A META-ANALYSIS OF

INTERNATIONAL TOURISM DEMAND ELASTICITIES

AND FORECASTING ACCURACY

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A Meta-Analysis of International Tourism Demand Elasticities and Forecasting Accuracy

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CERTIFICATE OF ORIGINALITY

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Bo PENG

ABSTRACT

Accurate analysis of tourism demand and forecasting is crucially important if tourism businesses are to develop effective marketing strategies and governments to formulate effective national/regional tourism policies. A number of methodologies, including qualitative, quantitative, and combined approaches, have been used to achieve this. Based on temporal structure and complexity, the quantitative methods can be further divided into the basic time series models, advanced time series models, static econometric models, dynamic econometric models and artificial intelligence models. However, no single method has been proved to outperform the others in all situations. Differences in data characteristics and the features of each study are possible reasons for this variation in performance.

This study uses meta-analysis to examine the relationships between each of international tourism demand elasticities and the accuracy of different forecasting models, and the data characteristics and study features which may affect these outcomes. By reviewing 262 studies published during the period 1961-2011, the meta-regression analysis shows that origin, destination, time period, modelling method, data frequency, variables and their measures, and sample size all significantly influence the estimates of the demand elasticities produced by a model, and its forecasting accuracy. The interaction effects between variables are also discussed and examined.

This study is the first attempt to pair forecasting models with the data characteristics and study features. The results provide suggestions for the choice of appropriate forecasting methods in different situations. Moreover, the demand elasticities at both product and destination levels are generalised by statistically integrating previous empirical estimates. This will be useful in developing effective marketing strategies across different tourism markets.

Keywords: Tourism demand analysis, tourism forecasting model, data characteristics, study features, and meta-analysis.

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Chapter 1 - Introduction

1.1 Research Background

The previous five decades have seen a rapid increase in worldwide tourism demand. As one of the largest and fastest-growing industries in the world, international tourism has shown virtually uninterrupted growth in spite of occasional shocks. International tourist arrivals expanded from 1990 to 2011 at an annual rate of 7.7%, from 435 million to 983 million. Globally, the income generated by tourist arrivals grew at an even stronger rate of 13.3% per year, reaching around US$1,030 billion in 2011. Although affected by the worldwide financial crisis, resulting in a decline of 5.7% in international tourist receipts in 2009, the industry soon recovered from the recession with international tourist arrivals increasing by 6.4% in 2010 and a further 4.6% in 2011, according to the United Nations World Tourism Organisation ([UNWTO], 2010; 2012). The UNWTO (2012) predicts that international tourist arrivals will reach 1.36 billion by 2020. Figures 1.1 and 1.2 summarise annual international tourist arrivals and receipts from 1995 to 2011.

International tourism is the fourth-ranked export category, after fuels, chemicals, and automotive products, accounting for 30% of the world's exports of commercial services and 6% of goods and services. The contribution of tourism to GDP in the advanced and diversified economies ranges from 2% to over 10%. Over time, an increasing number of destinations have been developed, turning the tourism industry into a key source of employment and export revenue generation, especially in the emerging economies.

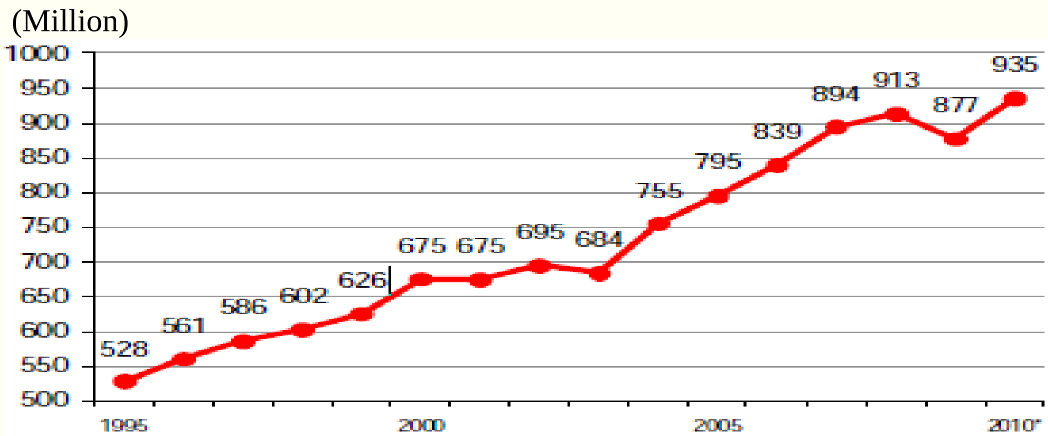

Figure1.1 International Tourist Arrivals (Source: UNWTO, 2012)

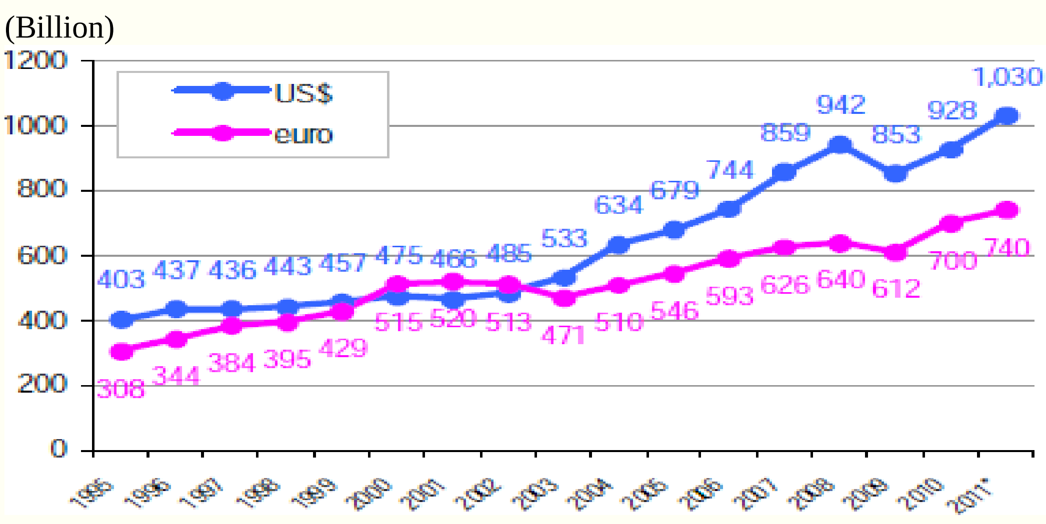

Figure1.2 International Tourist Receipts (Source: UNWTO, 2012)

Since international tourism has become increasingly important to worldwide economic development, both the public and private sectors have channelled a significant amount of resources into the industry. For tourism operators, a good understanding of the determinants of demand is essential for their product design and marketing activities; for governments, accurate tourism demand forecasting is fundamental to policy development. As both governments and businesses need high-quality tourism demand analysis and accurate forecasting to develop efficient public policy and make good business decisions, considerable efforts have been made to analyse the field and in particular to improve the accuracy of forecasting.

Numerous articles on tourism demand analysis have been published over the past five decades, especially since 1995, focusing mainly on forecasting accuracy assessment (Wong, Song, & Chon, 2006), model comparison (Chen, Bloomfield, & Cubbage, 2008), and the demand elasticities of various determinants (Crouch, 1992b; Gunadhi & Boey, 1986).

Before the 1990s, traditional regression approaches dominated the tourism forecasting and modelling literature. Since the mid-1990s, more researchers have started to use modern econometric techniques such as cointegration (CI), error correction models (ECM), vector autoregression (VAR), and time-varying parameter (TVP) models, to model and forecast tourism demand (Wong, Song, Witt, & Wu, 2007). However, according to the large number of studies published so far, no single forecasting method performs better than all the others across all possible situations. Each method has its own advantages in dealing with a particular problem, but none has been proved to be superior in every context.

A number of factors have been analysed as the determinants of tourism demand elasticities, including income, tourism product prices in the focal and competing destinations, travel costs, marketing expenditure, exchange rate, level of business activity and international trade, travel distance, migration, population, seasonal factors, and some one-off events. Income and price have generally been viewed as the most important of these. However, the elasticity of each determinant varies across studies for different measurements, methods, origins, and destinations, making the analysis more complex and difficult.

1.2 Problem Statement

1. Conflicting conclusions still exist in terms of which model generates the most accurate forecasts.

Accuracy, time, and cost savings are the measures generally used to evaluate the performance of a forecasting model, the first of which is the most frequently discussed by researchers. Archer (1987) states that the need to forecast accurately is especially acute because of the perishable nature of the tourism product. Unfilled airline seats and unoccupied hotel rooms cannot be stockpiled. Similar considerations apply to unfilled coach seats, unused hire cars, and so on (Witt & Witt, 1995; Song & Witt, 2000).

Considerable efforts have been made to improve the accuracy of tourism demand forecasting techniques during the past 50 years. Qualitative forecasting methods that have been used include mainly Delphi and scenario writing, while the use of quantitative techniques, especially econometric models, has recently experienced a fast growth. Other quantitative methods, such as gravity models, artificial neural networks (ANN), and time series models, have also played important roles in tourism demand forecasting. According to Martin and Witt (1989a), several simple time series models, including the random walk (no change) model, perform better than more sophisticated traditional econometric models. After incorporating up-to-date developments in econometric methodologies in recent years, the reputation of econometric forecasting models for improved accuracy has grown (Song & Li, 2008). However, conflicting conclusions still exists in terms of identifying the methods that will generate the most accurate forecasts. Kulendran and Witt (2001) suggest that simple univariate time series models outperform econometric models, while Song, Romilly, and Liu (2000) and Song, Witt, and Jensen (2003b) find that the performance of econometric models is superior to that of simple time series models. Some researchers have attempted to improve forecasting accuracy by combining different models. According to Wong et al. (2007)

and Shen, Li, and Song (2008), such combination forecasts can avoid the risk of complete failure, but still cannot always be more accurate than each of the components.

2. It is not possible to build a single model that is appropriate for all origin-destination pairs.

In addition to research on accuracy improvement, an emerging area of work is the synthesis of tourism demand forecasting techniques. In their literature review of empirical research in tourism demand forecasting, Witt and Witt (1995) find that it is not possible to build a single econometric model that is appropriate for all origin-destination pairs. They also show that the performance of tourism forecasting models varies according to the time interval of the data, the destination-origin pair, and the forecasting horizon. For example, the TVP model performs consistently well for one-period-ahead forecasting, while for both two- and three-period-ahead forecasting horizons, the VAR model is more accurate (Witt, Song, & Louvieris, 2003). However, until now, little effort has been made to select optimal forecasting models according to the data characteristics and study features comprehensively.

3. The magnitude of demand elasticities varies considerably across studies.

A wide array of tourism demand determinants has been examined in previous empirical studies, with tourist income and price of product playing central roles as determinants of the demand for international tourism (Crouch, 1996). Several attempts have been made to integrate these empirical studies (Crouch, 1992a & b, 1996; Lim, 1999) confirming that international tourism demand is positively related to income and negatively related to tourism product prices, consistent with the traditional demand theory. The magnitude of the elasticities, however, varies considerably across studies. Crouch (1996) attributes the variations in the estimated income and prices elasticities of tourism demand to the omission of variables, sampling errors, and different study features. However, these are only partial explanations. Lim (1999) concludes that different methodologies and data characteristics (such as measurement, time period, origin-destination pairs, and sample size) could be other reasons for demand elasticity variations.

The effects of noneconomic factors such as population, cultural background, and some one-off events have also caught the attention of researchers. O'Hagan and Harrison (1984a) show that noneconomic factors have a significant effect on US tourists travelling to Europe. Turner, Reisinger, and Witt (1998) use both economic and social variables in structural equation modelling (SEM) to analyse quarterly tourist flows from the UK to seven major destinations (France, Germany, Greece, Italy, Netherlands, Portugal, and Spain) over the period 1978-1995.

As the foundation of tourism policies and marketing strategies, the empirical results of tourism demand modelling require further explanation and comparison across studies (Johnson & Ashworth, 1990).

1.3 Research Objectives

This study attempts to identify the optimal tourism demand forecasting models according to the data characteristics and study features, and to generalise the determinants of tourism demand and demand elasticities across different studies. It therefore employs meta-analysis to synthesise the findings from previous studies of international tourism demand and explore the demand elasticities and forecasting accuracy of the models used. Li, Song, and Witt (2005) state that meta-analysis is a useful tool with which to review the literature. It allows statistical generalisations to be made with respect to the combined evidence from different studies.

The main objectives of this study are, therefore:

1. To test whether data characteristics and study features, including time interval, measurement of variables, purpose of trip, forecasting horizon, origin-destination pairs, number of explanatory variables, and sample size affect the accuracy of tourism demand forecasting models and demand elasticity estimates. Through a comprehensive review and integration of 262 articles and 6034 estimates of tourism demand modelling and forecasting 1961-2011, this study sets out to identify whether there is any association between forecasting accuracy and demand elasticities, data characteristics, and study features.

2. To pair the forecasting models with different data characteristics and study features to find out whether there is an optimal forecasting model that will generate the most accurate forecasts for each data category. This would be useful for practitioners and policymakers in choosing different forecasting models according to the features of the data and study purpose.
3. To generalise the demand elasticities of different variables across studies. In addition to calculating the average demand elasticity for each variable, this study also focuses on the diversity observed across studies. An attempt will be made to compare the magnitudes of the influencing factors of tourism demand across studies and to find out whether the estimates of demand elasticities are affected by the structure of the demand model, the data characteristics, and the study features.
4. To summarise the development of tourism demand forecasting techniques in order to demonstrate the achievements in this field in recent decades.

1.4 Contributions of the Study

Tourism demand analysis and forecasting has attracted a lot of attention from scholars and many studies have been published in this area over the past few decades. Meta-analysis is used in this study to examine the relationships between data characteristics, study features, and the accuracy of forecasting models and demand elasticities. Through integrating previous empirical results in the field of international tourism demand modelling and forecasting, the superior models will be identified according to the characteristics of the study and the data used.

This study is the first attempt to pair tourism forecasting models with specific datasets. Through generalizing the demand elasticities at disaggregated level, it will help to enhance our understanding of tourist behaviour. In addition, this study will summarise the progress of tourism demand modelling and forecasting research, and identify future research directions for this important topic.

Superior forecasting models can be identified based on the characteristics of the study and the data used in the model estimation, to assist practitioners in making effective policy and business decisions. The identification of demand elasticities at the product and destination level will help tourism practitioners understand the diversification of tourists' tastes, and develop more effective marketing strategies as a result.

1.5 Structure of Thesis

The thesis consists of seven chapters.

Chapter one introduces the background of the research, summarises the existing problems, and sets out the research objectives. It also presents the potential contributions of the study.

Chapter two provides a detailed review of the literature on tourism demand modelling and forecasting, with an emphasis on the advantages and disadvantages of each model and the characteristics of the data used in the past empirical studies. Based on this review, the historical and current statuses of tourism demand modelling and forecasting are revealed, the research gaps identified, and the methodology used in this study presented.

Chapter three presents the hypotheses to be tested. The possible influencing factors, including source market, destination, time period, modelling method, data frequency, variables used, and measures of variables, are discussed together with the justification for their inclusion in the study.

Chapter four describes the methodology of meta-analysis and gives a detailed account of why this approach was selected as the main analytical tool in this study. The main steps involved in this research method are problem formulation, literature search, information selection and gathering from existing studies, research outcome integration, evidence interpretation, and results presentation. Each of these is discussed and the basic searching process and selection criteria for previous research presented. The forecasting models used in the selected studies are identified and compared, and the calculation of the effect sizes of forecasting accuracy and demand elasticities are discussed.

Chapter five focuses on presenting descriptive analyses of different tourism demand models and the features of the data used. A detailed summary of the studies of international tourism demand modelling and forecasting included in the meta-analysis is also provided.

Chapter six summarises the variables that have been proved to have an influence on the estimates of international tourism demand elasticities and forecasting accuracy in the past studies. The results of the meta-regression are then presented to show the relationship between the demand elasticity estimates, forecasting accuracy, data characteristics, and study features. The hypothesis test results are also summarised.

Chapter seven presents the conclusions of the thesis together with the limitations of the study and future research directions. The average international tourism demand elasticities are generalised, and superior forecasting models identified, based on the characteristics of the datasets after synthesizing the previous empirical studies.

1.6 Chapter Summary

The rapid development of international tourism has accelerated work in the field of tourism demand modelling and forecasting. As the premise of tourism policies and marketing activities, tourism demand analysis especially the tourism demand forecasting plays a central role in tourism studies. Methodologies which improve the performance of demand forecasting can benefit destinations in developing their tourism industries.

Although different methodologies have been applied to tourism demand analysis and forecasting, no single model has been proved to be superior in all situations. Meta-analysis is used in this study to synthesise previous empirical studies and explore the relationships between forecasting accuracy of tourism demand models, tourism demand elasticities, data characteristics, and study features. This study is the first attempt to select optimal models according to data features, and its findings can help practitioners to understand tourists' behaviour in depth and hence to make effective business decisions.

Chapter 2 - Literature Review

2.1 Introduction

Tourism demand analysis and tourism forecasting techniques have experienced rapid development over the last five decades, in tandem with the growth of global tourism industries. Evaluating the effects of various determinants of tourism demand and forecasting future demand trends are two of the main foci of tourism demand studies (Li et al., 2005; Li, 2009). Over the past 50 years, many qualitative and quantitative models, such as the Delphi Method, time series models, and econometric models, have been applied in tourism modelling and forecasting research. Besides tourists' income and tourism product price, a number of other factors such as marketing expenditure, seasonal factors, and some one-off events have also been discussed and tested by researchers.

In this chapter, the main forecasting models employed in previous work are reviewed and their strengths and weaknesses analysed. The determinants of tourism demand they use are summarised and the characteristics of the data used in model estimation and forecasting discussed. The aims of this literature review are to identify the research gap and provide the rationale for this study.

2.2 Significance of Tourism Demand Analysis

Tourism activity is a complex issue which has been studied by researchers from a variety of disciplines. Hunziker and Krapf (1942, p .21) define tourism as "the sum of the phenomena and relationships arising from the travel and stay of nonresidents, insofar as they do not lead to permanent residence and are not connected with any earning activity." The Tourism Society of England (1976) states that "tourism is the temporary, short-term movement of people to destinations outside the places where they normally live and work and their activities during the stay at each destination. It includes movements for all purposes." (Beaver, 2002, p. 313). The International Association of Scientific Experts in Tourism (1981) defines tourism in terms of particular activities selected by choice and undertaken outside the home.

Nowadays, the most widely accepted definition is that given by the UNWTO, which defines tourists as people who "travel to and stay in places outside their usual environment for more than twenty-four 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" (UNWTO, 1995, p. 14).

An ever-increasing number of destinations are now actively engaged in tourism development, turning modern tourism into a key driver for socio-economic progress (UNWTO, 2010). Globally, international tourism, as an important source of foreign exchange earnings, has become one of the major categories of services being traded. Besides generating such revenues and alleviating the balance of payments problems encountered in many countries, as a labour-intensive industry tourism also creates a large amount of employment and absorbs an increasing percentage of the workforce released from agriculture and the manufacturing industries (Lim, 1997).

The rapid development of the international tourism industry is usually attributed mainly to the rapid increase of income worldwide. In return, it has also brought about a lot of benefits in terms of savings, investments, and economic growth. The attractiveness of tourism has led many developing countries to take part in the competition (Jud & Krause, 1976). Driven by the tourism industry, other, related economic sectors, such as transportation, accommodation, food services, retail, and entertainments have also expanded rapidly.

With the growing importance of international tourism to national economies, tourism demand analysis and forecasting has attracted much attention from tourism scholars. Tourism demand for a particular destination is defined by Song, Witt, and Li (2009, p. 2), as "the quantity of the tourism product (that is, a combination of tourism goods and services) that consumers are willing to purchase during a specified period under a given set of conditions.” One of the main purposes of tourism demand analysis is to improve the forecasting accuracy of its models, while the other is to analyse the determinants of tourism demand and their elasticities.

Some tourism destinations do appear to succeed without good forecasting, but the opportunity costs may be very high; problems may result from over- or underestimation of demand, or the poor timing of tourism attractions and facility development (Calantone, Benedetto, & Bojanic, 1987). Not only has tourism demand forecasting been an important task for policymakers and planners at national and local levels in the public sector, but it also provides important information for business and marketing decision making in the private sector. Short-term forecasts are required for scheduling and staffing; medium-term forecasts for planning tour operator brochures; and long-term forecasts for investment in aircraft, hotels, and infrastructure (Cho, 2003; Witt & Witt, 1995).

Tourism is undertaken for diverse motives, each of which is affected by different factors to varying degrees (Guanadhi & Boey, 1986). Tourism modelling can help business decision makers understand the determinants of demand for their products, and the analysis of demand elasticities can help them formulate effective business strategies (Song & Turner, 2006). Harrop (1973) suggests that the high growth of the tourism industry has mainly resulted from the coupling of high income and high price elasticity of demand. However, Jud (1974) attributes it to a wide variety of factors common to modern industrial societies, such as improvement in transportation systems and infrastructure, new information technologies and logistics, new lifestyle choices, and more leisure time (Matias, Neto & Nijkamp, 2007).

A good understanding of the determinants of tourism demand is fundamental in marketing and promotion. For example, understanding the influence of substitute prices allows companies to make prompt and accurate responses to competitors' price changes. At the country level, appropriate tourism demand modelling can help a destination counterbalance the shocks from the economic crisis. Nations compete aggressively to attract a share of the tourism market, so there has been significant research interest in developing a comprehensive and accurate analysis of demand.

2.3 Measures of Tourism Demand

As mentioned above, tourism demand refers to the quantity of the tourism product that consumers are willing to purchase during a specified period under a given set of conditions. However, it has been measured in a variety of ways in previous work, with some studies even using more than one dependent variable to represent it. Through reviewing studies published between 1961 and 2004, Crouch (1994a), Lim (1997) and Li et al. (2005) summarise four variables that are usually used to measure tourism demand, which include tourist arrivals (departures), tourist expenditure (receipts), length of stay, and nights spent at tourist accommodation (Mervar & Payne, 2007). Some other measures, such as conference tourist attendance, are also used (Witt, Dartus, & Sykes, 1992). Kim (1988) categorises measurements according to four criteria: (i) a doer criterion, such as tourist arrivals and visit rate; (ii) a pecuniary criterion, such as tourist expenditure and share of expenditure in income (Uysal & Crompton, 1984); (iii) a time-consumed criterion, like nights or days of stay (Song et al., 2003c); and (iv) a distance-travelled criterion, such as tourist journey in kilometres (Song, Li, Witt, & Athanasopoulos, 2010).

Of those measures, tourist arrivals and expenditure and their derivatives (such as arrivals and receipts divided by population of the origin country/region) are most frequently used in the demand modelling and forecasting literature. Data on tourist arrivals are often obtained from official frontier counts, which include the number of visitors, tourist flows, proportion of tourists going to a particular destination, and proportion of tourists with different objectives. Tourist expenditure data are commonly collected through surveys (Witt & Witt, 1995). Such data can also comprise real monthly sales tax receipts, share of total expenditure on airfares, and share of tourist expenditure out of the total consumption expenditure (Lim, 1997).

Although both arrivals and receipts are popular measures in tourism demand analysis, the empirical results obtained by Song et al. (2010) suggest that patterns of arrivals and expenditure are driven by different factors. Tourist arrivals are more likely to be affected by the original country's income and the habit persistence of tourists, while expenditure is more likely to be driven by the relative price of the product. The study also implies that econometric models for tourism demand forecasting are better estimated in aggregate than *per capita* form.

