the Government of the Hong Kong Special Administrative Region, HKTB fulfils its mission by working through a worldwide network of 15 branch offices and 5 representative offices around the world in Beijing, Shanghai, Guangdong, Chengdu, Tokyo, Seoul, Singapore, Taipei, New Delhi, Bangkok, Sydney, London, Paris, Middle East, New York, and Toronto.

HKTB always promotes Hong Kong as a vibrant, international city known for its year-round program of mega events, culinary delights, and being a leading global business, transportation, and communications hub. Based on the findings of its extensive research, HKTB uses shopping, dining, culture, heritage, the City, and the harbor and its green concepts as the focus of its marketing and promotional activities. These focal points highlight the city's depth, diversity, and vibrancy, and underpin HKTB's current incorporated international brand marketing slogan, "Hong Kong—Live it, Love it."

Collecting comprehensive tourism research data is another key role of HKTB. It works closely with all major travel trade and related associations, as well as relevant government departments to collect day-to-day tourist data to support the industry's research needs. The data it collects include visitor profiles, preferences, spending, and length of stay. These data, together with other information, can help entrepreneurs in the tourism sector plan their marketing strategy and development activities more effectively.

Every year, HKTB holds an annual Tourism Overview for the industry to explain the coming year's promotional and marketing strategy for Hong Kong tourism. During the briefing sessions, the industry representatives receive information on the latest macro environment and market developments, HKTB's projections, strategic focuses, as well as marketing initiatives for the year ahead. For 2010, HKTB predicted that business and consumer confidence would pick up as the economic conditions improve, that Hong

Kong is well placed to benefit from the demand for outbound travel among the global and mainland visitors, and that the mainland has emerged as the world's strongest single aviation market according to the International Air Transport Association. The theme for 2010 was announced by HKTB as "Festive Hong Kong." The theme highlights one of the core strengths of Hong Kong, which is East-meets-West cultural fusion, setting it apart from other destinations in the region.

1.6 Hong Kong Hotel Industry

Hong Kong is the centre in Asia for the regional offices of international hotel chains and the head offices of local hotel brands. Go, Pine, and Yu (1994) stated that the strategic location of Hong Kong helps hoteliers obtain the expertise for the further development of hotel management and investment.

1.6.1 Hong Kong Hotel Association

The Hong Kong Hotels Association (HKHA) was launched in 1961 to protect the lawful interests of hoteliers in Hong Kong. The main aim for HKHA is to promote greater industry unity and cooperation among its members. By providing useful information and data to members on related industry matters, it also ensures greater professionalism in the industry. HKHA is the largest hotel association in Hong Kong and it works closely with HKTB to obtain up-to-date demand information for the hotel sector and to provide other tourist profile information to HKTB with the help of its almost 110 members.

As a non-government association, HKHA can perform a consulting role for the government in formulating legislation arising from new government policies. HKHA can represent the members to provide collective views of the industry on all matters affecting hotel operations. Another goal of HKHA is to offer educational programs to members through training courses and seminars. Some programs are designed for more senior industry executives, in which professors from leading international hotel schools are invited to conduct these programs. Such initiatives have received widespread recognition among HKHA members.

There are more than 150 hotels in Hong Kong, and not every hotel is a member of HKHA. However, HKHA is still the biggest hotel association in Hong Kong. Most international hotel chains like Four Seasons, Inter-Continental, and Grand Hyatt, and local hotel chains, such as Regal Hotel Group, Kowloon Hotel, and Stanford Hotel, are members of the HKHA. Such a wide membership gives HKHA a unique status and enables it to gather crucial information and react speedily to industry needs.

1.6.2 Statistics of Hong Kong Hotels

HKTB publishes the hotel supply situation every quarter. From the data published in March 2010, there are a total of 171 hotels in Hong Kong and 59,671 rooms provided for the market. The estimated number of hotels in 2013 is expected to be 228 and the number of hotel rooms is expected to be 69,319. The estimates are based on the figures obtained from the Office of Licensing Authority, Home Affairs Department, the Hong Kong government, and the HKTB's hotel information survey. Another important statistic provided by HKTB is the number of employees working in the hotels based on their survey. According to respondent hotels, the hotel industry employs 30,269 workers.

Go, Pine, and Yu (1994) cited three reasons behind the development of hotels in Hong Kong with medium tariffs. First, most mainland Chinese visitors tend to choose budget accommodations. Second is the increasing labor costs and lack of skilled labor for the construction of deluxe hotels. Third, the global recession has reduced the budget of business travelers who cannot afford to stay in deluxe accommodations.

Chan, Lim, and McAleer (2005) said that tourism involves both consumption and purchase of goods and services; hence, it affects many sectors of the economy. The hotel industry has the longest lead time to develop projects. The hotel industry is characterized by high-risk and high-capital investment, and heavy fixed costs in property, facilities, staff, and equipment (Buttle, 1986; Danielson, 1987; Jeffrey and Barden, 2000).

According to HKTB statistics, there has been a decline from 2002 to 2008 in the length of stay from 3.62 nights to 3.26 nights per visitor on average. This is possibly reflective of increased transit travel, which in turn reflects upon hotel volatility as shorter stays tend to cause greater fluctuations in demand.

1.6.3 Hotel Occupancy

The HKTB monthly Hotel Room Occupancy Report provides a quick overview for hoteliers on the overall hotel occupancy situation in Hong Kong. It discusses the room occupancy of different hotel categories in each district. For example, in June 2010, the occupancy rate of the High Tariff A Hotels was 76%, the High Tariff B Hotels was 85%, and the Medium Tariff Hotels was also 85%. This report also contains the average achieved room rate for each hotel category, which most often relates to occupancy. The average achieved room rate for High Tariff A Hotels in June 2010 was HK$1,771, HK$805 for High Tariff B Hotels, and HK$496 for Medium Tariff Hotels.

The business indicator that is most commonly used in the hotel industry is the room occupancy rate (Moutinho and Peel, 1994; Law, 1998; Gonzalez, Morini, and Calatayud, 1999; Law, 2004). Law (2004) stated that inaccurate room occupancy forecasts will create excess supply of rooms and might lead to wasted resources; on the other hand, underestimation of room occupancy might lead to a failure of service standards and loss of business. Law (1998) pointed out that in general, a hotel would be profitable if on average room occupancy rate of 60% or higher can be achieved.

Middelton (1994) argued that when a hotel is facing low occupancy levels, the high fixed costs involved in hotel operations will reflect quickly in the short-term price; hotel managers will lower prices immediately so they can at least get some revenue from a potentially unsold and highly perishable facility.

1.6.4 Hong Kong Hotel Classification

In 2001, the HKTB began using a unique classification system to reflect the quality and service of hotels in Hong Kong. Under the classification, the system will identify five key indicators, namely, facilities, location, staff-to-room ratio, achieved room rate, and business mix of the hotel, as a basis for the classification. All hotels are assigned scores for each indicator, and the scores are based on the results of a survey and related reported statistics.

To decide on a score for the facilities indicator, the food and beverage outlets, and the availability of information technology facilities, recreation, and health facilities provided for the guest (e.g., swimming pool and health centre, among others) are assessed. For location, if the hotel is located in the prime city area, a high score is assigned, whereas a hotel situated in a remote country area is given a low score. The staff-to-room ratio is an indication of the level of face-to-face service provided by the hotel. A high score is assigned to hotels with a staff-to-room ratio greater than 1, that is, when the number of employees is greater than the number of rooms in the hotel. The achieved room rate is assigned a high score if the average room rate of the hotel is high. Business mix is assigned a high score if the hotel has more than 20% business visitors.

A composite score for each hotel is calculated by weighted scores of indicators obtained from the hotel against the relative importance of each indicator. The weighting of each indicator is based on the opinions of the hotel industry members collected in a survey. Each hotel is then grouped into one of three categories based upon the composite score. The HKTB does not make public listings of hotel categories by score. It has the sole right to change the category of a hotel at periodic reviews on the basis of changed scores.

Accommodation in Hong Kong is divided into four categories: High Tariff A hotels, High Tariff B hotels, Middle Tariff hotels, and tourist guesthouses. Tourist guesthouses are classified by the Hong Kong government, and all other hotels are under the classification system of the HKTB.

1.7 Conclusion

In this chapter, the importance of the present study as well as the overall situation in Hong Kong has been explained. As the hotel industry is very volatile, it would benefit from a comprehensive forecasting model to assist policy makers and hotel operators in predicting future trends in occupancy to maximize revenue and minimize cost.

The present study makes the first attempt to create two logistic and probit models with a constructed composite leading indicator and hotel demand determinants to predict the turns in hotel occupancy. The findings would help hotel managers from different hotel categories in Hong Kong to have a better understanding and knowledge of future trends.

1.8 Structure of the Thesis

Chapter 1 is the Introduction. Chapter 1 consists of two main parts, namely the research problem and the aim of the research, and an overview of the hotel and tourism industry in Hong Kong. The first half mainly focuses on the direction the present study is pursuing and the contribution it makes to knowledge and the industry. The second half provides a broad understanding of international tourism in Hong Kong and an explanation of the Hong Kong hotel industry.

Chapter 2 is the Literature Review. This chapter is a comprehensive review of previous studies in tourism forecasting. Three main methods are discussed, namely, qualitative, quantitative, and artificial intelligence in forecasting. The gap in the literature is identified to highlight evidence of the importance and uniqueness of the present study.

Chapter 3 presents the research process and methodology. The detailed explanation and justification for choosing such research process or method is shown in this chapter. The modelling and rationale behind each related methodologies are also discussed in this section.

Chapter 4 identifies the turning points for the occupancy rate. To predict the turns in the occupancy rate, it is necessary to identify the significant peaks and troughs of the original data set. Therefore, the method for smoothing the growth of the hotel occupancy rate in different categories in Hong Kong and recognizing the turns is demonstrated here. Given the variety of characteristics and the target market, the peak and trough points for each of the hotel categories are different. Therefore, the findings are unique for every category. Different operational and strategic planning suggestions conclude this chapter.

Chapter 5 presents the construction of countries' composite leading indicators. The formation of the composite leading indicator for the Hong Kong hotel industry was based on the economic variables from the original top five countries' overnight-stay tourists. Therefore, chapter 5 will start with the method for choosing the valid economic variables from these five countries, then move to the comprehensive and systematic procedures of combining the selected economic variables, and, finally, construct the countries' composite leading indicator for the Hong Kong hotel industry.

Chapter 6 presents the constructed composite leading indicator for the Hong Kong hotel industry. Chapter 6 will show the method for combining the constructed countries' composite leading indicators to form the composite leading indicator for the Hong Kong hotel industry for each category, but two different weighting approaches, namely, market share of the five countries that contribute most to Hong Kong as overnight-stay tourists, and the coefficient of the cross-correlation analysis. The identification of the upturns and downturns of the composite leading indicators and the estimated logistic and probit models with the indicators are also included in this chapter.

Chapter 7 presents the constructed composite leading indicator from OECD data. To provide different dimensions and comparison for the constructed composite leading indicators by the selected economic variables, this chapter aims to provide different composite leading indicators by OECD statistics. Three sets of statistics from OECD are transformed to create the composite leading indicators, namely, the OECD Composite Leading Indicator, OECD Business Survey Index, and OECD Consumer Confidence Index. All indicators in this chapter were subjected to the same research process as that in the preceding chapter. The results of the identification of peaks and troughs and the estimated logistic and probit model will also be shown.

Chapter 8 presents the estimated logistic and probit models with the hotel demand determinants. After the construction of a composite leading indicator to predict the turns for the Hong Kong hotel industry, this section uses the hotel demand determinants as the dependent variable to estimate logistic and probit models to predict the turning points of the Hong Kong hotel industry.

Chapter 9 provides the Conclusion. After all the construction and estimation in previous chapters, this chapter summarizes the major findings and highlights the contribution of the present study. It will also include the limitations of the present study as well as suggestions for future research.

Chapter 2

LITERATTURE REVIEW

2.1 Introduction

This chapter is a review of the previous studies on demand forecasting in the tourism sector. The first section will be an overview of forecasting methods. Given the perishable nature of the tourism industry, the need for accurate forecasts is crucial. Hence, Sheldon and Var (1985) stated that researchers, practitioners, and policy makers have long recognized the necessity of accurate forecasts for tourism demand by assessing the number of tourist arrivals. Law and Au (1999) explained that accurate forecasts would help managers and investors make operational, tactical, and strategic decisions. For the private sector, hotel managers can improve their operational, marketing, and strategic decisions; in the public sector, government organizations need accurate tourism demand forecasts to help them in tourism infrastructure planning and land-use development planning.

On the other hand, although different parties agree on the need for accurate forecasting and its value, there have been no ordinary providers or set methods for tourism forecasting (Witt and Witt, 1995). No single forecasting method can perform for every tourism forecast study. Therefore, both qualitative and quantitative methods are still used in different kinds of studies in the tourism sector. Different methods of qualitative and quantitative forecasting in the tourism sector will be explained in this chapter. With quantitative time series methods, it has been found that the complex time series forecasting methods are not necessarily more accurate than simple extrapolative methods. Studies have concluded that between quantitative causal and time series methods, and between time series methods themselves, there is no one “best” method (Makridakis et al., 1982).

2.2 Demand Forecasting in the Tourism Sector

The *Oxford Dictionary* defines forecasting as the act of estimating or calculating in advance, especially to predict by analysis of meteorological data, and also to serve as an advance indication. The accuracy of forecasting is based on the method of prediction and analysis. In business, forecasting is the essential tool for minimizing the gap between market supply and demand. Matching supply and demand is important to reduce losses of operators if the demand is far below supply. On the other hand, if the demand is more than the market supply, operators can create or provide more services or products to satisfy the needs of the market.

Demand forecasting is more important for the tourism sector than it is for the manufacturing industry. Simultaneously, perishability, intangibility, and heterogeneity are the characteristics of tourism services (Fitzsimmons and Fitzsimmons, 2011), which create constraints for service providers, unlike in the case of simply maintaining the stock quantity of a manufactured product. Frechtling (2001) emphasized that the specific uniqueness of tourism products (e.g., that they are inseparable from the consumption and production processes, customer satisfaction, on complementary services, demand being highly sensitive to emergencies and supply, the long lead time required for investment on fixtures) increases the difficulty for management to perceive future demand. Such special characteristics have made demand forecasting a key issue in helping management know more about the market’s needs for a specific time period and, more important, for tourism organizations to be able to allocate their resources more efficiently. Demand forecasting can also provide early signals for operators about the need for the allocation of resources, both human and material, to maximize profit from the different services or products they provide.

Frechtling (2001) concluded that tourism demand forecasting can help tourism marketers to set up their strategic marketing plan, explore potential or niche markets, and develop prospective markets. For tourism management, accurate tourism demand forecasts can provide evidence for upcoming facility development projects and facilitate budget planning. Well-built and accurately perceived tourism demand forecasts can directly impact the formulation of tourism policy and ensure infrastructure. Such forecasts can also help city development to provide sufficient capacity for the tourism sector and provide indications for the government to reallocate resources for the improvement or development of education in the economic and social aspects of tourism.

All tourism-related industries, such as airlines, travel agencies, hotel operators, cruise-ship lines, theme parks, recreation facility providers, and even retail enterprises, are interested in the future demand for their services and products by tourists (Song, Witt, and Li, 2009). Accurate demand forecasting can be the key to the success of a service provider. Another piece of evidence that indicates the increased importance of demand forecasting in the tourism sector is the number of research publications in this field. The tourism demand forecasting pioneer, Guthrie (1961), was one of the first academic researchers on tourism demand. Li, Song, and Witt (2005) stated that more than 400 hundred papers have been generated in the past 50 years, and from 2000 to 2007 alone, more than 120 studies have been published in different journals that deal with demand forecasting in the tourism sector (Song and Li, 2008). One of the key findings of Song and Li (2008) on the methods used to analyse and forecast demand in the tourism sector is the diversity of the techniques used in the last decade.

2.2.1 Importance of Forecasting in the toursim sector

Witt and Witt (1995) conducted a comprehensive review of the tourism demand forecasting literature and highlighted the importance of accurate tourism demand forecasting in directly influencing managerial decision making. Moreover, recent events such as wars and terrorism are factors that have made predicting tourist flows more difficult by using simple forecasting methods (Chan, Hui, and Yuen, 1999).

Accurate forecasts are essential to good management (Weatherford and Kimes, 2003). Accurate forecasts are the major inputs into most revenue management systems, and without precise forecasts, the pricing and availability recommendations produced by the revenue management system may be highly inaccurate.

Lee (1990) found that in the airline industry, a 10% increase in forecast accuracy increased revenue by 0.5%–3.0% on high demand flights. Green and Weaver (2005) commented that accurate forecasting of hotel occupancy rates and reservations is important in virtually all areas of hotel operations. Weatherford and Kimes (2003) pointed out that there are two measurements commonly used in hotel forecasting: the booking horizon, which is when the room is booked, and the actual usage, which is when the room is used. The choice of measurement is not the only issue that must be addressed. Weatherford and Kimes (2003) emphasized that lodging managers must also think about actual arrivals, cancellations, no-shows, number of room-nights, length of stay, and even the pattern of each market segment. By having such data, hotel managements can use their revenue management systems more efficiently. Highly accurate forecasting can lead to better staffing, purchasing, budgeting, and strategic planning decisions.

2.2.2 Overview of forecasting methods

Forecasting is the combination of art and science to predict the future. Historical data and past events are projected into the future with mathematical or econometric models. On the other hand, forecasts are made quite intuitively and subjectively based on human feelings, opinions, and experience. Frechtling (1996) stated that a forecasting method is a systematic sequence to organize the information from the past to infer the occurrence of an event in the upcoming future. More recently, forecasting has used past data to predict the future with advanced methodology to increase forecasting accuracy.

Forecasting methods can be generally divided into two types: quantitative and qualitative methods (Uysal and Crompton, 1985 and Song and Li, 2008). Frechtling (2001) defined quantitative forecasting as the way to organize the data by mathematical rule; on the other hand, if the data or phenomena are based on expert opinion, the forecast is qualitative. Song and Turner (2006) concluded that most forecasting models are quantitative. The most commonly used area of forecasting by researchers is time-series modelling (Song and Li, 2008). However, Fildes, and Ord (2002) pointed out that combination forecasting generally will have higher accuracy than just the use of a single method. Wong et al. (2007) contended that combining different forecasting methods can improve forecasting accuracy.

Qualitative methods can be categorized into three main types: jury method, Delphi method, and survey method. Quantitative methods are commonly divided into two subcategories: time-series (non-causal) methods and econometric (causal) methods.

Table 2.1 explains the differences between quantitative and qualitative research (Cavana, Delahaye, and Sekaran, 2001).

Table 2.1 explains the differences between quantitative and qualitative research (Cavana, Delahaye & Sekaran, 2001)

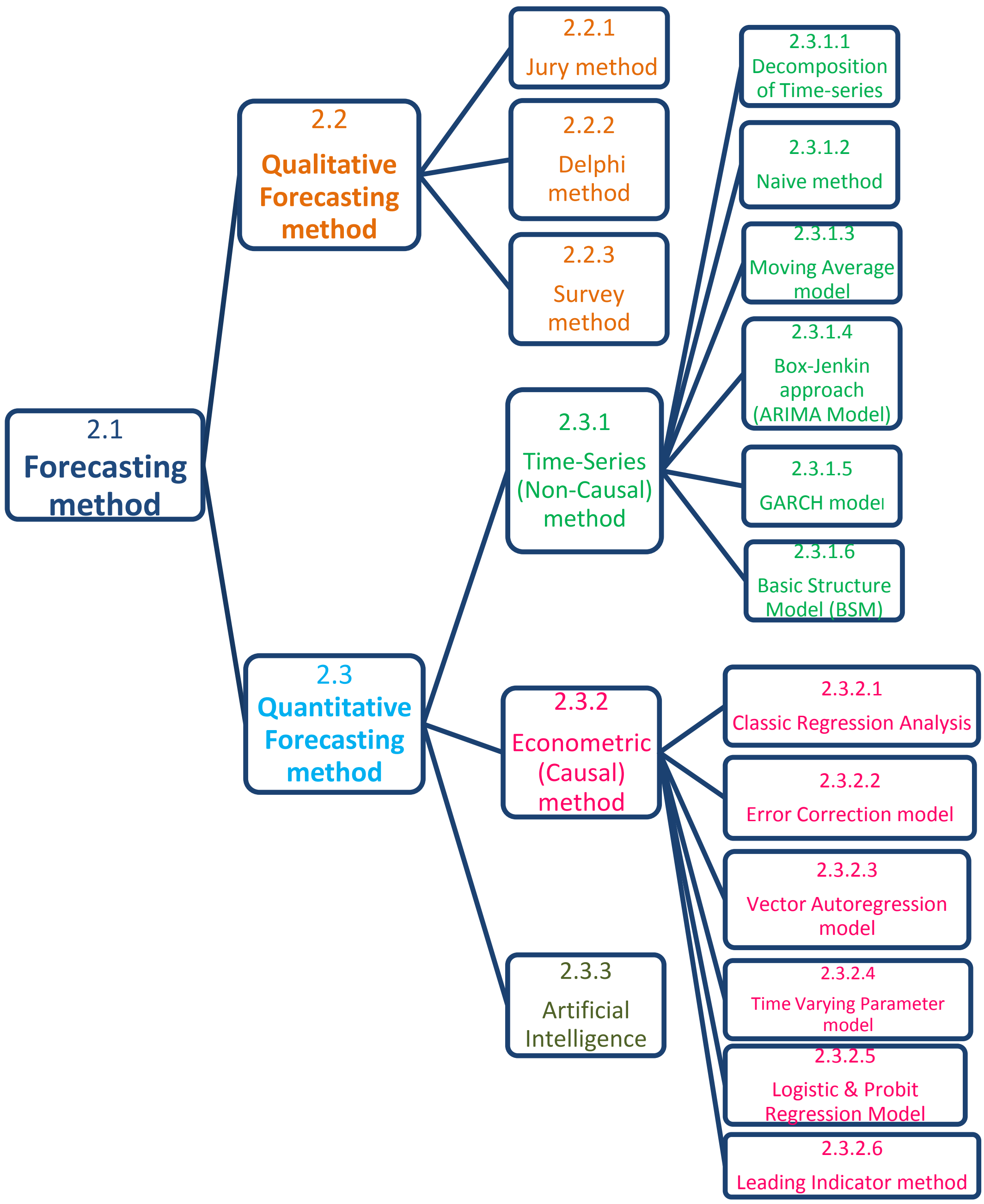
Quantitative research	Qualitative research
• Reality is objective and singular, and apart from the researcher	• Reality is subjective and multiple, as seen by participants in the study
• Researcher is independent of that being researched	• Researcher interacts with that being researched
• Research is assumed to be value-free and unbiased	• Research is value-laden and biased, with values generally made explicit
• Theory is largely causal and deductive	• Theory can be causal or non-causal, and often inductive
• Hypotheses that the researcher begins with are tested	• Meaning is captured and discovered once the researcher becomes immersed in the data
• Concepts are in the form of distinct variables	• Concepts are in the form of themes, motifs, generalization, taxonomies
• Measures are systematically created before data collection and are standardized	• Measures are created in an ad hoc manner and are often specific to the individual setting or researcher
• Data are in the form of numbers from precise measurement	• Data are in the form of words from documents, observations and transcripts
• Procedures are standard and replication is assumed	• Research procedures are particular and replication is rare
• Analysis proceeds by using statistics, tables or charts	• Analysis proceeds by extracting themes or generalizations from evidence and organizing data to present a coherent, consistent picture

Other than the two traditional classifications, that is, qualitative and quantitative, in the last decade, other kinds of quantitative methods such as artificial intelligence have emerged in tourism demand forecasting and will be dealt with later in this section.

Weatherford and Kimes (2003) said that traditional forecasting methods, such as exponential smoothing, moving average, and linear regression, can be used to obtain forecasts based solely on previous performance. Early researchers relied on fairly simple approaches compared to modern researchers who prefer econometric models and artificial intelligence to capture the trend.

Figure 2.1 demonstrates the classification of forecasting methods commonly used in tourism demand forecasting. Each method in the figure will be discussed in the following section.

Figure 2.1 Forecasting method classifications



2.3 Qualitative Tourism Demand Forecasting Methods

Qualitative forecasting is a subjective method because predictions incorporate the decision makers' intuition, emotions, personal experiences, and their own value system in the process of forecasting (Heizer and Render, 2011). Song and Li (2008) pointed out that between 2000 and 2007; only two out of 121 research papers used qualitative methods to conduct demand forecasts. However, qualitative forecasting is useful when services or products are relatively new and have no historical demand data to analyse.

2.3.1 The Jury Method

The jury method, or the jury of executive-opinion method, is a demand forecasting technique that uses a group of high-ranking executives or professionals to form a panel to predict the demand of a specific service or product based on their opinions. Moutinho and Witt (1995) stated that the jury method provides an opportunity for experts to interchange ideas, clarifying their reasoning and explaining their points of view though face-to-face discussion.

Moutinho and Witt (1995) gathered 25 tourism experts together in 1992 to conduct a jury forecast for a strategic vision of the future of tourism up to the year 2030. The jury members were well selected and represented a broad spectrum of the field of tourism. The jury was allocated enough time to discuss and express their ideas. More importantly, the experts were able to explain their views to the host and ask for clarifications on other views expressed prior to completing individual questionnaires.

2.3.2 Delphi Method

The Delphi method was developed by the RAND Corporation (Research and Development) in the 1950s. It has since been widely used in tourism demand forecasting (English and Kearman, 1976; Kaynak and Macaulay, 1984; Liu, 1988; Yong, Keng, and Leng, 1989; Moeller and Shafer 1994; Miller, 2001).

The Delphi method is a logical, interactive forecasting method that involves a panel of professionals who will not be discussing the issue face to face. It consists of a facilitator, who initiates several rounds of discussion among the panel members during the process. After the facilitator receives the first-round response of the participants, the facilitator identifies and analyses conflicting viewpoints, and sends a summary of the responses out to the panel. Such back-and-forth discussion would continue for about four to six rounds until a stable outcome is confirmed or a consensus is achieved. Anonymity is maintained in the process to minimize the conforming pressures and cognitive bias (Moutinho and Witt, 1995). The Delphi method is a highly systematic forecasting method involving human experience. The role of the facilitator is important, and the unbiased summary of responses is sent back to the panel as soon as possible to maintain the sense of participation. Llord, La Lopa, and Braunlich (2000) adopted the Delphi method to predict the changes that would occur in Hong Kong's hotel industry as a result of the handover in 1997.

2.3.3 Survey Method

The first two qualitative methods discussed above are based on expert and professional opinions. On the other hand, the survey method focuses on the consumers' opinions. Knowing the reasons for travelling can help increase the accuracy of demand forecasts in the tourism sector. Frechtling (2001) pointed out that "intentions are statements that consumers make about their planned behaviour or about events they can control." The purpose of gathering information and reasons for travel from the purchasers is to gain an advantage over expert opinion. However, considering that the respondents of the survey are not experts in the field, they may be biased due to lack of insight in the field of tourism. Frechtling (2001) explained that three kinds of errors may accrue from such consumer intention surveys, namely, sampling errors, non-response errors, and non-sampling errors.

2.4 Quantitative Tourism Forecasting Methods

Quantitative forecasting methods use a variety of statistical, econometric, and mathematical models that rely on analysing historical data and/or associative variables to forecast demand (Heizer and Render, 2011). According to Song and Turner (2006), the majority of demand forecast studies in the tourism sector have used quantitative methods. Previous studies of forecasting demand for tourism have been primarily based on time-series models and regression (causal) models (Wong, 1997). Research scholars separate quantitative forecasting methods into two groups, namely, time-series methods and causal methods. The difference between time-series and causal methods is in the identification of the casual relationship of the variables being used in the study (Song and Li, 2008). In addition to time-series and causal methods, a number of other quantitative methods have been developed for tourism forecasting, such as the artificial neural network model, the rough set model, the fuzzy time-series method, and methods using genetic algorithms (Song and Li, 2008).

2.4.1 Time-Series Methods

A time-series, is a sequence of observed data measured classically at consecutive, evenly spaced time frames (e.g., daily, weekly, monthly, quarterly, or annually) at consistent time periods. Time-series analysis is the analysis of time-series data to extract significant statistics and other distinctive characteristics of the series. Time-series models explicate a variable with regard to its own past trend, the seasonality and/or cyclical patterns, and random disturbance terms when predicting the future (Song and Li, 2008), and have been used by many researchers (Cho 2001; Gustavsson and Nordstrom 2001; Goh and Law 2003; Du Preez and Witt 2003; Smeral and Wuger, 2005; and Chan, Lim, and McAleer 2005). Song and Li (2008) also emphasized that time-series methods can spell out the data points with regard to expected regular past performance and any irregular performance.

The main advantage of time-series models is that they are relatively inexpensive with regard to data collection and model estimation. However, the disadvantage is that time-series models "cannot help under circumstances in which interdependent relationships among tourism demand and other related factors are major concerns of business and government" (Song and Li, 2008, p. 211). Andrew, Cranage, and Lee (1990) determined that time-series models give accurate occupancy forecasts and could be easily implemented through off-the-shelf software and hardware. Making no assumptions about other factors, time-series forecasting models use historical data of a variable to predict values in the future. Some scholars believe that time-series models are often able to achieve good forecasting results (Andrew, Cranage, and Lee, 1990; Witt and Witt, 1989).

2.4.1.1 Decomposition of Time-series

Observed time-series data are commonly composed and constructed by a number of component series, namely, trend, seasonality, and cyclical and irregular components. Each of the components has certain specific characteristics and behaviour that affect the observed series. By decomposing the time-series and extracting the original data from the components, the exact "meaning" of the data can be seen without any distraction or disturbance.

Quarterly and monthly seasonal tourist arrival data can exhibit seasonality. They will repeat themselves in a certain time frame with a particular pattern. Cyclical data fluctuate every several years and are generally associated with the business cycle. The irregular component mainly relates to random events that cannot be predicted, such as natural disasters or terrorism.

2.4.1.2 Naïve Method

The naïve method is the simplest forecasting method, which assumes that demand in the next period is the same as the demand in the most recent period (Heizer and Render, 2011). Such a simple demand forecast method is an excellent benchmark for the outcome of other sophisticated forecasting methods. Some scholars have found that in some instances, the naïve method outperforms complex forecasting methods (Witt and Witt, 1989; Witt and Witt, 1992; Witt and Witt, 1995).

2.4.1.3 Moving Average Model

The moving average model is a forecasting method that is easy to apply and widely adopted by researchers. It is a forecast made for future periods based on the average of certain past time periods. Generally, the moving average model is of three types, namely, the simple moving average model, the weighted moving average model, and the exponential moving average model.

The simple moving average (SMA) model is the unweighted mean of the data over a specific time period. The weighted moving average (WMA) is the mean of the data where unequal weights are attached to each data point of a specific time period to show the importance of time across the data set. This approach is more responsive to changes because a heavy weighting is applied to the data of the more significant time period. Typically, the more recent period will be allocated the heavier weighting than previous periods.

The exponential moving average model (EMA) is also called the exponential smoothing method. In the simple moving average model, past observations are weighted equally; however, in the exponential smoothing method, data points are assigned exponentially decreasing weights over time to remove the random noise of the data set. Single exponential smoothing is an exponential smoothing method commonly used to forecast stationary time-series data, whereas double exponential smoothing is a method used for data with a linear trend. Triple exponential smoothing is used for time-series data with both trend and seasonal components.

As a rule of thumb, a longer averaged period can provide a more stable forecast, but the true response to the demand market may be underestimated. Considering that the moving average model is easy to use and apply, business enterprises use the moving average model to forecast short-term and medium-term demand in their organizations (Witt and Witt, 1988).

In the review of tourism forecasting research done by Song and Li (2008), there was no study that used solely the moving average model to analyse and forecast demand. However, more recently, the moving average technique has been used more frequently with time-series data to smooth out short-term fluctuations and extract the main components from the original data series.

2.4.1.4 Box-Jenkins Model (ARIMA)

The Box-Jenkins model is the dominant time-series model that has been used in demand forecasting studies in the past 40 years (Song and Li, 2008). The integrated autoregressive moving average model (ARIMA) was proposed by statisticians George Box and Gwilyn Jenkins in 1970 (Box and Jenkins, 1976). ARIMA is a demand forecast model that estimates the best-fitting time series to past values of the data set.

The autoregressive model (AR) was developed by Yule in 1926 (Yule, 1926). Slutsky (1937) presented the moving average model (MA), and Wold (1938) combined the AR and MA to form the ARMA model, which can handle a large number of stationary data. At the same time, the number of AR terms, *p*, and the number of MA terms, *q*, in the model can be identified from the partial and sample autocorrelation plot. Box and Jenkins (1976) presented the ARIMA model with the help of computer systems that could handle a large amount of data and rendered Wold's (1938) idea economical and capable of being used widely in the world. ARIMA models became popular, and large empirical studies showed that such models outperformed other econometric models that were commonly used in the 1970s (Makridakis and Hibon, 1997).

In the tourism sector, ARIMA models and different versions of ARIMA models have been widely developed and used in tourism demand forecasting in the past few decades. Cho (2001) found that ARIMA was the best predictor for the number of visitor arrivals to Hong Kong from the United States and the United Kingdom. According to the review of Song and Li (2008), seasonal ARIMA (SARIMA) became more popular during this decade because the tourism industry is affected by seasonality. Goh and Law (2003) suggested that SARIMA outperformed eight other time-series methods in forecasting tourist arrivals to Hong Kong. On the other hand, Smeral and Wüger (2005) argued that ARIMA and SARIMA models could not outperform even the simple naïve method in forecasting tourist arrivals to Austria.

The univariate ARIMA models did not provide consistent outcomes in different studies; hence, researchers have modified the ARIMA models to apply selected economic leading indicators (Cho, 2001). The results showed that the modified ARIMA models outperformed others in forecasting tourist arrivals from Japan to Hong Kong. Goh and Law (2003) introduced the multivariate SARIMA (MARIMA) models, which showed significant improvement in the forecast results compared to the univariate SARIMA models. However, similar models applied to Sweden's inbound tourism by Gustavsson and Nordstrőm (2001) found that univariate models were better than the multivariate models.

2.4.1.5 GARCH Model

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is another extension of the univariate ARIMA model. The GARCH model was first presented by Bollerslev in 1986 (Bollerslev, 1986) and compared to the ARIMA model, was better in estimating the error variance. GARCH is widely used in finance modelling and in forecasting volatility patterns of time-series data to better manage risk.

In recent years, more tourism researchers have applied the GARCH model to test the volatility in tourism demand. Chan, Lim, and McAleer (2005) used three types of GARCH models to assess the related risk of the four major source tourist countries to Australia. Shareef and McAleer (2005) used GARCH models to evaluate the volatility pattern of small-island tourism economies. Kim and Wong (2006) applied three different versions of GARCH models to review the risk of new shocks on inbound tourist demand in South Korea. Hoti, McAleer, and Shareef (2007) used three different GARCH models to assess the influence of volatility on tourism patterns between Cyprus and Malta.

2.4.1.6 Basic Structural Model (BSM)

Basic structural time series models (BSM) are models that are formulated directly in terms of components such as trend, seasonality, and cycle (Engle, 1978; Nerlove, Grether & Carvalho, 1979; Kitagawa, 1981; Harvey, 1989). Structural time-series models, therefore, offer clear interpretations through decomposition into components (Kendall and Ord, 1990). This decomposition ability of structural models is a major attraction for time-series forecasting. Introduced by Harvey and Todd (1983), BSM enables non-stationary data to be handled directly without the need for explicit differencing operations. Furthermore, BSM is explained as a univariate time-series model consisting of a slowly changing trend component, a slowly changing seasonal component, and a random irregular component.

Turner, Kulendran, and Fernando (1995) compared the forecasting performance of the ARIMA model and the BSM with intervention variables. They fitted the ARIMA model and the BSM to quarterly tourist flows into Australia and New Zealand from the United States, Japan, and the United Kingdom. The model estimation period was from June 1978 to September 1993, and eight quarters (December 1991 to September 1993) were used as the post-sample period to assess the forecasting performance. It was found that the BSM showed a consistently high performance against the ARIMA model. In addition, the forecast errors were reduced when intervention variables (such as special events) were added to the models.

Turner and Witt (2001) analyzed the forecasting of inbound tourism to New Zealand from Australia, Japan, the United Kingdom, and the United States, disaggregated by purpose of visit, using both the BSM and multivariate structural time-series model. The models were estimated from the second quarter of 1978 to the fourth quarter of 1995, leaving a post-estimation period of 11 quarters, from the first quarter of 1996 to the third quarter of 1998, for forecasting performance assessment. The respective forecasting accuracy of the models is compared using MAPEs (mean absolute percentage errors). The study found that the structural time-series model was reasonably accurate and outperformed the seasonal naïve model, whereas the multivariate structural time-series model did not generate more accurate forecasts than the BSM. They concluded that the structural time-series model could reduce overall forecast error by 2%–3% against the seasonal naïve model—a significant result, because this had not been found to be the case for causal-based models.

Greenidge (2001) used structural time-series modelling to explain and forecast tourist arrivals in Barbados from its major generating markets, and found that the models offered valuable insights into the stylized facts of tourism behaviour and provided reliable out-of-sample forecasts.

2.4.2 Causal (Econometric) Models

Another very common forecasting technique is the econometric model (Fujii, Khaled, and Mark, 1985; Lim 1999; Song and Witt, 2000; Kulendran and Wilson, 2000; Kulendran and Witt, 2001; Shan and Wilson, 2001; Song, Wong, and Chon, 2003; Li, Song, and Witt, 2005; and Roget and Gonzalez, 2006). Moore (1989, p. 109) explained the casual method as "the development of projections based on the mathematical relationship between the series being examined and variables which influence that series."

Clements and Hendry (1998) stated that econometric analysis could be used in many ways other than just as a model to forecast. It could consolidate existing empirical and academic data on how economies work, provide a structure for progressive strategy development, and help to explain the failures of strategic plans. However, there are too many different econometric models in the forecasting field, which could lead to confusion and competition.

The biggest difference between time-series and causal methods is the cause-and-effect relationship between tourism demand and the influencing variables. The ability of econometric models to determine and analyse the causal relationships between dependent variables and independent variables has made researchers and industry professionals understand the rationale behind the forecast results and what factors most contribute to the prediction. More importantly, such causal relationships obtained from the econometric models can give reasonable and advanced signals to policy makers about what changes to expect down the road when they are reframing tourism-related policy, or help entrepreneurs make rational decisions in project development in the tourism sector.

Witt, Brooke, and Buckley (1991) contended that the demand for tourism is measured in terms of the number of holiday visits from an origin country to a foreign destination country, or in terms of holiday expenditure by visitors from the origin country in the destination country. Song, Witt, and Li (2009) defined "tourism demand" in a particular destination as the quantity of the tourism product that consumers are willing to purchase during a specific period under a given set of conditions. Those conditions may include the travel and living costs of the tourist; the availability of substitute destinations; the price offered by the substitute destination; GDP of the destination as well as that of the tourist's origin country; the consumer price indices (CPI) of the destination as well as that of the tourist's origin country; share price; oil price; marketing expenditure; personal tastes and preferences of the tourist; climatic influences or the difference between the destination and the tourist's origin country; and other social, political, cultural, and geographical reasons.

According to the consumer theory of choice, demand for a given commodity depends on consumer income, prices, and any other variable specific to the commodity. Song, Witt, and Li (2009) gave a common example of the demand function equation for the tourism product as:

$$Q = f\,(Y, P, Ps, T, A)$$

where Q is the quantity demanded of the tourism service or product by the tourist; Y is the level of income of the tourist origin country; P is the price the tourist paid for the destination, service, and products; *Ps* is the substitute price of the destination; *T* is the tourist taste; and *A* is the advertising cost of the destination country.

Understanding the dependent variable and the independent variables is important. The common dependent variable for studying international tourism demand is generally the number of tourist visits from an origin country to a destination city, or the total expenditure of the tourist in the destination, or the number of nights the tourist spends in the destination (Song, Witt, and Li, 2009). As far as the independent variables are concerned, there are many studies using different sets of variables depending on the scope of the research. Choosing the appropriate economic variable for each study will influence the accuracy of the forecast.

2.4.2.1 Classic Regression Analysis

The linear classic regression analysis is a statistical tool that tries to explain the movement in the dependent variable as a function of the independent variable. Studenmund (2001) further explained that regression analysis is used to predict the direction of change as well as the extent of the change in the variables to estimate the closeness of their relationship. Song, Witt, and Li (2009) said that most causal tourism demand forecasting research in 1990s adopted the classical regression method with ordinary least squares.

Frechtling (2001) commented that regression analysis was the most common approach in tourism forecasting. However, Song and Li (2008) said that due to the presence of spurious regression in traditional regression analysis, advanced econometric models such as error correction model (ECM) have been developed to overcome this issue. Another shortfall of the traditional regression model is that it assumes the data to be stationary. However, most variables used in tourism demand models are non-stationary. A further drawback of regression analysis is that even though it was the most sophisticated demand forecasting model in the 1990s, its forecast performance is often less accurate than the simple naïve method (Witt and Witt, 1989; Witt and Witt, 1992).

2.4.2.2 Error Correction Model (ECM)

As described in the previous section, the main problem with the traditional regression model was that the data being analysed are assumed to be stationary, whereas most tourism demand variables, both dependent and independent, are often trended, which means they are non-stationary. Commonly, such non-stationary problems comprise what is called spurious regression. Song, Witt, and Li (2009), stated that the error correction model could avoid the problems created by spurious regression. For this reason, ECM has continued to be widely used in tourism demand forecasting research.

Song, Witt, and Li (2009) also elaborated further that ECM is an excellent forecasting tool for modeling the behaviour of both the long-term and the short-term equilibrium of the data series. The long-term stability of a tourist forecast is significantly important to government strategy planners, whereas the short-term steadiness provides confidence to tourism service providers when planning short-term business strategies.

Kulendran and Wilson (2000) found that the error correction model outperformed the ARIMA and the naïve method when forecasting tourism demand in Australia for the United States, the United Kingdom, and Japan markets. Lim and McAleer (2001) used ECM to predict the tourism demand in Australia for the Hong Kong and Singapore markets. Kulendran and Witt (2003) found that ECM did better in the longer-term forecasting of international tourism demand from the United Kingdom to six major destinations. Song, Romilly, and Liu (2000) used different models to compare the forecast results of outbound United Kingdom tourism and indicated that the error correction model had the best overall performance over other models.

2.4.2.3 Vector Autoregression Model (VAR)

The vector autoregression (VAR) model is an econometric model designed to grasp the development as well as the interdependencies of multivariate time series. A common assumption in the single equation approach is that the independent variables are exogenous. If this assumption is invalid, then more than one equation needs to be used. Based on this foundation, Sims (1980) set up the VAR model to overcome problems in the single univariate time-series equation. All the variables in the VAR model are treated in parallel. Each variable has its own equation based on its own lags. The progress of each equation is compared to the progress of all other variables in the model. Sims (1980) described VAR as "a theory-free method to estimate economic relationships, thus being an alternative to structural models."

Song and Witt (2006) used the VAR modelling technique to forecast tourist flows to Macau from eight major origin countries/regions over the period 2003–2008. Shan and Wilson (2001) applied the VAR model to find out the causal relationship between international trade and tourism. Witt, Song & Wanhill (2004) proved that the VAR model is the most accurate forecasting method for the international tourist expenditure in Denmark.

However, Song, and Li (2008), after reviewing most of the tourism demand forecasting studies, suggested that the original VAR model did not perform as well as other methods. Wong, Song, and Chon (2006) created the three Bayesian VAR models, and the forecasting performance in their study marked a big improvement on the classical model.

2.4.2.4 Time Varying Parameter model (TVP)

Witt and Witt (1995) pointed out that the naïve time-series model can outperform the more sophisticated econometric forecasting model. Song, Witt, and Li (2009) explained that such an outcome was possible because of the instability of the econometric model structure. The time-varying parameter regression (TVP) model can address this issue of instability due to volatility and improve the performance accuracy of the econometric model. Song, Witt, and Li (2009) suggested that the TVP approach is a better and a more realistic paradigm to capture the structural change of the time series than using dummy variables.

Song and Wong (2003) utilized the TVP method to forecast the demand for Hong Kong tourism by residents from six major tourism origin countries. Song, Witt, and Jensen (2003) summarized that in the context of the demand for international tourism in Denmark, the TVP model is considered the best among six econometric models in terms of forecasting performance. Li, Song, and Witt (2006) combined the TVP model with the linear almost ideal demand system (LAIDS) model to examine the demand forecast for tourism in Western European destinations by UK residents. Li et al. (2006) also used a combination of the TVP model and the error correction model to forecast the UK tourist demand in five European destinations based on per capita spending.

2.4.2.5 *Logistic and Probit Regression Model*

Logistic and probit regression model is based on making a prediction of the probability that an incident will happen (p = 1) or will not happen (p = 0) in the future. It is a linear regression model using binomial probability. Given the dependent variable's being nominal, the model is estimated using the maximum likelihood estimation. Using the binary response, 1 or 0, researchers have deployed the logistic and probit model to predict the turning points in growth cycle, which means that the expansion period is represented by 1 and the contraction period is represented by 0. The basic equation is as follows:

$$Y^*_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon_i$$

where if the economy is in expansion Y=1, and if the economy is in contraction Y=0; X_i are potential explanatory variables that cause the turning points.

Widely used by macroeconomic and financial scholars for predicting turning points and estimating the associated risk, logistic and probit models had been seldom used in tourism forecasting field before the 21st century. Seddighi and Theocharous (2002) used the logistic model as a tool for capturing the impact of the characteristics of a tourism product name on foreign travel in Cyprus. In their study, the logistic model generates the probability of a revisit given the characteristics of the Cyprus tourism product and those of the tourist. Fleicher and Pizam (2002) applied the logistic model to determine the constraints on senior Israeli travellers. Although not many tourism-demand studies have used the logistic model directly for forecasting, some studies have recently used the logistic model to predict turning points in tourism demand growth cycle. Kulendran and Wong (2010) estimated that the logistic and probit models with the tourism demand determinants compare to the logistic and probit models with the composite leading indicators to determine the most accurate probability forecasting tools for Hong Kong's inbound tourism arrivals. This spectacular result from the Kulendran and Wong study (2010) shows that the logistic model is one of the latest methods to predict turning points in the tourism sector. Fernando (2010) also used the logistic and probit regression model to estimate a model with demand determinants to predict the turning points in the Australian tourism demand growth cycle. Logistic and probit regression models not only predict the turning points, but they can also capture the probability of occurrence associated with the expansion period in the tourism demand growth rate (Kulendran and Wong, 2010; Fernando, 2010).

2.4.2.6 Leading Indicator Method

National economic indicators can be a leading indicator, a coincident indicator, or a lagged indicator for tourism demand, and a leading indicator series must turn before the turn in tourism demand. In the business world, leading indicators are widely used for forecasting turning points and uniform calendar-time units. The leading indicator approach is sometimes referred to as measurement without theory, but economic theory does give clues to the selection of variables.

Zarnowitz and Moore (1977) stated that economic indicators are descriptive anticipatory data used as tools for business condition analysis and forecasting. Economic leading indicators were originally intended to predict traditional cyclical decline and growth in economic activity (Banerji and Hiris, 2001). Choi (2003) declared that the leading indicators can be an advance signal for the basic performance of the hotel industry as a whole. The leading indicators could provide early warning signals for future industry turning points.

A composite leading indicator is a basket of economic variables with different weights in a time-series model that can track the turns in the growth cycle of in a time-series data. Most scholars use the composite leading indicator in the prediction of the turning points or directional changes. Niemira and Klein (1994) stated that “composite leading indicators provide a more reliable gauge of economic activity” and are also useful to the management of early warning signals about the turns. A study by the Bureau of Tourism Research (1995) indicated that leading indicators are simpler to update and are better at predicting turning points or long-term changes in the rate of growth.

Past tourism forecasting studies have demonstrated the usefulness of leading indicators in predicting the turning points. Wong (1997) investigated the relevance of business cycles in forecasting Hong Kong (HK) inbound-tourism demand, but did not examine the accuracy of turning points. The publication by the American Express, Tourism Council Australia and CRC Tourism (1998) also examined the turning points in Australian inbound-tourism demand growth rate using the tourism leading indicator approach. Rosselo–Nadal (2001) used the leading indicator approach to predict the turning points of the international visitor arrivals to the Balearic Islands from the United Kingdom and Germany. The empirical results suggest that the leading indicator approach is favorable in turning-point forecasting. A study by Kulendran and Wong (2009) showed that composite leading indicator models are useful in predicting turning-points forecasts. Recently, the leading indicator method was applied with logistic and probit regression model to create an economic model in which leading indicator is used as an independent variable to predict the occurrence of the turns in Hong Kong tourist arrivals (Kulendaran and Wong, 2010). Fernando (2010) also used composite leading indicator to forecast and predict the directional changes in Australia inbound-tourist arrivals.

2.4.3 Artificial Intelligence

Song and Li (2008) have indicated the emergence of several new quantitative methods in the new millennium on demand forecasting in the tourism sector. The most predominant technique is artificial intelligence. There have been several artificial intelligence methods used recently by tourism scholars, such as the artificial neural network method, rough set approach, the fuzzy time-series method, and genetic algorithms. Basically, the advantage of using artificial intelligence techniques in demand forecasting is that the system extracts the information from the data and develops a unique model to fit the data.

The artificial neural network method (ANN) is an attempt to make an input-output system think and work like a human brain, and adapt according to the data. The output from an ANN can be compared to that of traditional statistical methods (Law, 2000). Huang, Moutinho, and Yu (2007) stated that the neural network is good at handling nonlinear data. Uysal & Roubi (1999), Law (2001) and Cho (2003) used the artificial neural network method to forecast the demand of tourism. Some of these studies compared the results with several other forecasting models, and concluded that artificial neural networks had the best performance. Kon and Turner (2005) suggested that the artificial neural network method outperforms the classic time-series tourism demand forecasting method when applied to forecasting and modelling inbound-tourism demand in Singapore.

The rough set approach is a decision rule-induction method for monitoring the relationship between variables (Song and Li, 2008). Au and Law (2000) pointed out that given the inability of current tourism demand forecasting models in tourism to capture information from numeric and non-numeric data simultaneously, an empirical study was done using the rough set approach to set up a forecasting model for sightseeing expenditures in Hong Kong. Two more studies (Law and Au, 2000; Au and Law, 2002) used the same approach to test tourist shopping and dining data. Goh and Law (2003) remarked that considering the unique ability of the rough set approach to capture functional statistics from complicated data, the approach has become a helpful tool for classifying and reconciling data. Furthermore, Goh, Law, and Mok (2008) applied the rough set approach to the Hong Kong tourism demand analysis and introduced two qualitative non-economic factors, namely, leisure time index and climate index, into the forecasting model.

The fuzzy time-series method and grey theory are two good instruments for analysing short-term time-series tourism demand forecasting. For example, the fuzzy time-series method was used to predict linguistic value data points and deal with the difference between the values of a current period and those of the previous period of a time series (Song and Chissom, 1993). The grey theory proposed by Deng (1982) formulates a time series from imperfect data. The advantage of grey theory is that it adapts the accumulated generation operation form to minimize the randomness to fit the data, and with only four data points, it can estimate future trend. Yu and Schwartz (2006) used fuzzy time-series and grey theory to form a forecasting model to predict annual US tourist arrivals. However, the study found that the results were not significantly different from those of the classical time-series forecasting model. Wang (2004) used fuzzy time-series and grey theory to estimate tourist arrivals to Taiwan from Hong Kong, the United States, and Germany during the period of 1989–2000. Huang, Moutinho, and Yu (2007) used the fuzzy time-series model to forecast international tourist arrivals in Taiwan, and the model outperformed other models.

Song and Li (2008, p. 213) maintained that genetic algorithms are "adaptive heuristic search algorithms premised on the evolutionary ideas of natural selection and genetics." Genetic algorithms have normally been used as an optimization method. Lopez (2004) applied genetic algorithms to tourism forecasting of the tourist population, and the results were more accurate. This suggests that such models can minimize the risk of the policy maker in tourism planning. Chen and Wang (2007) used the combined approach of vector regression and genetic algorithms using tourist arrivals to China from 1985 to 2001.

2.5 Gap in the Literature

Several findings in the literature review of tourism forecasting have shown the significance of the present study. The main reason for the need to know the direction of changes or turning points of tourism demand in a growth cycle is "the high practical value, because tourism-related firms are keen to know not only the overall changes in trends of tourism demand, but also the timing of the directional change in tourism growth" (Song and Li, 2008). In the past, tourism demand underwent periods of expansion and contraction due to changes in economic, social, and political circumstances and because of unexpected crises, such as terrorism and natural disasters in both tourists' countries of origin and destination countries. Positive and negative growth rates are associated with upturn and downturns periods, respectively. Turning points in tourism demand occur when growth rates move from an upturn period to a downturn period, or vice versa. During the positive growth period, tourism resources are in high demand; on the other hand, in the negative growth period, resources are in low or even no demand. Such a switch in demand for resources requires the development of an appropriate operational management planning tool in tourism destinations. To capture the switch in the demand, both the public and private sectors need early signals of the start and end of the turns in tourism demand for investment and planning purposes.

Having identified the necessity of knowing the directional changes or turns in tourism demand, some researchers have also noticed that the causal method may outperform other approaches to achieve higher accuracy in directional forecasting. Studies by Witt and Witt (1989, 1991) , Witt, Song & Louvieris (2003) and Fernando (2010), investigating the most accurate forecasting method to estimate changes in trends and changes in direction (positive or negative) of annual tourism demand, examined both econometric and time-series models. These studies concluded that econometric models outperform time-series models in terms of directional change forecasting. Recently in tourism forecasting, researches have begun to use the composite leading indicator approach to predict the turns in tourism demand. Although the leading indicator approach is sometimes referred to as measurement without theory, economic theory and econometric models do give clues to the selection of variables as well as for the construction of the indicator.

A composite leading indicator is a basket of economic variables with different weights in a time-series model that can track the turns in the growth cycle of in a time-series. Most researches have used composite leading indicators in the prediction of turning points or directional changes. Niemira and Klein (1994) indicated that "composite leading indicators provide a more reliable gauge of economic activity since they can be more comprehensive and, hence, are less dependent on any single measure, even if that measure has a comprehensive coverage. This is particularly helpful when some components are subject to a lot of revision or when one indicator runs counter to several other measures." Such information is useful for management to identify the early warning signals of the turns. A study by the Bureau of Tourism Research Australia (1995) indicated that leading indicators are simpler to update, and that they are better at predicting turning points or long-term changes in the rate of growth.

Although researchers have cited the need to know the turning points and directional changes in tourism demand, limited studies have produced such practical tools for the academe as well as the industry. Before the 21st century, Witt and Witt (1991) and Witt, Song & Louvieris (2003) already stressed the importance of forecasting turning points in tourism demand and tourism demand growth rates. However, in an article reviewing tourism research, Song and Li (2008) still concluded that although the forecast of turning points has a high practical value for the tourism industry, limited related studies have been produced, even though such information will contribute to the effectiveness of both strategic planning for a single hotel to policy making for a country.

Even if some researchers have started to use the composite leading indicator method in the tourism industry, there is still no such study related to the hotel industry. The review of literature has found the lack of research on forecasting for the hotel industry. In the past, Choi et al. (1999) examined the cyclical patterns of business activity in the hotel industry and indicated that further research is required to develop a leading indicator. Then, Choi (2003) developed a set of economic indicators for the hotel industry and said that leading indicators could provide signals in advance for the basic performance of the hotel industry as a whole. However, this study merely identifies those leading indicators without further developing a model for prediction. Moreover, his research was limited to the use of annual hotel receipts in the United States. Song and Li (2008) confirmed that annual data will not satisfy the needs of both the hotel management and policy makers. The present study will use the quarterly hotel occupancy rate as the data set to predict the turning points of the hotel growth cycle.

Law (1998, 2004) used different artificial intelligence forecasting methods to predict hotel occupancy rate. However, Law (1998) also addressed the disadvantage of using artificial intelligence systems to predict hotel occupancy rates, as these may not cover the social, political, and random factors that might affect the actual occupancy rate. However, when using the economic leading indicators, the social and political issue can be included. For example, GDP, as a common leading indicator used for many earlier studies, already involves the political elements as the GDP will invariably reflect the country's stability. The CPI can explain the spending power for the destination's citizens, which is also partly affected by the local social factor.

Fernando's (2010) study have used the composite leading indicator to forecast tourism demand for the entire tourism industry; however, such prediction methods may not be suitable for the hotel industry, given the latter's uniqueness. In tourism forecasting literature, most dependent data used in the composite leading indicator approach are the numbers of tourist arrivals for inbound tourism in the destination. However, such data will not directly reflect the real business in the hotel industry, especially in a metropolitan city destination such as Hong Kong. According to the HKTB, a lot of tourists will visit Hong Kong every day, but they will leave Hong Kong in 24 hours—the so-called same-day in-town visitors. Those visitors mostly likely have some special interests in visiting, such as shopping, leisure, or sightseeing. Such visitors have no need to stay overnight; hence there is no demand for accommodation facilities. There were more than 20 million overnight-tourist arrivals in Hong Kong in 2010, consisting of 55.7% of total tourist arrivals to Hong Kong (HKTB, 2011). For total tourism expenditure, the same-day in-town visitor spending was HK$22.69 billion, and the overnight-visitor spending was HK$97.66 billion.

To identify the specific model for the hotel industry, the present study will mainly forecast the turns in hotel occupancy rate using data based on overnight visitors rather than that of overall tourist arrivals. Furthermore, based on the unique hotel classifications in Hong Kong, four different models will be created for each hotel category, namely, High Tariff A hotel, High Tariff B hotel, Medium Tariff hotel, and the average of the three categories (Total) in Hong Kong. This approach is the first attempt to give such detailed and practical models for each hotel category to face the different timings of the demand switch. Specifically, such a new approach to predict the future turning points in hotel occupancy growth rate for different categories can provide advance information to hotel operators and offer them some lead time to get ready to face the changes in the occupancy rate, which, in turn, will reflect on their revenues.

Moreover, developing an econometric model using the logistic and probit regression models with the leading indicator and hotel demand determinants will be another aim of the present study. Such models will be the first econometric models for the hotel industry.

To conclude, there has been no previous research for the purpose of constructing a composite leading indicator exclusively for the hotel industry. The special characteristics of hotel products, namely, intangibility, inseparability, variability, and perishability, make the need for accurate forecasts more urgent than among other commodity tourism products, for example, clothing in the retail industry. The economic significance of the hotel industry's contribution to the Hong Kong economy points to the serious need for developing reliable and accurate tourism forecasting models that will provide the necessary information for strategic marketing and investment planning within the industry. This applies to both policy-making government agencies as well as significant industry players in the private sector.

Moreover, hotel occupancy rate is directly related to the revenue from the property. Yield management is the process of allocating the right type of capacity to the right kind of customer at the right price to maximize revenue or yield (Reynolds and Braithwaite, 1997; Brotherton and Mooney, 1992). The challenge for management is to balance supply with demand to maximize profits for the organization. The construction of the composite leading indicator for the hotel industry can provide solid direction and information for the hoteliers to get ready for the changes or shifts between different demand levels. Such practice can demonstrate the best use of resources to achieve the best yield management in hotels.

Composite leading indicators for hotels will also reflect the real situation of hotels considering that more than half of hotel revenue is historically generated by the "Rooms" department (HKTB, 2011). Although some studies (Law, 1998; Choi, 2003; Law, 2004; Kon and Turner, 2005; and Palmer, Montano, and Sese 2006) have been done on similar topics related to forecasting in hotels, there has been no research predicting the turning points of the hotel industry and identifying the economic variables affecting these turns. As yet there has been no study on the use of composite leading indicators in forecasting hotel occupancy rate patterns.

Chapter 3

RESEARCH PROCESS AND METHODOLOGY

3.1 Introduction

After the introduction and literature review, this section will seek to demonstrate the research process of the present study and illustrate the methodology involved. This chapter will cover every detail, namely, choosing the proper data, indicating a suitable statistical treatment for smoothing the data, choosing a proper cyclical pattern, deciding on a best-fit chronology for the series, combining the economic variables to construct the composite leading indicator, and evaluating the results.

First, the present study will transform the origin hotel occupancy rate to the growth rate and identify the turning points accordingly. Second, the composite leading indicator for the Hong Kong hotel industry will be constructed by combining selected economic variables from the top five overnight-stay tourist-origin countries in Hong Kong. Third, instead of the economic variables from the tourist-origin countries, the ready-to-use economic indicators from OECD will form the composite leading indicator to compare with the previous one. Fourth, the hotel demand determinants will use different points to choose the appropriate factors to combine as a model.

More importantly, to compare the turning point prediction performance of all these models, logistic and probit regression models will be used to estimate (1) the composite leading indicator by various economic variables, (2) the OECD composite leading indicators, and (3) the hotel demand determinants functions. Quadratic probability score (QPS) will be used as an assessing tool for finding the best model for turn prediction.

3.2 Data Used in the study

This section first examines the original time series of the hotel occupancy rate from Hong Kong. Second, the potential economic variables that can be used to construct the composite leading indicator for different categories of Hong Kong hotel industry will be explored. Third, this section will present the existing comparison leading indicators and indexes from OECD. Fourth, the hotel demand determinants for the econometric model will be shown. All the sources and formation of these data series will be explained in this section.

3.2.1 Data of the hotel Occupancy

As discussed in Chapter 1, the monthly occupancy rates of Hong Kong hotels were gathered from the official statistics of HKTB, which identifies three hotel categories in Hong Kong, namely, High Tariff A, High Tariff B, and Medium Tariff. Details of the weighting method were already discussed in Chapter 1.

The present study adds one more category, that is, the Total, which means the average of all the three categories. The Total can give the overall performance of hotel occupancy in Hong Kong to understand the hotel industry in its entirety. The HKTB began publishing the monthly hotel occupancy rate in 1972. The present study uses the monthly occupancy data of Hong Kong from January 1972 to September 2010.

Figure 3.1 Hong Kong (Total) hotel monthly occupancy rate (Hong Kong Tourism Board)

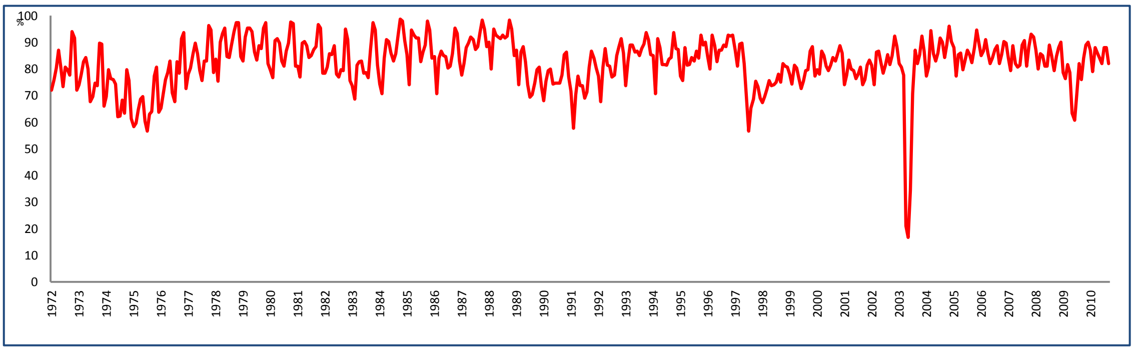


Figure 3.2 Hong Kong High Tariff A hotel monthly occupancy rate (Hong Kong Tourism Board)

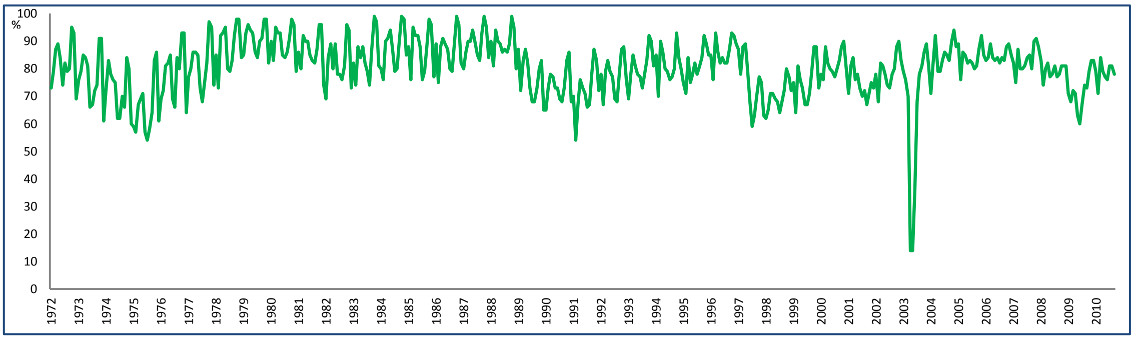


Figure 3.3 Hong Kong High Tariff B hotel monthly occupancy rate (Hong Kong Tourism Board)

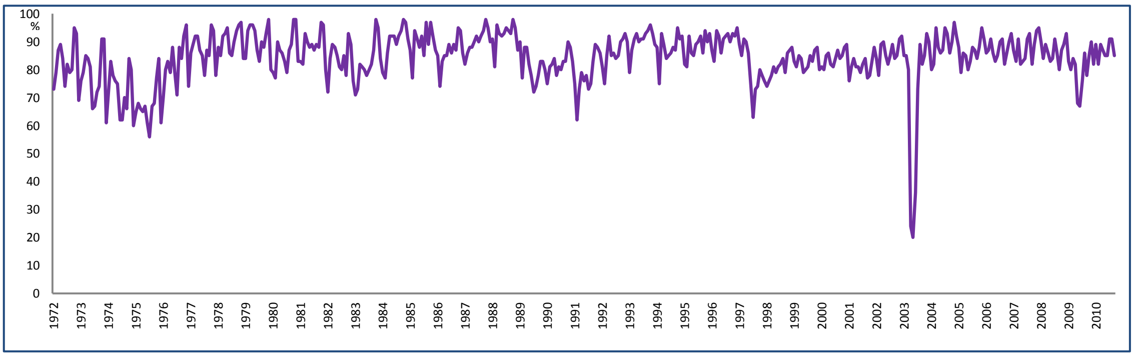
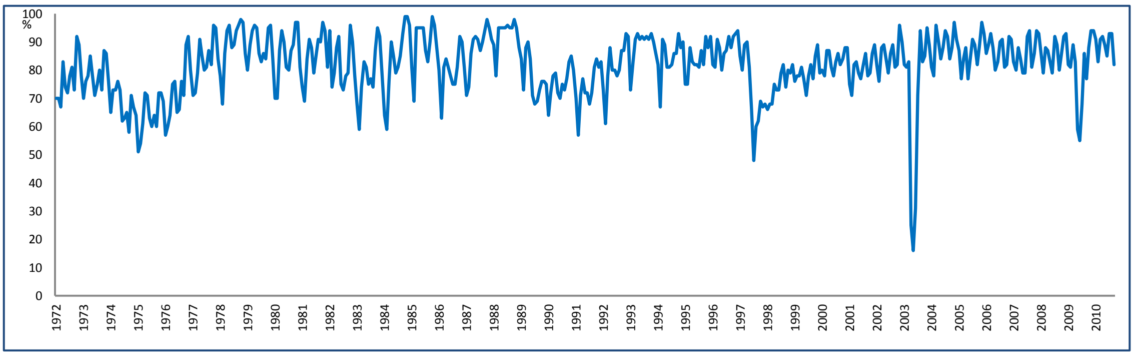


Figure 3.4 Hong Kong Medium Tariff hotel monthly occupancy rate (Hong Kong Tourism Board)



To get a different picture of the data, the monthly data of each category are converted to quarterly statistics. The quarterly occupancy rate data of hotel occupancy are formed by using the last month of each quarter. Therefore, the quarterly occupancy rate starts from the first quarter (Q1) of 1972 until the third quarter (Q3) of 2010.

Figure 3.5 Hong Kong (Total) hotel quarterly occupancy rate (Hong Kong Tourism Board)

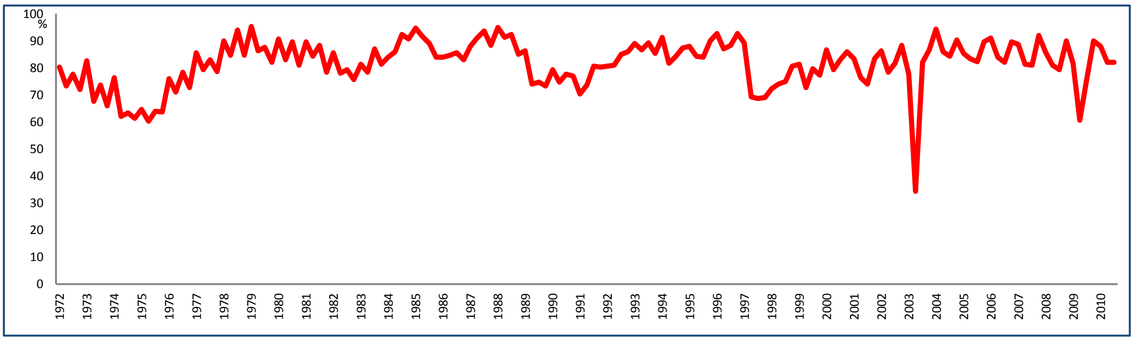


Figure 3.6 Hong Kong High Tariff A hotel quarterly occupancy rate (Hong Kong Tourism Board)

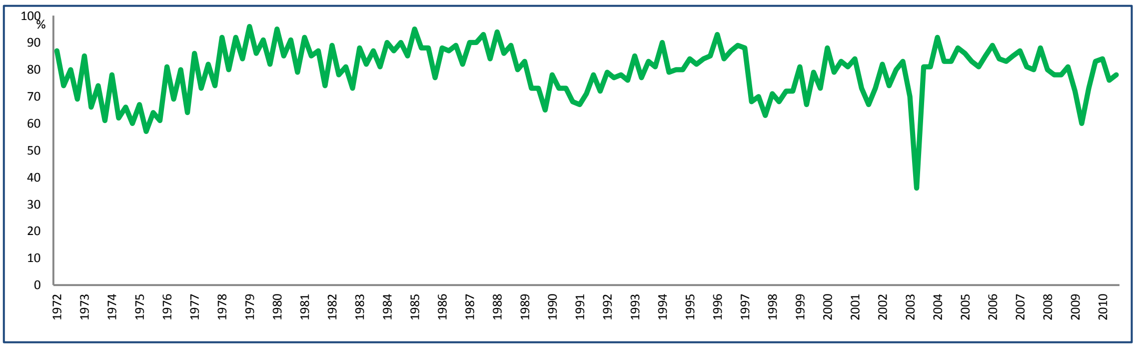


Figure 3.7 Hong Kong High Tariff B hotel quarterly occupancy rate (Hong Kong Tourism Board)

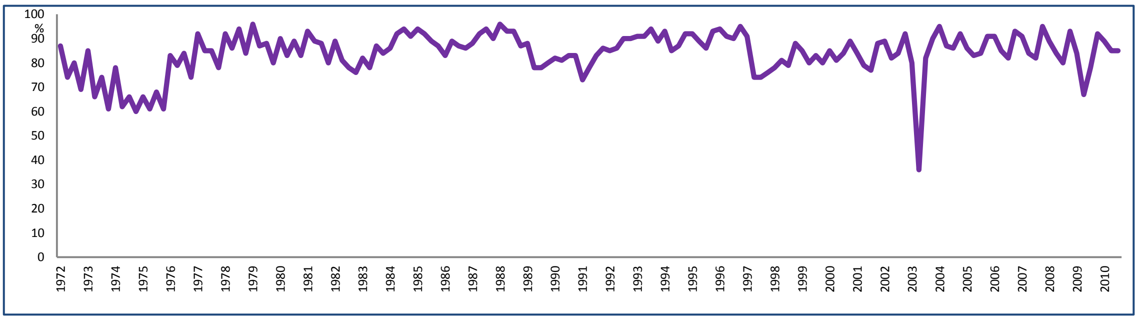
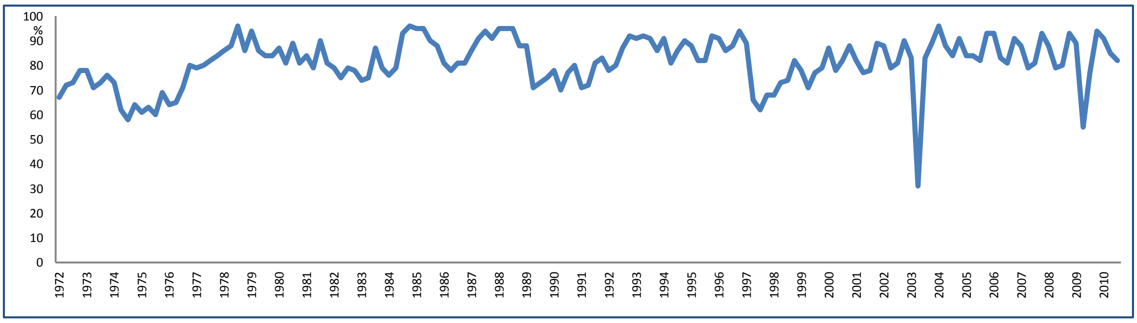


Figure 3.8 Hong Kong Medium Tariff hotel quarterly occupancy rate (Hong Kong Tourism Board)



3.2.2 Possible Economic variables for the formation of the Leading Indicators

The composite leading indicator is a combination of a series of economic variables. Common economic indicators can fall under three categories, namely, leading indicator, coincident indicator, and lagging indicator. Leading indicator series data should be turned before the actual turn of the time series. Past studies used different sets of economic variables to construct the composite leading indicator. As discussed in Chapter 1, the formation of the constructed composite leading indicator for the Hong Kong hotel industry will based on the selected economic variables of the top five overnight-stay tourist-origin markets, namely, China, Taiwan, Japan, United States, and Australia.

In a study, the Bureau of Tourism Research Australia (1995) examined retail sales activity, unemployment, gross domestic product (GDP), industrial production and employment, and the trade-weighted index, and found out that OECD gross domestic product, OECD unemployment, and the trade-weighted index of Australia's currency exchange rates were more reliable. Turner, Kulendran, and Fernando (1997) employed the GNP, money supply, unemployment rate, total imports, total exports, and forward exchange rate to construct a composite leading indicator for tourism demand in Australia. To forecast turning points in tourism demand growth rates, Rossello–Nadal (2001) examined the number of total construction, consumer prices, and exchange rates. Kulendran and Witt (2003) utilized the origin countries' real domestic product index, relative price, nominal exchange rates, exchange rate-adjusted relative price, and the origin countries' real disposable income to identify the leading indicator to forecast the international demand from the United Kingdom to six major destinations. Choi (2003) identified a set of leading economic indicators for the hotel industry in the United States.

These economic variables included the American stock exchange index, business failure number, CPI for motor fuels, dividends per share, GDP of service, hotel stock index, money supply in constant dollars, New York Stock Exchange, prime interstate charged by banks, S&P 500 stock price index, savings percentage of disposable income, and wages and salaries. Kulendran and Wong (2009) selected the potential leading indicators for HK inbound tourism demand from the following economic variables: tourist origin-country income measured by GDP, exchange rate between tourist-origin country and destination country, relative price adjusted with exchange rate, total export, total import, unemployment rate, and stock price index.

The present study is pioneering the construction of the composite leading indicator for the hotel industry; thus, there are no guidelines from which to choose. However, based on the Hong Kong study of Kulendran and Wong (2009), the selected economic variables for the present study are gross domestic product (GDP), exchange rate index (ER), total export (TE), total import (TI), unemployment rate (UR), real exchange rate (RER), oil price (OP), and share price index (SP). All these selected economic variables for the hotels are related to the tourism sector.

Data for China, Japan, the United States, and Australia are mainly obtained from the International Monetary Fund's (IMF) International Financial Statistics, OECD Statistics, the World Bank database, and the Taiwan National Statistics Bureau. The oil price for all countries will be the same as that of the IMF oil price index. Moreover, to get the uniqueness of the exchange rate for all countries involved, the exchange rate published by the Hong Kong Census and Statistics Department in Hong Kong will be used in the present study.

Given that the CPI of the original countries did not really reflect the true value of tourist spending in the destination country, the real exchange rate (RXR) will replace the CPI as one of the economic variables. RXR is calculated as (CPI of destination country/exchange rate between two countries)/CPI of the original country. Such calculation will arrive at the true spending power of the original countries' currencies that can be used by the tourists in the destination countries (Kulendran and Wong, 2010).

In the case of Japan, the United States, and Australia, the economic variables are available from the 1970s to 2010. For China, some economic variables such as GDP, total export, total import, and exchange rate are available from the 1970s to 2010, whereas the unemployment rates are available from 1985, and the share price and CPI are available from 1991. The Taiwan share price and exchange rate were available from the 1970s to 2008; GDP and CPI were available from 1981; total exports and total imports were available from 1998. The details are shown in the table below. OP for all countries will be the same as the IMF oil price index. Although data for some of the economic variables for some countries went as far back as 1960, all the data series in the present study will start from 1972 in the interest of uniformity with the Hong Kong data series.

Table 3.1 Summary of the information of economic variables

	Gross Domestic Product (GDP)		Total Export (TE)		Total Import (TI)		Unemployment Rate (UR)		Consumer Price Index (CPI)		Share Price index (SP)		Oil Price (OP)	Exchange Rate Index (ER)
China	Source:	OECD	Source:	IMF	Source:	IMF	Source:	National Bureau of Statistics, China	Source:	OECD	Source:	OECD	Source: IMF	Source: Hong Kong Census and Statisitcs Departement, Hong Kong
	Type:	Quarterly	Type:	Monthly	Type:	Monthly	Type:	Yearly	Type:	Yearly	Type:	Monthly		
	From:	1995	From:	1981	From:	1980	From:	1985	From:	1985	From:	1999		
Taiwan	Source:	National Statistics, Taiwan	Source:	IMF	Source:	IMF	Source:	National Statistics, Taiwan	Source:	National Statistics, Taiwan	Source:	National Statistics, Taiwan		
	Type:	Quarterly	Type:	Monthly	Type:	Monthly	Type:	Quarterly	Type:	Quarterly	Type:	Monthly		
	From:	1973	From:	1957	From:	1957	From:	1978	From:	1970	From:	1966		
Japan	Source:	OECD	Source:	IMF	Source:	IMF	Source:	OECD	Source:	OECD	Source:	OECD		
	Type:	Quarterly	Type:	Monthly	Type:	Monthly	Type:	Monthly	Type:	Monthly	Type:	Monthly	Type: Monthly	Type: Monthly
	From:	1980	From:	1957	From:	1957	From:	1960	From:	1960	From:	1972		
USA	Source:	OECD	Source:	IMF	Source:	IMF	Source:	OECD	Source:	OECD	Source:	OECD		
	Type:	Quarterly	Type:	Monthly	Type:	Monthly	Type:	Monthly	Type:	Monthly	Type:	Monthly		
	From:	1960	From:	1957	From:	1957	From:	1960	From:	1960	From:	1972		
Australia	Source:	OECD	Source:	IMF	Source:	IMF	Source:	OECD	Source:	OECD	Source:	OECD	From: 1957	From: 1975
	Type:	Quarterly	Type:	Monthly	Type:	Monthly	Type:	Monthly	Type:	Monthly	Type:	Monthly		
	From:	1960	From:	1957	From:	1957	From:	1960	From:	1960	From:	1972		

3.2.3 Data for the comparison of the constructed leading indicator

Given the importance of finding some existing leading indicators to test the performance of the constructed composite leading indicator in the present study, three indexes from the Organization for Economic Cooperation and Development (OECD) will be used as a contrast for the leading indicator. The three indexes from OECD used in the present study are the OECD Composite Leading Indicator (OECD CLI), OECD Business Survey Index (OECD BSI), and OECD Consumer Confidence Index (OECD CCI).

The construction of each comparison indicator will be the same as the constructed leading indicator. Each major market for Hong Kong overnight-stay tourists will be assigned a special weighting to form the unique indicator for Hong Kong. All the processes will be discussed in greater detail in the next few chapters. China, Japan, the United States, and Australia are members of the OECD, whose data on those member-countries will be used to construct the comparison indicator in the present study. However, the limitation of these comparison indicators is that there are no Taiwan data because the latter is not a member of OECD. The present study cannot overcome such an inadequacy.

Organization for Economic Cooperation and Development (OECD)

The Organization for Economic Cooperation and Development (OECD) was launched in 1957 to replace the Organization for European Economic Cooperation. OECD describes itself as “a forum of countries committed to democracy and the market economy, provide a setting to compare policy experiences, seek answers to common problems, identify good practices, and coordinate domestic and international polices”

(OECD, 2010). Although the treaties and discussions in the forum are not legal and binding among the member-countries, OECD has set up guidelines or basic core ideas for its members to follow and set up their own policy. There are now 34 OECD member-countries, including the United States, Japan, United Kingdom, Australia, Canada, and South Korea. Some 25 nonmember-countries participate in OECD as committee observers, such as China.

Statistics of member-countries, and even those of nonmember-countries, are key to OECD's function. Such statistics provide a solid database of worldwide economics. Moreover, OECD also develops different indicators for different aspects, such as the OECD composite leading indicator, the OECD business survey index, and the OECD consumer confidence index. All these indexes give businesspeople a better and more comprehensive picture of the global economy.

<u>OECD Composite Leading Indicator (OECD CLI)</u>

To validate the accuracy of the constructed composite leading indicator, the present study compared the constructed composite leading indicator with the other three sets of indexes provided by OECD. The first is the OECD composite leading indicator (OECD CLI). The OECD composite leading indicators were developed in the 1970s to give early signals of turning points in economic activity (Gyomai and Guidetti, 2008). The OECD used a set of comprehensive economic variables to construct the leading indicators. OECD started publishing the OECD composite leading indicators in 1981. The OECD CLI consists of main economic indicators, such as the GDP, which will directly reflect the economic situation of the local citizens. Therefore, the OECD CLI of the tourist-origin countries will influence the hotel occupancy rate of the destination country.

Aside from the constructed composite leading indicator, the present study will use the coefficient of the cross-correlation analysis (CC) and the market share of Hong Kong overnight-stay tourist countries (MS) as weighting. Such combined OECD composite leading indicator for the Hong Kong tourist market will form a comparable data with the newly constructed composite leading indicator. Therefore, two sets of OECD CLI will be developed, namely, OECDCLI CC (combined OECD composite leading indicator by the weighting of the coefficient of the correlation analysis), and OECDCLI MS (combined OECD composite leading indicator by the weighting of the market share of Hong Kong overnight-stay tourist countries).

<u>OECD Business Survey Index (OECD BSI)</u>

The OECD Business Survey Index (OECDBSI) is a collection of qualitative information from the top management or business executives of each country (OECD, 2003). Compared to the OECD composite leading indicators, the OECD business survey data are more qualitative and definitely reflect the confidence level of the respective countries' top management or chief executives about the local economic activity. Such information indicates the confidence level of the business sector regarding the overall economy. The motivation of business travel and conferencing may also be reflected in the data, which will directly affect the business of destination accommodations.

Business survey data have been around since the 1920s, and such a long historical development has imbued this set of data with high representative value and a solid reputation. Garcia–Ferrer and Bujosa–Brun (2000) stated that business tendency surveys in many countries have become increasingly popular as leading indicators, given their prompt availability and lack of systematic revisions.

The present study used data from the OECD's business survey confidence index, employed the same weighting, and combined the method of the OECDCLI, which is by the coefficient of the cross-correlation analysis (CC) and the market share of Hong Kong overnight-stay tourist countries (MS), to create a time series to compare with the Hong Kong hotel occupancy rate. Consequently, OECDBLI CC (combined OECD business survey index by the weighting of the coefficient of the correlation analysis) and OECDBSI MS (combined OECD business survey index by the weighting of the market share of Hong Kong overnight-stay tourist countries) will be developed as a comparison index to test the prediction accuracy of the constructed composite leading indicator.

<u>OECD Consumer Confidence Index (OECD CCI)</u>

The third index to compare to the constructed composite leading indicator will be the OECD Consumer Confidence Index (OECDCCI). The OECD collects the consumer opinion survey from 19 member- and nonmember-countries every month. Such qualitative surveys provide information on consumer sentiment based on both the general economic situation and the financial situation of the household. Afterward, the OECD uses a statistical method to form a comparable indicator, such as the consumer confidence index, which is published in the OECD Web site. The concept is similar to that of the OECD business opinion survey, but the OECD consumer opinion survey mainly collects consumer viewpoints on the national economy and global economies. If consumers feel positive toward the local economy, the chance for travelling for leisure will increase. Therefore, the destination's hotel occupancy rate will also be affected by such reasoning.

With the aim of testing the accuracy of the predicted turns of the constructed composite leading indicator, the present study used the information of the OECD consumer confidence index, used the same weighting and combined method of previous OECD indexes, which is by the coefficient of the cross-correlation analysis (CC) and the market share of Hong Kong overnight-stay tourist countries (MS), to generate a unique indicator to contrast with the other indicators. Accordingly, OECDCCI CC (combined OECD consumer confidence index by the weighting of the coefficient of the correlation analysis) and OECDCCI MS (combined OECD consumer confidence index by the weighting of the market share of Hong Kong overnight-stay tourist countries) will function as an evaluation tool for checking the forecast correctness of the constructed composite leading indicator.

Limitations for OECD data

The OECD statistics provide voluminous data of their member-countries and some nonmember-countries; however, there were no data for Taiwan for political and economic reasons after the Second World War. Although Taiwan is the second country, after China, with the highest number of overnight-stay tourists in Hong Kong, there are no OECD indicators provided. Therefore, the present study merely used data from four other countries, namely, China, Japan, the United States, and Australia, to construct the OECD composite leading indicator, the OECD business survey index, and the OECD consumer confidence index for the Hong Kong tourism industry.

3.2.4 Demand determinants for hotel industry

To provide another econometric model to compare to the composite leading indicator models, demand determinants for the hotel industry will be used. The selection of these demand determinants for the hotel industry will based on the tourism demand determinants. According to the consumer theory of choice, the demand for certain products generally depends on the consumer's income, prices, and substitute-product prices. However, the focus of the present study is hotel demand; thus, the demand determinants more specific to the hotel industry are considered in this study.

3.2.4.1 Selection of hotel demand determinants

Income

The tourist's income is the main factor that affects the choice of the destination as well as the category of hotel where the tourist will stay. However, as it is nearly impossible to determine every tourist's personal disposable income, the GDP of the tourist's country of origin will represent the tourist income in this study. The GDP used in the present study is a combined GDP growth rate. The weighting is based on the top five overnight-stay tourist arrivals in Hong Kong. Past studies have also used the GDP as a proxy for tourism income (Kulendran and Wong, 2010; Fernando, 2010)

Price of Accommodation

The price of a room in the destination is another important factor that affects the tourist's decision on hotel selection. The ideal way to construct the price of a room is to compare the destination-hotel price with the tourist origin country-hotel price adjusted by the exchange rate. However, data on the hotel price of the origin country are insufficient. Therefore, the real exchange rate (RER) was considered as a proxy for the price of the room in the destination. The RER was calculated by adjusting both the destination's CPI and the origin country's CPI by exchange rate. The reason for choosing CPI as a proxy is that the latter measures the price level of consumer goods and services generally purchased by consumers. In constructing the CPI, the hotel price is also included because the hotel industry is also part of the service sector. Therefore, the RER, which is actually the adjusted CPI of the destination and origin countries, can represent the general price level of the hotels.

Substitute Price

Song, Wong, and Chon (2003) introduced five suitable destinations for Hong Kong, namely, Taiwan, Singapore, Thailand, Korea, and Japan. However, at present, the Singapore real hotel price is the only datum available, which is considered as the proxy of the substitute hotel price of the destination.

Nominal Exchange Rate

The nominal exchange rate has not been considered as an independent variable in demand determinant in previous tourist forecasting studies because the nominal exchange rate was already in the calculation of RER. Witt and Witt (1987) even stated that the exchange rate on its own is not an acceptable proxy for tourist price in a tourism demand study. However, in the hotel industry, the nominal exchange rate may be more important than the international tourism demand. Having identified the vacation destination, there is more than one choice for the tourist with regard to hotel accommodations in the country of destination. Given the allocated budget for accommodation, the tourist can choose from different types of accommodation based on the nominal exchange rate. For example, Hong Kong has three categories of hotels with different price ranges and facilities that tourists can choose from when they travel to

Hong Kong. If the origin country's currency is strong, the tourist can choose the most expensive hotel; on the other hand, the tourist may choose the least expensive hotel when the exchange rate is weak.

<u>Cost of Travel</u>

The oil price will be used as a proxy for the cost of travel. All the transportation prices, for example, airline, car rental, or cruise, may be affected by changes in global oil prices. Due to location of Hong Kong, most of the tourists are come by different public transports which include airplane, cruise, train or coach, using oil price as a proxy is the best and simple way to estimate the cost of travel.

3.2.4.2 Hotel demand model for estimation

The hotel demand for Hong Kong will express as follow:

GHD = f (GY, GPD, GSP, GEX, GOIL)

GHD: $\left\{ \begin{array}{l} 1 = \text{expansion} \\ 0 = \text{contraction} \end{array} \right\}$

where:

GHD is the actual hotel occupancy growth in Hong Kong hotel industry.

GY is tourist income. GY is the growth rate of the combined gross domestic product (GDP) of the top five overnight-stay countries, which is constructed from the weighting of market share.

GPD is the cost of a room in the destination. GPD is the growth rate of the combined RER of the top five overnight-stay countries for Hong Kong.

GSP is the price of substitute destination. GSP is the growth rate of real hotel price of Singapore.

GEX is the nominal exchange rate. GEX is the growth rate of the combined nominal exchange rate between the destination and origin countries.

GOIL is the cost of transport. GOIL is the growth rate of real oil price.

3.3 Choosing a smoothing method

Fernando (2010) stated that smoothing the raw statistical data can capture the most important pattern of the data without disturbance from unobserved noise. Therefore, the first step for the original hotel occupancy rate and all the time-series economic variables is to smooth the data by basic structural model (BSM). BSM is a trend derivative approach that effectively smooths the original data to capture the turning points of each hotel category time series. The original hotel occupancy data contain high-volatility pattern disturbance by seasonal and irregular patterns caused by unpredictable events.

Seasonality has a strong impact on the tourism sector, given that tourists tend to choose the best seasons to travel around the world. Such environmental factor deeply affects the forecasting ability of the data series. Selecting the best technique involves the removal of the seasonal component and random factors to arrive at the key essentials for the prediction of turning points of the time series. Therefore, smoothing the data by extracting only the trend component is a preparatory step to the present study.

Scholars have developed several methods to smooth the data. Niemira and Klein (1994) pointed out that the most important consideration in choosing the appropriate smoothing method is that the smoothing process should not alter the configuration of the original pattern and not be adversely affected by outliers.

3.3.1 SMSAR and TQSAR

A simple technique such as the moving-average method, or more complicated procedures like the six-month smoothed annualised rate (SMSAR) and two-quarter smoothed annualised rate (TQSAR) by Niemira and Klein (1994), are the common nonstatistical ways to smooth the data. SMSAR and TQSAR are supported on the proportion of the existing value of the sequence to its average during the past 12 months or 4 quarters to smooth the annualized rate. Many tourism forecasting studies have used the SMSAR and TQSAR to smooth their statistical series in the last two decades (Rossello–Nadal, 2001; Kulendran and Wong, 2006). For example, Rosselo–Nadal (2001) used the six-month smooth growth rate method to generate the smooth cycle of monthly growth rate of tourism arrivals in the Balearic Islands. Kulendran and Wong (2009) indicated that the extraction of smoothed growth rates varied from single difference to more complicated higher-order moving averages. However, the disadvantage of the latter is that sometimes the smoothed data will become more volatile and thus reduce the currency of the observation (p. 94, Niemira and Klein, 1994).

However, in recent years, forecasting studies have pointed to the statistical trend derivative extraction method to smooth the data as being much easier and more systemic in capturing the unobserved component in the series. Garcia–Ferrer and Queralt (1998) said that such statistical smoothing method is an anticipative device for predicting turning points of the time-series data. Moreover, Garcia–Ferrer and Bujosa–

Burn (2000) commented that the trend derivative method can effectively show the data with significant turning points without distorting the irregular components.

3.3.2 HP Filter Approach

There are two common trend derivative methods, namely, the filter approach and the statistical modelling approach. The filter approach, commonly called the Hodrick–Prescott filter method (HP), is generally adopted by macroeconomists. In 1980, Hodrick–Prescott suggested the HP filter method to the business world and has since become popular in macroeconomic studies. The HP filter approach is commonly used by macroeconomists to get a smooth estimate of the long-term trend component of the series (*EView* 4.0, 2000, p. 190). Simply put, the HP filter is a linear sieve intended to eliminate the amount of low-frequency data in the time series. The HP filter (Hodrick and Prescott, 1997) is a procedure that decomposes the original series, *yt*, into stochastic growth and cyclical components, respectively, by minimizing the expression,

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

The parameter λ in Equation (1) controls the smoothness of the series, y_t^g. Note that as λ approaches infinity, the growth component corresponds to a linear trend.

3.3.3 Basic Structural Model (BSM)

Another statistical trend derivative method is the basic structural model (BSM). Basic structural time-series models (Engle, 1978; Nerlove, Grether & Carvalho, 1979; Kitagawa, 1981; Harvey, 1989) are those formulated directly in terms of components such as trend, seasonality, and cycle. Structural time-series models, therefore, offer clear interpretations through decomposition into components (Kendall and Ord, 1990). The decomposition ability of structural models is a major attraction for time-series forecasting. BSM was introduced by Harvey and Todd (1983), which enabled nonstationary data to be handled directly without the need for explicit differencing operations. The BSM, according to Harvey and Todd, is a univariate time-series model consisting of a slowly changing trend component, a slowly changing seasonal component, and a random irregular component. Statistically, the treatment of the BSM can be performed by casting it into the state space form (SSF) so that the Kalman filter (Kalman, 1960; Kalman and Bucy, 1961) can be used to evaluate the likelihood function.

BSM is a common smoothing method widely used in finance and economics. Recent studies showed that BSM can be easily and accurately applied on tourism data and can outperform other models. García–Ferrer et al. (1994) used the derivative of the unobserved trend component as a device for qualitative anticipation of peaks and troughs. Kulendran and Wong (2009) successfully smoothed the data of tourism arrivals in Hong Kong by BSM.

Given the disadvantages of all the other smoothing methods, as a result, Kulendran and Wong (2009) used the BSM method to estimate the smoothed growth rate and to identify significant turning points in tourism forecasting research. In the present study, BSM approaches will be used to extract the smooth growth from the Hong Kong hotel quarterly occupancy rate. The study of Fernando (2010) also confirmed that the best way to smooth tourism data is by BSM. Fernando (2010) used the TQSAR, HP filter approach, and BSM for his study on tourism demand in Australia, and concluded that BSM is the most suitable method to use for tourism industry time-series data. The smoothed data from TQSAR is still too volatile; hence, it would be difficult to locate the turning points. On the other hand, the smoothed series by HP filter approach is too smooth, which also makes it difficult to find significant up and down peak points. Therefore, in the present study, BSM was used to smooth the time-series data of the hotel occupancy rate as well as all the economic variables before the construction of the composite leading indicator. Structural time series analyser, modeller and predictor (STAMP) is a computer program for BSM. STAMP is a menu-driven program for automatically fitting univariate time-series models.

3.4 Selection of a cycle pattern

After the smoothing method has been chosen, the next step is to find a suitable cyclical pattern to identify the turning points for the present study. The business world typically uses two main types of cyclical patterns, namely, classic business cycle and growth cycle. Understanding the difference between these cyclical patterns will help researchers in choosing the best pattern for different research topics and scopes.

3.4.1 Classic Business cycle

The classic business cycle is widely used in research. The business cycle is originally defined as a cyclical pattern consisting of expansions, recessions, contractions, and revivals among many economic activities in a certain time frame (Burns and Mitchell, 1946). The business cycle uses absolute data to present the decline and rebounds (Niemira and Klein, 1994). García–Ferrer and Bujosa–Brun (2000) cited the long tradition of business cycle forecasting to focus on turning points. García–Ferrer, Queralt and Blazquez (2001) commented that most researchers have associated the measurement, modeling, and forecasting of economic situations and called it the classical cycle.

However, with the real decline in economic activities in industrial countries in the 1960s, increasingly more researchers have criticized the use of the business cycle due to the lack of downturns in the cycle (Bronfenbrenner, 1969). Diebold and Rudebusch (1989) said that business cycles have become more moderate in the postwar period, with shorter and shallower recessions.

Another drawback of the classic cycle is that the pattern of change is recurrent but not periodic, as some cycles will take one to two years but others may take longer than ten years. For comparison purposes, this would be very difficult for some studies (Rosselo–Nadal, 2001). Some researchers have used the growth cycle instead of the classic cycle to review economic movements. Furthermore, economists' search for other cyclical patterns that could be more in line with reality has led to the development of the growth cycle (Mintz, 1969).

3.4.2 Growth cycle

According to Niemira and Klein (1994), deviation cycle or growth cycle, is "a pronounced deviation around the trend rate of change." Niemira and Klein (1994) also stated that growth cycles were better than business cycles for the following reasons: (1) growth cycles happen more often than classical cycles; (2) growth cycle peaks lead their associated business cycle peaks; (3) the US Department of Commerce composite index of leading indicators has a better track record for forecasting growth cycles than business cycles; and (4) growth cycles are more symmetric in length and amplitude than business cycles. Mohanty, Bhupal, and Jain (2003) further explained that a growth cycle should clearly have two phases, namely, high-growth and low-growth phases. The high-growth phase should consist of business cycle recovery and expansion, whereas the low-growth phase is the latter half of the expansion period followed by recession.

In contrast to classical business cycles, growth cycles represent alternating periods of above and below trend rates of growth, and can be seen as short-term fluctuation around previous peaks and troughs (García–Ferrer, Queralt and Blazquez, 2001). Growth cycles have since become popular, being used today in projects of the OECD and the American National Bureau of Economic Review (NBER) to develop economic indicators.

Niemira and Klein (1994) also indicated that the growth cycle was more suitable for forecasting trends and directions rather than the classic business cycle. Taylor (1998) stated that the growth cycle can outperform the business cycle in the way it identifies major changes in economic events. Kulendran and Wong (2009) also used the growth cycle to identify the turning points of their study. Fernando (2010) used the growth cycle as the cyclical pattern for his study in identifying the turning point of tourism demand in Australia.

In general, the main aim of the present study is to recognize the peaks and troughs of Hotel Kong hotel occupancy. Consequently, the growth cycle will be used as the cyclical pattern to identify the turning point of the time-series data.

3.5 Dating the turning points

After deciding on the smoothing method and the cyclical pattern for the series, the next step is to identify the significant turning points. The growth of the hotel occupancy rate for all categories in Hong Kong, the constructed composite leading indicator, and all the other OECD comparison indicators will use the same dating process, or the unique reference chronology to harmonize the final result. Before the dating process starts, a turning point should be properly defined for the present study. A "turning point" for the growth of the hotel occupancy rate of all categories is a particular peak (trough) of the time series where the occupancy changes from high growth to slow growth (contraction), or from slow growth to high growth (expansion). Meanwhile, a "turning point" for the all the other leading indicators is a particular peak (trough) of the time series where the tourism demand changes from high growth to slow growth (contraction), or from slow growth to high growth (expansion).

Fernando (2010) stated that such identification process can perform at least two main aims. First, such algorithm can provide a possible set and sufficient points of turning. Second, the method sets clear procedures for the alternate and last points and determines rules for the whole time series. Until today, no official tourism organization provides any guideline in the dating process.

Hardings and Pagan (2003) said that two dating methods are commonly used, namely, parametric and nonparametric approaches. The parametric approach is mainly driven by the school of Markov switching model, which was developed by Hamilton in 1989. On the other hand, the non-parametric approach was dominated by Bry and Boschan's method in 1971.

3.5.1 Parametric dating approach – Markov Switching Model

The most popular parametric approach is the Markov switching model developed by James Hamilton (1989), which involves the estimation of the statistical model to draw out the turning points. Most of the other parametric models are based on the Markov switching model for further development.

Hamilton's switching idea (1989) to search for the differences between fast and slow growing regimes formulated the famous Hamilton's Markov regime switching model. Originally, the two states in the model represent the expansion and contraction of the business cycle. Fernando (2010) used the Markov switching model for his study of the tourism growth cycle to capture the peaks and troughs; similarly, the model can capture the tourism demand growth by defining the switching between the fast and slow tourism demand growth regimes.

However, the drawback in using the Markov switching model in the present study is the latter's scope of data. The Markov switching model is a very popular technique for identifying the turning points of macroeconomic data such as GDP or GNP. In addition, most of the macroeconomic data use the business cyclical pattern. The switching between high and low growth in the business cycle may happen more than once, which will not happen in the growth cycle. Moreover, the macroeconomic time series, like GDP, is normally in a growth phrase with infrequent long and deep downturn phrases in the whole cycle. On the other hand, the hotel industry is a microeconomy that is highly affected by the global political, climatic, social, seasonal, and economical factors, and even natural disasters or terrorism, both in the country of origin and the destination country. Thus, Markov switching may not capture every turning point in the extremely volatile status of hotel occupancy growth cycle.

3.5.2 Non-parametric Approach – Bry and Boschan's Approach

Different organizations and scholars use their own methodologies to date the turning points of their studies. For example, the US NBER has its own approach in identifying the turning of the business cycle. The method is relative, and depends on visual inspection. Other economists believe that a two-quarter decrease in GDP data is the signal for a recession period.

However, the most commonly use nonparametric approach was developed by Bry and Boschan (1971). Bry and Boschan's study (1971) used the formal algorithm to establish the dating of the turning points of the business cycle. The basic idea for this dating technique is the definition of the occurrence of peak (trough) at time (t) whenever $\{y_t >$ $(<)\ y_{t\pm k}\}$, where k can be set as any number greater than 1.

When it used to identify the turning points of quarterly data, originally k was suggested as 2, which means the duration of the upturn or downturn should be at least 2 quarters. Lesage (1992) suggested that the k=3 may even be better and more solid. Therefore, the duration to consider as a peak or trough is prolonged to 9 months. Therefore, the definition will be:

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

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

Many other researchers have used nonparametric methods to identify the turning points in different time series, and some of these were deployed in tourism studies. A variety of definitions exist, which differ according to the periodicity under study. Zellner, Hong and Min (1991), and Witt and Witt (1991) observed that in an annual time series, four consecutive observations are used to characterize downturns and upturns. Oller and Tallbom (1996) pointed out that in a quarterly time series, a turning point is observed when seasonal logarithmic difference, $\Delta 4yt$, changes sign and maintains it for at least four quarters. Several other studies, such as those by Lesage (1992), Birchenhall, Osborn & Sensier (2001), Hardings and Pagan (2003), and Gouveia and Rodrigues (2005), used such definition to identify the turning points in growth rates of quarterly and monthly data. To identify the turning points in the monthly tourist growth rate, the Rossello–Nadal (2001) study used the traditional NBER method, which mainly consists of visual inspection (or using a computer program). The Birchenhall et al. (2001) study used the rules implying that a peak was identified at t if the variable Yt was strictly greater than the values for the subsequent two quarters $t + 1$ and $t + 2$, while also being at least as large as all values within a year in the past and in the future. Troughs are defined in an analogous manner. Kulendran and Wong (2009) used three quarters for the dating method in their study.

3.5.3 Choosing the most suitable dating method

The nonparametric method is simpler, more vigorous and replicable, as well as clearer for readers (Hardings and Pagan 2002). Hardings and Pagan (2003) also commented that the "not very transparent" process of the Markov switching model is the big drawback, compared to the simple and flexible nonparametric method. Moreover, Fernando (2010) made a significant contribution in his study by choosing the dating method for tourism data. In his study, he used both the Markov switching model (parametric) and Bry and Bsochan's approach (nonparametric) to examine which method is the best fit for tourism time series. The results showed that the nonparametric approach is the most applicable method for data in the tourism sector time series. Some reasons for this are as follows:

- Bry and Boschan's approach can accurately capture almost all the turning points, but the Markov switching model cannot.
- The preselected mean value for the Markov switching model is the key to decide the accuracy of the estimation. However, the trial-and-error process to find the best-fit mean value will take time, and nothing can guarantee that it is the best-fit mean value forever.
- Although the Markov switching model is a huge success in macroeconomic studies, it may not fit studies in microeconomic environments. The highly volatile growth data in the tourism sector are totally different from the GDP data in business cycle.
- Bry and Boschan's approach has a simpler formula compared to the complicated statistical process of the Markov switching model.

Hardings and Pagan (2003) proposed a simple nonparametric approach that has been proven useful in establishing cycle chronology—an algorithm to date US business cycle turning points through GDP data. Their results are similar to those using the NBER and Hamilton approaches, and thus shows that the nonparametric method offers a simple, robust, transparent, and replicable dating rule—a useful way of establishing economic cycle information. Moreover, sharing the same aim of Fernando's study (2010), which is to identify the turning points in tourism data, as well as in consideration of the previous literature and the results of other studies, the present study used the nonparametric method to identify the turning points of the series.

3.6 Granger Causality Test

Granger causality describes the relationship between two variables when one causes the other (Granger 1969). Furthermore, the Granger causality approach can be used to identify the directional relationship between two longitudinal variables and examine whether any causal relationships exists between them (Granger, 1969). Maddala (2001) stated that the purpose of the Granger causality test is to find the "precedence" of two individual incidents that would or would not have a causal relationship. Granger (1988) explained that the correlation test cannot provide indications about the direction of the relationship between two variables, but the Granger causality can compensate for this weakness and show which variable caused a change in the others.

Granger causality selects the leading indicator if the direction of the causality goes from the economic variable to the hotel occupancy rate. On the other hand, if the selected economic variable is considered as a lagging indicator, the direction of the causality will go from the hotel occupancy growth rate to the economic variable. One of the basic definitions of Granger causality—"the cause occurs before the effect"—is a very important identification when constructing the composite leading indicator. Moreover, the growth series are identified as stationary time series I(o), which is appropriate for use in the Granger causality test to find out the significance of the directional relationship of two variables.

To test the null hypothesis, Ho: the economic variable does not Granger cause the hotel occupancy growth rate, the following regression was considered:

$$\gamma_t = \sum_{i=1}^{k} \alpha_i \, \gamma_{t-i} + \sum_{i=1}^{k} \beta_i \, \chi_{t-i} + u_i$$

where γ_t is the hotel occupancy growth rate; χ_t is the economic variable; k is the lag time; α_i and β_i are the coefficients; u_i is the random error. F-statistics were examined to test the null hypothesis that economic variable does not Granger cause the hotel occupancy rate. If the significance level was within 10%, then the economic variable was considered to have directionally caused the hotel occupancy rate. Furthermore, the null hypothesis that the hotel occupancy rate does not Granger cause the economic variable was also examined. If the significant level was within 10%, then the economic variable was considered as a lagged indicator and the inverse of the economic variable is considered a leading indicator (Klein and Moore, 1985). The economic variable does not Granger cause the hotel occupancy rate if all β_i are equal to zero.

β_i are equal to zero.

3.7 Cross correlation Analysis

After the Granger causality test, the selected economic variables will be tested using cross-correlation analysis to find out the cross-correlation coefficient of each economic variable with the occupancy rate. Haugh (1976) warned that any misleading cross correlations could occur due to the autocorrelation of hotel occupancy growth rate or the indicator series. To eliminate this dilemma, the seasonal ARIMA models were fitted to both series, and the cross-correlation coefficient of the residuals was examined.

The coefficient of the cross correlation is the key figure for the composite leading indicator because such coefficient will first act as the weight for the construction of composite leading indicators for each country. Second, the coefficients of the cross-correlation analysis and the market share of overnight-stay tourist-origin country to

Hong Kong will both become the weighting of the construction of the composite leading indicators.

3.8 Construction of the composite leading indicator

A composite leading indicator can be developed from a set of economic variables normally used to capture the cyclical character of the growth of the hotel occupancy rate. Furthermore, Niemira and Klein (1994) stated that composite leading indicators provide a more trustworthy measure of economic activities because these are more comprehensive and less dependent on any one gauge.

3.8.1 Importance when constructing the leading indicator

Kulendran and Wong (2009) cited the two important facts that should be under consideration when developing the composite leading indicators: the method of aggregation and the allocation of the weight among all the components. Bikker and Kennedy (1999) stated that before all the economic variables are combined to form the leading indicator, the series should be normalized and synchronized to make them comparable.

Normalization refers to de-trending the leading indicators series, which is achieved through differencing and adjusting the variance to avoid any high volatility among the components. Synchronization implies that the leading indicators series are lagged in line with the lead time, which is identified from the cross correlation, so that on the average, peaks and troughs happen at the same time.

3.8.2 Weighting Methods

To achieve uniformity and easy comparison, the present study will base the composition of different indexes on Niemira and Klein's method (1994). However, to reiterate, the weighting is based on the coefficient of cross-correlation analysis and the top five market share of the Hong Kong overnight-stay source markets. It is common and logical to use the coefficient of the cross correlation as the weighting method when constructing the composite leading indicators in tourism forecasting studies (Kulendran and Wong, 2010; Fernando, 2010). However, no previous research has used the market share of the overnight-stay tourist arrivals as a weighting to combine and construct the composite leading indicators. Using the market share of the overnight-stay tourist arrivals may be more directly related to the dynamic economic situation in the tourism sector, given that the coefficient of the cross-correlation analysis is based purely on the relationship between the economic variables and the historical occupancy rate. It may not easily detect and reflect the lively and vibrant changes in the hotel occupancy rate caused by the recent trend or issue. On the other hand, using the market share weighting method, which is solely affected by the actual numbers of overnight-stay visitors, can totally replicate the dynamic and latest developments in the hotel industry. Such empirical attempt may ascertain the better weighting method for constructing the composite leading indicator for hotels.

3.8.3 Niemira & Klein's Method

Niemira and Klein (1994) devised a method to construct the composite leading indicator and summing up the changes for individual composite while accounting for the component's importance and volatility. Such method has been used by most studies on the composite leading indicator in the tourism industry (Kulendaran and Wong, 2009; Fernando, 2010).

$$\Delta_4 Composite = \sum w_i \sigma_i \, \Delta_4 \, (component)_{1+S-x_i}$$

where i = 1 to n, the maximum number of components; w is the component's weight, which represents the component's relative importance assessed by the coefficient of cross correlation as well as the market share of the top five Hotel Kong source markets of overnight-stay arrivals; σ is the stardardized weight, which is calculated from the inverse value of the volatility measure, the average absolute deviation around the average growth rate to minimize the influence of highly volatile series on the composite leading indicator; s is the short lead time in the number of quarters among the n indicators; and x_i is the lead time of the indicator.

3.9 Logistic and Probit regression models

Logistic and probit regression models are the generalized linear econometric models commonly used in macroeconomics and finance to predict turning points. Witt and Witt (1989) commented that although the econometric model can provide an accurate forecast for turning points, most models cannot predict the probability occurrence of the peaks and troughs for tourism demand growth rate. However, Kulendran and Wong (2010) proved that using the logistic and probit regression models can overcome such shortfall in tourism forecasting. The classic econometric models are based on the assumption that the value of the dependent variable can be anything from positive infinity to negative infinity. However, in logistic and probit regression models, the dependent variable only can be “yes” or “no,” either 1 or 0. Such explicit rule not only allows logistic and probit regression models to predict point estimate for the tourism demand growth rate, but also the probability associated with the increasing and decreasing turns in the growth rate. The dependent variable is nominal, that is, 1 or 0; therefore, the model is estimated using the maximum likelihood estimation procedure.

Logistic and probit regression models are based on making a prediction of the probability that an incident will happen (p = 1) or will not happen (p = 0) in the future. In the present study, 1 will represent the expansion period and 0 will represent the contraction period in the dependent variable, which is the Hong Kong hotel occupancy growth rate.

For estimation purposes, the logistic and probit regression models in this study will have different types of explanatory variables to predict the turns and the associated risks. First, the logistic and probit regression models will estimate with the constructed composite leading indicator, which is constructed from the selected economic variables for the Hong Kong top five overnight-stay tourist-origin countries. Second, the logistic and probit regression models will estimate using the constructed OECD indicators, which include the OECD composite leading indicator, the OECD business survey index, and the OECD consumer confidence index. Finally, the logistic and probit models will estimate with the hotel demand determinants such as income, hotel room price of destination, cost of travel, and substitute price of destination. All the estimated models will have the same dependent variable, which is the Hong Kong hotel growth occupancy rate.

3.9.1 Logistic Regression Model

The logistic regression model is used to predict the probability of an incident's occurrence by fitting data to a logistic function curve. Studenmund (2001) explained that a regression model is used for estimation with dummy and dependent variables to avoid unboundedness error that normally appears in linear models by just using a variant of the cumulative logistic function. In the model, the dependent variable is the logarithm of the ratio of the probability that a particular event will happen to the probability that event will not happen. The binary logistic model is based on the cumulative distribution function. If the cumulative distribution of the error term (*e*) is "logit," then the model is called a logistic regression model.

Therefore the equation will be:

$$\mathrm{P_{it}} = \Lambda\,(.) = (\beta_o + \beta_1 X_i + \beta_2 X_i \ldots \ldots .. + \varepsilon_t)$$

Or equivalent to:

$$\mathrm{Ln}\left[\frac{\mathrm{P_{it}}}{(1-\mathrm{P_{it}})}\right] = \beta_o + \beta_1 X_i + \beta_2 X_i \ldots \ldots .. + \varepsilon_t$$

where P_{it} is the probability that the particular outcome of expansion (1) will occur in time t; 1-P_{it} is the probability that the particular outcome of contraction (0) will occur in time t; and Λ denotes the values of the logistic cumulative distribution.

3.9.2 Probit Regression Model

The probit regression model is an estimation method with dummy variables that use a variant of the cumulative normal distribution. The binary probit model is based on the cumulative distribution function. If the cumulative distribution of the error term (e) is normal, then the model is called a probit regression model.

The probability distribution can be represented as:

$$P_{it} = \Phi(.) = (\beta_o + \beta_1 X_i + \beta_2 X_i \dots\dots.. + \varepsilon_t)$$

where if, P_{it} is the probability that particular outcome of expansion (1) will occur in time t; and Φ denotes the values of the cumulative standard normal distribution.

The different between the binary logistic regression model and the probit regression model is the specification of the error term in the model. The distribution of the error term in logistic model is in a “logit” distribution, whereas the error term distribution in a probit model is a “normal” distribution. Although the cumulative of the normal and logistic distributions of both models is relatively similar, the result of the estimation of both models is expected not to vary greatly (Kulendran and Wong, 2010). Furthermore, Kulendran and Wong (2010) contended that for simplicity and easy interpretation, the logistic regression model may be a better choice than the probit regression model.

3.9.3 Diagnostic test

A comprehensive diagnostic test is necessary to prove that the model is statistically acceptable and significant. Witt and Witt (1995) argued that without a fruitful diagnostic result, the empirical study will be limited in usefulness and citation ability. The common tests in logistic and probit regression models are: (1) test for multicollinearity, (2) probability values of the independent variables (P-values), (3) the McFadden root squared (R^2_{McF}), (4) likelihood ratio statistic (LR statistic), and (5) probability of likelihood ratio statistic, or Prob(LR statistic).

Test for Multicollinearity

Multicollinearlity implies the close relationship among the explanatory variables that a simple cross-correlation test can overcome. Explanatory variables for hotel demand determinants will be examined in the correlation test to avoid the problem of multicollinearity. If the tested correlation coefficients between two variables are higher than 0.5, one variable should to be deleted to avoid multicollinearity.

Probability values of the independent variables (P-values)

The probability value (P-value) gives the significance of each independent variable, which can decide whether to reject or accept the hypothesis of zero coefficient. The traditional approach is considered at the 5% significant level. If the P-value is lower than 0.05, the null hypothesis can be rejected; on the other hand, if the P-value is more than 0.05, the null hypothesis cannot be rejected.

The McFadden Root Squared (R^2_{McF})

The conventional measure of goodness of fit, R^2, is not particularly meaningful in the binary regression model. To measure the goodness of fit, the McFadden root squared is considered. The McFadden root squared, like R^2, also has the property that it will always be between zero and one.

Likelihood Ratio Statistic (LR statistic)

The LR statistic test is used to test the join null hypothesis that all slope coefficients, except the constant, are zero. Given the null hypothesis, the LR statistic test follows the distribution equal to the number of explanatory variables.

Probability of likelihood ratio statistic or Prob(LR statistic)

Prob(LR statistic) is the probability value of the likelihood ratio statistic. Under the null hypothesis, the likelihood ratio test statistic is asymptotically distributed as a variable with the degrees of freedom equal to the number of the restrictions under test.

3.10 Accuracy of Probability Forecasting

After the construction of different models, it is necessary to compare the accuracy of the probability occurrence of each model. The quadratic probability score (QPS) is a common instrument to test the forecasting correctness of the logistic and probit regression models. QPS became popular after its illustration by Diebold and Rudebusch (1989). QPS was widely used in the finance industry to check the accuracy of the stock market index. Diebold and Rudebusch (1989) used the QPS as an evaluation tool for testing the accuracy of the turning points of the composite leading indicator. Recently, some scholars of tourism forecasting have used the QPS to check the prediction of turning points accuracy of the composite leading indicator model and tourism demand determinants model (Kulendran and Wong, 2010; Fernando, 2010).

For this purpose, the universe consists of only two (mutually exclusive) events—the occurrence or non-occurrence of a turning point in logistic and probit regression models, in which 1 represents the expansion period and 0 represents the contraction period. According to previous studies (Diebold and Rudebusch, 1989; and Niemmira and Klein, 1994), the basic concept of QPS is the possible outcome prediction, that is, the universe consists of only two outcomes, has turning points or does not have any, and the outcomes are mutually exclusive. From the estimated probability (p_e) of the logistic and probit regression models, the expansion and contraction periods could be identified by the following: if the estimated probability, (p_e) is "greater than 0.5," then it is considered an expansion period; if the estimated probability (p_e) is "smaller than 0.5," then it is considered a contraction period. Therefore, peak point (downturn) can be recognized when the estimated probability (p_e) changes from "greater than 0.5" to "smaller than 0.5;" trough point (upturn) can be recognized when the estimated probability (p_e) changes from "smaller than 0.5" to "greater than 0.5." Diebold and Rudebusch (1989) explained that QPS ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. QPS can be expressed as,

$$\boldsymbol{QPS = \frac{1}{T}\sum_{t=1}^{T} 2\,(P_1 - R_1)^2}$$

where P_t is the probability of the occurrence of a turning point at date t (or, over specific horizon H beyond date t); R_t equal one if the turning point occurs in period t and equal to zero otherwise.

The present study used QPS to evaluate the accuracy of the prediction of the turns dating by comparing the logistic and probit regression models estimated with the constructed composite leading indicator, the OECD composite leading indicator, the OECD business survey index, the OECD consumer confidence index, and hotel demand determinants. Initially, probability forecasts were projected within a sample period from Q1 1973 to Q4 2005, and the out-of-sample period from Q1 2006 to Q3 2010. However, due to the lack of turning after 2006, the whole time series of forecasting was used for estimation.

3.11 Summary of the Methodology

1. Transform the original hotel occupancy rate to the growth rate and identify the turning points of each category (High Tariff A, High Tariff B, Medium Tariff and the Total(average of all categories)

2. Identify the top five overnight arrival countries of Hong Kong. Identify the economic variables of each country and combine them as the composite leading indicators for Hong Kong hotel industry.

3. Identify the OECD composite leading indicator data of the top four countries (no data for Taiwan) and combine them as the OECD composite leading indicator for Hong hotel industry.

4. Identify the OECD business survey index data of the top four countries (no data for Taiwan) and combine them as the OECD business survey index for Hong hotel industry.

5. Select the related hotel demand determinants to create the logistic and probit regression models to predict the turns of hotel occupancy rate for Hong Kong hotel industry.

6. Compare all the indicators by different QPS to find out the accuracy of the forecast prediction.

Chapter 4

IDENTIFY THE TURNING POINTS FOR THE OCCUPANCY RATE

4.1 Introduction

The present study seeks to identify the turning points in quarterly hotel occupancy growth rate by extracting the smooth growth rates using the Basic Structural Method (BSM), which was developed by Harvey (1989). García–Ferrer and Queralt (1998) stated that "if the trend is smooth and does not contain irregular components, the trend can be considered as an indicator of underlying growth; also as an anticipative tool for predicting turning points in seasonal economic time series."

Having identified the annual smooth growth rate by the BSM model, the next step is to identify the significant turning points using the nonparametric approach. The nonparametric approach is derived from Bry and Boschan's study (1971), which used a formal algorithm to establish the dating of the turning points of the business cycle. The nonparametric method is simpler, more vigorous and replicable, and clearer for readers (Hardings and Pagan, 2002). Therefore, the present study uses the nonparametric method to identify the turning points of the series.

4.2 Smoothing the Data

As discussed in Chapter 3, the occupancy rates of the different hotel categories of the Hong Kong hotel industry are the key data in the present study. The first step is to use the BSM to obtain the smoothed growth cycle of the hotel occupancy rate in Hong Kong.

4.2.1 Application of BSM

The BSM is used to smooth the growth cyclical pattern, both for monthly and quarterly occupancy data. The unobserved components model can be written as:

a) $Y_t = T_t + S_t + \mathcal{E}_t$

where Y_t is the Hong Kong monthly/quarterly hotel occupancy rate; T_t is the series exhibit trend component; S_t is the seasonal component; and $\mathcal{E}_t$ is the irregular component. The irregular component is normally distributed with (0,σ_ε^2).

The trend component,T_t, is further developed as:

b) $T_t = T_{t-1} + \beta_{t-1} + \xi_t$

$\beta_t = \beta_{t-1} + \lambda_t$

where ξ_t is normally distributed with (0, σ_ξ^2) and λ_t is normally distributed with (0, σ_λ^2). β is the slope or derivative of the trend.

The equation is the seasonal component:

c) $S_t = \sum_{j=1}^{s-1}(S_{t-j} + \psi_t)$, $t = 1, \ldots, N$

Where ψ_t is normally distributed with (0, σ_ψ^2).

Using the (a), (b), and (c) equations, the BSM developed by Harvey (1989) was illustrated. Further restricting the $\sigma_\xi^2 = 0$, the equation can develop the smooth trend, which is most suitable for estimating the growth rate cycle that is obtained by taking the four differences of the smooth trend. STAMP program was used to estimate the smooth trend. Figures 4.1 to 4.4 show the results of the smoothed monthly data series.

Figure 4.1 The smoothed Hong Kong (Total) hotel monthly occupancy growth rate

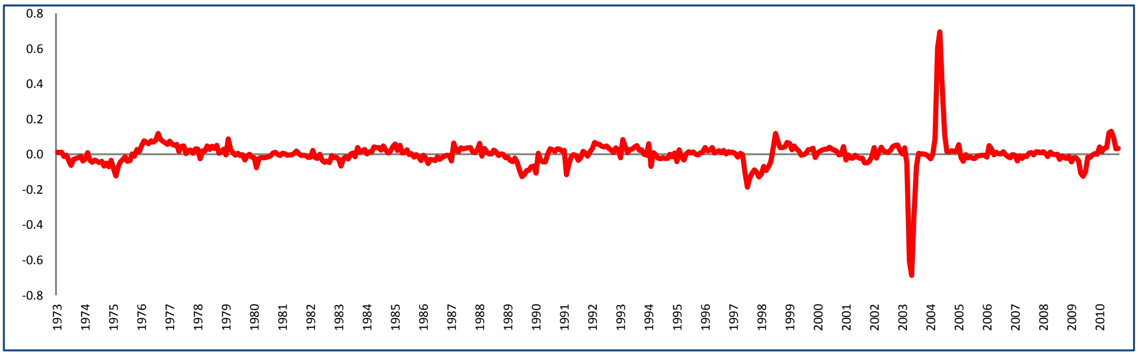


Figure 4.2 The smoothed Hong Kong High Tariff A hotel monthly occupancy growth rate

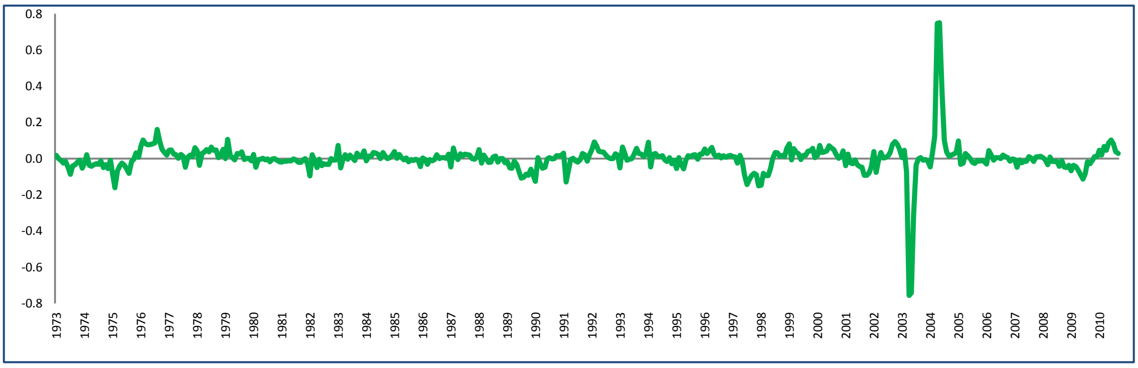


Figure 4.3 The smoothed Hong Kong High Tariff B hotel monthly occupancy growth rate

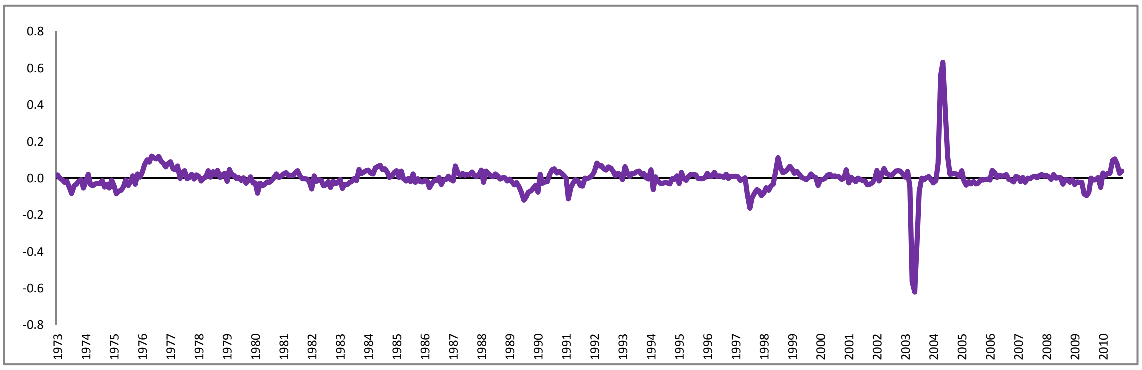
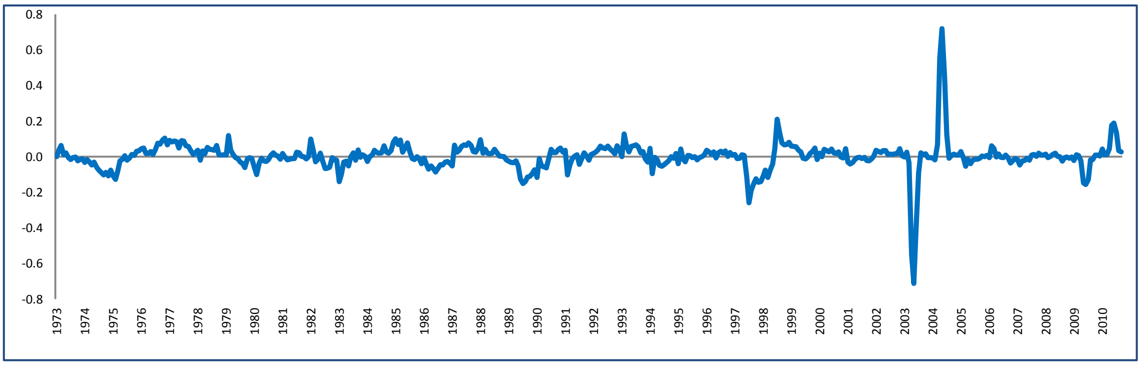


Figure 4.4 The smoothed Hong Kong Medium Tariff hotel monthly occupancy growth rate



Figures 4.5 to 4.8 show the results of the smoothed growth of quarterly hotel occupancy rate in different tariff categories.

Figure 4.5 The smoothed Hong Kong (Total) hotel quarterly occupancy growth rate

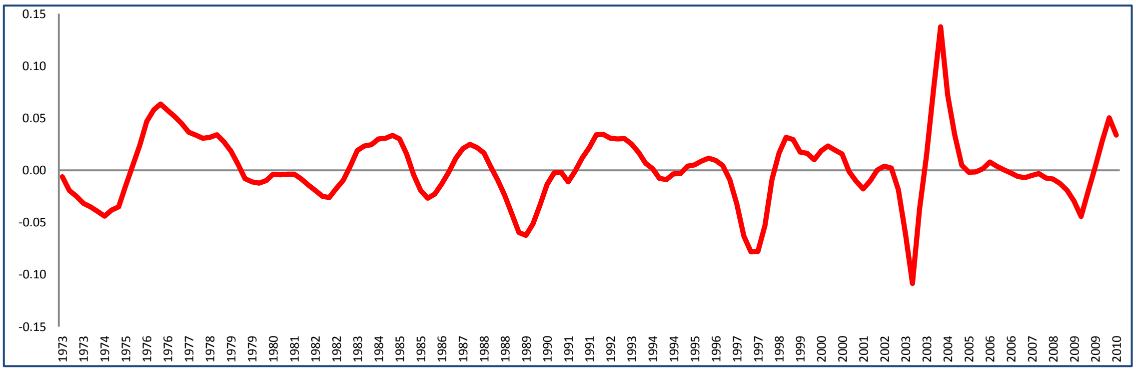


Figure 4.6 The smoothed Hong Kong High Tariff A hotel quarterly occupancy growth rate

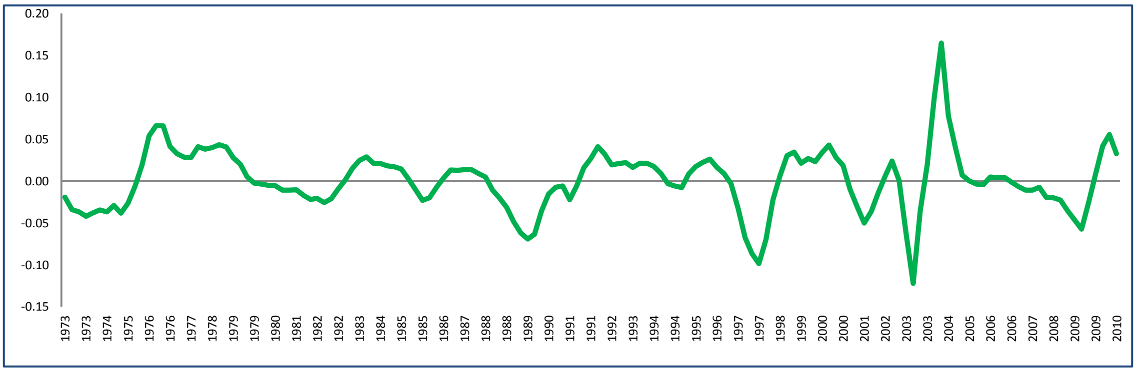


Figure 4.7 The smoothed Hong Kong High Tariff B hotel quarterly occupancy growth rate

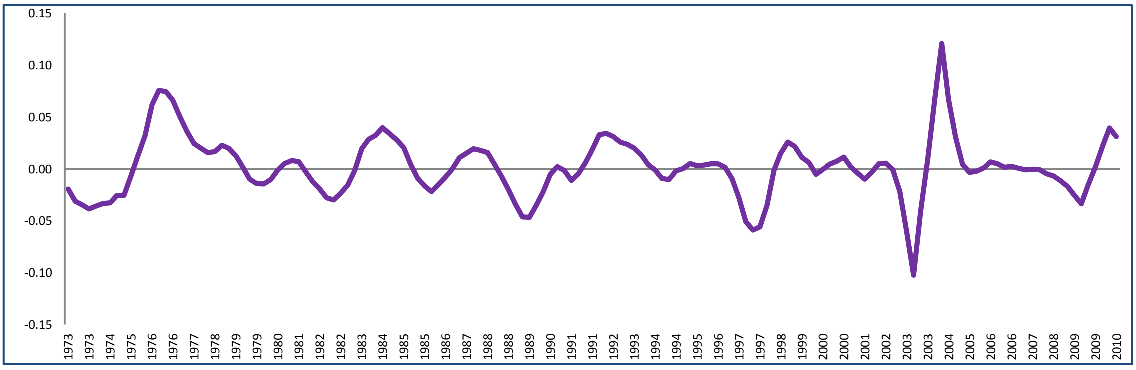
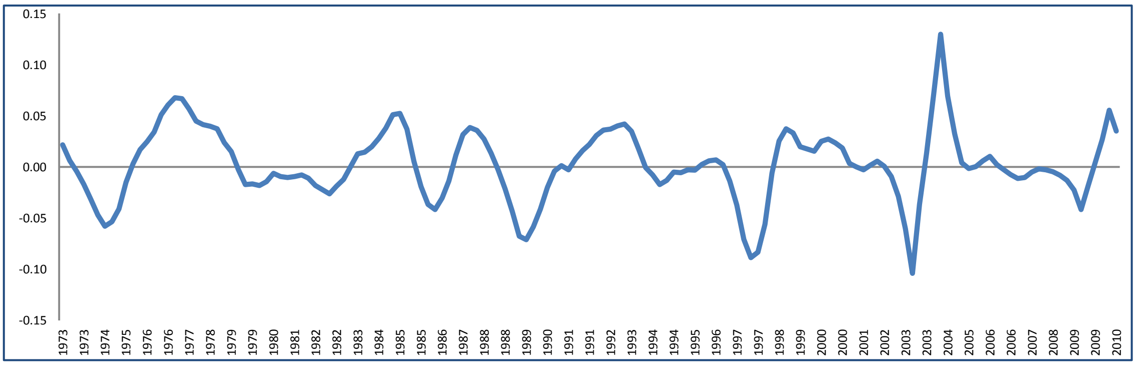


Figure 4.8 The smoothed Hong Kong Medium Tariff hotel quarterly occupancy growth rate



4.2.2 Choosing the quarterly data

After the visual examination of the data, quarterly data of the smoothed growth rate of the hotel occupancy are chosen for the present study. The reason is simple and straightforward. The excessive volatility of the monthly data can hardly identify significant turning points. On the other hand, the quarterly data shows the smoothness, allowing for easy identification of peaks and troughs in each series.

In previous studies, Choi (2003) developed a set of economic indicators for the hotel industry using annual data from hotel receipts, which was his research limitation. Song and Li (2008) confirmed that annual data would not satisfy the needs of the hotel management and policy makers. The present study used the quarterly smoothed hotel occupancy rate to predict the turning points and construct a composite leading indicator. This study is the first attempt to construct the composite leading indicator for different hotel categories in the hotel industry.

4.3 Dating the Turning Points

Bry and Boschan (1971) originally set that, if Y_t represents the peak in the growth rate cycle, the value of Y_s will be such that $s < t$ or $s > t$. The limitation of the window in time over the domain (t-k, t+k) should be set according to different circumstances. To set the k value, Bry and Boschan (1971) set $k=5$ in their monthly data study. Hardings and Pagan (2002) chose $k=2$ to analyze the quarterly data of the US GDP time series. After the discussion in Chapter 3, the present study will adopt Bry and Boschan's approach (1971), with a slight deviation from that of Leasge (1991); this means that in the current study, $k=3$ will be applied because the high volatility patterns of the hotel occupancy growth rate data. Many other researchers have used nonparametric methods to identify the turning points in difference time series, some of them on tourism studies (Witt and Witt, 1989; Oller and Tallbom, 1996; Rosselo–Nadal, 2001; Kulendran and Wong, 2009).

The downturn (DT) and upturn (UT) are defined below:

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

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

Note that Y_{t-3}, Y_{t-2} and Y_{t-1} are the past values of the growth rate, and Y_{t+1}, Y_{t+2} and Y_{t+3} are the future values of the growth rate. The following plots show the smoothed growth rate of each hotel category with the identified peaks (P) and troughs (T).

Figure 4.9 The smoothed Hong Kong (Total) hotel quarterly occupancy growth rate with the identification of peak (P) and trough (T)

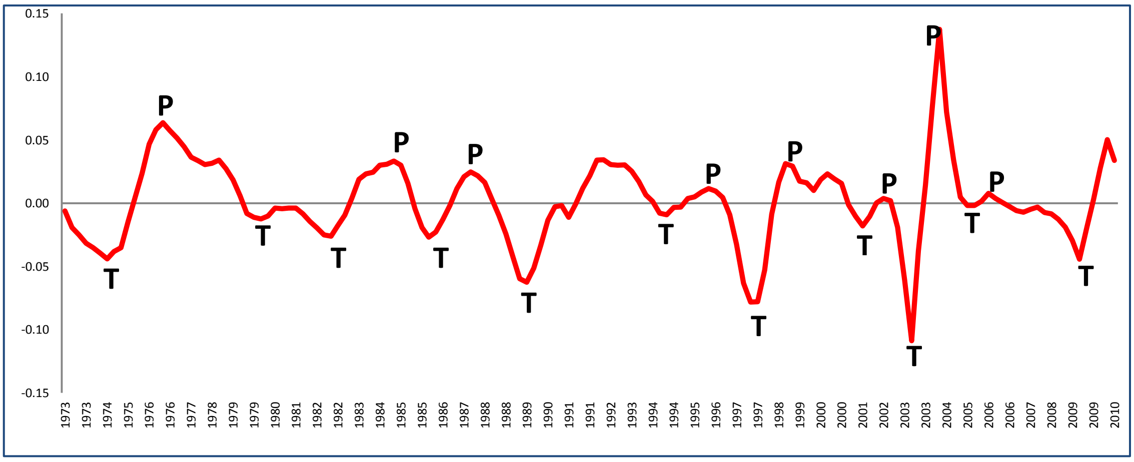


Figure 4.10 The smoothed Hong Kong High Tariff A hotel quarterly occupancy growth rate with the identification of peak (P) and trough (T)

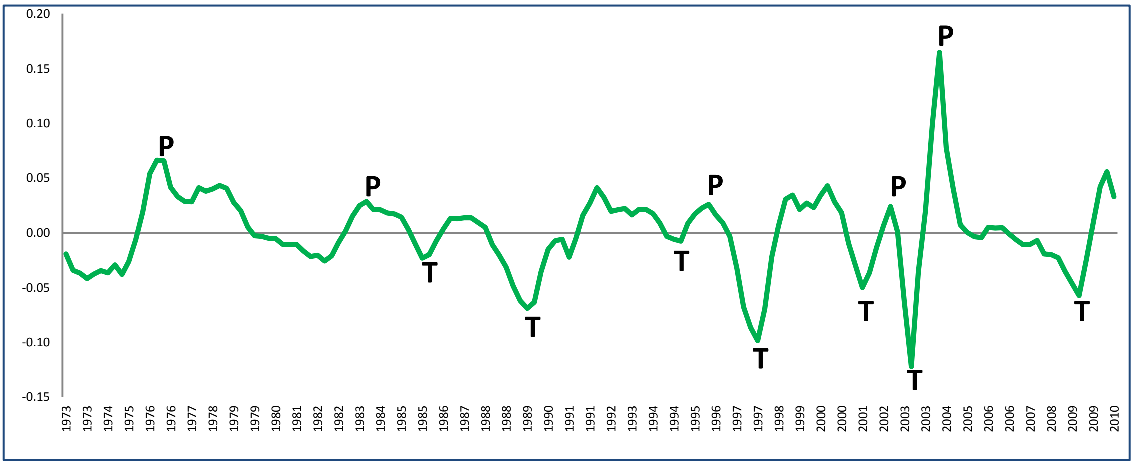


Figure 4.11 The smoothed Hong Kong High Tariff B hotel quarterly occupancy growth rate with the identification of peak (P) and trough (T)

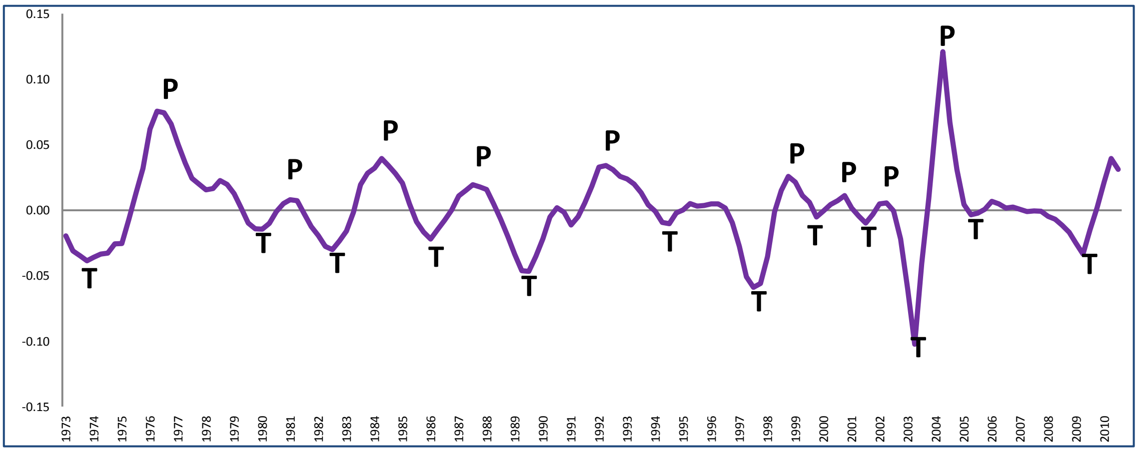
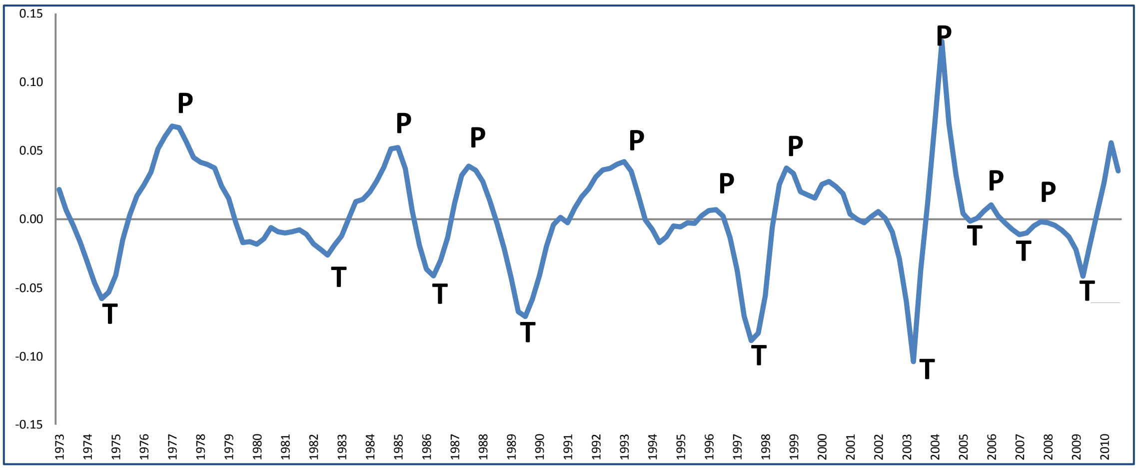


Figure 4.12 The smoothed Hong Kong Medium Tariff hotel quarterly occupancy growth rate with the identification of peak (P) and trough (T)



4.4 General Findings

Generally, there are some common peaks and troughs for all the categories, which can be explained by some typical reasons that affect the demand in the tourism industry. For example, the trough happened in the third quarter of 1989, which reflected the political event in China on June 4, 1989; another trough was identified in the second quarter of 2003, which was influenced by the outbreak of SARS (severe acute respiratory syndrome) in Hong Kong at the time. The only peak appearing in all categories was in the second quarter of 2004, which was mainly on account of the return of the confidence level of tourists following the fall in 2003. It was also due to the massive marketing campaign by HKTB after the SARS outbreak in 2003. The trough picked up by all the categories in the second quarter of 2009 clearly showed the impact of the global economic recession on travel.

From the results, there are 19 turning points for the Total category, which are 8 peak points and 11 trough turning points. The turning points in the High tariff A hotel category were only 12 (5 peak points and 7 trough points). Compared to the other two categories, High Tariff B hotel type got 21 turns (9 peak points and 12 trough points); the Medium Tariff hotel group had 18 points (9 peak points and 9 trough points), indicating that the demand for accommodations by tourists in Hong Kong differed across those categories.

The average contraction period (from one peak point to the next trough point) is longer than the expansion period (from one trough point to the next peak point) in the occupancy of all the categories of Hong Kong hotels. This may indicate that the "pick-up speed" of the hotel industry in Hong Kong is faster than its "slow-down speed." A further explanation could be because the dynamic and international image of Hong Kong has the effect of improving the mood of the tourists. Another reason may be the intensive promotional efforts of the HKTB, which mounted a marketing scheme every month to drum up the different festive occasions in Hong Kong for tourists all over the world, with a view toward increasing tourist arrivals. This shows the important contribution of the tourism sector to the Hong Kong economy, as reflected in greater government awareness of the sector's significant role.

The average lengths of the peak-to-peak period and trough-to-trough period are the total difference patterns among different hotel groups. A peak-to-peak period can be defined as the recession cycle, given that there is one or more than one contraction period and expansion period between peaks. A trough-to-trough period can be explained as a boom cycle, which should include one or more than one expansion period and contraction period. Such cycles can give policy makers or hoteliers a clear idea or bigger picture of the long-term movement of the hotel occupancy rate. Table 4.1 shows the number of peaks and troughs as well as the average time of expansion and contraction period for all hotel categories.

Table 4.1 Summary of the number of turns and the average time of expansion and contraction periods of Hong Kong hotel occupancy rate for different categories

Hotel Category	Numbers of Peak Turns	Numbers of Trough turns	Average			
			Expansion Period (Trough to Peak)	Contraction Period (Peak to Trough)	Peak to Peak Periods	Trough to Trough Periods
HK Total	**8**	**11**	**5.50**	**7.38**	**17.29**	**13.90**
HK High Tariff A	**5**	**7**	**6.75**	**9.50**	**22.60**	**15.57**
HK High Tariff B	**9**	**12**	**6.00**	**6.67**	**14.00**	**12.91**
HK Medium	**9**	**9**	**7.25**	**9.00**	**15.38**	**17.38**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.

4.5 Findings for category: Growth of Total (Average) of hotel occupancy

The Total category can perform as a benchmark for individual hotel performance standards from the hotel industry point of view. The growth of Hong Kong (Total) hotel occupancy indicated that the average expansion period is 5.5 quarters, whereas the average contraction period is 7.4 quarters. The data may let the hoteliers or policy makers understand the pattern of the growth in the occupancy more easily. The longer expansion period may be a good sign for business because it implies the opportunity for increasing revenue or for maintaining stability. On the other hand, if the contraction period is longer than expected, hotel managers cannot raise the hotel price because the demand for the hotel rooms slows down until the recession period ends when the trough appears.

Such indications can serve as benchmarks for all hotels to compare their performance with that of other hotels. For example, the hotel operator finds out from its own hotel occupancy that the number of turning points and the times these happened were different from those of the average hotels in Hong Kong. The hotel operator could thus explore the reasons for the difference, say, a wrong pricing strategy or its marketing campaign. Moreover, the difference in the lengths of the contraction and expansion periods may show recovery or the need for the hotel to deploy a better catch-up strategy.

Moreover, from the average of the peak-to-peak period, hoteliers can estimate the length of the whole recession cycle. Such indication may give the whole hotel industry several ideas on what could be done in an average of four-and-a-half years from the peak occupancy rate to another peak occupancy rate. Therefore, top management could have better strategic planning between those years and get ready to make another peak. On the other hand, the whole cycle for the boom is shorter compared to the recession cycle, which only takes about three-and-a-half years from the lowest occupancy rate point to another lowest point. The same theory applies here, as policy makers could have better planning to fulfill tourists' needs during the cycle.

Table 4.2 Summary of the turns and time periods for Hong Kong (Total) hotel occupancy rate

Hotel Occupancy	Peak	Trough	Expansion Period (Trough to Peak)	Contraction Period (Peak to Trough)	Peak to Peak Periods	Trough to Trough Periods
HK Total		**1974-3**				
	1976-3	**1979-4**	8	13		21
		1982-3				11
	1984-4	**1986-1**	9	5	33	14
	1987-3	**1989-3**	4	8	12	14
		1994-3				20
	1996-1	**1997-3**	6	4	34	12
	1998-4	**2001-2**	5	10	11	16
	2002-2	**2003-2**	3	4	14	7
	2004-2	**2005-2**	4	4	8	8
	2006-3	**2009-2**	5	11	9	16
Average			**5.50**	**7.38**	**17.29**	**13.90**

4.6 Findings for category: High Tariff A Hotel

The classification system of Hong Kong hotels has already been discussed in detail in Chapter 1. The High Tariff A hotel category comprises the most luxurious hotels whose average achieved room rate per night for June 2010 was HK$1,771. However, the High Tariff B hotel type can be described as transit business hotels because the average achieved room rate per night for June 2010 was just HK$805, less than half of the average achieved room rate of High Tariff A hotels. The less number of turning points in High Tariff A hotels meant that the fluctuation of the occupancy rate is lower. Such findings show that the occupancy rate of High Tariff A hotel may not be easily affected by environmental factors (social, political, or economic). Travellers who like to stay in High Tariff A hotel when they go to Hong Kong are wealthy and less price sensitive; moreover, those who stay in the High Tariff hotels would pay less heed to the cost of travel.

From the operations and marketing points of view, and from the historical data of the growth of Hong Kong High Tariff A hotel occupancy, less turning points identified on the time-series data meant that those tourists or businessmen who stay in High Tariff A hotel are less price sensitive, which further implies that price elasticity is lower. Such travellers are less vulnerable to environmental factors than the travellers who stay in the other hotel categories.

Marketers in this category should then focus on their own services and facilities upgrade rather than cut down their prices. Travellers who stay in High Tariff A hotels are mainly attracted by the personal services and luxury facilities; therefore, the feedback and changing demands or trends of this group of customers are relatively important. Regular customer surveys or loyalty programs may be worthy investments for this hotel group.

The contraction period in High Tariff A is 9.5 quarters, whereas the expansion period is 6.8 quarters. Compared to the other categories, the longest contraction period for High Tariff A hotels indicates that the hoteliers should really have a well-organized strategic planning during that time. Considering that the recession period can be longer than two years, the hotel price should not be increased, but the services and facilities should be maintained, implying higher operating costs. During this time, the hotel may release some long-term staff and hire some part-time staff to cut down on cost; lobby or room renovations could also be undertaken; restaurant concepts and menus could be redesigned or even changed; and a cross-training program could be provided for the staff. On the other hand, to speed up recovery, marketing schemes such as joint promotions with airlines, package offers to convention organizers, or a special treat for loyal customers could be carried out.

Hotel operators of the High Tariff A category should also pay more attention to the longest peak-to-peak period than the other two categories, as this should be a warning signal to have a well-considered, long-term operating plan. From the study, the average recession cycle for the High Tariff A hotel category can be long as seven-and-a-half years. This valley period suggests that after one peak in occupancy, it will take longer than seven years to catch another high-peak point. Therefore, hoteliers should plan to cut down the duration of such a valley period as a long-term goal. A lot of frustration may await the climb up to another prime time in many years. However, such indications simply act as an early signal for top management to better prepare for such a period.

Table 4.3 Summary of the turns and time periods for Hong Kong High Tariff A hotel occupancy rate

Hotel Occupancy	Peak	Trough	Expansion Period (Trough to Peak)	Contraction Period (Peak to Trough)	Peak to Peak Periods	Trough to Trough Periods
HK High Tariff A	**1976-3**					
	1983-4	**1985-4**		8	31	
		1989-3				15
		1995-1	15		23	22
	1996-1	**1997-4**	4	7	26	11
		2001-3				15
	2002-3	**2003-2**	4	3	26	7
	2004-2	**2009-2**	4	20	7	24
Average			**6.75**	**9.50**	**22.60**	**15.57**

4.7 Findings for category: High Tariff B Hotel

The High Tariff B hotel group faces a tough pricing strategy for customers. The more than 20 turning points for this category show that environmental factors impact the occupancy rate of High Tariff B hotels. Moreover, the price sensitivity of the customers in High Tariff B hotels is higher compared to the High Tariff A hotels based on the number of turns occurring in the same time period. Therefore, High Tariff B hoteliers should carefully use pricing strategies. Also, environmental factors such as the different festive occasions and business promotional events in Hong Kong or the date of different conventions and meetings will easily boost demand for this category. Increasing the number of corporate account clients may be a good way to maintain the average occupancy rate. Moreover, the updated convention facilities and guest room features may also help to raise the occupancy rate for such hotel operations.

There are 6 quarters on average of the expansion period and 6.7 quarters of the contraction period in High Tariff B hotels. Such figures show that hotel operators have around 18 months to prepare for the trough or climb up to the peak. A well-organized strategy should be regularly applied during those periods.

Table 4.4 Summary of the turns and time periods for Hong Kong High Tariff B hotel occupancy rate

Hotel Occupancy	Peak	Trough	Expansion Period (Trough to Peak)	Contraction Period (Peak to Trough)	Peak to Peak Periods	Trough to Trough Periods
HK High Tariff B		**1973-4**				
	1976-2	**1980-1**	10	15		25
	1981-1	**1982-3**	4	6	19	10
	1984-2	**1986-1**	7	7	13	14
	1987-3	**1989-3**	6	8	13	14
	1992-2	**1994-3**	11	9	19	20
		1997-3				12
	1998-4	**1999-4**	5	4	26	9
	2000-4	**2001-3**	4	3	8	7
	2002-2	**2003-2**	3	4	6	7
	2004-2	**2005-2**	4	4	8	8
		2009-2				16
Average			6.00	6.67	14.00	12.91

4.8 Findings for category: Medium Tariff Hotel

Among Medium Tariff hotels, the average achieved room rate for June 2010 was HK$496. Compared to the other two categories, Medium Tariff hotels expect lower profit margins due to their lower prices and fixed operating costs. Obviously, such pricing pattern will attract most tour groups and budget travellers. Eighteen turning points in total show that the Medium Tariff hotel category is relatively affected by environmental factors; the customers for this group are also quite price sensitive.

It is a common marketing strategy for this type of hotel to keep the price low to attract more customers. However, the minimum quality of the services and facilities should be maintained to keep the ranking in this category. Joint promotions with travel agents or airlines may secure some revenue.

For this category, the average contraction period is 9 quarters, whereas that of the expansion period is 7.3 quarters. More importantly, this category's low profit margins require other tactics to increase the revenue in an expansion period, as well as creative strategies to survive in the contraction period.

Another interesting finding for this hotel category is that the average trough-to-trough period is longer than the average peak-to-peak period, which makes this the only category with such a pattern. Further research may explore the reasons behind this phenomenon.

Table 4.5 Summary of the turns and time periods for Hong Kong Medium Tariff hotel occupancy rate

Hotel Occupancy	Peak	Trough	Expansion Period (Trough to Peak)	Contraction Period (Peak to Trough)	Peak to Peak Periods	Trough to Trough Periods
HK Medium		**1974-3**				
	1977-1	**1982-3**	10	22		32
	1985-1	**1986-2**	10	5	32	15
	1987-3	**1989-3**	5	8	10	13
	1993-1		14		22	
	1996-2	**1997-3**		5	13	32
	1998-4	**2003-2**	5	18	10	23
	2004-2	**2005-2**	8	4	22	8
	2006-1	**2007-1**	3	4	7	7
	2007-4	**2009-2**	3	6	7	9
Average			**7.25**	**9.00**	**15.38**	**17.38**

Chapter 5

CONSTRUCTION OF THE COUNTRIES' COMPOSITE LEADING INDICATORS

5.1 Introduction

This chapter will show the construction of each country's composite leading indicator for the Hong Kong hotel industry. National economic indicators can be grouped into three categories, namely, leading indicator, coincident indicator, and lagging indicator. Leading indicator series data should turn before the actual upturn or downturn of the growth of the hotel occupancy rate for different hotel categories in Hong Kong.

Past studies have provided clues for the selection of economic variables, namely, gross domestic product (GDP), exchange rate index (ER), total export (TE), total import (TI), unemployment rate (UR), real exchange rate (RER), oil price (OP), and share price index (SP). All these selected economic variables for the hotels are related to the tourism sector.

With all the economic variables for each country, the Granger causality test and cross-correlation analysis will be performed to find out which economic variables will be chosen to form the countries' respective leading indicators. All the selected economic variables for each country will be combined based on the coefficient from the cross-correlation analysis of the overnight-stay tourist-origin countries to the Hong Kong Hotel industry. Therefore, in this chapter, each country will have its own composite leading indicator.

5.2 Smoothing the data of the economic variables

The constructed composite leading indicator for the Hong Kong hotel industry will be based on the economic variables of the major top five overnight-stay tourist-origin markets, namely, China, Taiwan, Japan, the United States, and Australia. As has been explained in detail in Chapter 3, the elected economic variables are GDP, ER, TE, TI, UR, RER, OP, and SP. After gathering all the data from different sources, the next step is to smooth data by BSM, as discussed in Chapter 3.

The equation will be written as:

a) $Y_t = T_t + S_t + \mathcal{E}_t$

where Y_t is the time series data for each economic variable for each country; T_t is the series exhibit trend component; S_t is the seasonal component; and $\mathcal{E}_t$ is the irregular component. The irregular component is normally distributed with $(0,\sigma_\varepsilon^2)$.

The trend component, T_t, is further developed as:

b) $T_t = T_{t-1} + \beta_{t-1} + \xi_t$

$\beta_t = \beta_{t-1} + \lambda_t$

where ξ_t is normally distributed with (0, σ_ξ^2) and λ_t is normally distributed with (0, σ_λ^2). β is the slope or derivative of the trend.

The equation is the seasonal component:

c) $S_t = \sum_{j=1}^{s-1}(S_{t-j} + \psi_t)$, $t = 1, \ldots, N$

where ψ_t is normally distributed with (0, σ_ψ^2).

By using the (a), (b), and (c) equations, the BSM developed by Harvey (1989) was illustrated. Further restricting the $\sigma_{\xi}^{2} = 0$, the equation can develop the smooth trend, which is most suitable to estimate the cycle that is obtained by taking the four differences of the smooth trend. STAMP program was used to estimate the smooth trend.