2.4 Determinants and Elasticities of Tourism Demand

Analyzing and measuring the determinants of tourism demand are central topics in tourism demand analysis. The variables that have been generally accepted as the main determinants of international tourism are tourists' income, relative price of tourism products, substitute prices of tourism goods and services, transportation costs, population of origin market, exchange rates, marketing costs, and one-off events. The elasticity of each explanatory variable measures the sensitivities of the quantity of tourism demand in response to a change in this variable. However, significant distinctions can be drawn between the influences of different determinants for different visit purposes. Turner and Witt (2001a) show that international trade (in terms of volume) is the major determinant of business tourism demand, the volume of retail sales is the major determinant of holiday tourism demand, and the visit of friends and relatives (VFR) is mainly determined by gross domestic product (GDP).

Income is considered as a dominant explanatory variable, and tourist income is the most frequently-discussed determinant of tourism demand analysis. Most researchers employ either nominal or real GDP or gross national product (GNP), or their *per capita* form as a measure of tourists' income (see for example Greenidge, 2001; Turner & Witt, 2001a). Edwards (1979) uses real disposable income less expenditure on food, housing, fuel and light, beverages, and tobacco as a proxy for tourists' income. Other less commonly used measures include real consumption *per capita* (Dritsakis, 2004), superfluous income (real disposable income less expenditure on food, housing, fuel, and light; Edwards, 1979), foreign travel budget (Smeral & Witt, 1996), industrial production index (Gonzalez & Moral, 1995), and real household disposable income (Lim, 1997). Most of the empirical studies confirm that income has a positive effect on tourism demand and also conclude that international tourism is a luxury product. According to a meta-analysis of 1501 estimates by Crouch (1996), the mean income elasticity is +1.86, with a standard deviation of +1.78. However, Crouch (1992b) also suggests that the measurement of total income may result in a different estimated income elasticity than for *per capita* income. When holiday visits or VFR are concerned, the appropriate form of the income variable is private consumption or personal disposable income, while general income is more appropriate for business visits. Moreover, income elasticity may differ considerably across different origin-destination pairs. For example, the income elasticity of the demand for Aruba tourism varies from 1.43 for US tourists to 2.52 for Dutch visitors (Croes & Vanegas, 2005). Naude and Saayman (2005) show that income level of origin countries has little effect on the demand for tourism in Africa.

Relative tourism price is another important determinant of demand, and has been proved to have a negative effect on it. The Consumer Price Index (CPI) of the destination divided by the CPI of the origin country is the most frequently-used proxy. However, the CPI may not reflect the prices of goods and services which tourists actually purchase, because the reaction of consumers and tourists to CPI changes may be different. Therefore, some studies opt to use specific tourism price variables, such as service price indexes (Cheung & Law, 2001), hotel price indexes (Narayan, 2004) or the weighted prices of food, accommodation, transport, entertainment, and other services (Dwyer, Forsyth, & Rao, 2000). Exchange rates and inflation rates are sometimes used to adjust relative prices or may be included in the demand model as separate variables (Webber, 2001; Croes & Vanegas, 2005; Mangion, Durbarry, & Sinclair, 2005), especially in countries where the exchange rate is market-oriented. Transportation costs account for a large proportion of tourism expenditure, and are often measured by the cost of air travel (Turner & Witt, 2001a), distance, and private gasoline costs (Martin & Witt, 1988). However, studies using travel exports/imports as the dependent variable do not entirely support the idea that international tourism demand is inversely related to transport costs (Lim, 1999).

According to Crouch (1996), the price elasticity of tourism demand has a mean value of -0.63, with a standard deviation of 2.32. He attributes this variation principally to sampling errors. Furthermore, price elasticities vary considerably among different origin-destination country pairs (Mangion et al., 2005) and trip purposes (Sakai, 1988;

Lehto, Morrison, & O'Leary, 2001). Data frequency, the number of explanatory variables included in the models, and their definitions also influence elasticity estimates (Crouch, 1992a, 1996).

Substitute Prices elasticities measure the response to tourism demand in a destination to changes of price in its substitute destinations. Two possible substitutes are relevant. The substitute effect is usually considered in terms of domestic tourism, the price of which is usually measured by domestic CPI (or a derivative of it). Other studies examine the substitute effect by calculating a weighted tourism price for a set of substitute destinations (Martin & Witt, 1988; Witt & Witt, 1995; Song & Wong, 2003). The weights are decided according to the shares of international tourist arrivals from origin countries/regions to the substitute destinations. The latter are often selected based on geographical or cultural similarities with the origin and destination.

Population of the origin country is another factor that may influence demand. The level of outbound tourism from a given country is expected to be related to its population (Witt & Martin, 1987a; Turner & Witt, 2001a). Trends in the immigration patterns also affect international tourism demand (Seetaram & Dwyer, 2009). If population change is caused by immigration from a source market, this may well result in a large number of tourist flows to a particular destination in subsequent years for the purposes of VFR (Feng & Page, 2000). However, since the population variable tends to cause the multicollinearity problem in the demand model, since it is highly correlated to the income level of the source market, it has not been included as an explanatory variable in most studies. Instead, it has been used to calculate the *per capita* income variable for inclusion in the demand model (Witt & Witt, 1995).

Marketing costs may have a positive impact on the demand for tourism. Both government-based tourism organisations and private tourism businesses tend to engage in various forms of marketing activities, such as media advertising and public relations, to promote their products and services (Witt & Witt, 1995). Crouch, Schultz, and Valerio (1992) confirm a positive relationship between marketing expenditure and the demand for tourism in Australia. Based on HK Tourism Board marketing expenditure data, Zhang, Kulendran, and Song (2010) suggest that marketing elasticity and cost-effectiveness ratio varies from country to country and so it is necessary to develop different marketing strategies for different source markets. Moreover, according to Song and Witt (2000), promotional activities for a specific destination are more likely to have a positive influence on the demand for it than promotion of particular products. However, except for these studies, little empirical work on international tourism demand includes marketing expenditure as an explanatory variable due to data constraints. Another difficulty with its inclusion is that the impact of promotional activities on tourism demand is distributed over time, which is hard to measure (Witt & Martin, 1987b).

*One-off event*s may have a brief or long-term effect on demand. Dummy variables are normally used to assess their impact. For example, the financial and economic crisis in 1997 in Asia, and worldwide in 2008, has had a significant adverse effect on international tourism demand (Song & Lin, 2010; Smeral, 2010). Another example is related to the 9/11 terrorist attack on New York in 2001, which not only had a negative effect on tourism demand in North America, but also many other destinations (Sloboda, 2003; Wong et al., 2007; Yaya, 2009). Epidemic outbreak is another factor that may prevent tourists from travelling to affected countries/regions. For example, the severe acute respiratory syndrome (SARS) outbreak, Avian Flu in Asia (Kuo, Chen, Tseng, Ju, & Huang, 2008) and the Swine Flu virus (H1N1) in the US and UK (Page, Song, & Wu, 2011) significantly reduced tourist arrivals in these countries/regions. Besides, international tourism may suffer from tourists' perceptions of the uncertainties caused by natural disasters, military or economic conflicts, and political unrests, such as earthquakes (Mazzocchi & Montini, 2001; Huang & Min, 2002), the oil crises of 1974 and 1979 (Song et al. 2003c) and the Gulf War in 2002 (Garin-Munoz, 2004). Mega events such as the Olympics and World Expo also tend to have a positive impact on tourism demand (Teigland, 1999).

Other factors have also been included in demand models. Changes in tourists' tastes, which could be captured by time trends, seasonal variations (Lim, 2004; Koc & Altinay, 2007), climate change (Lise & Tol, 2002; Hamilton, Maddison, & Tol, 2005a), political instability (Dhariwal, 2005; Naude & Saayman, 2005), foreign direct investment, which relates mainly to business travel (Tang, Selvanathan, & Selvanathan, 2007), educational level of tourists and their age distribution (Alegre & Pou, 2004), rates of unemployment (Wander & Erden, 1979; Cho, 2001), income distribution (Morley, 1998), and lagged explanatory and dependent variables have all been found to have an impact.

2.5 Forecasting Methods

Tourism demand forecasting methods can be divided into categories based on different criteria. Van Doorn (1984) groups them into four categories; exploratory, speculative, normative, and integrative forecasting. Exploratory forecasting tries to predict tourism demand through extrapolation of past trends and the relationships between variables, including regression techniques, time series analysis, and gravity approaches. Speculative forecasting is based on experts' skill and judgment. Normative forecasting is goal-oriented, with an explicit description of the desired future states and the routes that will lead to them (Van Doorn, 1982). Integrating forecasting is a comprehensive method which combines several of the others. A much simpler classification is to divide the forecasting models into two broad categories – qualitative and quantitative. The latter mainly refers to the Delphi approach and scenario analysis, while the former can be categorised into time series, econometric, and spatial models (Witt & Witt, 1995). Frechtling (1996), however, divides quantitative forecasting methods into two categories, extrapolative and causal.

2.5.1 Qualitative Methods

Qualitative forecasting is also known as judgmental forecasting. Relative information is collected and organised by experts using their judgment and experience instead of mathematical rules. The advantage of these approaches is that they do not rely on historical data (Frechtling, 1996). The Delphi method is the most frequently used while the scenario writing technique has also demonstrated potential usefulness. As well as these, other qualitative forecasting methods, such as the consumer intentions survey (Frechtling, 2001), are also well developed.

The Delphi method. This involves producing a series of questionnaires that are distributed to experts in the field. The expert's judgment is evaluated at each step. Feedback is given to the experts to help them reconsider their answers before the next round of questionnaires, until a consensus is reached (Calantone et al., 1987). The Delphi method has been proved to be more accurate than both the jury of executive opinion method and traditional group meetings (Frechtling, 1996). Compared to other qualitative forecasting methods, it prevents specious persuasion and the herd effect from biasing the consensus result. According to Kaynak, Bloom, and Leibold (1983), the Delphi technique is suitable for dealing with uncertainties when our knowledge about the forecasting objects is imperfect and data are sparse or lacking. Tideswell, Mules, and Faulkner (2001) suggest using it to moderate the forecasts obtained from the statistical methods when the sample is small and with significant variability. However, the main disadvantage of the Delphi technique is that it may be difficult to identify genuine experts. It is more useful for aggregate forecasting than for predicting demand for specific territories, customer groups, or products.

Scenario writing. This is an important but relatively underused qualitative forecasting method. It attempts to state how a future circumstance would emerge and includes at least three parts: a description of the current situation, at least one potential state in the future, and the path along which the current situation could eventually develop to reach that future state (Calantone et al., 1987). Schwaninger's discussion (1989) of probable trends in tourism 2001-2010 in the western industrialised countries is an example of scenario writing. It considers a comprehensive list of economic, socio-cultural, ecological, technological, and political factors that may affect the future of tourism in the region. Prideaux, Laws, and Faulkner (2003) state that the incorporation of scenarios could compensate for the failure of quantitative forecasting techniques to deal with uncertainty. Moreover, scenario writing can also be used to test the causal relationships and sensitivities between variables (Hamilton, Maddison, & Tol, 2005b).

2.5.2 Quantitative Methods

The quantitative forecasting methods organise information about previous events using mathematical rules (Frechtling, 1996). There are three main subcategories: time series models, econometric approaches, and AI models. According to the complexities of the models and estimation techniques, time series forecasting methods can be further subdivided into basic and advanced categories. Based on their temporal structure, econometric models can be grouped into two categories, namely static and dynamic.

***Basic time series methods*.** Time series forecasting methods (see Tables 2.1 and 2.2) are also called extrapolative methods, because they extrapolate from previous data in the series to predict future trends. These models attempt to identify the patterns in the time series that cause shifts in the forecast variable and to see how they interact (Calantone et al., 1987). The advantage of such models is that they are relatively simple to estimate, requiring no more than one data series. They may be separated into basic and advanced categories. The former includes the Naive, Simple Moving Average (SMA), and Single Exponential Smoothing (SES) models. The advanced approaches include the double exponential smoothing (DES), exponential smoothing adjusted by trend, autoregressive moving average (ARMA), and basic structural time series (BSM) models.

The Naive 1 (or no change) model is the simplest. It assumes that the forecasting value for the period *t* is equal to the actual value in the last period (*t-1*). It has often been shown to generate more accurate one-year-ahead forecasts than other more sophisticated models (Martin & Witt, 1989a; Witt, Witt, & Wilson, 1994; Witt & Witt, 1995).

However, the performance of the Naive 1 model declines when it has to deal with sudden structural change and longer-term forecasting (Witt et al., 1994; Chan, Hui, & Yuen, 1999).

The Naive 2 (or constant change) model is another widely used but simple model employed when there is a continuous trend present in the data. The forecast value for period *t* is obtained by multiplying the demand over period *t*-1 by the growth rate between the period *t*-2 and the current period (*t*- 1). Chan et al. (1999) use the Gulf War as an example of sudden shock and show that the Naive 2 model performs better than the autoregressive integrated moving average (ARIMA), exponential smoothing, and quadratic trend curve models when dealing with unstable data.

Since the two Naive models often yield better results than econometric ones (Martin & Witt, 1989a; Witt & Witt, 1995), many researchers use them as benchmarks for forecasting evaluations (Turner & Witt, 2001b; Song et al., 2003c; Veloce, 2004).

The SMA model allows the past values of a variable to determine the forecast values with equal weights assigned to the former. The number of lagged observations included in the model determines its responsiveness and it is clear that the more lagged values that are included, the smoother the forecasts become. If a time series shows wide variations around a trend, including more lagged observations in the SMA model will help the model to pick up the trend. However, its main limitation is that it gives equal weight to all the lagged observations (Hu, Chen, & McChain, 2004), which may not be realistic, as more recent lagged values tend to have a much bigger impact on the current values of a time series. Therefore, the SMA method normally generates more accurate forecasts where the time series is less volatile (Frechtling, 1996; Makridakis, Wheelwright, & Hyndman, 1998). Systematic errors may occur when the SMA model deals with a time series that has a linear trend. To overcome this problem, researchers can use the double moving average method to further smooth the series (Hu et al., 2004; Lim & McAleer, 2008).

The SES model is used to forecast a time series when there is no trend or seasonal pattern. In a SES model, the forecast for period *t* is equal to the forecast for period (*t*-1) plus a smoothing constant multiplied by the forecasting error incurred in period (*t*-1). The smoothing constant must be between zero and one, which is set by the forecaster (Witt & Witt, 1992); the smaller its value, the more weight it gives to the previous forecast value (Moore, 1989). According to Chen et al., (2008), SES is more suitable for a time series with seasonality removed. Witt, Newbould, and Watkins (1992) show that the SES model generates forecasts with relative lower error magnitudes than the no change model for domestic tourism demand, which is less volatile than international tourism demand.

Table 2.1
Basic Time Series Models

Method	Equation
Naive 1	$F_t = A_{t-1}$
Naive 2	$F_t = A_{t-1} * \left[1 + \left(A_{t-1} - A_{t-2}\right) / A_{t-2}\right]$
SMA	$F_t = \left(A_{t-1} + A_{t-2} + A_{t-3} + \ldots A_{t-n}\right) / \mathrm{n}$
SES	$F_t = \alpha \mathrm{A}_{t-1} + \left(1 - \alpha\right) \mathrm{F}_{t-1}$

Note: F_t = forecast at time t; A_{t-1} = actual value at time t-1; n= number of lags in the moving average process; α = smoothing constant (0< α <1);

***Advanced time series methods*.** Brown's DES model was developed to deal with time series that have a linear trend over time, whether increasing or decreasing. When there is no trend, this technique is reduced to the SES. Geurts and Ibrahim (1975) were first to apply the Brown's DES model to forecast tourist arrivals in Hawaii. They suggest that it is cheaper and easier than the Box-Jenkins approach for use in forecasting domestic tourism demand. Sheldon (2008) shows that the Brown's DES and Naive 1 models also perform well in forecasting international tourism expenditure. However, the disadvantage of the DES is that it does not track nonlinear trends well and often fails to pick up structural breaks in the time series (Frechtling, 1996).

Holt's DES Model allows the trend and slope to be smoothed by different constants. Since the basic DES method only uses one constant, the estimated trend is very sensitive to random impacts, whereas Holt's version is more flexible in selecting the smoothing constants (Makridakis et al., 1998). However, according to Chen et al. (2008), Brown's DES models outperform Holt's based on mean absolute percentage error (MAPE) in forecasting tourist arrivals to US national parks. Holt-Winter's model (the triple exponential smoothing method) adds seasonal variation to Holt's model, and is appropriate when the time series has a linear trend with an additive seasonal pattern (Bowerman, O'Connell, & Koehler, 2005). Since Holt-Winter's model captures both the seasonal pattern and trend of the time series, it usually outperforms other exponential smoothing methods (Lim & McAleer, 2001). Grubb and Mason (2001) prove that adding a damped trend to Holt-Winter's method greatly improves long-run forecasting accuracy compared with the Box-Jenkins and basic structural models in the case of UK air passengers.

The Box-Jenkins model is the most frequently used time series approach in tourism demand forecasting. It is considered relatively sophisticated, with the ARMA process as its basic form. Box-Jenkins forecasting models are identified by examining the behaviour of the autocorrelation function (AF) and partial autocorrelation function (PAF) of a stationary time series. The time series must be stationary for the classical Box-Jenkins model to be used. This means it must have a constant mean and variance. If a time series is nonstationary, it should be differenced until it becomes so. When the *d*th differences of a time series have ARMA representation, it can be written as an ARIMA model. The AF can help determine the number of times that the series needs to be differenced.

Both the autoregressive (AR) and moving average (MA) models are useful forms of the Box-Jenkins model, and AF and PAF are used to determine whether the time series is an AR, MA, or ARMA process. When the PAF drops off to 0 after lag *p*, this indicates that it is an AR (*p*) process while if AF drops off to 0 after lag *q*, this denotes a MA (*q*) process (Chen et al., 2008).

The advantage of the Box-Jenkins method is not only that these models can track the behaviour of a diverse range of time series, but also that they require fewer parameters to be estimated in the final model. Such statistics as the Akaike information criterion (AIC), Akaike final prediction error (AFPE), and Bayesian information criterion (BIC) are used to add mathematical rigor to the process of identifying an appropriate ARMA or ARIMA model (De Gooijer & Hyndman, 2006). Since seasonality is an important feature in most of the tourism series, seasonal ARIMA (SARIMA) has also gained popularity in recent years.

Table 2.2
Advanced Time Series Models

Method	Equation
Brown's DES	$Y_t = \alpha A_{t-1} + (1-\alpha) Y_{t-1}$
	$Y'_t = \alpha Y_{t-1} + (1-\alpha) Y'_{t-1}$
	$C_t = Y_t + (Y_t - Y'_t)$
	$T_t = [(1-\alpha)/\alpha] * (Y_t - Y'_t)$
	$F_{t+n} = C_t + n * T_t$
Holt's DES	$L_t = \alpha A_t + (1-\alpha)(L_{t-1} + b_{t-1})$
	$b_t = \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1}$
	$F_{t+n} = L_t + n * b_t$
Holt-Winter's	$L_t = \alpha(A_t - sn_{t-h}) + (1-\alpha)(L_{t-1} + b_{t-1})$
	$b_t = \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1}$
	$sn_t = \gamma(A_t - L_t) + (1-\gamma) sn_{t-h}$
	$F_{t+n} = L_t + n * b_t + sn_{t+n-h}$
Box-Jenkins	$A_t = d + a_1 A_{t-1} + a_2 A_{t-2} + ... + a_p A_{t-p} - b_1 e_{t-1} - b_2 e_{t-2} - ... - b_q e_{t-q}$
Basic structure time series	$F_t = \mu_t + \gamma_t + \psi_t + \varepsilon_t$

Note: F_t = forecasts at time t; A_t = actual value at time t; Y_t =SES series at time t; Y'_t =DES series at time t; C_t =the intercept; T_t = the slope coefficient; n= the number of forecasting period; L_t = smoothed value at time t; b_t = trend estimate at period t; sn_t = seasonal variation at time t; e = error term; α, β, γ are smooth constants which are between 0 and 1; d = the constant; μ_t, γ_t, ψ_t, ε_t denote the trend, seasonal, cyclical and irregular components, respectively.

Researchers' evaluations of the Box-Jenkins models are mixed. Makridakis and Hibon (1979) argue that they produce little improvement in forecasting accuracy, and Kim, Wong, Athanasopoulos, and Liu (2011) conclude that the SARIMA model tends to underestimate the future uncertainty in interval forecasting. Other studies suggest that the ARIMA and SARIMA approaches are preferred in tourism demand forecasting when the time series are absent from interventions (see for example, Gustavasson & Nordstrom, 2001; Goh & Low, 2002; Lim & McAleer, 2002b; Chu, 2008). Preez and Witt (2003) show that the ARIMA model performs best in terms of forecasting accuracy and goodness of fit.

To improve the explanatory power of the ARMA or ARIMA models, some researchers have included causal variables. The resulting techniques are known as the ARMAX or ARIMAX models. The causal ARMAX models, on average, outperform both the purely extrapolative models and simple econometric models in terms of forecasting accuracy, as they are developed by incorporating both the short-term dynamics as well as the long-term CI relationships between the dependent and causal variables (Akal, 2004; Cho, 2001).

The BSM is constructed by decomposing a time series into its trend, seasonal, cycle, and irregular components. A stochastic trend captures changing consumer taste in tourism demand, whereas stochastic seasonality allows for variations in seasonal patterns. The irregular component represents transitory variations in tourism demand which are not explained by the other components. The trend, seasonal, and cycle components can be modelled in various ways. Greenidge (2001) successfully applies the BSM to forecasting tourist arrivals to Barbados, and shows that it offered valuable insights into tourist behaviour. Explanatory variables can be included in the BSM to form a multivariate structural time series model (STSM) (Gonzalez & Moral, 1995). However, according to Turner and Witt (2001b) and Kulendran and Witt (2003b), no evidence has yet emerged to suggest that the inclusion of explanatory variables improves the forecasting accuracy of the BSM. It should therefore be sufficient for practitioners who are only interested in forecasting (Kim & Moosa, 2005).

Static econometric models. Although time series approaches are useful tools in tourism demand forecasting, their major limitation is that their construction is not based on any economic theory that underlines tourists' decision-making processes. Therefore, not only can they not be used to analyse tourists' behaviour, but they are also incapable of assisting policymakers in evaluating the effectiveness of their strategies and policies for tourism development. From this perspective, then, econometric models are superior to the time series approaches (Song et al., 2009a).

Static econometric models (see Table 2.3) include explanatory variables, but not the lagged dependent or explanatory variables. Their main objective is to explore the factors that affect tourism demand. The traditional regression method, gravity models, and the static almost-ideal demand system (AIDS) are examples of static econometric models.

The Traditional Regression Approach (TRA) generally uses ordinary least squares (OLS) as the estimation procedure. This approach follows six main steps; 1) formulate hypotheses based on demand theory, 2) identify the model's functional form, 3) collect data, 4) estimate the model, 5) test hypotheses, and 6) generate forecasts or evaluate the policies (Song et al., 2009a).

The advantages of the static regression approach are as follows; 1) it explicitly addresses the causal relationships between tourism demand and the factors which influence it; 2) it is useful for the assessment of political and business plans; and 3) it provides several statistics to measure accuracy and validity and uses them to improve itself (Fretchling, 1996). However, there are a number of limitations which should not be ignored. The first of these is that tourism demand data tend to be trended (that is, nonstationary), and a regression model that contains such nonstationary series tends to generate a spurious relationship between dependent and independent variables which invalidates the model's diagnostic statistics. The second limitation is that it cannot take dynamic changes in tourists' behaviour into consideration when estimating, which is restrictive and unnecessary. The third limitation relates to the uncertainty involved in deriving the final model for forecasting. Because there is no clear procedure to be followed for estimating the model specification, it is very likely that different researchers armed with the same dataset will generate completely different models (Song et al., 2009a).

The gravity model examines the effects of variables such as distance and population size on tourism demand. It assumes that the attractiveness between two countries/regions is an inverse function of the square of their distance and proportional to the product of their populations. The gravity model is widely used in international trade research. Guo (2007) develops it to analyse the determinants of inbound tourism demand in China, and Khadaroo and Seetanah (2008) use it to investigate the role of transportation infrastructure in tourism flow. However, the reliability of the estimation of the gravity model is questionable given its lack of a strong theoretical underpinning, which leads to an *ad hoc* choice of explanatory variables (Che, 2004).

The static linear AIDS (LAIDS) model was originally introduced by Deaton and Muellbauer (1980). It is a system of equations method concerned with long-run consumer behaviour. It relates the budget share for good *i*, which is the dependent variable, to the logarithms of prices and total real expenditures. Since single equation models fail to estimate adequately the effect of a change in tourism prices in a specific destination on the demand for travelling to other destinations (the substitution effect), the system of equations model is introduced to overcome this limitation. The AIDS model is the most popular among a number of such methods, because it gives an arbitrary first-order approximation to any demand function and has a functional form which complies with known household budget data (Deaton & Muellbauer, 1980). It also has a flexible functional form which does not impose any *a priori* restrictions on the elasticities of demand. In other words, any good and service in the system can be either an inferior or a normal good (Fujii, Khaled, & Mark, 1985). Empirical studies show that the AIDS model is a popular technique for analyzing the market share of tourism demand, and also provides a range of information about the sensitivity of such demand to price and expenditure changes (Syriopoulos & Sinclair, 1993; Papatheodorou, 1999; De Mello, Pack, & Sinclair, 2002; Han, Durbarry, & Sinclair, 2006).

The static AIDS model, however, focuses on a long-term solution which assumes that consumers behave in the same manner over time and ignores the short-run dynamics of the demand system. In reality, consumer behaviour varies over time due to changes in tastes, adjustment costs, imperfect information, incorrect expectations, and misinterpreted real price changes (Song et al., 2009a). The error correction LAIDS (EC-LAIDS) model has been developed to capture these short-run dynamic features of the demand system (Durbarry & Sinclair, 2003; Mangion, Li, Song, & Witt, 2004; De Mello & Fortuna, 2005).

Although static econometric models have advantages in exploring and interpreting the elasticities of the explanatory variables, they still perform badly in forecasting tourism demand, as their estimation does not consider the long-run CI relationships and short-run dynamics (Song et al., 2009a). They cannot even compete with the simplest time series models, such as Naive 1 (Witt & Witt, 1992). Their poor performance may be due to the fact that they omit the “word-of-mouth” (WOM) effect. They ignore the dynamics of a demand system and assume that it is not affected by previous values of the economic variables. Furthermore, the static models ignore the stationarity properties of the variables, so spurious regression is very likely to occur (Li, 2009).

Table 2.3
Static Econometric Models

Method	Equation
TRA	$Y = \alpha + \sum_i \beta_i x_i + \varepsilon_i$
Gravity	$Y = G \frac{P_i P_j}{D^2}$
Static LAIDS	$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + b_i \log\left(\frac{x}{P^*}\right) + \sum_k \varphi_{ik} dum_k + \varepsilon_i$ $\log P^* = \sum_i w_i \log p_i$

Note: Y=forecasts of tourism demand; x_i =explanatory variables; P_i, P_j = population of region *i* and *j*; D= the distance from *i* to *j*; w_i =budget share of the *i*th good, p_j =price of the *j*th good; x =total expenditure on all goods in the system; P^* =aggregate price index; dum_k =dummy variables; ε_i =disturbance term; α = constant ; $\beta_i, G, \alpha_i, \gamma_{ij}, b_i, \varphi_{ik}$ are the parameters to be estimated.

Dynamic econometric models. The adoption of advanced techniques, such as the VAR, TVP, and ECM approaches, has greatly improved the forecasting performance of econometric models. These dynamic models capture the WOM effect and the inclusion of the causal variables further increases their explanatory power.

The Autoregressive Distributed Lag model (ADLM) is a dynamic econometric model which involves a general functional form containing both the current and lagged values of the variables. Stepwise reduction, which is also known as the general-to-specific approach, is applied to estimate the ADLM. This process continues until all the criteria are satisfied, including a high R^2 value, statistically significant coefficients of the explanatory variables, and a lack of autocorrelation and heteroskedasticity in the error term (Song & Witt, 2003).

The ADLM model selection process involves the following steps. First, a general demand model with a large number of explanatory variables, including the lagged dependent and independent variables, is constructed as a general ADLM. Second, the *t*, F, and Wald statistics are used to test the various restrictions, in order to achieve a simple but statistically significant specification. Third, the normal diagnostic tests are carried out to examine whether the final model is statistically acceptable, and in the final step, the resulting model is used for policy evaluation and forecasting (Song et al., 2009a). The main criteria for selecting an ADLM include consistency with economic theory, data coherency, parsimony, encompassing, parameter constancy, and exogeneity (Thomas, 1993).

The general-to-specific methodology overcomes the disadvantages of the specific-to-general method, which tends to produce a highly complicated final model involving too many variables but which nevertheless cannot capture the dynamic characteristics of the demand model and hence leads to poor forecasting performance. Furthermore, ADLM does not necessarily require *a priori* knowledge about the integration properties of the variables, and provides a robust estimation of the model parameters even in small samples (Narayan, 2004).

With different restrictions imposed on the parameters, an ADLM can be written into different econometric models, such as the static, autoregressive, or growth rate models (Witt & Witt, 1992), the leading indicator model (Turner, Kulendran, & Fernando, 1997; Kulendran & Witt, 2003a), the partial adjustment model (Song et al., 2003c), the common factor model (Lee, Var, & Blain, 1996), the finite distributed lag model, and the dead start model (Song et al., 2003c) (see Table 2.4). These models have been widely used in tourism forecasting in recent years, however, their performance varies under different situations.

The general-to-specific methodology has been popular in tourism demand analysis and has been used to explore its determinants in specific destinations (Jensen, 1998; Song & Witt, 2003; Nada & Sarath, 2007; Vanegas, 2008; Song & Lin, 2009; Smeral, 2010). Meanwhile, it has been shown to perform well in forecasting turning points (Nadal, 2001). However, one of the possible problems with this method is that the structure of the selected final model relies too much on the data used, even though economic theory plays an important role in the initial form of the general model (Song & Witt, 2003).

The ECM expresses the current value of the dependent variable as a linear function of its past values, the current and past values of the explanatory variables, and the previous values of the error term from the CI relationships (Kulendran & Witt, 2001). The general form of an ECM can be written as:

$$\Delta y_t = \text{(current and lagged } \Delta x_{jt} s \text{ , lagged } \Delta y_t s\text{)} - (1-\phi_1)\left[y_{t-1} - \sum_{j=1}^{k} \xi_j x_{jt-1} \right] + \varepsilon_t$$

The ECM (1, 1) takes the form of

$$\Delta y_t = \beta_0 \Delta x_t - (1-\phi_1)\left[y_{t-1} - k_0 - k_1 x_{t-1} \right] + \varepsilon_t$$

where $k_0 = \alpha / (1-\phi_1)$, $k_1 = (\beta_0 + \beta_1)/(1-\phi_1)$, β_0 is the impact parameter, $(1-\phi_1)$ is the feedback effect, and k_0 and k_1 are the long-run response coefficients.

CI describes the relationship between a pair of nonstationary economic variables which share a common stochastic trend. That is, if two or more time series are individually integrated, but some linear combination of them has a lower order of integration, the series are said to be cointegrated. Unit roots tests are used to examine the CI relationship between the two series (Song et al., 2009a). If the two variables are cointegrated, a regression model that relates them will not generate spurious relationships.

Table 2.4
Variations of ADLM

Model	Equation
Unrestricted ADLM	$y_t = \alpha + \sum_{j=1}^{k}\sum_{i=0}^{p}\beta_{ji}x_{jt-i} + \sum_{i=1}^{p}\phi_i y_{t-i} + \varepsilon_t$
Static	$y_t = \alpha + \sum_{j=1}^{k}\beta_j x_{jt} + \varepsilon_t$
AR	$y_t = \alpha + \sum_{i=1}^{p}\phi_i y_{t-i} + \varepsilon_t$
Growth Rate	$\Delta y_t = \alpha + \sum_{j=1}^{k}\beta_j \Delta x_{jt} + \varepsilon_t$
Leading Indicator	$y_t = \alpha + \sum_{j=1}^{k}\sum_{i=1}^{p}\beta_{ji}x_{jt-i} + \varepsilon_t$
Partial Adjustment	$y_t = \alpha + \sum_{j=1}^{k}\beta_j x_{jt} + \sum_{i=1}^{p}\phi_i y_{t-i} + \varepsilon_t$
Common Factor	$y_t = \alpha + \sum_{j=1}^{k}\beta_j x_{jt} + \varepsilon_t$ $\varepsilon_t = \sum_{i=1}^{p}\beta_i \varepsilon_{t-i} + \mu_i$
Finite Distributed Lag	$y_t = \alpha + \sum_{j=0}^{k}\sum_{i=0}^{p}\beta_j x_{jt-i} + \varepsilon_t$
Dead Start	$y_t = \alpha + \sum_{j=1}^{k}\sum_{i=1}^{p}\beta_{ji}x_{jt-i} + \sum_{i=1}^{p}\phi_i y_{t-i} + \varepsilon_t$

Note: y_t =the tourism demand variable; x_t =the explanatory variables; *k* = numbers of explanatory variables; *p* =the lag length; α =constant; ε_t and μ_i = error terms; β_{ji} and ϕ_i are the parameters to be estimated.
(Source: Adapted from Song, Witt & Li., 2009, p.48)

The ECM and CI are bi-directional transformations under what is often called the Granger Representation Theorem (Engle & Granger, 1987). Both are useful when both long-run equilibrium and short-run disequilibrium relationships are of interest (Daniel & Ramos, 2002; Dritsakis, 2004; Choyakh, 2008; Halicioglu, 2010).

The ECM has the following advantages: 1) it overcomes the spurious regression problem by differencing the variables and also avoids the problems of the growth rate model, where only differenced data are used; 2) it is another form of the ADLM, which fits in well with the general-to-specific methodology; and 3) it reduces the problem of data mining during estimation (Song et al., 2009a).

In their studies of demand for Canadian and Tunisian tourism, Veloce (2004) and Ouerfelli (2008) show that ECMs provide more precise forecasts than time series models when a differenced demand variable is concerned. Kulendran and Witt (2001) also demonstrate that the ECM and CI models are more accurate than traditional econometric models in forecasting tourism demand from the UK to Germany, Greece, the Netherlands, Portugal, Spain, and the US.

Three main estimation methods are used to estimate ECMs: the Engle-Granger two-stage (EG2S) approach, the Wickens-Breusch (WB), and the ADLM procedures. However, these methods perform differently when a different forecasting horizon is considered. Wickens and Breusch (1988) suggest that, in the case of the EG2S, the estimation bias in the first stage may be carried over to the second stage when the sample size is small.

The VAR model was developed by Sims (1980). Here, all the variables are modelled purely as dynamic processes, except for the deterministic variables such as trend, intercept, and dummy variables. In the VAR model, each variable is a linear function of the lagged values of all the variables in the system. It treats them all as endogenous, and does not rely on the assumption that all explanatory variables need to be exogenous to the dependent variables (as in the case of the single equation models). The general VAR (p) model can be written as:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + BZ_t + U_t$$

where Y_t is a k vector of variables included in the system; Z_t is a vector of deterministic variables; U_t is a vector of regression errors that are assumed to be contemporaneously correlated but not autocorrelated; and A_i and B are the matrices of the parameters to be estimated.

A general VAR model, also called the unrestricted VAR model, is its standard form, with lag lengths for each variable identical and every variable in the system included in each equation. In a mixed VAR model, different lag lengths are specified for each variable in each equation. A likelihood ratio test, the AIC, together with the Schwarz Bayesian Criterion (SBC) is usually suggested in order to determine the optimal lag length (Song, Witt & Li, 2009). The Bayesian VAR model combined *priors* with sample information has been found to overcome the problem of overfitting and improves the forecasting performance of the VAR models (Liu, Gerlow, & Irwin, 1994; Wong et al., 2006).

The VAR models have been proven to be capable of producing accurate medium- to long-term tourism forecasts (Song & Witt, 2006). The VAR technique is superior to the single equation for the following reasons (Wong et al., 2006). Firstly, the VAR models do not require an implicit theoretical framework for their construction and estimation. Secondly, forecasts using VAR are easy to generate, as it does not require forecasts of the explanatory variables to be produced first in order to generate the forecasts of the dependent variable. This makes it an easier way to produce tourism demand forecasts than using other econometric models. However, although the VAR technique has been widely and successfully used in macroeconomics, so far little effort has been made to apply it to tourism forecasting.

The TVP model takes into consideration the possibility of parameter changes over time, and hence overcomes the structural instability problem caused by external shocks. According to Song and Witt (2000), it can simulate different types of external shocks to the tourism demand system, including policy and regime shifts, economic reforms, and political uncertainties. Furthermore, the TVP model performs well in capturing external influences of a gradual and diffused nature, such as changes in consumer tastes and other social and psychological trends (Song & Wong, 2003). The TVP model can be written in a state space form:

$$y_t = \beta_t x_t + \mu_t$$

$$\beta_t = \phi \beta_{t-1} + R_t e_t$$

where y_t is tourism demand, x_t is a row vector of k explanatory variables, β_t is the column vector of k state variables, ϕ is a $k \times k$ matrix, R_t is a $k \times g$ matrix, μ_t is a residual with zero mean and constant covariance, and e_t is a $g \times 1$ vector of serially uncorrelated residuals with zero mean and constant covariance (Song, Witt & Li, 2009).

The TVP method incorporates structural changes in forecasting and puts more weight on most recent data in estimating the demand model to improve forecasting accuracy. It can be estimated using an efficient recursive algorithm called the Kalman filter. This method is increasingly used in tourism demand analysis (see for example Riddington, 1999; Song & Witt, 2000; Song & Wong, 2003; Wu, 2010). According to Song, Witt & Li (2009), based on their examination of tourist arrivals in the UK and US, the TVP model generated the most accurate short-run forecasts, consistent with previous studies (Song, Romilly, & Liu, 1998; Song & Wong, 2003). In their study of the demand for Danish tourism, Witt et al. (2003) state that the TVP model performs consistently well for one-year-ahead forecasting for the various error criterion.

The Dynamic AIDS model is the error-correction form of the AIDS (EC-AIDS) model. It incorporates a short-run adjustment mechanism, which is written as:

$$\Delta w_i = \delta_i \Delta w_{it-1} + \sum_j r_{ij} \Delta \log p_j + b_i \Delta \log\left(\frac{x}{P^*}\right) + \lambda_i \mu_{it-1}$$

where μ_{it-1} is the EC term, which measures the feedback effect and is estimated from the corresponding CI equation (Li, Song, & Witt, 2004).

Durbarry and Sinclair (2003) first applied the EC-AIDS approach to the analysis of tourist expenditure in France, but failed to include any short-run independent variables due to insignificant coefficients. Li et al. (2004) use the EC-AIDS model to evaluate the international tourism competitiveness of five western European countries and show that the dynamic AIDS performs better than the static AIDS model. De Mello and Fortuna (2005) examine the demand for European tourism by UK residents and suggest that the dynamic AIDS model is a data-coherent and theoretically consistent model which provides robust estimates and reliable forecasts.

Artificial Intelligence (AI) methods. As well as the time series and econometric forecasting methods, other techniques such as the AI model have emerged in the literature. AI is the study and design of intelligent agents, or systems that perceive their environment and take actions that maximise the chances of success. AI techniques have developed rapidly across various research areas. According to Wang (2004), AI forecasting methods, including neural networks, rough sets theory, fuzzy time series theory, grey theory, genetic algorithms, and expert systems, tend to perform better than traditional forecasting methods. Applications of AI techniques to tourism demand analysis include Uysal and El Roubi (1999), who look at Canadian tourists' expenditure in the US; Law and Au (1999)'s forecasts of the demand for Hong Kong tourism by the Japanese; the work of Cho (2003) on tourist arrivals in Hong Kong; Wang (2004) who examines the trend of tourist arrivals in Taiwan from Hong Kong; and Palmer, Montano, and Sese (2006) who study tourism expenditure in the Balearic Islands.

The main advantage of AI methods is that they do not require preliminary or additional data information, while their limitations are the lack of a theoretical underpinning and the inability to interpret demand from an economic perspective (Song & Li, 2008). These limitations restrict their practical application to in tourism demand analysis.

The ANN model, sometimes simply called the Neural Network model, is the one most widely used in tourism demand forecasting. It is a computational model inspired by the structure of biological neural networks. A typical ANN consists of a number of simple processing elements called neurons, nodes, or units. It is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. The typical architecture of ANN models includes one input layer, one or two hidden layers, and one output layer (Simpson, 1989). The input layer comprises the explanatory variables, and the output layer the dependent variable, that is, tourism demand. In the hidden layer, the core of the ANN model, different weights are given to each explanatory variable as well as the dependent variable. The computing process is repeated until a set of optimal weights is obtained. Each node y_i in the hidden layer can be expressed as:

$$y_i = \frac{1}{1+e^{-f_j}}$$

$$f_j = \sum_{i=1}^{2} x_i w_{ji}$$

and the final node Y of the output layer is obtained from:

$$Y = \sum_{j=1}^{3} y_j w_j$$

where w is the weight of interconnection and x is the input variable.

The ANN model was first applied in tourism demand forecasting in the late 1990s, and some improvements are reported in the literature after 2000. ANNs are useful for computing nonlinear threshold functions by overcoming the restrictions of multiple regression analysis. They can also be easily updated over time and perform fairly well in one-year-ahead forecasting due to the repetitions of expected similar seasonal patterns (see for example Burger et al., 2001, who use ANN to forecast demand for Durban tourism).

However, the limitations of the ANN model cannot be ignored. First, the learning process of the hidden layers needs a large amount of data; secondly, it cannot generate the impact of explanatory variables on tourism demand; and thirdly, it cannot calculate the elasticities of such demand (Wu, 2010).

The Rough Sets Approach was first used to forecast demand for hotel rooms in Hong Kong by Law and Au (1998). This model was generated from the rough sets theory and uses data mining techniques to discover knowledge. Its advantages are that: (1) it can model the decision processes underlying the data in both numeric and nonnumeric forms, which makes it a useful classification and pattern recognition technique, and (2) it can generate comprehensible decision rules that are useful for practitioners (Au & Law, 2002; Goh & Law, 2003). The only assumption of this approach is that the values of the attributes can be categorised.

The rough sets approach pays close attention to categorical variables such as demographic features and psychographic variables, and forecasts tourism demand levels instead of exact values. It analyses demand from a micro-perspective, and can be viewed as a complementary tool to econometric forecasting models (Goh, Law, & Mok, 2008; Song & Li, 2008).

The Support Vector Regression (SVR) mechanism is a novel learning machine based on statistical learning theory and adheres to the principle of structural risk minimisation. It seeks to minimise the upper bound of the generalisation error rather than the training error, which is the underlying principle of ANN. It is an alternative technique to solve classification, nonlinear regression estimations and forecasting problems by introducing a loss function.

Chen and Wang (2007) incorporate the Genetic Algorithm (GA) technique into SVR to form a GA-SVR model which improves forecasting accuracy. GA is a heuristic search algorithm that mimics natural evolution. This method is routinely used to generate useful solutions to optimisation and search problems. Using GA, Chen and Wang (2007) forecast tourist arrivals to China, and compare the forecasting performance of GA-SVR, Back Propagation Neural Network (BPNN, the most popular ANN model) and ARIMA. The results suggest that the GA-SVR generated more precise forecasts than both other models.

The Fuzzy Time Series Method is used to forecast a process using linguistic value observations and deals with the first-order difference of the time series. Its main assumption is that the variation of this year is related to that of the previous year and follows the trend of recent years. Therefore, if actual variation is considerably different from recent trends, the forecasting error is likely to be large (Yu & Schwartz, 2006). Human judgment should be involved in the fuzzy time series model when making decisions about two of its parameters. The first is the number of grades which describes the extent of variation and the second is the window basis size, or the number of previous observations used to generate the prediction (Yu & Schwartz, 2006). Wang (2004) confirms that the fuzzy time series technique is an appropriate tool for short-term forecasting of the demand for Hong Kong tourism by Taiwanese. However, one of its foremost disadvantages is that it lacks the ability to adapt to the shock caused by special events (Wang & Hsu, 2008).

Grey Theory is a generic theory that deals with systems with poor, incomplete, and/or uncertain information. It reduces randomness by using the accumulated generating operation, whereby an exponential function is fitted based on a differential equation to estimate future trends (Yu & Schwartz, 2006). The advantage of the grey model is that it can be constructed based on a very short time series. It can be fitted with as few as four observations (Chiang et al., 1998). However, the data used must be taken at equal intervals and in consecutive order (Lin, Su, & Hsu, 2001).

Both the grey and fuzzy time series models use linguistic variables and accumulated generating operations instead of original data. It is suggested that their strength lies in short-term forecasting with limited data (Song & Li, 2008). However, they are both very complicated methods, which are time-consuming to implement and not available through most of the commercial statistical packages. Furthermore, according to Yu and Schwartz (2006), more complicated methods do not necessarily generate more accurate forecasts than simpler models.

2.5.3 Forecast Combination

Although each of the models discussed above has its own advantages and disadvantages, the literature shows that no single model can outperform the others in every situation. To improve forecasting accuracy, attempts have been made to combine the forecasts of individual models. The general literature confirms that this can improve forecasting accuracy such that the combined result will always outperform the poorest individual forecast, thereby reducing the risk of complete forecasting failure (Song & Li, 2008). Individual forecasts are generally combined based on the following formula:

$$f_c = \sum_{i=1}^{n} w_i f_i$$

where f_c is the combined forecast generated by n individual forecasts, f_i is the ith individual forecast, and w_i is the weight given to f_i.

It is important to decide the weight to be given to each model in the combining process. Winkler and Clemen (1992) show that the performance of combination forecasts is very sensitive to such weighting. Several combination methods have been discussed in the literature (see Table 2.5). According to Shen et al. (2008), the variance-covariance combination methods perform best among the simple average, discounted MSFE, and variance-covariance methods.

One favourable feature of combination forecasts is that they enable diversity in the underlying models instead of focusing too much on a narrow specification. Coshall (2009) suggests that the combined forecasts of the ARIMA and exponential smoothing models were more accurate than that of the individual models over one-, two-, and three-years-ahead forecasts. Andrawis, Atiya, and El-Shishiny (2011) combine the forecasts of different time aggregations (short and long term) to forecast tourist arrivals to Egypt and conclude that different time scales will capture different dynamics and increase the diversity of the forecasts obtained, therefore improving the overall performance of the models.

Although combination forecasting methods have sometimes been shown to outperform the single best model (Chu, 1998b), there is no proof that the combined forecasts are always superior. Wong et al. (2007) conclude that the relative performance of the combined versus single-model forecasts varies across countries/regions as well as combination techniques. Song, Witt, Wong & Wu (2009) find that only approximately 50% of combined forecasts outperform the best individual model. Furthermore, combined forecasts tend to overlap in terms of the information included in each of the individual predictions, and to be unstable over different time horizons.