5.2.1 Economic variables for China

The data of China GDP date back to Q1 1995 to Q3 2010, as collected from the OECD. The data of the exchange rate between China and Hong Kong are from the Hong Kong Census and Statistics Department and date back to 1975. The TE time-series data of China are extracted from the IMF and date back to 1981. The TI time series for China dates back from 1981, from IMF. The UR data of China, gathered from 1985, are derived from China's National Bureau of Statistics. The RER of China is developed from the data of CPI collected from the OECD and date back to 1985. SP for China comes from OECD data in 1999.

Figure 5.1 The smoothed growth rate of China GDP (CHI GDP)

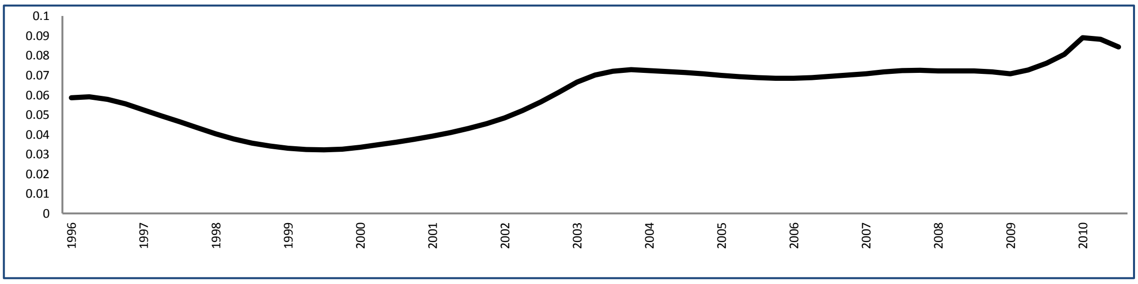


Figure 5.2 The smoothed growth rate of China exchange rate (CHI ER)

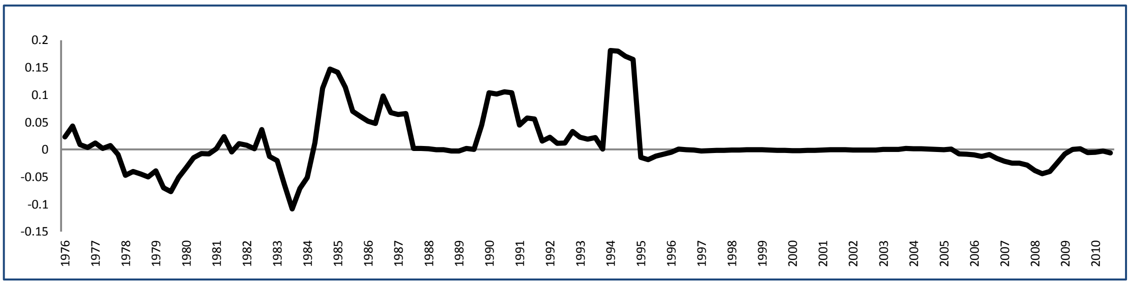


Figure 5.3 The smoothed growth rate of China total export (CHI TE)

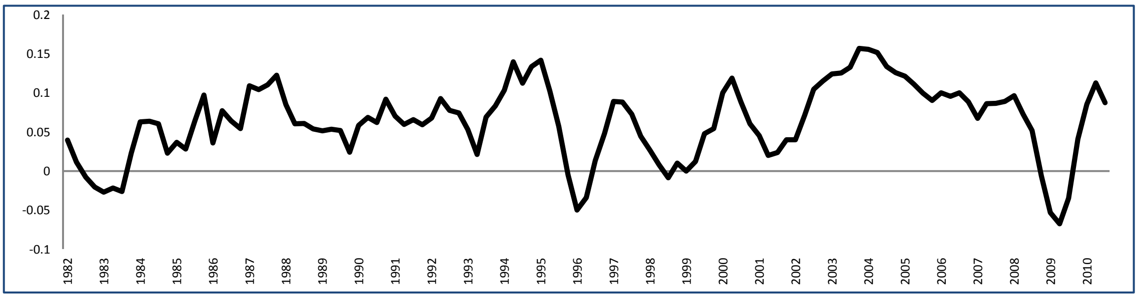


Figure 5.4 The smoothed growth rate of China total import (CHI TI)

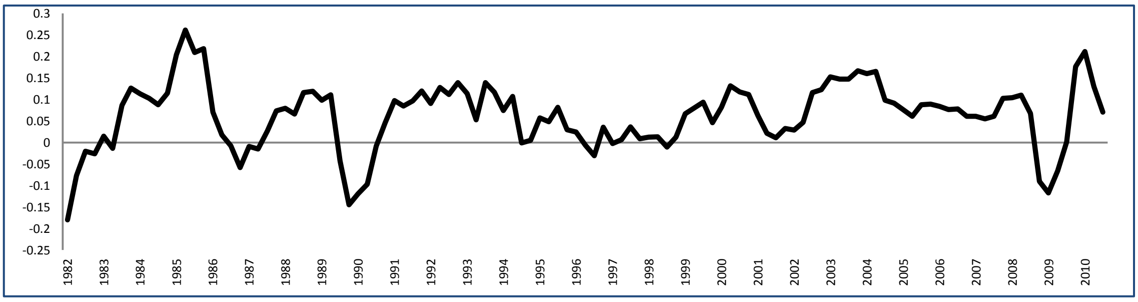


Figure 5.5 The smoothed growth rate of China unemployment rate (CHI UR)

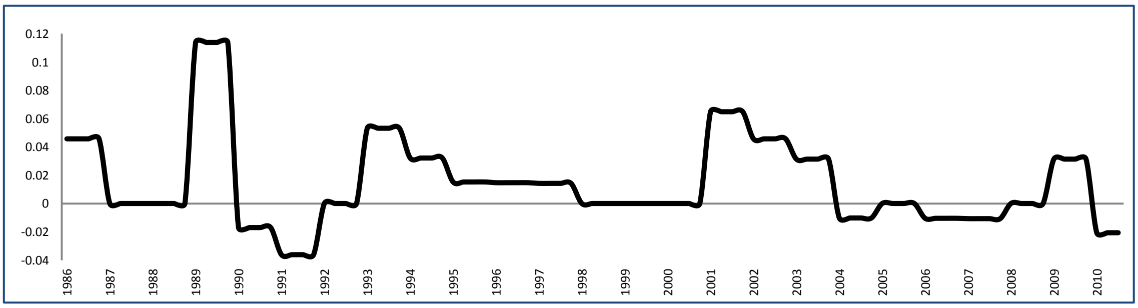


Figure 5.6 The smoothed growth rate of China real exchange rate (CHI RER)

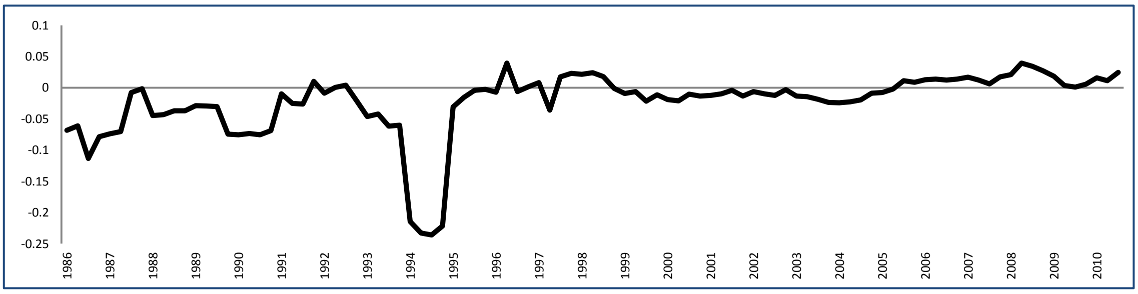
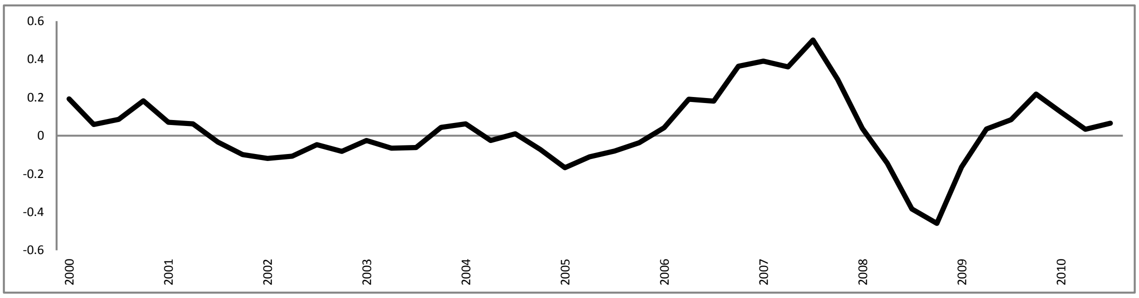


Figure 5.7 The smoothed growth rate of China share price (CHI SP)



5.2.2 Economic variables for Taiwan

The data of Taiwan GDP date back from Q1 1973 to Q3 2010, and collected from the National Statistics of Taiwan. The data of the exchange rate between Taiwan and Hong Kong are from the Hong Kong Census and Statistics Department and date back to 1975. The TE time-series data of Taiwan are extracted from the IMF and date back to 1972. The TI time series for Taiwan dates back to 1972, from the IMF. The data of UR of Taiwan are from the National Statistics of Taiwan and date back to 1978. The RER of Taiwan is developed from the data of CPI collected from the National Statistics of Taiwan and date back to 1975. SP for Taiwan is from the National Statistics of Taiwan in 1972.

Figures 5.8 to 5.14 show the smoothed growth rate of Taiwan economic variables (see Appendix)

5.2.3 Economic variables for Japan

The data of Japan GDP are examined from Q1 1980 to Q3 2010, and collected from the OECD. The data of the exchange rate between Japan and Hong Kong are from the Hong Kong Census and Statistics Department and date back to 1975. The TE time-series data of Japan are extracted from the IMF and date back to 1972. The TI time series for Japan dates back to 1972, from the IMF. The UR data of Japan are collected from OECD statistics from 1972. The RER of Japan is developed from the data of CPI collected from the OECD, dating back to 1975. SP for Japan comes from OECD data in 1972.

Figures 5.15 to 5.21 demonstrate the smoothed growth rate of the economic variables for Japan (see Appendix)

5.2.4 Economic variables for USA

The data of US GDP are examined from Q1 1972 to Q3 2010, and collected from OECD. The data of the exchange rate between the United States and Hong Kong are from the Hong Kong Census and Statistics Department and date back to 1975. The TE time-series data of the United States are extracted from the IMF and date back to 1972. The TI time-series data for the United States date back to 1972, from the IMF. The UR rate data for USA are from OECD statistics in 1972. The RER for USA is developed from the data of CPI collected from OECD Statistics dating back to 1975. SP for USA comes from OECD data in 1972.

Figures 5.22 to 5.28 show the smoothed growth rate of the economic variables for the United States (see Appendix).

5.2.5 Economic variables for Australia

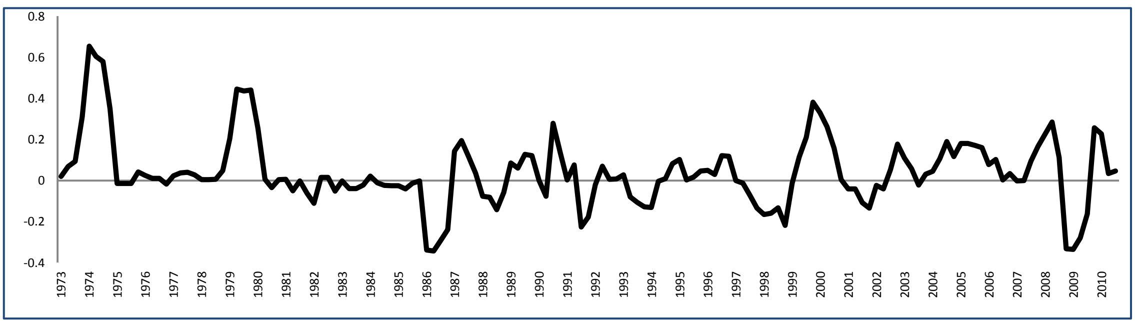
The data of Australia GDP are examined from Q1 1972 to Q3 2010, and collected from the OECD. The data of the exchange rate between Australia and Hong Kong are from the Hong Kong Census and Statistics Department and date back to 1975. The TE time-series data of Australia are extracted from the IMF dating back to 1972. The TI time-series data for Australia date back from 1972, from the IMF. The UR rate data of Australia are collected from OECD statistics from 1972. The RER of Australia is developed from the data of CPI collected from the OECD statistics dating back to 1975. SP for Australia comes from OECD data in 1972.

Figures 5.29 to 5.35 show the smoothed growth rate of the economic variables for Australia (see Appendix)

5.2.6 Growth of Oil Price

The oil price for will be collected from the commodity price in IMF statistics dating back to 1972. All countries will use the same data for oil price.

Figure 5.36 The smoothed growth rate of the oil price (OIL)



5.3 Granger Causality

After smoothing all the data, Granger causality will be used. Granger causality stipulates that "the cause occurs before the effect," which is very important identification when constructing the composite leading indicator (Granger, 1969).

To test the null hypothesis, Ho: the economic variable does not Granger cause the growth of hotel occupancy rate, the following regression was considered:

$$\gamma_t = \sum_{i=1}^{k} \alpha_i \gamma_{t-i} + \sum_{i=1}^{k} \beta_i \chi_{t-i} + u_i$$

where γ_t is the growth of hotel occupancy rate; χ_t is the economic variable; k is the lag time; α_i and β_i are the coefficients; and u_i is the random error. F-statistics were examined to test the null hypothesis, H_o, that economic variable does not Granger cause the hotel occupancy rate. If the significance level was within 10% and the lag time is within 5 quarters, that economic variable was considered directionally caused with the hotel occupancy rate. Furthermore, the null hypothesis, H_o, that the hotel occupancy rate does not Granger cause the economic variable, was also examined. If the significance level was within 10%, the economic variable was considered as a lagged indicator, and then the inverse of the economic variable is considered as a leading indicator (Klein and Moore, 1985). The economic variable does not Granger cause the hotel occupancy rate if all β_i are equal to zero. It is important to note that the data of oil price for all countries are the same, implying the same result for every country.

5.3.1 Result of the economic variables for China

After the Granger causality analysis, only three variables, namely, the exchange rate, share price, and oil price, have the leading power for all the categories of growth of the Hong Kong hotel occupancy rate. Interestingly, the time series of unemployment rate has been confirmed as one of leading indicators for the Medium Tariff hotel category. Results confirmed that the GDP of China, RER, TE, and TI do not cause any relationship between the growths of hotel occupancy in Hong Kong.

Table 5.1 Summary of the Granger causality test results of economic variables of China; number in brackets is the significant coefficient of that economic variable

Hotel Categories	Economic variables for China								No. of variables
	GDP	**Exchange Rate**	**Share Price**	**Real Exchange Rate**	**Unemployment Rate**	**Total Import**	**Total Export**	**Oil Price**	
HK Total	x	✔ (0.0011)	✔ (0.0047)	x	x	x	x	✔ (0.0998)	**3**
HK High Tariff A	x	✔ (0.0972)	✔ (0.0049)	x	x	x	x	✔ (0.0913)	**3**
HK High Tariff B	x	✔ (0.0012)	✔ (0.0046)	x	x	x	x	✔ (0.0902)	**3**
HK Medium Tariff	x	✔ (0.0852)	✔ (0.0023)	x	✔ (0.0976)	x	x	✔ (0.0950)	**4**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.

5.3.2 Result of the economic variables for Taiwan

Overall, six economic variables from Taiwan proved the leading relationship with the growth of Hong Kong hotel occupancy rate. However, considering that the test for Granger causality is done by each hotel category separately, for the total (the average of the other three categories) growth of the hotel occupancy rate and the Medium Tariff category shared the same variables, namely, GDP, ER, SP, TI, and OP. The High Tariff A category has six variables, including TE and the rest for the other two categories.

Finally, the High Tariff B hotel category only has GDP, ER, SP, and OP to compose the leading indicator, and there is no significant figure to prove the relationship between this category hotel and TE and TI.

Table 5.2 Summary of the Granger causality test results of economic variables of Taiwan; number in brackets is the significant coefficient of that economic variable

Hotel Categories	**Economic variables for Taiwan**								**No. of variables**
	GDP	**Exchange Rate**	**Share Price**	**Real Exchange Rate**	**Unemployment Rate**	**Total Import**	**Total Export**	**Oil Price**	
HK Total	✔ (0.0011)	✔ (0.0425)	✔ (0.0084)	x	x	✔ (0.0961)	x	✔ (0.0998)	**5**
HK High Tariff A	✔ (0.0014)	✔ (0.0214)	✔ (0.0035)	x	x	✔ (0.0704)	✔ (0.0958)	✔ (0.0913)	**6**
HK High Tariff B	✔ (0.0015)	✔ (0.0168)	✔ (0.0051)	x	x	X	x	✔ (0.0902)	**4**
HK Medium Tariff	✔ (0.0028)	✔ (0.0937)	✔ (0.0461)	x	x	✔ (0.0990)	x	✔ (0.0950)	**5**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.

5.3.3 Result of the economic variables for Japan

For the results of the Granger causality, all hotel categories shared the same economic variables, namely, GDP, ER, SP, RER, UR, TI, and OP. Interestingly, only the TE data series did not have any casual relationship with the growth of the Hong Kong hotel occupancy rate.

Table 5.3 Summary of the Granger causality test results of economic variables of Japan; number in brackets is the significant coefficient of that economic variable

Hotel Categories	Economic variables for Japan								No. of variables
	GDP	**Exchange Rate**	**Share Price**	**Real Exchange Rate**	**Unemployment Rate**	**Total Import**	**Total Export**	**Oil Price**	
HK Total	✓ (0.0986)	✓ (0.0434)	✓ (0.0319)	✓ (0.0134)	✓ (0.0095)	✓ (0.0178)	x	✓ (0.0998)	**7**
HK High Tariff A	✓ (0.0268)	✓ (0.0284)	✓ (0.0288)	✓ (0.0036)	✓ (0.0058)	✓ (0.0137)	x	✓ (0.0913)	**7**
HK High Tariff B	✓ (0.0917)	✓ (0.0285)	✓ (0.0346)	✓ (0.0345)	✓ (0.0143)	✓ (0.0463)	x	✓ (0.0902)	**7**
HK Medium Tariff	✓ (0.0929)	✓ (0.0284)	✓ (0.0506)	✓ (0.0240)	✓ (0.0202)	✓ (0.0142)	x	✓ (0.0950)	**7**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.

5.3.4 Result of the economic variables for USA

For the United States, the fourth top market share country for the Hong Kong overnight-stay tourists, GDP, SP, UR, TI, TE, and OP confirmed the causal leading relationship with the hotel categories of Total, High Tariff A hotel, and High Tariff B hotel data. However, for the Medium Tariff hotel category, there is no relationship with TI.

Table 5.4 Summary of the Granger causality test results of economic variables of the USA; number in brackets is the significant coefficient of that economic variable

Hotel Categories	Economic variables for Japan								No. of variables
	GDP	**Exchange Rate**	**Share Price**	**Real Exchange Rate**	**Unemployment Rate**	**Total Import**	**Total Export**	**Oil Price**	
HK Total	✓ (0.0068)	x	✓ (0.0005)	x	✓ (0.0913)	✓ (0.0988)	✓ (0.0937)	✓ (0.0998)	**6**
HK High Tariff A	✓ (0.0008)	x	✓ (0.0014)	x	✓ (0.0058)	✓ (0.0989)	✓ (0.0352)	✓ (0.0913)	**6**
HK High Tariff B	✓ (0.0197)	x	✓ (0.0003)	x	✓ (0.0143)	✓ (0.0695)	✓ (0.0954)	✓ (0.0902)	**6**
HK Medium Tariff	✓ (0.0227)	x	✓ (0.0019)	x	✓ (0.0202)	x	✓ (0.0851)	✓ (0.0950)	**5**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.

5.3.5 Result of the economic variables for Australia

The most extraordinary result is that all the variables for Australia had a significant causal leading relationship with all the hotel categories in Hong Kong. Therefore, a total of eight economic variables will construct Australia's composite leading indicator for the Hong Kong hotel industry, namely, GDP, ER, SP, RER, UR, TE, TI, and OP.

Table 5.5 Summary of the Granger causality test results of economic variables of Australia; number in brackets is the significant coefficient of that economic variable

Hotel Categories	Economic variables for Australia								No. of variables
	GDP	**Exchange Rate**	**Share Price**	**Real Exchange Rate**	**Unemployment Rate**	**Total Import**	**Total Export**	**Oil Price**	
HK Total	✓ (0.0040)	✓ (0.0757)	✓ (0.0845)	✓ (0.0622)	✓ (0.0110)	✓ (0.0022)	✓ (0.0105)	✓ (0.0998)	**8**
HK High Tariff A	✓ (0.0632)	✓ (0.0605)	✓ (0.0879)	✓ (0.0719)	✓ (0.0102)	✓ (0.0022)	✓ (0.0005)	✓ (0.0913)	**8**
HK High Tariff B	✓ (0.0004)	✓ (0.0688)	✓ (0.0261)	✓ (0.0588)	✓ (0.0022)	✓ (0.0016)	✓ (0.0260)	✓ (0.0902)	**8**
HK Medium Tariff	✓ (0.0008)	✓ (0.0890)	✓ (0.0793)	✓ (0.0997)	✓ (0.0213)	✓ (0.0068)	✓ (0.0694)	✓ (0.0950)	**8**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.

5.4 Cross Correlation Analysis

Granger causality tests show whether the economic variables lead to the growth of Hong Kong hotel occupancy rate from each country. To find out the lead time and cross-correlation coefficient of each economic variable toward the occupancy rate, a cross-correlation analysis will examine the selected economic variables. The coefficient of the cross correlation is the key figure for the composite leading indicator, as such the coefficient will act as the sole weighting method for the construction of the composite leading indicator for each country.

Haugh (1976) warned that misleading cross correlations could occur due to autocorrelation in the hotel occupancy growth rate or the indicator series. To eliminate this dilemma, the seasonal ARIMA models were fitted to both series and cross-correlation coefficient of the residuals that were examined. Only those variables that are proved from Granger causality will get through to this stage and be examined. The EView program can help to find out the coefficients of cross correlation of each selected variable, as well as the best-fit lead time for each variable.

Table 5.6 Summary of the cross-correlation coefficient of each selected economic variable; number in brackets is the significance lead time for each economic variable

Country	Hotel category	Economic Variables							
		GDP	Exchange Rate	Share Price	Real Exchange Rate	Unemployment Rate	Total Import	Total Export	Oil Price
China	HK Total		0.0617 (2)	0.1686 (5)					0.0802 (1)
	HK High Tariff A		0.0572 (5)	0.1756 (5)					0.0991 (3)
	HK High Tariff B		0.0615 (2)	0.1718 (5)					0.0964 (1)
	HK Medium Tariff		0.0510 (4)	0.1534 (5)		0.2274 (1)			0.0789 (1)
Taiwan	HK Total	0.5872 (1)	0.2093 (3)	0.1421 (1)			0.1123 (3)		0.0802 (1)
	HK High Tariff A	0.5998 (1)	0.2835 (3)	0.2013 (1)			0.1332 (3)	0.1226 (2)	0.0991 (3)
	HK High Tariff B	0.5813 (1)	0.1980 (3)	0.1641 (1)					0.0964 (1)
	HK Medium Tariff	0.5257 (1)	0.1851 (5)	0.1092 (4)			0.0963 (3)		0.0789 (1)
Japan	HK Total	0.0603 (4)	0.1209 (5)	0.1951 (1)	0.2579 (1)	0.1435 (2)	0.0726 (2)		0.0802 (1)
	HK High Tariff A	0.1756 (4)	0.1173 (3)	0.1944 (1)	0.1565 (2)	0.1473 (2)	0.0857 (3)		0.0991 (3)
	HK High Tariff B	0.1321 (4)	0.1609 (2)	0.2022 (1)	0.1302 (2)	0.1797 (2)	0.0859 (2)		0.0964 (1)
	HK Medium Tariff	0.1109 (4)	0.1257 (3)	0.1767 (1)	0.1397 (2)	0.1076 (5)	0.0649 (2)		0.0789 (1)
USA	HK Total	0.1347 (2)		0.2215 (1)		0.1413 (3)	0.1335 (2)	0.1079 (3)	0.0802 (1)
	HK High Tariff A	0.1665 (2)		0.2162 (1)		0.1802 (3)	0.1806 (2)	0.1171 (3)	0.0991 (3)
	HK High Tariff B	0.1123 (2)		0.2453 (1)		0.1490 (4)	0.1635 (2)	0.1142 (5)	0.0964 (1)
	HK Medium Tariff	0.1164 (2)		0.1790 (1)		0.1299 (5)		0.1115 (5)	0.0789 (1)
Australia	HK Total	0.2413 (1)	0.2162 (1)	0.1063 (5)	0.1627 (1)	0.2037 (5)	0.0857 (2)	0.0573 (3)	0.0802 (1)
	HK High Tariff A	0.0930 (4)	0.1094 (4)	0.1347 (5)	0.1754 (2)	0.1956 (5)	0.1168 (2)	0.0859 (2)	0.0991 (3)
	HK High Tariff B	0.2351 (2)	0.2208 (1)	0.1390 (1)	0.1298 (4)	0.2056 (5)	0.1263 (2)	0.0627 (3)	0.0964 (1)
	HK Medium Tariff	0.2382 (1)	0.1096 (4)	0.0979 (3)	0.1445 (2)	0.1909 (5)	0.0591 (5)	0.0565 (3)	0.0789 (1)

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.

5.5 The weighting of each economic variables

A composite leading indicator can be developed from a set of economic leading indicators, which normally capture the cyclical character of the growth rate of the hotel occupancy rate. Niemira and Klein (1994) provided a method to construct the composite leading indicator and sum up the changes for individual composites while accounting for the component's importance and volatility.

$$\boldsymbol{\Delta_4 Composite = \sum w_i \sigma_i \, \Delta_4 \, (component)_{1+S-x_i}}$$

where i = 1 to n, the maximum number of components; w is the component's weight, which represents the component's relative importance assessed by the coefficient of cross correlation; σ is the standardized weight, which is calculated from the inverse value of the volatility measure, the average absolute deviation around the average growth rate to minimize the influence of highly volatile series on the composite leading indicator; s is the short lead time in number of quarters among the n indicators; and x_i is the lead time of the indicator.

Following are all the weighting tables for the top five source markets, namely, China, Taiwan, Japan, the United States, and Australia, of Hong Kong's overnight-stay tourists. According to the finalized weighting, the construction of each country's composite leading indicator toward different categories of Hong Kong hotel industry can begin.

5.5.1 China Weighting Table

Tables 4.7 to 4.10 are the detail demonstration of the calculation of the final weighting for China composite leading indicator for difference hotel categories in Hong Kong

Hotel industry. Table 5.11 is the summary weighting of all categories for China composite leading indicator.

Table 5.7 Weights for the construction of China composite leading indicator for Hong Kong (Total) hotel category (CHI CLI TOTAL)

(CHI CLI TOTAL)								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
Exchange Rate	0.0617	0.2363	0.0325	0.1145	30.7514	0.6576	0.1554	**0.5471**
Share Price	0.1192	0.4565	0.1362	0.4795	7.3417	0.1570	0.0717	**0.2523**
Oil Price	0.0802	0.3072	0.1153	0.4060	8.6714	0.1854	0.0570	**0.2005**
Total	0.2611	1.0000	0.2840	1.0000	46.7644	1.0000	0.2840	**1.0000**

(2) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.
Apply to Table 5.7 to 5.10

Table 5.8 Weights for the construction of China composite leading indicator for Hong Kong High Tariff A hotel category (CHI CLI HIGH A)

(CHI CLI HIGH A)								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
Exchange Rate	0.0399	0.1533	0.0325	0.1145	30.7514	0.6576	0.1008	**0.4122**
Share Price	0.1213	0.4660	0.1362	0.4795	7.3417	0.1570	0.0732	**0.2992**
Oil Price	0.0991	0.3807	0.1153	0.4060	8.6714	0.1854	0.0706	**0.2887**
Total	0.2603	1.0000	0.2840	1.0000	46.7644	1.0000	0.2446	**1.0000**

Table 5.9 Weights for the construction of China composite leading indicator for Hong Kong High Tariff B hotel category (CHI CLI HIGH B)

(CHI CLI HIGH B)								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
Exchange Rate	0.0615	0.2334	0.0325	0.1145	30.7514	0.6576	0.1535	**0.5400**
Share Price	0.1056	0.4008	0.1362	0.4795	7.3417	0.1570	0.0629	**0.2214**
Oil Price	0.0964	0.3658	0.1153	0.4060	8.6714	0.1854	0.0678	**0.2387**
Total	0.2635	1.0000	0.2840	1.0000	46.7644	1.0000	0.2842	**1.0000**

Table 5.10 Weights for the construction of China composite leading indicator for Hong Kong Medium Tariff hotel category (CHI CLI MEDIUM)

(CHI CLI MEDIUM)								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
Exchange Rate	0.051	0.1071	0.0325	0.1054	30.7514	0.3505	0.0375	**0.1261**
Share Price	0.1188	0.2495	0.1362	0.4416	7.3417	0.0837	0.0209	**0.0701**
Unemployment	0.2274	0.4776	0.0244	0.0791	40.9694	0.4670	0.2230	**0.7488**
Oil Price	0.0789	0.1657	0.1153	0.3739	8.6714	0.0988	0.0164	**0.0550**
Total	0.4761	1.0000	0.3085	1.0000	87.7339	1.0000	0.2978	**1.0000**

Table 5.11 Summary of the final weighting of all hotel categories for China composite leading indicator

Selected economic variables	Final weighting			
	CHI CLI TOTAL	**CHI CLI HIGH A**	**CHI CLI HIGH B**	**CHI CLI MEDIUM**
Exchange Rate	**0.5471**	**0.4122**	**0.5400**	**0.1261**
Share Price	**0.2523**	**0.2992**	**0.2214**	**0.0701**
Unemployment	**-**	**-**	**-**	**0.7488**
Oil Price	**0.2005**	**0.2887**	**0.2387**	**0.0550**
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**

CHI is China.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator.

5.5.2 Taiwan Weighting Table

Tables 5.12 to 5.15 show the details of the calculation of the final weighting for the Taiwan composite leading indicator for different hotel categories in the Hong Kong hotel industry (see Appendix). Table 5.16 summarizes the weighting of all categories for the Taiwan composite leading indicator.

Table 5.16 Summary of the final weighting of all hotel categories for Taiwan composite leading indicator

Selected economic variables	Final weighting			
	TAI CLI TOTAL	**TAI CLI HIGH A**	**TAI CLI HIGH B**	**TAI CLI MEDIUM**
GDP	**0.6542**	**0.5621**	**0.6846**	**0.6591**
Exchange Rate	**0.2525**	**0.2877**	**0.2525**	**0.2513**
Share Price	**0.0318**	**0.0389**	**0.0388**	**0.0275**
Import	**0.0425**	**-0.0424**	**-**	**0.0410**
Export	**-**	**0.0567**	**-**	**-**
Oil Price	**0.0190**	**0.0132**	**0.0242**	**0.0211**
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**

TAI is Taiwan.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator.

5.5.3 Japan Weighting Table

Tables 5.17 to 5.20 show the details of the calculation of the final weighting for the Japan composite leading indicator for different hotel categories in the Hong Kong hotel industry (see Appendix). Table 5.21 summarizes the weighting of all categories for the Japan composite leading indicator.

Table 5.21 Summary of the final weighting of all hotel categories for Japan composite leading indicator

Selected economic variables	Final weighting			
	JAP CLI TOTAL	**JAP CLI HIGH A**	**JAP CLI HIGH B**	**JAP CLI MEDIUM**
GDP	**0.1270**	**0.3261**	**0.2534**	**0.2636**
Exchange Rate	**0.1084**	**0.0927**	**0.1314**	**0.1272**
Share Price	**0.1135**	**0.0998**	**0.1072**	**0.1161**
Real Exchange Rate	**0.3359**	**0.1797**	**0.1545**	**0.2053**
Unemployment	**0.2089**	**0.1891**	**0.2383**	**0.1768**
Import	**0.0684**	**0.0712**	**0.0737**	**0.0690**
Oil Price	**0.0379**	**0.0414**	**0.0415**	**0.0421**
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**

JAP is Japan.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator.

5.5.4 USA Weighting Table

Tables 5.22 to 5.25 show the details of the calculation of the final weighting for the USA composite leading indicator for different hotel categories in the Hong Kong hotel industry (see Appendix). Table 5.26 summarizes the weighting of all categories for the USA composite leading indicator.

Table 5.26 Summary of the final weighting of all hotel categories for USA composite leading indicator

Selected economic variables	Final weighting			
	USA CLI TOTAL	**USA CLI HIGH A**	**USA CLI HIGH B**	**USA CLI MEDIUM**
GDP	**0.3343**	**0.3449**	**0.2717**	**0.3919**
Share Price	**0.1535**	**0.1250**	**0.1657**	**0.1683**
Unemployment	**0.1321**	**0.1406**	**0.1358**	**0.1647**
Import	**0.1820**	**0.2054**	**0.2172**	**-**
Export	**0.1610**	**0.1458**	**0.1660**	**0.2256**
Oil Price	**0.0372**	**0.0383**	**0.0435**	**0.0496**
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator.

5.5.5 Australia Weighting Table

Tables 5.27 to 5.30 show the details of the calculation of the final weighting for the Australia composite leading indicator for different hotel categories in the Hong Kong hotel industry (see Appendix). Table 5.31 summarizes the weighting of all categories for the Australia composite leading indicator.

Table 5.31 Summary of the final weighting of all hotel categories for Australia composite leading indicator

Selected economic variables	Final weighting			
	AUS CLI TOTAL	**AUS CLI HIGH A**	**AUS CLI HIGH B**	**AUS CLI MEDIUM**
GDP	**0.4114**	**0.2142**	**0.3898**	**0.4688**
Exchange Rate	**0.1649**	**0.1128**	**0.1638**	**0.0965**
Share Price	**0.0484**	**0.0828**	**0.0615**	**0.0514**
Real Exchange Rate	**0.1202**	**0.1751**	**0.0933**	**0.1241**
Unemployment	**0.1104**	**0.1432**	**0.1083**	**0.1194**
Import	**0.0730**	**0.1344**	**0.1046**	**0.0581**
Export	**0.0499**	**0.1011**	**0.0531**	**0.0568**
Oil Price	**0.0218**	**0.0364**	**0.0255**	**0.0248**
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**

AUS is Australia.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator.

5.6 The result of each country's composite leading indicator

After the calculation of the weighting for each country's selected economic variables for every hotel category in Hong Kong, the graphs below represent the results of each country's composite leading indicator with the original growth of hotel occupancy rate of each hotel category. The visual examination shows that all the composite leading indicators lead the original occupancy rate.

5.6.1 China Composite Leading Indicators

Figures 5.37 to 5.40 compare the original growth of Hong Kong hotel occupancy rate with the China composite leading indicator for different Hong Kong hotel categories.

Figure 5.37 Comparison between the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) and the China composite leading indicator for the Hong Kong (Total) hotel category (CHI CLI TOTAL)

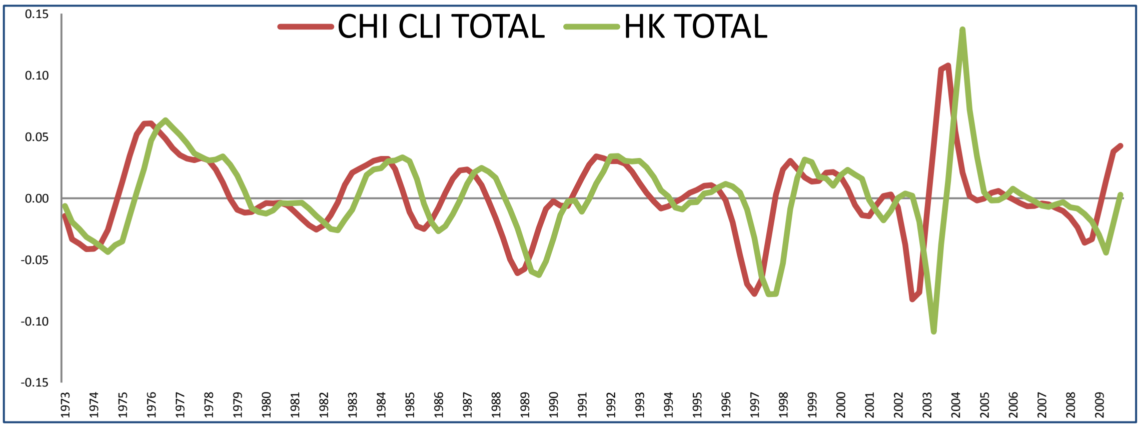


Figure 5.38 Comparison between the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) and the China composite leading indicator for the Hong Kong High Tariff A hotel category (CHI CLI HIGH A)

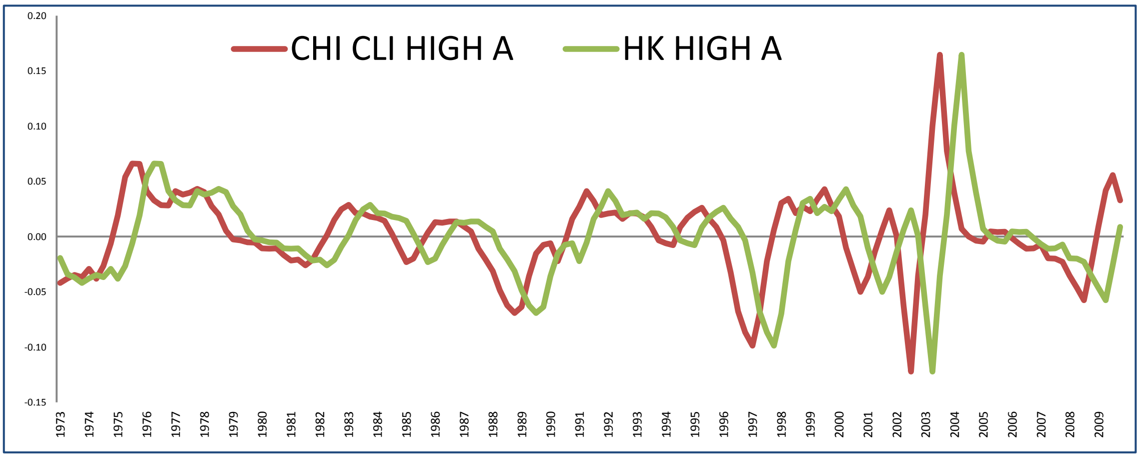


Figure 5.39 Comparison between the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) and the China composite leading indicator for the Hong Kong High Tariff B hotel category (CHI CLI HIGH B)

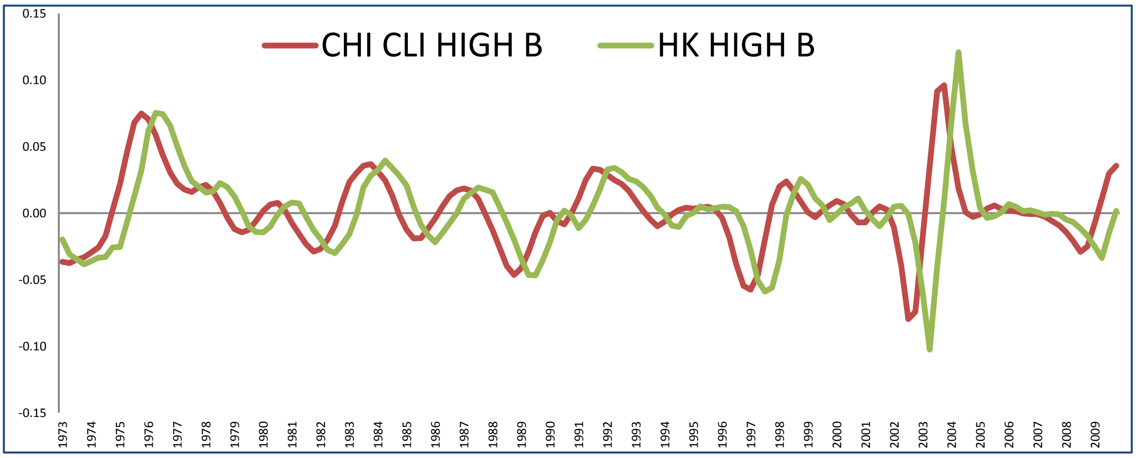
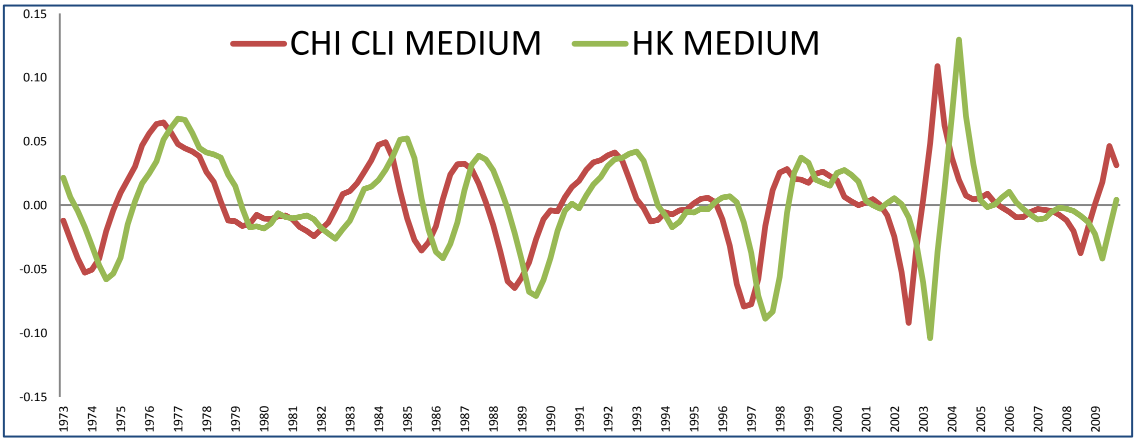


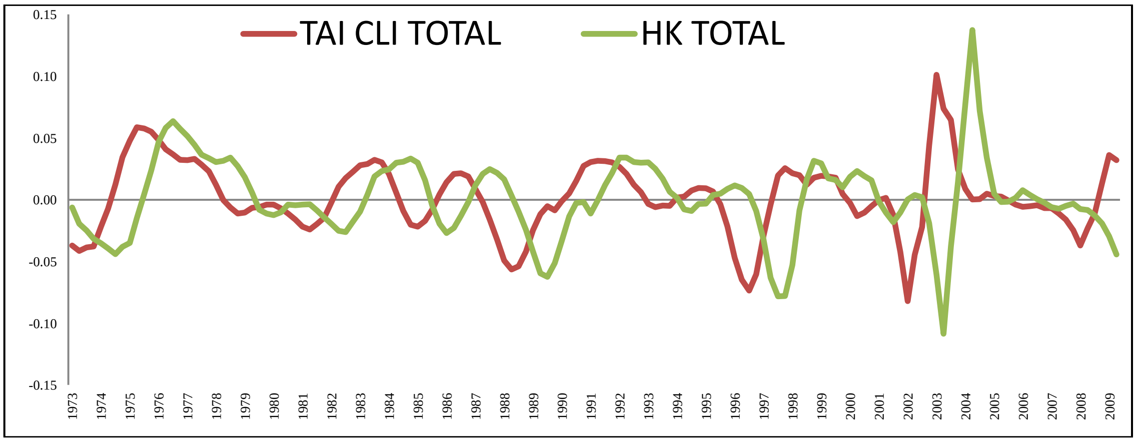
Figure 5.40 Comparison between the original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) and the China composite leading indicator for the Hong Kong Medium Tariff hotel category (CHI CLI MEDIUM)



5.6.2 Taiwan Composite Leading Indicators

Figures 5.41 to 5.44 compare the original growth of Hong Kong hotel occupancy rate with the Taiwan composite leading indicator for different Hong Kong hotel categories. (Figures 5.42 to 5.44 are in the Appendix.)

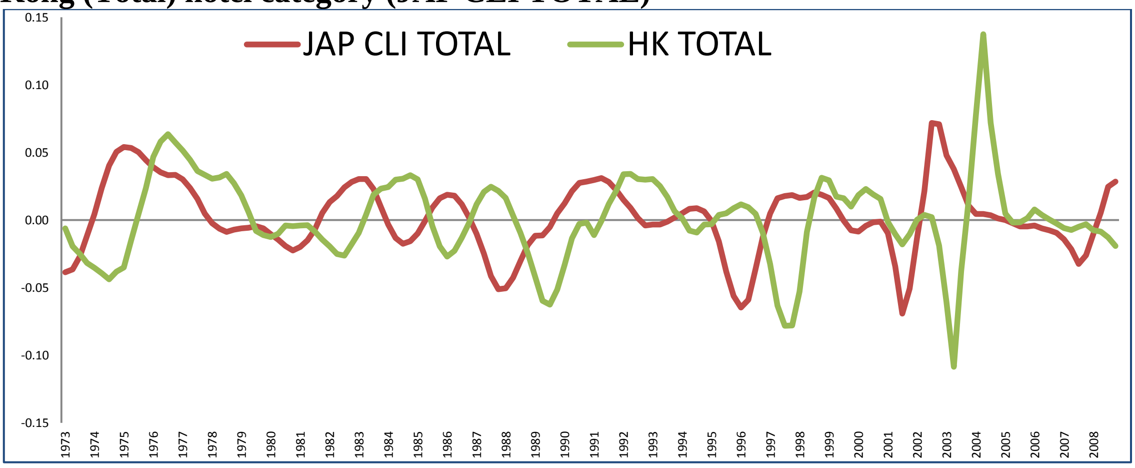
Figure 5.41 Comparison between the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) and the Taiwan composite leading indicator for the Hong Kong (Total) hotel category (TAI CLI TOTAL)



5.6.3 Japan Composite Leading Indicators

Figure 5.45 to 5.48 compare the original growth of Hong Kong hotel occupancy rate with the Japan composite leading indicator for different Hong Kong hotel categories. (Figures 5.46 to 5.48 are in the Appendix.)

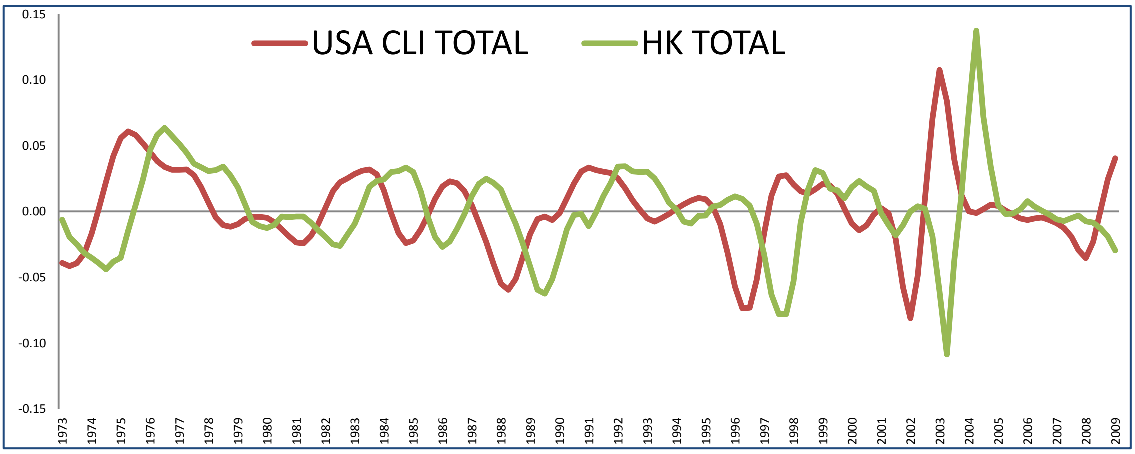
Figure 5.45 Comparison between the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) and the Japan composite leading indicator for the Hong Kong (Total) hotel category (JAP CLI TOTAL)



5.6.4 USA Composite Leading Indicators

Figures 5.49 to 5.52 compare the original growth of Hong Kong hotel occupancy rate with the USA composite leading indicator for different Hong Kong hotel categories. (Figures 5.50 to 5.52 are in the Appendix.)

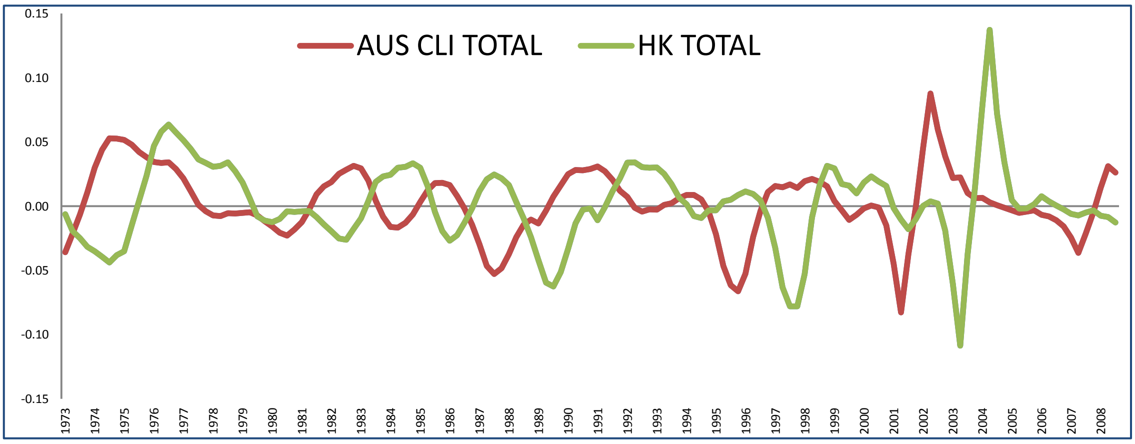
Figure 5.49 Comparison between the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) and the USA composite leading indicator for the Hong Kong (Total) hotel category (USA CLI TOTAL)



5.6.5 Australia Composite Leading Indicators

Figures 5.53 to 5.56 compare the original growth of Hong Kong hotel occupancy rate with the Australia composite leading indicator for different Hong Kong hotel categories. (Figures 5.54 to 5.56 are in the Appendix.)

Figure 5.53 Comparison between the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) and the Australia composite leading indicator for the Hong Kong (Total) hotel category (AUS CLI TOTAL)



5.7 Conclusion

After selecting the suitable and eligible economic variables for each country, the construction of the top five overnight-stay countries' composite leading indicators for every category in Hong Kong hotel occupancy rate are formed. The next chapter will discuss the procedures to combine the countries' composite leading indicators as one grand leading indicator for each tariff category in the Hong Kong hotel industry. Such empirical study will give a wider scope for the hoteliers and policy makers in forecasting turns in the occupancy rate.

Considering that the composite leading indicators can predict the turns for the occupancy rate, such insights will help the management work out a better strategic plan to capture the maximum revenue and reduce operation costs by the best-fit timing for different organizational moves, such as launching the marketing scheme just before the predicted turn for the expansion period, or arranging the international cross-training scheme during the contraction period, or else recruiting well-trained staff in anticipation of the next peak point. All these organizational adjustments could be undertaken with better timing using the prediction from the composite leading indicator.

5.8 Appendix

Figure 5.8 The smoothed growth rate of Taiwan GDP (TAI GDP)

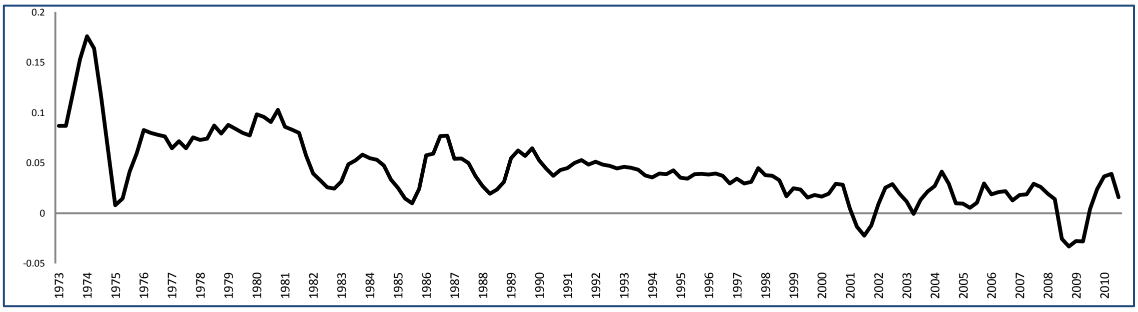


Figure 5.9 The smoothed growth rate of Taiwan exchange rate (TAI EX)

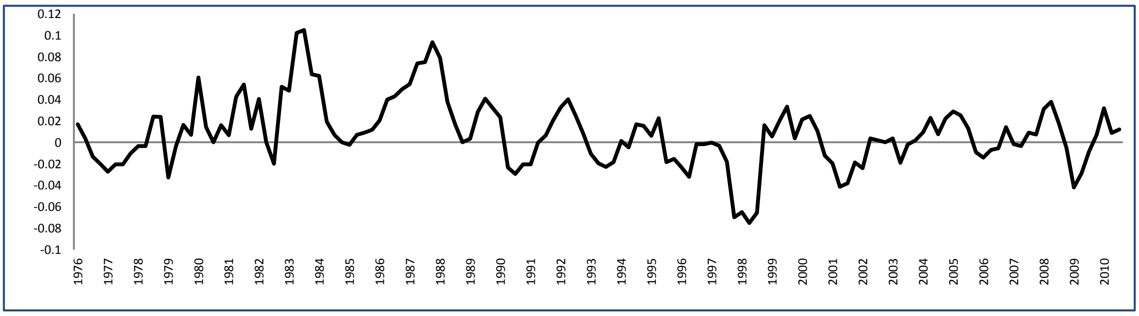


Figure 5.10 The smoothed growth rate of Taiwan total export (TAI TE)

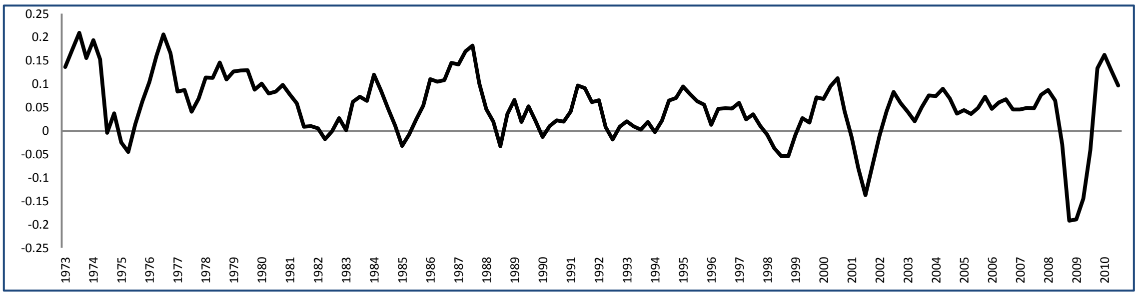


Figure 5.11 The smoothed growth rate of Taiwan total import (TAI TI)

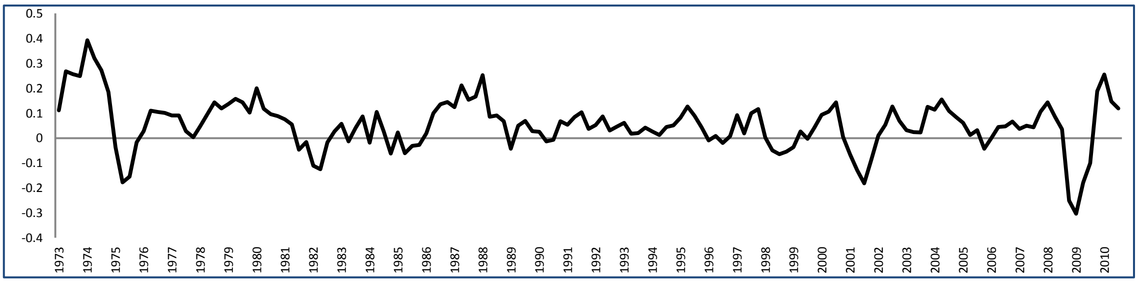


Figure 5.12 The smoothed growth rate of Taiwan unemployment rate (TAI UR)

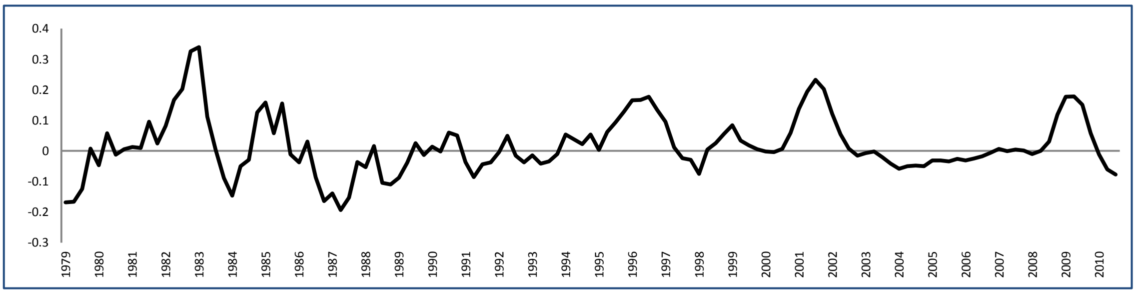


Figure 5.13 The smoothed growth rate of Taiwan real exchange rate (TAI RER)

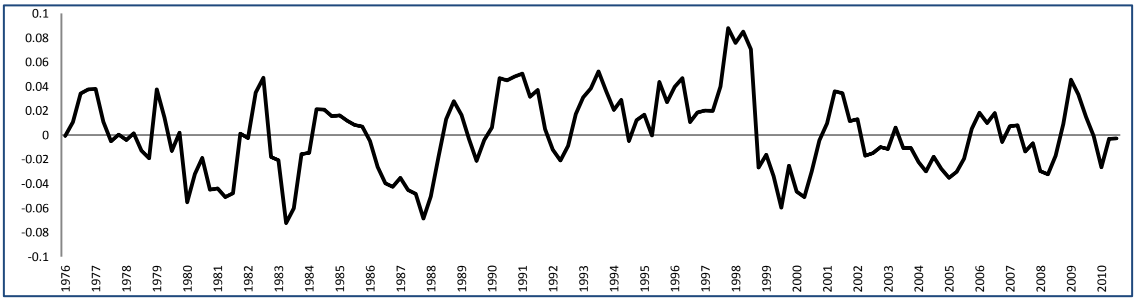


Figure 5.14 The smoothed growth rate of Taiwan share price (TAI SP)

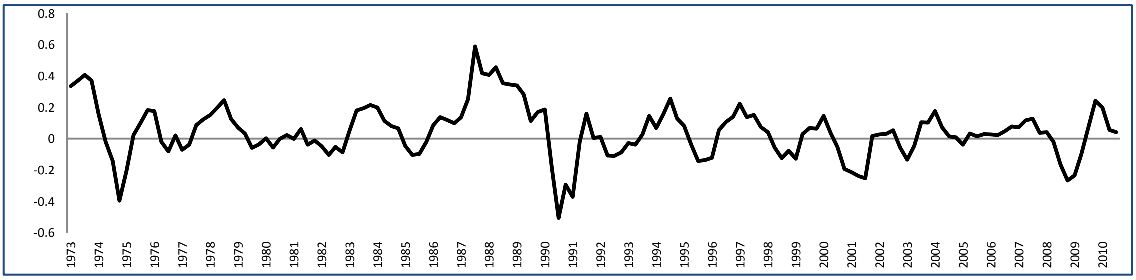


Figure 5.15 The smoothed growth rate of Taiwan GDP (TAI GDP)

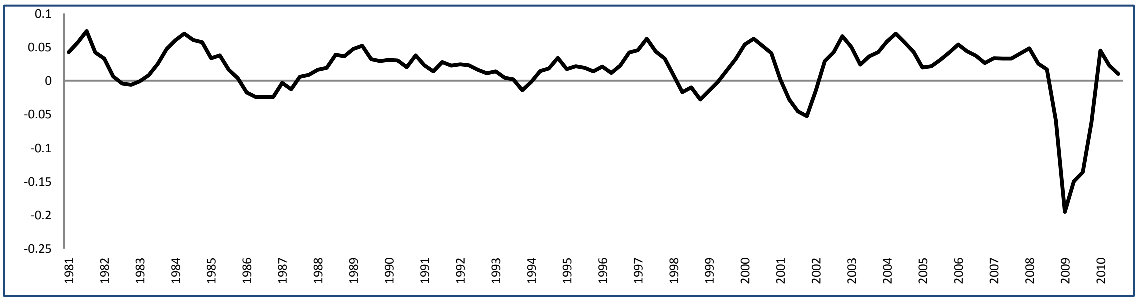


Figure 5.16 The smoothed growth rate of Japan exchange rate (JAP ER)

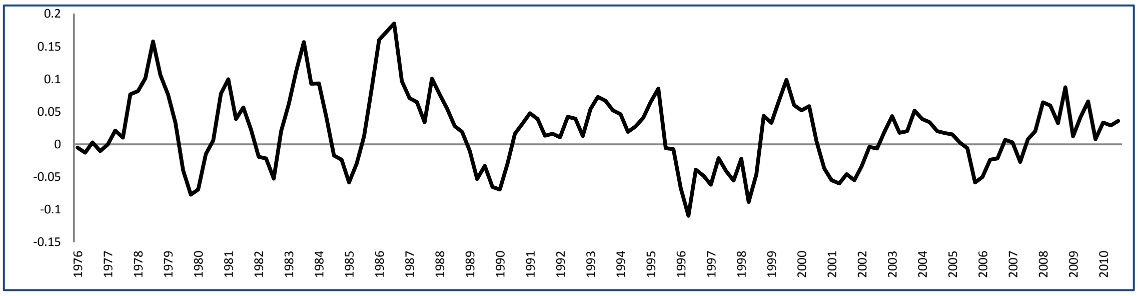


Figure 5.17 The smoothed growth rate of Japan total export (JAP TE)

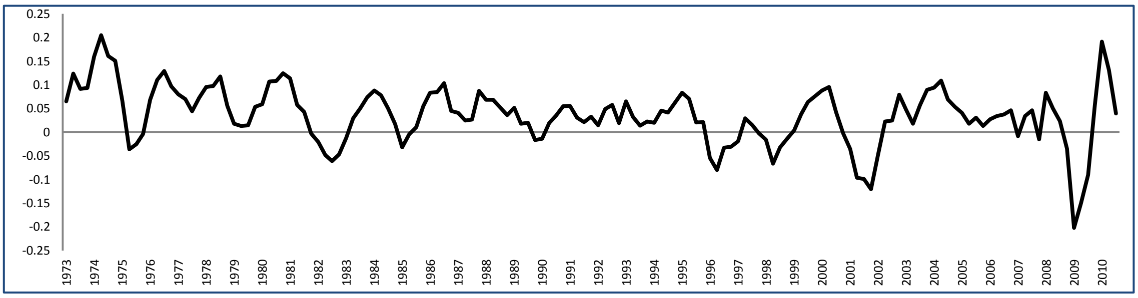


Figure 5.18 The smoothed growth rate of Japan total import (JAP TI)

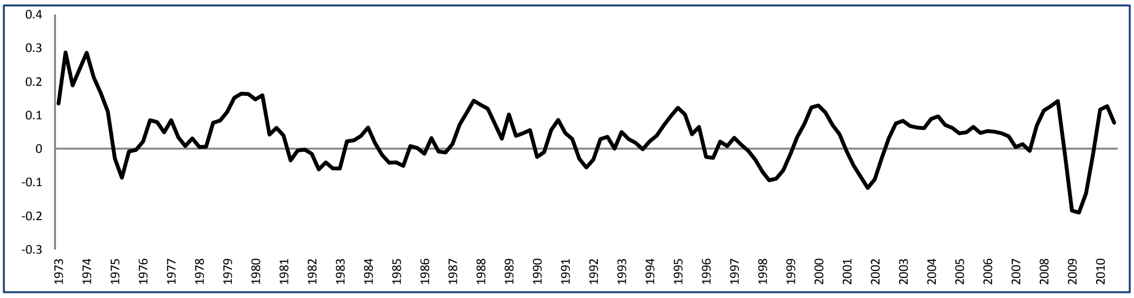


Figure 5.19 The smoothed growth rate of Japan unemployment rate (JAP UR)

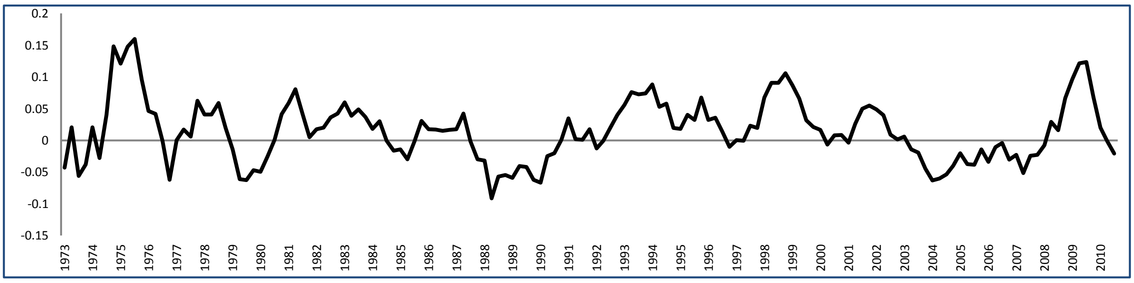


Figure 5.20 The smoothed growth rate of Japan real exchange rate (JAP RER)

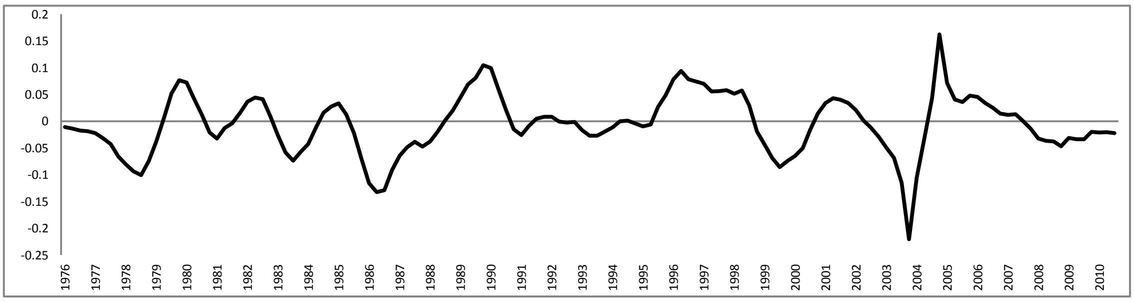


Figure 5.21 The smoothed growth rate of Japan share price (JAP SP)

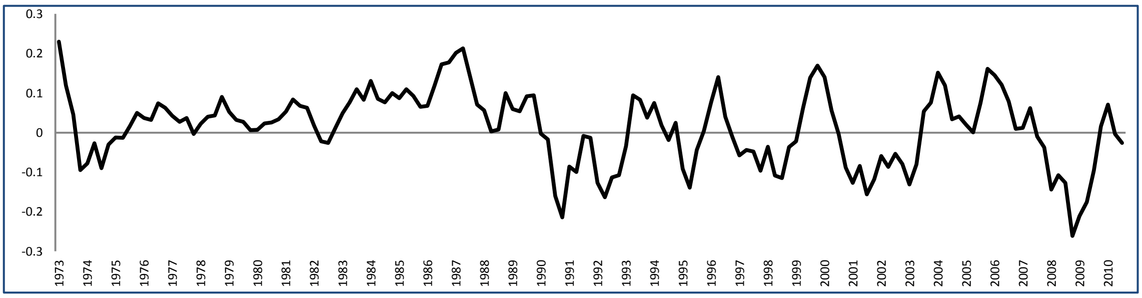


Figure 5.22 The smoothed growth rate of USA GDP (USA GDP)

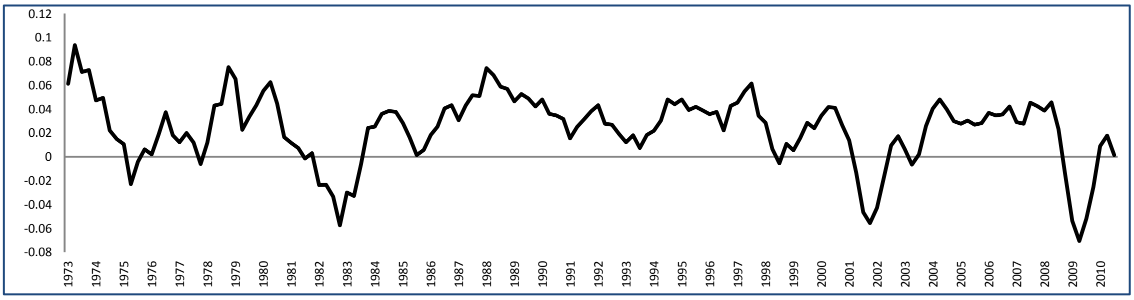


Figure 5.23 The smoothed growth rate of USA exchange rate (USA ER)

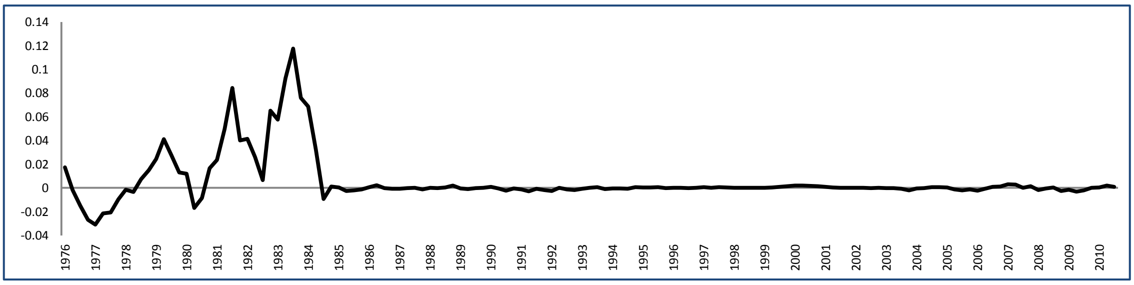


Figure 5.24 The smoothed growth rate of USA total export (USA TE)

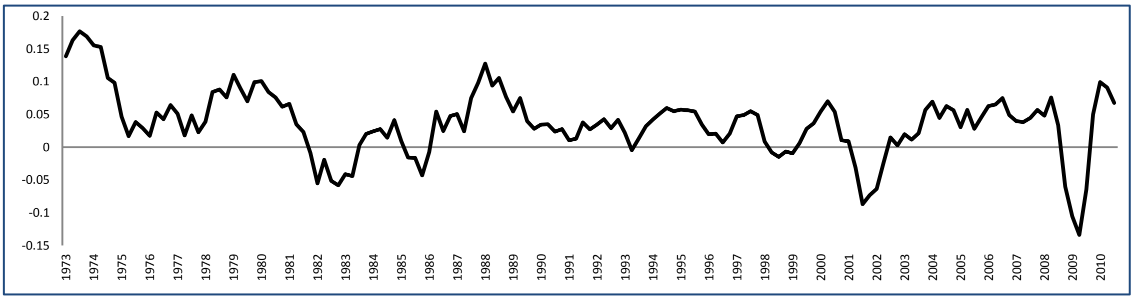


Figure 5.25 The smoothed growth rate of USA total import (USA TI)

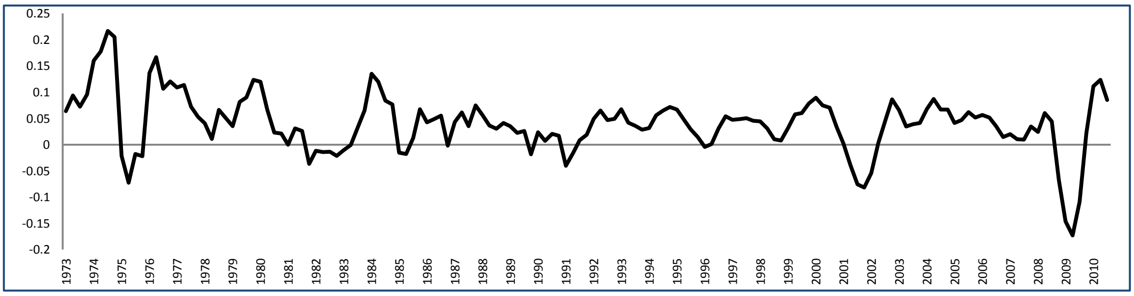


Figure 5.26 The smoothed growth rate of USA unemployment rate (USA UR)

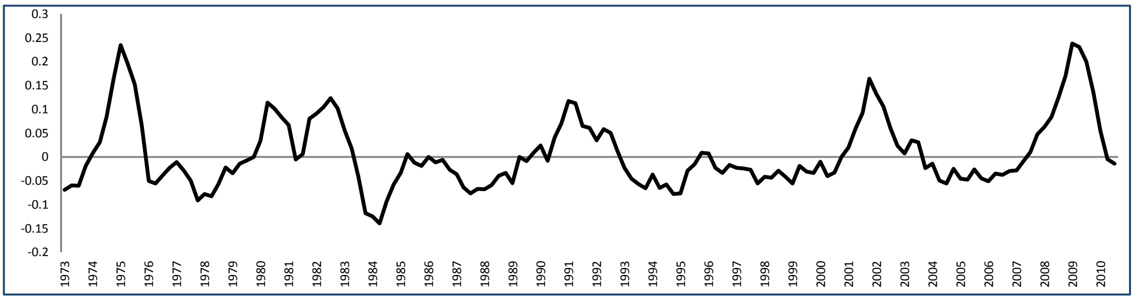


Figure 5.27 The smoothed growth rate of USA real exchange rate (USA RER)

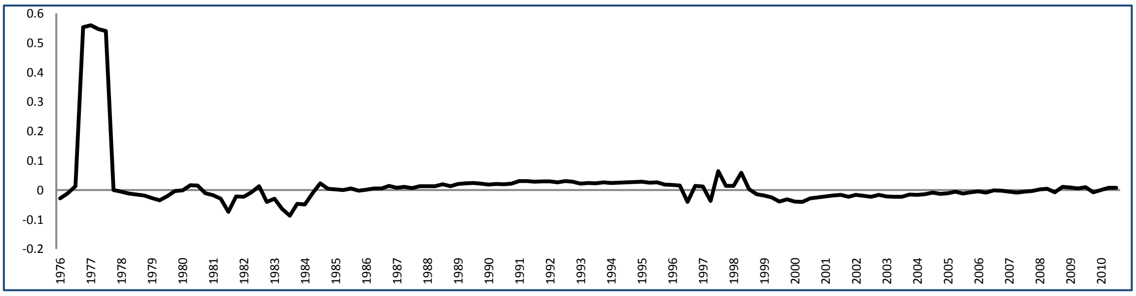


Figure 5.28 The smoothed growth rate of USA share price (USA SP)

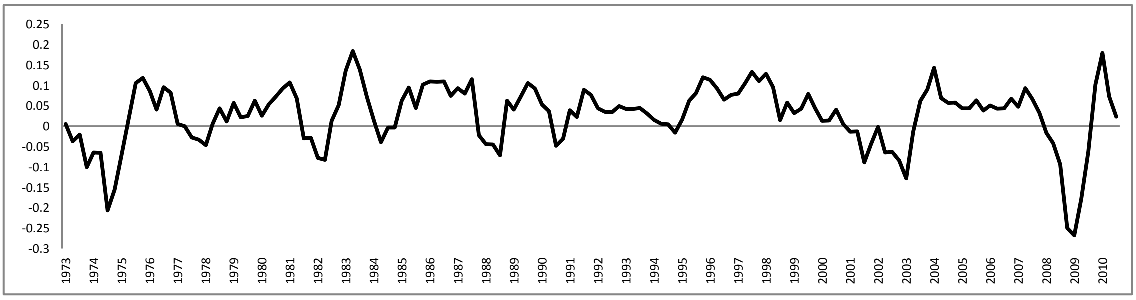


Figure 5.29 The smoothed growth rate of Australia GDP (AUS GDP)

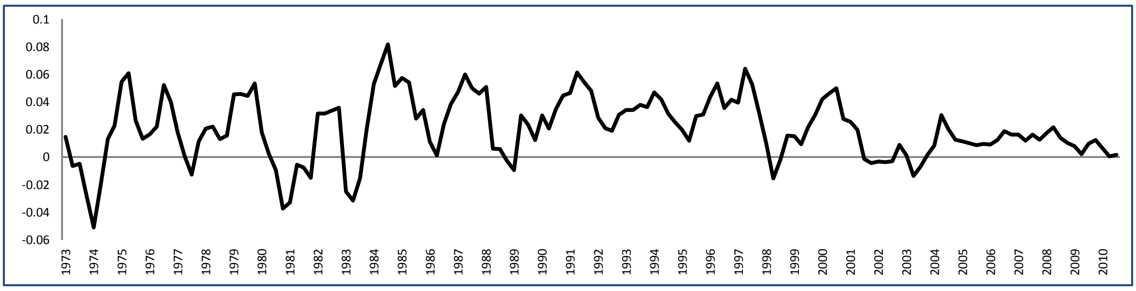


Figure 5.30 The smoothed growth rate of Australia exchange rate (AUS ER)

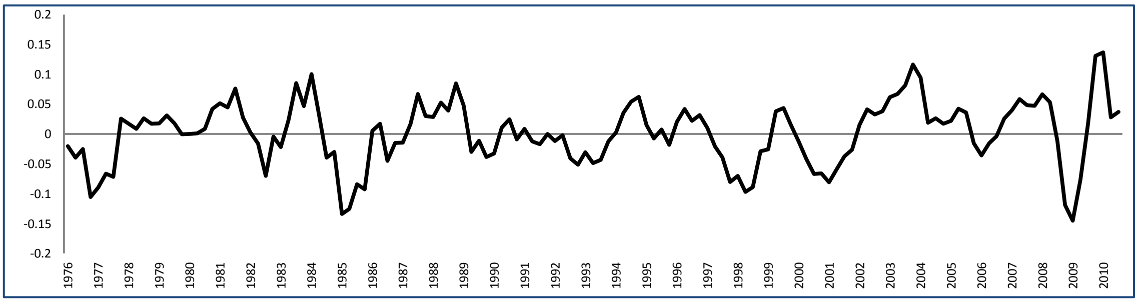


Figure 5.31 The smoothed growth rate of Australia total export (AUS TE)

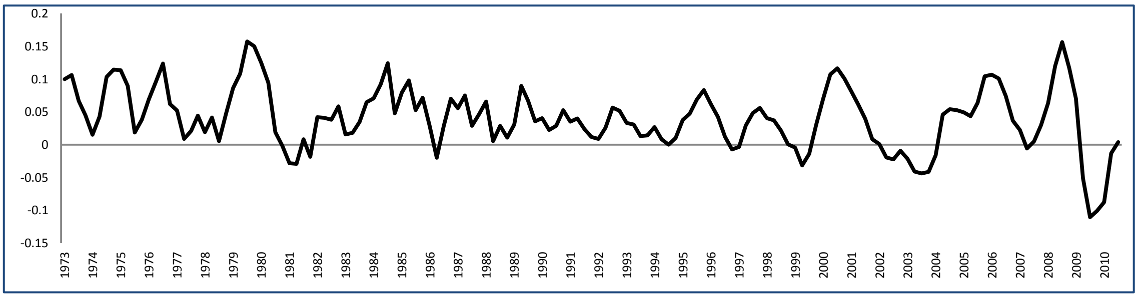


Figure 5.32 The smoothed growth rate of Australia total import (AUS TI)

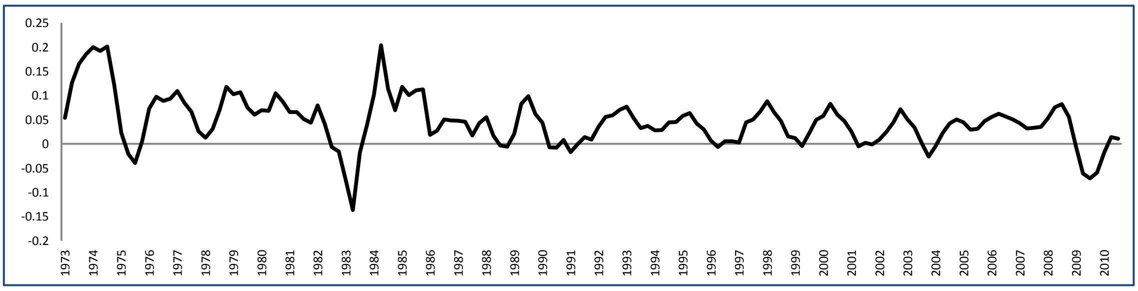


Figure 5.33 The smoothed growth rate of Australia unemployment rate (AUS UR)

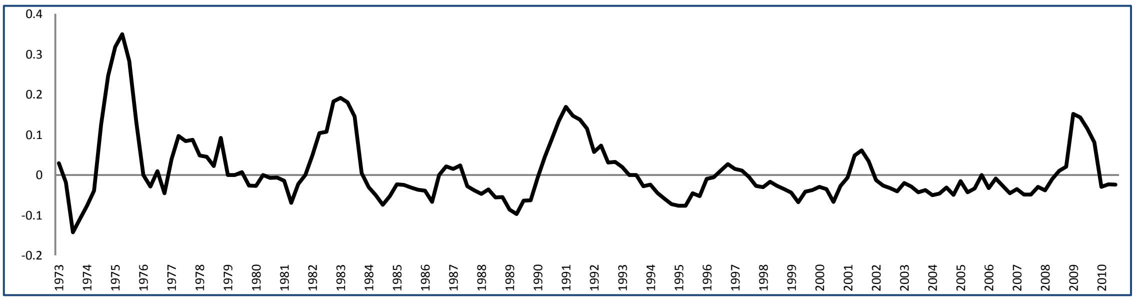


Figure 5.34 The smoothed growth rate of Australia real exchange rate (AUS RER)

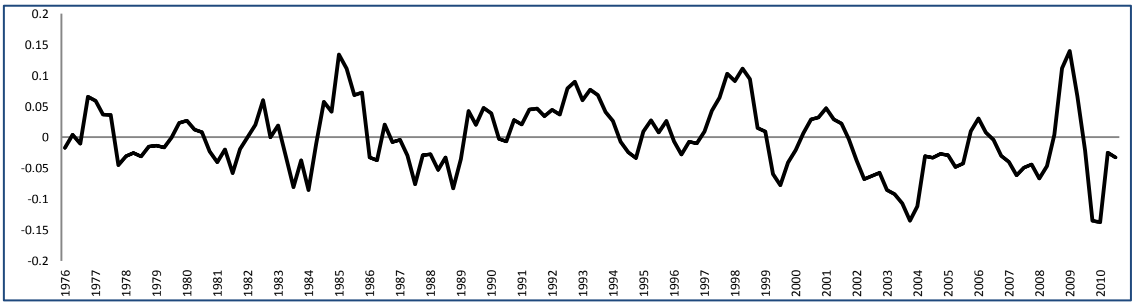


Figure 5.35 The smoothed growth rate of Australia share price (AUS SP)

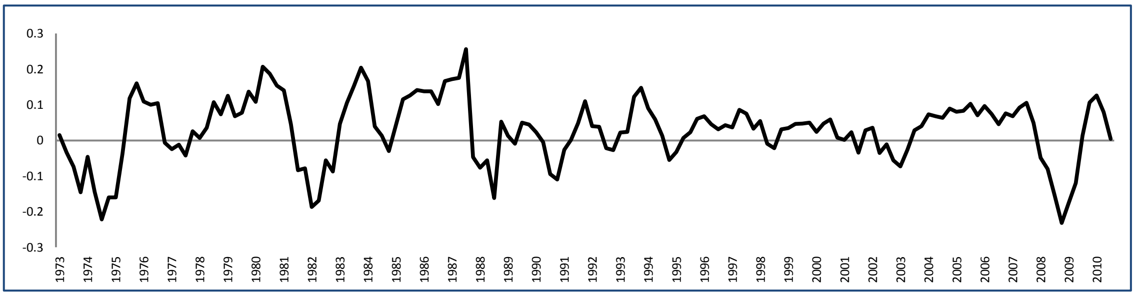


Table 5.12 Weights for the construction of Taiwan composite leading indicator for Hong Kong (Total) hotel category (TAI CLI TOTAL)

TAI CLI TOTAL								
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Selected economic variables	**Coefficient of the cross correlation**	**Converted percentage of assigned Weight**	**Average of the Absolute Average Deviation**	**Converted percentage of the Absolute Average Deviation**	**Inverse of the Absolute Average Deviation**	**Converted percentage of Inverse of the Absolute Average Deviation**	**Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation**	**Converted Percentage of Finalized weighting**
GDP	0.5872	0.5191	0.0245	0.0687	40.7366	0.3526	0.1830	**0.6542**
Exchange Rate	0.2093	0.1850	0.0227	0.0635	44.1092	0.3818	0.0706	**0.2525**
Share Price	0.1421	0.1256	0.1223	0.3424	8.1793	0.0708	0.0089	**0.0318**
Import	0.1123	0.0993	0.0723	0.2024	13.8378	0.1198	0.0119	**0.0425**
Oil Price	0.0802	0.0709	0.1153	0.3230	8.6714	0.0751	0.0053	**0.0190**
Total	1.1311	1.0000	0.3571	1.0000	115.5343	1.0000	0.2798	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.
Apply to Table 5.12 to 5.15, 5.17 to 5.20, 5.22 to 5.25 and 5.27 to 5.30

Table 5.13 Weights for the construction of Taiwan composite leading indicator for Hong Kong High Tariff A hotel category (TAI CLI HIGH A)

TAI CLI HIGH A								
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Selected economic variables	**Coefficient of the cross correlation**	**Converted percentage of assigned Weight**	**Average of the Absolute Average Deviation**	**Converted percentage of the Absolute Average Deviation**	**Inverse of the Absolute Average Deviation**	**Converted percentage of Inverse of the Absolute Average Deviation**	**Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation**	**Converted Percentage of Finalized weighting**
GDP	0.5998	0.4265	0.0246	0.0604	40.73660	0.3003	0.1281	**0.5621**
Exchange Rate	0.2835	0.2016	0.0227	0.0558	44.1092	0.3252	0.0656	**0.2877**
Share Price	0.2013	0.1431	0.1223	0.3006	8.1793	0.0603	0.0086	**0.0379**
Import	0.1332	0.0947	0.0723	0.1777	13.8378	0.1020	0.0097	**0.0424**
Export	0.1226	0.0872	0.0497	0.1222	20.1098	0.1483	0.0129	**0.0567**
Oil Price	0.0659	0.0469	0.1153	0.2835	8.6714	0.0639	0.0030	**0.0132**
Total	1.4063	1.0000	0.4068	1.0000	135.6441	1.0000	0.2279	**1.0000**

Table 5.14 weights for the construction of Taiwan composite leading indicator for Hong Kong High Tariff B hotel category (TAI CLI HIGH B)

TAI CLI HIGH B								
(1) Selected economic variables	**(2) Coefficient of the cross correlation**	**(3) Converted percentage of assigned Weight**	**(4) Average of the Absolute Average Deviation**	**(5) Converted percentage of the Absolute Average Deviation**	**(6) Inverse of the Absolute Average Deviation**	**(7) Converted percentage of Inverse of the Absolute Average Deviation**	**(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation**	**(9) Converted Percentage of Finalized weighting**
GDP	0.5813	0.5590	0.0245	0.0862	40.7366	0.4006	0.2239	**0.6846**
Exchange Rate	0.198	0.1904	0.0227	0.0796	44.1092	0.4337	0.0826	**0.2525**
Share Price	0.1641	0.1578	0.1223	0.4293	8.1793	0.0804	0.0127	**0.0388**
Oil Price	0.0964	0.0927	0.1153	0.4049	8.6714	0.0853	0.0079	**0.0242**
Total	1.0398	1.0000	0.2848	1.0000	101.6966	1.0000	0.3271	**1.0000**

Table 5.15 weights for the construction of Taiwan composite leading indicator for Hong Kong Medium Tariff hotel category (TAI CLI MEDIUM)

TAI CLI MEDIUM								
(1) Selected economic variables	**(2) Coefficient of the cross correlation**	**(3) Converted percentage of assigned Weight**	**(4) Average of the Absolute Average Deviation**	**(5) Converted percentage of the Absolute Average Deviation**	**(6) Inverse of the Absolute Average Deviation**	**(7) Converted percentage of Inverse of the Absolute Average Deviation**	**(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation**	**(9) Converted Percentage of Finalized weighting**
GDP	0.5257	0.5282	0.0245	0.0687	40.7366	0.3526	0.1863	**0.6591**
Exchange Rate	0.1851	0.1860	0.0227	0.0635	44.1092	0.3818	0.0710	**0.2513**
Share Price	0.1092	0.1097	0.1223	0.3424	8.1793	0.0708	0.0078	**0.0275**
Import	0.0963	0.0968	0.0723	0.2024	13.8378	0.1198	0.0116	**0.0410**
Oil Price	0.0789	0.0793	0.1153	0.3230	8.6714	0.0751	0.0060	**0.0211**
Total	0.9952	1.0000	0.3571	1.0000	115.5343	1.0000	0.2826	**1.0000**

Table 5.17 weights for the construction of Japan composite leading indicator for Hong Kong (Total) hotel category (JAP CLI TOTAL)

JAP CLI TOTAL								
(1) Selected economic variables	**(2) Coefficient of the cross correlation**	**(3) Converted percentage of assigned Weight**	**(4) Average of the Absolute Average Deviation**	**(5) Converted percentage of the Absolute Average Deviation**	**(6) Inverse of the Absolute Average Deviation**	**(7) Converted percentage of Inverse of the Absolute Average Deviation**	**(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation**	**(9) Converted Percentage of Finalized weighting**
GDP	0.0603	0.0648	0.0259	0.0598	38.5923	0.2715	0.0176	**0.1270**
Exchange Rate	0.1209	0.1299	0.0609	0.1405	16.4311	0.1156	0.0150	**0.1084**
Share Price	0.1951	0.2097	0.0938	0.2165	10.6656	0.0750	0.0157	**0.1135**
Real Exchange Rate	0.2579	0.2772	0.0419	0.0967	23.8664	0.1679	0.0465	**0.3359**
Unemployment	0.1435	0.1542	0.0375	0.0865	26.6771	0.1876	0.0289	**0.2089**
Import	0.0726	0.0780	0.0579	0.1337	17.2646	0.1214	0.0095	**0.0684**
Oil Price	0.0802	0.0862	0.1153	0.2662	8.6714	0.0610	0.0053	**0.0379**
Total	0.9305	1.0000	0.4332	1.0000	142.1685	1.0000	0.1385	**1.0000**

Table 5.18 weights for the construction of Japan composite leading indicator for Hong Kong High Tariff A hotel category (JAP CLI HIGH A)

JAP CLI HIGH A								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.1756	0.1799	0.0259	0.0598	38.5923	0.2715	0.0488	**0.3261**
Exchange Rate	0.1173	0.1202	0.0609	0.1405	16.4311	0.1156	0.0139	**0.0927**
Share Price	0.1944	0.1992	0.0938	0.2165	10.6656	0.0750	0.0149	**0.0998**
Real Exchange Rate	0.1565	0.1604	0.0419	0.0967	23.8664	0.1679	0.0269	**0.1797**
Unemployment	0.1473	0.1509	0.0375	0.0865	26.6771	0.1876	0.0283	**0.1891**
Import	0.0857	0.0878	0.0579	0.1337	17.2646	0.1214	0.0107	**0.0712**
Oil Price	0.0991	0.1015	0.1153	0.2662	8.6714	0.0610	0.0062	**0.0414**
Total	0.9759	1.0000	0.4332	1.0000	142.1685	1.0000	0.1498	**1.0000**

Table 5.19 weights for the construction of Japan composite leading indicator for Hong Kong High Tariff B hotel category (JAP CLI HIGH B)

JAP CLI HIGH B								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.1321	0.1338	0.0259	0.0598	38.5923	0.2715	0.0363	**0.2534**
Exchange Rate	0.1609	0.1630	0.0609	0.1405	16.4311	0.1156	0.0188	**0.1314**
Share Price	0.2022	0.2048	0.0938	0.2165	10.6656	0.0750	0.0154	**0.1072**
Real Exchange Rate	0.1302	0.1319	0.0419	0.0967	23.8664	0.1679	0.0221	**0.1545**
Unemployment	0.1797	0.1820	0.0375	0.0865	26.6771	0.1876	0.0342	**0.2383**
Import	0.0859	0.0870	0.0579	0.1337	17.2646	0.1214	0.0106	**0.0737**
Oil Price	0.0964	0.0976	0.1153	0.2662	8.6714	0.0610	0.0060	**0.0415**
Total	0.9874	1.0000	0.4332	1.0000	142.1685	1.0000	0.1433	**1.0000**

Table 5.20 weights for the construction of Japan composite leading indicator for Hong Kong Medium Tariff hotel category (JAP CLI MEDIUM)

JAP CLI MEDIUM								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.1109	0.1379	0.0259	0.0598	38.5923	0.2715	0.0374	**0.2636**
Exchange Rate	0.1257	0.1563	0.0609	0.1405	16.4311	0.1156	0.0181	**0.1272**
Share Price	0.1767	0.2197	0.0938	0.2165	10.6656	0.0750	0.0165	**0.1161**
Real Exchange Rate	0.1397	0.1737	0.0419	0.0967	23.8664	0.1679	0.0292	**0.2053**
Unemployment	0.1076	0.1338	0.0375	0.0865	26.6771	0.1876	0.0251	**0.1768**
Import	0.0649	0.0807	0.0579	0.1337	17.2646	0.1214	0.0098	**0.0690**
Oil Price	0.0789	0.0981	0.1153	0.2662	8.6714	0.0610	0.0060	**0.0421**
Total	0.8044	1.0000	0.4332	1.0000	142.1685	1.0000	0.1420	**1.0000**

Table 5.22 weights for the construction of USA composite leading indicator for Hong Kong (Total) hotel category (USA CLI TOTAL)

USA CLI TOTAL								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.1347	0.1644	0.0215	0.0622	46.4425	0.3341	0.0549	**0.3343**
Share Price	0.2215	0.2704	0.0771	0.2228	12.9678	0.0933	0.0252	**0.1535**
Unemployment	0.1413	0.1725	0.0572	0.1651	17.4920	0.1258	0.0217	**0.1321**
Import	0.1335	0.1630	0.0392	0.1133	25.5071	0.1835	0.0299	**0.1820**
Export	0.1079	0.1317	0.0358	0.1035	27.9124	0.2008	0.0265	**0.1610**
Oil Price	0.0802	0.0979	0.1153	0.3331	8.6714	0.0624	0.0061	**0.0372**
Total	0.8191	1.0000	0.3462	1.0000	138.9932	1.0000	0.1644	**1.0000**

Table 5.23 weights for the construction of USA composite leading indicator for Hong Kong High Tariff A hotel category (USA CLI HIGH A)

USA CLI HIGH A								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.1665	0.1735	0.0215	0.0622	46.4425	0.3341	0.0580	**0.3449**
Share Price	0.2162	0.2253	0.0771	0.2228	12.9678	0.0933	0.0210	**0.1250**
Unemployment	0.1802	0.1878	0.0572	0.1651	17.4920	0.1258	0.0236	**0.1406**
Import	0.1806	0.1882	0.0392	0.1133	25.5071	0.1835	0.0345	**0.2054**
Export	0.1171	0.1220	0.0358	0.1035	27.9124	0.2008	0.0245	**0.1458**
Oil Price	0.0991	0.1033	0.1153	0.3331	8.6714	0.0624	0.0064	**0.0383**
Total	0.9597	1.0000	0.3462	1.0000	138.9932	1.0000	0.1681	**1.0000**

Table 5.24 weights for the construction of USA composite leading indicator for Hong Kong High Tariff A hotel category (USA CLI HIGH B)

USA CLI HIGH B								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.1123	0.1275	0.0215	0.0622	46.4425	0.3341	0.0426	**0.2717**
Share Price	0.2453	0.2785	0.0771	0.2228	12.9678	0.0933	0.0260	**0.1657**
Unemployment	0.1490	0.1692	0.0572	0.1651	17.4920	0.1258	0.0213	**0.1358**
Import	0.1635	0.1856	0.0392	0.1133	25.5071	0.1835	0.0341	**0.2172**
Export	0.1142	0.1297	0.0358	0.1035	27.9124	0.2008	0.0260	**0.1660**
Oil Price	0.0964	0.1095	0.1153	0.3331	8.6714	0.0624	0.0068	**0.0435**
Total	0.8807	1.0000	0.3462	1.0000	138.9932	1.0000	0.1568	**1.0000**

Table 5.25 weights for the construction of USA composite leading indicator for Hong Kong Medium Tariff hotel category (USA CLI MEDIUM)

USA CLI MEDIUM								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.1164	0.1891	0.0215	0.0701	46.4425	0.4092	0.0774	**0.3919**
Share Price	0.1790	0.2907	0.0771	0.2512	12.9678	0.1143	0.0332	**0.1683**
Unemployment	0.1299	0.2110	0.0572	0.1862	17.4920	0.1541	0.0325	**0.1647**
Export	0.1115	0.1811	0.0358	0.1167	27.9124	0.2460	0.0445	**0.2256**
Oil Price	0.0789	0.1281	0.1153	0.3757	8.6714	0.0764	0.0098	**0.0496**
Total	0.6157	1.0000	0.3070	1.0000	113.4861	1.0000	0.1974	**1.0000**

Table 5.27 weights for the construction of Australia composite leading indicator for Hong Kong (Total) hotel category (AUS CLI TOTAL)

AUS CLI TOTAL								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.2413	0.2092	0.0184	0.0441	54.3358	0.2751	0.0575	**0.4114**
Exchange Rate	0.2162	0.1874	0.0411	0.0986	24.3142	0.1231	0.0231	**0.1649**
Share Price	0.1063	0.0922	0.0689	0.1653	14.5055	0.0734	0.0068	**0.0484**
Real Exchange Rate	0.1627	0.1411	0.0425	0.1018	23.5440	0.1192	0.0168	**0.1202**
Unemployment	0.2037	0.1766	0.0579	0.1389	17.2689	0.0874	0.0154	**0.1104**
Import	0.0857	0.0743	0.0368	0.0883	27.1491	0.1374	0.0102	**0.0730**
Export	0.0573	0.0497	0.0360	0.0864	27.7584	0.1405	0.0070	**0.0499**
Oil Price	0.0802	0.0695	0.1153	0.2765	8.6714	0.0439	0.0031	**0.0218**
Total	1.1534	1.0000	0.4170	1.0000	197.5473	1.0000	0.1399	**1.0000**

Table 5.28 weights for the construction of Australia composite leading indicator for Hong Kong High Tariff A hotel category (AUS CLI HIGH A)

(AUS CLI HIGH A)								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.0930	0.0921	0.0184	0.0441	54.3358	0.2751	0.0253	**0.2142**
Exchange Rate	0.1094	0.1083	0.0411	0.0986	24.3142	0.1231	0.0133	**0.1128**
Share Price	0.1347	0.1334	0.0689	0.1653	14.5055	0.0734	0.0098	**0.0828**
Real Exchange Rate	0.1754	0.1737	0.0425	0.1018	23.5440	0.1192	0.0207	**0.1751**
Unemployment	0.1956	0.1937	0.0579	0.1389	17.2689	0.0874	0.0169	**0.1432**
Import	0.1168	0.1157	0.0368	0.0883	27.1491	0.1374	0.0159	**0.1344**
Export	0.0859	0.0851	0.0360	0.0864	27.7584	0.1405	0.0120	**0.1011**
Oil Price	0.0991	0.0981	0.1153	0.2765	8.6714	0.0439	0.0043	**0.0364**
Total	1.0099	1.0000	0.4170	1.0000	197.5473	1.0000	0.1182	**1.0000**

Table 5.29 weights for the construction of Australia composite leading indicator for Hong Kong High Tariff B hotel category (AUS CLI HIGH B)

AUS CLI HIGH B								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.2351	0.1934	0.0184	0.0441	54.3358	0.2751	0.0532	**0.3898**
Exchange Rate	0.2208	0.1816	0.0411	0.0986	24.3142	0.1231	0.0224	**0.1638**
Share Price	0.1390	0.1143	0.0689	0.1653	14.5055	0.0734	0.0084	**0.0615**
Real Exchange Rate	0.1298	0.1068	0.0425	0.1018	23.5440	0.1192	0.0127	**0.0933**
Unemployment	0.2056	0.1691	0.0579	0.1389	17.2689	0.0874	0.0148	**0.1083**
Import	0.1263	0.1039	0.0368	0.0883	27.1491	0.1374	0.0143	**0.1046**
Export	0.0627	0.0516	0.0360	0.0864	27.7584	0.1405	0.0072	**0.0531**
Oil Price	0.0964	0.0793	0.1153	0.2765	8.6714	0.0439	0.0035	**0.0255**
Total	1.2157	1.0000	0.4170	1.0000	197.5473	1.0000	0.1365	**1.0000**

Table 5.30 weights for the construction of Australia composite leading indicator for the Hong Kong Medium Tariff hotel category (AUS CLI MEDIUM)

AUS CLI MEDIUM								
(1) Selected economic variables	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
GDP	0.2382	0.2439	0.0184	0.0441	54.3358	0.2751	0.0671	**0.4688**
Exchange Rate	0.1096	0.1122	0.0411	0.0986	24.3142	0.1231	0.0138	**0.0965**
Share Price	0.0979	0.1002	0.0689	0.1653	14.5055	0.0734	0.0074	**0.0514**
Real Exchange Rate	0.1455	0.1490	0.0425	0.1018	23.5440	0.1192	0.0178	**0.1241**
Unemployment	0.1909	0.1955	0.0579	0.1389	17.2689	0.0874	0.0171	**0.1194**
Import	0.0591	0.0605	0.0368	0.0883	27.1491	0.1374	0.0083	**0.0581**
Export	0.0565	0.0579	0.0360	0.0864	27.7584	0.1405	0.0081	**0.0568**
Oil Price	0.0789	0.0808	0.1153	0.2765	8.6714	0.0439	0.0035	**0.0248**
Total	0.9766	1.0000	0.4170	1.0000	197.5473	1.0000	0.1431	**1.0000**

Figure 5.42 Comparison between the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) and the Taiwan composite leading indicator for the Hong Kong High Tariff A hotel category (TAI CLI HIGH A)

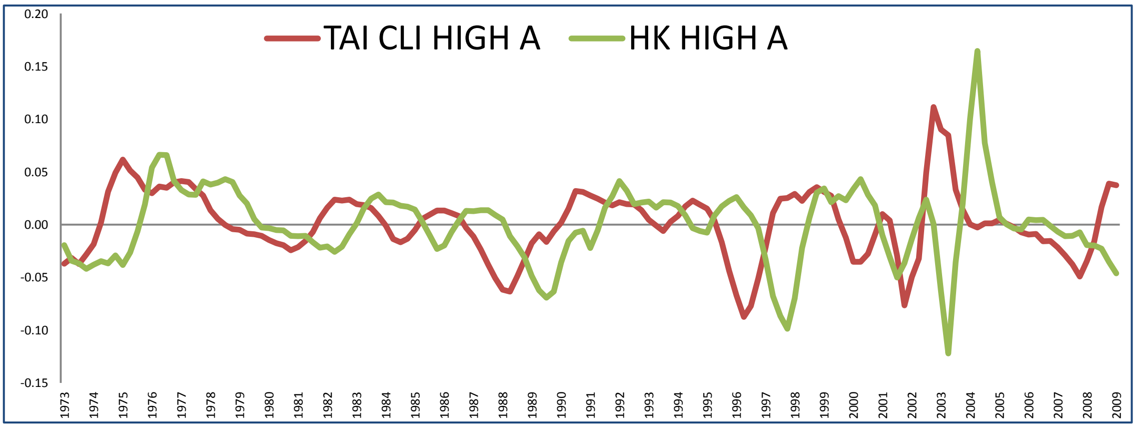


Figure 5.43 Comparison between the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) and the Taiwan composite leading indicator for the Hong Kong High Tariff B hotel category (TAI CLI HIGH B)

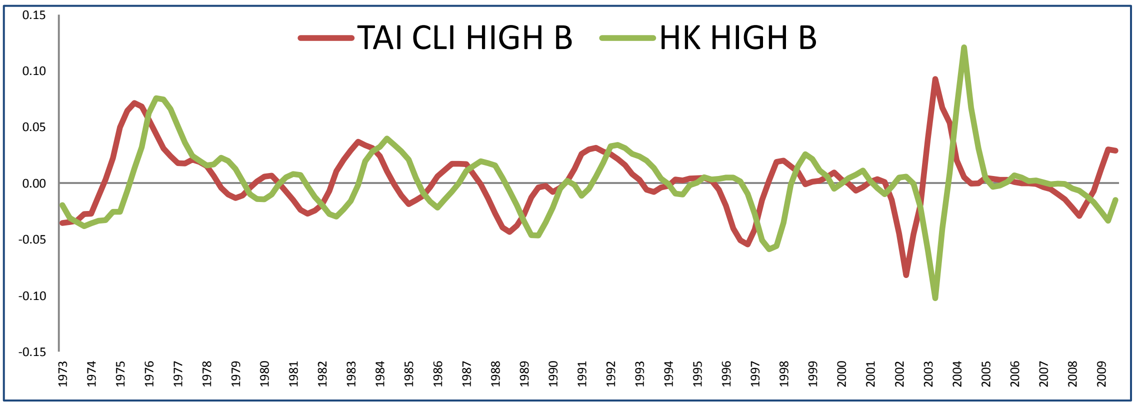


Figure 5.44 Comparison between The original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) and the Taiwan composite leading indicator for the Hong Kong Medium Tariff hotel category (TAI CLI MEDIUM)

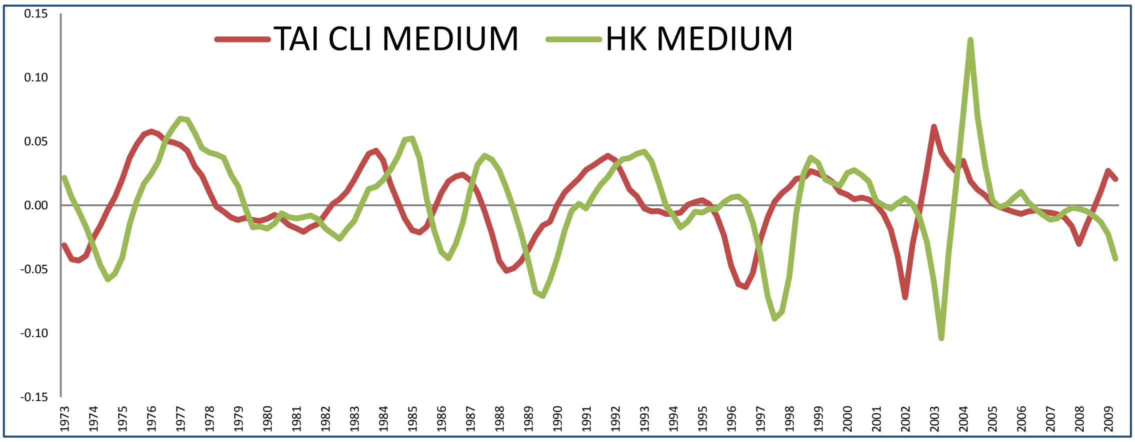


Figure 5.46 Comparison between the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) and the Japan composite leading indicator for the Hong Kong High Tariff A hotel category (JAP CLI HIGH A)

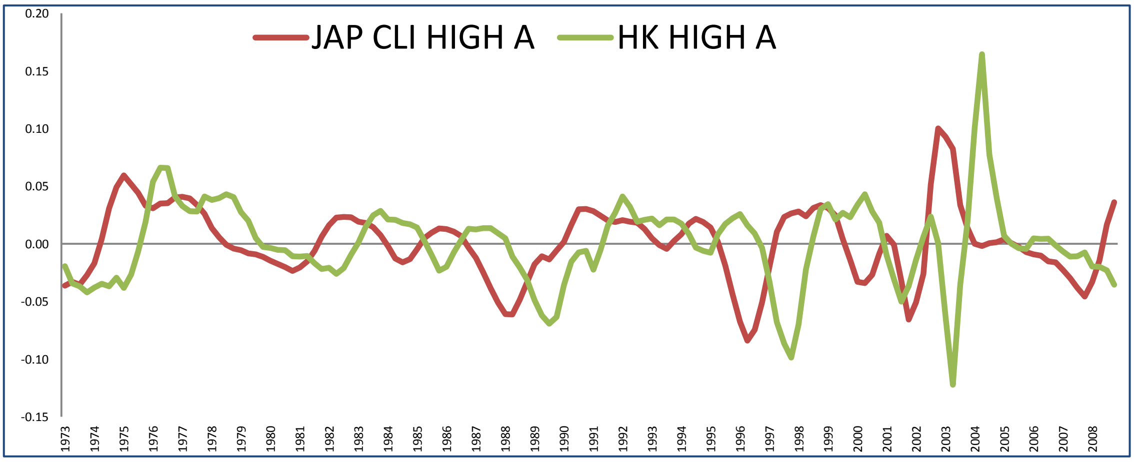


Figure 5.47 Comparison between the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) and the Japan composite leading indicator for the Hong Kong High Tariff B hotel category (JAP CLI HIGH B)

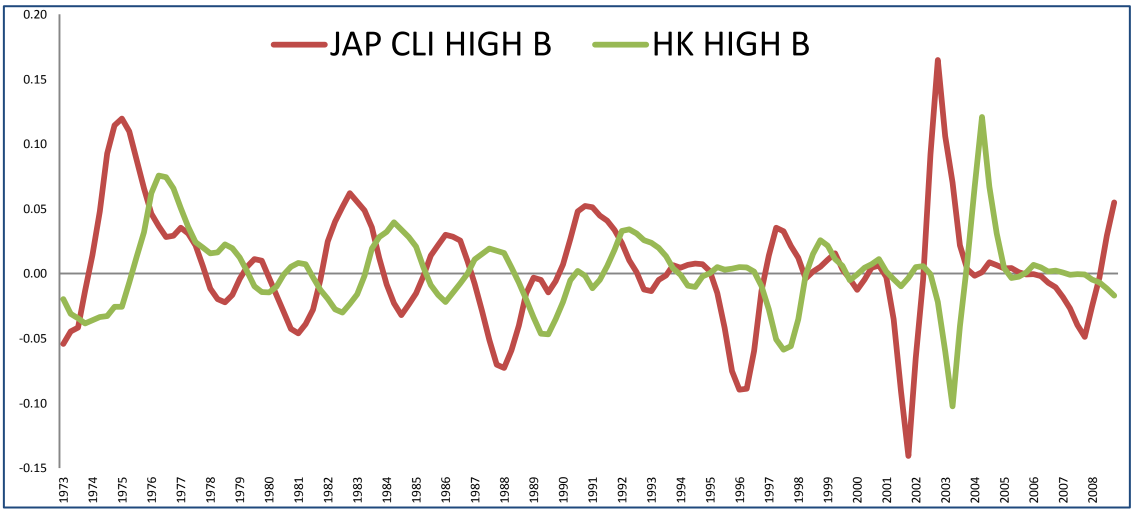


Figure 5.48 Comparison between the original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) and the Japan composite leading indicator for the Hong Kong Medium Tariff hotel category (JAP CLI MEDIUM)

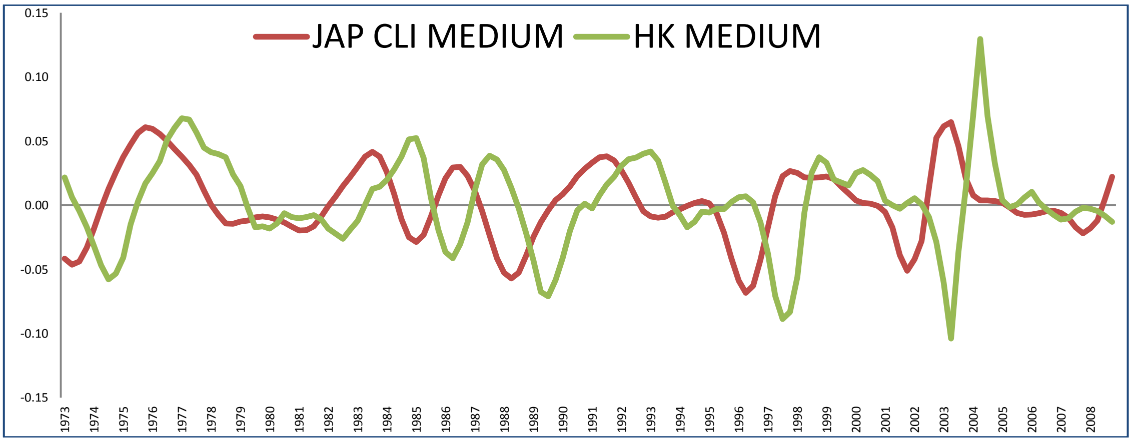


Figure 5.50 Comparison between the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) and the USA composite leading indicator for the Hong Kong High Tariff A hotel category (USA CLI HIGH A)

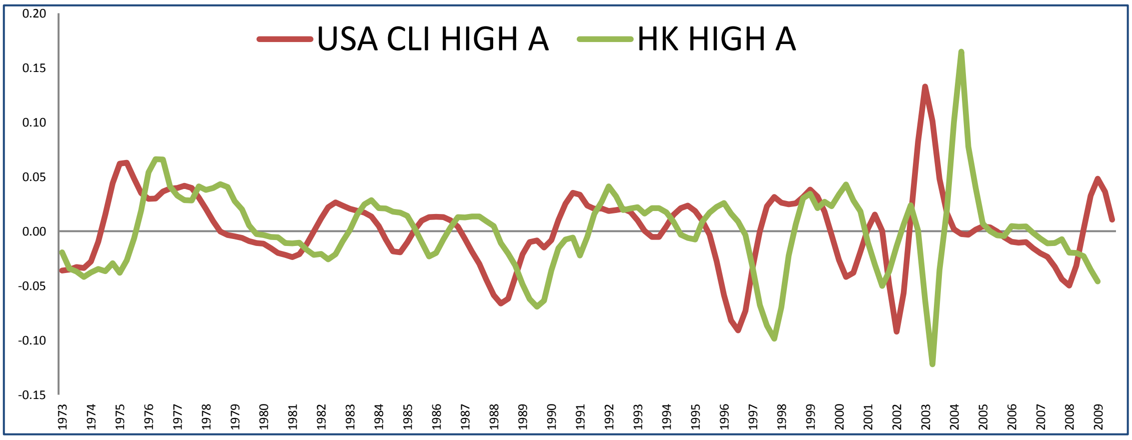


Figure 5.51 Comparison between the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) and the USA composite leading indicator for the Hong Kong High Tariff B hotel category (USA CLI HIGH B)

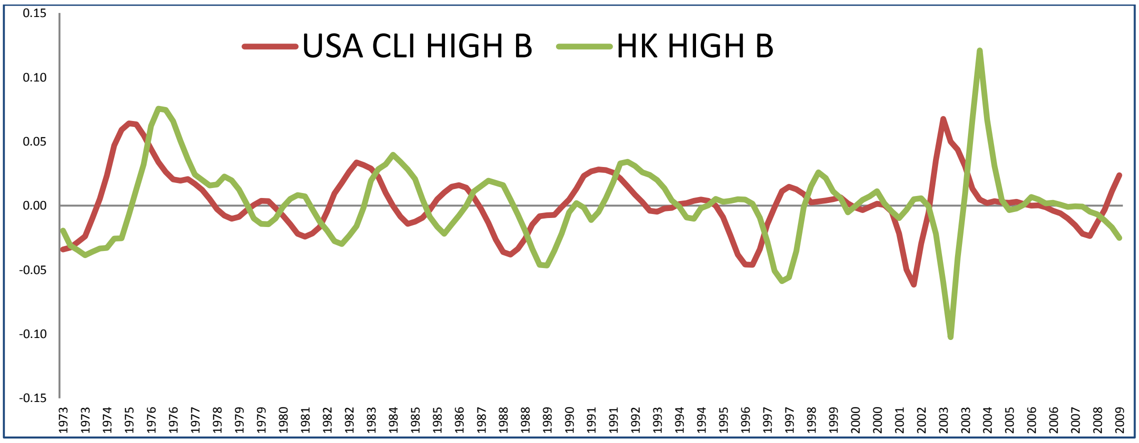


Figure 5.52 Comparison between the original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) and the USA composite leading indicator for the Hong Kong Medium Tariff hotel category (USA CLI MEDIUM)

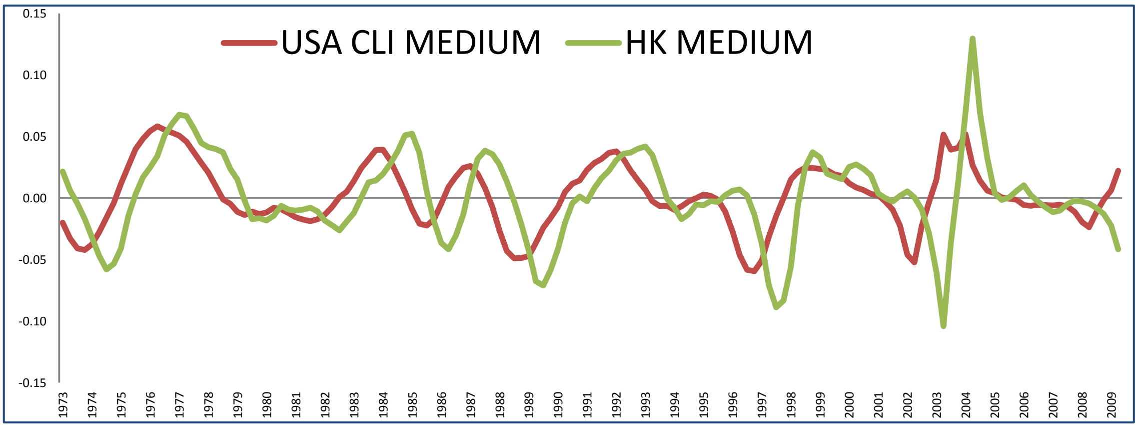


Figure 5.54 Comparison between the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) and the Australia composite leading indicator for the Hong Kong High Tariff A hotel category (AUS CLI HIGH A)

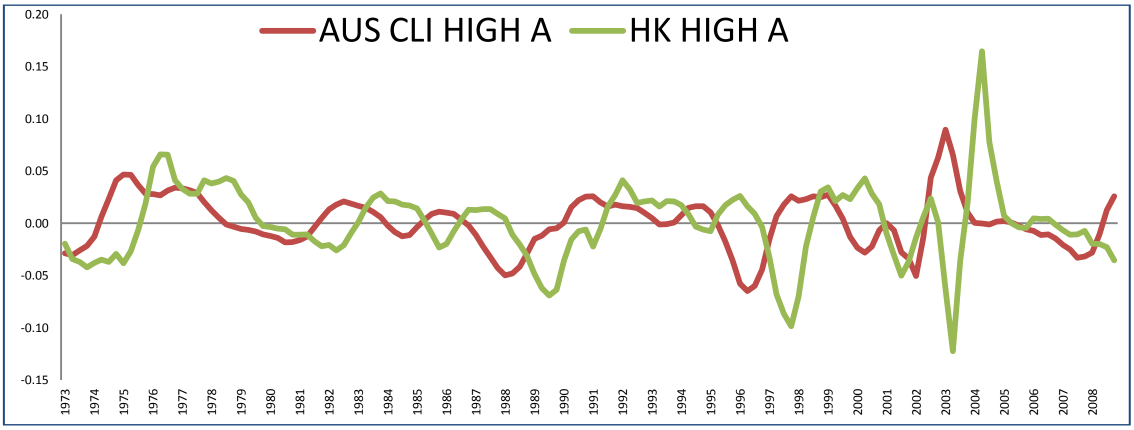


Figure 5.55 Comparison between the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) and the Australia composite leading indicator for the Hong Kong High Tariff B hotel category (AUS CLI HIGH B)

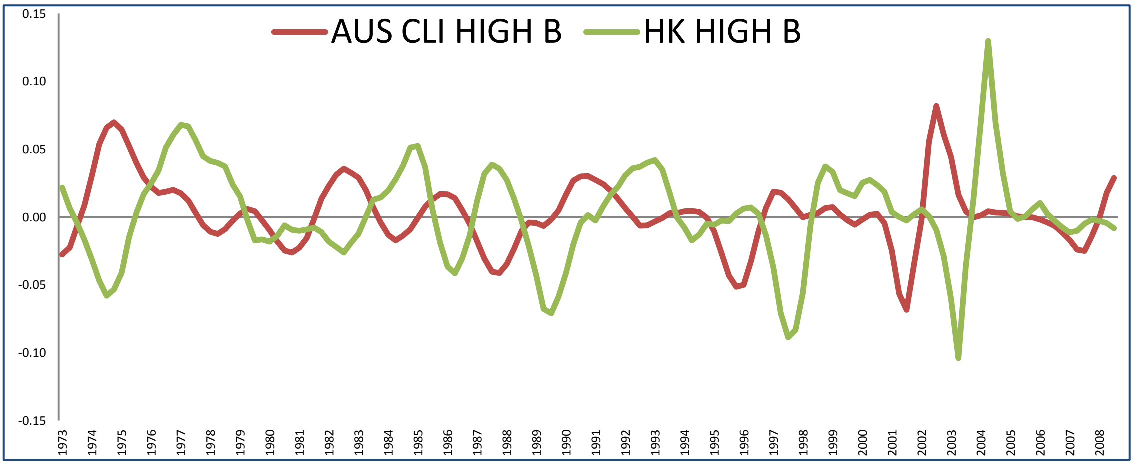
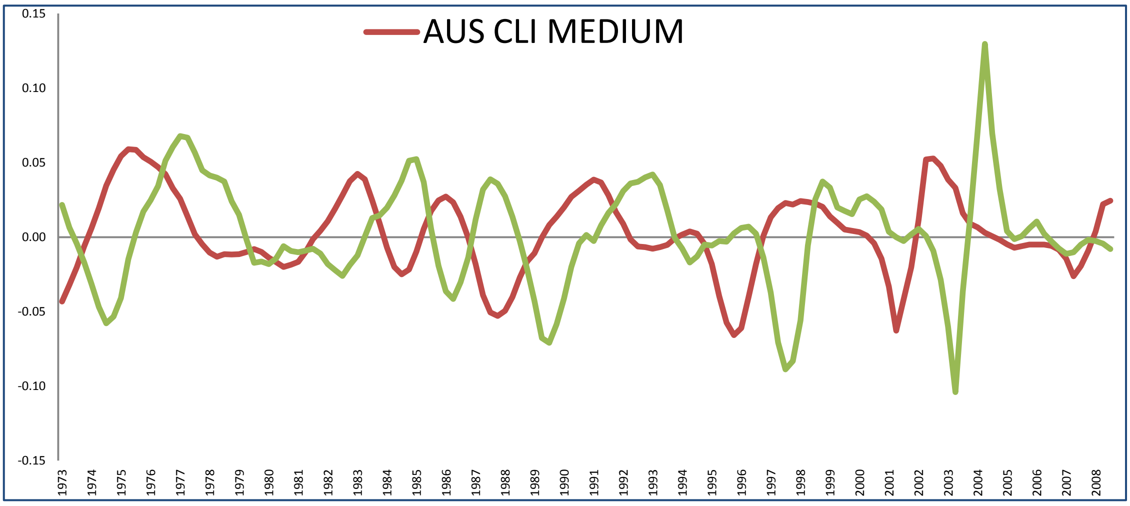


Figure 5.56 Comparison between the original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) and the Australia composite leading indicator for the Hong Kong Medium Tariff hotel category (AUS CLI MEDIUM)



Chapter 6

CONTRUCTING THE COMPOSITE LEADING INDICATOR FOR THE HONG KONG HOTEL INDUSTRY

6.1 Introduction

Chapter 5 has shown that in order to construct an unique composite leading indicator for the Hong Kong hotel industry, the composite leading indicators of the top five source market countries for Hong Kong overnight-stay arrivals must be similarly constructed. In this chapter, those countries' respective composite leading indicators will be combined to construct a composite leading indicator for each hotel category in Hong Kong.

In this study, two different weighting methods will be used for the construction of the composite leading indicators, namely, the coefficient of cross-correlation analysis and the market share of the Hong Kong overnight-stay tourists. After the composition, the peaks and troughs of the newly constructed composite indicator will be identified by Bry and Boschan's approach. The purpose of the composite leading indicator is to predict the peaks and troughs of the swings in the economy sufficiently far in advance so that parties and people concerned could react to the changing demand. The purpose of using different weighting methods to construct the composite leading indicator is to ascertain the usefulness of the different weighting methods in predicting the point estimate.

Further, the logistic and probit regression model will be estimated with the constructed composite leading indicator in order to predict turning points for the Hong Kong hotel industry. At this chapter's conclusion, the turning points' forecasting performance will compare both logistic and probit regression models estimated with the composite leading indicators.

6.2 Weighting method for the composite leading indicators

The constructed countries' composite leading indicators from the preceding chapter are combined with the economic variables of the top five source markets of Hong Kong's overnight-stay tourists. Those economic variables have been tested by Granger causality and confirmed as the leading economic variables for the hotel occupancy rate before their selection to construct the countries' composite leading indicators. Therefore, it is not necessary to run the causal relationship test again between the constructed countries' composite leading indicators with the original hotel occupancy data. As the result, the initial step is to develop a weighting method for the construction of the composite leading indicator. The present study uses two approaches to construct the composite leading indicator for the Hong Kong hotel industry, namely, the coefficient of the cross-correlation analysis and the market share of the top five countries of Hong Kong's overnight-stay tourist arrivals.

6.2.1 Weighting by the coefficient of the cross correlation analysis

The coefficient of the cross correlation is one of the weighting methods to construct the composite leading indicator; therefore, to find out the cross-correlation coefficient of each constructed country's composite leading indicator, the cross-correlation analysis will run between the original occupancy rate and the country's constructed composite leading indicators.

Haugh (1976) had warned that any misleading cross correlations could occur due to the autocorrelation of hotel occupancy growth rate or the indicator series. To eliminate this dilemma, the seasonal ARIMA models fitted to both series and cross-correlation coefficient of the residuals were examined. Only those variables that have been proved by the Granger causality test will get through to this stage and be examined. The EView program can help to find out the coefficients of cross correlation of each selected variable as well as the best-fit lead time for each variable.

6.2.2 Weighting by the Market share of Hong Kong overnight stay tourists

The HKTB classifies total tourist arrivals into two categories, namely, overnight visitors and same-day in-town visitors. The latter are also referred to as transit visitors, with special interests in visiting Hong Kong such as shopping, without the need to spend the night. Such tourists still contribute to the Hong Kong tourism economy. However, same-day in-town visitors do not use any accommodation facilities in Hong Kong. Consequently, the origin countries chosen to construct the countries' composite leading indicators are based on the market share of the top five countries' overnight-stay visitor arrivals in Hong Kong. These countries are China, Taiwan, Japan, the United States, and Australia. The total market share of these five countries comprises 75% of the total overnight-stay visitor arrival in Hong Kong (HKTB, 2011).

Given the high contribution of these top five countries, the present study will use their market share as a second weighting method to construct the composite leading indicator. This is the first attempt in a tourism forecasting study to use the market share of tourist arrivals as a weighting approach to construct the composite leading indicators. Table 6.1 summarizes the two weighting methods.

Table 6.1 Summary for the weighting methods; the number in brackets is the significance lead time for each constructed country's composite leading indicator

Countries' composite leading indicator	MS	HK Total	HK High A	HK High B	HK Medium
		CC			
China	59.5	(1) 0.7578	(3) 0.9887	(3) 0.5119	(2) 0.2818
Taiwan	4.8	(5) 0.9041	(2) 0.2012	(4) 0.9471	(5) 0.7806
Japan	4.7	(5) 0.5099	(1) 0.2575	(3) 0.1624	(2) 0.4815
USA	3.8	(5) 0.5603	(5) 0.4903	(3) 0.5836	(2) 0.5564
Australia	2.9	(5) 0.2344	(5) 0.5450	(4)0.3477	(4) 0.3083

HK TOTAL is the Hong Kong (Total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CC is the weighting method of the coefficient of cross-correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrivals in Hong Kong.

6.3 The weighting approach

To combine the constructed countries' composite leading indicators into one constructed composite leading indicator for the Hong Kong hotel industry, the Niemira and Klein (1994) approach will be used again to construct the composite leading indicator and sum up the changes for individual composite while accounting for the component's importance and volatility.

$$\boldsymbol{\Delta_4 Composite = \sum w_i \sigma_i \, \Delta_4 \, (component)_{1+S-x_i}}$$

where i = 1 to n, the maximum number of components; w is the component's weight, which represents the component's relative importance assessed by the coefficient of cross correlation and the market share of the Hong Kong overnight-stay visitor arrivals; σ is the standardized weight, which is calculated from the inverse value of the volatility measure, the average absolute deviation around the average growth rate to minimize the influence of highly volatile series on the composite leading indicator; s is the short lead time in the number of quarters among the n indicators; and x_i is the lead time of the indicator.

6.3.1 Weighting table by the coefficient of cross correlation analysis

Tables 6.2 to 6.5 show the calculated weights for different hotel categories in Hong Kong from the coefficient of the cross-correlation analysis using Niemira and Klein's (1994) approach. The finalized weighting is used to construct the composite leading indicator for different hotel categories in Hong Kong accordingly.

Table 6.2 Weights for the construction of composite leading indicator for the Hong Kong (Total) hotel category from the coefficient of the cross-correlation analysis (HK TOTAL CC)

HK TOTAL CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.7578	0.2555	0.0227	0.2147	44.0867	0.1857	0.0474	**0.2412**
Taiwan	0.9041	0.3048	0.0216	0.2045	46.2908	0.1949	0.0594	**0.3022**
Japan	0.5099	0.1719	0.0197	0.1865	50.7481	0.2137	0.0367	**0.1868**
USA	0.5603	0.1889	0.0220	0.2085	45.3875	0.1911	0.0361	**0.1836**
Australia	0.2344	0.0790	0.0196	0.1858	50.9452	0.2145	0.0170	**0.0862**
Total	2.9665	1.0000	0.1057	1.0000	237.4583	1.0000	0.1966	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.
Apply to Table 6.2 to 6.5

Table 6.3 Weights for the construction of composite leading indicator for Hong Kong High Tariff A hotel category by the coefficient of the cross-correlation analysis (HK HIGH A CC)

HK HIGH A CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.9887	0.3982	0.0267	0.2235	37.4885	0.1769	0.0705	**0.3573**
Taiwan	0.2012	0.0810	0.0243	0.2040	41.0712	0.1938	0.0157	**0.0797**
Japan	0.2575	0.1037	0.0238	0.1992	42.0485	0.1985	0.0206	**0.1044**
USA	0.4903	0.1975	0.0252	0.2108	39.7303	0.1875	0.0370	**0.1878**
Australia	0.5450	0.2195	0.0194	0.1625	51.5403	0.2433	0.0534	**0.2708**
Total	2.4827	1.0000	0.1194	1.0000	211.8787	1.0000	0.1972	**1.0000**

Table 6.4 Weights for the construction of composite leading indicator for Hong Kong High Tariff B hotel category by the coefficient of the cross-correlation analysis (HK HIGH B CC)

HK HIGH B CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.5119	0.2005	0.0194	0.1902	51.6755	0.2005	0.0402	**0.1903**
Taiwan	0.9471	0.3710	0.0183	0.1802	54.5332	0.2116	0.0785	**0.3716**
Japan	0.1624	0.0636	0.0302	0.2973	33.0623	0.1283	0.0082	**0.0386**
USA	0.5836	0.2286	0.0165	0.1618	60.7418	0.2357	0.0539	**0.2551**
Australia	0.3477	0.1362	0.0173	0.1704	57.6726	0.2238	0.0305	**0.1443**
Total	2.5527	1.0000	0.1017	1.0000	257.6854	1.0000	0.2113	**1.0000**

Table 6.5 Weights for the construction of composite leading indicator for Hong Kong Medium Tariff hotel category by the coefficient of the cross-correlation analysis (HK MEDIUM CC)

HK MEDIUM CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.2818	0.1170	0.0237	0.2199	42.1529	0.1814	0.0212	**0.1048**
Taiwan	0.7806	0.3241	0.0206	0.1912	48.4964	0.2086	0.0676	**0.3340**
Japan	0.4815	0.1999	0.0220	0.2041	45.4305	0.1955	0.0391	**0.1930**
USA	0.5564	0.2310	0.0206	0.1910	48.5412	0.2088	0.0482	**0.2383**
Australia	0.3083	0.1280	0.0209	0.1939	47.8090	0.2057	0.0263	**0.1300**
Total	2.4086	1.0000	0.1079	1.0000	232.4299	1.0000	0.2025	**1.0000**

6.3.2 Weighting Table by the Market Share of the Overnight-stay Tourist Arrivals

Table 6.6 to 6.10 shows the weights for different hotel categories in Hong Kong by the coefficient of the market share of the overnight say tourist arrival in Hong Kong after the transformation of the Niemira & Klein (1994) approach. The calculated weight will be used to construct the composite leading indicator for different hotel categories in Hong Kong accordingly.

Table 6.6 Weights for the construction of composite leading indicator for Hong Kong (Total) hotel category by the market share of overnight-stay tourist arrivals (HK TOTAL MS)

HK TOTAL MS								
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Country	Coefficient of the cross correlation	Converted percentage of assigned Weight	Average of the Absolute Average Deviation	Converted percentage of the Absolute Average Deviation	Inverse of the Absolute Average Deviation	Converted percentage of Inverse of the Absolute Average Deviation	Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	Converted Percentage of Finalized weighting
China	59.5	0.7860	0.0227	0.2147	44.0867	0.1857	0.1459	**0.7873**
Taiwan	4.8	0.0634	0.0216	0.2045	46.2908	0.1949	0.0124	**0.0667**
Japan	4.7	0.0621	0.0197	0.1865	50.7481	0.2137	0.0133	**0.0716**
USA	3.8	0.0502	0.0220	0.2085	45.3875	0.1911	0.0096	**0.0518**
Australia	2.9	0.0196	0.0196	0.1858	50.9452	0.2145	0.0042	**0.0227**
Total	75.7	0.9813	0.1057	1.0000	237.4583	1.0000	0.1854	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.
Apply to Table 6.6 to 6.9

Table 6.7 Weights for the construction of composite leading indicator for Hong Kong High Tariff A hotel category by the market share of overnight-stay tourist arrivals (HK HIGH A MS)

HK HIGH A MS								
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Country	Coefficient of the cross correlation	Converted percentage of assigned Weight	Average of the Absolute Average Deviation	Converted percentage of the Absolute Average Deviation	Inverse of the Absolute Average Deviation	Converted percentage of Inverse of the Absolute Average Deviation	Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	Converted Percentage of Finalized weighting
China	59.5	0.7860	0.0267	0.2235	37.4885	0.1769	0.1391	**0.7821**
Taiwan	4.8	0.0634	0.0243	0.2040	41.0712	0.1938	0.0123	**0.0691**
Japan	4.7	0.0621	0.0238	0.1992	42.0485	0.1985	0.0123	**0.0693**
USA	3.8	0.0502	0.0252	0.2108	39.7303	0.1875	0.0094	**0.0529**
Australia	2.9	0.0194	0.0194	0.1625	51.5403	0.2433	0.0047	**0.0265**
Total	75.7	0.9811	0.1194	1.0000	211.8787	1.0000	0.1778	**1.0000**

Table 6.8 Weights for the construction of composite leading indicator for Hong Kong High Tariff B hotel category by the market share of overnight-stay tourist arrivals (HK HIGH B MS)

HK HIGH B MS								
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Country	Coefficient of the cross correlation	Converted percentage of assigned Weight	Average of the Absolute Average Deviation	Converted percentage of the Absolute Average Deviation	Inverse of the Absolute Average Deviation	Converted percentage of Inverse of the Absolute Average Deviation	Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	Converted Percentage of Finalized weighting
China	59.5	0.7860	0.0194	0.1902	51.6755	0.2005	0.1576	**0.7904**
Taiwan	4.8	0.0634	0.0183	0.1802	54.5332	0.2116	0.0134	**0.0673**
Japan	4.7	0.0621	0.0302	0.2973	33.0623	0.1283	0.0080	**0.0399**
USA	3.8	0.0502	0.0165	0.1618	60.7418	0.2357	0.0118	**0.0593**
Australia	2.9	0.0383	0.0173	0.1704	57.6726	0.2238	0.0086	**0.0430**
Total	75.7	1.0000	0.1017	1.0000	257.6854	1.0000	0.1994	**1.0000**

Table 6.9 Weights for the construction of composite leading indicator for Hong Kong Medium Tariff hotel category by the market share of overnight-stay tourist arrivals (HK MEDIUM MS)

HK MEDIUM MS								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	59.5	0.7860	0.0237	0.2199	42.1529	0.1814	0.1425	**0.7652**
Taiwan	4.8	0.0634	0.0206	0.1912	48.4964	0.2086	0.0132	**0.0710**
Japan	4.7	0.0621	0.0220	0.2041	45.4305	0.1955	0.0121	**0.0651**
USA	3.8	0.0502	0.0206	0.1910	48.5412	0.2088	0.0105	**0.0563**
Australia	2.9	0.0383	0.0209	0.1939	47.8090	0.2057	0.0079	**0.0423**
Total	75.7	1.0000	0.1079	1.0000	232.4299	1.0000	0.1863	**1.0000**

6.4 Constructed composite leading indicator for Hong Kong Hotels

After the calculation of the weighting by the two different methods, the composite leading indicators for each hotel category in Hong Kong is constructed respectively. Figure 6.1 below compares the results of the original growth of hotel occupancy rate with the newly constructed composite leading indicators. A visual examination shows that all the composite leading indicators, by different weighting methods, are leading the original occupancy rate.

Figure 6.1 Comparison of the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) with the constructed composite leading indicator by coefficient of the cross correlation (HK TOTAL CLI CC) and the constructed composite leading indicator by the market share of the overnight-stay visitor arrivals (HK TOTAL CLI MS)

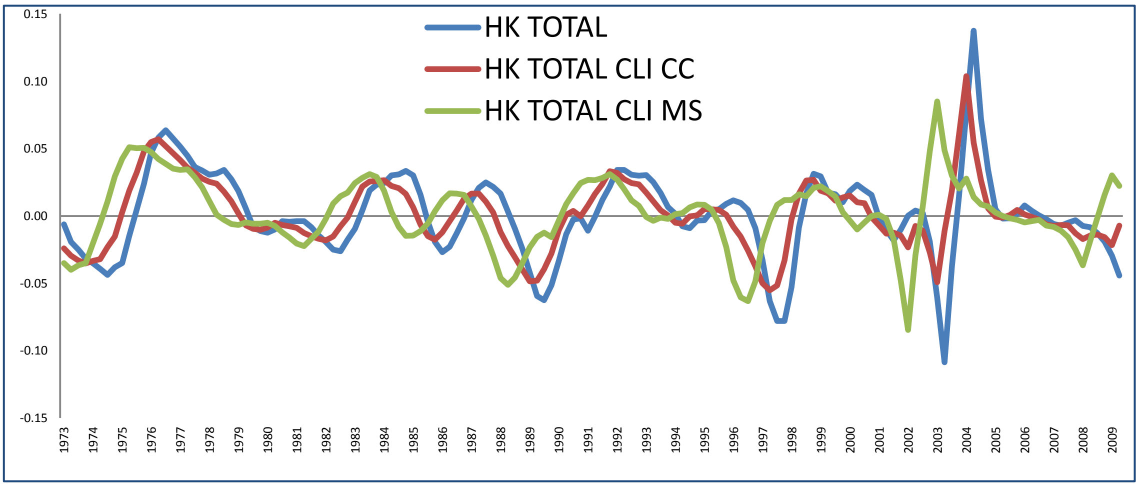


Figure 6.2 Comparison of the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) with the constructed composite leading indicator by coefficient of the cross correlation (HK HIGH A CLI CC) and the constructed composite leading indicator by the market share of the overnight-stay visitor arrivals (HK HIGH A CLI MS)

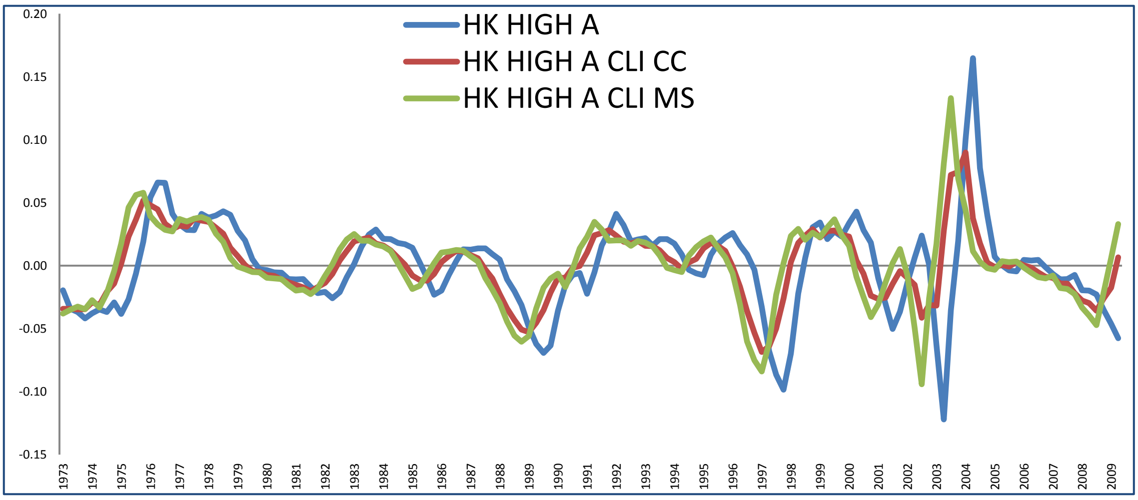


Figure 6.3 Comparison of the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) with the constructed composite leading indicator by coefficient of the cross correlation (HK HIGH B CLI CC) and the constructed composite leading indicator by the market share of the overnight-stay visitor arrivals (HK HIGH B CLI MS)

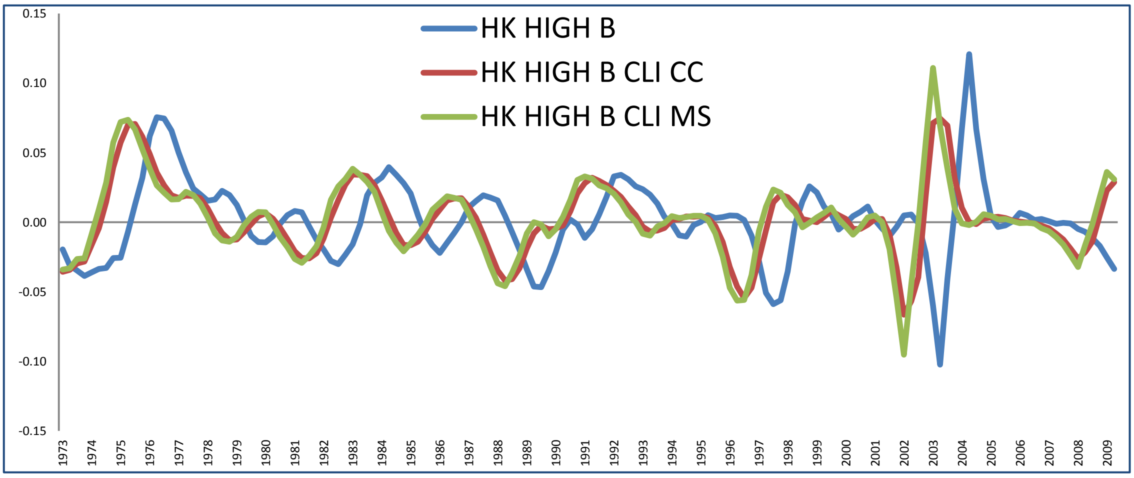
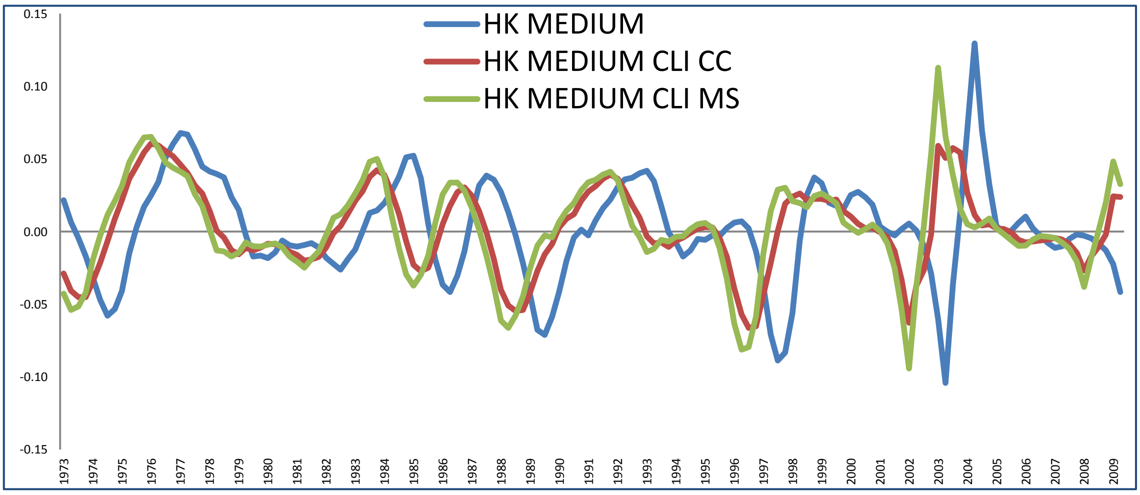


Figure 6.4 Comparison of the original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) with the constructed composite leading indicator by coefficient of the cross correlation (HK MEDIUM CLI CC) and the constructed composite leading indicator by the market share of the overnight-stay visitor arrivals (HK MEDIUM CLI MS)



6.5 Lead time of the Constructed composite leading indicator

After the construction of the composite leading indicators for Hong Kong hotel industry, the cross correlation analysis is run again between the newly constructed composite leading indicator and the original growth of the hotel occupancy rate. The cross correlation analysis can check the correlation as well as the lead time of the newly constructed composite leading indicator with the original growth of the hotel occupancy rate. The seasonal ARIMA models were fitted to both series and cross-correlation coefficient of the residuals are examined.

The constructed composite leading indicator by the weighting method of coefficient of cross correlation lead the original hotel occupancy rate by 1 quarter for the Hong Kong (total) hotel category; 1 quarter for the High Tariff A hotel; 5 quarters for the High tariff B hotel and 2 quarters for the Medium Tariff hotel in Hong Kong. Whereas the constructed composite leading indicator by the weighting method of the market share for the overnight stay visitor arrivals in Hong Kong lead the original hotel occupancy rate by 3 quarters for the Hong Kong (total) hotel category; 2 quarter for the High Tariff A hotel; 3 quarters for the High tariff B hotel and 3 quarters for the Medium Tariff hotel in Hong Kong. Table 6.10 shows the summary of the result from the cross correlation analysis. The different lead times provided by the two weighting methods provide hoteliers a different scope of information when they make decisions on investment, planning and risk management in a medium to long run.

Table 6.10 Summary of the results from the cross-correlation analysis between the growth of the Hong Kong hotel occupancy rate and the newly constructed composite leading indicator; the number in brackets is the best-fit lead time of the constructed composite leading indicators lead the original occupancy rate

	Hong Kong hotel category			
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM
CLI CC	**(1) 0.5802**	**(1) 0.6289**	**(5) 0.7776**	**(2) 0.4958**
CLI MS	**(3) 0.4664**	**(2) 0.7548**	**(3) 0.5257**	**(3) 0.5504**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator.
CC is the weighting method of the coefficient of cross correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival in Hong Kong.

6.6 Dating the Turning Points

Originally, in the Bry and Boschan (1971) set, if Y_t represents the peak in the growth rate cycle, the value of Y_s will be such that $s < t$ or $s > t$. Following the discussion in Chapter 2, Bry and Boschan's approach (1971) will be adopted with a slight change from the approach of Leasge (1991). That means in the present study, $k=3$ will be applied because the high volatility patterns of the hotel occupancy growth rate data were used.

The downturn (DT) and upturn (UT) are defined below:

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

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

Note that Y_{t-3}, Y_{t-2} and Y_{t-1} are the past values of the growth rate, and Y_{t+1}, Y_{t+2} and Y_{t+3} are the future values of the growth rate.

Identifying turns in the constructed composite leading indicator from the coefficient of cross-correlation analysis

Figure 6.5 The constructed composite leading indicator of the Hong Kong (Total) hotel category by coefficient of the cross correlation (HK TOTAL CLI CC) with the identification of peak (P) and trough (T)

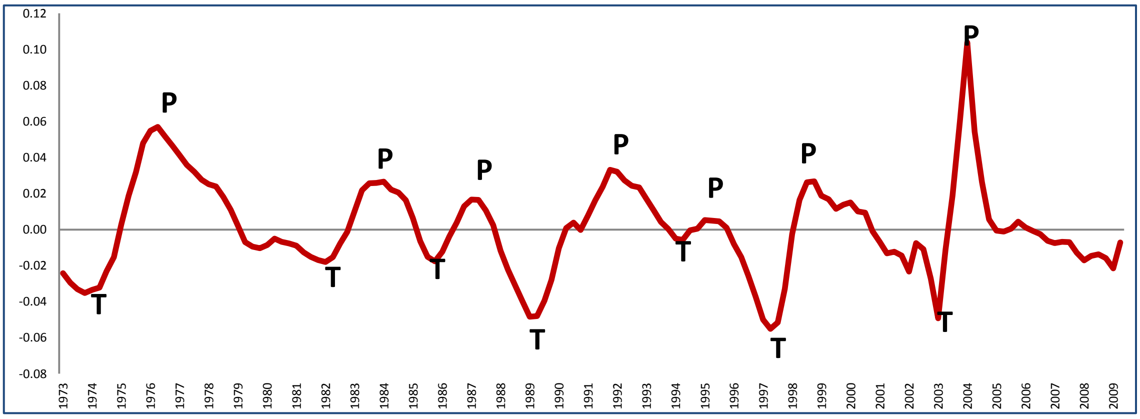


Figure 6.6 The constructed composite leading indicator of the Hong Kong High Tariff A hotel category by coefficient of the cross correlation (HK HIGH A CLI CC) with the identification of peak (P) and trough (T)

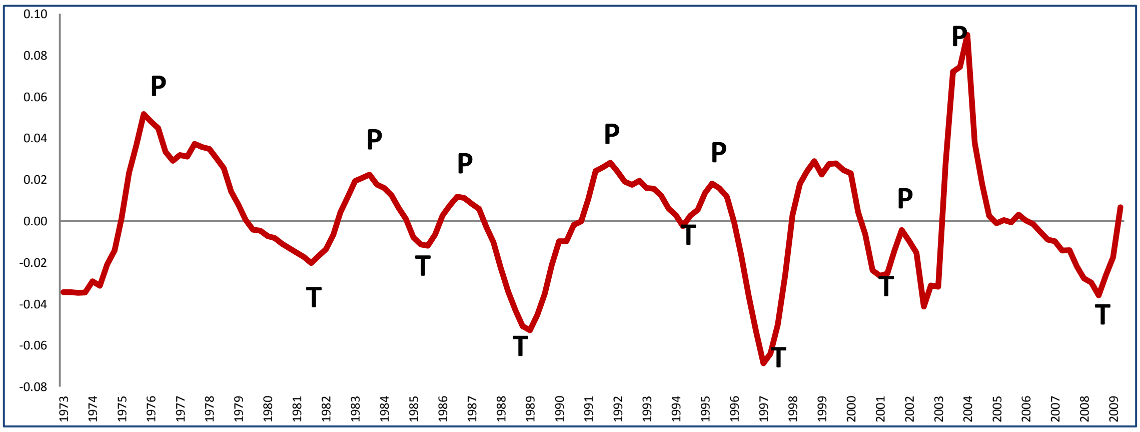


Figure 6.7 The constructed composite leading indicator of the Hong Kong High Tariff B hotel category by coefficient of the cross correlation (HK HIGH B CLI CC) with the identification of peak (P) and trough (T)

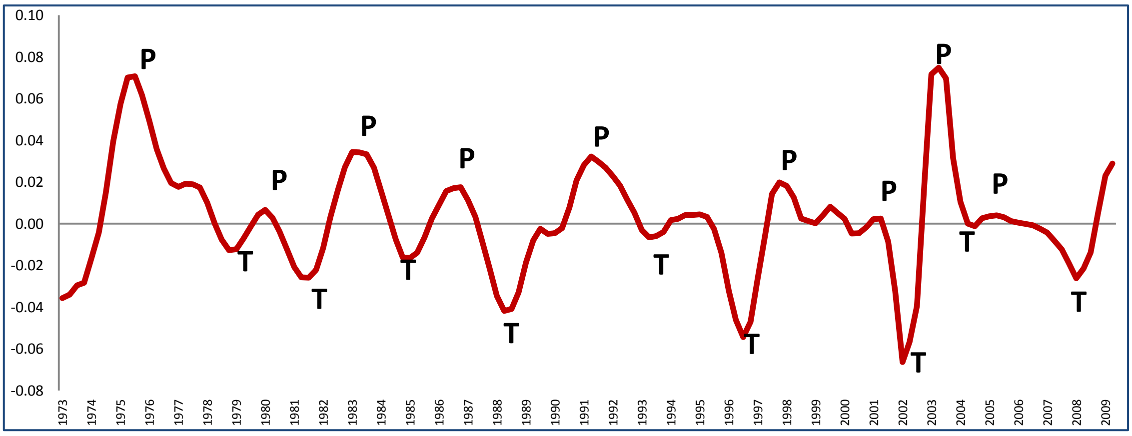
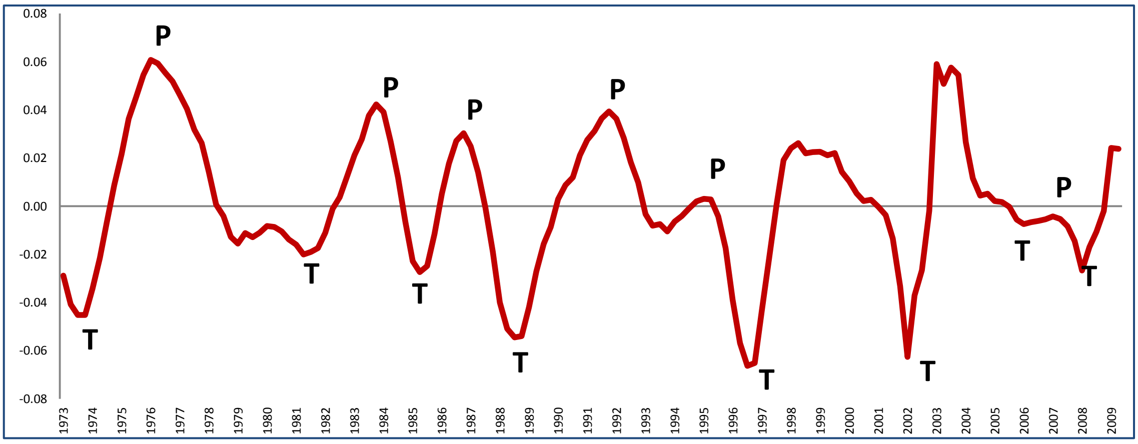


Figure 6.8 The constructed composite leading indicator of the Hong Kong Medium Tariff hotel category by coefficient of the cross correlation (HK MEDIUM CLI CC) with the identification of peak (P) and trough (T)



Identify turns in the constructed composite leading indicator from the market share of the overnight stay visitor arrivals

Figure 6.9 The constructed composite leading indicator of the Hong Kong (Total) hotel category by market share of the overnight-stay visitor arrivals (HK TOTAL CLI MS) with the identification of peak (P) and trough (T)

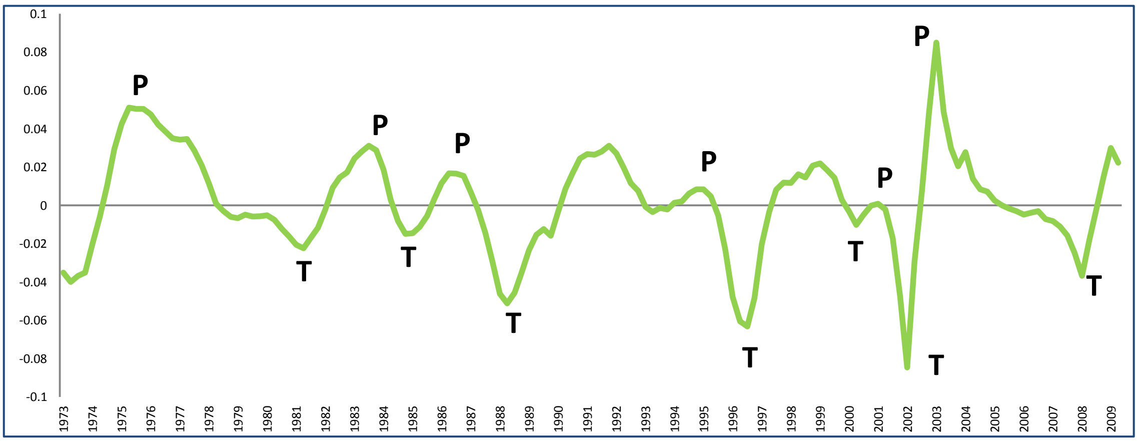


Figure 6.10 The constructed composite leading indicator of the Hong Kong High Tariff A hotel category by market share of the overnight-stay visitor arrivals (HK HIGH A CLI MS) with the identification of peak (P) and trough (T)

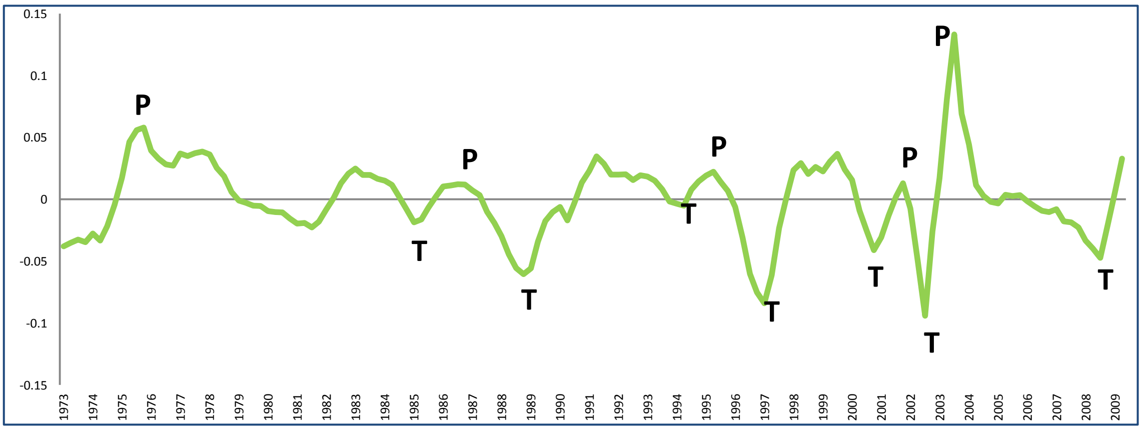


Figure 6.11 The constructed composite leading indicator of the Hong Kong High Tariff B hotel category by market share of the overnight-stay visitor arrivals (HK HIGH B CLI MS) with the identification of peak (P) and trough (T)

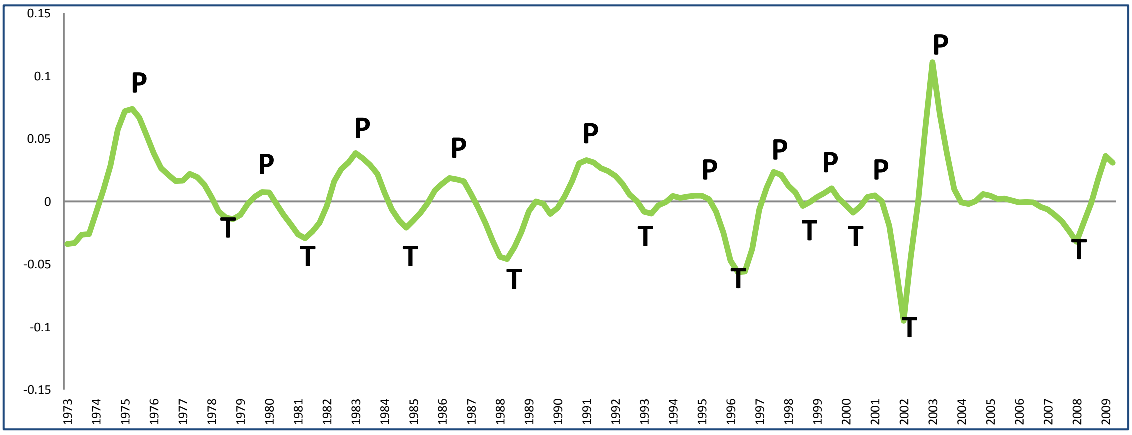
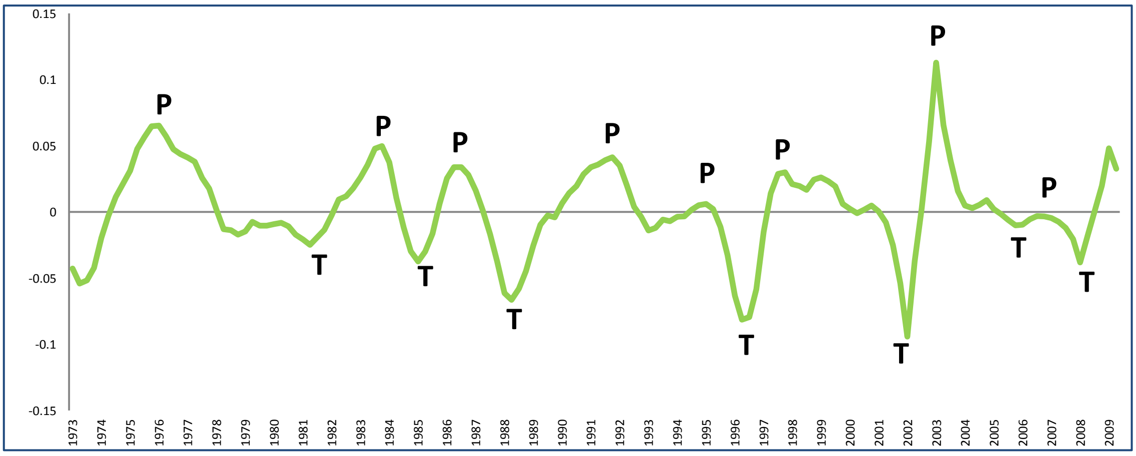


Figure 6.12 The constructed composite leading indicator of the Hong Kong Medium Tariff hotel category by market share of the overnight-stay visitor arrivals (HK MEDIUM CLI MS) with the identification of peak (P) and trough (T)



6.7 Logistic and Probit regression models

Logistic and probit regression models are generalized linear econometric models commonly used in macroeconomics and finance to predict the turning points. Kulendran and Wong (2010) proved that logistic and probit regression models could also be used in tourism forecasting. In this section, after the construction of composite leading indicators, logistic and probit regression models will estimate with the composite leading indicators, which had been constructed by the economic variables from the Hong Kong top five overnight-stay tourist-origin countries.