Table 2.5
Forecasting Combination Methods

Method	Weights
Simple average (AVR)	$w_1 = w_2 = 1/2$
Variance based (VAR)	$w_1 = \dfrac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_1\sigma_2}$ $w_2 = 1 - w_1$
Inverse of the mean square error (INV-MSE)	$w_1 = \dfrac{\sum_{-k}^{k} MSE_l^{(2)}}{\sum_{-k}^{k} MSE_l^{(1)} + \sum_{-k}^{k} MSE_l^{(2)}}$ $w_2 = 1 - w_1$
Rank based (RANK)	$w_1 = \dfrac{R_2}{R_1 + R_2}$ $w_2 = 1 - w_1$
Least squares estimation (LSE)	$f_c = w_0 + w_1 f_1 + w_2 f_2 + \varepsilon$
Shrinkage method (SHRINK)	$w_i = \psi w_i^* + (1-\psi)(1/n)$ $\psi = \max\left(0, 1 - \alpha n / (T - h - n - 1)\right)$

Note: w_1, w_2 are weights for each single forecasts; σ_1^2, σ_2^2 are variance of two individual forecasts and $\sigma_1\sigma_2$ is the covariance of the two individual forecasts; $MSE_l^{(1)}$, $MSE_l^{(2)}$ are the mean square errors of the two individual forecasts in step l and *MSE* is estimated from step l–k to l+k ; R_1, R_2 are the performance ranks of the two individual forecasts; w_0 denotes the intercept of the estimation; w_i^* denotes the weights of the underlying combination method; α is the strength of the shrinkage; n is the number of forecasting models, T is the sample size used for estimation and Ψ is the parameter governing the degree of shrinkage.

However, when a few forecasting models are available and the researcher is uncertain about the accuracy of the prediction produced by each, combining the forecasts is the best and safest approach (Wong et al., 2007). Moreover, such combination produces more benefit in terms of long-term forecasts (Song, Witt, Wong & Wu, 2009)

2.6 Assessment of Forecasting Performance

Ex post and ex ante forecasting. These are two different concepts. As Figure 2.1 shows, if the data are available from period t=1 to t=N, a forecast from time n to N is *ex post*, and after time N is called *ex ante*. In practice, only the accuracy of *ex post* forecasts can be evaluated using actual data. While *ex ante* forecasts are more important for practitioners, they cannot be produced until the explanatory variables have themselves been forecast (Song et al., 2009a).

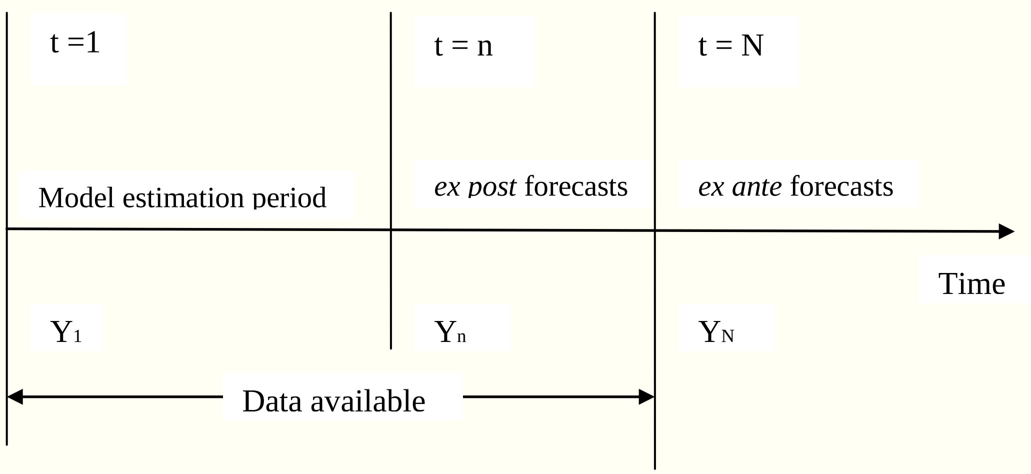

Figure 2.1 Time Horizons of Forecasts. From: Song et al., 2009a, p.183.

***Measures of forecasting accuracy*.** A number of forecasting evaluation criteria are available, such as accuracy, cost (time and/or money), and model complexity.

Researchers tend to be more concerned with the first of these criteria, as forecasting accuracy is crucial in tourism practitioners' and policymakers' decision making. In practice, the most widely used methods of measuring forecasting accuracy are the error magnitude measures (Table 2.6) such as MAPE, root mean square percentage error (RMSPE), and mean absolute error (MAE).

Table 2.6
Error Magnitude Measures

Measure	Equation
MAPE	$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left\lvert Y_t - \hat{Y}_t \right\rvert}{Y_t}$
RMSPE	$RMSPE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\frac{Y_t - \hat{Y}_t}{Y_t}\right)^2}$
MAE	$MAE = \frac{1}{n}\sum_{t=1}^{n}\left\lvert Y_t - \hat{Y}_t \right\rvert$

Note: *n* denotes the length of forecasting horizon; Y_t is the actual value of the dependent variable; $\hat{Y}_t$ is the forecast value of the dependent variable.

As well as these, other statistical measures can be used to assess the performance of forecasting models, such as Theil's U statistic, which is used to compare the Naive 1 no-change model with other approaches; the acceptable output percentage and the normalized correlation coefficient, which are often used to evaluate the ANN models (Law & Au, 1999); and the unbiasedness test, which is used to test forecasting consistency (Witt et al., 2003) (Table 2.7).

Table 2.7
Other Forecasting Assessment Measures

Measures	Equation
Theil's U statistic	$U = \sqrt{\dfrac{\sum_{i=1}^{n}\left(\Delta Y_{t+h} - \Delta \hat{Y}_{t+h}\right)^2}{\sum_{i=1}^{n}\left(\Delta \hat{Y}_{t+h}\right)^2}}$
Acceptable output percentage	$Z = \dfrac{\sum_{i=1}^{n} t_i}{n} \times 100\%$, for $\begin{cases} t_i = 1, & \text{if } \dfrac{\left\lvert Y_i - \hat{Y}_i \right\rvert}{Y_i} \le 5\% \\ t_i = 0, & \text{otherwise} \end{cases}$
Normalized correlation coefficient	$r = \dfrac{\sum_{i=1}^{n}\left(Y_i \times \hat{Y}_i\right)}{\sqrt{\sum_{i=1}^{n} Y_i^2 \times \sum_{i=1}^{n} \hat{Y}_i^{\,2}}}$
Unbiasedness test	$Y_{t+h} = \beta_0 + \beta_1 \hat{Y}_{t+h} + u_{t+h}$ $H_0 : \beta_0 = 0, \beta_1 = 1$

Note: Y_t is the actual value of the dependent variable; $\hat{Y}_t$ is the forecast value of the dependent variable; and *h* is the length of the forecasting horizon.

Another forecasting measure introduced by Witt and Witt (1991) is the group of directional change measures, which assess the probability of correctly forecasting directional change. Turning point accuracy and trend measures are particular subsets of these (Witt & Witt, 1991, 1995). According to Henriksson and Merton (1981), the probabilities of directionally correct forecasts can be written as:

$$p_1 = prob\left(\Delta \hat{Q}_t \, \Delta Q_t > 0 \middle| \Delta Q_t < 0\right),$$

$$p_2 = prob\left(\Delta \hat{Q}_t \, \Delta Q_t > 0 | \Delta Q_t \geq 0\right).$$

where p_1 is the probability of a directionally correct forecast on the condition that the tourism demand falls at time *t*, and p_2 is the probability of a directionally correct forecast conditional on no fall in tourism demand at time *t*. Suppose that n_1 is the number of observations for decrease in tourism demand, n_2 is the number of observations for increase in tourism demand, m_1 is the number of correct forecasts given a fall in tourism demand, and m_2 is the number of incorrect forecasts given no fall in tourism demand. Then, the estimated value of $p_1 + p_2$ is:

$$\hat{p}_1 + \hat{p}_2 = m_1 / n_1 + \left(n_2 - m_2\right) / n_2$$

For a forecasting model to generate rational forecast, the condition $p_1 + p_2 \geq 1$must be obtained; otherwise the Naive 1 no change model is preferred (Witt et al., 2003). The directional change error measures have been used in many other areas, but few efforts have been made to use them to evaluate tourism demand forecasting models (except, for example, Witt & Witt, 1989, 1991; Witt et al., 2003).

In fact, different measures of forecasting accuracy usually lead to different conclusions about performance. According to Witt et al. (2003), univariate models are outperformed by econometric models in terms of the error magnitude measure, a finding consistent with that of Kim and Song (1998) and Song et al. (2000). Witt et al. (2003) also report that the econometric model is ranked first in terms of direction of change error for one-year-ahead forecasting, which supports the earlier conclusions of Witt and Witt (1991).

Forecasting Competition. As well as improving accuracy by using different models, a number of studies have tried to compare the performance of various models (forecasting competition). Oh and Morzuch (2005) compare the within- and post-sample forecasting accuracy of several time series models of tourism demand in Singapore. Their results suggest that two ARIMA models provide consistent and reliable forecasts across different horizons. Chen et al. (2008) compare the accuracy of several models related to three US national parks and show that the ARIMA, SES, Naive 1, time series analysis with explanatory variables, Holt's, and SMA models were respectively ranked first in six different situations.

Goh and Law (2011) attribute the poor performance of early forecasting models to spurious regression, in which the nonstationarity of the data is not accounted for. They show that the more advanced econometric methods, such as CI, ECM, and TVP, produce better results. Song et al. (2000) compare the forecasting performance of ECM with that of the AR, ARIMA, and VAR models using UK outbound tourism demand data. They show that ECM is superior to all other competitors. Song et al. (2003c) compare six alternative econometric models including a static regression, two ECMs (one based on the WB and one on the Johansen maximum-likelihood (JML-ECM) approach), an ADLM, an unrestricted VAR model, and a TVP model, in the context of demand for international tourism in Denmark. Their empirical findings show that the TVP and static model generate the most accurate one- and two-year-ahead forecasts, respectively. For three- and four-years-ahead forecasts the static model is ranked first.

Athanasopoulos et al. (2011) carry out a competition between time series approaches and econometric models, and conclude that the pure version of the former forecast tourism demand more accurately than models with explanatory variables. Among the pure time series methods, the ARIMA and damped trend models consistently forecast more accurately than the seasonal Naive approach for seasonal data (both monthly and quarterly). For yearly data, the Naive approach produced the most accurate forecasts, especially for one-year-ahead.

These mixed findings shows that no single forecasting method is superior to others in all situations. The performance of models varies considerably depending on the forecast error measurement, forecasting horizon, data frequency, destination-origin pairs, and the competitors included in a comparison. According to the review of forecasting models, the TVP model tend to perform well in most situations, especially for short-term forecasts, while the VAR model is the least accurate. The JML-ECM performs better with seasonal data than annual data (Song et al., 2009a).

2.7 Data in Tourism Demand Modelling and Forecasting

Previous work supports the idea that the performance of forecasting models and estimates of demand elasticities is related to the characteristics of the data used and also to the key features of the study itself, such as data frequency, measures of demand, origins and destinations under study, travel distance, and time period of the data (Crouch, 1992a, 1996; Song et al., 2009a). This section summarises the characteristics of the data used in past tourism forecasting and modelling studies.

Data frequency. Annual (most frequently), quarterly, and monthly data are commonly used in tourism demand analysis (Lim, 1997; Song et al., 2009a). According to Li (2010), 82% and 60% of tourism demand studies focusing on China and worldwide, respectively, used annual data. The use of quarterly and monthly data has the advantage of capturing seasonality patterns, which is crucial for policy development. Crouch (1996) tests the effect of data frequency on the income elasticity of international tourism demand and suggests that estimated income elasticity increases with the time frequency. Witt et al. (1994) attribute the differences in performance of the various forecasting techniques to the different frequencies of the data used in the estimation. Therefore, different data frequency calls for a different forecasting model (Li et al., 2005). For example, the JML-ECM performs better with seasonal data, whereas annual data are more suitable for ADLM (Song et al., 2009a).

Measures of demand. As mentioned in section 2.3, there are different measures of tourism demand, such as arrivals, expenditure, and number of nights spent in destination. These different measures influence estimates of income and price elasticities. Since tourists are more likely to reduce their length of stay as a response to price increases, the price elasticity of demand as measured by length of stay is likely to be more sensitive than that measured by tourist arrivals. As well as using total tourism demand data, some researchers have employed disaggregated data to examine tourist expenditure, including accommodation, dining, and shopping (Law & Au, 2000), showing that the income and price elasticities of demand vary greatly across products. Disaggregated data by trip purpose also influences the accuracy of the forecasting models (Turner, Kulendran, & Pergat, 1995).

Origin and destination countries/regions. Tourism demand varies according to origin-destination pairs. People in large countries have many options for travelling within national boundaries, so are more sensitive to price changes in international tourism (Little, 1980). Tremblay (1989) uses dummy variables to test the effects of origin countries on international tourism demand and suggests that the country dummy variables are statistically significant. Crouch (1996) confirms that both nationality and destination may affect the income and price elasticity of international tourism demand.

Yu, Schwartz, and Humphreys (2007) show that the performance of the four forecasting models differs depending on country of origin, a finding confirmed by Song et al. (2009a).

Travel distance. Long-haul tourism has long been considered a luxury product. Crouch (1996) uses meta-analysis to review previous studies and shows that long-haul tourists are more income- and less price-sensitive than short-haul tourists. With the advent of low-cost carriers and the strong competition in the travel industry, the boundaries of long- and short-haul destinations have become increasingly vague. Whether geographic distance still plays a role in determining price and income elasticities has been questioned by researchers such as Crouch (1996) and Naude and Saayman (2005).

Forecasting horizon. Oh and Morzuch (2005) suggest that the rankings of different models in *ex post* forecasting are different from *ex ante* forecasting. Furthermore, the performance of the models changes with horizon variations (Song et al., 2009a). As mentioned in section 2.5, the TVP and STSM models are superior in short-run forecasting (Li et al., 2005); the JML-ECM and WB-ECM perform better in the medium to long run (Song et al., 2009a), and the Naive model outperforms others in one-year-ahead forecasting (Witt & Witt, 1995). Forecasting horizon also influences estimates of elasticities of demand, as tourists appear to be more income- and less price-sensitive over time (Crouch, 1996).

2.8 Research Gap

1. Limited efforts have been made to statistically synthesise empirical research findings.

Elasticity analysis and demand forecasting have long been the two central topics in tourism economics. Over the past 50 years, many researchers have focused on examining the determinants of demand and the ways in which forecasting techniques can be improved. However, limited efforts have been made to synthesise the research findings statistically in order to reach a general consensus.

2. No studies have generalised tourism demand elasticities at the disaggregated level.

Some researchers have tried to investigate the general effects of income and price on international tourism demand based on demand theory. These studies have partially succeeded in synthesizing the demand elasticities of aggregated demand, but have failed to analyse disaggregated demand. In practice, studying demand elasticities at both the product and destination levels is equally important for decision making in tourism policy and management.

3. There is no statistical evidence confirming a relationship between forecasting accuracy, tourism demand elasticities, and the data characteristics and study features.

With the rapid development of modelling and forecasting techniques, some studies have tried to compare the performance of various models by applying them to the same dataset. However, the conclusions drawn from these studies, in terms of forecasting performance and elasticities estimation, have been inconclusive. Other studies have assessed the forecasting performance of various models by reviewing the relevant literature, but these reviews tend to have limited coverage both in terms of time span and breadth. Furthermore, no statistical evidence has been made available to confirm the research findings of these reviews.

4. No attempt has been made to pair the forecasting models with specific datasets.

Until now, no single forecasting model has been proved to be superior to all others in all situations, as performance is influenced by data characteristics such as the time interval of data, the destination-origin pairs, and the length of the forecasting horizon (Witt & Witt, 1995). However, no empirical study has yet been carried out to support this claim. Moreover, no attempt has been made to match the forecasting models with the various data characteristics. A good combination of forecasting models and data characteristics would be of great significance in terms of improving the accuracy of forecasting models as well as for tourism policy and business decision making.

5. No attempt has been made to test the interaction effects of the data characteristics and study features on estimates of international tourism demand elasticities and forecasting accuracy.

Past meta-analyses (Crouch, 1992 a & b, 1995; Lim, 1999) of international tourism demand focus mainly on evaluating the single effect of either data characteristics or study features on estimates of international tourism demand elasticities. However, no study so far has tried to explore the interactive effects of the two factors combined.

It is therefore anticipated that this research will fill these gaps by analyzing and summarizing the empirical studies of the past 50 years, thereby contributing to a better understanding of forecasting methods and tourist behaviour. Using meta-analysis and coding the empirical results of studies of tourism demand modelling and forecasting, this study aims to estimate the income and price elasticities at both the destination and product levels and find the best matches between data characteristics, study features, and forecasting models.

2.9 Chapter Summary

This chapter has presented an overview of the significance of tourism demand analysis and forecasting and various measures of tourism demand, followed by a discussion of the determinants and elasticities of tourism demand. These include tourist income, tourism price, price of substitutes, population of origin country, travel distance, marketing expenditure, and one-off events, among others.

This chapter has also provided a comprehensive review of studies on tourism demand modelling and forecasting. Although it has covered all the methods used in forecasting tourism demand, including qualitative and quantitative methods, the focus has been mainly on the latter. Finally, the chapter has also outlined the different performance measures used for evaluating tourism forecasting models and the characteristics of the data used in previous studies.

Chapter 3 - Hypotheses

3.1 Introduction

As discussed in chapter two, estimates of international tourism demand elasticities and forecasting accuracy are influenced by the characteristics of the dataset used in the model estimation and the individual features of each study. In this chapter, a series of hypotheses will be developed to explore the effects of data and study characteristics on estimates of income and own-price elasticity and forecasting accuracy. These incorporate source markets, destinations, modelling methods, time period of the data covered, data frequency, measures of tourism demand, omissions of variables, and other, related factors. The influences of some interaction factors are also considered. Those hypotheses will then be tested by the meta-analysis and logistic regressions reported in chapter six. The hypotheses provided in this section are mainly developed based on the past studies that reported the forecasting accuracy measures and demand elasticities and they are not driven by existing demand theories.

3.2 Origin Market

Under the influence of different economic conditions and cultural and customer habits, the income and price sensitivities of tourists from different origins may vary. Tourists from developed regions may view international tourism as less of a luxury than those from less-developed countries. Therefore, there tends to be more income elastic for international tourism among the latter group of tourists. Tourists from countries where international travel is common are likely to be less sensitive to income and price changes. Furthermore, tourists from countries with large geographic areas, tend to have more options for holidaying within their national boundaries, and may therefore be more sensitive to changes in the price of international tourism (Little, 1980).

The fluctuation in demand in the source market may also affect the performance of forecasting methods. It is much easier to forecast worldwide total tourism demand than to predict demand from a specific source market. For mature origin countries, which generate a more stable demand, the forecasting error is likely to be lower than for emerging markets which are more volatile.

H_{1a}: The estimated income elasticities of international tourism demand depend on the source market.

H_{1b}: The estimated own-price elasticities of international tourism demand depend on the source market.

H_{1c}:The forecasting accuracy of international tourism demand depends on the source market.

3.3 Destination

The characteristics of a tourism destination may influence its uniqueness and popularity as well as the estimated income and own-price elasticities of international tourism demand. According to demand theory, income elasticity will be lower for inferior destinations. Anastasopoulos (1984) points out that price elasticity will be lower for more unique destinations. For destinations with many substitutes and competitors, price competition tends to be intense and there is likely to be greater price elasticity associated with the tourists who visit them.

Destination may influence the performance of forecasting models in three possible ways. Firstly, forecasting international tourism demand for a mature tourism destination is usually easier than for a developing destination; secondly, accuracy may be higher for a unique destination than one with many potential substitutes; and thirdly, the social and political risks of a destination may influence demand, making it easier to produce forecasts for a stable area than for one affected by social or political conflict.

H_{2a}: The estimated income elasticities of international tourism demand depend on the destination involved.

H_{2b}: The estimated own-price elasticities of international tourism demand depend on the destination involved.

H_{2c}: The forecasting accuracy of international tourism demand depends on the destination involved.

3.4 Time Period

Tourists' income and the prices of tourism products change over time, as may the income and own-price elasticity of international tourism demand. Therefore, analyses conducted over different time periods could result in different estimates of these elasticities. During a period of economic prosperity, tourists are more likely to travel internationally and to be less sensitive to income and price changes. However, during a recession, personal wealth is reduced and income elasticity may increase. Price competition is also very common during periods of economic crisis, which may result in higher than normal own-price elasticity (Song & Lin, 2010).

The performance of forecasting models may also depend on the time period of the data collected. Forecasting errors may increase when the study was conducted over a period of fluctuating demand. Developments in forecasting techniques over different time periods could also influence the accuracy of predictions.

H_{3a}: The estimated income elasticities of international tourism demand depend on the time period of the data covered.

H_{3b}: The estimated own-price elasticities of international tourism demand depend on the time period of the data covered.

H_{3c}:The forecasting accuracy of international tourism demand depends on the time period of the data covered.

3.5 Modelling Method

In chapter two, current forecasting models were divided into five subgroups according to their complexity and temporal structure. Different models perform significantly differently across the published studies. In addition to their effect on forecasting accuracy, the structure and characteristics of different models also influence the estimates of demand elasticities. For example, traditional regression models assume that income and price elasticities are constant over the sample period, while the TVP techniques permit these parameters to be varied over time (Song & Wong, 2003). Therefore, whether or not the model specification provides for behavioural changes among tourists over time, the estimates of demand elasticities would be expected to change. Moreover, in the dynamic models, which include lagged dependent and independent variables, the effect of tourists' loyalty and WOM are considered. As a result, both long-run and short-run elasticities may be estimated, and the estimated demand elasticities may vary as a function of the modelling methods used. For example, Tellis' meta-analysis (1988) of econometric models in sales shows that the estimation method and function form of the model used may bias the estimated demand price elasticity.

H_{4a}: The estimated income elasticities of international tourism demand depend on the modelling methods.

H_{4b}: The estimated own-price elasticities of international tourism demand depend on the modelling methods.

H_{4c}:The forecasting accuracy of international tourism demand depends on the modelling methods.

3.6 Data Frequency

Annual data have been most frequently used in tourism demand modelling. In recent years, the use of monthly and quarterly data has been increasing as interest has grown in the analysis of seasonality. The use of different data frequencies in demand studies is evidence that researchers have different concerns in terms of the time-dependent response to demand elasticities. Therefore, estimates of elasticity may vary depending on data frequency. Crouch (1996) suggests that the estimated income elasticities will increase with data frequency, and that price elasticity will also vary as a function of time interval.

The tourism industry is strongly affected by seasonality. Compared to monthly and quarterly data, annual data is usually much smoother. It is also more difficult for an analyst to capture the seasonal patterns of tourism products. Therefore, monthly and quarterly demand will be more difficult to predict than annual data.

H_{5a}: The estimated income elasticities of international tourism demand depend on the data frequency employed.

H_{5b}: The estimated own-price elasticities of international tourism demand depend on the data frequency employed.

H_{5c}:The forecasting accuracy of international tourism demand depends on the data frequency employed.

3.7 Variables

Omission of variables**.** Econometrics studies (Gujarati, 2003; Hatekar, 2010) show that the omission of relevant variables in a regression model may bias the estimated coefficients of the others. The magnitude of such a bias will depend on the relationship between the omitted variable, the dependent variable, and the other remaining variables. Economic variables, such as income, own-price, substitute prices, exchange rates, and travel costs, are often collinear. Accordingly, estimates of income and own-price elasticities may be biased if the omitted variable is correlated with both international tourism demand and the income or own-price variable used (Crouch, 1992a).

H_{6a}: The omission of variables may bias the estimates of income elasticity of international tourism demand.

H_{6b}: The omission of variables may bias the estimates of own-price elasticity of international tourism demand.

Number of variables. The number of variables included in the model may influence the estimates of the demand elasticities for the same reason as explained above for omitted variables. Due to the collinearity problem, estimates of income and price elasticities may vary as a function of the number of variables included in the model.

In terms of forecasting, the inclusion of more and relevant variables would be helpful to explain the variation in demand and reduce forecasting errors. However, in *ex ante* forecasting, the explanatory variables must be predicted before forecasts of demand can be produced, and any errors in that process may be carried forward. Therefore, the inclusion of more explanatory variables may increase forecasting errors.

H_{7a}: The estimated income elasticities of international tourism demand depend on the number of variables included in the model.

H_{7b}: The estimated own-price elasticities of international tourism demand depend on the number of variables included in the model.

H_{7c}:The forecasting accuracy of international tourism demand depends on the number of variables included in the model.