Logistic and probit regression models are based on making a prediction of the probability that an incident will happen (p = 1) or will not happen (p = 0) in the future. In this study, 1 will represent the expansion period and 0 will represent the contraction period in the dependent variable, which is the Hong Kong hotel occupancy growth rate.

The logistic regression model is used for predicting the probability of occurrence of an incident by fitting data to a logistic function curve. In the model, the dependent variable is the logarithm of the ratio of the probability that a particular event will happen to the probability that the event will not happen. The probit regression model is an estimation method with dummy variables used as variants of cumulative normal distribution. The binary probit model is based on the cumulative distribution function. If the cumulative distribution of the error term (e) is normal, then the model is called a probit regression model.

The logistic regression equation with composite leading indicators:

$$\mathrm{Ln}\left[\frac{\mathrm{P_{it}}}{(1-\mathrm{P_{it}})}\right] = \beta_o + \beta_1 \mathrm{CLI}_{t-k}$$

The probit regression equation with composite leading indicators:

$$\mathrm{P_{it}} = \beta_o + \beta_1 \mathrm{CLI}_{t-k}$$

where k is the lead time of the composite leading indicator; CLI is the constructed composite leading indicator from the selected economic variables for Hong Kong hotels; P_{it} is the probability that the particular outcome of expansion (1) will occur in time t; and 1-P_{it} is the probability that the particular outcome of contraction (0) occur in time t.

The estimated logistic and probit regression models with the constructed composite leading indicators for different hotel categories in Hong Kong are shown in Tables 6.11 and 6.12. All the estimated models are valid because LR statistics are significant at the 5% level.

Table 6.11 Estimated logistic models with the constructed composite leading indicator; sample period: Q2 1973 to Q2 2009

	Estimated regression logistic models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean of CLI
HK TOTAL CLI CC LG	**$Ln(P_{it}/(1-P_{it}))$ = -0.903 + 22.166HK_TOTAL_CCLI_CC_LG$_{t-1}$ (z = -4.737) (z = 2.809)**	145	8.749	0.003	0.049	0.001445
HK TOTAL CLI MS LG	**$Ln(P_{it}/(1-P_{it}))$ = -1.019 + 38.644HK_TOTAL_CCLI_MS_LG$_{t-3}$ (z = -4.822) (z = 4.059)**	143	21.591	0.000	0.122	0.001850
HK HIGH A CLI CC LG	**$Ln(P_{it}/(1-P_{it}))$ = -0.530 + 22.474HK_HIGHA_CCLI_CC_LG$_{t-1}$ (z = -2.961) (z = 3.090)**	145	10.827	0.001	0.056	-0.000064
HK HIGH A CLI MS LG	**$Ln(P_{it}/(1-P_{it}))$ = -0.559 + 21.570HK_HIGHA_CCLI_MS_LG$_{t-2}$ (z = -3.078) (z = 4.175)**	144	12.212	0.000	0.064	0.000344
HK HIGH B CLI CC LG	**$Ln(P_{it}/(1-P_{it}))$ = -0.432 + -14.370HK_HIGHB_CCLI_CC_LG$_{t-5}$ (z = -2.471) (z = -1.959)**	141	4.098	0.043	0.022	0.002114
HK HIGH B CLI MS LG	**$Ln(P_{it}/(1-P_{it}))$ = -0.637 + 51.360HK_HIGHB_CCLI_MS_LG$_{t-3}$ (z = -3.173) (z = 4.634)**	143	35.604	0.000	0.186	0.002464
HK MEDIUM CLI CC LG	**$Ln(P_{it}/(1-P_{it}))$ = -0.243 + 46.448HK_MEDIUM_CCLI_CC_LG$_{t-2}$ (z = -1.257) (z = 5.139)**	144	39.177	0.000	0.197	0.001614
HK MEDIUM CLI MS LG	**$Ln(P_{it}/(1-P_{it}))$ = -0.256 + 47.971HK_MEDIUM_CCLI_MS_LG$_{t-3}$ (z = -1.285) (z = 5.193)**	143	44.83	0.000	0.227	0.002005

n is the number of observations.
The LR statistic tests joint hypothesis is all slope coefficients except the constant are zero.
Prob(LR Statistic) is the p value of the LR statistic.
R^2_{McF} is the McFadden R-squared.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator.
CC is the weighting method of the coefficient of cross correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival in Hong Kong.
LG is the logistic regression model.
PB is the probit regression model.
Apply to table 6.11 and 6.12.

Table 6.12 Estimated probit models constructed composite leading indicator; sample period: Q2 1973 to Q2 2009

	Estimated regression probit models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean of CLI
HK TOTAL CLI CC PB	**P_{it} = -0.552 + 13.429HK_TOTAL_CCLI_CC_PB$_{t-1}$ (z = -4.892) (z = 2.868)**	145	8.781	0.003	0.049	0.001445
HK TOTAL CLI MS PB	**P_{it} = -0.623 + 23.795HK_TOTAL_CCLI_MS_PB$_{t-3}$ (z = -5.051) (z = 4.237)**	143	22.227	0.000	0.260	0.001850
HK HIGH A CLI CC PB	**P_{it} = -0.323 + 13.871HK_HIGHA_CCLI_CC_PB$_{t-1}$ (z = -2.970) (z = 3.154)**	145	10.852	0.001	0.056	-0.000064
HK HIGH A CLI MS PB	**P_{it} = -0.340 + 13.296HK_HIGHA_CCLI_MS_PB$_{t-2}$ (z = -3.098) (z = 3.273)**	144	12.317	0.000	0.065	0.000344
HK HIGH B CLI CC PB	**P_{it} = -0.268 + -8.713HK_HIGHB_CCLI_CC_PB$_{t-5}$ (z = -2.479) (z = -1.985)**	141	4.055	0.044	0.022	0.002114
HK HIGH B CLI MS PB	**P_{it} = -0.380 + 30.013HK_HIGHB_CCLI_MS_PB$_{t-3}$ (z = -3.214) (z = 5.006)**	143	35.487	0.000	0.185	0.002464
HK MEDIUM CLI CC PB	**P_{it} = -0.159 + 28.067HK_MEDIUM_CCLI_CC_PB$_{t-2}$ (z = -1.364) (z = 5.544)**	144	39.552	0.000	0.199	0.001614
HK MEDIUM CLI MS PB	**P_{it} = -0.166 + 28.924HK_MEDIUM_CCLI_MS_PB$_{t-3}$ (z = -1.391) (z = 5.577)**	143	45.34	0.000	0.230	0.002005

6.8 Accuracy of Probability Forecasting

This section will compare the accuracy of the probability occurrence of each constructed model. The quadratic probability score (QPS) is a common instrument to test the forecasting correctness of the logistic and probit regression models.

From the estimated probability (p_e) of the logistic and probit regression models, the expansion and contraction period could be identified as follows: if the estimated probability (p_e) is "greater than 0.5," it is considered an expansion period; if the estimated probability (p_e) is "smaller than 0.5," it is considered a contraction period. Therefore, the timing of the turn change and the turning point (peak point) can be recognized when the estimated probability (p_e) changes from "greater than 0.5" to "smaller than 0.5"; the timing of the turn change and the turning point (trough point) can be recognized when the estimated probability (p_e) changes from "smaller than 0.5" to "greater than 0.5". Diebold and Rudebusch (1989) explained that QPS ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. The simplified formula to calculate the QPS is as follows:

$$\boldsymbol{QPS = \frac{1}{T}\sum_{t=1}^{T} 2\,(P_1 - R_1)^2}$$

where P_t is the probability of the occurrence of a turning point at date t (or, over specific horizon H beyond date t); and R_t equals one if the turning point occurs in period t and is equal to zero otherwise. Table 6.13 illustrates the results of forecasting accuracy by QPS. For the results, both estimated regression models, that is, logistic and probit, with the constructed composite leading indicator by the market share weighting method have a lower score. This proves that the constructed composite leading indicator provides a higher accuracy model to predict turning points in hotel occupancy using the weighting method of the market share of the overnight-stay visitor arrivals.

Figures 6.13 to 6.20 show the estimated probability by the logistic regression models and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong. Figures 6.21 to 6.28 show the estimated probability by the probit regression models and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong.

Table 6.13 Summary of the QPS results for the logistic and probit regression composite leading indicator models

	Hong Kong hotel category				
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM	Average
HK CLI CC LG	**0.36448**	**0.29355**	**0.67726**	**0.30037**	**0.40891**
HK CLI MS LG	**0.38760**	**0.29724**	**0.31526**	**0.29644**	**0.32414**
HK CLI CC PB	**0.35607**	**0.29198**	**0.67455**	**0.30142**	**0.40600**
HK CLI MS PB	**0.38634**	**0.29555**	**0.31868**	**0.29742**	**0.32450**

HK CLI is the constructed composite leading indicator.
CC is the weighting method of the coefficient of cross correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival in Hong Kong.
LG is the logistic regression model.
PB is the probit regression model.

Figure 6.13 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL), and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method (HK TOTAL CLI CC LG) for Hong Kong (Total) hotel category

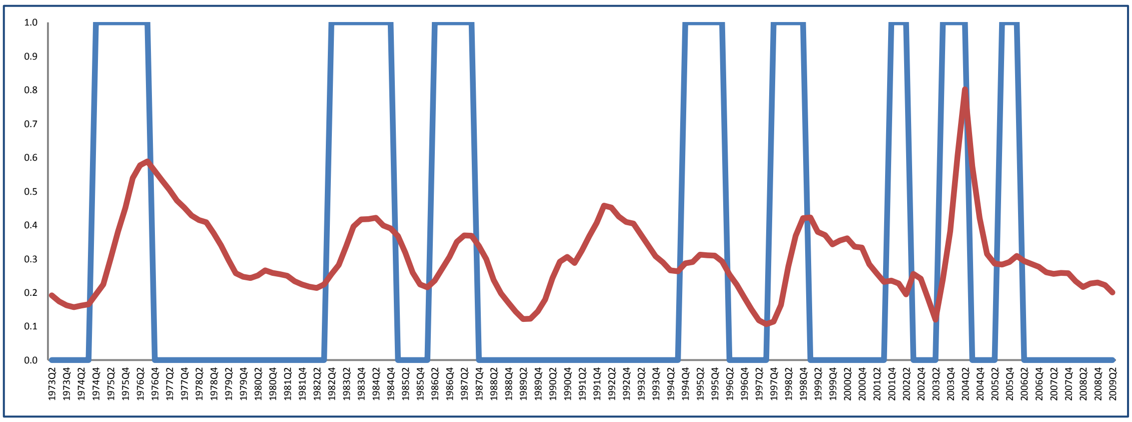


Figure 6.14 The Hong Kong High Tariff A hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH A), and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method (HK HIGH A CLI CC LG) for Hong Kong High Tariff A hotel category

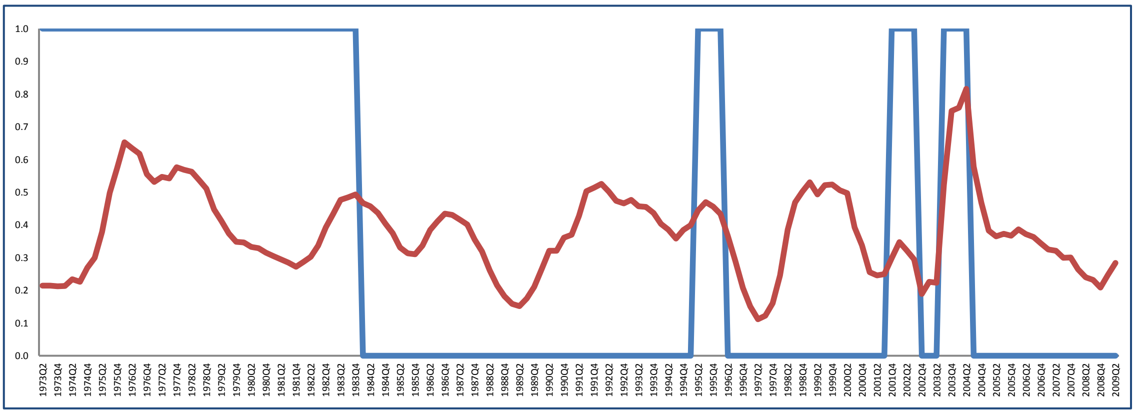


Figure 6.15 The Hong Kong High Tariff B hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH B), and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method (HK HIGH B CLI CC LG) for Hong Kong High Tariff B hotel category

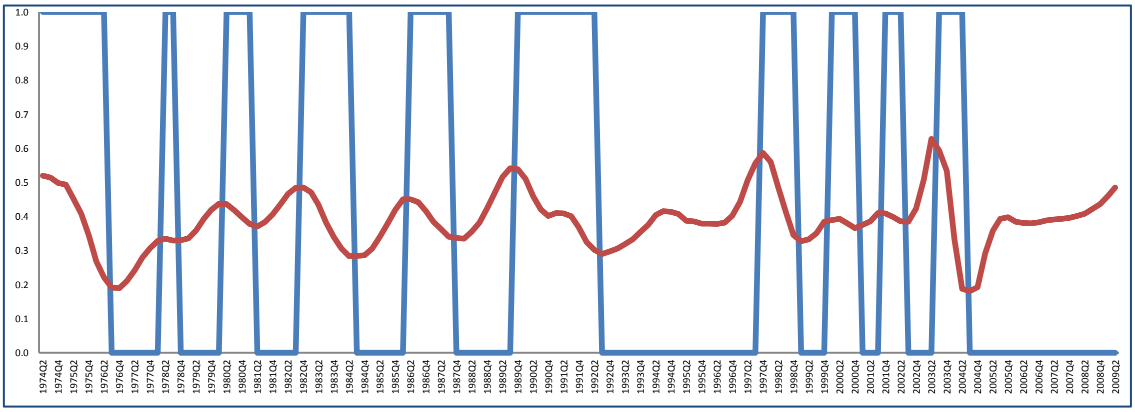


Figure 6.16 The Hong Kong Medium Tariff hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK MEDIUM), and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method (HK MEDIUM CLI CC LG) for Hong Kong Medium Tariff hotel category

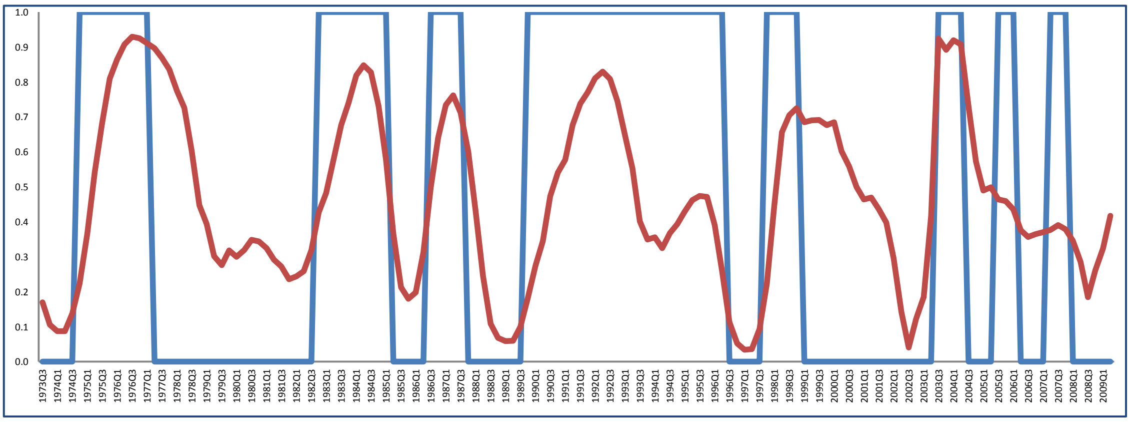


Figure 6.17 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL), and the estimated probability with the logistic regression models by the market share of the overnight-stay tourist arrivals (HK TOTAL CLI MS LG) for Hong Kong (Total) hotel category

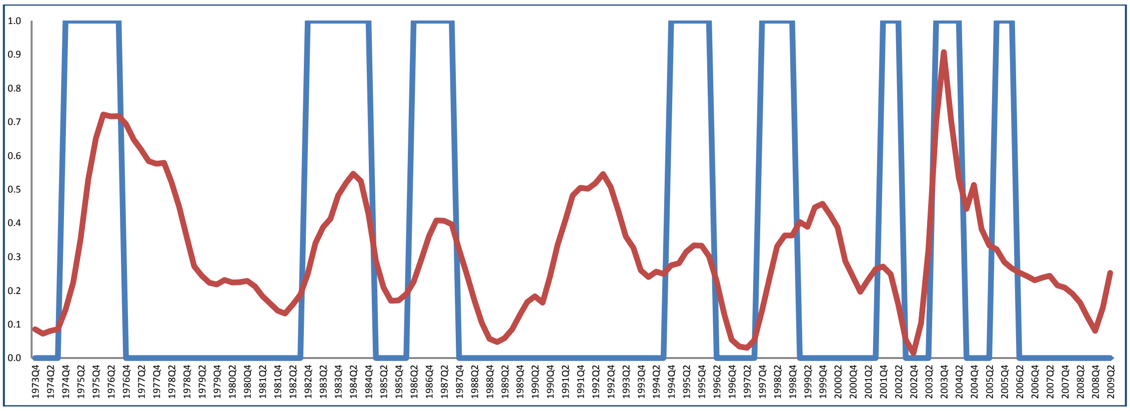


Figure 6.18 The Hong Kong High Tariff A hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH A), and the estimated probability with the logistic regression models by the market share of the overnight-stay tourist arrivals (HK HIGH A CLI MS LG) for Hong Kong High Tariff A hotel category

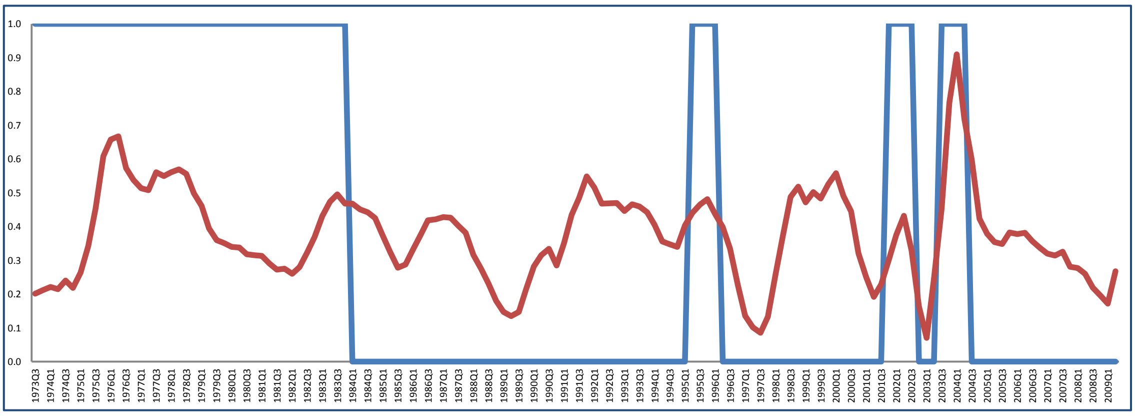


Figure 6.19 The Hong Kong High Tariff B hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH B), and the estimated probability with the logistic regression models by the market share of the overnight-stay tourist arrivals (HK HIGH B CLI MS LG) for Hong Kong High Tariff B hotel category

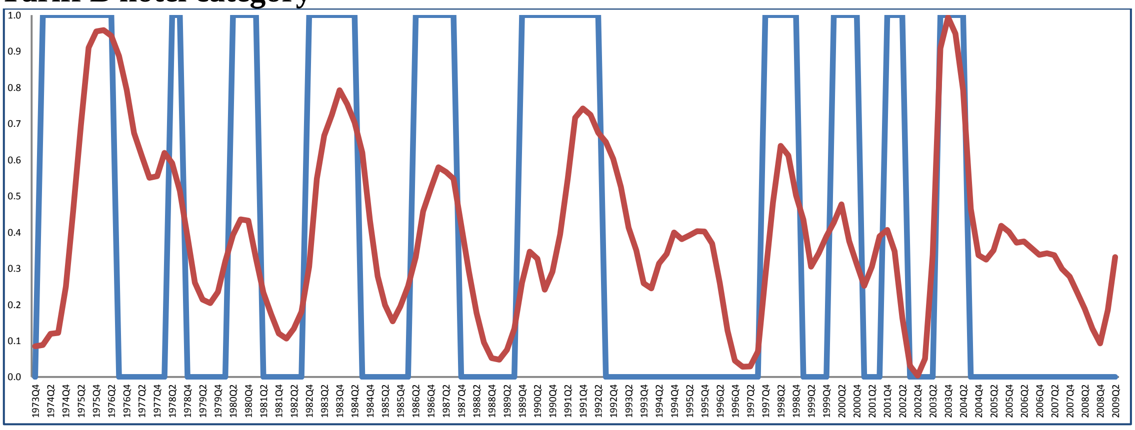


Figure 6.20 The Hong Kong Medium Tariff hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK MEDIUM), and the estimated probability with the logistic regression models by the market share of the overnight-stay tourist arrivals (HK MEDIUM CLI MS LG) for Hong Kong Medium Tariff hotel category

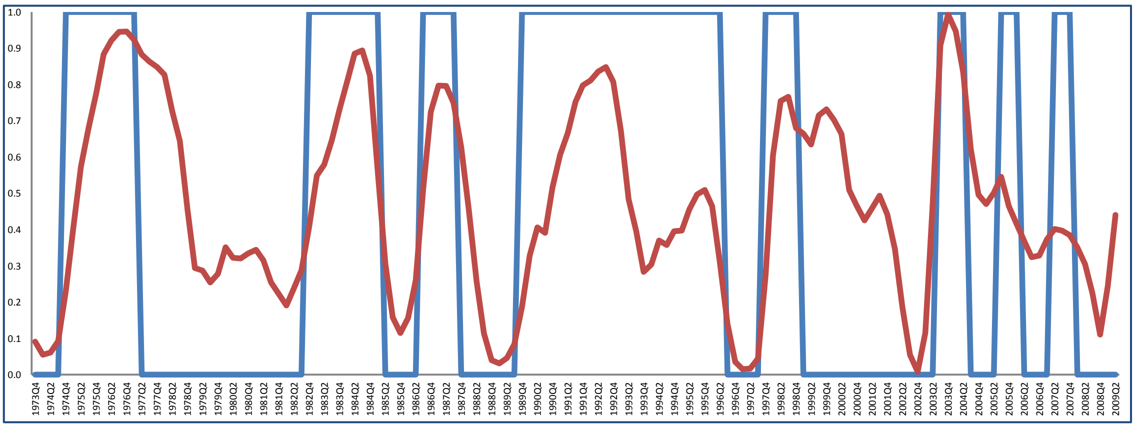


Figure 6.21 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL), and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method (HK TOTAL CLI CC PB) for Hong Kong (total) hotel category

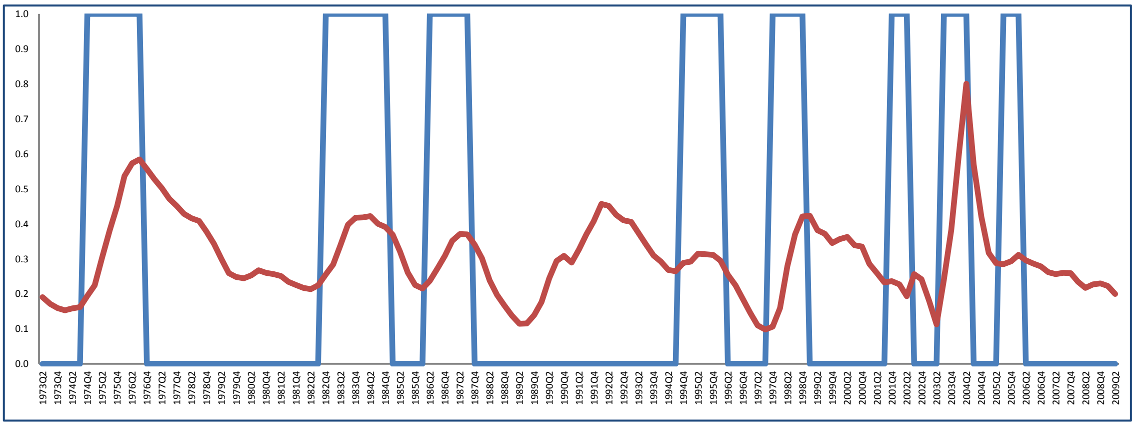


Figure 6.22 The Hong Kong High Tariff A hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH A), and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method (HK HIGH A CLI CC PB) for Hong Kong High Tariff A hotel category

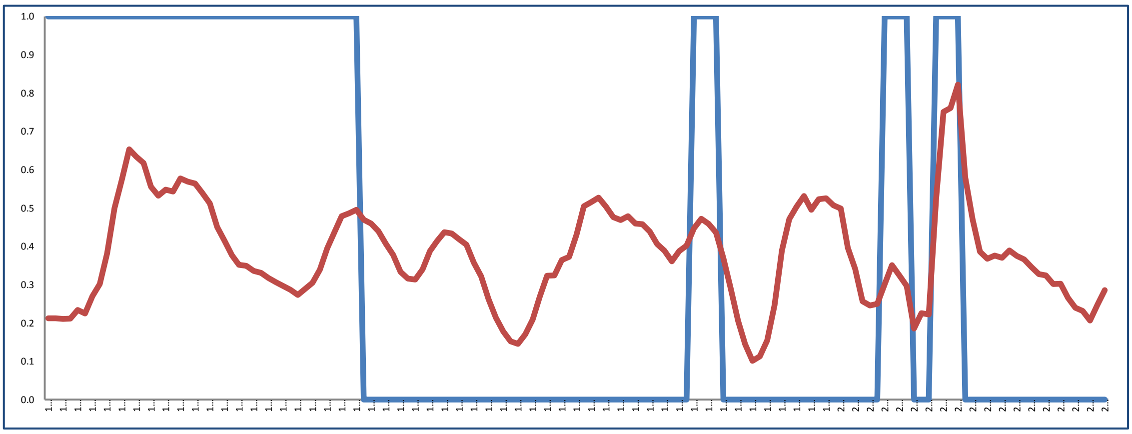


Figure 6.23 The Hong Kong High Tariff B hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH B), and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method (HK HIGH B CLI CC PB) for Hong Kong High Tariff B hotel category

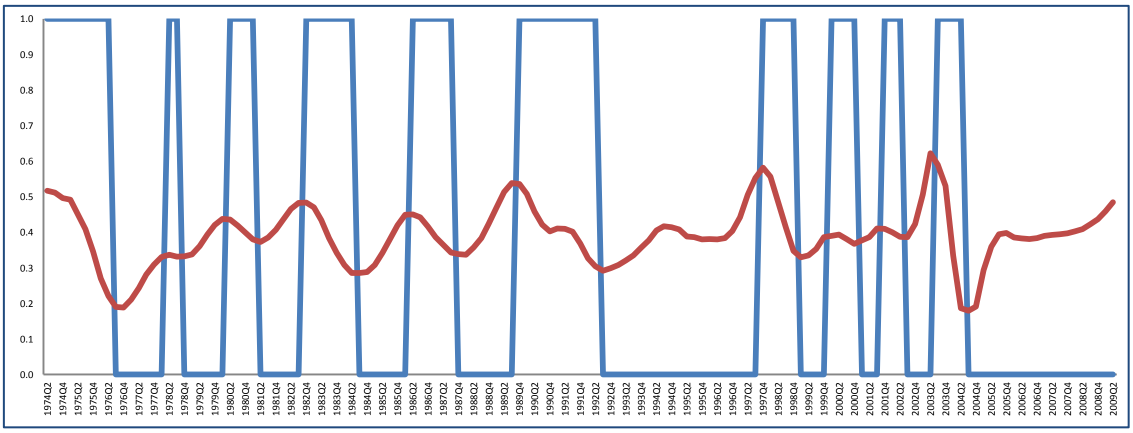


Figure 6.24 The Hong Kong Medium Tariff hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK MEDIUM), and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method (HK MEDIUM CLI CC PB) for Hong Kong Medium Tariff hotel category

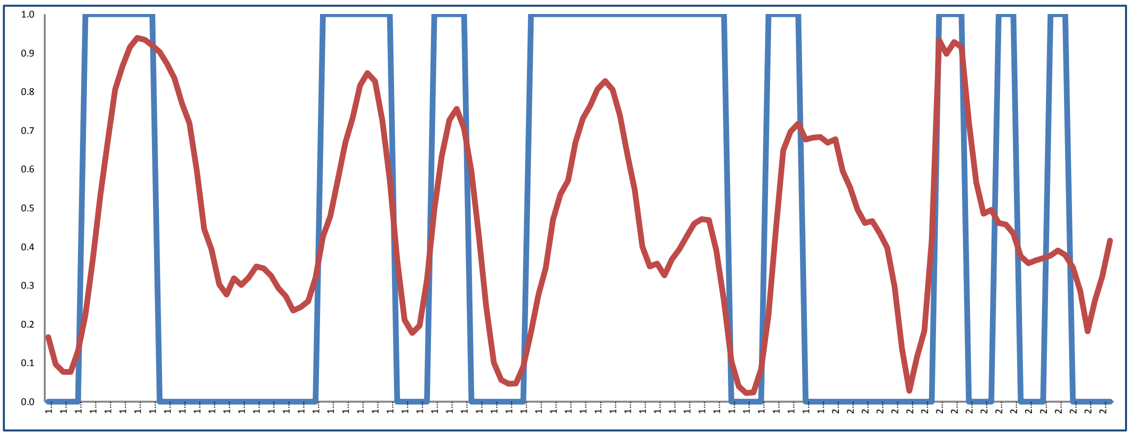


Figure 6.25 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL), and the estimated probability with the probit regression models by the market share of the overnight-stay tourist arrivals (HK TOTAL CLI MS PB) for Hong Kong (total) hotel category

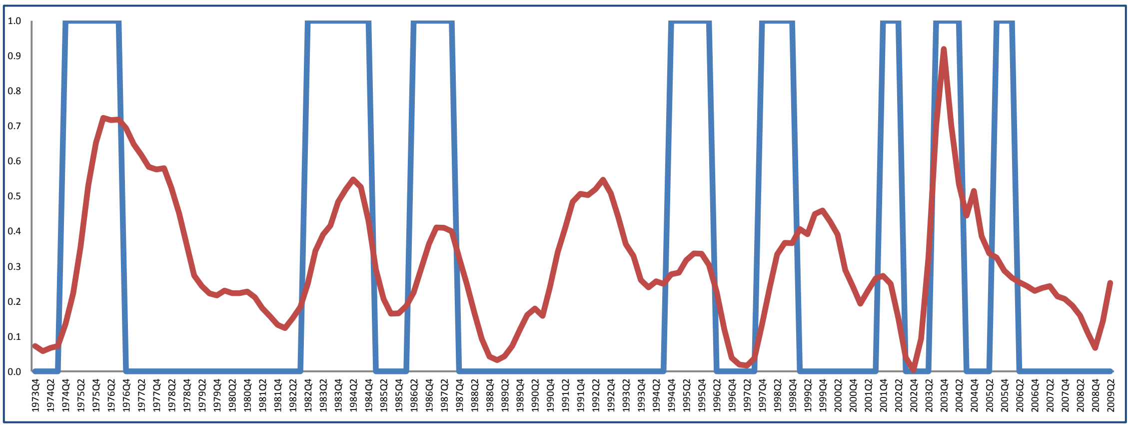


Figure 6.26 The Hong Kong High Tariff A hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH A), and the estimated probability with the probit regression models by the market share of the overnight-stay tourist arrivals (HK HIGH A CLI MS PB) for Hong Kong High Tariff A hotel category

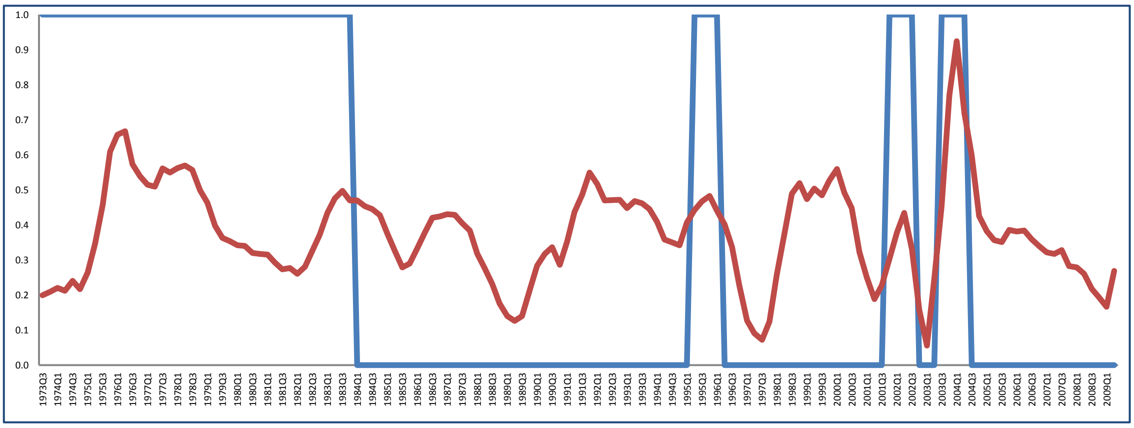


Figure 6.27 The Hong Kong High Tariff B hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH B), and the estimated probability with the probit regression models by the market share of the overnight-stay tourist arrivals (HK HIGH B CLI MS PB) for Hong Kong High Tariff B hotel category

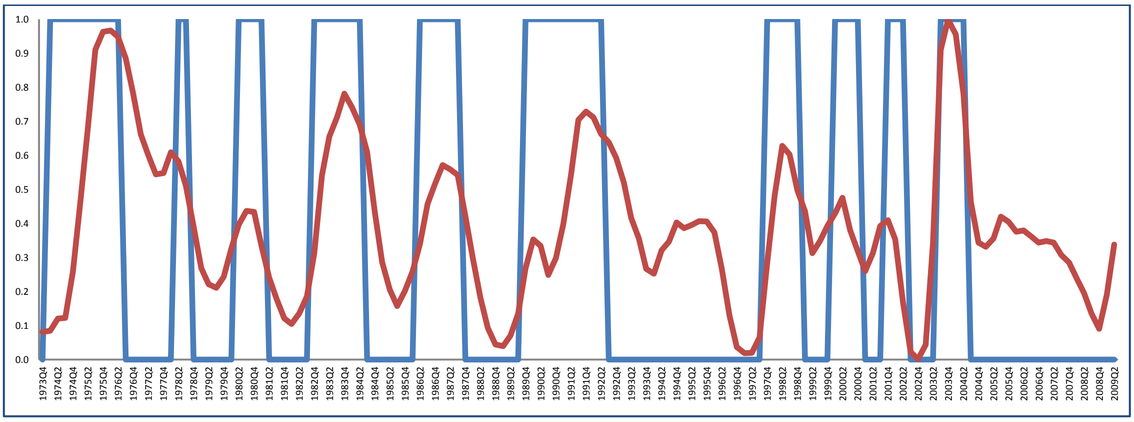
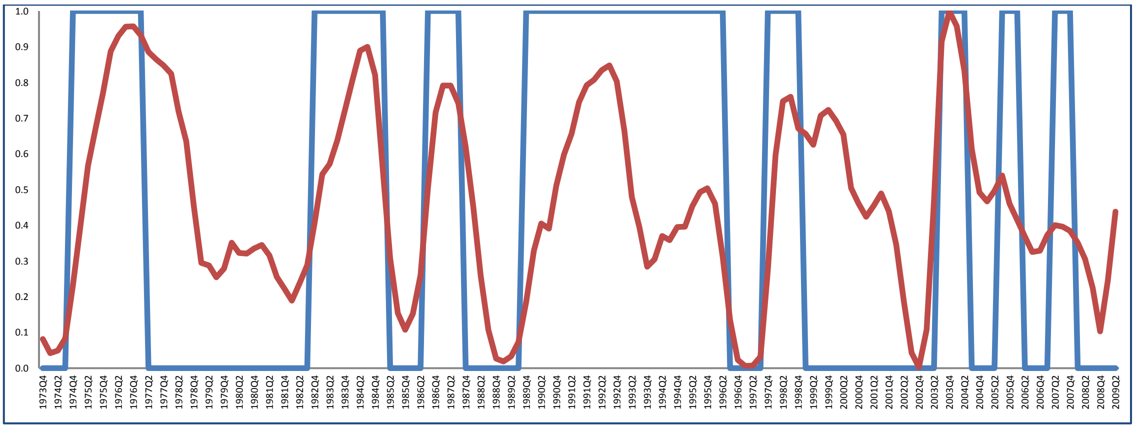


Figure 6.28 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM), and the estimated probability with the probit regression models by the market share of the overnight-stay tourist arrivals (HK MEDIUM CLI MS PB) for Hong Kong Medium Tariff hotel category



6.9 Conclusion

The goal of constructing the composite leading indicators for the Hong Kong hotel industry is to find an appropriate way to forecast the turning points in the occupancy rate, so that hoteliers and policy makers may have advance signals for the changes in demand for hotel accommodation. The present study is the first attempt to construct composite leading indicators for the hotel industry. Moreover, two different weighting methods for the construction of the composite leading indicator contribute an in-depth insight for future studies on different weighting methods for the construction of the composite indicator. The QPS results show that the market share weighting method provided a higher accuracy for predicting turning points in hotel occupancy rate.

If hoteliers wish to obtain advance warning of the upturn and downturn as well as their timing in the hotel occupancy rate, the construction of the composite leading indicator could provide such early signals. On the other hand, if hoteliers want to gather information about the estimated risks on the probability of a downturn in the occupancy rate growth cycle, the most appropriate method would be by way of the logistic and probit regression models estimated with the composite leading indicators.

Chapter 7

THE COMPOSITE LEADING INDICATOR FOR HONG KONG HOTEL INDUSTRY FROM OECD DATA

7.1 Introduction

The Organization for Economic Cooperation and Development (OECD) is an international economic organization that provides a forum for different countries to share policies and experiences, seek answers to common problems, identify good practices, and coordinate domestic and international policies. One of the key roles of the OECD is to gather economic statistics from their member-countries. Those statistics provide comprehensive information on the global economy. Moreover, the OECD also develops different indicators in different aspects. All these indicators and indexes give a better and clearer idea of the overview of the global economy for the public and for businesses.

This chapter will construct the composite leading indicator for the Hong Kong hotel industry from the available OECD indicators and indexes, such as the OECD composite leading indicator, the OECD business survey index, and the OECD consumer confidence index. After smoothing the data and the test for Granger causality, the construction of each OECD comparison indicator will be the same as the constructed composite leading indicators in Chapter 6. The constructed composite leading indicator, the coefficient of the cross-correlation analysis (CC), and the market share of Hong Kong overnight-stay tourist countries (MS) will be used as weighting.

However, the limitation of these comparison indicators is the lack of Taiwan data because the latter is not a member of the OECD. Such shortfall cannot be overcome by the present study.

7.2 Smoothing the OECD data

The construction of the OECD data, namely, the OECD composite leading indicator (OECD CLI), OECD business index (OECD BSI), and OECD consumer confidence index (OECD CCI) for the Hong Kong hotel industry will share the same rationale of the constructed composite leading indicator as discussed in the previous chapter. Based on the major overnight-stay tourist markets, namely, China, Taiwan, Japan, the United States, and Australia, the OECD data will be collected accordingly.

The initial step is to smooth the data. However, because the OECD CLI is a ready-to-use composite leading indicator, that is, it has already been smoothed and tested, the present study will use it as is. The other two data sets, namely, OECD BSI and OECD CCI, will be smoothed by Basic Structural Model (BSM) as discussed in Chapter 3.

The equation will be written as:

a) $Y_t = T_t + S_t + \mathcal{E}_t$

where Y_t is the time series data for OECD data for each country; T_t is the series exhibit trend component; S_t is the seasonal component; and $\mathcal{E}_t$ is the irregular component. The irregular component is normally distributed with $(0,\sigma_\varepsilon^2)$.

The trend component is further developed as:

b) $T_t = T_{t-1} + \beta_{t-1} + \xi_t$

$$\beta_t = \beta_{t-1} + \lambda_t$$

where ξ_t is normally distributed with (0, σ_ξ^2) and λ_t is normally distributed with (0, σ_λ^2). β is the slope or derivative of the trend.

The equation is the seasonal component:

c) $S_t = \sum_{j=1}^{s-1}(S_{t-j} + \psi_t)$, $t = 1, \ldots, N$

where ψ_t is normally distributed with (0, σ_ψ^2).

By using the (a), (b), and (c) equations, the BSM developed by Harvey (1989) was illustrated. Further restricting the $\sigma_\xi^2 = 0$, the equation can develop the smooth trend, which is most suitable for estimating the cycle that is obtained by taking the four differences of the smooth trend. The STAMP program was used to estimate the smooth trend.

Figures 7.1 to 7.4 show the smoothed growth of the OECD BSI of the Hong Kong main source markets of Hong Kong overnight-stay tourist arrivals. Figures 7.5 to 7.8 show the smoothed growth of the OECD CCI of the Hong Kong main source markets of Hong Kong overnight-stay tourist arrivals.

Figure 7.1 The smoothed growth rate of the OECD BSI, China (CHI BSI)

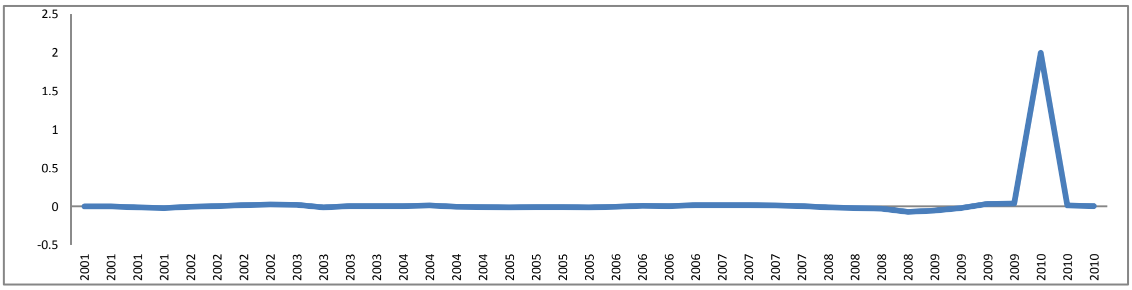


Figure 7.2 The smoothed growth rate of the OECD BSI, Japan (JAP BSI)

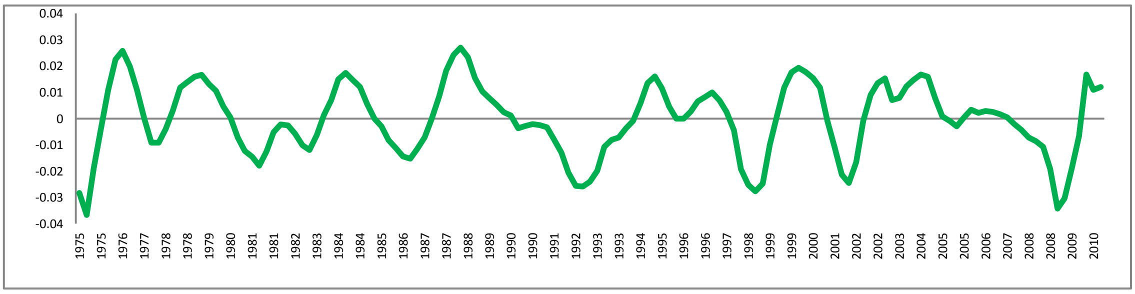


Figure 7.3 The smoothed growth rate of the OECD BSI, USA (USA BSI)

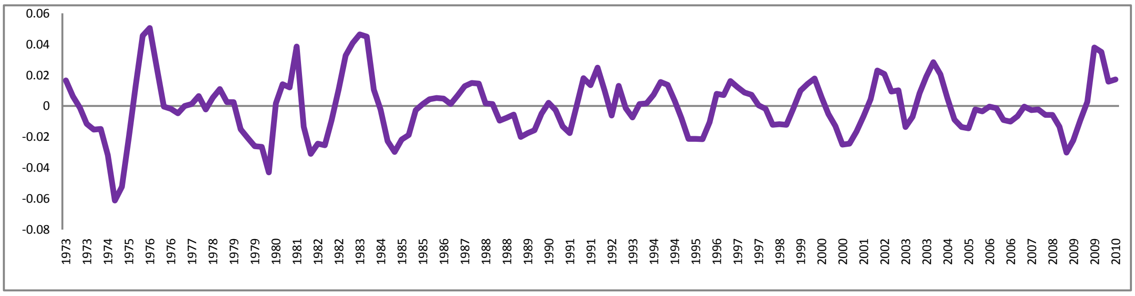


Figure 7.4 The smoothed growth rate of the OECD BSI, Australia (AUS BSI)

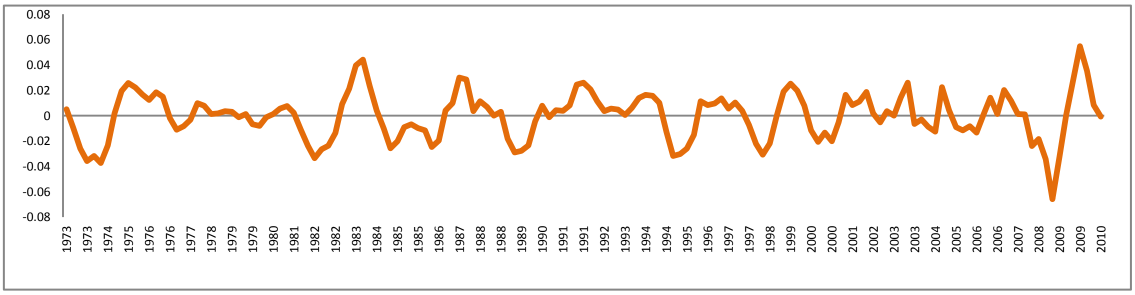


Figure 7.5 The smoothed growth rate of the OECD CCI, China (CHI CCI)

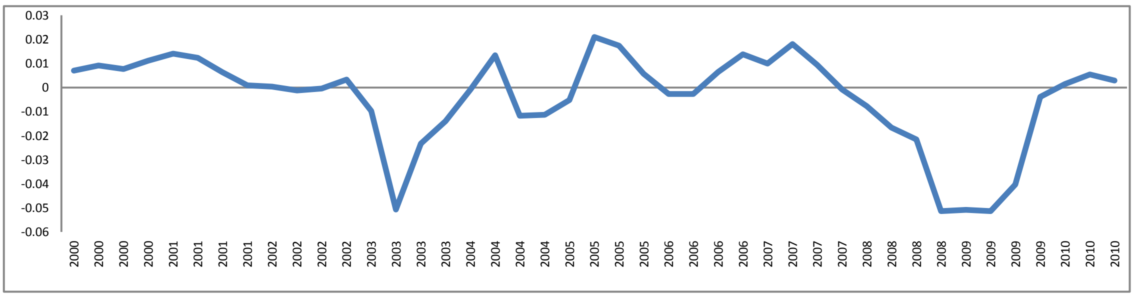


Figure 7.6 The smoothed growth rate of the OECD CCI, Japan (JAP CCI)

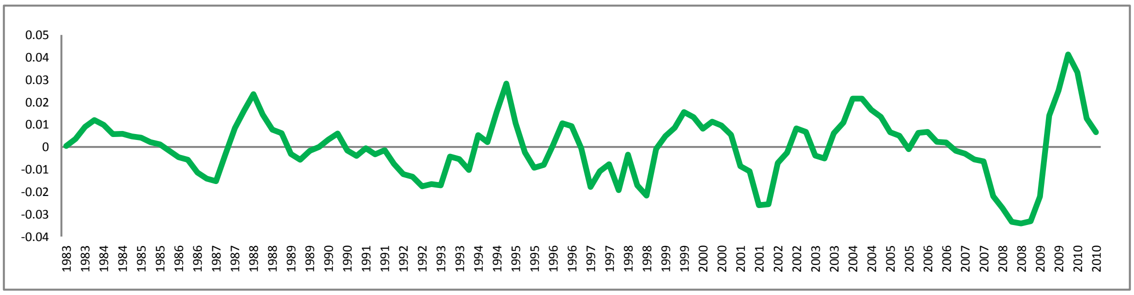


Figure 7.7 The smoothed growth rate of OECD CCI, USA (USA CCI)

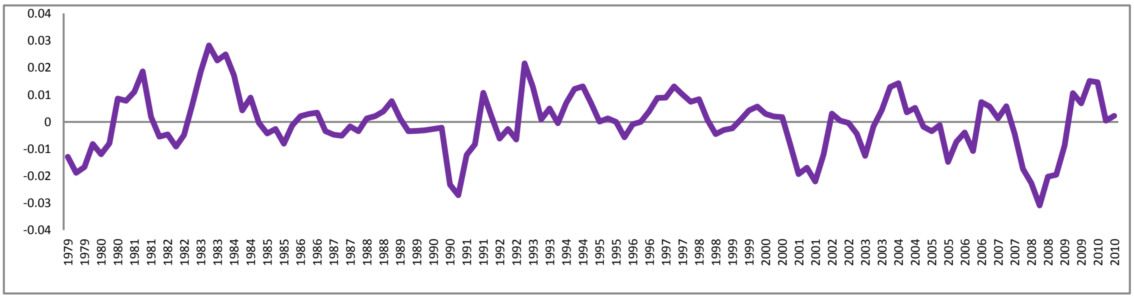
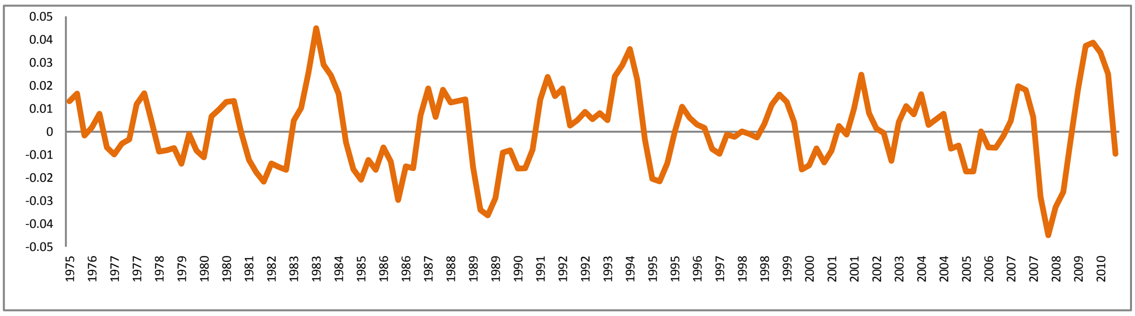


Figure 7.8 The smoothed growth rate of OECD CCI, Australia (AUS CCI)



7.3 Granger Causality

After smoothing the data, the Granger causality will be applied. The basic definition of Granger causality is "the cause occurs before the effect," which is a very important identification when constructing the composite leading indicator. The testing hypothesis will be, H_o: The OECD data do not cause the growth of hotel occupancy rate. If the significant level is within 10%, the OECD data of that country will be considered directionally caused with the hotel growth rate.

To test the null hypothesis, Ho: the OECD data does not Granger cause the growth of hotel occupancy rate, the following regression was considered:

$$\gamma_t = \sum_{i=1}^{k} \alpha_i \gamma_{t-i} + \sum_{i=1}^{k} \beta_i \chi_{t-i} + u_i$$

where γ_t is the growth of hotel occupancy rate; χ_t is the growth rate of OECD data; k is the lag time; α_i and β_i are the coefficients; and u_i is the random error. F-statistics were examined to test the null hypothesis, H_o that economic variable does not Granger cause the hotel occupancy rate. If the significant level was within 10% and the lag time within 5 quarters, the OECD data of that country are considered directionally caused with the hotel occupancy rate. Furthermore, the null hypothesis, H_o that the hotel occupancy rate does not Granger cause the economic variable, was also examined. If the significance level is within 10%, the OECD data are considered as a lagged indicator, and then the inverse of the economic variable is considered a leading indicator (Klein and Moore, 1985). From the results of the Granger causality test, all the OECD data are a leading factor for the Hong Kong hotel industry. Table 7.1 shows the results of the Granger causality test of OECD BSI and OECD CCI for the different categories in the Hong Kong hotel industry.

Table 7.1 Summary of the significant coefficients of countries in OECD BSI and OECD CCI

	Country	Hong Kong hotel categories			
		HK Total	HK High Tariff A	HK High Tariff B	HK Medium Tariff
OECD BSI	China	**0.0967**	**0.0953**	**0.0964**	**0.0982**
	Japan	**0.0173**	**0.0103**	**0.0207**	**0.0442**
	USA	**0.0044**	**0.0024**	**0.0009**	**0.0385**
	Australia	**0.0099**	**0.0695**	**0.0051**	**0.0061**
OECD CCI	China	**0.0026**	**0.0048**	**0.0018**	**0.0033**
	Japan	**0.0975**	**0.0936**	**0.0959**	**0.0910**
	USA	**0.0041**	**0.0162**	**0.0054**	**0.0523**
	Australia	**0.0026**	**0.0057**	**0.0014**	**0.0058**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.

7.4 Weighting method for the composite leading indicators

Two approaches, the same ones used in constructing the constructed composite leading indicator in the previous chapter, will be used to construct the OECD indicators and indexes for the Hong Kong hotel industry, namely, the coefficient of the cross-correlation analysis and the market share of the top five countries of Hong Kong overnight-stay tourists arrivals.

7.4.1 Weighting by the coefficient of the cross correlation analysis

The coefficient of the cross correlation is one of the weighting methods used to construct the OECD indicators. To find out the cross-correlation coefficient of each country's OECD data, cross-correlation analysis was conducted between the original occupancy rate and the OECD data of each country.

Haugh (1976) had warned that misleading cross correlations could occur due to the autocorrelation of the hotel occupancy growth rate or the indicator series. To eliminate this dilemma, the seasonal ARIMA models fitted to both series and cross-correlation coefficient of the residuals were examined.

7.4.2 Weighting by the Market share of Hong Kong overnight stay tourists

The HKTB divides total tourist arrivals into two categories, namely, overnight visitors and same-day in-town visitors. The present study will use the overnight-stay tourist arrivals market share as a weighting method to construct the OECD data for the Hong Kong hotel industry. Table 7.2 summarizes the two weighting methods.

Table 7.2 Summary of the weighting methods; the number in brackets is the best-fit lead time for each OECD data set

	Country	MS	HK Total	HK High A	HK High B	HK Medium
			CC			
OECD CLI	China	59.5	(3) 0.1063	(3) 0.0790	(3) 0.1133	(3) 0.1161
	Japan	4.7	(4) 0.0943	(4) 0.1453	(3) 0.0908	(4) 0.0842
	USA	3.8	(1) 0.0863	(1) 0.1065	(1) 0.0945	(3) 0.0942
	Australia	2.9	(1) 0.1816	(1) 0.2054	(1) 0.2092	(1) 0.1283
OECD BSI	China	59.5	(2) 0.2128	(2) 0.0569	(2) 0.0585	(2) 0.0749
	Japan	4.7	(4) 0.2066	(4) 0.2064	(4) 0.1969	(4) 0.2053
	USA	3.8	(1) 0.1253	(1) 0.1308	(1) 0.1331	(1) 0.1026
	Australia	2.9	(1) 0.2820	(1) 0.2973	(1) 0.2777	(1) 0.2609
OECD CCI	China	59.5	(4) 0.3425	(4) 0.3505	(4) 0.3566	(4) 0.3164
	Japan	4.7	(2) 0.2191	(1) 0.2172	(1) 0.2017	(1) 0.2146
	USA	3.8	(1) 0.2489	(1) 0.2218	(1) 0.2646	(1) 0.2394
	Australia	2.9	(1) 0.2455	(1) 0.1650	(1) 0.2221	(1) 0.2930

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
CC is the weighting method of the coefficient of cross correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival in Hong Kong.

7.5 The weighting approach

To combine each OECD data set to become one OECD indicator for the Hong Kong hotel industry, Niemira and Klein’s (1994) approach will be used again to construct the composite leading indicator and sum up the changes for individual composite while accounting for the component's importance and volatility.

$$\boldsymbol{\Delta_4 Composite} = \sum \boldsymbol{w_i \sigma_i \Delta_4 \, (component)_{1+S-x_i}}$$

where i = 1 to n, the maximum number of components; w is the component's weight, which represents the component's relative importance assessed by the coefficient of cross correlation and the market share of the Hong Kong overnight-stay visitor arrivals; σ is the standardized weight, which is calculated from the inverse value of the volatility measure, the average absolute deviation around the average growth rate to minimize the influence of highly volatile series on the composite leading indicator; s is the short lead time in the number of quarters among the n indicators; and x_i is the lead time of the indicator.

7.5.1 Calculated Weight Based on the Coefficient of Cross-correlation Analysis

This section shows the weights for the construction of the composite leading indicator based on the Niemira and Klein (1994) approach. The weights that can be used to construct the composite leading indicator for different hotel categories in Hong Kong are reported accordingly. Tables 7.3 to 7.6 (7.4 to 7.6 are in the Appendix) are the weighting tables for the OECD CLI of different Hong Kong hotel categories. Tables 7.7 to 7.10 (7.8 to 7.10 are in the Appendix) are the weighting tables for the OECD CLI of different Hong Kong different categories. Tables 7.11 to 7.14 (7.12 to 7.14 are in the Appendix) are the weighting tables for the OECD CLI of different Hong Kong hotel categories. Table 7.15 summarizes all OECD data with the final weighting.

Table 7.3 Weights for the construction of OECD CLI for Hong Kong (Total) hotel categories by the coefficient of the cross-correlation analysis (OECD CLI TOTAL CC)

OECD CLI TOTAL CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.1063	0.2269	13.3134	0.5142	0.0751	0.0869	0.0197	**0.0720**
Japan	0.0943	0.2013	6.0674	0.2343	0.1648	0.1908	0.0384	**0.1402**
USA	0.0863	0.1842	3.6617	0.1414	0.2731	0.3161	0.0582	**0.2126**
Australia	0.1816	0.3876	2.8489	0.1100	0.3510	0.4062	0.1575	**0.5751**
Total	0.4685	1.0000	25.8913	1.0000	0.8640	1.0000	0.2738	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.

Tables 7.4 to 7.6 in Appendix.

Table 7.7 Weights for the construction of OECD BSI for Hong Kong (Total) hotel categories by the coefficient of the cross-correlation analysis (OECD BSI TOTAL CC)

OECD BSI TOTAL CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentag e of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.2128	0.2574	0.1149	0.7470	8.7062	0.0358	0.0092	**0.0373**
Japan	0.2066	0.2499	0.0109	0.0709	91.6675	0.3767	0.0942	**0.3813**
USA	0.1253	0.1516	0.0137	0.0892	72.9417	0.2998	0.0454	**0.1840**
Australia	0.2820	0.3411	0.0143	0.0929	69.9979	0.2877	0.0981	**0.3974**
Total	0.8267	1.0000	0.1538	1.0000	243.3133	1.0000	0.2469	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.

Table 7.11 Weighting of OECD CCI for the growth of Hong Kong (Total) hotel categories by the coefficient of the cross-correlation analysis (OECD CCI TOTAL CC)

OECD CCI TOTAL CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.3425	0.3243	0.0143	0.3134	70.0972	0.1896	0.0615	**0.2516**
Japan	0.2191	0.2075	0.0104	0.2278	96.4410	0.2609	0.0541	**0.2214**
USA	0.2489	0.2357	0.0079	0.1745	125.8465	0.3405	0.0802	**0.3282**
Australia	0.2455	0.2325	0.0129	0.2844	77.2453	0.2090	0.0486	**0.1987**
Total	1.0560	1.0000	0.0455	1.0000	369.6301	1.0000	0.2445	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.

Table 7.15 Summary of all OECD data with all the final weighting by coefficient of the cross-correlation analysis (CC)

	Country	Final weighting of each hotel categories			
		HK TOTAL	**HK HIGH A**	**HK HIGH B**	**HK MEDIUM**
OECD CLI	China	**0.0720**	**0.0453**	**0.0693**	**0.0934**
	Japan	**0.1402**	**0.1827**	**0.1220**	**0.1486**
	USA	**0.2126**	**0.2219**	**0.2103**	**0.2756**
	Australia	**0.5751**	**0.5501**	**0.5984**	**0.4824**
OECD BSI	China	**0.0373**	**0.0100**	**0.0107**	**0.0144**
	Japan	**0.3813**	**0.3802**	**0.3783**	**0.4162**
	USA	**0.1840**	**0.1917**	**0.2035**	**0.1655**
	Australia	**0.3974**	**0.4182**	**0.4075**	**0.4039**
OECD CCI	China	**0.2516**	**0.2634**	**0.2634**	**0.2319**
	Japan	**0.2214**	**0.2050**	**0.2050**	**0.2164**
	USA	**0.3282**	**0.3509**	**0.3509**	**0.3150**
	Australia	**0.1987**	**0.1808**	**0.1808**	**0.2367**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.

7.5.2 Calculated Weight Based on the Market Share of the Overnight-stay Tourist Arrivals

This section shows the weights for the construction of the composite leading indicator based on the Niemira and Klein (1994) approach. The weights that can be used to construct the composite leading indicator for different hotel categories in Hong Kong are reported accordingly. The market share of overnight-stay tourist arrivals in Hong Kong is the same figure for all hotel categories; thus, the final weighting of each hotel category is the same as well. Table 7.16 shows the calculated weight for the OECD CLI of Hong Kong hotels. Table 7.17 shows the calculated weight for the OECD BSI of Hong Kong hotels. Table 7.18 shows the calculated weight for the OECD CCI of Hong Kong hotels.

Table 7.16 Weights for the calculation of OECD CLI for Hong Kong hotels by the market share of overnight-stay tourist arrivals (OECD CLI MS)

OECD CLI MS								
(1) Country	**(2) Coefficient of the cross correlation**	**(3) Converted percentage of assigned Weight**	**(4) Average of the Absolute Average Deviation**	**(5) Converted percentage of the Absolute Average Deviation**	**(6) Inverse of the Absolute Average Deviation**	**(7) Converted percentage of Inverse of the Absolute Average Deviation**	**(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation**	**(9) Converted Percentage of Finalized weighting**
China	59.5	0.8392	13.3134	0.5142	0.0751	0.0869	0.0730	**0.6123**
Japan	4.7	0.0663	6.0674	0.2343	0.1648	0.1908	0.0126	**0.1061**
USA	3.8	0.0536	3.6617	0.1414	0.2731	0.3161	0.0169	**0.1422**
Australia	2.9	0.0409	2.8489	0.1100	0.3510	0.4062	0.0166	**0.1395**
Total	70.9	1.0000	25.8913	1.0000	0.8640	1.0000	0.1192	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.

Table 7.17 Weights for the calculation of OECD BSI for Hong Kong hotels by the market share of overnight-stay tourist arrivals (OECD BSI MS)

OECD BSI MS								
(1) Country	**(2) Coefficient of the cross correlation**	**(3) Converted percentage of assigned Weight**	**(4) Average of the Absolute Average Deviation**	**(5) Converted percentage of the Absolute Average Deviation**	**(6) Inverse of the Absolute Average Deviation**	**(7) Converted percentage of Inverse of the Absolute Average Deviation**	**(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation**	**(9) Converted Percentage of Finalized weighting**
China	59.5	0.8392	0.1149	0.7470	8.7062	0.0358	0.0300	**0.3625**
Japan	4.7	0.0663	0.0109	0.0709	91.6675	0.3767	0.0250	**0.3015**
USA	3.8	0.0536	0.0137	0.0892	72.9417	0.2998	0.0161	**0.1940**
Australia	2.9	0.0409	0.0143	0.0929	69.9979	0.2877	0.0118	**0.1421**
Total	70.9	1.0000	0.1538	1.0000	243.3133	1.0000	0.0828	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.

Table 7.18 Weights for the calculation of OECD CCI for Hong Kong hotels by the market share of overnight-stay tourist arrivals (OECD CCI MS)

OECD CCI MS								
(1) Country	**(2) Coefficient of the cross correlation**	**(3) Converted percentage of assigned Weight**	**(4) Average of the Absolute Average Deviation**	**(5) Converted percentage of the Absolute Average Deviation**	**(6) Inverse of the Absolute Average Deviation**	**(7) Converted percentage of Inverse of the Absolute Average Deviation**	**(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation**	**(9) Converted Percentage of Finalized weighting**
China	59.5	0.8392	0.0143	0.3134	70.0972	0.1896	0.1591	**0.7831**
Japan	4.7	0.0663	0.0104	0.2278	96.4410	0.2609	0.0173	**0.0851**
USA	3.8	0.0536	0.0079	0.1745	125.8465	0.3405	0.0182	**0.0898**
Australia	2.9	0.0409	0.0129	0.2844	77.2453	0.2090	0.0085	**0.0421**
Total	70.9	1.0000	0.0455	1.0000	369.6301	1.0000	0.2032	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.

7.6 Constructed composite leading indicator

After the calculation of the weighting by the two different methods, the respective OECD leading indicators for each hotel category in Hong Kong are constructed. The figures below show the constructed OECD leading indicators based on the two different weighting methods. Figures 7.9 to 7.12 (7.10 to 7.12 are in Appendix) graphically compare the original growth of Hong Kong hotel occupancy rate with the OECD composite leading indicator by the coefficient of the cross correlation and the OECD composite leading indicator by the market share of the overnight-stay visitor arrivals. Figures 7.13 to 7.16 (7.14 to 7.16 are in the Appendix) graphically compare the original growth of Hong Kong hotel occupancy rate with the OECD business survey index by the coefficient of the cross correlation and the OECD business survey index by the market share of the overnight-stay visitor arrivals. Figures 7.17 to 7.20 (7.18 to 7.20 are in the Appendix) graphically compare the original growth of Hong Kong hotel occupancy rate with the OECD consumer confidence index by the coefficient of the cross correlation and the OECD consumer confidence index by the market share of the overnight-stay visitor arrivals.

Figure 7.9 Comparison of the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) with the OECD composite leading indicator by coefficient of the cross correlation (TOTAL OECD CLI CC) and the OECD composite leading indicator by the market share of the overnight-stay visitor arrivals (TOTAL OECD CLI MS)

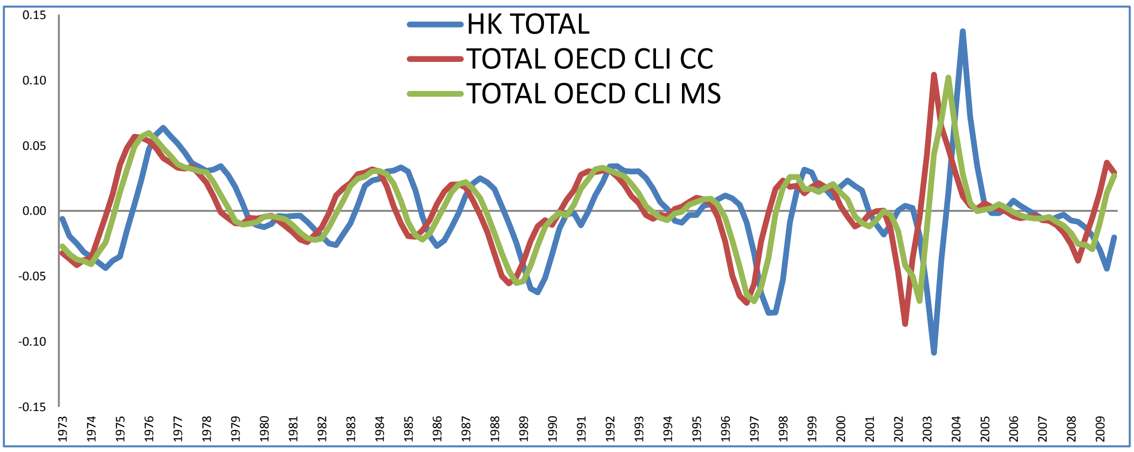


Figure 7.13 Comparison of the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) with the OECD business survey index by coefficient of the cross correlation (TOTAL OECD CSI CC) and the OECD business survey index by the market share of the overnight-stay visitor arrivals (TOTAL OECD BSI MS)

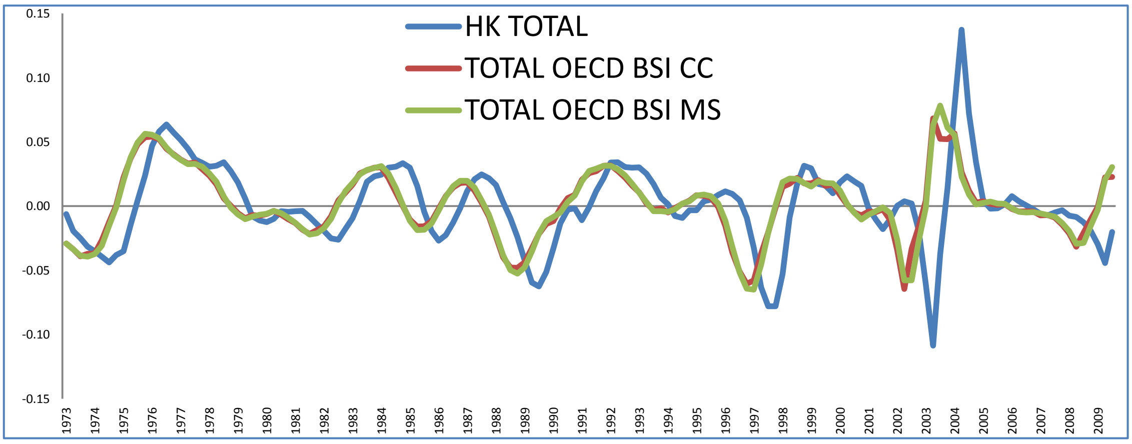
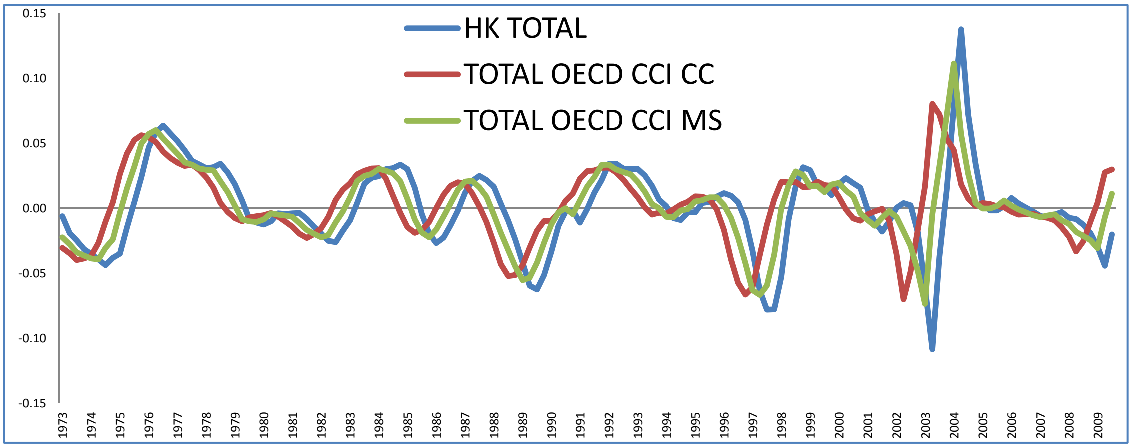


Figure 7.17 Comparison of the original Hong Kong (Total) hotel occupancy growth rate (HK TOTAL) with the OECD consumer confidence index by coefficient of the cross correlation (TOTAL OECD CCI CC) and the OECD consumer confidence index by the market share of the overnight-stay visitor arrivals (TOTAL OECD CCI MS)



7.7 Lead time of the OECD data

After the construction of the OECD data for the Hong Kong hotel industry, the cross-correlation analysis will run again between the newly constructed OCED indicators and the original growth of the hotel occupancy rate. The cross-correlation analysis provides the lead time of each constructed OECD indicator. The seasonal ARIMA models fitted to both series and cross-correlation coefficient of the residuals are examined.

The constructed OECD composite leading indicator by the weighting method of coefficient of cross correlation leads the original hotel occupancy rate by 1 quarter for the Hong Kong (Total) hotel category, 2 quarters for the High Tariff A hotel, 5 quarters for the High tariff B hotel, and 2 quarters for the Medium Tariff hotel in Hong Kong. On the other hand, the constructed OECD composite leading indicator by the weighting method of the market share for the overnight-stay visitor arrivals in Hong Kong leads the original hotel occupancy rate by 2 quarters for the Hong Kong (Total) hotel category, 2 quarters for the High Tariff A hotel, 2 quarters for the High tariff B hotel, and 2 quarters for the Medium Tariff hotel in Hong Kong.

The constructed OECD business survey index by the weighting method of coefficient of cross correlation leads the original hotel occupancy rate by 1 quarter for the Hong Kong (total) hotel category, 2 quarters for the High Tariff A hotel, 4 quarters for the High tariff B hotel, and 1 quarter for the Medium Tariff hotel in Hong Kong. Meanwhile, the constructed OECD business survey index by the weighting method of the market share for the overnight stay visitor arrivals in Hong Kong leads the original hotel occupancy rate by 2 quarters for the Hong Kong (Total) hotel category, 2 quarters for the High Tariff A hotel, 4 quarters for the High tariff B hotel, and 2 quarters for the Medium Tariff hotel in Hong Kong.

The constructed OECD consumer confidence index by the weighting method of coefficient of cross correlation leads the original hotel occupancy rate by 2 quarters for the Hong Kong (Total) hotel category, 1 quarter for the High Tariff A hotel, 1 quarter for the High tariff B hotel, and 2 quarters for the Medium Tariff hotel in Hong Kong. On the other hand, the constructed OECD consumer confidence index by the weighting method of the market share for the overnight stay visitor arrivals in Hong Kong leads the original hotel occupancy rate by 1 quarter for the Hong Kong (Total) hotel category, 1 quarter for the High Tariff A hotel, 1 quarter for the High tariff B hotel, and 1 quarter for the Medium Tariff hotel in Hong Kong. Table 7.19 summarizes the results from the cross-correlation analysis.

Table 7.19 Summary of the results from the cross-correlation analysis between the growth of the Hong Kong hotel occupancy rate and the OECD indicators; the number in brackets is the best-fit lead time of the OECD indicators and leads the original occupancy rate

	Hong Kong hotel category			
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM
OECD CLI CC	**(1) 0.2492**	**(2) 0.2265**	**(5) 0.1485**	**(2) 0.2992**
OECD CLI MS	**(2) 0.8387**	**(2) 0.8494**	**(2) 0.8892**	**(2) 0.9498**
OECD BSI CC	**(1) 0.4407**	**(2) 0.3762**	**(4) 0.6495**	**(1) 0.3616**
OECD BSI MS	**(2) 0.3306**	**(2) 0.3315**	**(4) 0.8080**	**(2) 0.3329**
OECD CCI CC	**(2) 0.6168**	**(1) 0.3109**	**(1) 0.3364**	**(2) 0.2469**
OECD CCI MS	**(1) 0.9557**	**(1) 0.9431**	**(1) 0.9406**	**(1) 0.9557**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
CC is the weighting method of the coefficient of cross correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival in Hong Kong.

7.8 Dating the Turning Points

Originally, Bry and Boschan (1971) set that if Y_t represents the peak in the growth rate cycle, the value of Y_s will be such that $s < t$ or $s > t$. Following the discussion in Chapter 2, Bry and Boschan's approach (1971) will be adopted with a slight change from that of

Leasge (1991). This means that in the present study, $k=3$ will be applied because the high volatility patterns of the hotel occupancy growth rate data were used.

The downturn (DT) and upturn (UT) are defined as follows:

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

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

Note that Y_{t-3}, Y_{t-2} and Y_{t-1} are the past values of the growth rate, and Y_{t+1}, Y_{t+2} and Y_{t+3} are the future values of the growth rate.

<u>Identifying turns in the constructed OECD leading indicators by coefficient of the cross-correlation analysis</u>

Figures 7.21 to 7.24 (7.22 to 7.24 are in the Appendix) are the graphs of the constructed OECD composite leading indicators by coefficient of the cross correlation with the identification of peak (P) and trough (T). Figures 7.25 to 7.28 (7.26 to 7.28 are in the Appendix) are the graphs of the constructed OECD business survey indexes by the coefficient of the cross correlation with the identification of peak (P) and trough (T). Figures 7.29 to 7.32 (7.30 to 7.32 are in the Appendix) are the graphs of the constructed OECD consumer confidence indexes by the coefficient of the cross correlation with the identification of peak (P) and trough (T).

Figure 7.21 The OECD composite leading indicator of the Hong Kong (Total) hotel category growth rate by coefficient of the cross correlation (TOTAL OECD CLI CC) with the identification of peak (P) and trough (T)

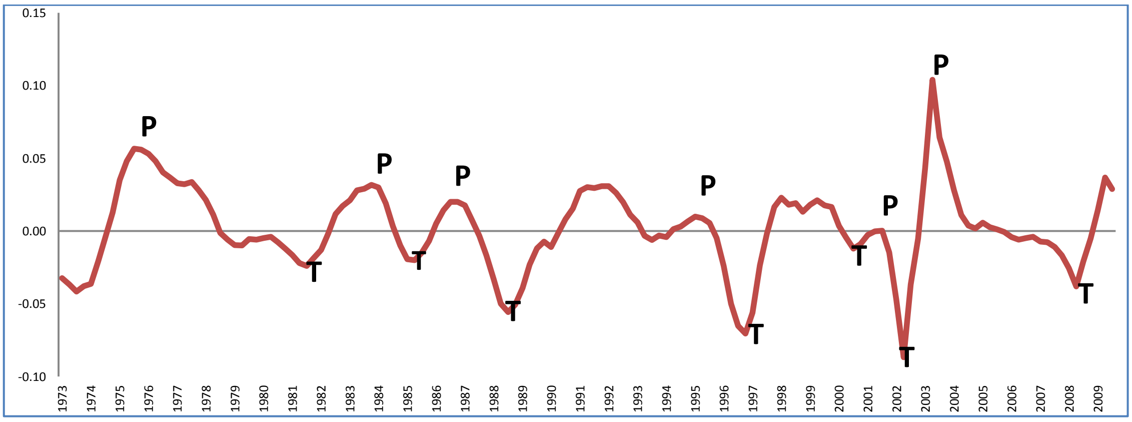


Figure 7.25 The OECD business survey index of the Hong Kong (Total) hotel category growth rate by coefficient of the cross correlation (TOTAL OECD BSI CC) with the identification of peak (P) and trough (T)

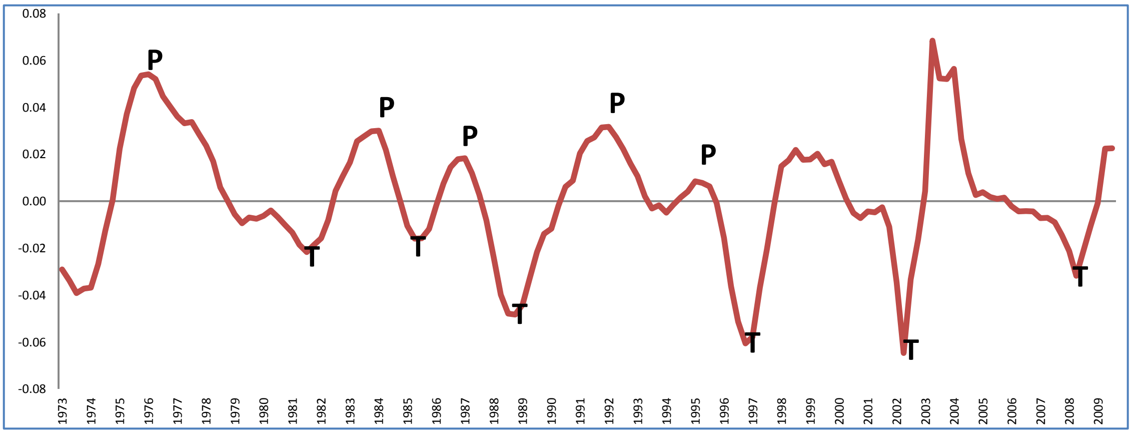
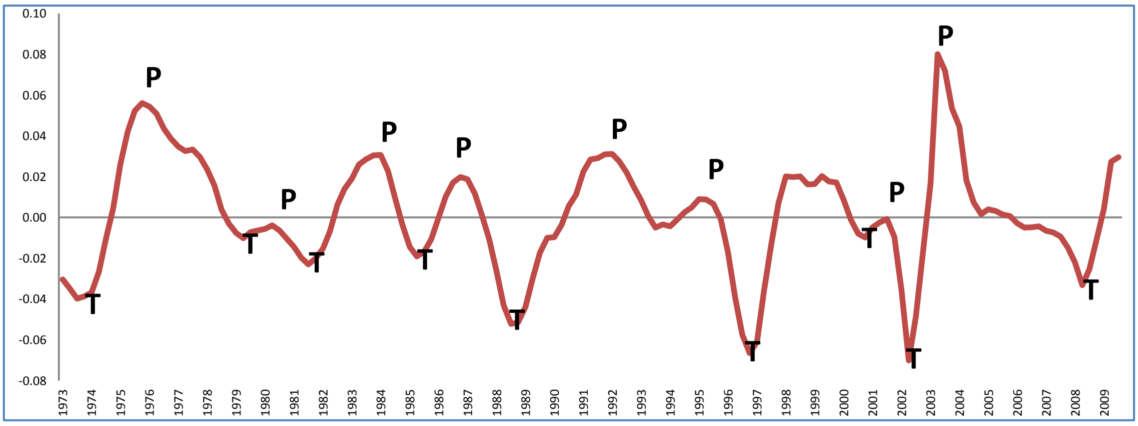


Figure 7.29 The OECD consumer confidence index of the Hong Kong (Total) hotel category growth rate by coefficient of the cross correlation (TOTAL OECD CCI CC) with the identification of peak (P) and trough (T)



Identifying turns in the constructed OECD leading indicators by the market share of the overnight-stay visitor arrivals

Figures 7.33 to 7.36 (7.34 to 7.36 are in the Appendix) are the graphs of the constructed OECD composite leading indicators by the market share of the overnight-stay visitor arrivals with the identification of peak (P) and trough (T). Figures 7.37 to 7.40 (7.38 to 7.40 are in the Appendix) are the graphs of the OECD business survey indexes by the market share of the overnight-stay visitor arrivals with the identification of peak (P) and trough (T). Figures 7.41 to 7.44 (7.42 to 7.44 are in the Appendix) are the graphs of the OECD consumer confidence indexes by the market share of the overnight-stay visitor arrivals with the identification of peak (P) and trough (T).

Figure 7.33 The OECD composite leading indicator of the Hong Kong (Total) hotel category growth rate by coefficient of the market share of the overnight-stay visitor arrivals (TOTAL OECD CLI MS) with the identification of peak (P) and trough (T)

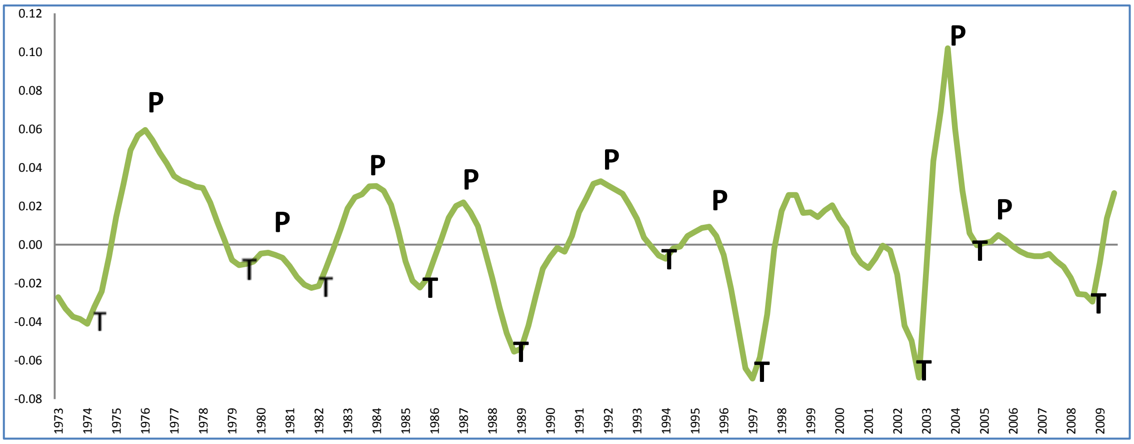


Figure 7.37 The OECD business survey index of the Hong Kong (Total) hotel category growth rate by coefficient of the market share of the overnight-stay visitor arrivals (TOTAL OECD BSI MS) with the identification of peak (P) and trough (T)

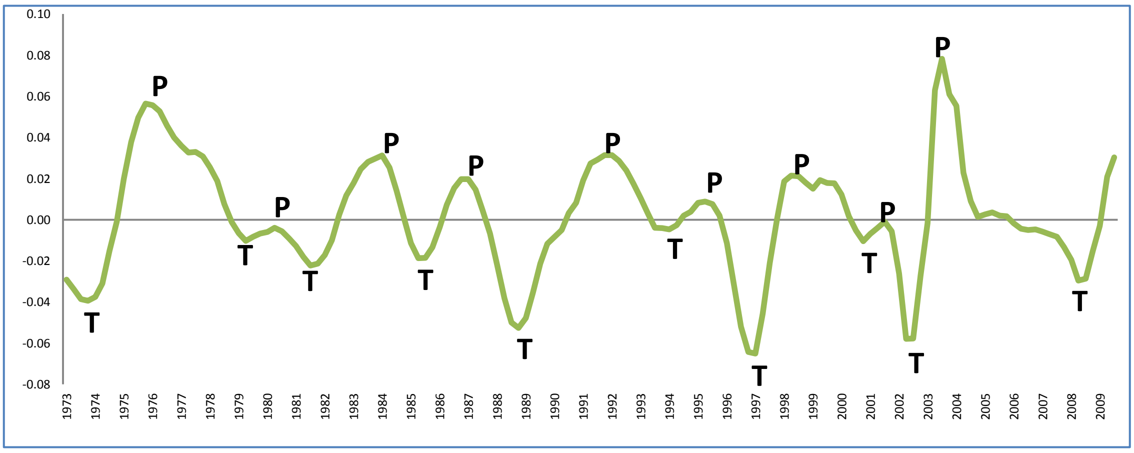
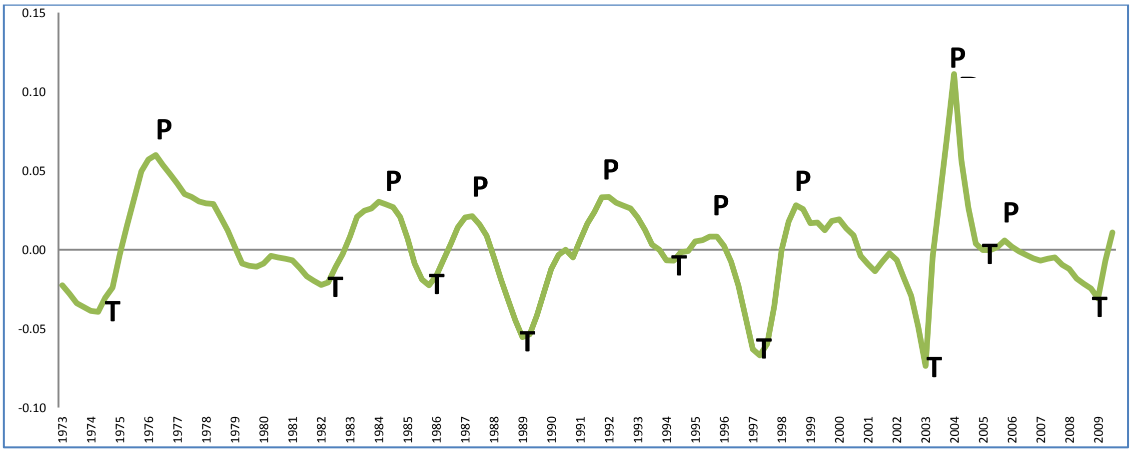


Figure 7.41 The OECD consumer confidence index of the Hong Kong (Total) hotel category growth rate by coefficient of the market share of the overnight-stay visitor arrivals (TOTAL OECD CCI MS) with the identification of peak (P) and trough (T)



7.9 Logistic and Probit regression models

Logistic and probit regression models are generalized linear econometric models commonly used in macroeconomics and finance to predict the turning points. Kulendran and Wong (2010) proved that the logistic and probit regression models could also be used in tourism forecasting. In this section, after the construction of OECD leading indicators for the Hong Kong hotel industry, logistic and probit regression models will estimate with all OECD leading indicators.

Logistic and probit regression models are based on making a prediction of the probability that an incident will happen (p = 1) or will not happen (p = 0) in the future. In the present study, (1) will represented the expansion period and (0) will represent the contraction period in the dependent variable, which is the Hong Kong hotel occupancy growth rate.

The logistic regression model is used for the prediction of the probability of an incident's occurrence by fitting data to a logistic function curve. In the model, the dependent variable is the logarithm of the ratio of the probability that a particular event will happen to the probability that the event will not happen. The probit regression model is an estimation method with dummy variables used as a variant of cumulative normal distribution. The binary probit model is based on the cumulative distribution function. If the cumulative distribution of the error term (*e*) is normal, then the model is called a probit regression model.

The logistic regression equation with composite leading indicators is as follows:

$$\text{Ln}\left[\frac{\mathrm{P_{it}}}{(1-\mathrm{P_{it}})}\right] = \beta_{\mathrm{o}} + \beta_1 \text{OECD CLI}_{t-k}$$

$$\text{Ln}\left[\frac{\mathrm{P_{it}}}{(1-\mathrm{P_{it}})}\right] = \beta_{\mathrm{o}} + \beta_1 \text{OECD BSI}_{t-k}$$

$$\text{Ln}\left[\frac{\mathrm{P_{it}}}{(1-\mathrm{P_{it}})}\right] = \beta_{\mathrm{o}} + \beta_1 \text{OECD CCI}_{t-k}$$

The probit regression equation with composite leading indicators is as follows:

$$\mathrm{P_{it}} = \beta_{\mathrm{o}} + \beta_1 \text{OECD CLI}_{t-k}$$

$$\mathrm{P_{it}} = \beta_{\mathrm{o}} + \beta_1 \text{OECD BSI}_{t-k}$$

$$\mathrm{P_{it}} = \beta_{\mathrm{o}} + \beta_1 \text{OECD CCI}_{t-k}$$

where k is the lead time of the composite leading indicator; OECD CLI is the constructed OECD composite leading indicators for Hong Kong hotels; OECD BSI is the constructed OECD business survey index for Hong Kong hotels; OECD CCI is the constructed OECD consumer confidence index for Hong Kong hotels; P_{it} is the probability that the particular outcome of expansion (1) will occur in time t; and 1-P_{it} is the probability that the particular outcome of contraction (0) occur in time t.

All the estimated models are valid because LR statistics are significant at the 5% level. Tables 7.20 to 7.22 show the results of the logistic regression models estimated with the

OECD data models. Tables 7.23 to 7.25 show the results of the probit regression models estimated with the OECD data models.

Table 7.20 Estimated logistic regression models with the constructed OECD composite leading indicator; sample period: Q2 1973 to Q2 2009

	Estimated regression logistic models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean of OECD data
TOTAL OECD CLI CC LG	**$Ln (P_{it} /(1-P_{it})) = -1.143 + 48.470TOTAL\_OECD\_CLI\_CC\_LG_{t-1}$ (z = -5.030) (z = 4.735)**	145	33.671	0.000	0.189	0.001561
TOTAL OECD CLI MS LG	**$Ln (P_{it} /(1-P_{it})) = -0.900 + 20.911TOTAL\_OECD\_CLI\_MS\_LG_{t-2}$ (z = -4.679) (z = 2.893)**	144	9.413	0.002	0.053	0.001088
HIGH A OECD CLI CC LG	**$Ln (P_{it} /(1-P_{it})) = -0.565 + 21.284HIGHA\_OECD\_CLI\_CC\_LG_{t-2}$ (z = -3.107) (z = 3.180)**	144	11.970	0.000	0.063	0.000885
HIGH A OECD CLI MS LG	**$Ln (P_{it} /(1-P_{it})) = -0.544 + 17.138HIGHA\_OECD\_CLI\_MS\_LG_{t-2}$ (z = -3.043) (z = 2.774)**	144	8.672	0.003	0.046	0.000367
HIGH B OECD CLI CC LG	**$Ln (P_{it} /(1-P_{it})) = -0.449 + -30.240HIGHB\_OECD\_CLI\_CC\_LG_{t-5}$ (z = -2.452) (z = -3.515)**	141	15.745	0.000	0.083	0.002101
HIGH B OECD CLI MS LG	**$Ln (P_{it} /(1-P_{it})) = -0.505 + 20.615HIGHB\_OECD\_CLI\_MS\_LG_{t-2}$ (z = -2.836) (z = 2.775)**	144	8.650	0.003	0.045	0.001585
MEDIUM OECD CLI CC LG	**$Ln (P_{it} /(1-P_{it})) = -0.197 + 29.949MEDIUM\_OECD\_CLI\_CC\_LG_{t-2}$ (z = -1.089) (z = 4.179)**	144	21.807	0.000	0.110	0.001484
MEDIUM OECD CLI MS LG	**$Ln (P_{it} /(1-P_{it})) = -0.166 + 16.093MEDIUM\_OECD\_CLI\_MS\_LG_{t-2}$ (z = -0.962) (z = 2.767)**	144	8.479	0.004	0.042	0.001228

N is the number of observations.
The LR statistic tests joint hypothesis is all slope coefficients except the constant are zero.
Prob(LR Statisitc) is the p value of the LR statistic.
R^2_{McF} is the McFadden R-squared.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
CC is the weighting method of the coefficient of cross correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival in Hong Kong.
LG is the logistic regression model.
PB is the probit regression model.
Apply to Table 7.20 to 7.25.

Table 7.21 Estimated logistic regression models with the constructed OECD business survey index; sample period: Q2 1973 to Q2 2009

	Estimated regression logistic models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean of OECD data
TOTAL OECD BSI CC LG	**$Ln (P_{it} /(1-P_{it})) = -1.0755 + 44.455TOTAL\_OECD\_BSI\_CC\_LG_{t-1}$ (z = -4.962) (z = 4.556)**	145	28.014	0.000	0.157	0.001306
TOTAL OECD BSI MS LG	**$Ln (P_{it} /(1-P_{it})) = -0.939 + 27.235TOTAL\_OECD\_BSI\_MS\_LG_{t-2}$ (z = -4.739) (z = 3.442)**	144	13.842	0.000	0.078	0.001623
HIGH A OECD BSI CC LG	**$Ln (P_{it} /(1-P_{it})) = -0.550 + 18.893HIGHA\_OECD\_BSI\_CC\_LG_{t-2}$ (z = -3.067) (z = 2.797)**	144	8.638	0.003	0.045	0.000605
HIGH A OECD BSI MS LG	**$Ln (P_{it} /(1-P_{it})) = -0.550 + 18.894HIGHA\_OECD\_BSI\_MS\_LG_{t-2}$ (z = -3.063) (z = 2.919)**	144	9.538	0.002	0.050	0.000556
HIGH B OECD BSI CC LG	**$Ln (P_{it} /(1-P_{it})) = -0.416 + -19.620HIGHB\_OECD\_BSI\_CC\_LG_{t-4}$ (z = -2.372) (z = -2.356)**	142	6.039	0.014	0.032	0.001778
HIGH B OECD BSI MS LG	**$Ln (P_{it} /(1-P_{it})) = -0.425 + -26.071HIGHB\_OECD\_BSI\_MS\_LG_{t-2}$ (z = -2.376) (z = -3.081)**	144	11.045	0.000	0.058	0.001714
MEDIUM OECD BSI CC LG	**$Ln (P_{it} /(1-P_{it})) = -0.253 + 46.293MEDIUM\_OECD\_BSI\_CC\_LG_{t-1}$ (z = -1.315) (z = 5.109)**	145	38.200	0.000	0.191	0.001519
MEDIUM OECD BSI MS LG	**$Ln (P_{it} /(1-P_{it})) = -0.194 + 28.298MEDIUM\_OECD\_BSI\_MS\_LG_{t-2}$ (z = -1.079) (z = 4.0127)**	144	19.739	0.000	0.099	0.001449

Table 7.22 Estimated logistic models with the constructed OECD confidence index; sample period: Q2 1973 to Q2 2009

	Estimated regression logistic models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean of OECD data
TOTAL OECD CCI CC LG	**$Ln(P_{it}/(1-P_{it})) = -0.990 + 33.913TOTAL\_OECD\_CCI\_CC\_LG_{t-2}$ (z = -4.811) (z = 3.946)**	144	19.630	0.000	0.111	0.001390
TOTAL OECD CLI MS LG	**$Ln(P_{it}/(1-P_{it})) = -0.912 + 22.055TOTAL\_OECD\_CCI\_MS\_LG_{t-1}$ (z = -4.738) (z = 2.995)**	145	10.288	0.001	0.058	0.000772
HIGH A OECD CCI CC LG	**$Ln(P_{it}/(1-P_{it})) = -0.532 + 18.179HIGHA\_OECD\_CCI\_CC\_LG_{t-1}$ (z = -2.987) (z = 2.763)**	145	8.550	0.003	0.044	0.000767
HIGH A OECD CCI MS LG	**$Ln(P_{it}/(1-P_{it})) = -0.517 + 16.584HIGHA\_OECD\_CCI\_MS\_LG_{t-1}$ (z = -2.926) (z = 2.646)**	145	7.857	0.005	0.040	-0.000057
HIGH B OECD CCI CC LG	**$Ln(P_{it}/(1-P_{it})) = -0.612 + 50.878HIGHB\_OECD\_CCI\_CC\_LG_{t-1}$ (z = -3.266) (z = 4.579)**	145	31.424	0.000	0.162	0.001937
HIGH B OECD CCI MS LG	**$Ln(P_{it}/(1-P_{it})) = -0.612 + 50.878HIGHB\_OECD\_CCI\_CC\_LG_{t-1}$ (z = -3.266) (z = 4.579)**	145	7.688	0.006	0.040	0.001242
MEDIUM OECD CCI CC LG	**$Ln(P_{it}/(1-P_{it})) = -0.266 + 48.570MEDIUM\_OECD\_CCI\_CC\_LG_{t-2}$ (z = -1.336) (z = 5.236)**	144	45.737	0.000	0.077	0.001815
MEDIUM OECD CCI MS LG	**$Ln(P_{it}/(1-P_{it})) = -0.195 + 24.275MEDIUM\_OECD\_CCI\_MS\_LG_{t-1}$ (z = -1.108) (z = 3.612)**	145	15.439	0.000	0.077	0.001193

Table 7.23 Estimated regression probit models with the constructed OECD composite leading indicator; sample period: Q2 1973 to Q2 2009

	Estimated regression probit models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean of OECD data
TOTAL OECD CLI CC PB	**$P_{it} = -0.679 + 28.374TOTAL\_OECD\_CLI\_CC\_PB_{t-1}$ (z = -5.286) (z = 5.000)**	145	33.732	0.000	0.190	0.001561
TOTAL OECD CLI MS PB	**$P_{it} = -0.549 + 12.604TOTAL\_OECD\_CLI\_MS\_PB_{t-2}$ (z = -4.831) (z = 2.960)**	144	9.437	0.002	0.053	0.001088
HIGH A OECD CLI CC PB	**$P_{it} = -0.342 + 12.973HIGHA\_OECD\_CLI\_CC\_PB_{t-2}$ (z = -3.117) (z = 3.265)**	144	11.953	0.000	0.063	0.000885
HIGH A OECD CLI MS PB	**$P_{it} = -0.334 + 10.619HIGHA\_OECD\_CLI\_MS\_PB_{t-2}$ (z = -3.069) (z = 2.836)**	144	8.735	0.003	0.046	0.000367
HIGH B OECD CLI CC PB	**$P_{it} = -0.271 + -18.061HIGHB\_OECD\_CLI\_CC\_PB_{t-5}$ (z = -2.440) (z = -3.674)**	141	15.676	0.000	0.083	0.002101
HIGH BOECD CLI MS PB	**$P_{it} = -0.312 + 12.738HIGHB\_OECD\_CLI\_MS\_PB_{t-2}$ (z = -2.872) (z = 2.855)**	144	8.702	0.003	0.045	0.001585
MEDIUM OECD CLI CC PB	**$P_{it} = -0.125 + 18.354MEDIUM\_OECD\_CLI\_CC\_PB_{t-2}$ (z = -1.130) (z = 4.405)**	144	21.944	0.000	0.110	0.001484
MEDIUM OECD CLI MS PB	**$P_{it} = -0.103 + 9.931MEDIUM\_OECD\_CLI\_MS\_PB_{t-2}$ (z = -0.962) (z = 2.841)**	144	8.480	0.004	0.043	0.001228

Table 7.24 Estimated regression probit models with the constructed OECD business survey index; sample period: Q2 1973 to Q2 2009

	Estimated regression probit models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean
TOTAL OECD BSI CC PB	**$P_{it} = -0.647 + 26.844TOTAL\_OECD\_BSI\_CC\_PB_{t-1}$ (z = -5.207) (z = 4.787)**	145	28.458	0.000	0.160	0.001306
TOTAL OECD BSI MS P	**$P_{it} = -0.572 + 16.575TOTAL\_OECD\_BSI\_MS\_PB_{t-2}$ (z = -4.922) (z = 3.557)**	144	14.042	0.000	0.079	0.001623
HIGH A OECD BSI CC PB	**$P_{it} = -0.336 + 11.579HIGHA\_OECD\_BSI\_CC\_PB_{t-2}$ (z = -3.091) (z = 2.848)**	144	8.626	0.003	0.045	0.000605
HIGH A OECD BSI MS PB	**$P_{it} = -0.337 + 11.659HIGHA\_OECD\_BSI\_MS\_PB_{t-2}$ (z = -3.088) (z = 2.980)**	144	9.578	0.002	0.050	0.000556
HIGH B OECD BSI CC PB	**$P_{it} = -0.257 + -11.848HIGHB\_OECD\_BSI\_CC\_PB_{t-4}$ (z = -2.383) (z = -2.406)**	142	5.976	0.015	0.031	0.001778
HIGH BOECD BSI MS PB	**$P_{it} = -0.259 + -15.649HIGHB\_OECD\_BSI\_MS\_PB_{t-2}$ (z = -2.374) (z = -3.186)**	144	10.939	0.000	0.161	0.001714
MEDIUM OECD BSI CC PB	**$P_{it} = -0.164 + 37.972MEDIUM\_OECD\_BSI\_CC\_PB_{t-1}$ (z = -1.424) (z = 5.507)**	145	38.200	0.000	0.191	0.001519
MEDIUM OECD BSI MS PB	**$P_{it} = -0.122 + 17.357MEDIUM\_OECD\_BSI\_MS\_PB_{t-2}$ (z = -1.114) (z = 4.216)**	144	19.847	0.000	0.100	0.001449

Table 7.25 Estimated regression probit models with the constructed OECD consumer confidence index; sample period: Q2 1973 to Q2 2009

	Estimated regression probit models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean of OECD data
TOTAL OECD CCI CC PB	**P_{it} = -0.602 + 20.698TOTAL_OECD_CCI_CC_PB$_{t-2}$ (z = -5.022) (z = 4.120)**	144	20.042	0.000	0.113	0.001390
TOTAL OECD CCI MS PB	**P_{it} = -0.556 + 13.270TOTAL_OECD_CCI_MS_PB$_{t-1}$ (z = -4.895) (z = 3.076)**	145	10.310	0.001	0.058	0.000772
HIGH A OECD CCI CC PB	**P_{it} = -0.322 + 10.822HIGHA_OECD_CCI_CC_PB$_{t-1}$ (z = -2.981) (z = 2.803)**	145	8.341	0.004	0.043	0.000767
HIGH A OECD CCI MS PB	**P_{it} = -0.318 + 10.292HIGHA_OECD_CCI_MS_PB$_{t-1}$ (z = -2.945) (z = 2.700)**	145	7.910	0.005	0.041	-0.000057
HIGH B OECD CCI CC PB	**P_{it} = -0.379 + 29.619HIGHB_OECD_CCI_CC_PB$_{t-1}$ (z = -3.282) (z = 4.935)**	145	31.071	0.000	0.161	0.001937
HIGH B OECD CCI MS PB	**P_{it} = -0.315 + 12.518HIGHB_OECD_CCI_MS_PB$_{t-1}$ (z = -2.918) (z = 2.705)**	145	7.731	0.005	0.040	0.001242
MEDIUM OECD CCI CC PB	**P_{it} = -0.173 + 29.287MEDIUM_OECD_CCI_CC_PB$_{t-2}$ (z = -1.448) (z = 5.623)**	144	46.265	0.000	0.233	0.001815
MEDIUM OECD CCI MS PB	**P_{it} = -0.121 + 14.821MEDIUM_OECD_CCI_MS_PB$_{t-1}$ (z = -1.121) (z = 3.764)**	145	15.430	0.000	0.077	0.001193

7.10 Accuracy of Probability Forecasting

This section compares the accuracy of the probability occurrence of each constructed model with the OECD leading indicators. Quadratic probability score (QPS) is a common instrument to test the forecasting correctness of the logistic and probit regression models.

From the estimated probability (p_e) of the logistic and probit regression models, the expansion and contraction periods could be identified as follows: if the estimated probability (p_e) is "greater than 0.5," it is considered an expansion period; if the estimated probability (p_e) is "smaller than 0.5," it is considered a contraction period. Therefore, the timing of the turn/change and the turning point (peak point) can be recognized when the estimated probability (p_e) changes from "greater than 0.5" to "smaller than 0.5"; the timing of the turn/change and the turning point (trough point) can be recognized when the estimated probability (p_e) changes from "smaller than 0.5" to "greater than 0.5". Diebold and Rudebusch (1989) explained that QPS ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. The simplified formula to calculate the QPS is as follows:

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2\,(P_1 - R_1)^2$$

where P_t is the probability of the occurrence of a turning point at date t (or, over specific horizon H beyond date t); R_t equals one if the turning point occurs in period t and is equal to zero otherwise. Table 7.26 illustrates the results of forecasting accuracy by QPS.

From the results, two aspects can be identified. First, generally, both logistic and probit regression models with the constructed OECD leading indicators by the market share weighting method has a lower score, which means that all the constructed OECD leading indicators more accurately predict turning points in hotel occupancy using the weighting method of the market share of the overnight-stay visitor arrivals.

Second, among all the constructed OECD leading indicators, the best QPS (closest to zero) is that of the constructed OECD consumer confidence index compared with the constructed OECD composite leading indicator and the constructed business survey index.

Table 7.26 Summary of the QPS results for the logistic and probit regression OECD indicator models

	Hong Kong hotel category				
	HK TOTAL	**HK HIGH A**	**HK HIGH B**	**HK MEDIUM**	**Average**
OECD CLI CC LG	0.48744	0.37775	0.80272	0.24119	**0.47728**
OECD CLI MS LG	0.33197	0.26230	0.29970	0.27499	**0.29224**
OECD CLI CC PB	0.48667	0.37983	0.79666	0.24118	**0.47609**
OECD CLI MS PB	0.33115	0.25971	0.29876	0.27492	**0.29114**
OECD BSI CC LG	0.37753	0.35426	0.70151	0.30502	**0.43458**
OECD BSI MS LG	0.33735	0.33239	0.76396	0.25762	**0.42283**
OECD BSI CC PB	0.37760	0.35516	0.69805	0.30622	**0.43426**
OECD BSI MS PB	0.36299	0.33121	0.75927	0.25783	**0.42783**
OECD CCI CC LG	0.33350	0.47134	0.40536	0.30792	**0.37953**
OECD CCI MS LG	0.33177	0.26837	0.31135	0.24333	**0.28871**
OECD CCI CC PB	0.33136	0.47494	0.40886	0.30873	**0.38097**
OECD CCI MS PB	0.33112	0.26583	0.31054	0.24389	**0.28785**

OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
CC is the weighting method of the coefficient of cross correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival in Hong Kong.
LG is the logistic regression model.
PB is the probit regression model.

Figures 7.45 to 7.52 (Figures 7.46 to 7.48 and Figures 7.50 to 7.52 are in the Appendix) show the estimated probability by the logistic regression models of the OECD composite leading indicator and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong. Figures 7.53 to 7.60 (Figures 7.54 to 7.56 and Figures 7.58 to 7.60 are in the Appendix) show the estimated probability by the logistic regression models of the OECD composite leading indicator and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong.

Figures 7.61 to 7.68 (Figures 7.62 to 7.64 and Figures 7.66 to 7.68 are in the Appendix) show the estimated probability by the logistic regression models of the OECD business survey index and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong. Figures 7.69 to 7.76 (Figures 7.70 to 7.72 and Figures 7.74 to 7.76 are in the Appendix) show the estimated probability by the logistic regression models of the OECD business survey index and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong.

Figures 7.77 to 7.84 (Figures 7.78 to 7.80 and Figures 7.82 to 7.84 are in the Appendix) show the estimated probability by the logistic regression models of the OECD consumer confidence index and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong. Figures 7.85 to 7.92 (Figures 7.86 to 7.88 and Figures 7.90 to 7.92 are in the Appendix) show the estimated probability by the logistic regression models of the OECD consumer confidence index and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong.

Figure 7.45 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD composite leading indicator (TOTAL OECD CLI CC LG) for Hong Kong (Total) hotel category

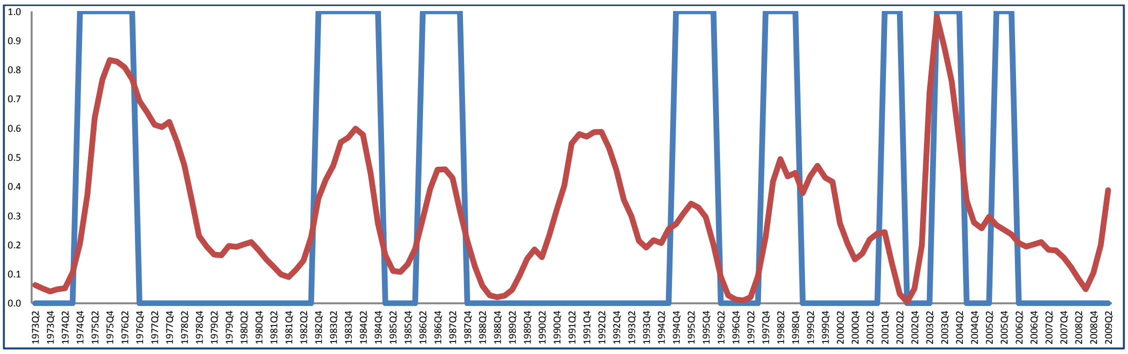


Figure 7.49 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD composite leading indicator (TOTAL OECD CLI MS LG) for Hong Kong (Total) hotel category

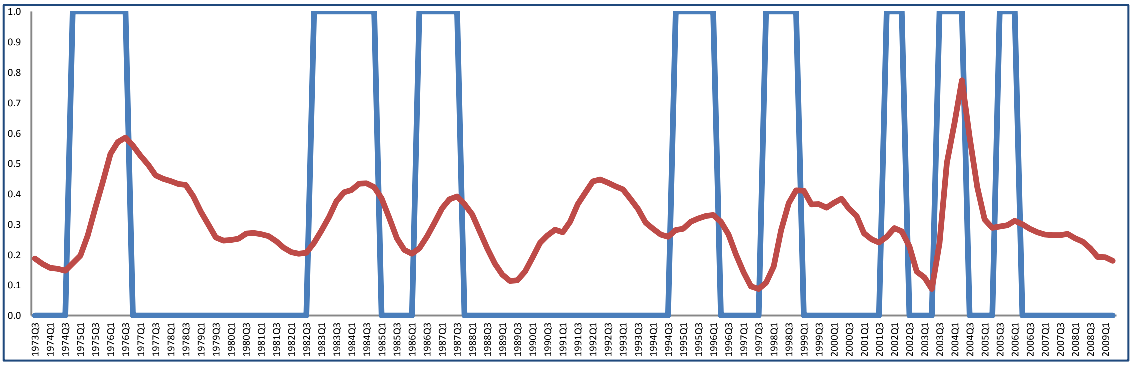


Figure 7.53 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD composite leading indicator (TOTAL OECD CLI CC PB) for Hong Kong (Total) hotel category

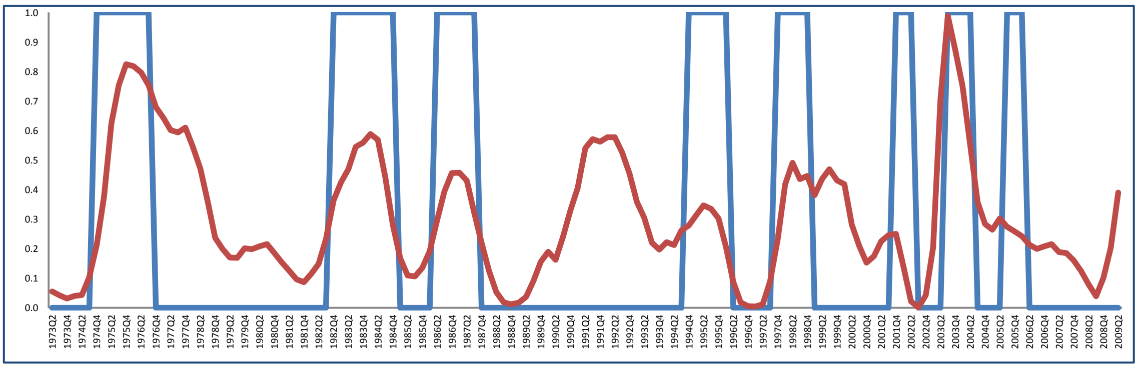


Figure 7.57 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD composite leading indicator (TOTAL OECD CLI MS PB) for Hong Kong (Total) hotel category

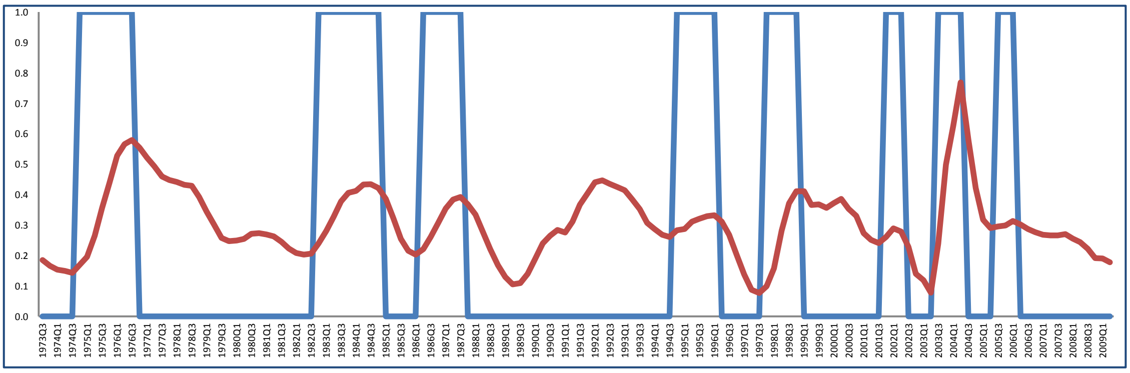


Figure 7.61 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD business survey index (TOTAL OECD BSI CC LG) for Hong Kong (Total) hotel category

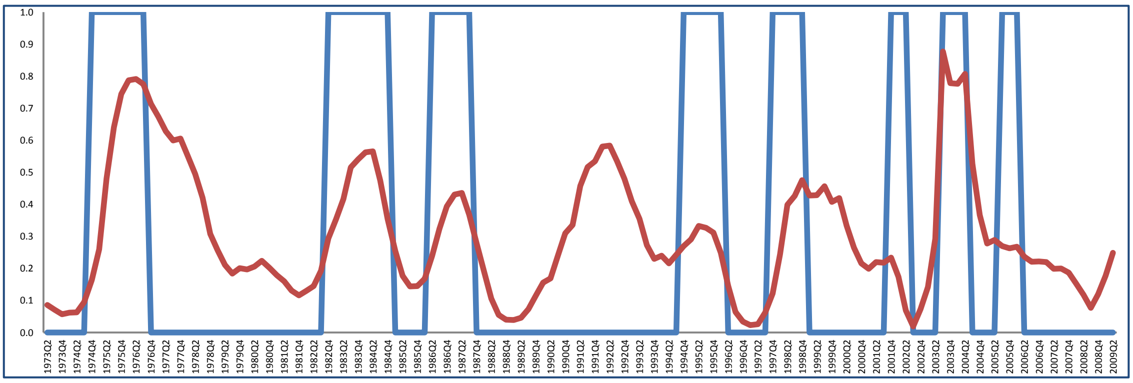


Figure 7.65 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD business survey index (TOTAL OECD BSI MS LG) for Hong Kong (Total) hotel category

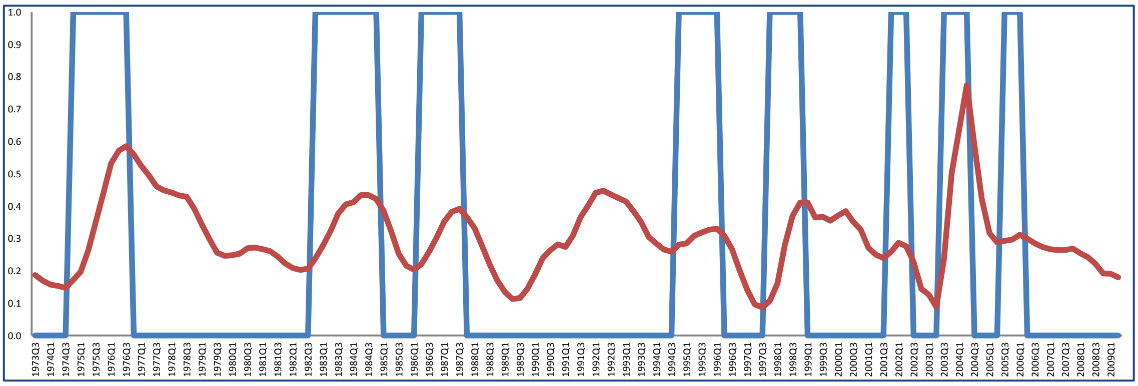


Figure 7.69 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD business survey index (TOTAL OECD BSI CC PB) for Hong Kong (Total) hotel category

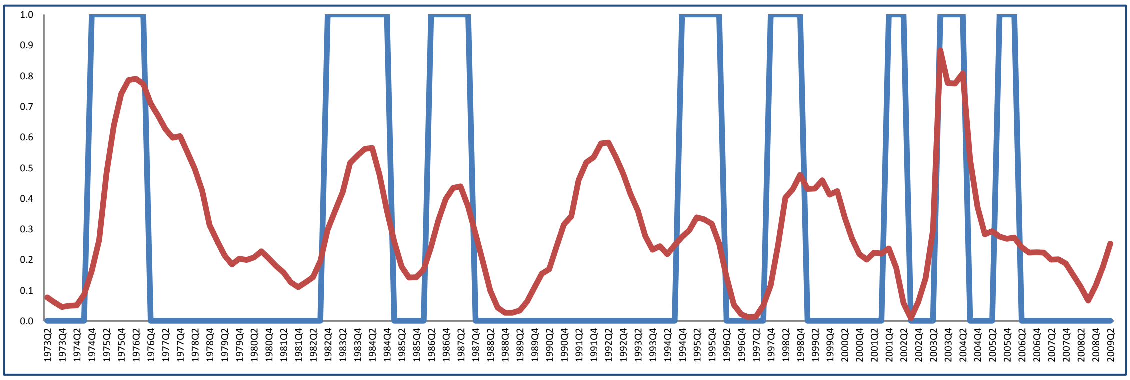


Figure 7.73 The hotel occupancy rate in expansion(1) and contraction(0) periods (HK TOTAL, 1=expansion & 0=contraction) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD business survey index (TOTAL OECD BSI MS PB) for Hong Kong (Total) hotel category

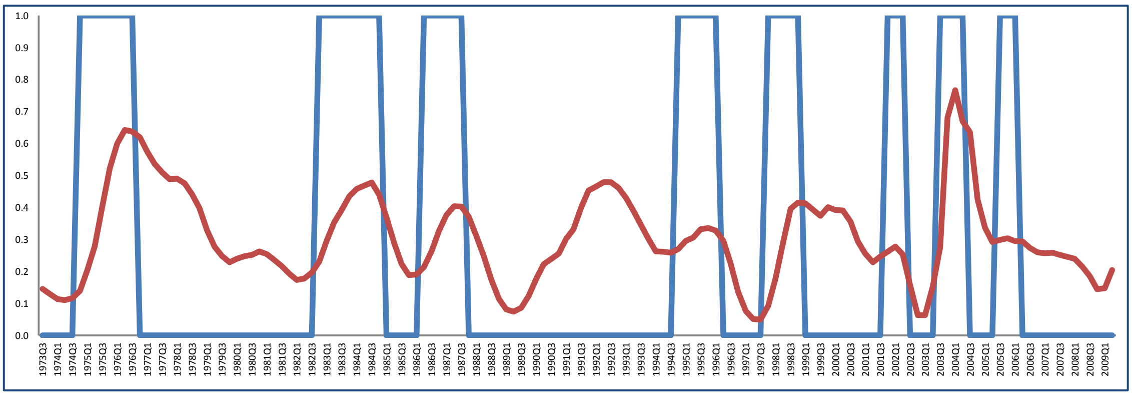


Figure 7.77 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD consumer confidence index (TOTAL OECD CCI CC LG) for Hong Kong (Total) hotel category

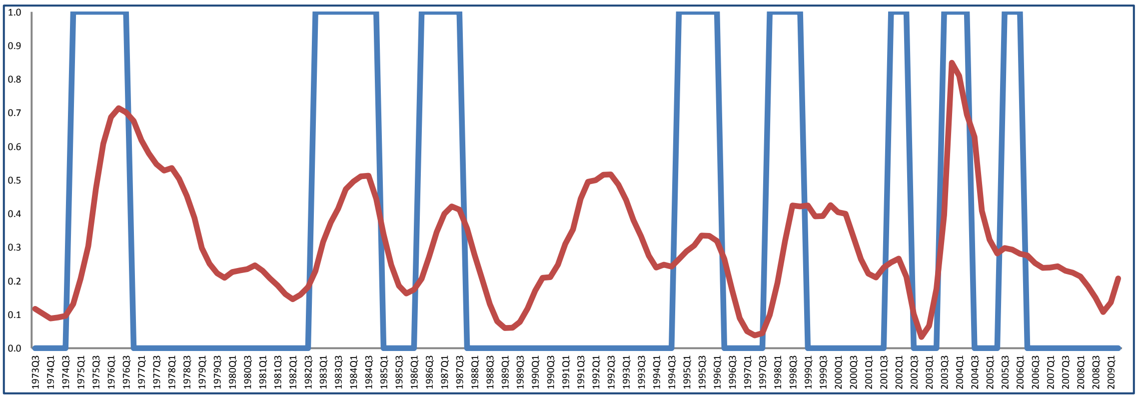


Figure 7.81 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD consumer confidence index (TOTAL OECD CCI MS LG) for Hong Kong (Total) hotel category

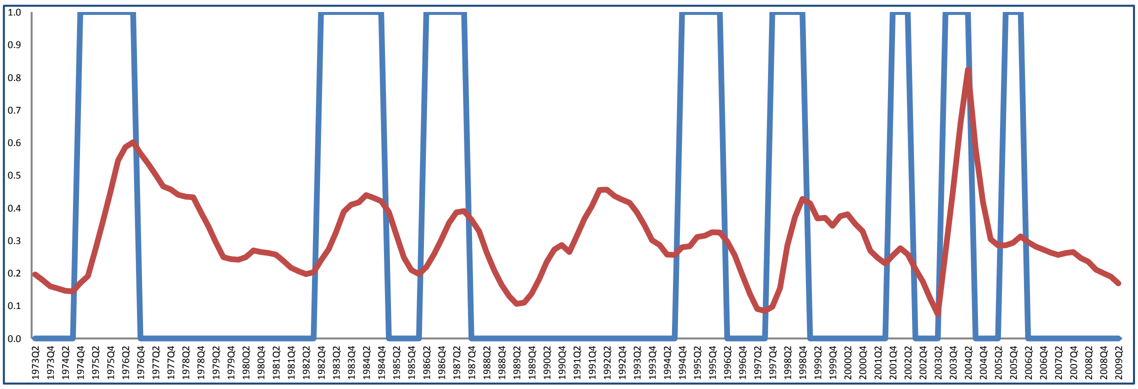


Figure 7.85 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD consumer confidence index (TOTAL OECD CCI CC PB) for Hong Kong (Total) hotel category

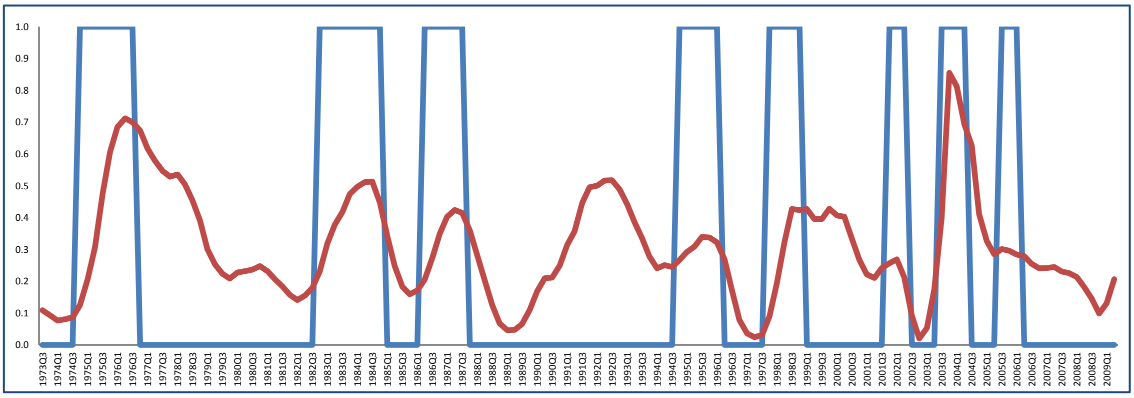
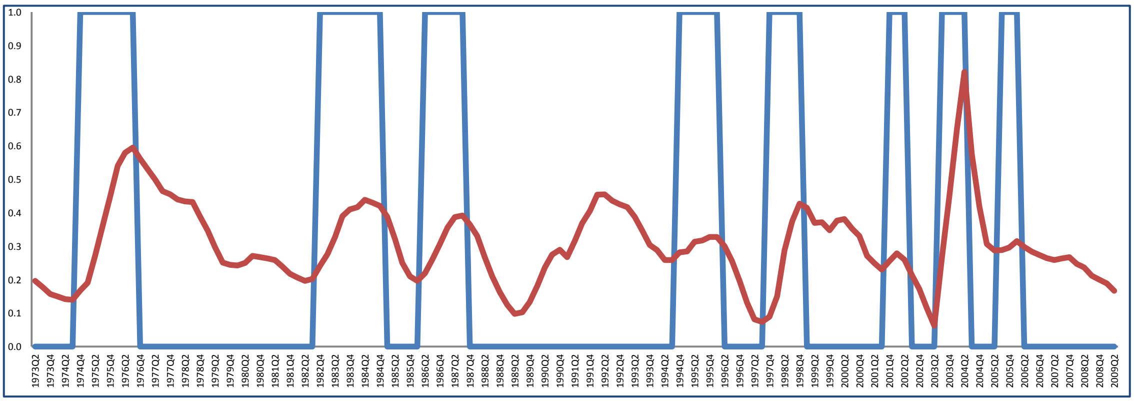


Figure 7.89 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD consumer confidence index (TOTAL OECD CCI MS PB) for Hong Kong (Total) hotel category



7.11 **Conclusion**

Using different published indicators and indexes from the OECD to construct the composite leading indicators for the Hong Kong hotel industry provides different information to help hoteliers and policy makers in decision making and operations planning. Using the composite leading indicator approach can give early signals of the shifting demand for hotel accommodation. The present study is the first attempt to construct composite leading indicators for the hotel industry. The literature review has established that there has been no previous research on constructing composite leading indicators for the hotel industry. Therefore, the present study uses different economic variables, namely, published indicators and indexes, to construct composite leading indicators to find the most accurate model to predict the turns in hotel occupancy rate.

Accurate forecasting of the turning points can provide the hotel management with practical advice on resource allocation and strategic planning. Moreover, two different weighting methods for the construction of the composite leading indicators contribute in-depth insights that could be used in future studies of different weighting methods for the construction of the composite indicator. The QPS results, consistent with the findings in the last chapter, show that the market share-weighting method delivers higher accuracy in predicting the turns for the hotel industry. Moreover, the constructed OECD consumer confidence index has the best probability forecast compared with the other two published OECD indicators.

7.12 Appendix

Table 7.4 Weights for the construction of OECD CLI for Hong Kong High Tariff A hotel category by the coefficient of the cross-correlation analysis (OECD CLI HIGH A CC)

OECD CLI HIGH A CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.0790	0.1473	13.3134	0.5142	0.0751	0.0869	0.0128	**0.0453**
Japan	0.1453	0.2710	6.0674	0.2343	0.1648	0.1908	0.0517	**0.1827**
USA	0.1065	0.1986	3.6617	0.1414	0.2731	0.3161	0.0628	**0.2219**
Australia	0.2054	0.3831	2.8489	0.1100	0.3510	0.4062	0.1556	**0.5501**
Total	0.5362	1.0000	25.8913	1.0000	0.8640	1.0000	0.2829	**1.0000**

(3) = (1) over column total;
(5) = (4) over column total;
(6) = 1 over (4);
(7) = (6) over column total;
(8) = (3) multiply (7);
(9) = (8) over column total.
Apply to Table 7.4 to 7.6, 7. 8 to 7.10 and 7.12 to 7.14.

Table 7.5 Weights for the construction of OECD CLI for Hong Kong High Tariff B hotel category by the coefficient of the cross-correlation analysis (OECD CLI HIGH B CC)

OECD CLI HIGH B CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.1133	0.2231	13.3134	0.5142	0.0751	0.0869	0.0194	**0.0693**
Japan	0.0908	0.1788	6.0674	0.2343	0.1648	0.1908	0.0341	**0.1220**
USA	0.0945	0.1861	3.6617	0.1414	0.2731	0.3161	0.0588	**0.2103**
Australia	0.2092	0.4120	2.8489	0.1100	0.3510	0.4062	0.1674	**0.5984**
Total	0.5078	1.0000	25.8913	1.0000	0.8640	1.0000	0.2797	**1.0000**

Table 7.6 Weights for the construction of OECD CLI for Hong Kong Medium Tariff hotel category by the coefficient of the cross-correlation analysis (OECD CLI MEDIUM CC)

OECD CLI MEDIUM CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.1161	0.2746	13.3134	0.5142	0.0751	0.0869	0.0239	**0.0934**
Japan	0.0842	0.1991	6.0674	0.2343	0.1648	0.1908	0.0380	**0.1486**
USA	0.0942	0.2228	3.6617	0.1414	0.2731	0.3161	0.0704	**0.2756**
Australia	0.1283	0.3035	2.8489	0.1100	0.3510	0.4062	0.1233	**0.4824**
Total	0.4228	1.0000	25.8913	1.0000	0.8640	1.0000	0.2556	**1.0000**

Table 7.8 Weights for the calculation of OECD BSI for Hong Kong High Tariff A hotel category by the coefficient of the cross-correlation analysis (OECD BSI HIGH A CC)

OECD BSI HIGH A CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.0569	0.0823	0.1149	0.7470	8.7062	0.0358	0.0029	**0.0100**
Japan	0.2064	0.2985	0.0109	0.0709	91.6675	0.3767	0.1125	**0.3802**
USA	0.1308	0.1892	0.0137	0.0892	72.9417	0.2998	0.0567	**0.1917**
Australia	0.2973	0.4300	0.0143	0.0929	69.9979	0.2877	0.1237	**0.4182**
Total	0.6914	1.0000	0.1538	1.0000	243.3133	1.0000	0.2958	**1.0000**

Table 7.9 Weights for the calculation of the OECD BSI for Hong Kong High Tariff B hotel category by the coefficient of the cross-correlation analysis (OECD BSI HIGH B CC)

OECD BSI HIGH B CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.0585	0.0878	0.1149	0.7470	8.7062	0.0358	0.0031	**0.0107**
Japan	0.1969	0.2956	0.0109	0.0709	91.6675	0.3767	0.1114	**0.3783**
USA	0.1331	0.1998	0.0137	0.0892	72.9417	0.2998	0.0599	**0.2035**
Australia	0.2777	0.4168	0.0143	0.0929	69.9979	0.2877	0.1199	**0.4075**
Total	0.6662	1.0000	0.1538	1.0000	243.3133	1.0000	0.2943	**1.0000**

Table 7.10 Weights for the calculation of OECD BSI for Hong Kong Medium Tariff hotel category by the coefficient of the cross-correlation analysis (OECD BSI MEDIUM CC)

OECD BSI MEDIUM CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.0749	0.1164	0.1149	0.7470	8.7062	0.0358	0.0042	**0.0144**
Japan	0.2053	0.3189	0.0109	0.0709	91.6675	0.3767	0.1202	**0.4162**
USA	0.1026	0.1594	0.0137	0.0892	72.9417	0.2998	0.0478	**0.1655**
Australia	0.2609	0.4053	0.0143	0.0929	69.9979	0.2877	0.1166	**0.4039**
Total	0.6437	1.0000	0.1538	1.0000	243.3133	1.0000	0.2887	**1.0000**

Table 7.12 Weights for the calculation of OECD CCI for Hong Kong High Tariff A hotel category by the coefficient of the cross-correlation analysis (OECD CCI HIGH A CC)

OECD CCI OF HK HIGH A CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.3505	0.3672	0.0143	0.3134	70.0972	0.1896	0.0696	**0.2851**
Japan	0.2172	0.2276	0.0104	0.2278	96.4410	0.2609	0.0594	**0.2431**
USA	0.2218	0.2324	0.0079	0.1745	125.8465	0.3405	0.0791	**0.3239**
Australia	0.1650	0.1729	0.0129	0.2844	77.2453	0.2090	0.0361	**0.1479**
Total	0.9545	1.0000	0.0455	1.0000	369.6301	1.0000	0.2442	**1.0000**

Tables 7.13 Weights for the calculation of OECD CCI for Hong Kong High Tariff B hotel category by the coefficient of the cross-correlation analysis (OECD CCI HIGH B CC)

OECD CCI HIGH B CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.3566	0.3412	0.0143	0.3134	70.0972	0.1896	0.0647	**0.2634**
Japan	0.2017	0.1930	0.0104	0.2278	96.4410	0.2609	0.0504	**0.2050**
USA	0.2646	0.2532	0.0079	0.1745	125.8465	0.3405	0.0862	**0.3509**
Australia	0.2221	0.2125	0.0129	0.2844	77.2453	0.2090	0.0444	**0.1808**
Total	1.0450	1.0000	0.0455	1.0000	369.6301	1.0000	0.2457	**1.0000**

Tables 7.14 Weights for the calculation of OECD CCI for Hong Kong Medium Tariff hotel category by the coefficient of the cross-correlation analysis (OECD CCI MEDIUM CC)

OECD CCI MEDIUM CC								
(1) Country	(2) Coefficient of the cross correlation	(3) Converted percentage of assigned Weight	(4) Average of the Absolute Average Deviation	(5) Converted percentage of the Absolute Average Deviation	(6) Inverse of the Absolute Average Deviation	(7) Converted percentage of Inverse of the Absolute Average Deviation	(8) Converted percentage of assigned Weight (multiply) converted percentage of Inverse of the Absolute Average Deviation	(9) Converted Percentage of Finalized weighting
China	0.3164	0.2975	0.0143	0.3134	70.0972	0.1896	0.0564	**0.2319**
Japan	0.2146	0.2018	0.0104	0.2278	96.4410	0.2609	0.0527	**0.2164**
USA	0.2394	0.2251	0.0079	0.1745	125.8465	0.3405	0.0766	**0.3150**
Australia	0.2930	0.2755	0.0129	0.2844	77.2453	0.2090	0.0576	**0.2367**
Total	1.0634	1.0000	0.0455	1.0000	369.6301	1.0000	0.2433	**1.0000**

Figure 7.10 Comparison of the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) with the OECD composite leading indicator by coefficient of the cross correlation (HIGH A OECD CLI CC) and the OECD composite leading indicator by the market share of the overnight-stay visitor arrivals (HIGH A OECD CLI MS)

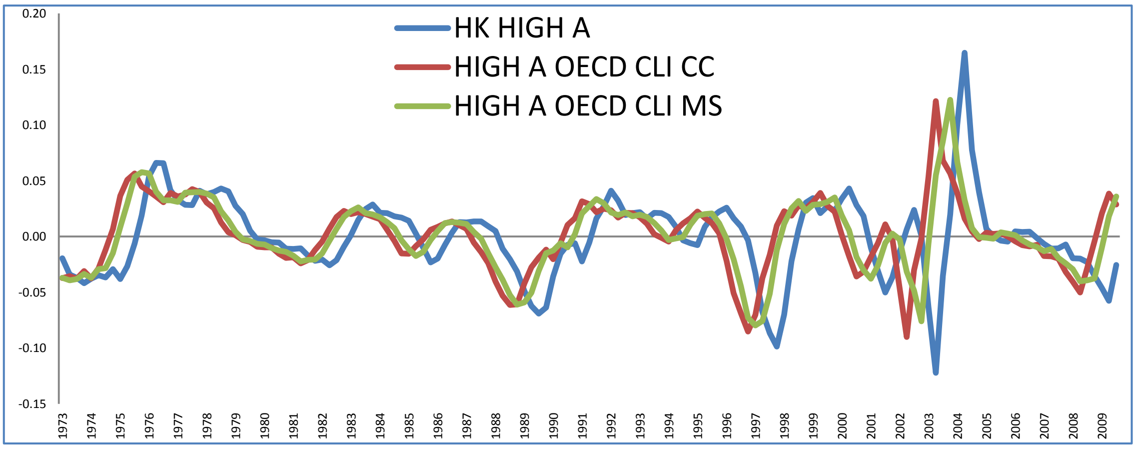


Figure 7.11 Comparison of the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) with the OECD composite leading indicator by coefficient of the cross correlation (HIGH B OECD CLI CC) and the OECD composite leading indicator by the market share of the overnight-stay visitor arrivals (HIGH B OECD CLI MS)

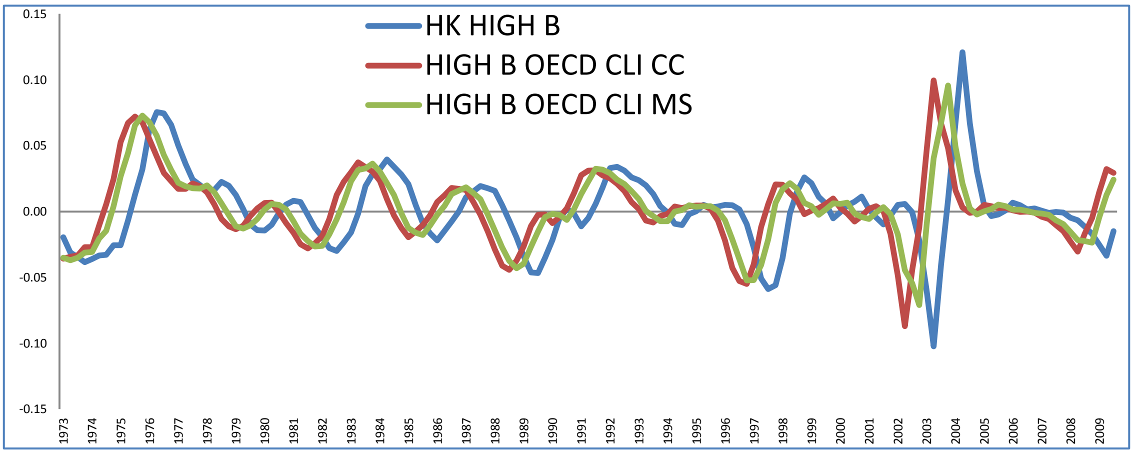


Figure 7.12 Comparison of the original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) with the OECD composite leading indicator by coefficient of the cross correlation (MEDIUM OECD CLI CC) and the OECD composite leading indicator by the market share of the overnight-stay visitor arrivals (MEDIUM OECD CLI MS)

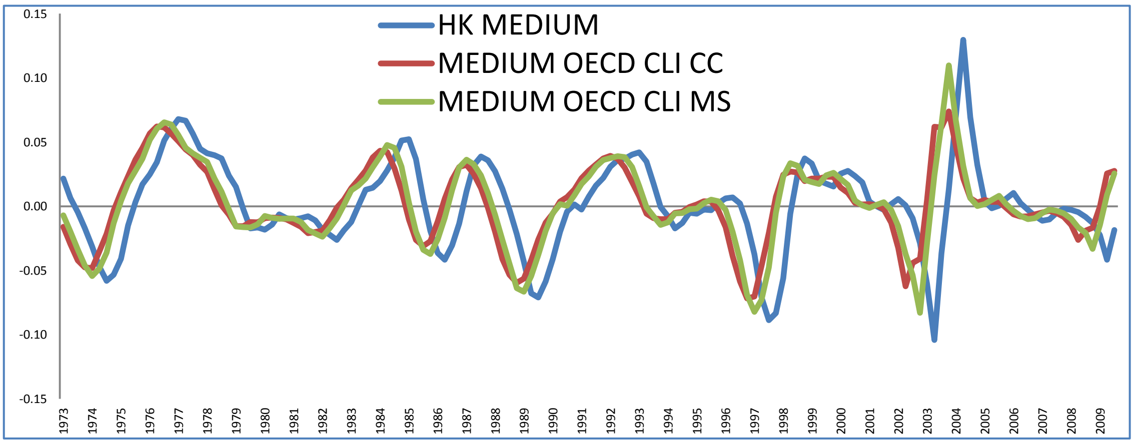


Figure 7.14 Comparison of the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) with the OECD business survey index by coefficient of the cross correlation (HIGH A OECD BSI CC) and the OECD business survey index by the market share of the overnight-stay visitor arrivals (HIGH A OECD BSI MS)

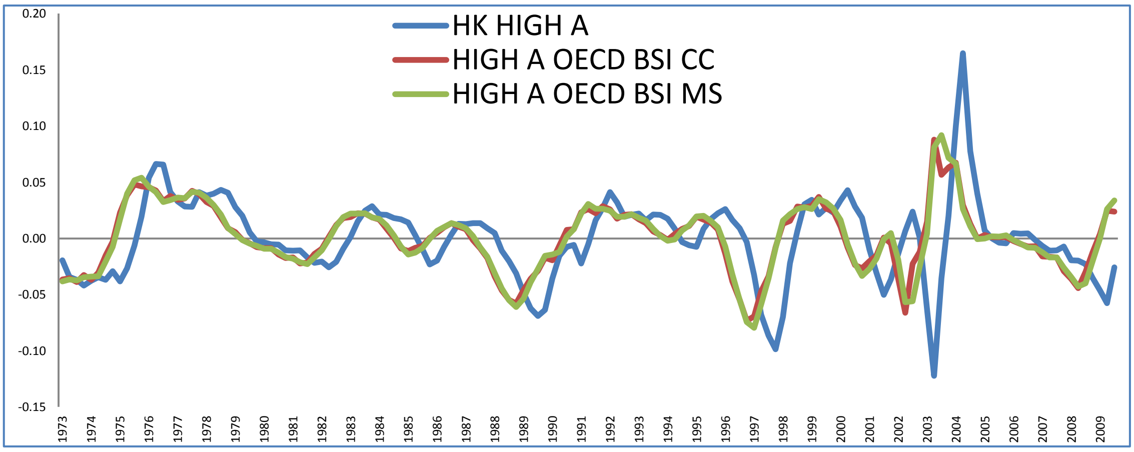


Figure 7.15 Comparison of the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) with the OECD business survey index by coefficient of the cross correlation (HIGH B OECD BSI CC) and the OECD business survey index by the market share of the overnight-stay visitor arrivals (HIGH B OECD BSI MS)

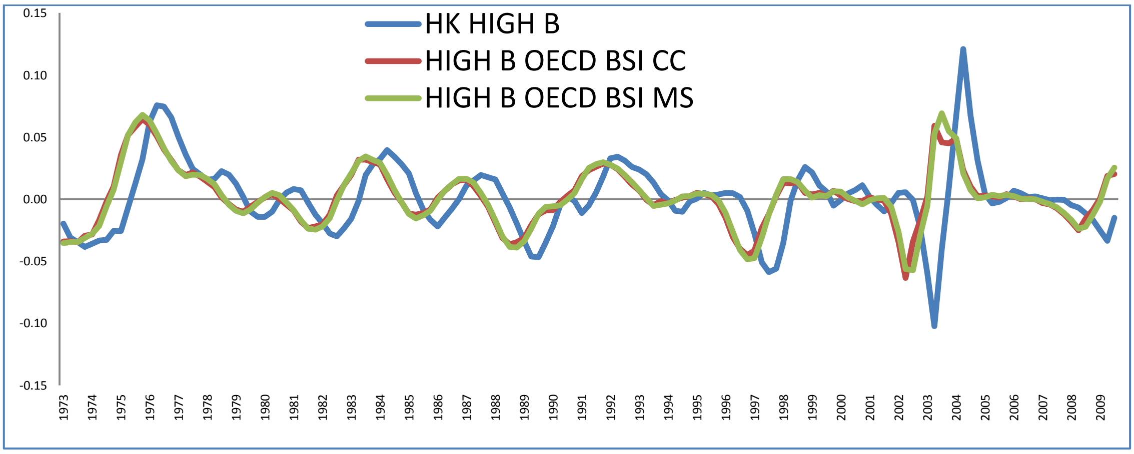


Figure 7.16 Comparison of the original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) with the OECD business survey index by coefficient of the cross correlation (MEDIUM OECD BSI CC) and the OECD business survey index by the market share of the overnight-stay visitor arrivals (MEDIUM OECD BSI MS)

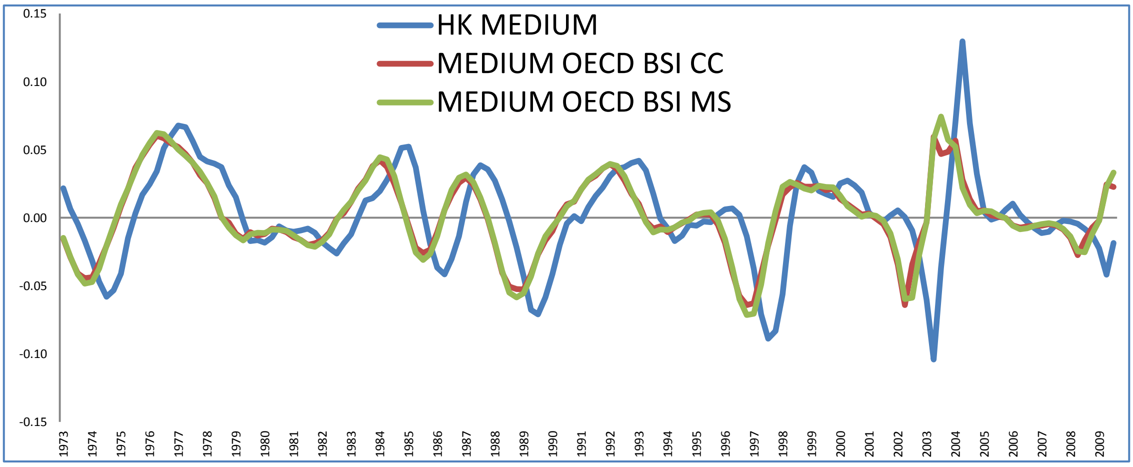


Figure 7.18 Comparison of the original Hong Kong High Tariff A hotel occupancy growth rate (HK HIGH A) with the OECD consumer confidence index by coefficient of the cross correlation (HIGH A OECD CCI CC) and the OECD consumer confidence index by the market share of the overnight-stay visitor arrivals (HIGH A OECD CCI MS)

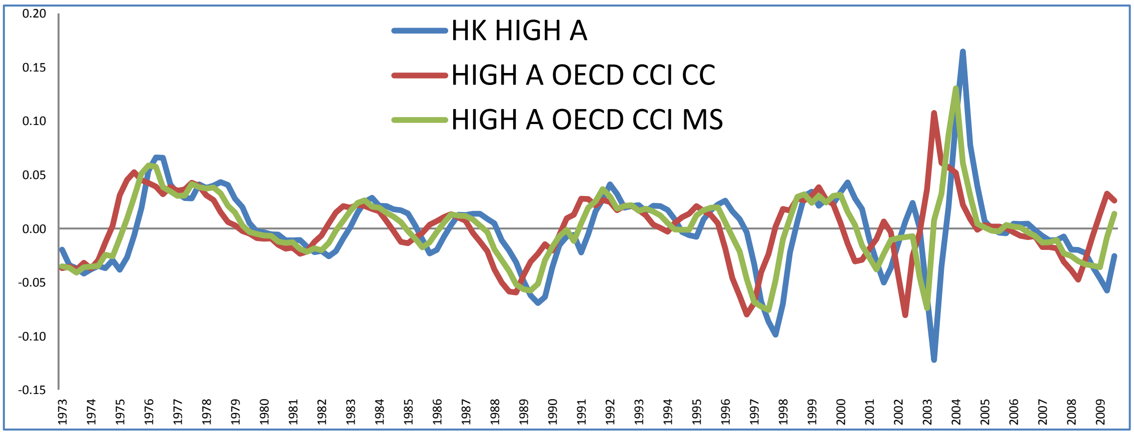


Figure 7.19 Comparison of the original Hong Kong High Tariff B hotel occupancy growth rate (HK HIGH B) with the OECD consumer confidence index by coefficient of the cross correlation (HIGH B OECD CCI CC) and the OECD consumer confidence index by the market share of the overnight-stay visitor arrivals (HIGH B OECD CCI MS)

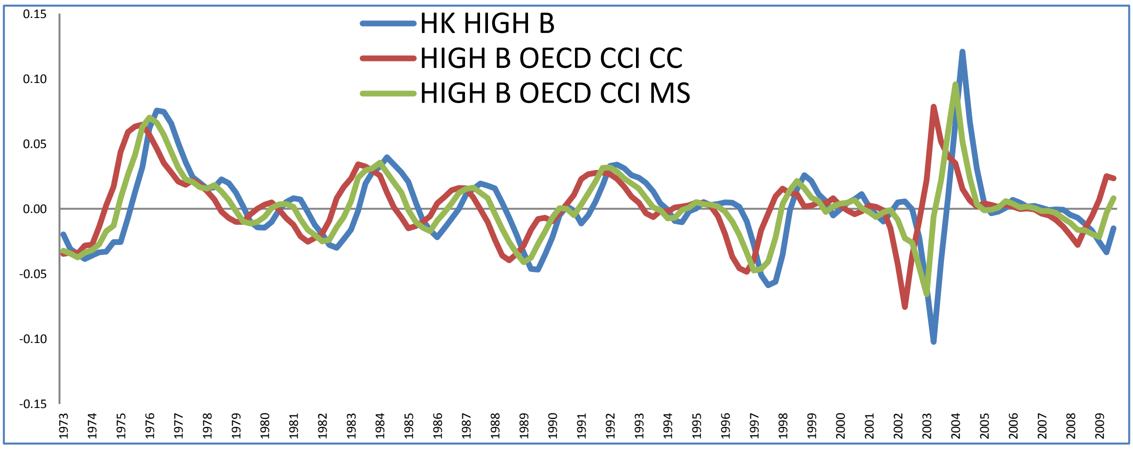


Figure 7.20 Comparison of the original Hong Kong Medium Tariff hotel occupancy growth rate (HK MEDIUM) with the OECD consumer confidence index by coefficient of the cross correlation (MEDIUM OECD CCI CC) and the OECD consumer confidence index by the market share of the overnight-stay visitor arrivals (MEDIUM OECD CCI MS)

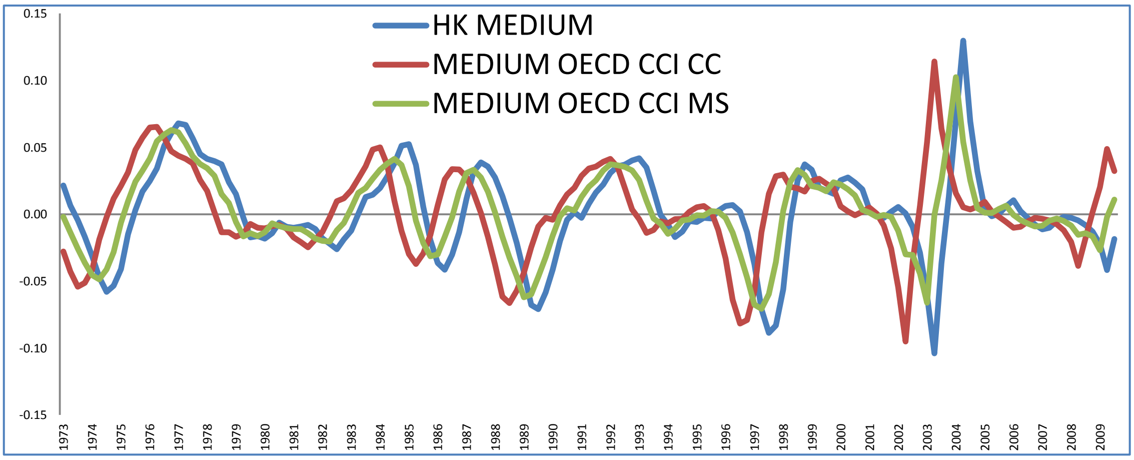


Figure 7.22 The OECD composite leading indicator of the Hong Kong High Tariff A hotel category by coefficient of the cross correlation (HIGH A OECD CLI CC) with the identification of peak (P) and trough (T)