Lag length of dependent variable. Different models deal with the lag effects between independent variables and the dependent variable in different ways in order to capture the effects of tourists' habit persistence. The lag length of the dependent variable is often determined by AIC or SIC. Since the lagged dependent variables in a forecasting model are likely to be correlated with the explanatory variables, the length of the lags may influence the estimates of demand elasticities. Keele and Kelly (2006) show that the inclusion of lagged dependent variables may affect the estimates of the coefficients of the other variables in the model. They conclude that if the demand process is dynamic, the OLS method with a lagged dependent variable gives better estimates than other approaches.

In terms of forecasting accuracy, the lag length of the demand model usually uncovers the loyalty of tourists to a destination. The longer the lagged dependent variables, the more likely it is that tourists are loyal. For such a destination, the tourism demand time series may be much smoother and easier to predict as a result.

H_{8a}: The estimated income elasticities of international tourism demand depend on the lag length of the dependent variable in the model.

H_{8b}: The estimated own-price elasticities of international tourism demand depend on the lag length of the dependent variable in the model.

H_{8c}:The forecasting accuracy of international tourism demand depends on the lag length of the dependent variable in the model.

3.8 Travel Distance

Travel costs account for a major part of expenditure on international tourism. Even with the advent of low-cost carriers, costs usually still increase with distance travelled. Therefore, long-haul tourism is usually relatively more expensive and has higher income elasticity than short-haul. Long-haul tourism has been considered as a luxury good, while short-haul tourism is, by comparison, regarded as a necessity. However, Anastasopoulos (1984) suggests that long-haul tourists tend to come from wealthy regions, and therefore may be less income sensitive. Turning to price elasticity, long-haul tourists are less sensitive to price changes than short-haul tourists, according to Crouch (1994b) and Brons et al. (2002). This may because of the unique features of such destinations and the lack of available substitutes.

In addition, as a luxury product, long-haul tourism is more sensitive to economic fluctuations. As a result, demand for long-haul will be more difficult to model and thus to predict accurately.

H_{9a}: The estimated income elasticities of international tourism demand depend on travel distance.

H_{9b}: The estimated own-price elasticities of international tourism demand depend on travel distance.

H_{9c}: The forecasting accuracy of international tourism demand depends on travel distance.

3.9 Measures of Variables

Measures of* t*ourism* d*emand. The meta-analysis performed by Crouch (1992a) identifies 28 different ways of measuring tourism demand, of which tourist arrivals and tourism expenditure are the two most commonly used. The response of different demand measures to price and income changes is likely to be different. With the development of international tourism, more and more people now consider it a habit. Therefore, instead of reducing the number of trips taken, tourists will tend to reduce their expenditure per trip as a response to reduced income due to recession, or to reduce their length of stay in response to price increases. That is to say, tourists are likely to be more income and price elastic when international tourism demand is measured in terms of expenditure or receipts than by other methods (Song et al., 2010).

Different measures of tourism demand may also influence the performance of the models. As discussed earlier, international tourism has become an important part of people's lives, and the number of trips taken is expected to remain relatively stable. However, the expenditure per trip is likely to reduce in response to financial and economic crisis, making it more difficult to model and forecast expenditure than arrivals.

H_{10a}: The estimated income elasticities of international tourism demand are higher when demand is measured by expenditure and receipts than by other means.

H_{10b}: The estimated own-price elasticities of international tourism demand are higher when demand is measured by expenditure and receipts than by other means.

H_{10c}: The forecasting accuracy of international tourism demand is lower when demand is measured by expenditure and receipts than by other means.

Some studies focus on modelling demand at the destination level, while others explore the demand elasticities of specific products such as business travel, VFR, or holiday tourism. Elasticities are expected to vary according to the level of aggregation of demand. Law and Au (2000) conclude that income and own-price elasticity vary significantly across products. Turner et al. (1995) find that the relative performance of the ARIMA and Winters models is affected by levels of aggregation. Vu and Turner (2005) also show that forecasts of tourist arrivals at the destination level are more accurate than those for disaggregated products.

H_{11a}: The estimated income elasticities of international tourism demand depend on the level of aggregation in international tourism demand measurement.

H_{11b}: The estimated own-price elasticities of international tourism demand depend on the level of aggregation in international tourism demand measurement.

H_{11c}:The forecasting accuracy of international tourism demand depends on the level of aggregation in international tourism demand measurement.

Measures of income variable. Income in the origin country is the variable most commonly used as a determinant of international tourism demand in previous studies. It can be expressed in either the aggregated or *per capita* form. Witt (1995) suggests that if demand for leisure travel or VFR is considered, personal disposable income is the preferred measure of the income variable. However, if the focus is on business travel, a more general income variable such as GDP or GNP should be used. The response of individual tourists to income changes tends to differ from that of tourists as a whole. Since individual income changes are usually greater than collective shifts, the individual response is more sensitive than the aggregated. If the income variable is in *per capita* form, the estimated income elasticity is likely to be higher than if aggregated income is used.

H_{12a}: The estimated income elasticities of international tourism demand are higher when the income variable is measured in a *per capita* form.

3.10 Other Issues

Year of publication. The year in which a piece of research is published may be viewed as representing a time trend in international tourism studies. With the growth in consumer income, international tourism has become more common worldwide, so income elasticity may have declined over time. With the development of the international tourism industry, more destinations are emerging and tourists have more channels than ever before through which to access information about them. As tourists have more choices and become more aware of the costs of travelling to and staying in destinations, the estimated price elasticities in more recent studies may be higher than found in the past. In addition, modelling techniques have improved in recent years, reducing forecasting errors over time.

H_{13a}: The estimated income elasticities of international tourism demand have a negative relationship with the year of publication of the study.

H_{13b}: The estimated own-price elasticities of international tourism demand have a positive relationship with the year of publication of the study.

H_{13c}:Forecasting errors of international tourism demand have a negative relationship with the year of publication of the study.

Sample size. Sample size has been shown to be correlated with the estimates of coefficients (Glass et al, 1981). Crouch (1992a) shows that estimated demand elasticities vary significantly across different sample sizes. Sample size may also affect forecasting accuracy. For example, Markham and Rakes (1998) find that the performance of ANNs for linear regression problems depends on sample size and noise level. A large sample is needed to build up a successful ANN model (Zhang, 2003).

H_{14a}: The estimated income elasticities of international tourism demand depend on the sample size.

H_{14b}: The estimated own-price elasticities of international tourism demand depend on the sample size.

H_{14c}:The forecasting accuracy of international tourism demand depends on the sample size.

***Long- or short-run effects*.** Tourists usually plan international travel several weeks or months ahead. Therefore, in the short term, their response to income and price changes may be constrained by existing travel arrangements. However, in the long run, they have time to adjust their behaviour and are likely to become more income and price elastic.

H_{15a}: The long-run estimated income elasticities of international tourism demand are higher than the short-term estimates.

H_{15b}: The long-run estimated price elasticities of international tourism demand are higher than short-term estimates.

3.11 Forecasting Horizon

The longer the forecasting horizon, the more uncertainties are involved in the analysis. Therefore, short-run forecasts are usually more accurate than long-run predictions.

H_{16c}: The forecasting accuracy of international tourism demand will decline with an increase in the forecasting horizon.

3.12 Interaction Effect

Besides the factors discussed above, estimates of international tourism demand elasticities and forecasting accuracy may also be influenced by the interactions between them (Crouch, 1994b). For example, the number of trips taken and expenditure of tourists from different countries of origin may produce different responses to income and price changes. The performance of forecasting models may differ when international tourism demand is measured using tourist arrivals or expenditure.

H_{1d}, H_{2d}, H_{3d},H_{4d},H_{5d},H_{6d},H_{7d}, H_{8d},H_{9d},H_{11d},H_{12d},H_{13d},H_{14d},H_{15d}:

The effects of source market, destination, time period of data covered, modelling method, data frequency, omission of variables, number of variables, lag length of dependent variable, travel distance, level of aggregation of demand measurement, form of income variable, year of publication, sample size, and estimation period on estimates of income elasticity vary across tourism demand measures.

H_{1e}, H_{2e}, H_{3e},H_{4e},H_{5e},H_{6e},H_{7e}, H_{8e},H_{9e},H_{11e},H_{13e},H_{14e},H_{15e}:

The effects of source market, destination, time period of data covered, modelling method, data frequency, omission of variables, number of variables, lag length of dependent variable, travel distance, level of aggregation of demand measurement, year of publication, sample size, and estimation period on estimates of price elasticity vary across tourism demand measures.

H_{1f}, H_{2f}, H_{3f},H_{4f},H_{5f},H_{7e}, H_{8e} ,H_{9e},H_{11e} ,H_{13e} ,H_{14e} ,H_{16e} :

The effects of source market, destination, time period of data covered, modelling method, data frequency, number of variables, lag length of dependent variable, travel distance, level of aggregation of demand measurement, year of publication, sample size, and forecasting horizon on forecasting accuracy vary across tourism demand measures.

3.13 Chapter Summary

This chapter has presented the hypotheses to be tested in this study. Based on the literature review in chapter two, a series of hypotheses have been developed to explore the effects of data characteristics and study features on the estimates of income and own-price elasticity and the forecasting accuracy of international tourism demand. The reasons for establishing the hypotheses are also provided.

Estimates of income and price elasticities are assumed to be influenced by source market, destination, modelling method, time period of data covered, data frequency, omission of variables, number of variables, lag length of dependent variable, travel distance, measure and aggregation level of tourism demand, year of publication, estimation period and the interactions between them. The estimations of income elasticities may also be influenced by the way the income variable is measured.

Forecasting accuracy is expected to vary by source market, destination, modelling method, time period of data covered, data frequency, number of variables, lag length of dependent variable, travel distance, measure and aggregation level of tourism demand, year of publication, forecasting horizon, and the interactions between them.

Chapter 4 - Methodology

4.1 Introduction

This study aims to summarise and analyse the empirical studies of tourism demand modelling and forecasting published over the past five decades. Meta-analysis techniques are applied to examine the relationships between the data characteristics, study features, and each of demand elasticity and forecasting accuracy.

Meta-analysis is a statistical method which combines the empirical results of published studies to test a set of related hypotheses. Compared to single studies, meta-analysis has the power to generate a true effect size through a comprehensive and systematic review of past studies. This improves the validity of the conclusions and is helpful in explaining variations across studies. The method was first applied in medical research to measure the treatment effect of specific medicines. Recently, some scholars have applied it to social science research; however, the application of meta-analysis in tourism demand analysis has so far been fairly limited (but see Crouch, 1992 a & b, 1995, 1996; Lim, 1997, 1999; Brons et al., 2002).

In this chapter, the main steps in meta-analysis are discussed, including problem formulation, literature searching, information gathering and evaluating, outcomes integration, and result interpretation. The weakness and limitations of this method are also addressed.

4.2 Steps in Meta-analysis

Formulating the problem. Formulating the research problem is the first task of each empirical study. As discussed in chapter three, the aim of this study is to explore the relationship between international tourism demand elasticities and forecasting accuracy, and various study features and data characteristics. Researchers are interested in whether the forecasting accuracy of different models and demand elasticities are consistent across different datasets. If they are, forecasting accuracy and demand elasticities could be estimated accurately to show that they are robust across a large number of published studies. However, if they are not consistent, the extent of variance and the predictor variables should be examined. The meta-analysis technique is superior to the narrative literature review approach in addressing these issues, as it provides a mathematically rigorous mechanism to combine the effects of different studies and evaluate the statistical significance of the summary effect (Borenstein, Hedges, Higgins, & Rothstein, 2009).

To achieve the objectives of the study, a clear and operational definition of the dependent and independent variables is essential. Tourism demand elasticities and the accuracy of forecasting models are the dependent variables. Since they are dimensionless, they can be easily compared across studies. Income elasticity and own-price elasticity are the main concerns of this study. Data characteristics and study features include origin countries/regions, destination countries/regions, travel distance, data frequency, measure of dependent and independent variables, sample size, the time period of data covered, forecasting horizon, lag length of dependent variables, number of independent variables in the demand model, and the interactions among the explanatory variables.

After examining these relationships, the next step is to match the forecasting methods with the related data characteristics and identify the best forecasting model for the specific datasets. This is followed by summarizing the own-price and income elasticities of tourism demand according to the various data characteristics.

Literature search and selection. A comprehensive and appropriate search of the literature is the first premise of the research synthesis and meta-analysis process. This literature search has two objectives. One is to identify all the previous studies related to the problem; the other is to ensure the research results pertain to the relevant target population. The replicability and soundness of a meta-analysis both depend heavily on whether the search for relevant studies is thorough, systematic, unbiased, transparent, and clearly documented (Cooper, Hedges, & Valentine, 2009).

White, Wilson, and Bates (1992) summarise five major categories of literature search modes; footnote chasing, consultation, subject index search, browsing, and citation search. The first two are popular with meta-analysts, but may be more affected by personal bias than the other three methods. In order to include as many studies as possible, this study uses a combination of citation search and footnote chasing to collect the data. In terms of the quality and acceptability of the articles, only published studies are included.

Citation search. This is a strategy for gathering articles which includes manual and computer searching of citation indexes, such as the Social Science Citation Index (SSCI) and Scopus. Google Scholar is now a widely accepted citation searching tool. It yields articles related to the topic that have relatively little overlap with those found by other means (Pao & Worthen, 1989), since the databases are usually multidisciplinary and vocabulary-independent.

Footnote chasing. This means using other authors' references, such as those found in review papers, books, nonreview papers from journals subscribed by or browsed through at the library, topical bibliographies compiled by others and related record search. Footnote chasing is an immediate way for researchers to obtain the primary studies on the research topic. Another reason why it is used here is that the footnotes of a substantive work are not unevaluated listings, but choices made using an author's critical judgment. However, one's own footnotes reflect personal biases as well as one's collection of books and journals. Authors doing footnote chasing tend to cite works compatible with their own biases, therefore reinforcing the homogeneity of their findings. Other methods are therefore required to identify unknown but relevant articles.

Google Scholar was first used to find articles containing at least one relevant search term such as "tourism demand," "tourism forecasting," and "tourism modelling" over the period of 1961-2011. This time period was selected for two reasons. Firstly, 1961 was the year the earliest known work in international tourism demand analysis was published (Guthrie, 1961). Secondly, the aim was to extend the sample size to include most if not all of the published studies on international tourism demand elasticity estimates and forecasting accuracy assessment, so that a more comprehensive meta-analysis could be carried out compared to previous studies. Google Scholar was selected as the search engine mainly for its comprehensive coverage of English-language articles in various disciplines and its reputation among academics. Following the primary website search, footnote chasing was also used to ensure the comprehensiveness of the article scan.

After identifying potential sources, some studies were rejected according to the following exclusion criteria: 1) the article did not report any income and own-price elasticities or forecasting accuracy measures; 2) the article was not written in English; 3) the article reported empirical results that have been included in other studies; and 4) the article was published after the completion of the meta-analysis, that is March 2012.

Coding the literature. After collecting the published studies on tourism modelling and forecasting, a coding protocol is needed to extract useful information from each article. This section outlines the procedures used to extract information from the published studies and gives guidelines on how to translate this narrative information into a structured and quantitative form for analysis. A well-designed coding protocol describes the characteristics of the studies and captures the relevant findings, which are then suitable for comparison and meta-analysis (Cooper et al., 2009). Report identification, study settings, participants and sample characteristics, methodology, dependent measures, and effect size data are the categories most often included in a coding protocol. However, specific items may vary across studies depending on their purpose. An important rule in developing a coding sheet for meta-analysis is that any relevant information that might be useful should be retrieved (Cooper, 2009). Since the quality of the meta-analysis depends largely on the coding, this part of the study is the most time-consuming (Crouch, 1996). A thorough reading of each article is needed to reveal all of the relevant empirical findings and the clues that explain them (Crouch, 1992b).

Report identification. The primary unit of analysis for any meta-analysis is an independent research study. In this study, the term refers to a single tourism demand and forecasting model, instead of the whole paper. The same model in the same article should not be recorded more than once. Therefore, the coding sheet has to capture basic information about the study, such as the author's name; title; source, page number (journal article, book, dissertation, or conference paper); and year of publication. Not only does this information identify a study, but it also improves the reliability and validity of the meta-analysis. The page numbers on which information is found are also included in the coding sheet. This makes it easy to locate where the codes come from, and also helps in testing the reliability of the records.

Effect size. This is a measure of the strength of the relationship between two variables in a population, or a sample-based estimate of that quantity. In a meta-analysis, the effect sizes should be comparable, substantively interpretable, computable, and have desirable properties, which means that their distribution should be known. This study aims to determine the relationship between elasticity (own-price or income), forecasting accuracy, and the data characteristics or features of the studies included. Therefore, the effect sizes to be extracted from the articles will refer to estimated price and income elasticity and the forecasting accuracy of different models. Since different studies may use different or mixed measures of accuracy, the value as well as the measure was coded.

Study settings. As discussed in chapters two and three, the forecasting performance and estimated demand elasticities of a given model may be different as a result of different settings across studies. Therefore, information on those settings also needs to be coded for further comparisons to be made. Regions of source markets, destinations, geographic distance between origin and destination country/region (short- or long-haul tourism), and tourism products were all coded to identify the characteristics of studies. The number of years of data covered was also included, as this is useful in explaining the diversity of price and income elasticities for the same product in the same location.

Methodology. The relevant methodological features include the basic research design, the nature of assignment to conditions, subjects, the sampling method, the nature of the control condition, and other changes to assignment (Cooper, 2009). In studies of tourism demand modelling and forecasting, the estimated price and income elasticities and the measures of forecasting accuracy often vary across methodologies. Coding items reflecting these features were therefore developed to assess the effects of variations in method on the results. The items to be coded included types of tourism demand analysis models, measures of tourism demand, data frequency, sample size, independent variables (number and title), and forecasting horizon.

An Excel database is created to record the information collected during the coding process. It is better to code directly into a computer database than to use paper forms, in order to enhance data entry accuracy and reduce the likelihood of data loss (Cooper et al., 2009).

Meta-Regression. In this study, the estimates of own-price and income elasticities and the forecasting accuracy of different models are the dependent variables, whereas the various data characteristics, study features, and modelling methods are regarded as independent variables which explain the variance in these estimations. The observations are divided into several categories based on the hypotheses formulated, and three multiple regressions specified to assess the effects of each category on the dependent variable. Regression analysis is used in this study to identify and evaluate the effects of the independent variables on the dependent ones. The single log-linear regression model suggested by Sargan (1964) is selected to analyse the data:

$$logY = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + C + \mu$$

where Y refers to income elasticity, own-price elasticity of international tourism demand, and international tourism demand forecasting accuracy, respectively; X_1 is a matrix of explanatory variables; X_2 represents the dummy variable for studies in which international tourism demand is measured by tourism expenditure or receipts; $X_1 X_2$ is a matrix of interactions among the explanatory variables; β is the parameter matrix to be estimated, which indicates the fractional change of Y in response to one unit change in

X;C is the intercept vector; and μ refers to the residual vector.

The explanatory variables for the regressions with income and own-price elasticities as dependent variables include continuous variables such as year of publication, number of variables included in the study, lag length of the dependent variables, sample size, and a set of dummy variables (taking the value of unity or zero). The dummy variables reflect the following parameters; source markets (set to 1 if the origin country in the study is in Europe, America, Australia, Asia, or Africa, otherwise 0); destination regions (set to 1 if the destination is in Europe, Americas, Australia, Asia, or Africa, otherwise 0); years of data covered (set to 1 if the study was done in the 1970s, 1980s, 1990s, or 2000s, otherwise 0); frequency of the data (set to 1 if the study used monthly or quarterly data, otherwise 0); type of model used (set to 1 if the study used the advanced time series, dynamic econometric, static econometric, dynamic econometric, or AI models, otherwise 0); travel distance (set to 1 if the study focuses on cross-continental tourism demand analysis, otherwise 0); omission of variables (set to 1 if the study excluded the income, own-price, substitute-price, exchange rate, or travel cost variable, otherwise 0); measurement of demand (set to 1 if demand is measured using tourist expenditure/receipts, otherwise 0); the level of aggregation of tourism demand (set to 1 if the study addresses disaggregated demand, otherwise 0); the measurement of income variable (set to 1 if measured using the *per capita* form, otherwise 0) and estimation period (set to 1 for a short- and 0 for a long-run estimates). In the regression on accuracy, the explanatory variables also included the length of forecasting horizon.

In the regression models without interaction effects, which assume $\beta_3 = 0$, β_1 and β_2 measure the effect of each individual variable on the estimates of international tourism demand elasticities and forecasting accuracy when other factors are held constant. When the interaction factors are included, $\beta_1^{'}$ represents the effect of each factor on the estimates of demand elasticities and forecasting accuracy only when demand is *not* measured using expenditure/receipts. $\beta_2^{'}$ measures the single effect of the studies in which demand *is* measured by tourism expenditure/receipts when all other variables are equal to zero. $\beta_3^{'}$ measures the impact difference of each individual variable between studies using expenditure/receipts and those using other forms of demand.

The meta-regression estimations follow the general-to-specific process (see the detailed explanation in Song & Witt, 2003), in which variables that are insignificant or contradict economic theory are removed until all the coefficients in the models are significantly different from zero and consistent with theoretical restrictions.

Integrating the research results. After testing the relationships between the price and income elasticities, the forecasting accuracy measures, and each of the data characteristics and study features, a further task was to generalise the elasticities at the product or origin/destination level, while at the same time pairing the models with different data characteristics and study features. To achieve this goal, it was necessary to integrate previous research results.

Since not many studies report the variance of the estimates, only a simple average for the elasticities is summarized. The mean elasticities and forecasting accuracies of different models for different data groups are also summarised. By ranking the average forecasting accuracy of each model, it is possible to select the most appropriate one for that specific dataset.

4.3 Chapter Summary

This chapter has introduced the meta-analysis technique and the steps involved. The regression analysis is proposed to test the hypotheses in chapter three. After examining the factors influencing forecasting accuracy and demand elasticities estimation of international tourism, the process of summarizing the results of the past empirical studies has been discussed. The simple average method is proposed to integrate the results of the study.

Chapter 5 - Data Description

5.1 Introduction

A comprehensive search of the literature generated 702 articles on international tourism demand elasticities and forecasting. Based on the selection criteria set out in chapter four, 8267 figures were coded, of which 2836 referred to demand elasticity estimates and 5431 to measures of forecasting accuracy.

In the past studies, forecasting accuracy measures such as MAPE (47.6%), Thiel's U (16.0%), RMSE (16%), and RMSPE (11.3%) have been most commonly used. However, RMSE is not a dimensionless measure and so cannot be compared across studies. Although Thiel's U is dimensionless, there are several different methods to calculate it, which makes it difficult to compare the Thiel's U statistics reported in different studies. Therefore, for reasons of comparability, only MAPE and RMSPE are included in the meta-regression analysis.

Table 5.1 Summary of the data

	publish year	Articles	Estimates
Income elasticity	1961-2011	190	1,633
Price elasticity	1972-2011	161	1,200
MAPE	1980-2011	65	2,584
RMSPE	1989-2011	15	614

Finally, a total of 6034 estimates from 262 articles were used, of which 1633 are income elasticity estimates, 1200 own-price elasticity estimates, 2584 MAPEs, and 614 RMSPEs (see Table 5.1). Details of the studies are given in appendices A-D.

5.2 International Tourism Demand Elasticities

As discussed above, data characteristics and study features, such as origin and destination countries, demand measurement, data frequency, data coverage, travel distance, types of models, and different tourism products, may influence estimates of international tourism demand elasticities. Before testing the hypotheses, the objectives of previous studies are summarised in this section and the number and proportion of estimates for each subgroup discussed above calculated (see Tables 5.2 and 5.3).