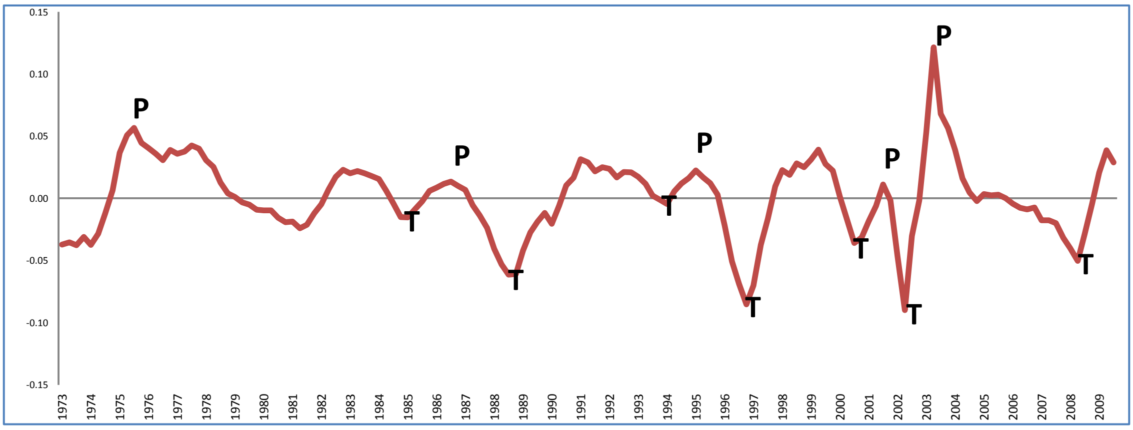


Figure 7.23 The OECD composite leading indicator of the Hong Kong High Tariff B hotel category by coefficient of the cross correlation (HIGH B OECD CLI CC) with the identification of peak (P) and trough (T)

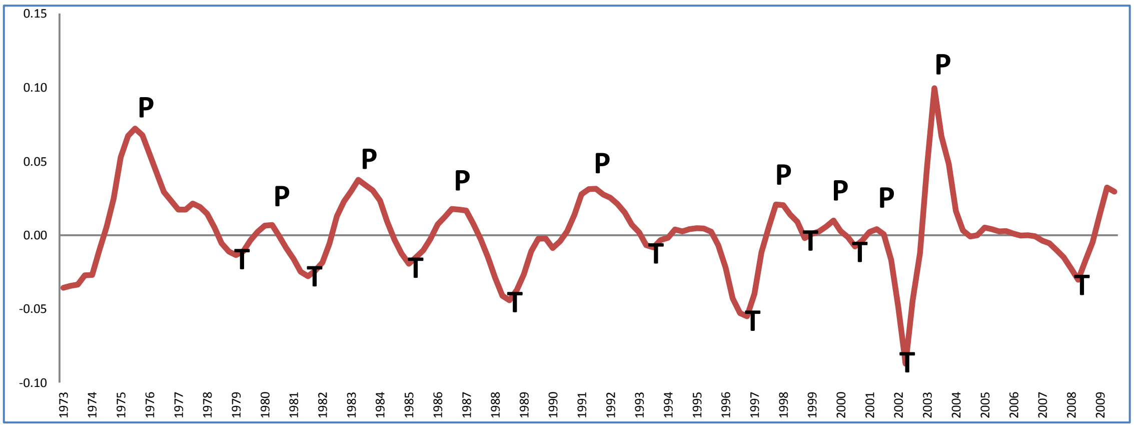


Figure 7.24 The OECD composite leading indicator of the Hong Kong Medium Tariff hotel category by coefficient of the cross correlation (MEDIUM OECD CLI CC) with the identification of peak (P) and trough (T)

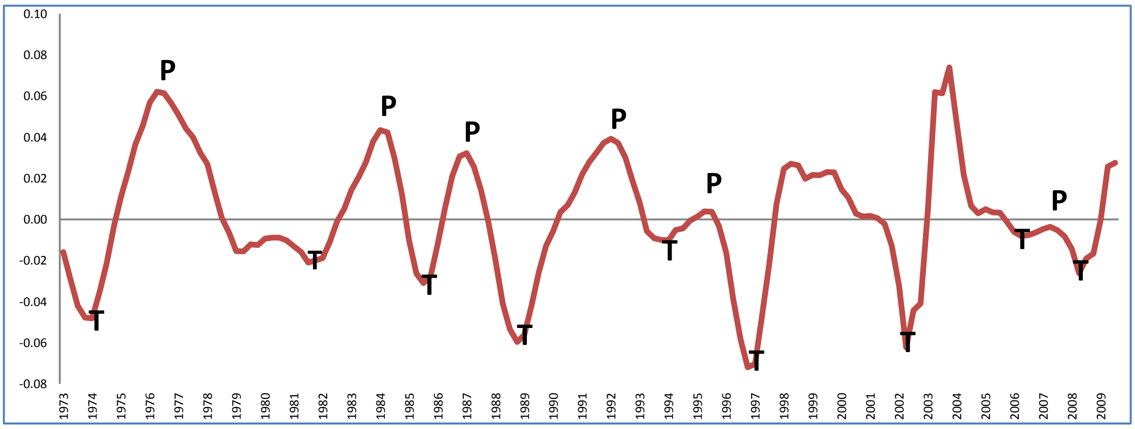


Figure 7.26 The OECD business survey index of the Hong Kong High Tariff A hotel category by coefficient of the cross correlation (HIGH A OECD BSI CC) with the identification of peak (P) and trough (T)

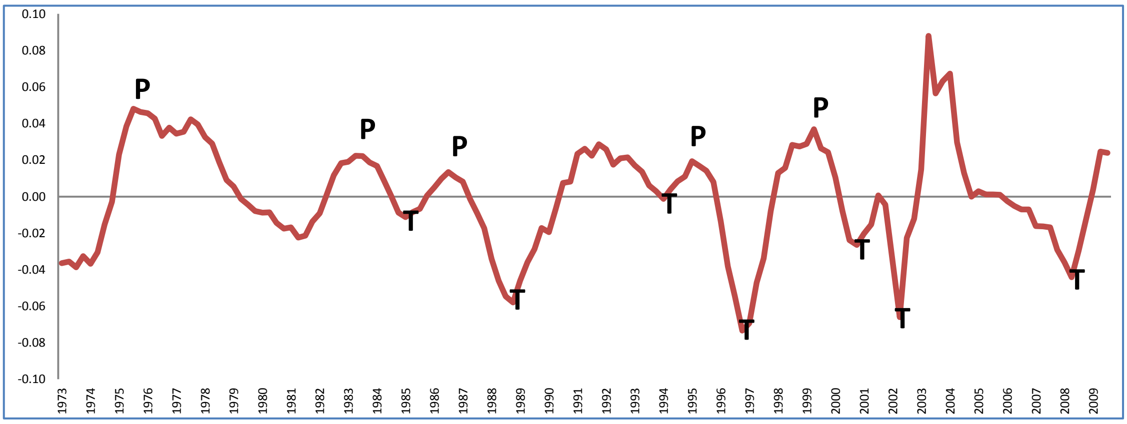


Figure 7.27 The OECD business survey index of the Hong Kong High Tariff B hotel category by coefficient of the cross correlation (HIGH B OECD BSI CC) with the identification of peak (P) and trough (T)

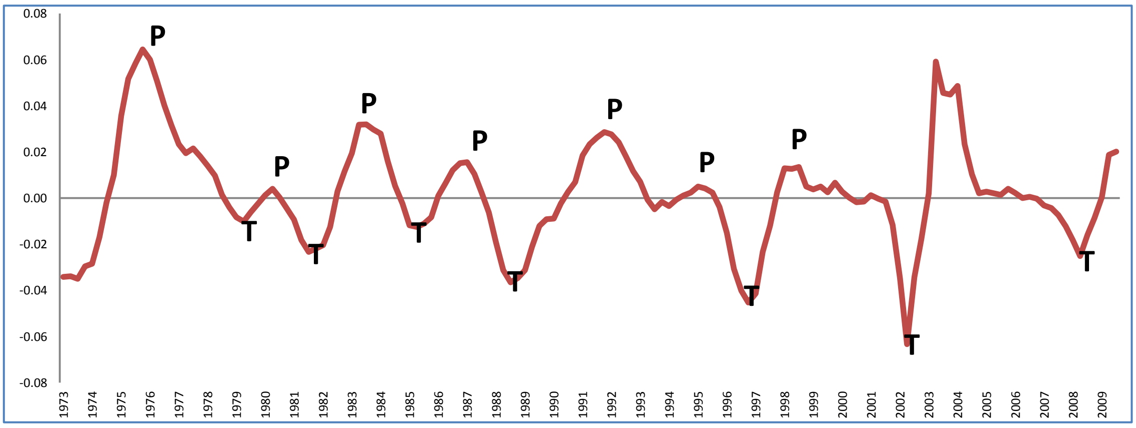


Figure 7.28 The OECD business survey index of the Hong Kong Medium Tariff hotel category by coefficient of the cross correlation (MEDIUM OECD BSI CC) with the identification of peak (P) and trough (T)

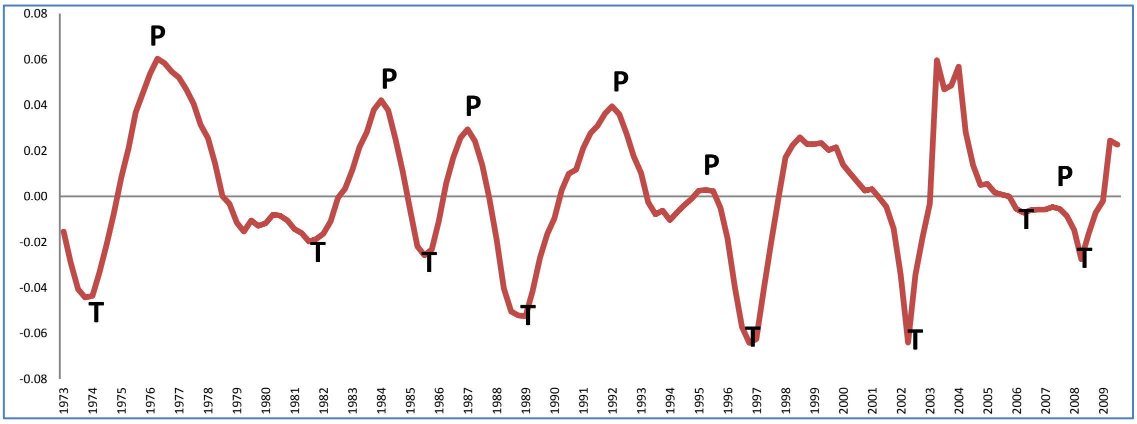


Figure 7.30 The OECD consumer confidence index of the Hong Kong High Tariff A hotel category by coefficient of the cross correlation (HIGH A OECD CCI CC) with the identification of peak (P) and trough (T)

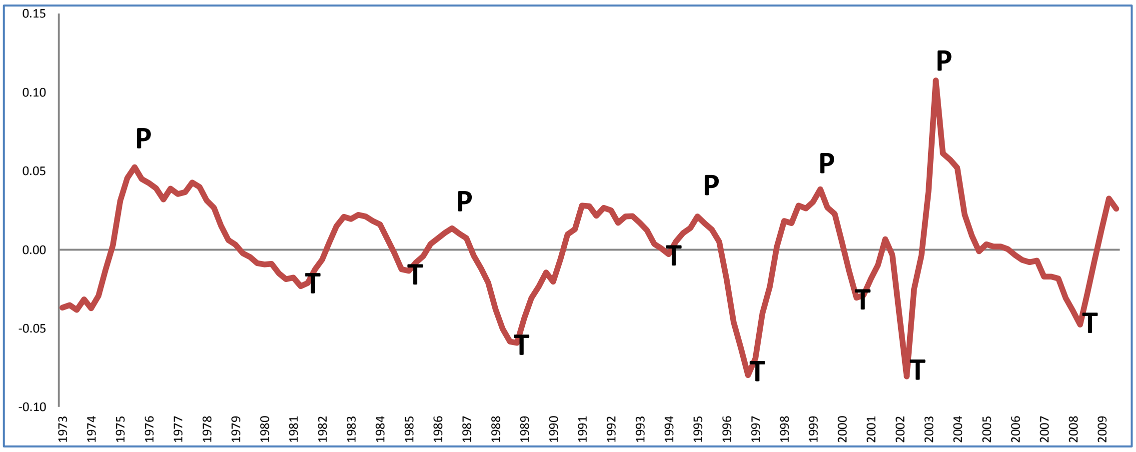


Figure 7.31 The OECD consumer confidence index of the Hong Kong High Tariff B hotel category by coefficient of the cross correlation (HIGH B OECD CCI CC) with the identification of peak (P) and trough (T)

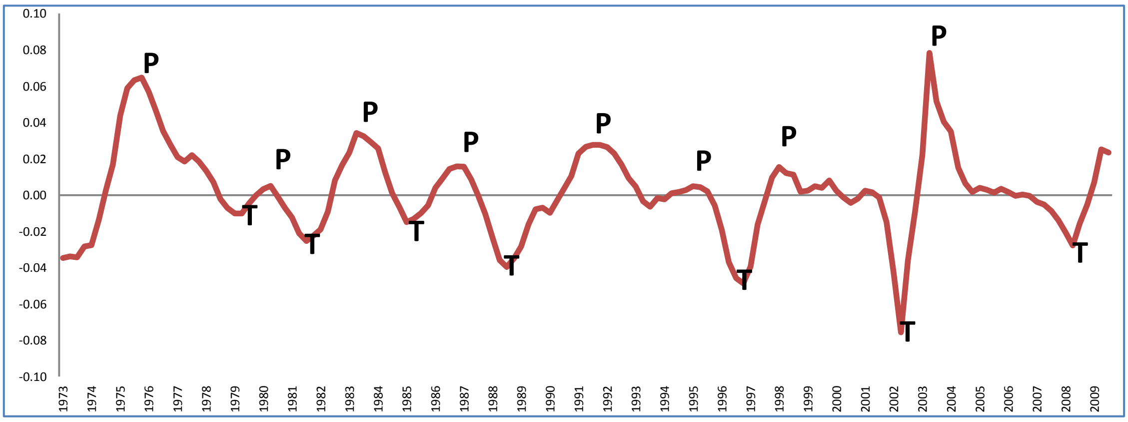


Figure 7.32 The OECD consumer confidence index of the Hong Kong Medium Tariff hotel category by coefficient of the cross correlation (MEDIUM OECD CCI CC) with the identification of peak (P) and trough (T)

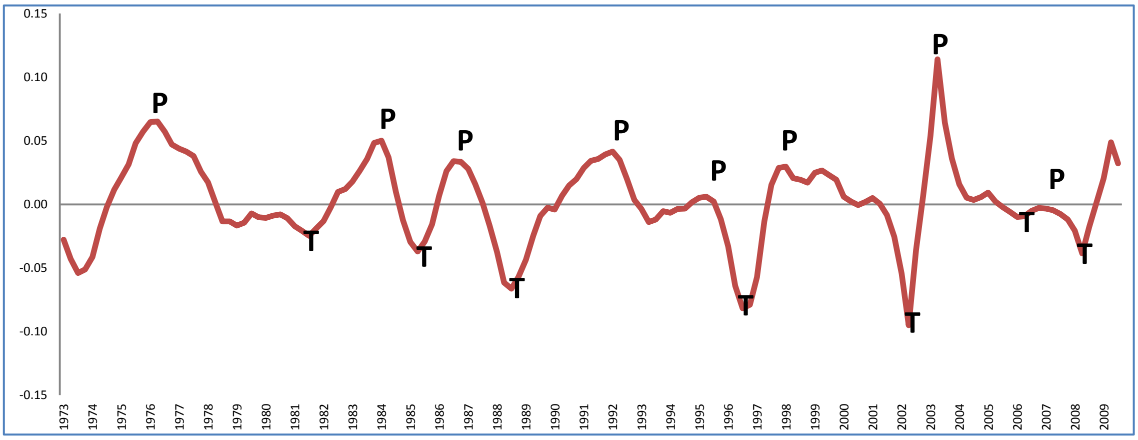


Figure 7.34 The OECD composite leading indicator of the Hong Kong High Tariff A hotel category by coefficient of the market share of the overnight stay visitor arrivals (HIGH A OECD CLI MS) with the identification of peak (P) and trough (T)

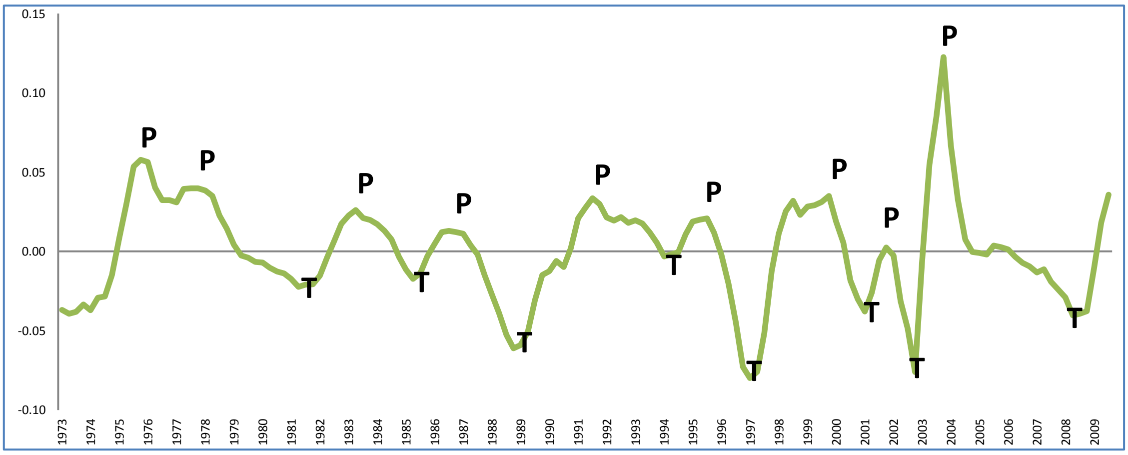


Figure 7.35 The OECD composite leading indicator of the Hong Kong High Tariff B hotel category by coefficient of the market share of the overnight stay visitor arrivals (HIGH B OECD CLI MS) with the identification of peak (P) and trough (T)

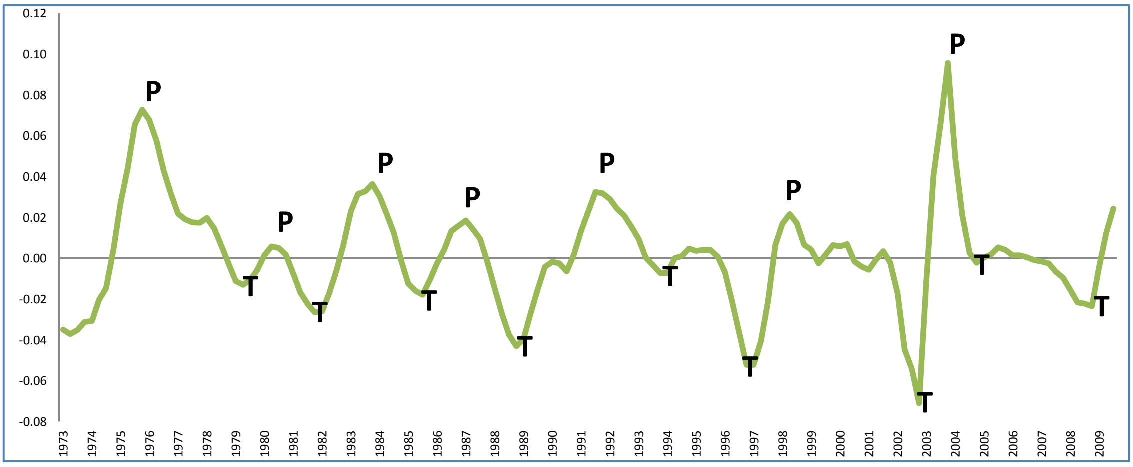


Figure 7.36 The OECD composite leading indicator of the Hong Kong Medium Tariff hotel category by coefficient of the market share of the overnight stay visitor arrivals (MEDIUM OECD CLI MS) with the identification of peak (P) and trough (T)

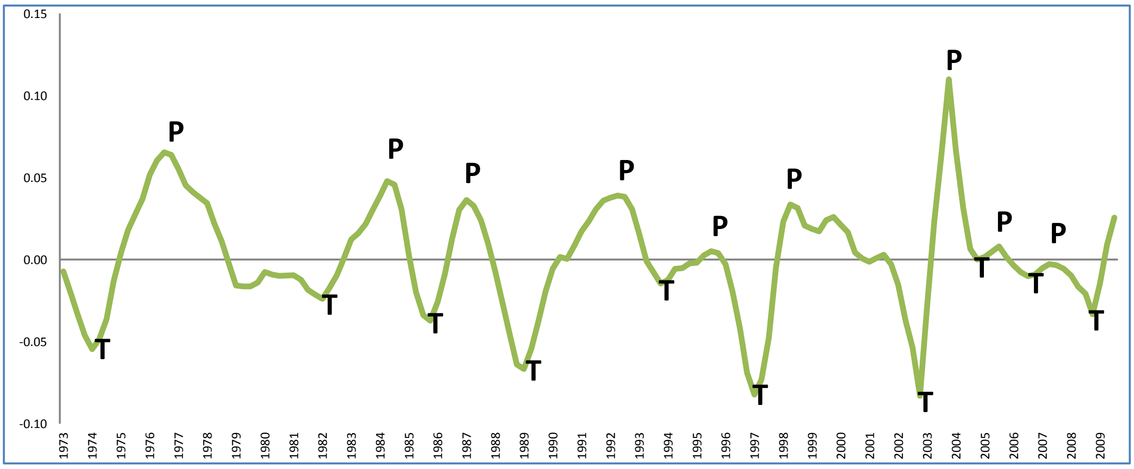


Figure 7.38 The OECD business survey index of the Hong Kong High Tariff A hotel category by coefficient of the market share of the overnight stay visitor arrivals (HIGH A OECD BSI MS) with the identification of peak (P) and trough (T)

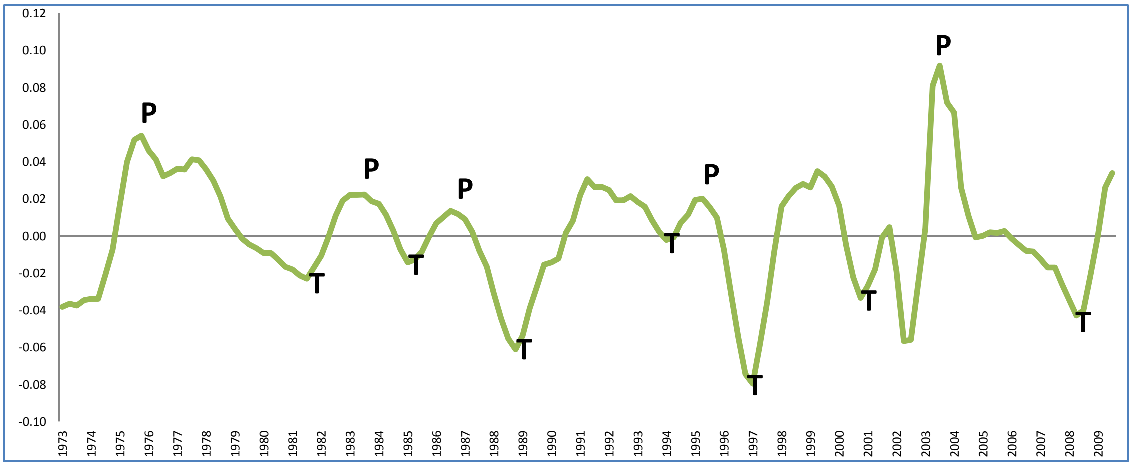


Figure 7.39 The OECD business survey index of the Hong Kong High Tariff B hotel category by coefficient of the market share of the overnight stay visitor arrivals (HIGH B OECD BSI MS) with the identification of peak (P) and trough (T)

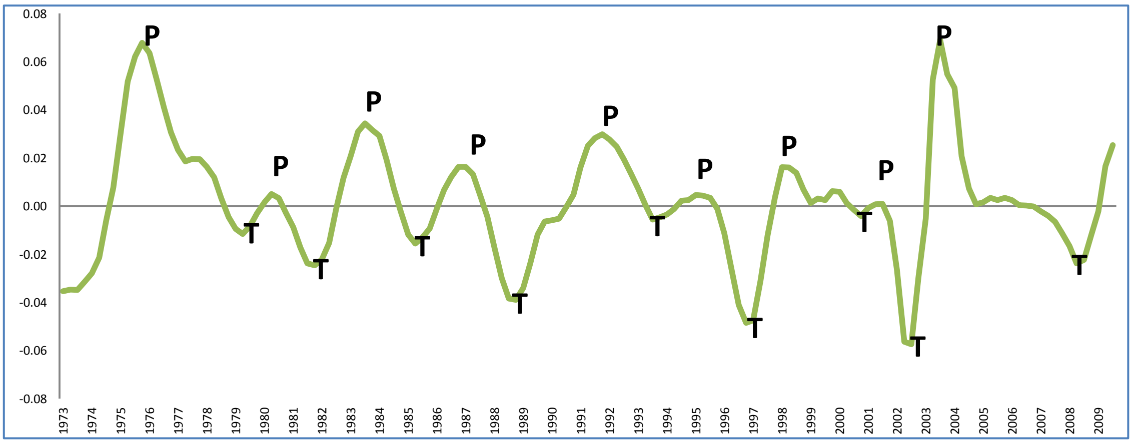


Figure 7.40 The OECD business survey index of the Hong Kong Medium Tariff hotel category by coefficient of the market share of the overnight stay visitor arrivals (MEDIUM OECD BSI MS) with the identification of peak (P) and trough (T)

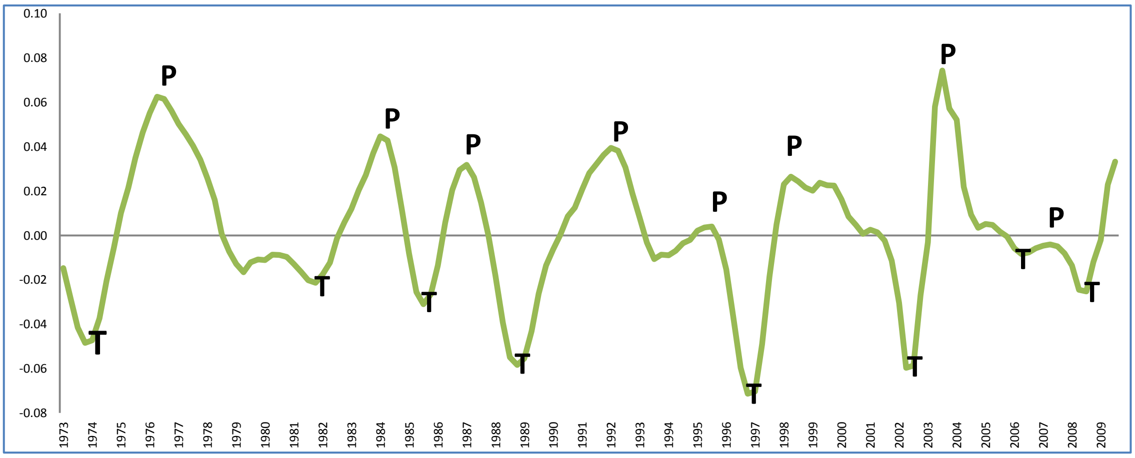


Figure 7.42 The OECD consumer confidence index of the Hong Kong High Tariff A hotel category by coefficient of the market share of the overnight stay visitor arrivals (HIGH A OECD CCI MS) with the identification of peak (P) and trough (T)

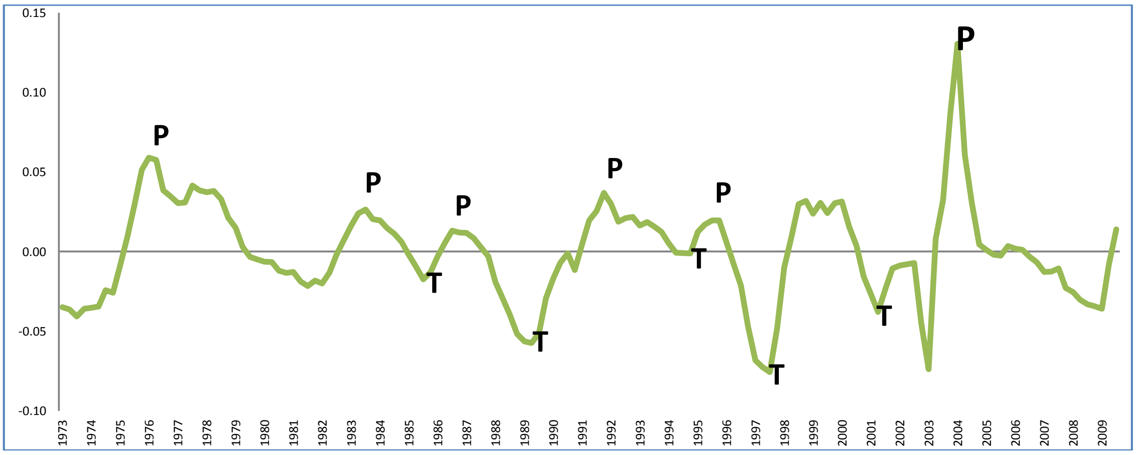


Figure 7.43 The OECD consumer confidence index of the Hong Kong High Tariff B hotel category by coefficient of the market share of the overnight stay visitor arrivals (HIGH B OECD CCI MS) with the identification of peak (P) and trough (T)

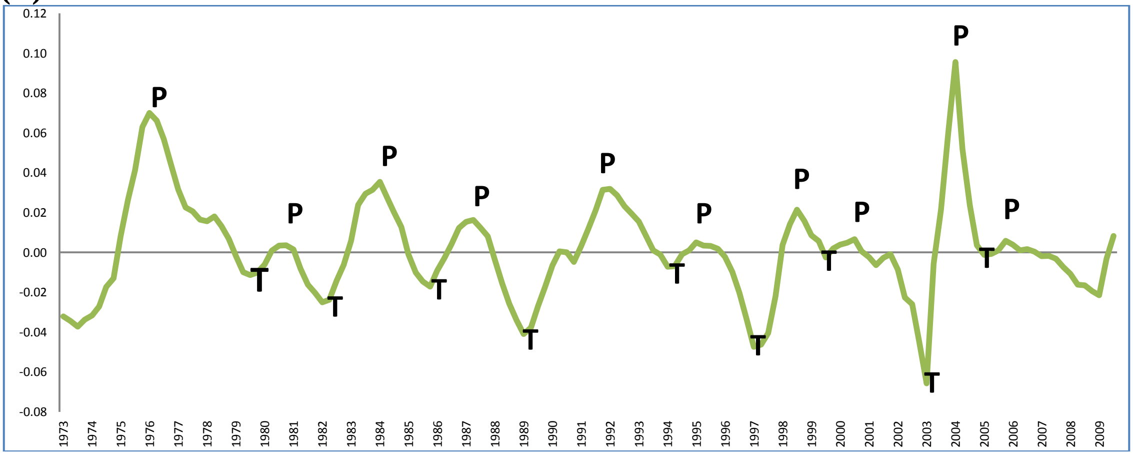


Figure 7.44 The OECD consumer confidence index of the Hong Kong Medium Tariff hotel category by coefficient of the market share of the overnight stay visitor arrivals (MEDIUM OECD CCI MS) with the identification of peak (P) and trough (T)

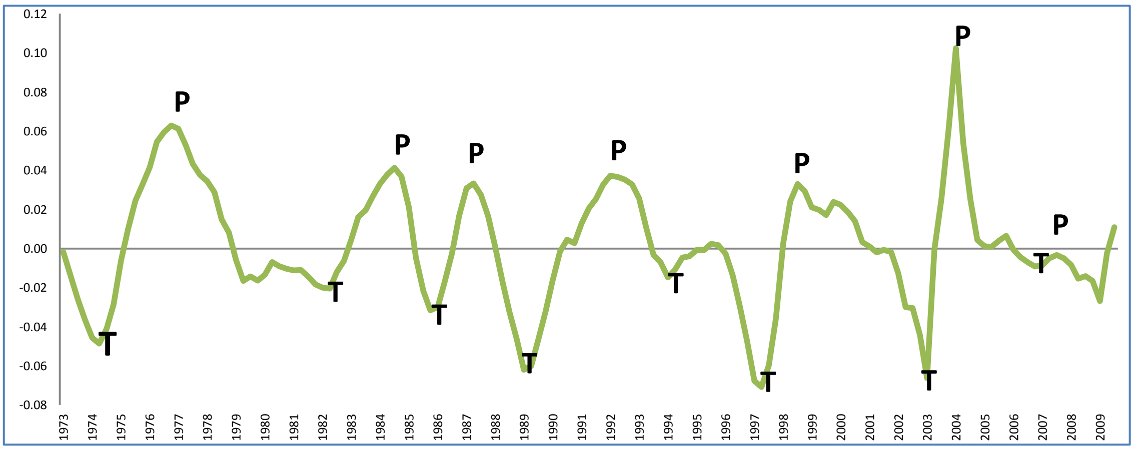


Figure 7.46 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD composite leading indicator (HIGH A OECD CLI CC LG) for Hong Kong High Tariff A hotel category

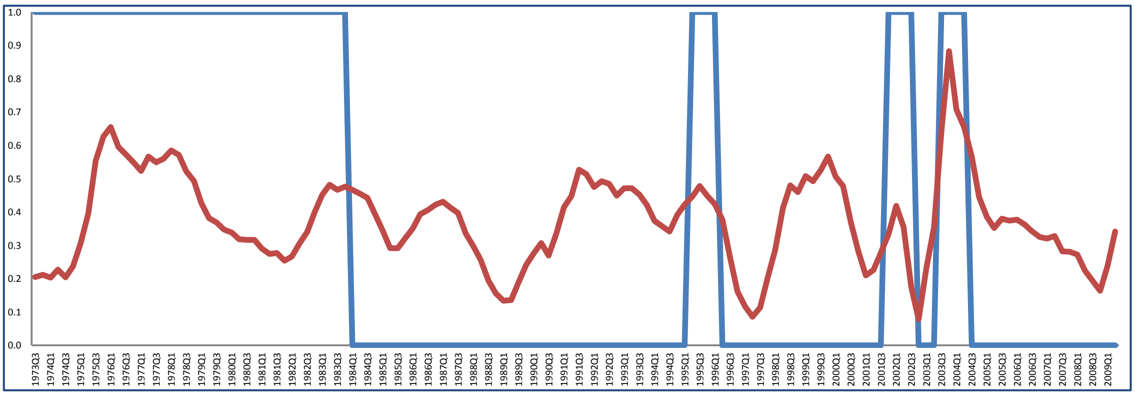


Figure 7.47 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD composite leading indicator (HIGH B OECD CLI CC LG) for Hong Kong High Tariff B hotel category

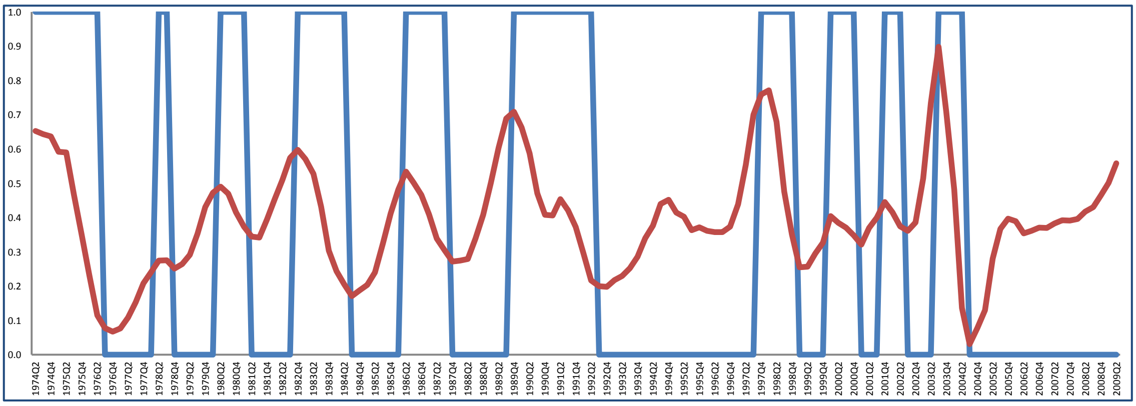


Figure 7.48 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD composite leading indicator (MEDIUM OECD CLI CC LG) for Hong Kong Medium Tariff hotel category

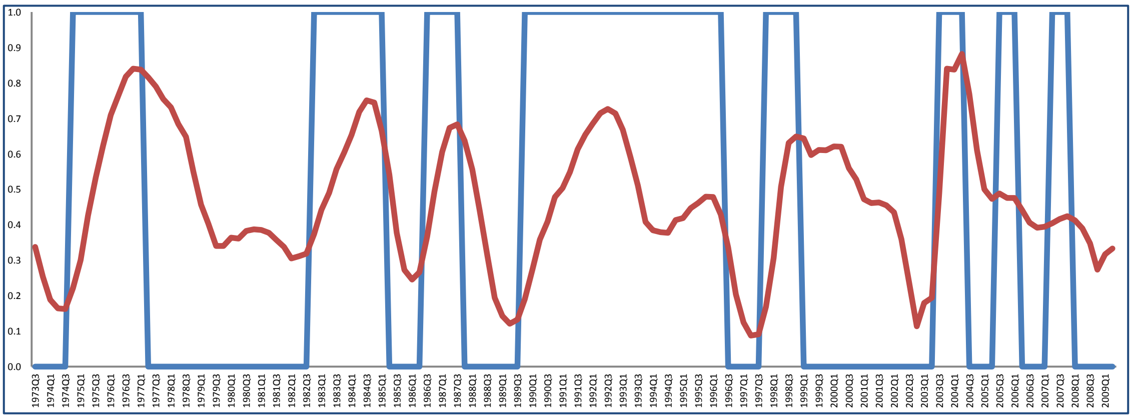


Figure 7.50 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD composite leading indicator (HIGH A OECD CLI MS LG) for Hong Kong High Tariff A hotel category

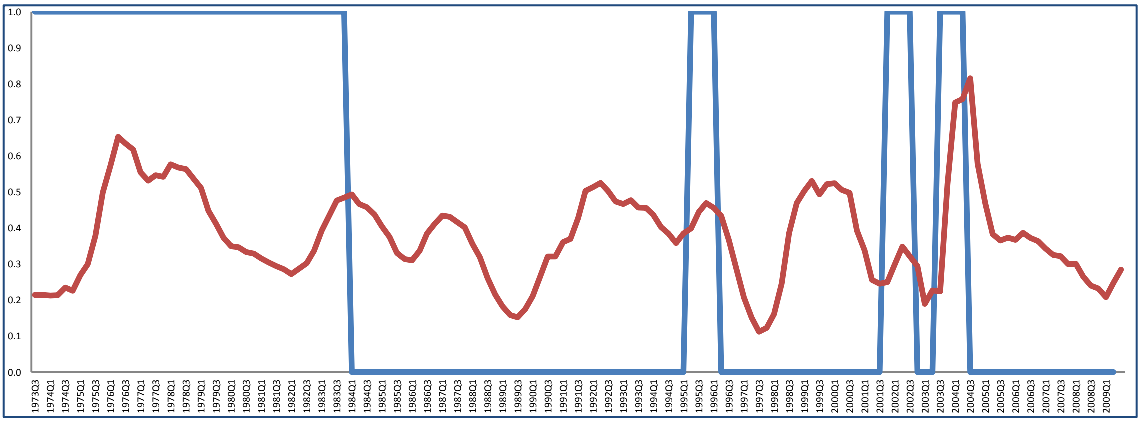


Figure 7.51 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD composite leading indicator (HIGH B OECD CLI MS LG) for Hong Kong High Tariff B hotel category

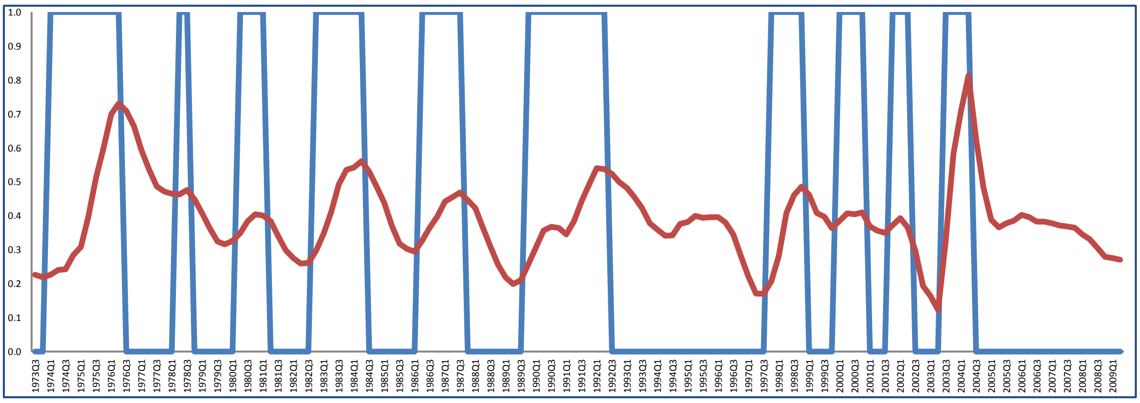


Figure 7.52 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD composite leading indicator (MEDIUM OECD CLI MS LG) for Hong Kong Medium Tariff hotel category

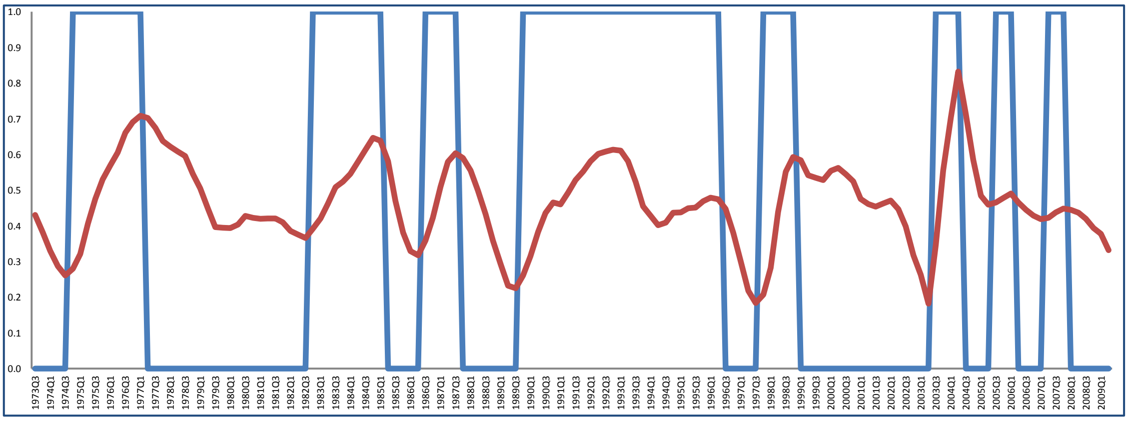


Figure 7.54 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD composite leading indicator (HIGH A OECD CLI CC PB) for Hong Kong High Tariff A hotel category

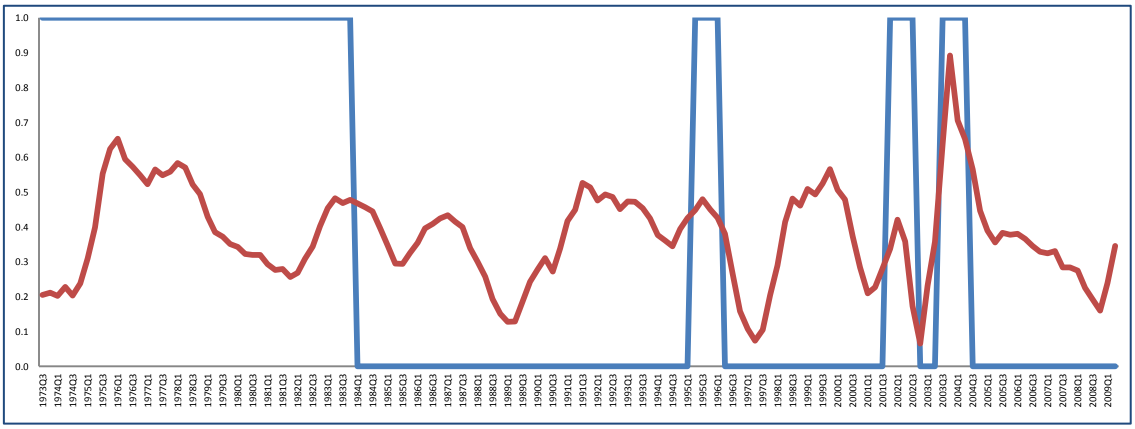


Figure 7.55 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD composite leading indicator (HIGH B OECD CLI CC PB) for Hong Kong High Tariff B hotel category

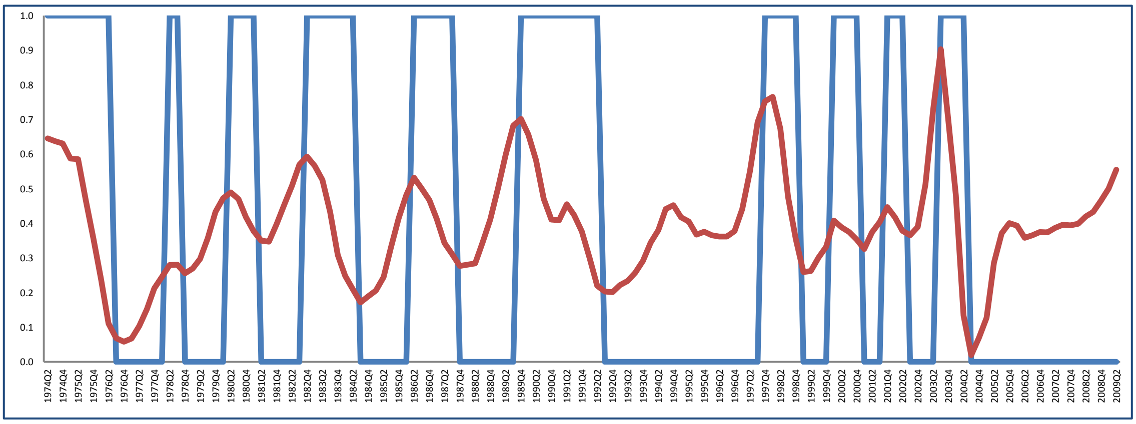


Figure 7.56 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) period (HK MEDIUM) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD composite leading indicator (MEDIUM OECD CLI CC PB) for Hong Kong Medium Tariff hotel category

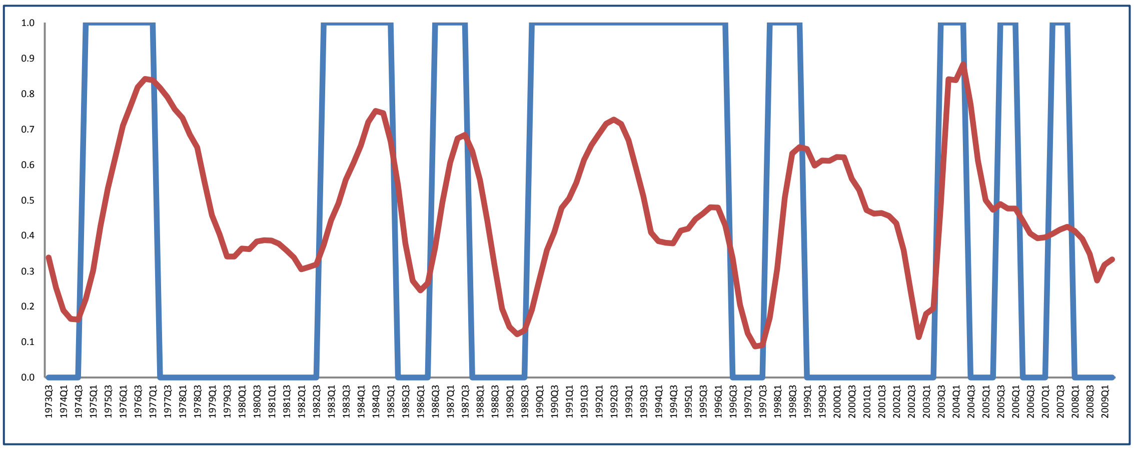


Figure 7.58 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD composite leading indicator (HIGH A OECD CLI MS PB) for Hong Kong High Tariff A hotel category

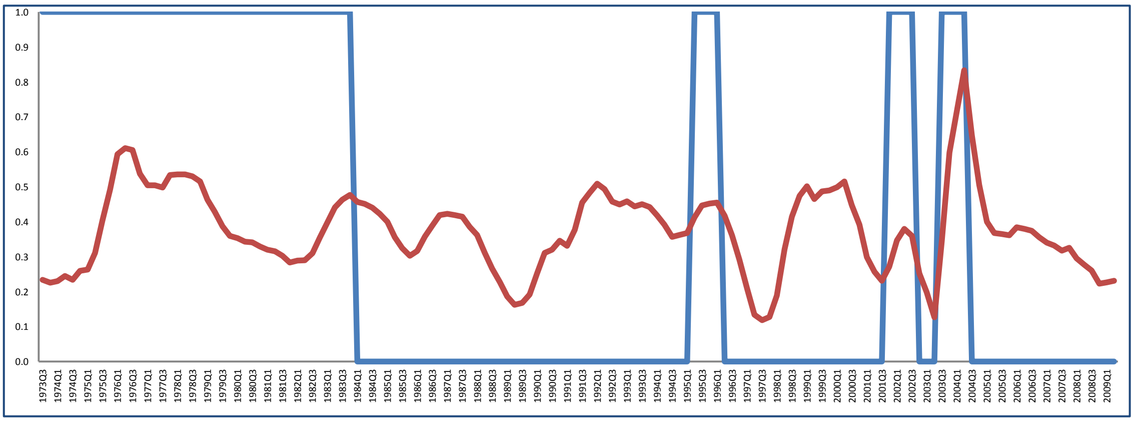


Figure 7.59 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD composite leading indicator (HIGH B OECD CLI MS PB) for Hong Kong High Tariff B hotel category

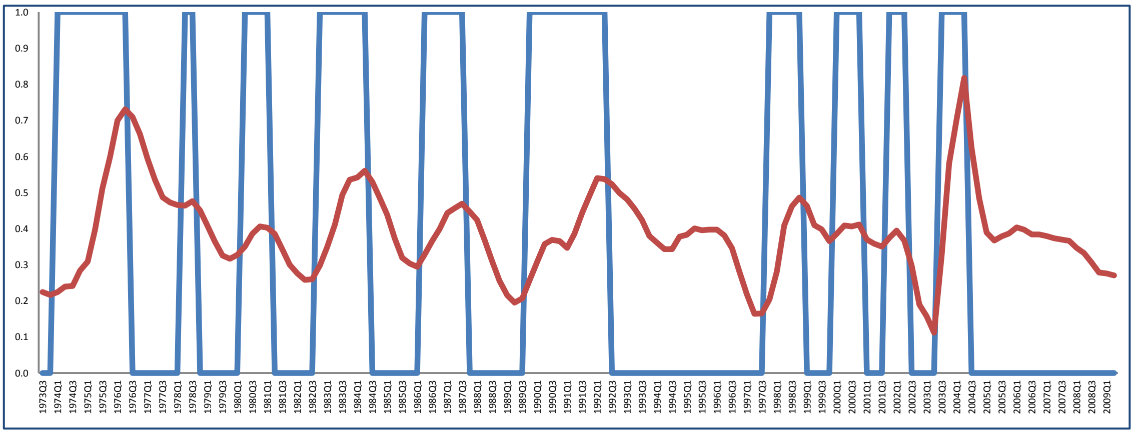


Figure 7.60 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD composite leading indicator (MEDIUM OECD CLI MS PB) for Hong Kong Medium Tariff hotel category

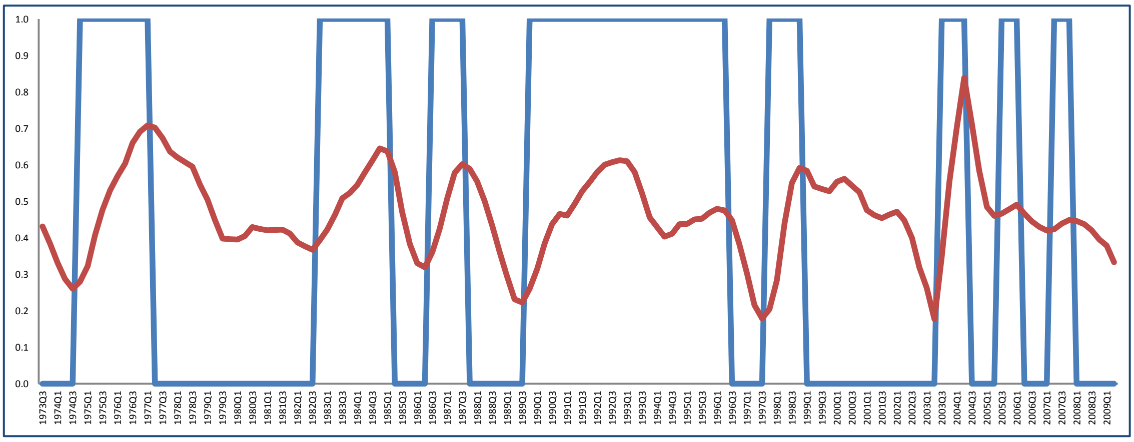


Figure 7.62 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD business survey index (HIGH A OECD BSI CC LG) for Hong Kong High Tariff A hotel category

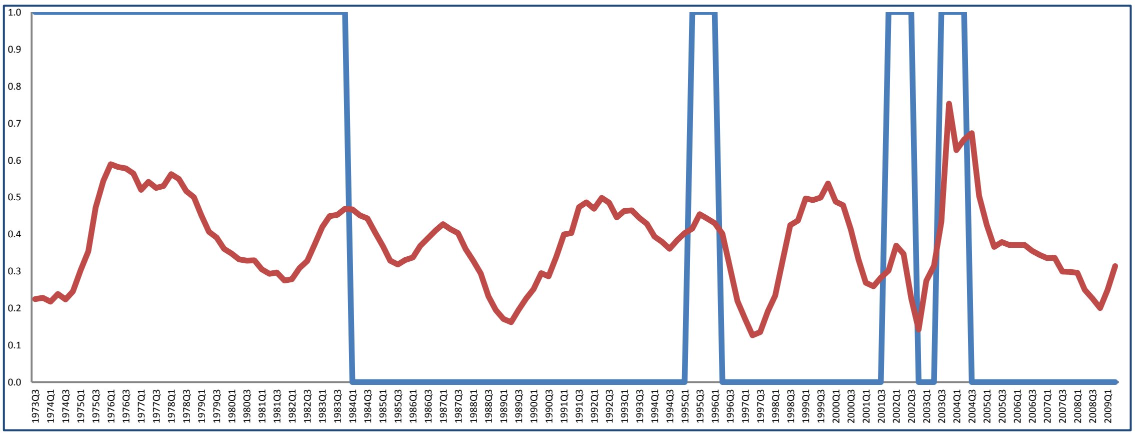


Figure 7.63 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD business survey index (HIGH B OECD BSI CC LG) for Hong Kong High Tariff B hotel category

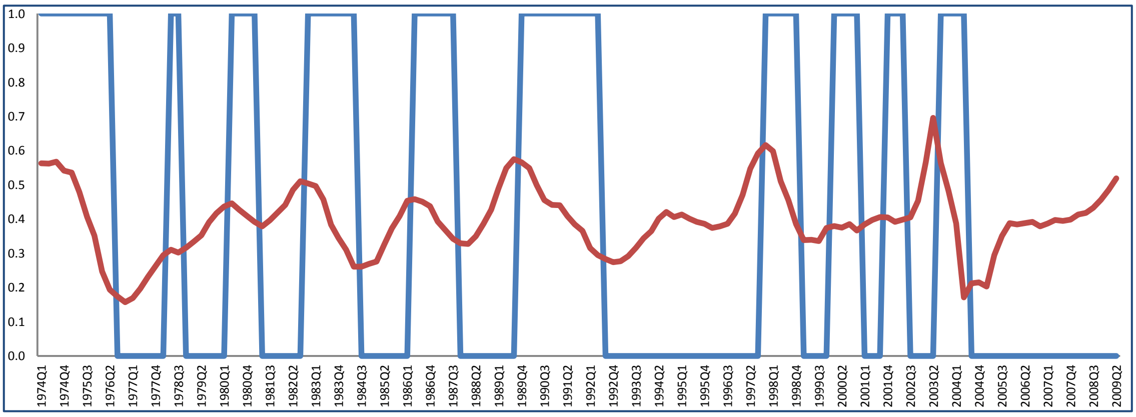


Figure 7.64 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD business survey index (MEDIUM OECD BSI CC LG) for Hong Kong Medium Tariff hotel category

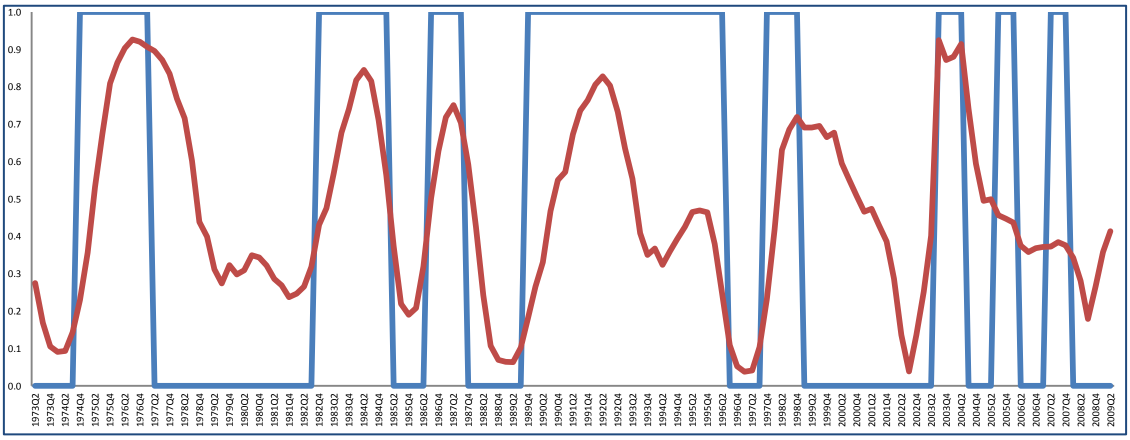


Figure 7.66 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD business survey index (HIGH A OECD BSI MS LG) for Hong Kong High Tariff A hotel category

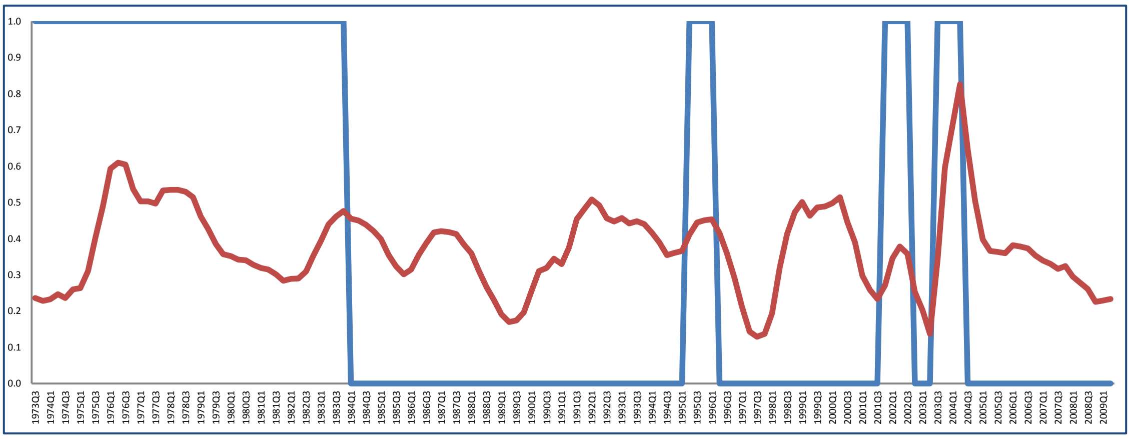


Figure 7.67 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD business survey index (HIGH B OECD BSI MS LG) for Hong Kong High Tariff B hotel category

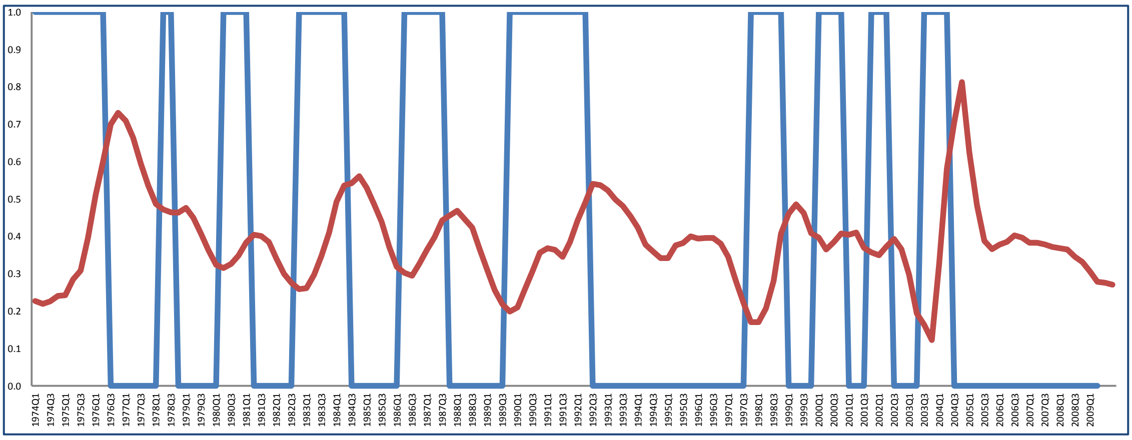


Figure 7.68 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD business survey index (MEDIUM OECD BSI MS LG) for Hong Kong Medium Tariff hotel category

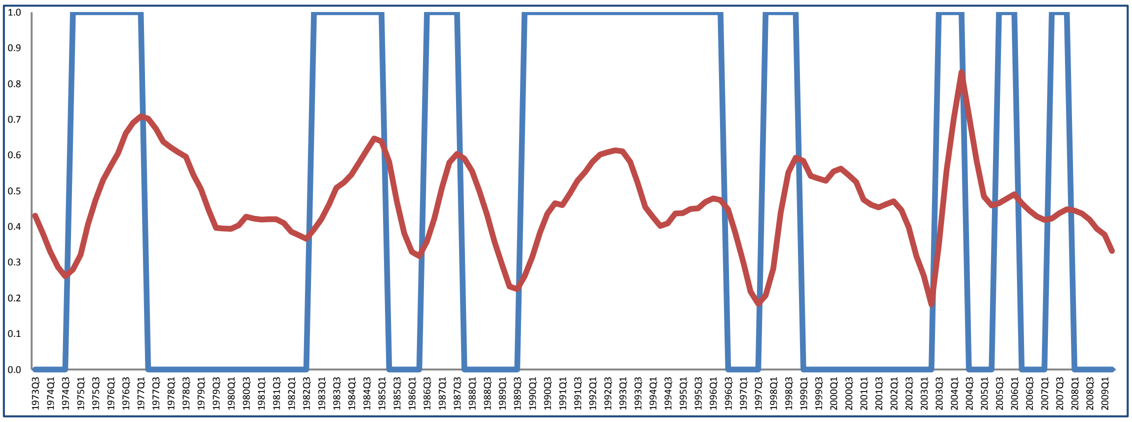


Figure 7.70 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD business survey index (HIGH A OECD BSI CC PB) for Hong Kong High Tariff A hotel category

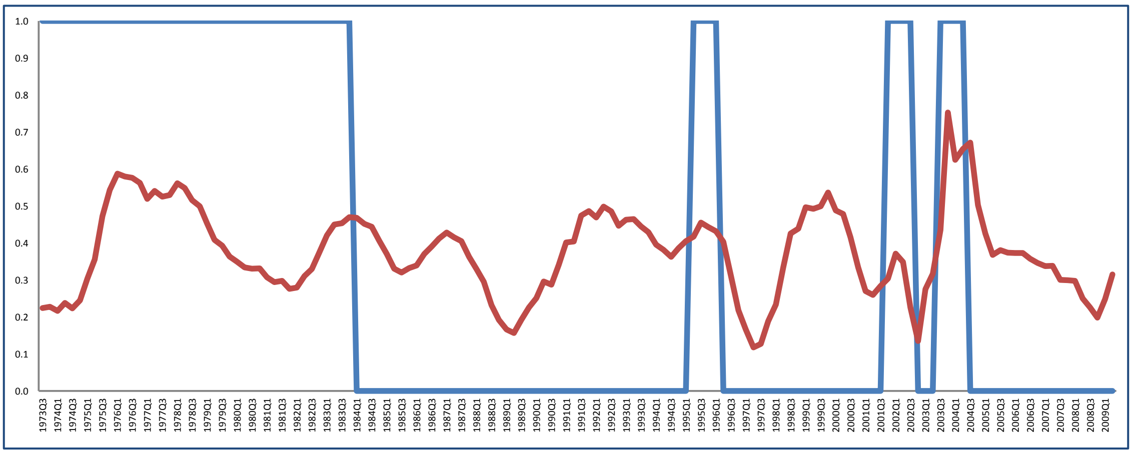


Figure 7.71 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD business survey index (HIGH B OECD BSI CC PB) for Hong Kong High Tariff B hotel category

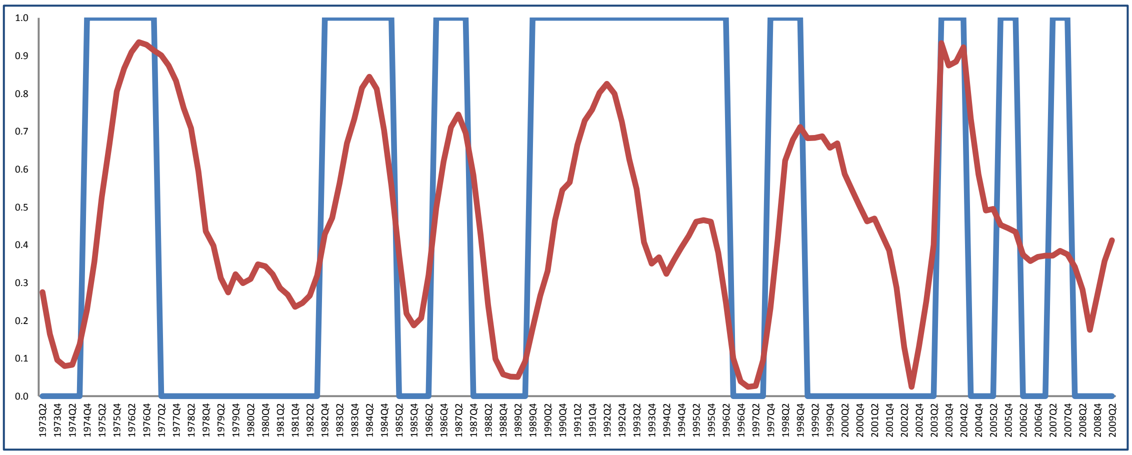


Figure 7.72 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD business survey index (MEDIUM OECD BSI CC PB) for Hong Kong Medium Tariff hotel category

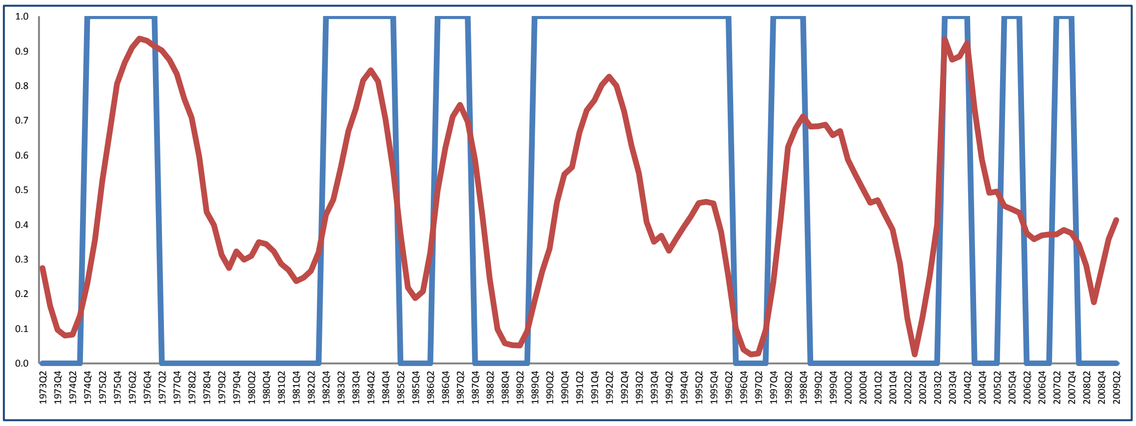


Figure 7.74 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD business survey index (HIGH A OECD BSI MS PB) for Hong Kong High Tariff A hotel category

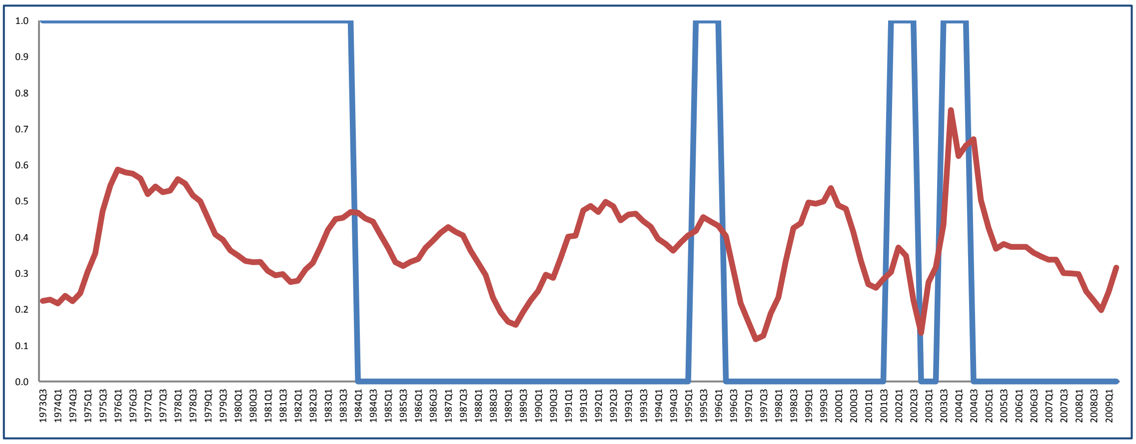


Figure 7.75 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD business survey index (HIGH B OECD BSI MS PB for Hong Kong High Tariff B hotel category

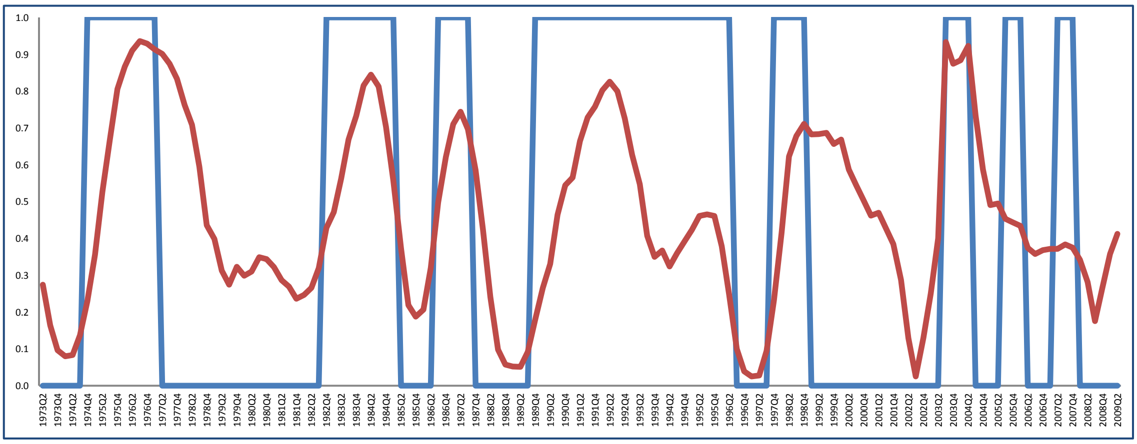


Figure 7.76 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD business survey index (MEDIUM OECD BSI MS PB) for Hong Kong Medium Tariff hotel category

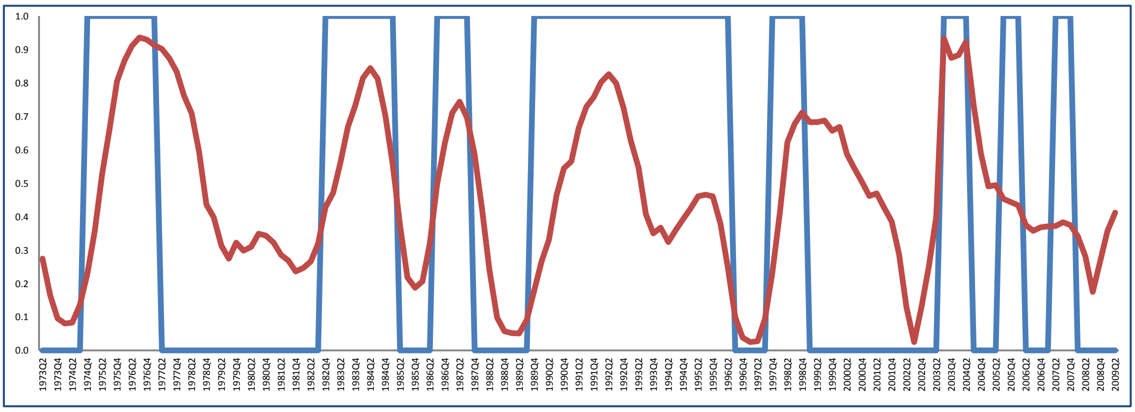


Figure 7.78 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD consumer confidence index (HIGH A OECD CCI CC LG) for Hong Kong High Tariff A hotel category

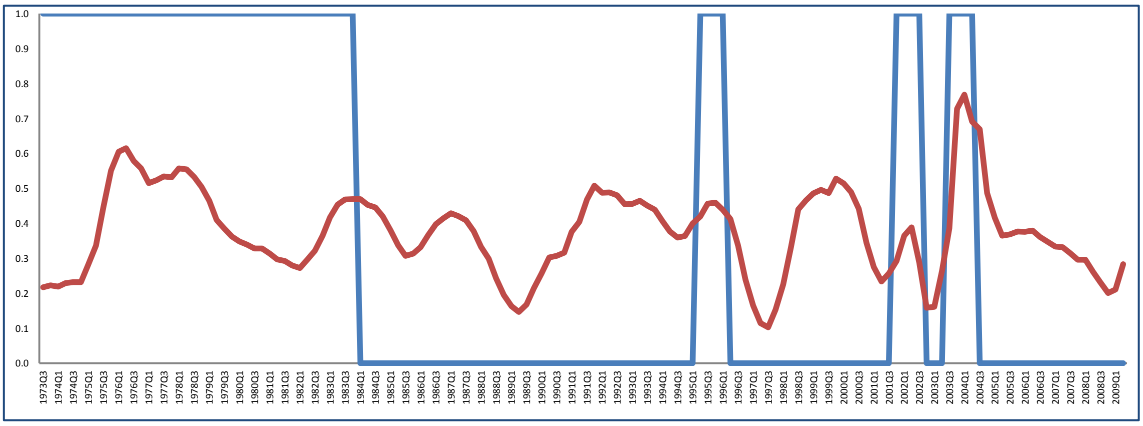


Figure 7.79 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD consumer confidence index (HIGH B OECD CCI CC LG) for Hong Kong High Tariff B hotel category

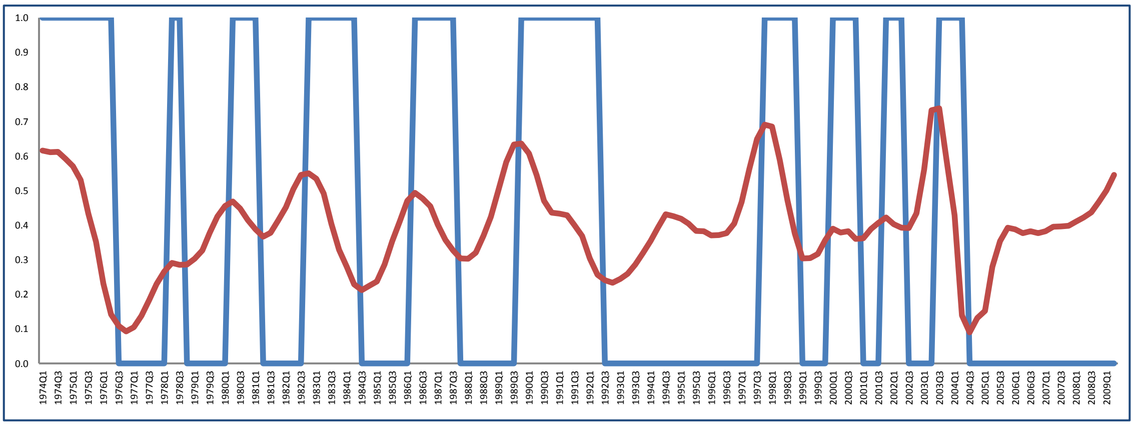


Figure 7.80 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the logistic regression models by the coefficient of cross-correlation analysis weighting method for the OECD consumer confidence index (MEDIUM OECD CCI CC LG) for Hong Kong Medium Tariff hotel category

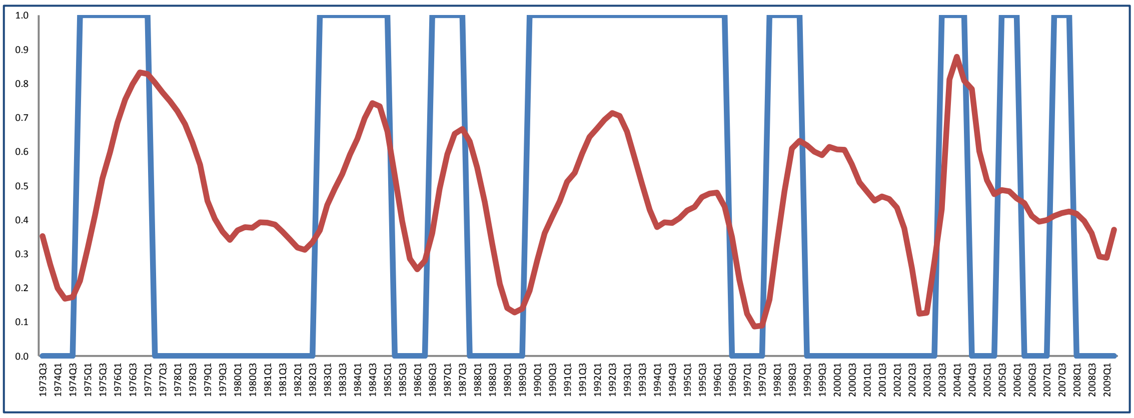


Figure 7.82 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD consumer confidence index (HIGH A OECD CCI MS LG) for Hong Kong High Tariff A hotel category

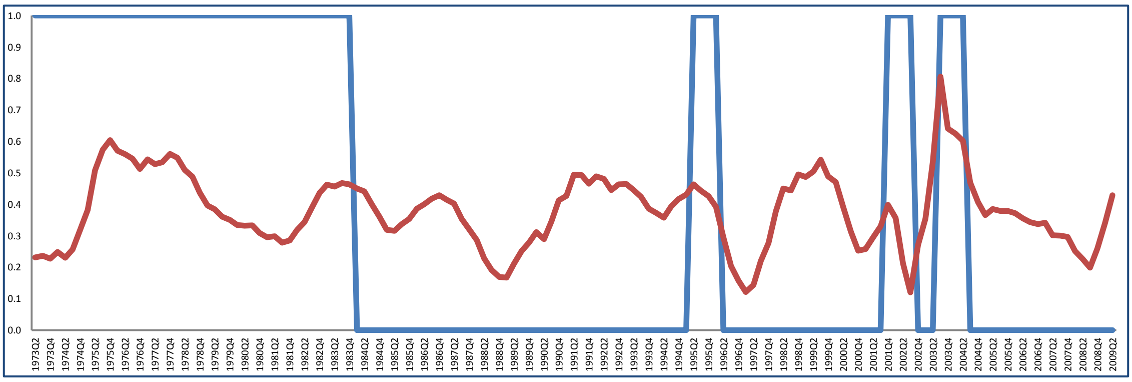


Figure 7.83 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD consumer confidence index (HIGH B OECD CCI MS LG) for Hong Kong High Tariff B hotel category