European countries are the most frequently studied source markets of international tourism. In total, 695 estimates (42.6%) of income elasticities and 495 (41.1%) of price elasticities were related to European tourists. Limited effort has so far been made to analyse international tourism demand in Africa. Only 7 studies (12 estimates) analysed the income elasticities of African tourists, with 5 studies (11 estimates) reporting on price elasticities in this region. Most of these studies focused on intra-regional tourism and all on tourists from richer African countries like South Africa. Estimates in which the author did not clearly state the original countries are categorised as “not specified.”

The most studied destination regions are Asia and Europe. Estimates of the income elasticity of tourists travelling to Asia and Europe account for 593 (36.3%) and 472 (28.9%), respectively. Own-price elasticity estimates for Asia and European destinations account for 373 (31.0%) and 368 (30.6%).

Econometrics models dominate international tourism demand analysis. Only 8 studies (52 estimates) used advanced time series models to analyse the income elasticity of international tourism demand and 6 studies (15 estimates) own-price elasticity. Dynamic and static econometric models share the remaining studies equally, with static econometric models dominating the pre-1995 literature and dynamic models developing very quickly after that. The ADLM is the most commonly used dynamic econometric model (293 income and 252 price elasticities estimates), with the CI and ECM approaches ranking second and third. VAR and TVP techniques are two emerging forecasting methods, which have not yet been widely applied.

In terms of data frequency, 1123 (68.8%) and 846 (70.3%) estimates used yearly data to analyse income and price elasticities, respectively. Yearly data was particularly common in studies conducted before 2000.

A large amount of studies analysed international tourists’ behaviour at the destination level (76.1% for income and 67.2% for price elasticity). At the product level, accommodation, transportation, holiday tourism, and VFR tourism are the most frequently-discussed topics.

Tourist arrivals and expenditure, and their *per capita* forms, are the most commonly used tourism demand measures. Studies using the first of these as the measure of international tourism demand accounted for 64.9% and 67% of all estimates of income and price elasticities estimates. The second most popular demand measure is tourism expenditure, with 349 (21.4%) and 230 (19.1%) estimates of income and price elasticities related to this parameter.

Where origins and destinations are concerned, these studies can be separated into two groups; cross-continent and inner-continent tourism demand analysis. Studies in which the origins or destinations cannot be clearly identified are classified as “other.” Cross-continental tourism is usually considered long- and inner-continent tourism as short-haul tourism. As shown in Table 5.3, there were more studies on the former.

Table 5.2

Estimates of Income Elasticity of International Tourism Demand

Data Category	Subgroup	No.	Prop.
Origin	Africa	12	0.007
	America	306	0.187
	Asia	270	0.165
	Australia	113	0.069
	Europe	695	0.426
	Not Specified	237	0.145
Destination	Africa	57	0.035
	America	205	0.126
	Asia	593	0.363
	Australia	238	0.146
	Europe	472	0.289
	Overseas	68	0.042
Model	Advanced Time-series	52	0.032
	Dynamic Econometrics	737	0.451
	Static Econometrics	844	0.517
Data	Monthly	154	0.094
	Quarterly	356	0.218
	Yearly	1123	0.688
Product	Accommodation	75	0.046
	Holiday	98	0.060
	Transportation	83	0.051
	VFR	52	0.032
	Business	17	0.010
	Destination	1242	0.761
	Others	66	0.040
Demand	Arrival	1060	0.649
	Arrival/POP	179	0.110
	Expenditure	349	0.214
	Expenditure /POP	45	0.028
Travel	Cross-continent	739	0.453
	Inner-continent	606	0.371
	others	288	0.176
Total		1633	

Table 5.3

Estimates of Price Elasticity of International Tourism Demand

Data Category	Subgroup	No.	Prop.
Origin	Africa	11	0.009
	America	241	0.200
	Asia	207	0.172
	Australia	84	0.070
	Europe	495	0.411
	Not Specified	165	0.137
Destination	Africa	52	0.043
	America	144	0.120
	Asia	373	0.310
	Australia	210	0.175
	Europe	368	0.306
	Overseas	56	0.047
Model	Advanced Time-series	15	0.012
	Dynamic Econometrics	630	0.524
	Static Econometrics	558	0.464
Data Frequency	Monthly	99	0.082
	Quarterly	258	0.214
	Yearly	846	0.703
Product	Accommodation	92	0.076
	Holiday	105	0.087
	Transportation	108	0.090
	VFR	33	0.027
	Business	9	0.007
	Destination	808	0.672
	Others	48	0.040
Demand Measure	Arrival	806	0.670
	Arrival/POP	122	0.101
	Expenditure	230	0.191
	Expenditure /POP	45	0.037
Travel Distance	Cross-continent	544	0.452
	Inner-continent	455	0.378
	Others	204	0.170
Total		1200	

5.3 International Tourism Demand Forecasting Accuracy

As an important area of tourism research, international tourism forecasting has attracted significant attention from researchers, especially since 1995. Improving forecasting performance by searching for the best models has been the main focus of studies in recent decades. Advanced time series models are the most popular methods used. Among the 65 articles which use MAPE to evaluate forecasting accuracy, 47 (1471 estimates, 56.9%) used such methods (see Tables 5.4 and 5.5). AI and dynamic econometrics models are the two currently emerging techniques in tourism forecasting, having developed very quickly in recent years.

According to the statistics, most previous studies have focused on forecasting international tourist arrivals (2374 MAPEs and 488 RMSPEs). In recent years, quarterly international tourism demand has been most studied due to its relevance to decision makers. In addition, the forecasting accuracy of quarterly demand models has been lower than that of annual demand models.

In terms of source markets, Asian and European countries are the two most frequently forecast. In particular, 24.8% (642) of forecasts are for Asian and 33.0% (853) forecasts are for European countries (both using MAPE). Meanwhile, Asia and Europe are the two markets that are most difficult to forecast due to high volatilities in demand. Asia is also the most popular destination in previous forecasting studies (45.7% of reported MAPEs and 30.3% of RMSPEs).

The tourism products studied are diverse. The overall demand for a specific destination is the main focus, accounting for 66.7% of the forecasts (MAPE). Among those disaggregated products, forecasts of business (11.9%) and leisure (13.6%) travel have attracted the most attention. Only 2 studies (8 estimates) forecast demand for hotel rooms. Since studies at the product level are very limited, the RMSPE measures are not reported in this study.

5.4 Chapter Summary

A total of 8267 figures were selected based on the criteria discussed in the methodology chapter, of which 2836 estimates covered the demand elasticity of international tourism and 5431 pertained to forecasting accuracy measures. The chapter has provided information about the studies included, and summarised the details of the focus and trends in the data.

Table 5.4

Estimates of MAPE of International Tourism Demand

Data	Subgroups	No.	Prop.
Model	Artificial	264	0.102
	Advanced Time-series	1471	0.569
	Dynamic Econometrics	223	0.086
	Naïve	481	0.186
	Static Econometrics	145	0.056
Demand	Arrival	2371	0.918
	Arrival/POP	3	0.001
	Expenditure	111	0.043
	Expenditure /POP	99	0.038
Data	Monthly	534	0.207
	Quarterly	1618	0.626
	Yearly	408	0.158
Origin	Africa	14	0.005
	America	313	0.121
	Asia	642	0.248
	Australia	210	0.081
	Europe	853	0.330
	Not Specified	552	0.214
Destination	Africa	14	0.005
	America	106	0.041
	Asia	1181	0.457
	Australia	612	0.237
	Europe	480	0.186
	Not Specified	191	0.074
Product	Accommodation	8	0.003
	Business	307	0.119
	Holiday	351	0.136
	VFR	123	0.048
	Transportation	27	0.010
	Destination	1722	0.666
	Others	46	0.018
Travel	Cross-continent	996	0.385
	Inner-continent	839	0.325
	Others	749	0.271
Total		2584	

Table 5.5

Estimates of RMSPE of International Tourism Demand

Data Categories	Subgroups	No.	Prop.
Model	Artificial	32	0.052
	Advanced Time-series	248	0.404
	Dynamic Econometrics	147	0.239
	Naïve	150	0.244
	Static Econometrics	37	0.060
Demand Measure	Arrival	488	0.795
	Expenditure	126	0.205
Data Frequency	Monthly	119	0.194
	Quarterly	234	0.381
	Yearly	261	0.425
Origin	America	96	0.156
	Asia	157	0.256
	Australia	55	0.090
	Europe	255	0.415
	Not Specified	51	0.083
Destination	America	44	0.072
	Asia	186	0.303
	Australia	96	0.156
	Europe	124	0.202
	Not Specified	164	0.267
Travel Distance	Cross-continent	174	0.283
	Inner-continent	226	0.368
	Others	214	0.349
Total		614	

Chapter 6 -Results of Meta-Regression

6.1 Introduction

In this chapter, the meta-regression models are estimated with a view to testing the hypotheses developed in chapter five (see Tables 6.1, 6.2, 6.5, and 6.6). The estimation results of the meta-regression are also interpreted and discussed (see Tables 6.3, 6.5, and 6.7).

The meta-regressions were estimated in two steps. In the first step, only the single variables without interactions were included. In the second, interaction factors were added to distinguish the effects of data characteristics and study features on the estimated demand elasticities and forecasting accuracy of international tourism expenditure from other forms of demand measures. The category selected as a comparator within each subgroup is marked as the benchmark in the tables reporting that set of regression results.

6.2 Meta-Regression for International Tourism Demand Elasticities

Tables 6.1 and 6.2 show the coefficients of the meta-regressions related to the income and own-price elasticities of international tourism demand, with and without interaction variables. The adjusted R^2 value shows that the meta-regression models are successful in explaining 25.2% of the variation in estimated income elasticities and 21.3% in the estimated own-price elasticities. Given the nature of the dataset, these goodness-of-fit measures are considered to be reasonable.

***Origin and destination*.** The results of the regression analyses support the hypotheses that estimated income and own-price elasticities of international tourism demand depend on origins and destinations. They show that tourists from Europe tend to have significantly higher income elasticities than those from other source markets. One possible reason is that European tourists prefer to travel within Europe, where tourism products are usually viewed as luxury goods. Asian, Australasian, and African countries as tourism destinations have negative effects on estimates of the income elasticity, which means that people who choose these countries tend to have lower income elasticities compared with those who choose American and European destinations. This indicates that in the eyes of tourists, international tourism in Asia, Australasia, and Africa is less luxurious than travelling to Europe and America.

Compared to those from other origins, tourists from Asia and America are more sensitive to price changes in tourism products. Meanwhile, Asian, American, and European destinations all have positive effects on the value of own-price elasticity. This confirms that for destinations with more substitutes or competitors, tourists tend to have higher price elasticities (Little, 1980).

Time period. The estimated coefficients associated with the dummy variables accounting for the time periods of the data coverage all have a significant influence on estimates of income elasticities. The different signs and values of the coefficients show that the elasticities have varied considerable over the past 50 years. This may be due to fluctuations in worldwide economic activity and changes in people's expectations of their future income and job situation (Smeral, 2012). This finding also indicates that the assumption of constant income elasticities in studies of tourism demand modelling may increase estimation error. However, only the dummy variable for the 1980s is significant in the regression model of price elasticity estimates, which indicates that this parameter has not changed much in recent decades. The price elasticity in the 1980s is significantly higher than at other times, which may be due to the oil crisis at the end of the 1970s (Martin & Witt, 1987; Lim & McAleer, 2002a; Song et al., 2003c). These results confirmed that the estimated income and price own-elasticities of international tourism demand depend on the time period of data covered.

Modelling method. The results of the meta-regressions show that the estimated income elasticities of international tourism demand depend on the modelling methods used. Compared to other methods, the dynamic econometric models tend to overestimate income elasticity, while own-price elasticity seems to be constant across different approaches. However, when interaction factors are considered, it can be seen that if international tourism demand is not measured by expenditure/receipts, the dynamic modelling methods (including the advanced time series and dynamic econometrics models) tend to generate lower price elasticities than the static ones. This suggests that the complexity and temporal structure of the model will influence the elasticity estimates it produces.

Data frequency. Monthly data has a significant positive effect on estimates of the income elasticity. In other words, the income elasticity of tourism demand generated using monthly data is higher than that generated from quarterly and yearly data. This indicates that the estimated income elasticities depend on data frequency. However, this is not the case for price elasticity. Only when interactions are considered does monthly data have a significant effect on the estimates of own-price elasticity of international tourism demand.

Variables. The regression results suggest that omission of the substitute-price variable in the demand model would have a negative impact, and omission of the exchange rate variable a positive influence, on the estimates of the income elasticity. For price elasticity, the omission of the income variable would have a positive influence, and the omission of the substitute price and travel cost variables a negative impact. These findings support the hypotheses that omission of variables may influence estimates of income and own-price elasticities, which is consistent with the past findings that the omission of relevant variables in a regression model may bias the estimated coefficients of the other variables.

The number of variables included in the regression model has a negative influence on the estimates of income elasticity, but no significant effect on price elasticity. The regression results also show that the lag length of the dependent variables included in the models is likely to have a positive effect on estimates of the own-price elasticity. This is to say that the more lags of the dependent variable included in the model, the higher the price elasticity which results. However, the hypothesis that the lag length of the dependent variable in the model would influence estimated income elasticities is not supported by these results.

Travel distance. The regression results confirm that the income elasticity of cross-continental tourism is significantly higher than that for within-continent tourism, which means long-haul travellers are more income sensitive than short-haul. This is consistent with the economic theory which usually considers long-haul tourism as a luxury product and short-haul tourism a necessity. The results also show that the price elasticity of international tourism does not vary significantly with travel distance.

Measures of variables. Somewhat unexpectedly, the meta-regression results show that tourist expenditure/receipts as a measure of international demand has a significant negative effect on estimates of income elasticity. A possible explanation is that more than half of the studies analyzing tourism expenditure were conducted using static econometric models, which tend to under-estimate the income elasticities. However, the finding on price elasticity confirms that tourists' expenditure is more price elastic than other forms of demand, which supports the hypotheses.

According to the regression results, income elasticity is not greatly affected by whether demand for the whole destination or for specific products is considered. However, when considering the disaggregated international tourism demand for specific products, the means of price elasticities are significantly lower than that for the destination as a whole. This may because tourists have many potential substitutes when they choose a destination but may be loyal to specific products, such as airplane travel and luxury hotels. Another possible reason is that the articles studying disaggregated tourism products focus primarily on accommodation and transportation, which are necessary to most tourists.

In chapter five, it was assumed that the estimated income elasticity of international tourism demand will be higher when the income variable is measured *per capita*. The result of the regression model without interactions does not support this hypothesis. When the interaction variables are included, *per capita* income has a significant positive effect on the estimates of income elasticity when not measured by expenditure/receipts. However, the effect is different when measured by expenditure only.

Other factors. The dummy variable for the short-run estimates shows that international tourists are less sensitive to income and price changes in the short- than the long-run, which may be due to the fact that people need more time to change their behaviour in response to income and price changes. At the same time, the coefficient for the year of publication is significant negative, implying that in general, international tourists' sensitivity to income has been gradually declining over the past 50 years. However, this is not the case for price sensitivity. Sample size also has a significant influence on the estimates of income and price elasticity of international tourism demand. However, the magnitude of the coefficients suggests that the effect is very limited.

Interaction factors. The results of the meta-regression analyses with interactions support the hypotheses that the effects of the data characteristics and study features on the estimated income and own-price elasticities vary across different measures of international tourism demand. For example, when monthly data were used, lower income elasticity is generated when tourism demand is measured by expenditure/receipts than when other measures are used. If the income variable is employed in *per capita* form, the estimates of income elasticity measured by expenditure/receipts are also significantly lower than when demand is measured by tourist arrivals or length of stay. The short-run income elasticity measured by tourist expenditure tends to be larger than that obtained using other measures. This indicates that tourists are quicker to adjust their expenditure than the number of trips they take. However, not all the coefficients of interactions are significant. The effects of travel distance, sample size, modelling methods, and lag length of dependent variable have no significant different effect on the estimates of income and price elasticities across different demand measures.

Table 6.1Meta-regression for tourism demand elasticity without interactions

	log(Income Elasticity)	**t-value**	**Prob.**	**log(-Price Elasticity)**	**t-value**	**Prob.**
constant	69.211	6.916	0.00	-0.550	-5.540	0.00
Origin Region						
Asia				0.152	1.727	0.08
America				0.141	1.795	0.07
Europe	0.321	5.922	0.00			
Australia						
Africa						
not specified	drop			drop		
Destination Region						
Asia	-0.198	-2.722	0.00	0.346	3.953	0.00
America				0.312	2.952	0.00
Europe				0.375	4.522	0.00
Australia	-0.164	-1.807				
Africa	-0.454	-3.139	0.00			
not specified	benchmark			benchmark		
Time Period						
1960s and before	benchmark			benchmark		
1970s	-0.189	-2.511	0.00			
1980s	0.295	4.080	0.00	0.119	1.782	0.08
1990s	0.444	4.747	0.00			
2000s	0.330	3.438	0.00			

	log(Income Elasticity)	t-value	Prob.	log(-Price Elasticity)	t-value	Prob.
Model						
advanced time-series						
dynamic econometrics	0.132	2.105	0.00			
static econometrics	benchmark			benchmark		
Data Frequency						
monthly	0.978	9.134	0.00			
quarterly						
annually	benchmark			benchmark		
Omission of Variable						
income				0.257	1.965	0.05
own-price						
substitute-price	-0.328	-5.467	0.00	-0.133	-1.739	0.08
exchange rate	0.248	4.059	0.00			
travel cost				-0.228	-3.242	0.00
Travel Distance						
cross-continent	0.230	3.803	0.00			
inner-continent or not specified	benchmark			benchmark		
Demand and Variable Measure						
demand measured by expenditure	-0.182	-2.938	0.00	0.451	6.022	0.00
demand measured by others	benchmark			benchmark		
tourism demand at product level				-0.257	-3.589	0.00
tourism demand at destination level	benchmark			benchmark		
income measured by per capita form						
income measured by aggregated form	benchmark			benchmark		
Other Factors						
short-run estimate	-0.321	-3.416	0.00	-0.47	-4.9	0.00
long-run estimate	benchmark			benchmark		
sample size	-1.29E-05	-2.659	0.00	-3.03E-05	-5.951	0.00
No. of Variables	-0.02	-2.292				
lag length of dependent variable				0.12	4.068	0.00
publication year	-0.035	-6.879	0.00			
Adjusted R^2	**0.230**		**0.00**	**0.147**		0.00

Table 6.2Meta-regression for tourism demand elasticity with interactions

	log(Income Elasticity)	t-value	Prob.	log(-Price Elasticity)	t-value	Prob.
Constant	54.194	5.322	0.00	-1.144	-9.498	0.00
Origin Region						
Asia				0.187	2.099	0.04
America				0.384	4.444	0.00
Europe	0.331	6.020	0.00			
Australia				0.226	1.723	0.09
Africa	-0.565	-1.962	0.05			
not specified	benchmark			benchmark		
Destination Region						
Asia	-0.221	-2.970	0.00	0.487	5.702	0.00
America						
Europe				0.473	4.956	0.00
Australia	-0.215	-2.290	0.02			
Africa	-0.454	-3.041	0.00			
not specified	benchmark			benchmark		
Time Period						
1960s and before	benchmark			benchmark		
1970s	-0.200	-2.674	0.01			
1980s	0.406	5.404	0.00	0.549	6.145	0.00
1990s	0.412	4.395	0.00			
2000s	0.287	2.968	0.00	0.372	4.228	0.00
Model						
advanced time-series				-1.023	-3.725	0.00
dynamic econometrics	0.133	2.119	0.03	-0.138	-1.785	0.07
static econometrics	benchmark			benchmark		
Data Frequency						
monthly	1.208	10.861	0.00	0.421	2.949	0.00
quarterly						
annually	benchmark			benchmark		
Omission of Variable						
income				0.424	3.317	0.00
own-price						
substitute-price	-0.272	-4.464	0.00			
exchange rate	0.267	2.968	0.00			
travel cost				-0.328	-4.665	0.00
Travel Distance						
cross-continent	0.274	4.464	0.00			
inner-continent or not specified	benchmark			benchmark		

	log(Income Elasticity)	t-value	Prob.	log(-Price Elasticity)	t-value	Prob.
Demand and variable measure						
demand measured by expenditure				2.442	6.248	0.00
demand measured by others	benchmark			benchmark		
tourism demand at product level						
tourism demand at destination level	benchmark			benchmark		
income measured by per capita form	0.147	2.361	0.02			
income measured by aggregated form	benchmark			benchmark		
Other Factors						
short-run estimate	-0.278	-2.912	0.00			
long-run estimate	benchmark			benchmark		
sample size	-1.38E-05	-2.860	0.00	-2.81E-05	-5.714	0.00
No. of Variables	-0.015	-1.671	0.09			
lag length of dependent variable				0.094	2.679	0.01
publication year	-0.027	-5.324	0.00			
Interact Factors						
Demand measured by expenditure together with						
Origin Region						
Asia						
America				-0.603	-3.532	0.00
Europe						
Australia				-0.540	-1.758	0.08
Africa						
Destination Region						
Asia	0.387	2.444	0.01	-1.237	-3.801	0.00
America				-0.861	-2.624	0.01
Europe				-1.504	-5.235	0.00
Australia				-1.293	-4.010	0.00
Africa						
Time Period						
1970s				-0.333	-1.864	0.06
1980s	-0.436	-3.698	0.00	-0.407	2.137	0.03
1990s						
2000s				-0.833	-4.481	0.00
Model						
advanced time-series						
dynamic econometrics						
Data Frequency						
monthly	-1.248	-2.515	0.01			
quarterly						

	log(Income Elasticity)	t-value	Prob.	log(-Price Elasticity)	t-value	Prob.
Omission of Variable						
income						
own-price						
substitute-price						
exchange rate	-0.363	-3.145	0.00			
travel cost						
Travel Distance						
cross-continent						
Demand and Variable Measure						
income measured by per capita form	-0.476	-5.178	0.00			
tourism demand at product level				-0.597	-2.981	0.00
Other Factors						
short-run estimates	0.541	3.140	0.00			
sample size						
No. of Variables	-0.087	-3.285	0.00	0.120	3.791	0.00
lag length of dependent variables						
publication year	0.0004	4.933	0.00			
Adjusted R^2	**0.252**		**0.00**	**0.213**		**0.00**

Table 6.3 Verification of Hypotheses for Income Elasticity

	Hypothesis	Supported?
1a:	The estimated income elasticities of international tourism demand depend on source markets	yes
2a:	The estimated income elasticities of international tourism demand depend on destinations	yes
3a:	The estimated income elasticities of international tourism demand depend on time period of the data covered	yes
4a:	The estimated income elasticities of international tourism demand depend on the modelling methods	yes
5a:	The estimated income elasticities of international tourism demand depend on the data frequency employed	yes
6a:	Omission of variables will produce bias on the estimates of income elasticities of tourism demand	yes
7a:	The estimated income elasticities of international tourism demand depend on number of variables included in the model	yes
8a:	The estimated income elasticities of international tourism demand depend on the lag length of dependent variable in the model	no
9a:	The estimated income elasticities of international tourism demand depend on travel distance	yes
10a:	The estimated income elasticities of international tourism demand are higher when demand is measured by expenditure and receipts than measured by other form	no
11a:	The estimated income elasticities of international tourism demand depend on level of aggregation in international tourism demand measurement	no
12a:	The estimated income elasticities of international tourism demand are higher when income variable is measured by per capita form	yes
13a:	The estimated income elasticities of international tourism demand has a negative relationship with the publication year of the study	yes
14a:	The estimated income elasticities of international tourism demand depend on the sample size	yes
15a:	Long-run Estimated income elasticities of international tourism demand are higher than short-run estimates	yes
1d:	Effect of source markets on the estimated income elasticites of international tourism demand varies cross tourism demand measures	no
2d:	Effect of destinations on the estimated income elasticities of international tourism demand varies cross tourism demand measures	yes
3d:	Effect of the time period of data covered on the estimated income elasticities of international tourism demand varies cross tourism demand measures	yes
4d:	Effect of the modelling methods on the estimated income elasticities of international tourism demand varies cross tourism demand measures	no
5d:	Effect of data frequency employed on the estimated income elasticities of international tourism demand varies cross tourism demand measures	yes
6d:	Effect of omission of variables on the estimated income elasticities of international tourism demand varies cross tourism demand measures	yes
7d:	Effect of number of variables on the estimated income elasticities of international tourism demand varies cross tourism demand measures	yes
8d:	Effect of the lag length of dependent variable on the estimated income elasticities of international tourism demand varies cross tourism demand measures	no
9d:	Effect of travel distance on the estimated income elasticities of international tourism demand varies cross tourism demand measures	no
11d:	Effect of the level of aggregation of tourism demand measurement on the estimated income elasticities of international tourism demand varies cross tourism demand measures	no
12d:	Effect of income variable measured by per capita form on the estimated income elasticities of international tourism demand varies cross tourism demand measures	yes
13d:	Effect of the publication year of the study on the estimated income elasticities of international tourism demand varies cross tourism demand measures	yes
14d:	Effect of the sample size on the estimated income elasticities of international tourism demand varies cross tourism demand measures	no
15d:	Effect of the estimation period on the estimated income elasticities of international tourism demand varies cross tourism demand measures	yes

Table 6.4 Verification of Hypotheses for Own-price Elasticity

	Hypothesis	Supported?
1b:	The estimated own-price elasticities of international tourism demand depend on source markets	yes
2b:	The estimated own-price elasticities of international tourism demand depend on destinations	yes
3b:	The estimated own-price elasticities of international tourism demand depend on the time period of data covered	yes
4b:	The estimated own-price elasticities of international tourism demand depend on the modelling methods	no
5b:	The estimated own-price elasticities of international tourism demand depend on the data frequency employed	no
6b:	Omission of variables will produce bias on estimates of own-price elasticities of international tourism demand	yes
7b:	The estimated own-price elasticities of international tourism demand depend on number of variables included in the model	no
8b:	The estimated own-price elasticities of international tourism demand depend on the lag length of dependent variable in the model	yes
9b:	The estimated own-price elasticities of international tourism demand depend on travel distance	no
10b:	The estimated own-price elasticities of international tourism demand is higher when demand is measured by expenditure and receipts than measured by others	yes
11b:	The estimated own-price elasticities of international tourism demand depend on the level of aggregation of international tourism demand measurement	no
13b:	The estimated own-price elasticities of international tourism demand have a positive relationship with the publication year of the study	no
14b:	The estimated own-price elasticities of international tourism demand depend on the sample size	yes
15b:	Long-run Estimated price elasticities of international tourism demand are higher than short-run estimates	yes
1e:	Effect of source markets on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	yes
2e:	Effect of destinations on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	yes
3e:	Effect of the time period of data covered on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	yes
4e:	Effect of the modelling methods on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	no
5e:	Effect of data frequency employed on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	no
6e:	Effect of omission of variables on the estimated own-price elasticity of international tourism demand varies cross tourism demand measures	no
7e:	Effect of number of variables on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	yes
8e:	Effect of the lag length of dependent variable on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	no
9e:	Effect of travel distance on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	no
11e:	Effect of the level of aggregation of international tourism demand measurement on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	yes
13e:	Effect of the publication year of the study on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	no
14e:	Effect of the sample size on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	no
15e:	Effect of the estimation period on the estimated own-price elasticities of international tourism demand varies cross tourism demand measures	no

6.3 Forecasting Accuracy of International Tourism Demand

Tables 6.5 and 6.6 show the estimated coefficients of the meta-regressions (with MAPE and RMSPE the dependent variables) for international tourism demand forecasting with and without interaction variables. The adjusted R^2 values show that the meta-regression models are successful in explaining 33.9% of the variation in MAPE and 82.0% in RMSPE. Since the number of studies using RMSPE (15 studies, 614 estimates) is much lower than those reporting MAPE (65 studies, 2584 estimates), the meta-regression for RMSPE should be viewed as a supplement to the MAPE regression.

***Origin and destination*.** The regression results show that forecasting international tourism demand for a specific region is more difficult than predicting aggregated demand. The different magnitudes of the coefficients indicate different levels of difficulty in forecasting demand for different continents, which supports the hypothesis that forecasting accuracy depends on the source market. For mature markets such as North America (with most previous studies focusing on the US and Canada), where demand is relatively stable, the forecasting errors are lower than those for other source markets. The meta-regression results also show that forecasting accuracy depends on the destination. For African destinations, where international tourism development is just at the initial stage, the amount of inbound tourists is very small, which may make the forecasting easier. The forecasting errors for European countries are significantly higher than for others, perhaps because there are many countries in Europe which can substitute for each other. Moreover, tourism prices in Europe are very high, which may increase fluctuation in demand in an economic crisis. The results for Asian destinations are mixed, which reflects the complexity of the Asian tourism markets. There are also many destinations within Asia, which have been developed in different stages. For a developed tourist country such as Singapore and South Korea, international tourism demand is stable and relatively easier to predict. However, for the countries where the industry is rapidly developing, like China, inbound tourism demand changes considerable each year, which may also increase the forecasting error.

Time period. The dummy variables for the decades of data covered all have a significant influence on forecasting accuracy, indicating that this depends on the time period of the data used. In the 1970s and 1980s, international tourism was just emerging, so the amount of international tourists may have been small and the choice of destinations limited, making demand easier to predict. With the rapid development of the international tourism industry in the 1990s, the resulting boom would increase the forecasting difficulty. Moreover, there were several economic and social crises in the 1990s, such as the Southeast Asian financial crisis (Law, 2001), which may have resulted in greater fluctuation in demand. Then, in the 2000s, the improvement of modelling techniques may have once again decreased overall forecasting errors.

Forecasting method. The regression results show that the forecasting accuracies of different models vary significantly. Compared to the static modelling method, the dynamic econometric, advanced time series, and AI models produce more accurate forecasts. Among them, the dynamic econometrics model is the most precise technique.

Data frequency. The results of the meta-regression also support the hypothesis that forecasting accuracy depends on data frequency. Monthly and quarterly data have significant positive effects on MAPE; that is to say, it is more difficult to forecast monthly and quarterly than annual demand. This may be due to the strong seasonality of international tourism, with monthly and quarterly demand fluctuations much stronger than the annual.

Travel distance. The results confirm that forecasting errors in cross-continental demand are significantly higher than for inner-continent tourism, indicating that it is more difficult to forecast long- than short-haul demand. This finding is consistent with predictions, since long-haul tourism is usually considered a luxury product, the demand for which will therefore fluctuate more than for necessities.

Tourism demand measure. Contrary to expectation, no significant difference in forecasting difficulty across different measures was found. However, the regression results show it is easier to forecast demand for a whole destination than for specific products, supporting the hypothesis that forecasting accuracy varies according to the level of aggregation.

Other factors. The sample size used in the studies has a significant positive relationship with MAPE and RMSPE. This finding contradicts the common viewpoint. It indicates that in most cases, increasing the sample size does not improve accuracy. However, the coefficients of the number of variables and the lag length of dependent variable are significantly negative, which means the inclusion of more explanatory variables or lagged dependent variable may decrease forecasting error. Year of publication, as a variable representing time-dependent trend in technique development, has a significant negative relationship with MAPE and RMSPE. This means that forecasting methods have greatly improved over recent decades, which is an inspiring finding for academics. The coefficients of the forecasting horizon are positive, which confirms that the longer the horizon, the more uncertainty involved and the less accurate the forecast.

Interaction factors. Finally, according to the coefficients of the interaction variables, the effect of source markets, destinations, modelling methods, time periods of data covered, data frequency employed, travel distance, the level of aggregation of tourism demand and number of variables on forecasting accuracy is significantly different according to whether demand is measured using expenditure/receipts or other forms. However, there is no significant difference in the effects of sample size, lag length of dependent variable, year of publication, and forecasting horizon across measures of international tourism demand.

Table 6.5 Meta-regression for tourism forecasting accuracy without interactions

	log(MAPE)	t-value	Prob.	log(RMSPE)	t-value	Prob.
constant	138.477	14.702	0.00	449.030	15.547	0.00
Origin Region						
Asia	0.292	7.037	0.00	1.342	8.810	0.00
America				1.181	6.951	0.00
Europe	0.264	6.425	0.00	1.647	9.852	0.00
Australia				1.517	8.529	0.00
Africa	0.641	2.823	0.00			
not specified	benchmark			benchmark		
Destination Region						
Asia	-0.324	-5.841	0.00	2.009	8.884	0.00
America				4.142	16.428	0.00
Europe	0.307	4.856	0.00	2.956	13.712	0.00
Australia	-0.307	-4.429	0.00			
Africa	-0.499	-2.301	0.02			
not specified	benchmark			benchmark		
Time Period						
1960s and before	benchmark			benchmark		
1970s	-0.189	-3.895	0.00			
1980s	-0.538	-8.142	0.00	-0.677	-7.433	0.00
1990s	0.512	7.867	0.00			
2000s	-0.269	-4.786	0.00			
Model						
advanced time-series	-0.199	-5.175	0.00	-0.131	-1.813	0.07
dynamic econometrics	-0.513	-7.843	0.00	-0.490	-5.114	0.00
artificial intelligence	-0.114	-1.839	0.07			
static econometrics						
basic time-series	benchmark			benchmark		
Data Frequency						
monthly	0.294	2.538	0.01			
quarterly	0.438	6.959	0.00	0.779	3.800	0.00
annually	benchmark			benchmark		
Travel Distance						
cross-continent	0.109	2.594	0.01			
inner-continent or not specified	benchmark			benchmark		
Demand Measure						
tourism demand at product level	0.104	2.290	0.02			
tourism demand at destination level	benchmark					
demand measured by expenditure						
demand measured by others	benchmark					
Other Factors						
sample size	0.001	2.131	0.03	0.008	13.748	0.00
No. of Variables	-0.031	-7.875	0.00			
lag length of dependent variable				-0.048	-4.827	0.00
publication year	-0.068	-14.437	0.00	-0.225	-15.485	0.00
forecasting horizon	0.047	4.492	0.00	0.163	6.079	0.00
Adjusted R^2	**0.319**		**0.00**	**0.767**		**0.00**

Table 6.6 Meta-regression for tourism forecasting accuracy with interactions

	log(MAPE)	t-value	Prob.	log(RMSPE)	t-value	Prob.
constant	142.278	15.205	0.00	0.580	3.117	0.00
Origin Region						
Asia	0.279	6.827	0.00	2.184	13.931	0.00
America				1.843	10.969	0.00
Europe	0.251	5.755	0.00	2.280	14.189	0.00
Australia				2.284	13.033	0.00
Africa	0.627	2.799	0.01			
not specified	benchmark					
Destination Region						
Asia	-0.342	-6.189	0.00	1.966	10.313	0.00
America				4.459	19.726	0.00
Europe	0.371	5.350	0.00	1.312	3.575	0.00
Australia	-0.321	-4.559	0.00			
Africa	-0.619	-2.912	0.00			
not specified	benchmark					
Time Period						
1960s and before	benchmark					
1970s	-0.184	-4.060	0.00			
1980s	-0.436	-7.289	0.00	-0.429	-5.545	0.00
1990s	0.632	9.900	0.00	-4.217	-18.448	0.00
2000s	-0.245	-4.074	0.00			
Model						
advanced time-series	-0.194	-5.576	0.00	-0.261	-3.892	0.00
dynamic econometrics	-0.643	-8.652	0.00	-0.880	-7.225	0.00
artificial intelligence						
static econometrics						
basic time-series	benchmark					
Data Frequency						
monthly	0.513	6.570	0.00			
quarterly	0.535	7.771	0.00	1.244	6.616	0.00
annually	benchmark					
Travel Distance						
cross-continent	0.117	2.708	0.01			
inner-continent or not specified	benchmark					
Demand Measure						
tourism demand at product level						
tourism demand at destination level	benchmark					
demand measured by expenditure						
demand measured by others	benchmark					
Other Factors						
sample size				0.012	17.201	0.00
No. of Variables	-0.032	-8.948	0.00			
lag length of dependent variable				-0.021	-2.303	0.02
publication year	-0.070	-14.93	0.00			
forecasting horizon	0.048	4.352	0.00	0.254	9.822	0.00

	log(MAPE)	t-value	Prob.	log(RMSPE)	t-value	Prob.
Interact Factors						
Demand measured by expenditure together with						
Origin Region						
Asia						
America				0.990	2.568	0.01
Europe	-0.736	-5.216	0.00			
Australia						
Africa						
Destination Region						
Asia	-3.886	-5.697	0.00			
America	1.149	3.598	0.00			
Europe				2.049	5.605	0.00
Australia						
Africa						
Model						
advanced time-series				0.816	3.607	0.00
dynamic econometric	0.519	3.593	0.00	0.901	4.970	0.00
artificial intelligence	-0.801	-3.633	0.00			
static econometrics						
Time Period						
1970s						
1980s						
1990s						
2000s	3.752	5.698	0.00			
Data Frequency						
monthly data						
quarterly data	-3.488	-5.503	0.00			
Travel Distance						
cross-continent	-0.831	-4.330	0.00	-0.738	-2.098	0.04
Demand and variable measure						
tourism demand at product level						
Other Factors						
sample size				-0.013	-5.021	0.00
No. of Variables	0.110	5.428	0.00	0.083	1.975	0.05
lag length of dependent variable						
publication year						
forecasting horizon						
Adjusted R^2	**0.339**		**0.00**	**0.820**		**0.00**

Table 6.7 Verification of Hypotheses for International Tourism Forecasting Accuracy

	Hypothesis	Supported?
1c:	Forecasting accuracy of international tourism demand depends on source markets	yes
2c:	Forecasting accuracy of international tourism demand depends on destinations	yes
3c:	Forecasting accuracy of international tourism demand depends on the time period of data covered	yes
4c:	Forecasting accuracy of international tourism demand depends on the modelling methods	yes
5c:	Forecasting accuracy of international tourism demand depends on data frequency employed	yes
7c:	Forecasting accuracy of international tourism demand depends on number of variables included in the model	yes
8c:	Forecasting accuracy of international tourism demand depends on the lag length of dependent variable in the model	yes
9c:	Forecasting accuracy of international tourism demand depends on the travel distance	yes
10c:	Forecasting accuracy of international tourism demand is lower when demand is measured by expenditure and receipts than measured by others	no
11c:	Forecasting accuracy of international tourism demand depends on the level of aggregation of international tourism demand measurement	yes
13c:	Forecasting errors of international tourism demand has a negative relationship with the publication year of the study	yes
14c:	Forecasting accuracy of international tourism demand depends on the sample size	yes
16c:	Forecasting accuracy of international tourism demand declines with the increase of forecasting horizon	yes
1f:	Effect of source markets on forecasting accuracy of international tourism demand varies cross tourism demand measures	yes
2f:	Effect of destinations on forecasting accuracy of international tourism demand varies cross tourism demand measures.	yes
3f:	Effect of the time period of data covered on forecasting accuracy of international tourism demand varies cross tourism demand measures.	yes
4f:	Effect of the modelling methods on forecasting accuracy of international tourism demand varies cross tourism demand measures.	yes
5f:	Effect of data frequency employed on forecasting accuracy of international tourism demand varies cross tourism demand measures.	yes
7f:	Effect of number of variables on forecasting accuracy of international tourism demand varies cross tourism demand measures.	yes
8f:	Effect of the lag length of dependent variable on forecasting accuracy of international tourism demand varies cross tourism demand measures.	no
9f:	Effect of travel distance on forecasting accuracy of international tourism demand varies cross tourism demand measures.	yes
11f:	Effect of the level of aggregation of international tourism demand measurement on forecasting accuracy of international tourism demand varies cross tourism demand measures	no
13f:	Effect of the publication year of the study on forecasting accuracy of international tourism demand varies cross tourism demand measures.	no
14f:	Effect of the sample size on forecasting accuracy of international tourism demand varies cross tourism demand measures.	yes
16f:	Effect of forecasting horizon on forecasting accuracy of international tourism demand varies cross tourism demand measures.	no

6.4 Collinearity Diagnostics

Econometrics is always concerned with the collinearity problem, especially when using a regression model with a large number of independent variables. If there are correlations or multicollinearity between variables, the estimates of coefficients may be biased, leading to erroneous conclusions. To establish the reliability of the regression models reported above, a set of collinearity diagnostics were also performed.

The correlation matrices for those eight regression models show that none of the bivariate correlation indexes are larger than 0.8, which indicates no strong linear association between any two variables in the model (Mason and Perreault, 1991). The VIF indexes for all the variables in the regressions without interactions are not significantly larger than 10, indicating no significant multicollinearity problem in those models without interactions (Marquardt, 1970). When the interaction variables are added, the VIF of some variables (11.7%) exceed the critical value of 10, but are not larger than 60, indicating a moderate but not serious multicollinearity. However, when the sample size is large enough (above 300), the moderate multicollinearity problem is not considered to greatly harm the estimates of coefficients (Mason and Perreault, 1991). Furthermore, when the models with or without interactions are compared, the coefficients of variables do not change significantly in either direction or magnitude, which suggests that they are stable and reliable.

6.5 Chapter Summary

This chapter has presented the results of the meta-regressions and discussed the coefficients of the regression models. The results confirm that data characteristics and study features influence estimates of international tourism demand elasticities, and also affect forecasting performance. The support provided by the regression results for the hypotheses set out in chapter three has been summarised, and the collinearity diagnostics carried out to test the stability and reliability of the models reported.

Chapter 7 - Conclusion and Discussion

7.1 Introduction

Using meta-analysis, this study set out to explore whether, and if so how, data characteristics and study features would influence estimates of the demand elasticities of international tourism and the accuracy of forecasting. The research background and objectives were first introduced, followed by a comprehensive review of the literature on tourism demand modelling and forecasting. The hypotheses and the meta-regression models used to test them were then discussed.

In the meta-regression analysis, the effects of data characteristics and study features on estimated income and own-price elasticities and the forecasting accuracy of international tourism demand were discussed and summarised, and the effects of interaction factors described.

Following on from this analysis, this chapter summarises the key findings and economic implications of the study, and discusses its significance and contribution. Finally, its limitations are addressed, followed by some suggestions for future research.

7.2 Key Findings and Implications

7.2.1 Average international tourism demand elasticities

Income and own-price elasticity of international tourism demand reveal tourists' preferences and intentions to visit specific destinations. These are the basis for destination development plans and the design of marketing strategies. According to the results of the meta-analyses, the demand elasticities of international tourism are significantly different between source markets, destinations, products, data coverage, measurements of demand variables, modelling methods, and travel distances. Understanding the differences in demand elasticities between different source markets across time periods would help considerably in developing effective destination marketing strategies.

The overall average income elasticity of international tourism demand is 2.526, which means that most tourists view this as a luxury product. The overall average price elasticity is -1.250. As stated in chapter six, data characteristics and study features, such as the source market and destinations, demand measurement, data frequency, data coverage, travel distance, modelling methods, and different tourism products, influence estimates of elasticities. In this section, the average income and own-price elasticities for each category are summarised statistically based on previous studies. Since only a small number of studies report standard deviations, only the simple averages were calculated (see Tables 7.1 and 7.2).

Table 7.1 shows that European tourists had the highest income elasticity (3.419), with Africans (mainly South Africans) the lowest (1.147). Tourists who travelled to Asia showed the highest income (3.165), and the second-highest price (-1.456) elasticity. These findings indicate that the international tourism demand by European tourists and by tourists travelling to Asia are more likely to be influenced by the economic fluctuations than tourists from or travelling to other regions. Both the public and private sectors related to these two markets should make good preparation when dealing with economic crises. Asian tourists and tourists travelling to America showed the highest price elasticities (-1.42 and -1.545), indicating that appropriate pricing strategies should be effective in attracting those tourists. Tourists going to Australia exhibited the lowest income elasticity (2.067) and were also the least price sensitive, with an average own-price elasticity of -0.844. Therefore, a better strategy for Australia is to improve the quality of its tourism services/products instead of competing with its competitors on prices.

In terms of modelling methods, the dynamic models produced the highest estimates of both income (3.093) and own-price (-1.415) elasticity than the static models. Since the estimated income and own-price elasticities are different based on different modelling methods, the government and private sectors should be careful in using the estimated results. With regard to data frequency, studies using monthly data tended to generate higher income (6.454) and price (-1.683) elasticities than those employing lower-frequency data. The income and price elasticities for models using quarterly data were 1.923 and -1.134 respectively. Furthermore, the income and price elasticities vary over time, the time varying parameters models should be used in tourism demand analysis.

As far as tourism products are concerned, the demand for accommodation, transportation, leisure travel, and VFR tourism are the most frequently discussed topics. Different tourism products also have significantly different demand elasticities, therefore, different marketing strategies should be developed for different products. Among the products studied, accommodation, which is a necessity for most international tourists, has the lowest income (1.166) and price (-0.727) elasticity. Studies that considered the destination as an aggregated tourism product tended to show the highest income and price elasticities. The demand for international air travel is the main focus of studies of tourism transportation. Since the substitutes for most travel modes are limited, the average price elasticity of transportation is relatively low (-0.920). Compared to holiday and VFR tourists, business tourism had an average income elasticity of 1.605 and an own-price elasticity of -0.35, which is the lowest of all three tourism products studied. Studies on the demand for medical tourism, although small in number, tended to exhibit much lower income and price elasticities than vocational tourism. This may be due to the fact that tourists who travelled for medical purposes tended to be richer and their destinations to have relatively cheaper but higher-quality medical services.

The measurement of demand for international tourism also influences the estimates of demand elasticities. Studies that analysed tourist arrivals tended to generate greater income (2.724 for all arrivals and 3.160 for arrivals *per capita*) and lower price (-1.240 for all arrivals and -0.749 for arrivals *per capita*) elasticity than studies examining expenditure.

The finding on travel distance is consistent with previous studies which conclude that long-haul tourism is considered more luxurious than short-haul. The income elasticity for cross-continental tourism (3.188) is significantly higher than for intra-continental. And the short-haul tourists (-1.381) are more price sensitive than the long-haul tourists (-1.201),

The difference between the elasticity estimates for each subgroup indicates that tourists from different source markets, going to different destinations, and consuming different products have different sensitivities to income and price changes. Therefore, different marketing strategies should be applied in different markets. For example, American and Asian tourists are the most sensitive to price changes, so maintaining a stable price level would be an effective marketing strategy for them. This is less of an issue for Australian tourists, so it would be better to emphasise the uniqueness of products in marketing activities directed at them.

Other than origin and destination effects, demand elasticities also vary over time, so governments and tourism businesses should also design their marketing strategies in response to changing markets and changing travel tastes and preferences. Furthermore, different modelling methods, data frequencies, and measures of tourism demand generate different estimates of elasticities, so governments and tourism enterprises should pay particular attention to the data and modelling features of relevant studies when examining demand for their products.