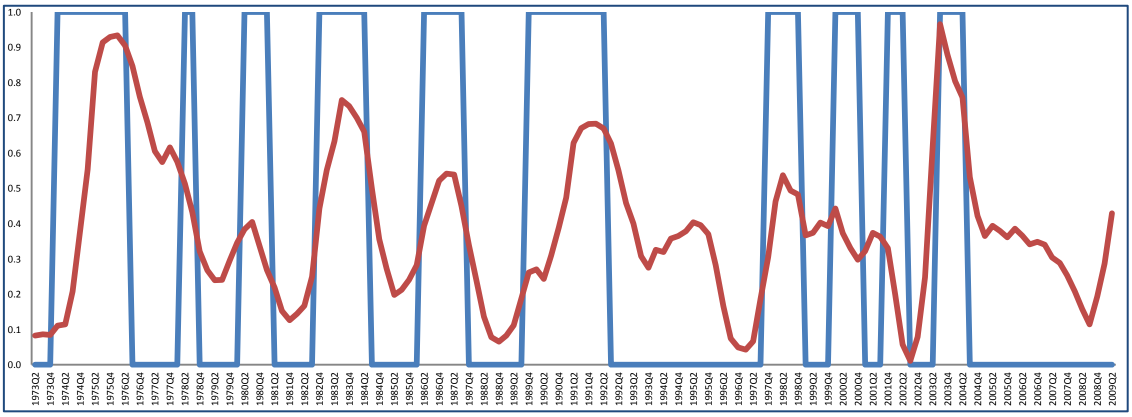


Figure 7.84 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the logistic regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD consumer confidence index (MEDIUM OECD CCI MS LG) for Hong Kong Medium Tariff hotel category

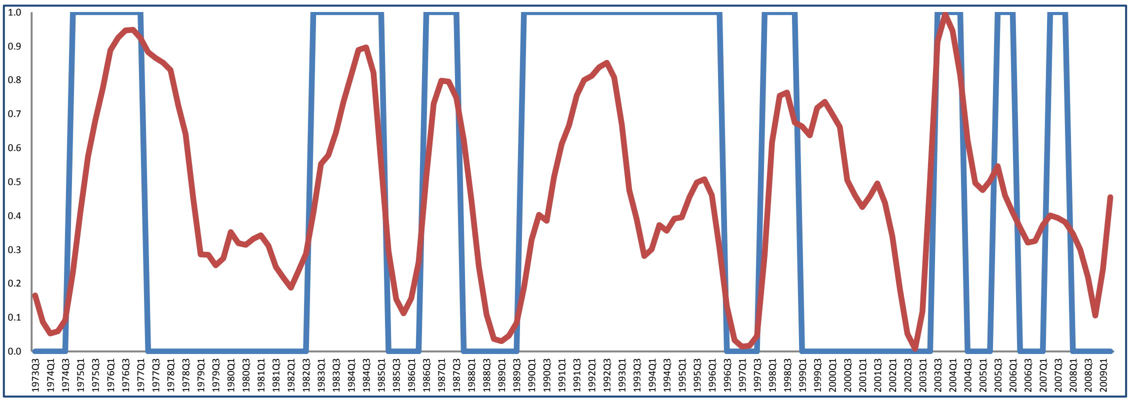


Figure 7.86 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD consumer confidence index (HIGH A OECD CCI CC PB) for Hong Kong High Tariff A hotel category

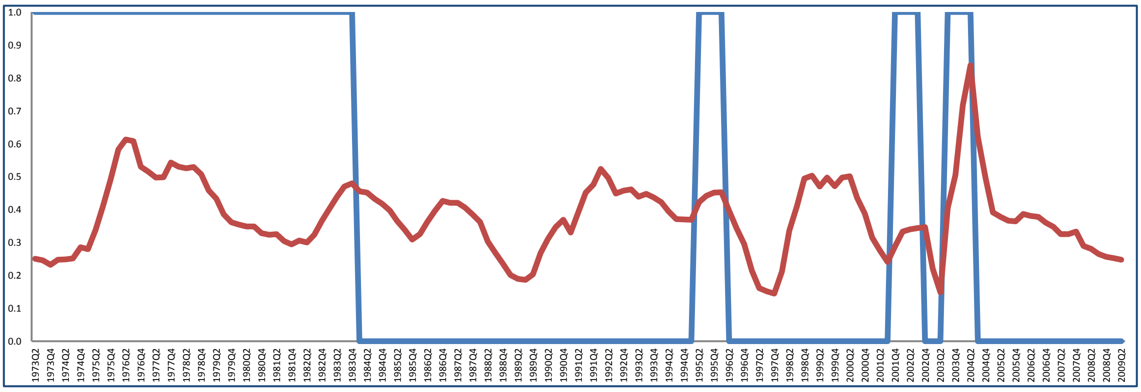


Figure 7.87 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD consumer confidence index (HIGH B OECD CCI CC PB) for Hong Kong High Tariff B hotel category

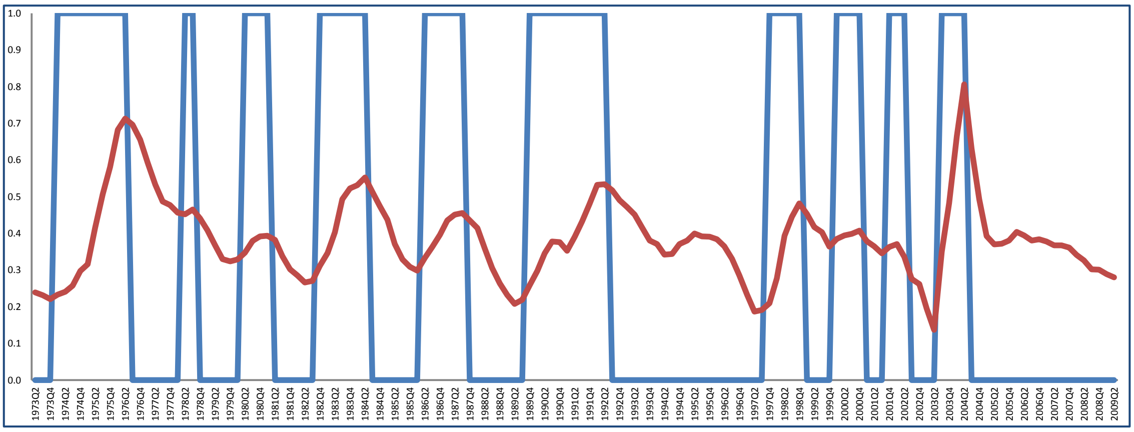


Figure 7.88 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the probit regression models by the coefficient of cross-correlation analysis weighting method for the OECD consumer confidence index (MEDIUM OECD CCI CC PB) for Hong Kong Medium Tariff hotel category

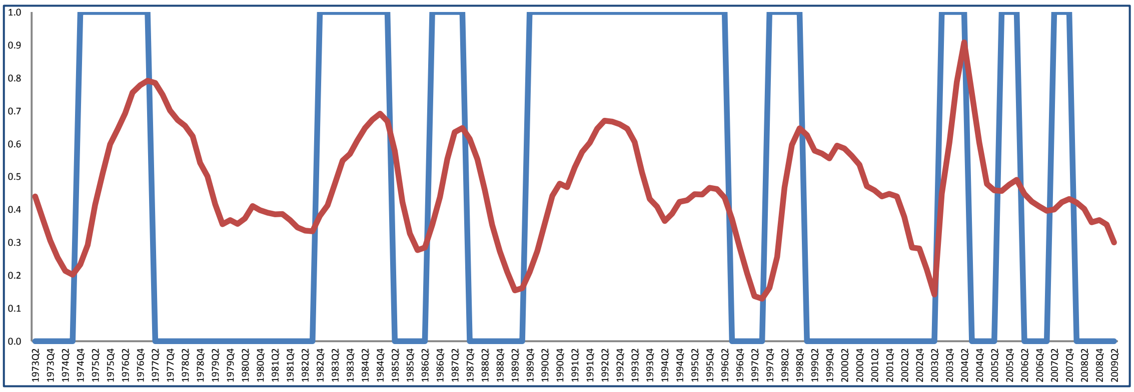


Figure 7.90 The Hong Kong High Tariff A hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD consumer confidence index (HIGH A OECD CCI MS PB) for Hong Kong High Tariff A hotel category

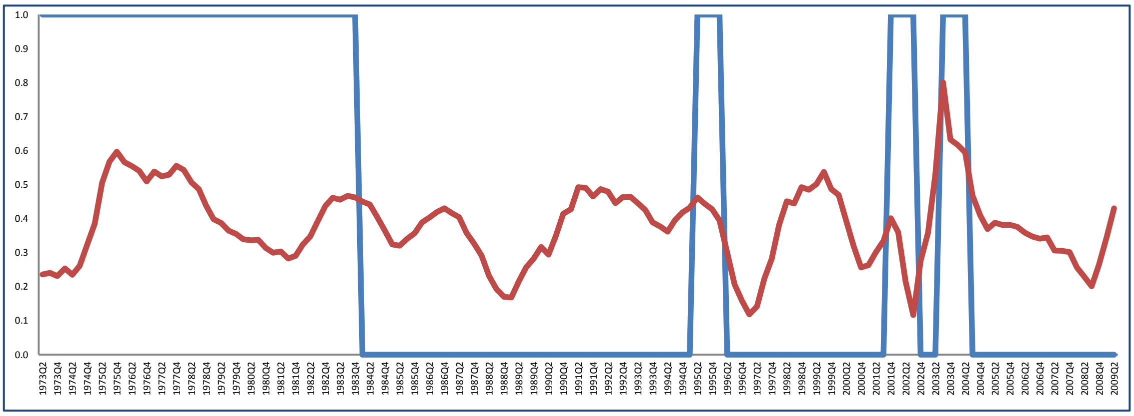


Figure 7.91 The Hong Kong High Tariff B hotel occupancy rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD consumer confidence index (HIGH B OECD CCI MS PB) for Hong Kong High Tariff B hotel category

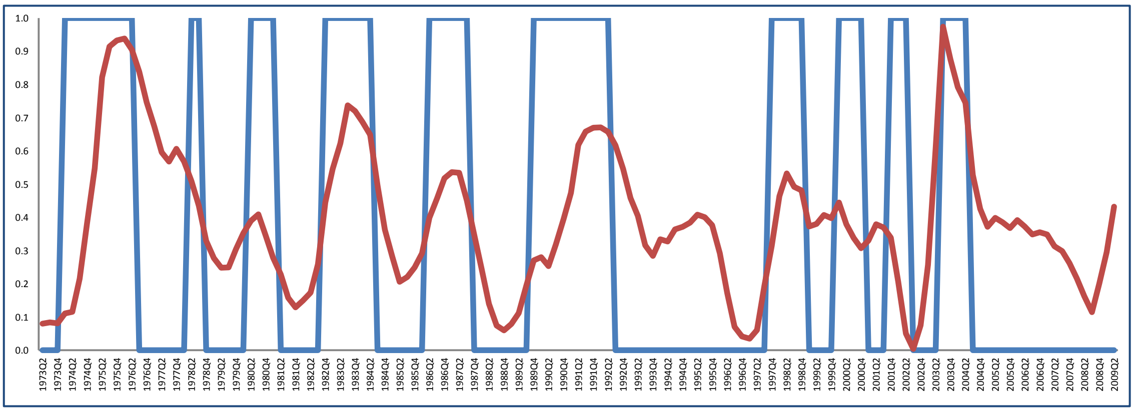
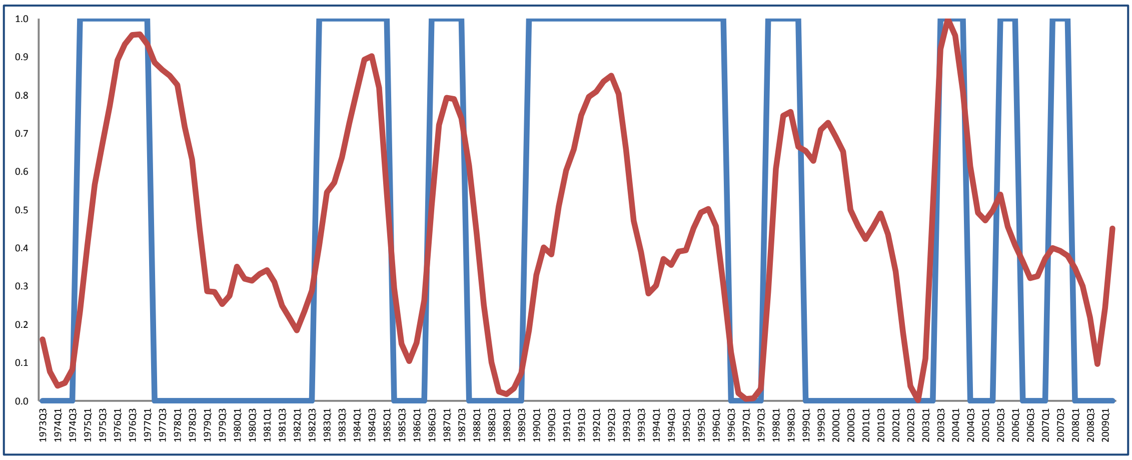


Figure 7.92 The Hong Kong Medium Tariff hotel occupancy rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the probit regression models by the market share of Hong Kong overnight-stay tourist arrivals weighting method for the OECD consumer confidence index (MEDIUM OECD CCI MS PB) for Hong Kong Medium Tariff hotel category



Chapter 8

ESTIMATED LOGISTIC AND PROBIT MODELS WITH HOTEL DEMAND DETERMINANTS

8.1 Introduction

This chapter aims to estimate the logistic and probit regression models with hotel demand determinants. Logistic and probit regression models are generalized linear econometric models with binary dependent variables. The key advantages of logistic and probit regression models are their capability to estimate the probability associated with the expansion period in the growth of hotel occupancy rate and to predict turning points.

The probability models are developed with hotel demand determinants, such as tourists' country income, cost of hotel room in destination, exchange rate, substitute destination hotel price, and travel cost.

The logistic regression model can also estimate the risks associated with the downturn of the hotel occupancy rate in the future. It is important for the hoteliers to know the probability of demand shifting from high to low or vice versa. The estimated coefficients in the logistic regression models can measure the impact of each hotel demand determinant, which means that a 1% change in that hotel demand determinant will result in an increase or decrease in the probability of an expansion period on the probability.

8.2 Selection of hotel demand determinants

Demand determinants of the hotel industry can provide another econometric model that can be compared with the composite leading indicator models. The selection of those demand determinants for the hotel industry will be based on tourism demand determinants. According to the consumer theory of choice, the demand for certain products generally depends on the consumer's income, prices, and other substitute products' prices. However, the focus of the present study is the hotel demand; as a result, the demand determinants that are more specific to hotel demand are considered here.

Kulendran and Dwyer (2009) applied the consumer theory of choice on the tourism sector and explained that tourism demand may be defined for a particular destination as the quantity of the tourism product, which may refer to the combination of tourism goods and services provided by the destination country. Therefore, tourism demand can be determined by the tourist income and the costs associated with travel. The selection of hotel demand determinants has already been discussed in Chapter 3.

8.3 Hotel demand model for estimation

According to the consumer theory of choice, the demand for certain products generally depends on the consumer's income, prices, and other substitute products' prices. In the present study, the specific hotel demand for a given country will be expressed as follows:

$GHD = f\,(GY, GPD, GSP, GEX, GOIL)$

$$GHD: \begin{Bmatrix} 1 = \text{expansion} \\ 0 = \text{contraction} \end{Bmatrix}$$

where:

GHD is the actual hotel occupancy growth in the Hong Kong hotel industry.

GY is the tourist income. GY is the growth rate of the combined gross domestic product (GDP) of the top five overnight-stay countries, which is constructed from the weighting of market share.

GPD is the cost of a room in the destination. GPD is the growth rate of the combined real exchange rate (RER) of the top five overnight-stay countries for Hong Kong.

GSP is the price of substitute destination. GSP is the growth rate of real hotel price of Singapore.

GEX is the nominal exchange rate. GEX is the growth rate of the combined nominal exchange rate between the destination and origin countries.

GOIL: cost of transportation. GOIL is the growth rate of real oil price.

8.4 Test for Multicollinearity

Every explanatory variable for hotel demand determinants will be tested with the cross correlation test to avoid a multicollinearity problem before model estimation. If the tested coefficients between two variables is higher than 0.5, one variable needs to be deleted to avoid the multicollinearity.

The correlation analysis, from table 8.1 shows that the GPD (the cost of purchasing room in the destination), GEX (the growth of exchange rate between the destination and origin countries) and GOIL (travelling cost), are highly correlated.

Table 8.1 Correlation analysis of hotel demand determinants

	GY	GPD	GSP	GEX	GOIL
GY	1.000	-0.299	-0.053	0.330	0.135
GPD	-0.299	1.000	-0.081	-0.535	-0.609
GSP	-0.053	-0.081	1.000	-0.304	0.406
GEX	0.330	-0.535	-0.304	1.000	0.135
GOIL	0.135	-0.609	0.406	0.135	1.000

No previous research has been carried out to determine which hotel demand determinant outperforms the others; thus, it is too early to arbitrarily delete one of them to cure multicollinearity. Therefore, the present study will try to use all three hotel demand determinants separately with other hotel demand determinants in the regression models to find out the best-fit hotel demand determinants for the Hong Kong hotel industry. The empirical result is that GEX is significant for the High Tariff A hotel in Hong Kong and GOIL is significant for (Total) hotel category. However, GPD is not significant at all in any hotel category. Therefore, the model is refined as follows:

$$GHD = f\,(GY,\; GSP, GEX, GOIL)$$

$$GHD\!: \begin{Bmatrix} 1 = \text{expansion} \\ 0 = \text{contraction} \end{Bmatrix}$$

where:

GHD represents the actual hotel occupancy growth in the Hong Kong hotel industry, in which 1 is equal to expansion in the growth of occupancy rate and 0 is equal to contraction in the growth of occupancy rate.

GY is the tourist income. The combined GDP growth rate, by the weighting of market share of the top five overnight-stay countries, is used as the proxy for tourist income.

GSP is the price of the substitute destination. The growth rate of hotel price in Singapore is used as the proxy for the substitute price for Hong Kong hotels.

GEX represents the growth of exchange rate between the destination and origin countries.

GOIL represents the travel cost. The oil price is the proxy of travel cost.

The reason why the GPD is not valid in all the hotel categories in the present study may be because of the unique characteristics of the hotel industry. Kulendran and Wong (2009) used the adjusted CPI with the nominal exchange rate as a proxy for the cost of living of the destination as one of the tourism demand determinants for Hong Kong tourist arrivals. The present study, under the same rationale, used the adjusted CPI with the nominal exchange rate as the proxy of the cost of a room in the destination, which may not be a true reflection of the room cost in the destination. The choice of a room or hotel is a highly personal and subjective decision of the tourist, which is informed by any number of reasons—personal preference, trend, location, transportation, some loyalty program of which he or she is a member, and reason for travel, among many other factors. Such individual choice may not be truly captured by a macroeconomic national index such as the CPI.

As mentioned earlier, the ideal way to construct the cost of the room in the destination is to compare the destination hotel price with that of the tourist-origin country adjusted by the nominal exchange rate. Unfortunately, data on the hotel prices of the countries of origin are lacking. Thus, the adjusted CPI with the nominal exchange rate is used as the proxy for the cost of a room in the destination, which proves that there is not a perfect hotel demand determinant in the present study. However, the importance of the nominal exchange rate cannot be overlooked. Therefore, the nominal exchange rate is used as an individual hotel demand determinant in the present study, which confirms that it is a valid hotel demand determinant in the model.

8.5 Logistic and probit regression models

Logistic and probit regression models are generalized econometric models commonly used in macroeconomics and finance to predict the turning points. Kulendran and Wong (2010) and Fernando (2010) applied the logistic and probit regression models with tourism demand determinants to obtain the turning point forecast and estimate the probability of the impact of changes by those determinants.

Logistic and probit regression models are based on making a prediction of the probability that an incident will happen (p = 1) or will not happen (p = 0) in the future. In the present study, (1) will represent the expansion period and (0) will represent the contraction period in the dependent variable, which is the Hong Kong hotel occupancy growth rate.

The logistic regression model is used for the prediction of the probability of an incident's occurrence by fitting data to a logistic function curve. In the model, the dependent variable is the logarithm of the ratio of the probability that a particular event will happen to the probability that the event will not happen. The probit regression model is an estimation method with dummy variables using a variant of cumulative normal distribution. The binary probit model is based on the cumulative distribution function. If the cumulative distribution of the error term (e) is normal, then the model is called a probit regression model.

Again, the binary regression logistic model is:

$$Ln\left\{\frac{P_{it}}{(1-P_{it})}\right\} = \beta_o + \sum_{k=0}^{4}\beta_1 GY_{t-k} + \sum_{k=0}^{4}\beta_1 GSP_{t-k} + \sum_{k=0}^{4}\beta_1 GEX_{t-k} + \sum_{k=0}^{4}\beta_1 GOIL_{t-k}$$

Meanwhile, the binary regression probit model is:

$$P_{it} = \Phi\,(.)$$

$$= \beta_o + \sum_{k=0}^{4}\beta_1 GY_{t-k} + \sum_{k=0}^{4}\beta_1 GSP_{t-k} + \sum_{k=0}^{4}\beta_1 GEX_{t-k} + \sum_{k=0}^{4}\beta_1 GOIL_{t-k}$$

where P_{it} is the probability that the particular outcome of expansion(1) will occur in time t for the dependent variable, which is the growth of hotel occupancy rate; 1-P_{it} is the probability that the particular outcome of contraction(0) occur in time t for the dependent variable, which is the growth of hotel occupancy rate; *i* is the type of hotel category; Φ denotes the values of the cumulative standard normal distribution; GY is the tourist income; GEX represents the growth of the exchange rate between the destination and origin countries; and GOIL represents the travel cost.

8.6 Estimated models

Logistic and probit regression models were estimated with EView (version 6.0). Table 8.2 shows the results of the logistic regression models estimated with the hotel demand determinants. Table 8.3 shows the results of the probit regression models estimated with the hotel demand determinants. After refinement, all the estimated models are valid because LR statistics are significant at the 5% level. Kulendran and Wong (2010) have explained that no huge differences are to be expected from the results of the estimation of both models because the normal distribution from the probit model and the logistic distribution from logistic model are relatively similar.

GY, the growth rate of real income of the origin country, is a significant hotel demand determinant for both models in all hotel categories. The combined GDP, by the weighting of market share of the major overnight-stay tourist arrivals in Hong Kong, is used as the proxy for the real income of the origin country. It may indicate that GDP from the tourist-origin country is the main economic variable for the impact of the hotel demand in Hong Kong.

Furthermore, GOIL is a significant hotel demand determinant for the (Total) hotel category in Hong Kong. It may be because the oil price not only affects the cost of airfare, but also other the prices of other transport such as cars, trains, and cruise ships. For example, the tourist may start looking for accommodation only while he or she is en route to the chosen destination. The tourist may choose a hotel based on his or her budget, and the hotel's location and facilities, among other considerations. If the hotel is not strategically located, the tourist may need to factor in the cost of transportation to reach the hotel. Therefore, other transport costs will be involved in this stage, which the tourist must evaluate aside from the airfare. The global oil price can thus be supported as a valid hotel demand determinant in developing econometric models for the hotel industry.

GEX is a significant hotel demand determinant for the High Tariff A hotel category in Hong Kong. It may suggest that the change in nominal exchange rate will affect the demand for this hotel category in Hong Kong, and confirms that the nominal exchange rate is one of the sufficient hotel demand determinants for the hotel industry.

Table 8.2 Estimated regression logistic models with hotel demand determinants; sample period: Q1 1996 to Q2 2009

	Estimated regression logistic models	n	LR Statistic	Prob(LR Statisitc)	R2McF	Mean
HK TOTAL HD LG	**Ln(Pit / (1-Pit)) = -2.319 +3.553GYt -6.851GOILt** **(z= -3.852) (z= 4.480) (z=-2.559)**	59	31.764	0.000	0.428	GY=0.394667 GOIL=0.043602
HK HIGH A HD LG	**Ln (Pit /(1-Pit)) = -3.755 +3.917GYt +200.751GEXt** **(z = -3.450) (z = 3.245) (z = 2.426)**	59	29.987	0.000	0.503	GY=0.394667 GEX=-0.004880
HK HIGH B HD LG	**Ln (Pit /(1-Pit)) = -7.278 +11.347GYt** **(z = -2.168) (z = 2.620)**	59	66.468	0.000	0.880	GY=0.394667
HK MEDIUM HD LG	**Ln (Pit /(1-Pit)) = -1.674 +1.988GYt** **(z = -3.694) (z = 3.140)**	59	11.422	0.000	0.154	GY=0.394667

n is the number of observations.
The LR statistic tests joint hypothesis is all slope coefficients except the constant are zero.
Prob(LR Statisitc) is the p value of the LR statistic.
R^2_{McF} is the McFadden R-squared.
HD is the hotel demand determinants.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CC is the weighting method of the coefficient of cross correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival in Hong Kong.
LG is the logistic regression model.
PB is the probit regression model.
Apply to table 8.2 and 8.3.

Table 8.3 Estimated probit models with hotel demand determinants; sample period: Q1 1996 to Q2 2009

	Estimated regression probit models	n	LR Statistic	Prob(LR Statisitc)	R^2_{McF}	Mean
HK TOTAL HD PB	**P_{it} = -1.301 +2.060GY_t -3.710$GOIL_t$** **(z = -4.370) (z = 4.911) (z = -2.567)**	59	31.421	0.000	0.424	GY=0.394667 GOIL=0.043602
HK HIGH A HD PB	**P_{it} = -2.085 +2.171GY_t +119.002GEX_t** **(z = -3.862) (z = 3.536) (z = 2.461)**	59	30.027	0.000	0.503	GY=0.394667 GEX=-0.004880
HK HIGH B HD PB	**P_{it} = -3.754 +5.885GY_t** **(z = -2.425) (z = 3.011)**	59	66.399	0.000	0.879	GY=0.394667
HK MEDIUM HD PB	**P_{it} = -0.019 +1.215GY_t** **(z = -3.967) (z = 3.282)**	59	11.563	0.000	0.156	GY=0.394667

8.7 Impact on Probability of significant hotel demand determinants

The difference between the binary logistic model and the probit model is the specification of the error term in the model. The distribution of the error term in a logistic model is in a “logit” distribution; on the other hand, the error term distribution in probit model is a “normal” distribution. Although the cumulative of the normal and logistic distributions of both models is relatively similar, the result of the estimation of both models is expected not to vary greatly (Kulendran and Wong, 2010). Furthermore, Kulendran and Wong (2010) contended that for simplicity and easy interpretation, the logistic regression model may be a better choice than the probit regression model.

However, the cumulative logistic distribution in the logistic model can calculate the impact on the probability of expansion occurring due to a 1% change in the explanatory variables, that is, significant hotel demand determinants in the model.

The estimated coefficient of each significant hotel demand determinant in the logistic regression model can measure the impact of those hotel demand determinants on the probability. It means that a 1% change in the significant hotel determinants will result in an increase or decrease in the probability of the occurrence of the expansion period. It can be measured by the following formula (Maddala, 2001):

$$\Delta p = \beta_j p_i (1 - p_i)$$

where Δp is the impact in probability; and β_j is the estimated coefficient of the significant hotel demand determinants.

Kulendran and Wong (2010), and Pindyck and Rubinfeld (1998) proved that although no single value can be assigned to the probability p_i, the most useful single value for measuring the impact of the explanatory variable on the probability is the mean value of significant hotel demand determinant. Therefore in the present study, the mean of the significant hotel demand determinants will be the value of p_i.

In the Hong Kong (Total) hotel category, a 1% increase in GY, the growth rate of real income of the origin countries, will result in an increase in the probability of the expansion period by 0.005866. The meaning of the impact on the probability is as follows: *if the combined GDP growth rate of Hong Kong's top five overnight-stay* *tourist arrival-origin countries increases by 1%, the chance that the growth of the Hong Kong (Total) hotel category occupancy rate will go up is 0.59%.*

A 1% increase in GOIL, the growth of travel cost, will result in a decrease in the probability of the expansion period by -.011311 in the growth of Hong Kong (Total) hotel occupancy rate. Given that the growth of the oil price is the proxy of GOIL, the growth of travel cost, the meaning of the impact on the probability is as follows: *if the growth of the international oil price increases by 1%, there is a 1.13% chance that the growth of the (Total) hotel occupancy rate will decrease.*

For the growth of occupancy rate in the High Tariff A hotel category, a 1% increase in GY, the growth rate of real income of the origin countries, will result in an increase in the probability of the expansion period by 0.001487. *This means that a 1% increase in the combined GDP growth rate of the Hong Kong top five overnight-stay tourist arrivals origin-countries, the chance that the growth of the High Tariff A hotel occupancy rate will go up is 0.13%.*

A 1% increase in GEX, the growth of exchange rate between the destination and origin countries, will result in a decrease in the probability of the expansion period by 0.076209 in the growth of Hong Kong High Tariff A hotel occupancy rate. The growth of exchange rate is actually the combined growth rate of the nominal exchange rate of the major overnight-stay tourist arrivals in Hong Kong. *Thus, if the growth of the combined nominal exchange rate between Hong Kong and the major overnight-stay arrivals' origin-countries increases by 1%, the probability that the growth of the High Tariff A hotel occupancy will decrease is 7.62%.*

For the growth of occupancy rate in High Tariff B hotel category, a 1% increase in GY, the growth rate of real income of the origin-countries, will result in an increase in the probability of the expansion period by 0.006111. *Thus, if the combined GDP growth rate of the Hong Kong top five overnight-stay arrivals' origin-countries increases by 1%, the probability that the growth of the High Tariff B hotel occupancy rate will increase is 0.61%.*

Finally, for the Medium Tariff hotel in Hong Kong, a 1% percent increase in GY, the growth rate of real income of the origin-countries, will result in an increase in the probability of the expansion period by 0.003668. *Thus, if the combined GDP growth rate of the Hong Kong top five overnight-stay tourist arrivals' origin-countries increases by 1%, the probability that the growth of the Medium Tariff hotel occupancy rate will rise is 0.37%.* Table 8.4 lists the estimates of change in the probability of expansion period as a result of a 1% change in the significant hotel demand determinants.

From the calculated coefficients, the GY (average impact coefficient: 0.004283) appeared in every hotel category as one of the significant hotel demand determinants. However, compared to the calculated coefficients of GOIL (coefficient: -0.011311) in HK (Total) category and GEX (coefficient: 0.076209) in High Tariff A hotel category, the impacts of these two hotel-demand determinants are much higher than the GY, respectively. The relatively high impact of GOIL and GEX shows that the oil price and the nominal exchange rate are the key hotel demand determinants for the tourists when they choose the accommodation in the destination.

Table 8.4 Impact on the probability due to a 1% change in the significant hotel demand determinants

Hotel category	Significant Hotel demand determinants		
	GY	GOIL	GEX
HK Total	ΔGY = 0.005866	ΔGOIL = -0.011311	
HK High A	ΔGY = 0.001487		ΔGEX = 0.076209
HK High B	ΔGY = 0.006111		
HK Medium	ΔGY = 0.003668		

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
GY is the growth rate of real income of the origin country.
GOIL is the growth rate of the oil price.
GEX is the growth rate of the nominal exchange rate.

8.8 Accuracy of Probability Forecasting

After the construction of all the different models, it is necessary to compare the accuracy of the probability occurrence of each model. QPS is a common instrument to test the forecasting correctness of the logistic and probit regression models. QPS became popular after the illustration of Diebold and Rudebusch (1989). For these purposes, the universe consists only of two (mutually exclusive) events, namely, the occurrence or non-occurrence of a turning point, in which, in the logistic and probit regression models, 1 represents the expansion period and 0 represents the contraction period. QPS is the possible outcome prediction, that is, the universe consists only of two outcomes, namely, a turning point or none, which are mutually exclusive. From the estimated probability (p_e) of the logistic and probit regression models, the expansion and contraction periods could be identified as follows: if the estimated probability (p_e) is "greater than 0.5," it is considered an expansion period; if the estimated probability (p_e) is "smaller than 0.5," it is considered a contraction period. Therefore, the timing of the turn and the turning point (peak point) can be recognized when the estimated probability (p_e) changes from "greater than 0.5" to "smaller than 0.5"; the timing of the change and the turning point (trough point) can be recognized when the estimated probability (p_e)

changes from "smaller than 0.5" to "greater than 0.5." Diebold and Rudebusch (1989) have explained that QPS ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. The simplified formula to calculate the QPS is as follows:

$$\boldsymbol{QPS = \frac{1}{T}\sum_{t=1}^{T} 2\,(P_1 - R_1)^2}$$

where P_t is the probability of the occurrence of a turning point at date t (or, over specific horizon H beyond date t); R_t equals 1 if the turning point occurs in period t and is equal to 0 otherwise. Table 8.5 illustrates the results of forecasting accuracy by QPS score, and Figures 8.1 to 8.4 show the estimated probability by the logistic regression models and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong. Figures 8.5 to 8.8 show the estimated probability by the probit regression models and the occupancy rate in expansion(1) and contraction(0) periods for different hotel categories in Hong Kong.

Table 8.5 Summary of the QPS results for the logistic and probit regression models with hotel demand determinants

	Hong Kong hotel category				
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM	Average
HD LG	**0.21525**	**0.36674**	**0.00798**	**0.43516**	**0.25628**
HD PB	**0.21342**	**0.36956**	**0.01121**	**0.39408**	**0.24707**

HD is the hotel demand determinants.
LG is the regression logistic model.
PB is the regression probit model.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.

Figure 8.1 The Hong Kong (Total) hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the logistic regression models with hotel demand determinants for Hong Kong (Total) hotel category (HK TOTAL HD LG)

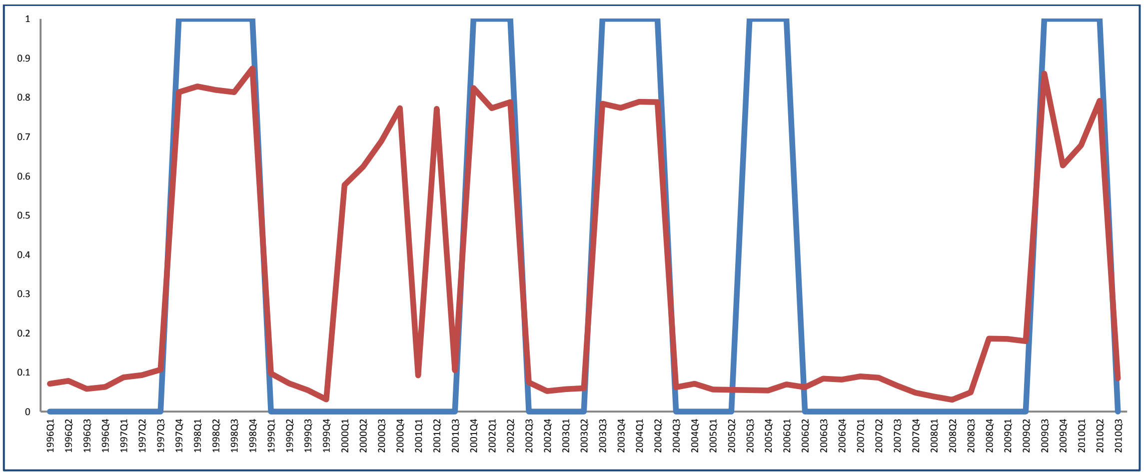


Figure 8.2 The Hong Kong High A hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the logistic regression models with hotel demand determinants for Hong Kong High Tariff A hotel category (HK HIGH A HD LG)

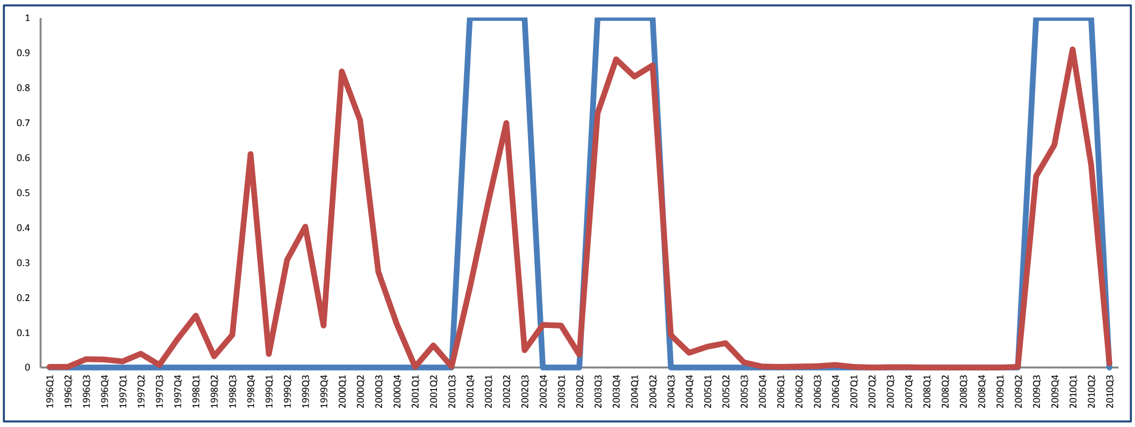


Figure 8.3 The Hong Kong High Tariff B hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the logistic regression models with hotel demand determinants for Hong Kong High Tariff B hotel category (HK HIGH B HD LG)

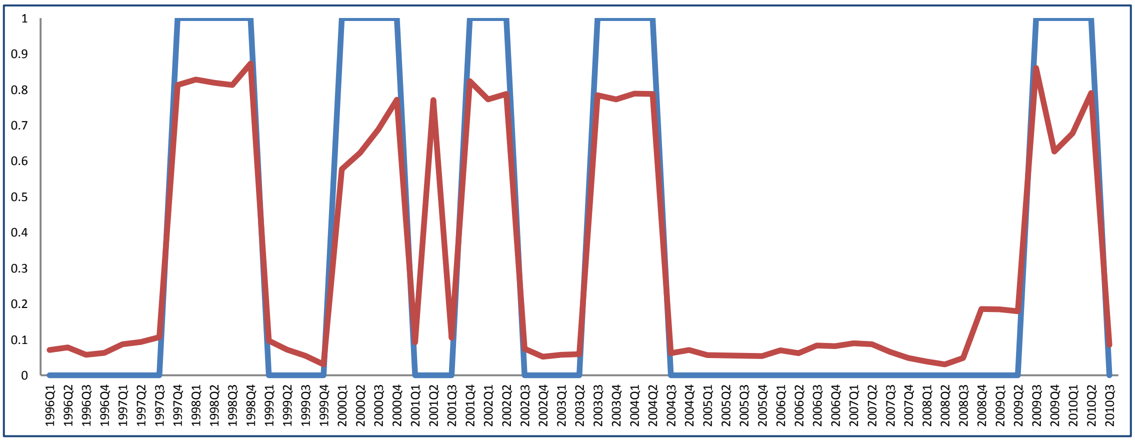


Figure 8.4 The Hong Kong Medium Tariff hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the logistic regression models with hotel demand determinants for Hong Kong Medium Tariff hotel category (HK MEDIUM HD LG)

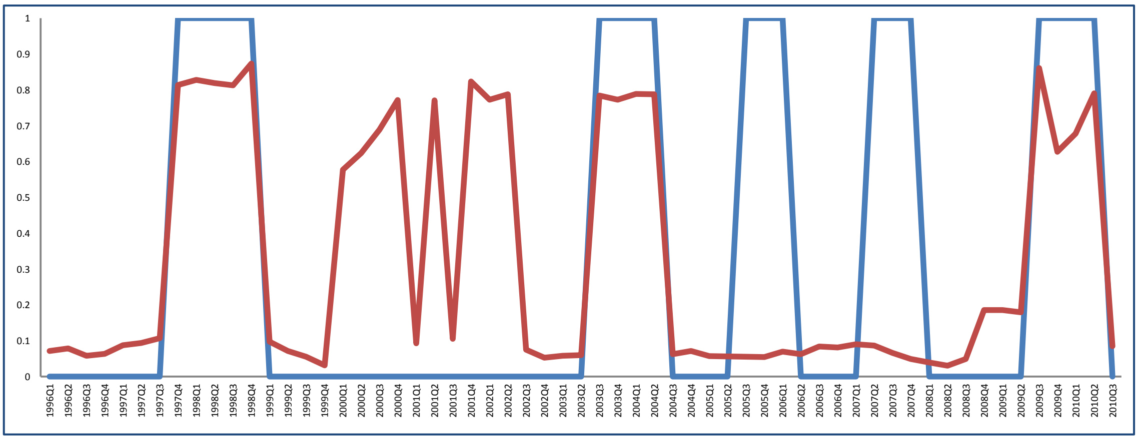


Figure 8.5 The Hong Kong (Total) hotel occupancy rate in expansion(1) and contraction(0) periods (HK TOTAL) and the estimated probability with the probit regression models with hotel demand determinants for Hong Kong (Total) hotel category (HK TOTAL HD PB)

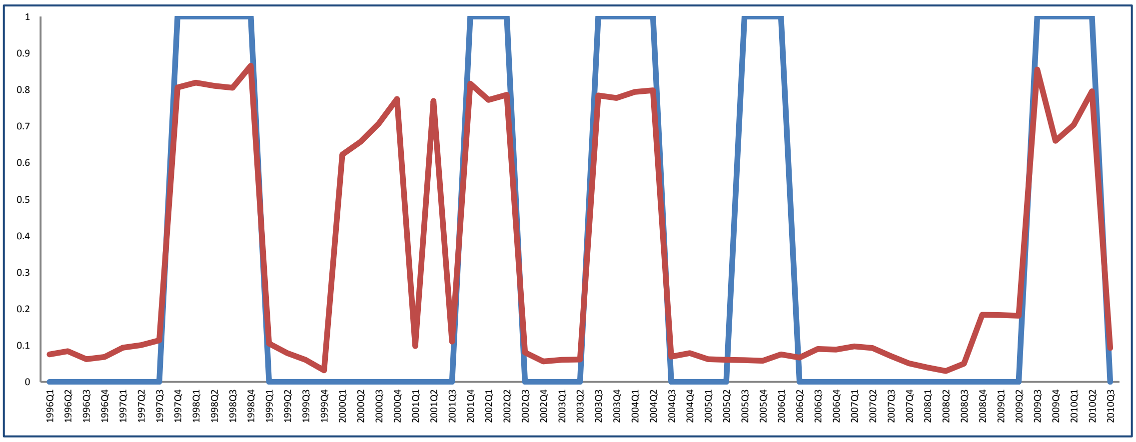


Figure 8.6 The Hong Kong High Tariff A hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH A) and the estimated probability with the probit regression models with hotel demand determinants for Hong Kong High Tariff A hotel category (HK HIGH A HD PB)

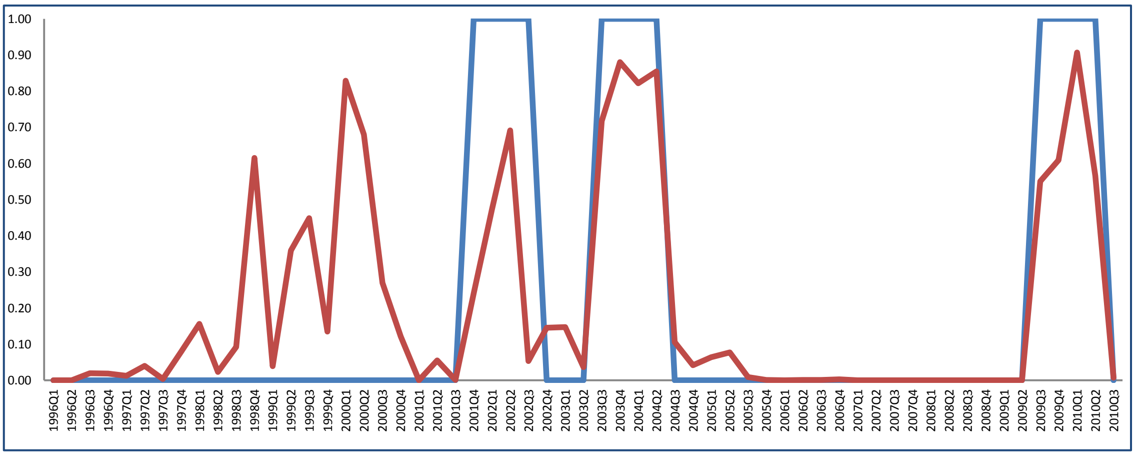


Figure 8.7 The Hong Kong High Tariff B hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK HIGH B) and the estimated probability with the probit regression models with hotel-demand determinants for Hong Kong High Tariff B hotel category (HIGH B HD PB)

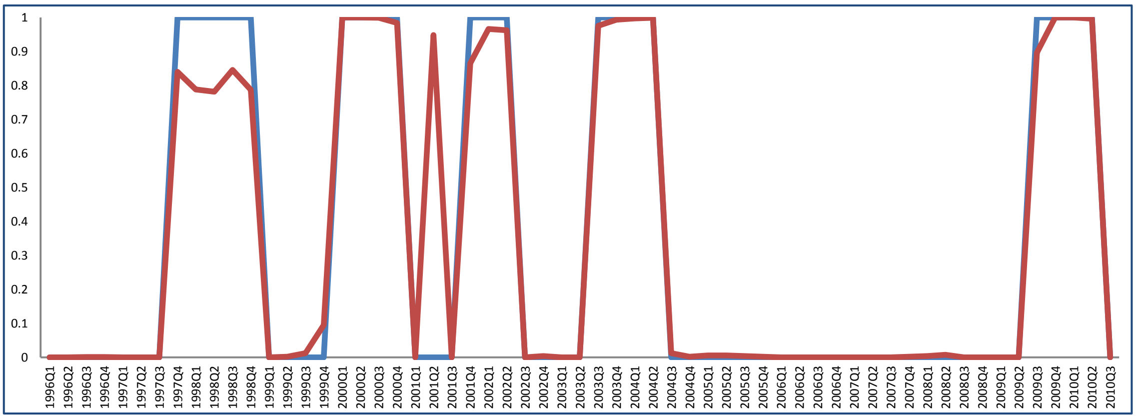
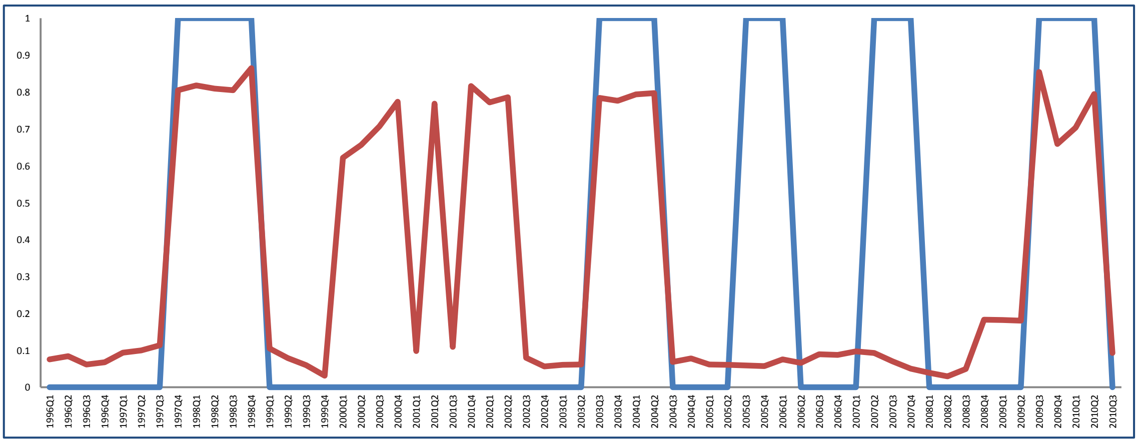


Figure 8.8 The Hong Kong Medium Tariff hotel occupancy growth rate in expansion(1) and contraction(0) periods (HK MEDIUM) and the estimated probability with the probit regression models with hotel-demand determinants for Hong Kong Medium Tariff hotel category (HK MEDIUM HD PB)



8.9 Conclusion

Five hotel demand determinants were used to estimate the models; however, only the growth of real income of the origin-countries was significant for all hotel categories in Hong Kong. This may indicate that the identification of the hotel demand determinants has not successfully represented the true demand function for the hotel industry.

The use of the impact on probability is a practical indication for hoteliers if the highly related hotel demand determinants are identified. For example, in the present study, the growth of oil price and the nominal exchange rate are the high-impact hotel demand determinants that would affect the hotel industry in Hong Kong. Such indications could provide advance signals for hoteliers to anticipate the shifting demand of the hotel occupancy rate. The search for potential hotel demand determinants will be a key topic in future research.

Chapter 9

CONCLUSION

9.1 Introduction

After all the construction and estimation in previous chapters, it is time to compare and contrast each model. As stated in Chapter 1, the occupancy rate is the number of rooms occupied by inbound tourists in proportion to the total number of rooms available for occupation. This is a common business indicator for the international hotel industry. Forecasting the occupancy rate can help hoteliers prepare through strategic planning for the estimated risk associated with the changing demand for hotel rooms. However, complex global economic, political, and social factors have made such accurate predictions for hotel management increasingly difficult. Moreover, there have been few studies in the academe to help the hotel industry develop a method to find a systematic approach to manage information toward the better management of human and capital resources in the hotel industry. The present study seeks to fill this gap.

The present study aims to develop econometric models that could predict the turning points of the upturn and downturn in hotel occupancy growth rates of tourists so that hoteliers would know in advance when the current trend would change for the better or worse. The use of different composite leading indicators and hotel demand determinants in the search for the most accurate forecasting method for the hotel industry has been presented in previous chapters. Different models can provide different scopes of information for hoteliers to use to help them make short-term, medium-term, and long-term decisions.

9.2 Chapter Overview

After identifying the important contribution of the hotel industry to Hong Kong's gross domestic income (GDP) and employment and the further illustration of the situation in the Hong Kong hotel industry and the classification of hotel categories in Chapter 1, the conclusion is that the hotel industry is highly volatile and influenced by global economic and political factors. Such instability makes it difficult to predict the exact occupancy rates for the hotel industry, even as it exposes hoteliers to greater risks when they make decisions in their long-term strategic development and even in their short-run daily operations.

In Chapter 2's review of literature, no study has been identified as one that could help develop an econometric model to help hotel industry practitioners that would provide better and more useful information to help them deal with their day-to-day operations. Furthermore, as confirmed by Song and Li (2008), tourism-related firms are devoted to knowing the timing of the directional change in forecasts, which gives turning point forecasting a highly practical value in the tourism industry. There is a lack of studies done in this field, even though such information would contribute immensely to the effectiveness for both strategic planning, from the point of view of a single hotel to government-level policy making.

Therefore, in Chapter 3, the methodology and research process for constructing the turning point forecasting are shown. The present study mainly uses two different dimensions in constructing the econometric models. First, several identified economic variables have been confirmed by past studies as affecting tourism products. Such economic variables will combine and construct the composite leading indicators for the Hong Kong hotel industry. Second, according to the customer theory of choice, several specific economic variables can become the hotel demand determinants that can affect the change in hotel demand. Therefore, comparison of the results of these two main concepts can give different scopes of information for hoteliers to apply in their respective situations.

Considering that it would be unfair to compare the results of the forecasting performance especially if these are not on equal grounds, the composite leading indicators and hotel demand determinants should serve as the explanatory variables for the logistic and probit regression models. Estimated logistic and probit regression models with the composite leading indicators and hotel demand determinants will then compare their forecast performance accuracy by the QPS score method.

Before the models for the hotel industry were constructed and estimated, the identification of the turning points of the original occupancy rate of Hong Kong hotels was taken as the initial step. Following the outcome of previous studies, Chapter 4 smoothed the data by basic structure modelling. The modified Bry and Boschan's method (1971) was applied to date the turning points. The chapter findings discuss the meaning and usage of the lead time found in different hotel categories in Hong Kong.

Chapters 5 and 6 constructed the composite leading indicators for the Hong Kong hotel industry. Based on the market share of the top five overnight-stay visitor arrivals in Hong Kong as the basic reason for the present study, the selected economic variables for those countries were taken into the construction of the countries' composite leading indicators for the Hong Kong hotel industry in Chapter 5. Then in Chapter 6, the countries' composite leading indicators were combined with two weighting methods, namely, the coefficient of the cross-correlation analysis and the market share of the overnight-stay visitor arrivals in Hong Kong. The constructed composite leading indicators also worked as the explanatory variables to estimate the logistic and probit regression models. The accuracy of the probability forecasting was then measured by QPS.

Chapter 7 constructed the composite leading indicators based on the published OECD data, with methodologies and research procedures that are identical to those in the previous chapter. The constructed OECD composite leading indicators, namely, the OECD business survey index and the OECD consumer confidence index for Hong Kong hotels, were used as comparison indicators for the constructed composite leading indicators in Chapter 6.

After using the composite leading indicator approach to forecast the turning points in the hotel industry, Chapter 8 used the hotel demand determinants as the explanatory variables to estimate the logistic and probit regression models to predict the turns in hotel occupancy rate. One more function the logistic regression model can perform is to measure the impact of the probability of the significant hotel demand determinants on the Hong Kong hotel occupancy rate.

Finally in this chapter, all the findings and results of the forecasting performance are compared and explained in detail.

To reiterate, the aim of the present study is to predict the turning points in hotel occupancy growth rates in Hong Kong using composite leading indicators and hotel demand determinants. The following specific aims, stated in Chapter 1, have been executed and fully achieved in the different chapters:

<u>The specific objectives of the present study as stated in Chapter 1 were to:</u>

- ➢ Extract the growth cycle of the hotel occupancy rate for different hotel categories (✓Chapter 4).

- Identify the turning points in the growth cycle of occupancy rates (✔Chapter 4).

- Construct a composite leading indicator using selected economic variables of the top five markets of Hong Kong overnight stay tourists (✔Chapter 5 and 6).

- Construct a composite leading indicator using the existing composite leading indicator or indexes, such as the OECD composite leading indicator, the OECD business survey index, and the OECD consumer confidence index (✔Chapter 7).

- Combine the composite leading indicators using two different weighting methods, namely, the market share of the top five countries of overnight-stay tourists in Hong Kong and the cross-correlation coefficient of the series (✔Chapter 6 and 7).

- Estimate the logistic and probit regression models with the constructed composite leading indicator and the OECD existing composite leading indicators or indexes (✔Chapter 6 and 7).

- Estimate the logistic and probit models with hotel demand determinants (✔Chapter 8).

- Assess the forecasting performance of logistic and probit regression models that are estimated by the composite leading indicators and hotel demand determinants using the quadratic probability score method (✔Chapter 6, 7 and 8).

9.3 Contribution of the study

The first part of this section will briefly reiterate the important contributions of the present study. The second part of this section will show the significant findings of the present study. Both parts demonstrate the necessity and uniqueness of the present study.

9.3.1 Highlights of the Research Contributions

The extraction of a smooth growth rate and the dating of peak and trough points of the hotel occupancy rate have been demonstrated in Chapter 4 of the present study. The identification of the lead time of each hotel category is summarized in the findings that follow shortly.

The principal aim of the present study has been achieved by developing an econometric model using the logistic and probit regression models that could predict the turning points in the hotel occupancy growth rates to provide advance warning for hoteliers. To identify the specific model for the hotel industry, the present study uses data based on overnight-stay visitor arrivals. Such models will be the first econometric models for the hotel industry.

The present study predicts the turns and directional change in the hotel occupancy growth rate as estimated with logistic and probit regression models with two approaches, namely, composite leading indicators, and hotel demand determinants. The empirical results of these two approaches will be compared and contrasted later in this section.

Using the published OECD indicators and indexes to construct the composite leading indicators for the Hong Kong hotel industry has provided an opportunity for the constructed composite leading indicator to be compared with selected economic variables.

Given the unique hotel classification in Hong Kong, four different models were created for each hotel category, namely, High Tariff A hotel, High Tariff B hotel, Medium Tariff hotel, and the average of the three categories (Total) in Hong Kong. This approach is the first attempt in literature to give details and practical models for each hotel category with a view to assessing the different timings of the demand switch. The comparisons of each category will be discussed in the second part of this section.

Aside from providing a concrete approach to constructing the composite leading indicator for the hotel industry, another contribution of the present study is the provision of two different weighting methods for the construction of the composite leading indicator for the hotel industry. The two types of weighting methods are the coefficient of cross-correlation analysis, and the market share of the overnight-stay tourist arrivals. These weighting approaches will be compared in the next part of this section.

Furthermore, the present study also provides an empirical basis for the development of unique demand determinants for the hotel industry. These hotel demand determinants include tourist income, cost of the room in the destination, substitute destination pricing, nominal exchange rate, and cost of travel, which may have a leading correlation with the turning points of hotel occupancy rates.

9.3.2 Summary of Findings

⇒ The average length of a contraction period is longer than the average expansion period in the hotel occupancy rate.

⇒ The shortest lead time among all the composite leading indicators constructed by both weighting methods (cross correlation analysis and the market share of the overnight stay tourist arrivals) for Hong Kong hotel industry is from the OECD consumer confidence index.

⇒ The best forecasting performance of all the composite leading indicators by the weighting method of cross correlation analysis for each tariff category:

→ *the OECD consumer confidence index estimated by the probit regression model for Hong Kong (Total) hotel category.*

→ *the constructed composite leading indicator estimated by the probit regression model for Hong Kong High Tariff A hotel category.*

→ *the OECD consumer confidence index estimated by the logistic regression model for Hong Kong High Tariff B hotel category.*

→ *the OECD composite leading indicator estimated by the probit regression model for Hong Kong Medium Tariff hotel category.*

⇒ The best forecasting performance of all the composite leading indicators by the weighting method of the market share of the overnight stay tourist arrivals for each tariff category:

→ *the OECD consumer confidence index estimated by the probit regression model for Hong Kong (Total) hotel category.*

→ *the OECD composite leading indicator estimated by the probit regression model for Hong Kong High Tariff A hotel category.*

→ *the OECD composite leading indicator estimated by the probit regression model for Hong Kong High Tariff B hotel category*

→ *the OECD composite leading indicator estimated by the logistic regression model for Hong Kong Medium Tariff hotel category*

⇒ Among the two weighting methods, market share of the overnight stay tourist arrivals has a better forecasting performance than cross correlation analysis.

⇒ Nominal exchange rate is a significant hotel demand determinant for the Hong Kong High Tariff A hotel category.

⇒ Among all the significant hotel demand determinants, GOIL (growth rate of the travel cost) and GEX (growth rate of the nominal exchange rate) have a higher impact probability than the GY (growth rate of the real income).

⇒ Among all the estimated models, the most accurate forecasting performance model is the probit regression model estimated with the hotel demand determinants

9.3.2.1 The length of contraction and expansion periods from the original occupancy rate

From the findings in Chapter 4, the average contraction period (from one peak point to the next trough point) is longer than the expansion period (from one trough point to the next peak point) in the Hong Kong hotel occupancy rate. This may be due to the dynamic and international image of Hong Kong, which makes it highly appealing to tourists. The aggressive monthly marketing schemes by the HKTB have also consistently conveyed Hong Kong's vibrancy to tourists all over the world.

Another finding consists of the average length of the peak-to-peak period and trough-to-trough period. In the present study, the different hotel groups exhibit totally different patterns. A peak-to-peak period can be defined as the recession cycle, as between peaks there are one or more than one contraction and expansion periods. A trough-to-trough period can be explained as a boom cycle, which should include one or more than one expansion and contraction periods. Such cycles can give policy makers or hoteliers a clearer idea of the long-term movement of the hotel occupancy rate. For example, the longest peak-to-peak period happened in the High Tariff A hotel category (22.6 quarters or 5.7 years). This may imply that this hotel category has a longer recession cycle, which will require careful strategic planning to survive. Policy makers may need to be cautious when approving a new hotel development in this category during the recession cycle. On the other hand, the hoteliers may consider different kinds of promotions to keep the business of this hotel category going well.

9.3.2.2 Weighting methods for constructing the composite leading indicators

The present study uses two kinds of weighting methods for constructing the composite leading indicators for the Hong Kong hotel industry. The first is by the coefficient of the cross-correlation analysis, and the second is by the market share of the overnight-stay tourist arrivals in Hong Kong.

Using the coefficient of the cross-correlation analysis is based purely on the relationship between the economic variables and the historical occupancy rate. It may not easily detect and reflect the lively and vibrant switch in the hotel occupancy rate caused by a recent trend or issue. On the other hand, using the market share of the overnight-stay tourist arrivals may be more directly related to the dynamic economic situation in the tourism sector. The market share weighting method, which is solely affected by the actual numbers of overnight-stay visitors, can totally capture the dynamic and latest happenings in the hotel industry. No previous research has ever used the market share of the overnight-stay tourist arrivals as a weighting to combine and construct composite leading indicators.

A. Findings from the coefficient of cross-correlation analysis (CC)

Lead-time identification of all the composite leading indicators (CC)

Different lead times computed from different indicators for different hotel categories can provide sound information for hoteliers to apply to their own property occupancy rates. For example, if hotel management believes that one of the published indicators is a better forecasting tool to predict the turns in its own property, the estimated lead time can provide management with a quick reference about the timing of the demand changing in a specific hotel category. Another approach for the hoteliers may be if they believe that the shorter lead time is most suitable for hotel industry, they can choose the OECD consumer confidence index as the indicator since this indicator had the shortest lead among all the others. Table 9.1 summarizes all the lead times calculated from the weighting method of the coefficient of the cross-correlation analysis.

Table 9.1 Summary of the lead times computed from the coefficient of the cross-correlation analysis weighting method

Composite leading indicators	Hong Kong hotel category			
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM
HK CLI CC	**1**	**1**	**5**	**2**
OECD CLI CC	**1**	**2**	**5**	**2**
OECD BSI CC	**1**	**2**	**4**	**1**
OECD CCI CC	**2**	**1**	**1**	**2**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator by the selected economic variables
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
CC is the weighting method of the coefficient of cross correlation analysis.

Forecasting performance of all the constructed composite leading indicators (CC)

Table 9.2 summarizes the results of QPS for all the composite leading indicators that used the weighting method by the coefficient of cross-correlation analysis. The best forecaster for the Hong Kong (Total) hotel category is the constructed OECD consumer confidence index estimated with the probit regression model. The best forecast performance in the Hong Kong High Tariff A category is that of the constructed composite leading indicator estimated with the probit regression model. For the High Tariff B hotel category, the best forecasting performance is that of the constructed OECD consumer confidence index estimated with the logistic regression model. The constructed OECD composite leading indicator has the best forecasting performance in the Hong Kong Medium Tariff hotel category.

Among all the estimated models with the constructed composite leading indicator, the best forecast performance appeared in the Hong Kong High Tariff A hotel category. For all the constructed OECD models, the best forecast performance is that of the Hong Kong Medium Tariff hotel category.

Table 9.2 Summary of the QPS results for all the constructed composite leading indicators by the coefficient of cross-correlation analysis weighting method

Composite leading indicators	Hong Kong hotel category			
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM
HK CLI CC LG	**0.36448**	**0.29355**	**0.67726**	**0.30037**
HK CLI CC PB	**0.35607**	**0.29198**	**0.67455**	**0.30142**
OECD CLI CC LG	**0.48744**	**0.37775**	**0.80272**	**0.24119**
OECD CLI CC PB	**0.48667**	**0.37983**	**0.79666**	**0.24118**
OECD BSI CC LG	**0.37753**	**0.35426**	**0.70151**	**0.30502**
OECD BSI CC PB	**0.37760**	**0.35516**	**0.69805**	**0.30622**
OECD CCI CC LG	**0.33350**	**0.47134**	**0.40536**	**0.30792**
OECD CCI CC PB	**0.33136**	**0.47494**	**0.40886**	**0.30873**

Coefficient in red font is the best forecast performance in that hotel category.
Coefficient in yellow shade is the best forecast performance in that composite leading indicator.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator by the selected economic variables
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
CC is the weighting method of the coefficient of cross correlation analysis.
LG is the regression logistic model.
PB is the regression probit model.

B. Findings from the market share of the overnight-stay tourist arrivals in Hong Kong (MS)

Lead-time identification of all the constructed composite leading indicators (MS)

Identifying lead times from different indicators for different hotel categories can provide an early signal for policy makers or hoteliers on the changing demand in the hotel occupancy rate. If hoteliers consider one of the composite leading indicators the shadow of their own hotel occupancy model, the lead time can give sufficient information and time for them to prepare for the coming upturn or downturn. Second, if the hoteliers believe the hotel industry should have a shorter lead time, they can choose to use the OECD consumer confidence index as the benchmarking indicator for their own hotel. Table 9.3 summarizes the lead times calculated from the weighting method of the market share of the overnight-stay tourist arrivals.

Table 9.3 Summary of the lead times computed from the coefficient of the market share weighting method

Composite leading indicators	Hong Kong hotel category			
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM
HK CLI MS	**3**	**2**	**3**	**3**
OECD CLI MS	**2**	**2**	**2**	**2**
OECD BSI MS	**2**	**2**	**4**	**2**
OECD CCI MS	**1**	**1**	**1**	**1**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator by the selected economic variables
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
MS is the weighting method of the market share of the overnight stay tourist arrival..

Forecasting Performance of all the constructed composite leading indicators (MS)

Table 9.4 summarizes the results of QPS for all the composite leading indicators using the weighting method by the market share of overnight-stay tourist arrivals in Hong Kong. The best forecaster for the Hong Kong (total) hotel category is the constructed OECD consumer confidence index estimated with the probit regression model. The best forecast performance in both Hong Kong High Tariff A and High Tariff B are the constructed OECD composite leading indicators estimated with the probit regression model. For the Medium Tariff hotel category, the best performance is that of the constructed OECD consumer confidence index estimated with the logistic regression model.

Among all the estimated models with the constructed composite leading indicator and the constructed OECD composite leading indicator, the best forecast performance appeared in the Hong Kong High Tariff A hotel category. For the constructed OECD business survey index and the constructed OECD consumer confidence index models, the best forecast performance was that of the Hong Kong Medium Tariff hotel category.

Table 9.4 Summary of the QPS results for all the constructed composite leading indicators by the coefficient of the market share weighting method

Composite leading indicators	Hong Kong hotel category			
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM
HK CLI MS LG	**0.38760**	**0.29724**	**0.31526**	**0.29644**
HK CLI MS PB	**0.38634**	**0.29555**	**0.31868**	**0.29742**
OECD CLI MS LG	**0.33197**	**0.26230**	**0.29970**	**0.27499**
OECD CLI MS PB	**0.33115**	**0.25971**	**0.29876**	**0.27492**
OECD BSI MS LG	**0.33735**	**0.33239**	**0.76396**	**0.25762**
OECD BSI MS PB	**0.36299**	**0.33121**	**0.75927**	**0.25783**
OECD CCI MS LG	**0.33177**	**0.26837**	**0.31135**	**0.24333**
OECD CCI MS PB	**0.33112**	**0.26583**	**0.31054**	**0.24389**

Coefficient in red font is the best forecast performance in that hotel category.
Coefficient in yellow shade is the best forecast performance in that composite leading indicator.
HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator by the selected economic variables
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
MS is the weighting method of the market share of the overnight stay tourist arrival of Hong Kong.
LG is the regression logistic model.
PB is the regression probit model.

C. Comparison of the results between two weighting methods (CC and MS)

Lead-time identification of all the constructed composite leading indicators (CC and MS)

Table 9.5 shows that the longest lead time, 5 quarters, appeared in the constructed composite leading indicator and the constructed OECD composite leading indicator by the coefficient of cross-correlation analysis in the High Tariff B hotel category. Another finding is all the indicators have only 1 or 2 quarters' lead time in the High Tariff A hotel category.

Table 9.5 Summary of the lead times of all constructed composite leading indicators

Composite leading indicators	Hong Kong hotel category			
	HK TOTAL	HK HIGH A	HK HIGH B	HK MEDIUM
HK CLI CC	**1**	**1**	**5**	**2**
HK CLI MS	**3**	**2**	**3**	**3**
OECD CLI CC	**1**	**2**	**5**	**2**
OECD CLI MS	**2**	**2**	**2**	**2**
OECD BSI CC	**1**	**2**	**4**	**1**
OECD BSI MS	**2**	**2**	**4**	**2**
OECD CCI CC	**2**	**1**	**1**	**2**
OECD CCI MS	**1**	**1**	**1**	**1**

HK TOTAL is the Hong Kong (total) hotel category.
HK HIGH A is the Hong Kong High Tariff A hotel category.
HK HIGH B is the Hong Kong High Tariff B hotel category.
HK MEDIUM is the Hong Kong Medium Tariff hotel category.
CLI is the constructed composite leading indicator by the selected economic variables
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
MS is the weighting method of the market share of the overnight stay tourist arrival..
CC is the weighting method of the coefficient of the cross correlation analysis.

Forecasting performance of all the constructed composite leading indicators (CC and MS)

Table 9.6 shows the QPS results of all the regression logistic and probit models estimated with different composite leading indicators. Comparison of the average QPS results of each model shows that the most accurate constructed composite leading indicator to predict turns is the constructed OECD consumer confidence index for both weighting methods. It may be because the constructed OECD consumer confidence index gathers the most adequate information for the hotel industry and thus provides the most suitable data that help predict the turning points. Moreover, the best QPS result is the constructed OECD consumer confidence index by the market share weighting method. This may be because the market share weighting method is a much more direct reflection of the recent trends and changes in the tourism sector.

Table 9.6 Summary of QPS results for all constructed composite leading indicators

Composite leading indicators	Average
HK CLI CC LG	**0.40891**
HK CLI CC PB	**0.40600**
HK CLI MS LG	**0.32414**
HK CLI MS PB	**0.32450**
OECD CLI CC LG	**0.47728**
OECD CLI CC PB	**0.47609**
OECD CLI MS LG	**0.29224**
OECD CLI MS PB	**0.29114**
OECD BSI CC LG	**0.43458**
OECD BSI CC PB	**0.43426**
OECD BSI MS LG	**0.42283**
OECD BSI MS PB	**0.42783**
OECD CCI CC LG	**0.37953**
OECD CCI CC PB	**0.38097**
OECD CCI MS LG	**0.28871**
OECD CCI MS PB	**0.28785**

Coefficient in red font is the best forecast performance indicator.
CLI is the constructed composite leading indicator by the selected economic variables
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
CC is the weighting method of coefficient of cross-correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival of Hong Kong.
LG is the regression logistic model.
PB is the regression probit model.

9.3.2.3 Most significant hotel demand determinants

A. Real exchange rate vs. nominal exchange rate

The price of a room in the destination is one of the factors affecting the decision of the tourist as to the choice of hotel. The ideal way to construct the price of a room is to compare the destination hotel price with that of the tourist-origin country adjusted by the exchange rate. However, data on the price of hotel rooms in the origin-countries are insufficient. Therefore, the real exchange rate was considered as the proxy for the growth rate of the price of the room in the destination hotel (GPD). The real exchange rate was calculated by adjusting both destination country consumer price index and origin country consumer price index by the nominal exchange rate.

CPI was chosen as proxy because it measures the price level of goods and services generally purchased by the consumers. In constructing the consumer price index, the hotel price was also included because the hotel industry is also part of the service sector. Therefore, the real exchange rate, which is actually the adjusted consumer price index of the destination and origin countries, can represent the general price level of the hotels.

Witt and Witt (1987) have commented that the nominal exchange rate on its own is not an acceptable proxy for tourist price in tourism demand studies because the nominal exchange rate was already calculated in the real exchange rate. However, in the hotel industry, the nominal exchange rate may be more important than international tourism demand. Having identified the vacation destination, the tourist has a range of choices as to the hotel accommodation in the destination. Given the allocated budget for accommodation, the tourist can choose from different types of accommodations based on the nominal exchange rate. For example, Hong Kong has three hotel categories, each with different pricing and facilities, which tourists can choose from when they travel to Hong Kong. If the origin country's currency is strong, the tourist can choose the most expensive hotel, whereas tourist may choose the least expensive hotel when the exchange rate is weak. Therefore in this study, the growth rate of the combined nominal exchange rate (GEX) is considered as one of the hotel demand determinants.

To find out which hotel demand determinants (between the GPD and GEX) is a better hotel demand determinant and avoid the problem of multicollinearity, the present study uses both hotel demand determinants separately with other hotel demand determinants in the regression models to determine the best-fit hotel demand determinants for the Hong Kong hotel industry. The empirical result is that the GEX is significant for the High Tariff A hotel in Hong Kong and GPD is not significant at all in any hotel category.

GPD is not valid in the entire hotel industry maybe because of the unique characteristics of the hotel industry. Choosing a hotel is a much more personal and subjective decision for the tourist. A lot of personal reasons go into the tourist's hotel choice, which may not be easily captured by a macroeconomic national index such as the consumer price index. Moreover, the nominal exchange rate can replace the real exchange rate as an individual hotel demand determinant in the present study. The test results confirm that nominal exchange rate is a valid hotel demand determinant in the model.

B. Impact on the probability of significant hotel demand determinants

As explained in Chapter 8, the estimated coefficient of each significant hotel demand determinant in the logistic regression model can measure the impact of the hotel demand determinant on the probability. This means that a 1% change in the significant hotel determinant will result in an increase or decrease in the probability of the expansion period's occurrence.

GY (growth rate of the real income) is the only significant hotel demand determinant for all hotel categories with the average impact probability at 0.004283. GOIL (growth rate of the travelling cost) is significant in the (Total) hotel category with the impact probability coefficient at -0.011311.GEX (growth rate of the nominal exchange rate) is a significant determinant in the High Tariff A hotels with the impact probability coefficient at 0.076209.

From the calculated impact probability coefficients, although the GY appeared in every hotel category as one of the significant hotel demand determinants, compared to the calculated coefficients of GOIL and GEX, the impacts of these two hotel demand determinants are much higher than the GY. Table 8.5 (refer to Chapter 8) lists the estimates of change in the probability of an expansion period as a result of a 1% percent change in the significant hotel demand determinants.

C. Accuracy of the probability forecasting of the hotel demand determinants

After the construction of all the different models, it is necessary to compare the accuracy of the probability occurrence of each model. Diebold and Rudebusch (1989) explained that QPS ranged from 0 to 2, with a score of 0 corresponding to perfect accuracy. The most accurate model of all the regression models in each category is the logistic regression model in High Tariff B hotel types. Table 8.6 summarizes the QPS results for the logistic and probit regression hotel demand determinants models (refer to Chapter 8). Both regression models provide good QPS results.

9.3.2.4 Comparison of forecasting performance results between models of composite leading indicators and hotel demand determinants

Finally, among all the estimated models, the most accurate forecast performance is that of the regression models estimated with the hotel demand determinants. Such empirical results may indicate that the hotel demand determinants approach could be a better and more accurate predictor of turning points for the hotel industry rather than the composite leading indicator. Further research may support this. However, the lead-time identified from the composite leading indicator approach can provide an advance sign for hoteliers to get ready for the shift in hotel demand. Therefore, both approaches have a different function and practical use for the hotel industry.

Table 9.7 Summary of the QPS results for all the regression logistic models

Composite leading indicators	Average
HK CLI CC LG	**0.40891**
HK CLI CC PB	**0.40600**
HK CLI MS LG	**0.32414**
HK CLI MS PB	**0.32450**
OECD CLI CC LG	**0.47728**
OECD CLI CC PB	**0.47609**
OECD CLI MS LG	**0.29224**
OECD CLI MS PB	**0.29114**
OECD BSI CC LG	**0.43458**
OECD BSI CC PB	**0.43426**
OECD BSI MS LG	**0.42283**
OECD BSI MS PB	**0.42783**
OECD CCI CC LG	**0.37953**
OECD CCI CC PB	**0.38097**
OECD CCI MS LG	**0.28871**
OECD CCI MS PB	**0.28785**
HD LG	**0.25629**
HD PB	**0.24707**

Coefficient in red font is the best forecast performance indicator.
CLI is the constructed composite leading indicator by the selected economic variables
OECD CLI is the composite leading indicator from OECD.
OECD BSI is the business survey index from OECD.
OECD CCI is the consumer confidence index from OECD.
HD is Hotel demand determinants.
CC is the weighting method of the coefficient of the cross- correlation analysis.
MS is the weighting method of the market share of the overnight stay tourist arrival of Hong Kong.
LG is the regression logistic model.
PB is the regression probit model.

9.3.2.5 Comparison the result between regression logistic and probit models

The difference between the binary logistic regression model and the probit regression model is the specification of the error term in the model. The distribution of the error term in the logistic model is in a “logit” distribution, whereas the error term distribution in the probit model is in a “normal” distribution.

The results of the estimation of both models are expected not to differ greatly, as there is no big difference between the cumulative of the normal and logistic distribution of both models (Kulendran and Wong, 2010). Table 9.8 shows the average performance of the QPS results for all the estimated models of the regression logistic and probit models, proving that both models have similar forecasting performance results in the present study.

Kulendran and Wong (2010) have commented that for simplicity and easy interpretation, the logistic regression model may be a better choice than the probit regression model. Another advantage in using regression logistic model is that the cumulative logistic distribution in the model can calculate the impact on probability of expansion occurring due to a 1% percent change in the explanatory variables. In the present study, the estimated coefficient of each significant hotel demand determinant in the logistic regression model can measure the impact of those hotel demand determinants on the probability.

Table 9.8 Summary of the QPS results of the regression logistic and probit models

Composite leading indicators	Average
LG	0.364946
PB	0.363968

LG is the regression logistic model.
PB is the regression probit model.

9.4 Limitations of the study

Although the Bry and Boschan approach is widely used in tourism forecast studies, it has yet no benchmarking or approved dating approach from any tourist organization, for example, the UNWTO, for the identification of a turning point. Moreover, no official definition has been provided for a “turning point” in the tourism sector.

This is the first study to attempt the construction of composite leading indicators for the hotel industry. This is also the first attempt to develop unique demand determinants for the hotel industry. Thus, no previous research could provide guidance for the present study. All the referenced literature is based in tourism arrival forecasting research. To be sure, it will take a much longer process to identify the significant economic variables and develop hotel industry-specific demand determinants.

The lack of sufficient data has been another limitation of the present study. For example, no data are available for Taiwan in the OECD databank. Furthermore, insufficient data on the hotel price of the substitute destinations comprise another shortfall in the present study's research on developing hotel demand determinants.

9.5 Suggestion for future study

The present study is just the start for using econometric models to identify turning points in the hotel industry. As such, future research could build on its present findings. For example, using the occupancy rate of an operating hotel to construct the composite leading indicators for that hotel could provide a practical guide for the hotel industry. Also, study each country turning points structure may find out what is the pattern of those countries travelling to Hong Kong.

The present study relied on the Hong Kong hotel occupancy rate to construct the composite leading indicator for the hotel industry. Future research could use different countries' hotel occupancy data to construct the composite leading indicator model to compare and contrast, and more importantly, to verify the forecast performance results of this study.

In the present study, only economic variables have been selected to construct the composite leading indicator for the hotel industry. Certainly, other variables may be used for the construction, for example, the weather index. Kulendran and Dwyer (2010) used the factors of temperature, rainfall, storm, and wind speed as variables to construct the composite leading indicator in their study on Australian inbound holiday tourism. Furthermore, the weather index could also be developed as a hotel demand determinant. Further studies could include different kinds of variables to determine the best-fit model for predicting turning points in the hotel industry.

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