Table 7.1

Average Income Elasticity of International Tourism Demand

Data Category	Subgroup	Mean
Origin	Africa	1.147
	America	1.995
	Asia	1.716
	Australia	2.141
	Europe	3.419
	Not specified	1.771
Destination	Africa	2.169
	America	2.266
	Asia	3.165
	Australia	2.067
	Europe	2.225
	Not specified	1.734
Model	Advanced Time-series	1.941
	Dynamic Econometrics	3.093
	Static Econometrics	2.067
Data Frequency	Monthly	6.454
	Quarterly	1.923
	Yearly	2.179
Product	Accommodation	1.166
	Holiday	2.401
	Transportation	2.475
	VFR	2.192
	Business	1.605
	Destination	2.729
	Others	1.007
Demand Measure	Arrival	2.724
	Arrival/POP	3.16
	Expenditure	1.691
	Expenditure /POP	1.822
Travel Distance	Cross-continent	3.188
	Inner-continent	2.053
	Others	1.827
Total		2.526

Table 7.2

Average Price Elasticity of International Tourism Demand

Data Category	Subgroup	Mean
Origin	Africa	-0.783
	America	-1.277
	Asia	-1.42
	Australia	-1.112
	Europe	-1.265
	Not specified	-1.279
Destination	Africa	-1.165
	America	-1.545
	Asia	-1.456
	Australia	-0.844
	Europe	-1.291
	Not specified	-1.107
Model	Advanced Time-series	-1.605
	Dynamic Econometrics	-1.415
	Static Econometrics	-1.121
Data	Monthly	-1.683
	Quarterly	-1.134
	Yearly	-1.279
Product	Accommodation	-0.727
	Holiday	-1.102
	Transportation	-0.92
	VFR	-0.8
	Business	-0.35
	Destination	-1.489
	Others	-0.546
Demand	Arrival	-1.24
	Arrival/POP	-0.749
	Expenditure	-1.704
	Expenditure /POP	-1.287
Travel	Cross-continent	-1.201
	Inner-continent	-1.381
	Others	-1.269
Total		-1.281

7.2.2 Pairing data characteristics and study features with forecasting methods

In chapter six, the meta-regression results showed that data characteristics and features of the models used significantly influenced the performance of forecasting models. Therefore, pairing data categories with a specific forecasting model is one way to improve forecasting performance. In this section, previous studies of forecasting are synthesised in order to rank the forecasting models according to their average MAPEs for each data category. Since most of the past studies did not report standard errors, only simple average MAPEs are calculated.

Overall ranking of models. Consistent with previous research, the dynamic econometric models performed best overall, while the static econometric models were the poorest. Advanced time series models are the most often used for forecasting international tourism demand. However, their performance ranked below that of the dynamic econometric and AI models. This finding suggests that forecasters should make great efforts in developing the dynamic econometric models in order to improve the forecasting accuracy.

Table 7.3 Overall Rankings of Forecasting Models

RANK	Model	MAPE	S.D	N
1	Dynamic Econometrics	10.467	10.413	223
2	Artificial Intelligence	12.626	9.237	264
3	Advanced Time-series	13.134	14.873	1471
4	Naive	16.031	25.846	481
5	Static Econometrics	17.992	39.238	145
	Average	13.664	18.897	2584

Demand measures. According to the past studies, the econometric models tend to generate more accurate forecasts compared to the time-series models when tourist expenditure is concerned. Table 7.4 shows that the dynamic econometric models perform very well (ranked first) when tourism demand is measured by arrivals and reasonably well (ranked second) when expenditure is used. Although the static econometric models are not good at forecasting tourist arrivals, they performed very well (ranked first) when demand is measured by expenditure. The advanced time series models perform poorly in forecasting based on expenditure data.

Table 7.4 Forecasting Model Rankings for Different Demand Measure

RANK	Arrival	MAPE	N	RANK	Expenditure	MAPE	N
1	DE	12.132	124	1	SE	8.315	30
2	AI	12.981	233	2	DE	8.381	99
3	AT	13.189	1438	3	AI	9.955	31
4	Naive	16.232	464	4	Naive	10.538	17
5	SE	20.516	115	5	AT	10.700	33
	Average	14.094	2374		Average	9.143	210

Data frequency. Previous studies imply that the dynamic econometric models rank first when forecasting annual tourism demand. Errors increase significantly when quarterly demand is used, where the AI approach is the best choice. The static econometric and advanced time series models are the best options for forecasting monthly demand (see Table 7.5). However, since the dynamic econometric models have been rarely applied in modelling monthly data, their performance in forecasting monthly tourism demand still needs to be further assessed.

Table 7.5 Forecasting Model Rankings for Different Data Frequency

RANK	yearly	MAPE	N	RANK	quarterly	MAPE	N	RANK	monthly	MAPE	N
1	DE	6.302	146	1	AI	12.967	149	1	SE	6.402	31
2	AT	9.784	61	2	Naïve	13.104	320	2	AT	9.769	370
3	AI	11.684	47	3	AT	14.527	1040	3	AI	12.964	44
4	SE	20.823	82	4	DE	18.364	77	4	Naive	16.163	89
5	Naive	28.875	72	5	SE	21.964	32		DE		
	Average	14.345	408		Average	14.432	1618		Average	10.902	534

Origin and Destination. Tables 7.5 and 7.6 list the rankings of the forecasting models for different origins and destinations. It can be seen that performance varied significantly across regions. The dynamic econometric model is the top performer (four out of five) when origin is considered, but do less well than the time series models when the focus is destination. In fact, in three cases where accuracy was assessed according to destination, the Naive models outperformed the dynamic econometric methods. Specifically, when the forecasting exercises are related to Asia as both a source market and destination, the dynamic econometric models perform best. This is also the case for Europe as a destination. Another interesting thing to note is that the Naive models perform reasonably well when destination is the basis for evaluating forecasting accuracy.

Table 7.6 Forecasting Model Rankings according to Origins

RANK	Not specified	MAPE	N	RANK	Asia	MAPE	N	RANK	America	MAPE	N
1	DE	4.499	8	1	DE	3.658	17	1	DE	3.554	33
2	AT	8.405	353	2	AI	12.521	79	2	Naive	10.946	64
3	AI	10.978	72	3	Naive	14.281	131	3	AI	11.861	34
4	SE	21.579	48	4	SE	15.327	20	4	SE	12.923	8
5	Naive	31.238	71	5	AT	17.128	395	5	AT	13.068	174
	Average	12.767	552		Average	15.567	642		Average	11.496	313

RANK	Europe	MAPE	N	RANK	Australia	MAPE	N
1	DE	12.981	157	1	AI	6.891	18
2	AT	14.412	406	2	AT	9.964	134
3	Naive	14.426	164	3	DE	10.085	8
4	AI	16.949	59	4	Naive	10.574	48
5	SE	16.988	67	5	SE	12.450	2
	Average	14.529	853		Average	9.868	210

Table 7.7 Forecasting Model Rankings according to Destinations

RANK	Not	MAPE	N	RANK	Asia	MAPE	N	RANK	America	MAPE	N
1	AT	12.58	97	1	DE	2.33	60	1	Naive	11.63	14
2	Naive	13.95	66	2	SE	9.27	65	2	AI	11.87	36
3	SE	17.10	16	3	AT	10.5	711	3	AT	12.27	41
4	AI	17.90	8	4	AI	11.2	125	4	DE	15.31	9
5	DE	18.00	4	5	Naive	14.0	220	5	SE	21.54	6
	Average	13.77	19		Average	10.79	1181		Average	12.834	106

RANK	Europe	MAPE	N	RANK	Australia	MAPE	N
1	DE	13.59	13	1	Naive	10.0	91
2	AI	14.67	62	2	DE	10.1	16
3	AT	15.46	14	3	AI	13.3	28
4	SE	27.99	57	4	AT	16.4	477
5	Naive	29.98	86		SE		
	Average	18.92	48		Average	15.2	612

Tourism product. After comparing the forecasting accuracy of different models across products, we find that the dynamic econometric models perform best at forecasting aggregated demand. The Naive model is the best choice for forecasting relatively stable demand such as holiday or VFR tourism. The AI methods generate the most accurate forecasts for business tourism. However, the number of studies focusing on disaggregated tourism demand is relative small, this conclusion needs to be treated with caution. With the increasing number of studies that use different models to forecast different tourism products, more convincing conclusions would be generated in the future.

Table 7.8 Forecasting Model Rankings for Different Product

RANK	Destination	MAPE	N	RANK	Holiday	MAPE	N	RANK	Business	MAPE	N
1	DE	7.255	155	1	Naive	13.457	65	1	AI	8.461	36
2	AT	10.894	931	2	AI	15.416	36	2	DE	10.185	16
3	AI	12.759	186	3	AT	17.178	174	3	Naïve	10.541	53
4	SE	17.491	121	5	DE	20.126	52	4	AT	15.159	202
5	Naive	17.705	329	6	SE	20.514	24		SE		
	Average	12.533	1722		Average	16.973	351		Average	13.317	307

RANK	VFR	MAPE	N	RANK	Others	MAPE	N
1	Naive	12.810	22	1	Naive	14.248	12
2	AT	15.060	101	2	AI	16.742	6
	SE			3	AT	25.481	63
	DE				SE		
	AI				DE		
	Average	14.658	123		Average	23.169	81

Forecasting horizon. Generally speaking, the accuracy of all models tends to decline along with the extension of the forecasting horizon, although some models still perform better than others when this is the basis for evaluation. The advanced time series models provide the most accurate forecasts in short-term (less than one year) forecasting, while the dynamic econometrics models are best for longer periods.

Table 7.9 Forecasting Model Rankings according to Forecasting Horizon

RANK	<=1quarter	MAPE	N	RANK	1 quarter to 1 year	MAPE	N
1	AT	7.458	322	1	AT	10.934	350
2	AI	11.014	64	2	DE	11.041	80
3	Naïve	11.686	97	3	SE	12.308	69
4	SE	14.229	9	4	Naïve	12.975	204
5	DE	15.204	17	5	AI	15.481	70
	AVERAGE	9.089	509		AVERAGE	12.018	773
RANK	1 to 2 years	MAPE	N	RANK	2 to 5 years	MAPE	N
1	DE	12.903	73	1	DE	5.250	37
2	AI	13.121	83	2	AI	6.433	10
3	SE	14.248	50	3	SE	13.023	11
4	Naïve	15.918	125	4	AT	13.751	274
5	AT	16.305	484	5	Naïve	17.099	43
	AVERAGE	15.490	815		AVERAGE	13.080	375

As stated before, origin, destination, time period, modelling method, data frequency, variables and their measures, and sample size all have significantly influence on the accuracy of the forecasting models. Superior forecasting models should be identified based on the characteristics of the study and the data used in the model estimation in order to assist practitioners in making effective policy and business decisions. Furthermore, for academics who are interested in the specifications of the forecasting models, should pay a particular attention to the analysis of the relationship between modeling structure and data characteristics.

7.3 Study Limitations and Future Research Directions

Compared to the two major prior meta-analytical studies on international tourism demand (Crouch, 1992b; Lim, 1999), which focused only on demand elasticities, this study has greatly enlarged the broader elasticity dataset by collecting the published studies over the 50-year period from the 1960s to 2011. In addition, it has also statistically examined the factors that may contribute to the performance of international tourism demand forecasting models.

Due to time constraints, only published articles (journal papers, book chapters, and conference proceedings) are included in this analysis. Such a publication bias could be a possible limitation of the study. Since published articles are unlikely to report estimates that are either statistically insignificant or theoretically unacceptable, this can influence the completeness of the meta-analysis. Therefore, the inclusion of unpublished studies, such as working papers, PhD theses, and articles obtained through personal contacts, could be one way to improve reliability of future meta-analytical studies. However, including too many unpublished studies could also be problematic, as the controversies generated by such work might even undermine the reliability of the research synthesis.

Other problems of meta-analysis include the lack of homogeneous measurement scales and statistical independence. Such research is only useful when considering the results of studies using different methods or procedures to test the same hypotheses, which cannot be used to support the claims of a causal relationship. Moreover, the coding and interpretation of an effect size in a meta-analysis is totally subjective, making it difficult to eliminate author bias. One possible way to address this is to invite co-authors to participate in the research.

Due to the constraints of the sample, only the effects of origins and destinations at the continent level were evaluated in the regression analysis. With an increase in published studies in the future, the effect of a single country could also be evaluated. For the same reason, the forecasting models were grouped into five categories in this study, but the analysis could be carried out on specific methods if the sample increases significantly in future. Furthermore, the regression models used here only included the interactions between international tourism demand measures and other factors. Further studies could also consider examining the other interactions between forecasting models, data frequency, origins, and destinations. Since the studies on interval forecasting are still limited (except for Song & Lin, 2010; Kim et. al, 2011), this research only focuses on the point forecasts. Future studies should include more interval forecasts when they become available in order to reduce the risk of complete forecasting failure.

Appendix A: Articles on Income Elasticity of International Tourism Demand

Author	Title	Year	Estimates
Akis	A Compact Econometric Model of Tourism Demand for Turkey	1998	18
Algieri	An Econometric Estimation of the Demand for Tourism: the Case of Russia	2006a	1
Algieri	International Tourism Specialisation of Small Countries	2006b	1
Algieri and Kanellopoulou	Determinants of Demand for Exports of Tourism: An Unobserved Component Model	2009	4
Anastasopoulos	The U.S. Travel Account: the Impact of Fluctuations of the U.S. Dollar	1989	20
Asgary et al.	The Determinants of Expenditures by Mexican Visitors to the Border Cities of Texas	1997	2
Bankole and Babatunde	Elasticities of Demand for Tourism in Nigeria: An Ardl Approach	2010	1
Barry and O'Hagan	An Econometric Study of British Tourist Expenditure in Ireland	1972	6
Blackwell	Tourist Traffic and the Demand for Accommodation: Some Projections	1970	4
Bond and Ladman	International Tourism and Economic Development: A Special case for Latin America	1972	3
Bonham,Gangnes and Zhou	Modeling Tourism: A Fully Identified VECM Approach	2009	1
Botti et al.	An Econometric Model of Tourism Demand in France	2007	5
Brakke	International Tourism, Demand, and GDP Implications: A Background and Empirical Analysis	2005	1
Brida and Risso	A Dynamic Panel Data Study of the German Demand for Tourism in South Tyrol	2009	1
Brida, Risso and Carrera	A Long-run Equilibrium Demand Function: Tourism in Mexico	2008	1
Campbell and Mitchell	Determinants of Outbound Holiday Travel for Barbados	2007	2
Carey	Estimation of Caribbean Tourism Demand: Issues in Measurement and Methodology	1991	2
Carey	Tourism Development in LDCs: Hotel Capacity Expansion with Reference to Barbados	1989	1
Chadee and Mieczkowski	An Empirical Analysis of the Effects of the Exchange Rate on Canadian Tourism	1987	1
Chaitip and Chaiboonsri	Thailand's International Tourism Demand: The ARDL Approach to Cointegration	2009	23
Chaiboonsri, Chaitip and Rangaswamy	A Panel Unit Root and Panel Cointegration Test of The Modeling International Tourism Demand in India	2008	19
Chaiboonsri, Chaitip and Rangaswamy	Modelling International Tourism Demand in Thailand	2009	12
Chattopadhyay	International Tourism Demand for India	1995	23

Author	Title	Year	Estimates
Chon et al.	Recovery of Tourism Demand in Hong Kong From the Global Financial and Economic Crisis	2010	9
Choyakh	A Model of Tourism Demand for Tunisia: Inclusion of the Tourism Investment Variable	2008	12
Cigliano	Price and Income Elasticities for Airline Travel: the North Atlantic Market	1980	5
Cortés-Jiménez and Blake	Tourism Demand Modeling by Purpose of Visit and Nationality	2011	33
Cortés-Jiménez, Durbarry and Pulina	Estimation of Outbound Italian Tourism Demand: A Monthly Dynamic EC-LAIDS Model	2009	4
Crampton and Tan	A Model of Tourism Flow into the Pacific	1973	2
Croes and Vanegas	An Econometric Study of Tourist Arrivals in Aruba and Its Implications	2005	6
Crouch,Schultzb and Valerio	Marketing international tourism to Australia: A regression analysis	1992	18
Daniel and Ramos	Modelling Inbound International Tourism Demand to Portugal	2002	6
Day	Impact of Exchange Rates on Air Travel	1986	4
De Mello and Fortuna	Testing Alternative Dynamic Systems for Modelling Tourism Demand	2005	9
De Mello and Nell	The Forecasting Ability of A Cointegrated VAR System of the UK Tourism Demand for France, Spain and Portugal	2005	3
Di Matteo and Di Matteo	An Analysis of Canadian Cross-border Travel	1996	12
Diamond	Tourism's Role in Economic Development: The Case Reexamined	1977	10
Divisekera	Economics of Tourist’s Consumption Behaviour: Some Evidence From Australia	2010	25
Divisekera	Ex Post Demand for Australian Tourism Goods and Services	2009	50
Divisekera and Kulendran	Economic Effects of Advertising on Tourism Demand: A Case Study	2006	8
Dritsakis	Cointegration Analysis of German and British Tourism Demand for Greece	2004	2
Dritsakis and Gialetaki	Cointegration analysis of tourism revenues by the member countries of European Union to Greece	2004a	3
Dritsakis and Gialetaki	Seasonal Tourism Demand Models from USA to Greece	2004b	2
Durbarry	Tourism Taxes: Implications for Tourism Demand in the UK	2008	6
Durbarry and Sinclair	Market Shares Analysis: The Case of French Tourism Demand	2003	3
Durbarry，Nicolas and Seetanah	The Determinants of Tourism Demand in South Africa Using A Dynamic Panel Data Approach	2009	8
Duval and Schiff	Effect of Air Services Availability on International Visitors to New Zealand	2011	10

Author	Title	Year	Estimates
Eita,Jordaan and Jordaan	An Econometric Analysis of the Determinants Impacting on Businesses in the Tourism Industry	2011	3
Eryigit,Kotil and Eryigit	Factors Affecting International Tourism Flows to Turkey: A Gravity Model Approach	2010	6
Fernandes and Karnik	Estimating Elasticity of Demand for Tourism in Dubai	2010	4
Fildesa, Weib and Ismailc	Evaluating the Forecasting Performance of Econometric Models of Air Passenger Traffic Flows Using Multiple Error Measures	2011	3
Fourie and Santana-Gallego	The Impact of Mega-sport Events on Tourist Arrivals	2011	6
Garc á-Ferrer and Queralt	A Note on Forecasting International Tourism Demand in Spain	1997	1
Garın-Munoz	Inbound International Tourism to Canary Islands: A Dynamic Panel Data Model	2006	4
Gar ń-Mu ñoz	Madrid as a Tourist Destination: Analysis and Modelization of Inbound Tourism	2004	5
Gar ń-Mu ñoz	Tourism in Galicia: Domestic and Foreign Demand	2009	3
Gar ń Mu ñoz	German Demand for Tourism in Spain	2007	2
Gar ń-Mu ñoz and Montero-Martın	Tourism in the Balearic Islands: A Dynamic Model for International Demand Using Panel Data	2007	1
Gonzailez and Moral	An Analysis of the International Tourism Demand in Spain	1995	1
G örm üs and G öçer	The Socio-Economic Determinant of Tourism Demand in Turkey: A Panel Data Approach	2010	11
Gray	The Demand for International Travel by the United States and Canada	1966	12
Greenidge	Forecasting Tourism Demand: An STM Approach	2001	4
Guizzardi and Mazzocchi	Tourism Demand for Italy and The Business Cycle	2010	1
Gunadhi and Chow	Demand Elasticities of Tourism in Singapore	1986	6
Guthrie	Demand for Tourists' Goods and Services in a World Market	1961	1
Habibi, Rahim and Ramchandran	Dynamic Model for International Tourism Demand for Malaysia: Panel Data Evidence	2009	1
Halicioglu	An ARDL Model of Aggregate Tourism Demand for Turkey	2004	4
Halicioglu	An Econometric Analysis of The Aggregate Outbound Tourism Demand of Turkey	2010	4
Hamal	Australian Outbound Holiday Travel Demand: Long-haul Versus Short-haul	1998	5
Han, Durbarry and Sinclair	Modelling US Tourism Demand for European Destinations	2006	4
Hanafiah, Harun and Jamaluddin	Bilateral Trade and Tourism Demand	2010	1

Author	Title	Year	Estimates
Hanim et al.	Malaysian Tourism Demand From the Middle East Market: a Preliminary Analysis	2010	3
Hao,Var and Chon	A Forecasting Model of Tourist Arrivals From Major Markets to Thailand	2003	5
Hiemstra and Wong	Factors Affecting Demand for Tourism in Hong Kong	2002	4
Ibrahim	The Determinants of International Tourism Demand for Egypt: Panel Data Evidence	2011	1
Idowu and Bello	What Are the Factors Determining Tourists Destinations in Africa?	2010	2
Jud and Joseph	International Demand for Latin American Tourism	1974	16
Ketenci	Cointegration Analysis of Tourism Demand for Turkey	2010	119
Ketenci	The ARDL Approach to Cointegration Analysis of Tourism Demand in Turkey with Greece As The Substitution Destination	2009	12
Khadaroo and Seetanah	The Role of Transport Infrastructure in International Tourism Development: A Gravity Model Approach	2008	9
Khadaroo and Seetanah	Transport Infrastructure and Tourism Development	2007	8
Kim and Song	Analysis of Inbound Tourism Demand in South Korea: A Cointegration and Error Correction Approach	1998	7
Kim, Park and Sakai	Forecasting International Tourism Demand from Japan to Korea	2002	6
Kliman	A Quantitative Analysis of Canadian Overseas Tourism	1981	10
Kraipornsak	The World Economy, Competition, External Shocks and Demand for International Tourist Arrivals in Thailand	2011	10
Kulendran	Modelling Quarterly Tourist Flows to Australia Using Cointegration Analysis	1996	4
Kulendran and Divisekera	Australian Tourism Marketing Expenditure Elasticity Estimates	2006	8
Kulendran and Divisekera	Measuring the Economic Impact of Australian Tourism Marketing Expenditure	2007	8
Kulendran and Dwyer	Measuring the Return from Australian Tourism Marketing Expenditure	2009	4
Kulendran and Wilson	Modelling Business Travel	2000	4
Kulendran and Witt	Cointegration Versus Least Squares Regression	2001	11
Kulendran and Witt	Forecasting the Demand for International Business Tourism	2003	1
Kwack	Effects of Income and Prices on Travel Spending Abroad, 1960 III-1967 IV	1972	7
Laber	Determinants of International Travel between Canada and the United States	1969	4
Lathiras and Siriopoulos	The Demand for Tourism to Greece: A Cointegration Approach	1998	11

Author	Title	Year	Estimates
Ledesma-Rodriguez, Navarro-Ibanez and Perez-Rodriguez	Panel Data and Tourism: A Case Study of Tenerife	2001	8
Leitao	Does Trade Help to Explain Tourism Demand? The Case of Portugal	2010	3
Lelwala and Guanratne	Modelling Tourism Demand Using Cointegration Analysis: A Case Study for Tourists Arriving from United Kingdom to Sri Lanka	2009	1
Li et al.	Tourism Demand Forecasting: A Time Varying Parameter Error Correction Model	2006	14
Li,Song and Witt	Modeling Tourism Demand: A Dynamic Linear AIDS Approach	2004	10
Lim	The Major Determinants of Korean Outbound Travel to Australia	2004	2
Lim and McAleer	A Cointegration Analysis of Annual Tourism Demand by Malaysia for Australia	2002	12
Lim, McAleer and Min	ARMAX Modelling of International Tourism Demand	2009	4
Lim, Min and McAleer	Modelling Income Effects on Long and Short Haul International Travel from Japan	2008	38
Little	International Travel in the U.S.: Balance of Payments	1980	10
Loeb	International Travel to The United States An Econometric Evaluation	1982	14
Lyssiotou	Dynamic Analysis of British Demand for Tourism Abroad	2000	4
Mangion,Durbarry and Sinclair	Tourism Competitiveness: Price and Quality	2005	2
Martin and Witt	Accuracy of Econometric Forecasts of Tourism	1989b	6
Martin and Witt	Substitute Prices in Models of Tourism Demand	1988	36
Martin and Witt	Tourism Demand Forecasting Models: Choice of Appropriate Variable to Represent Tourists' Cost of Living	1987	21
McDermott and Jackson	The Economic Determinants of Tourist Arrivals in Australia and New Zealand	1985	18
Mervar and Payne	Analysis of Foreign Tourism Demand for Croatian Destinations: Long-run Elasticity Estimates	2007	12
Morley	A Dynamic International Demand Model	1998	10
Morley	An Evaluation of the Use of Ordinary Least Squares for Estimating Tourism Demand Models	1997	12
Morris, Wilson and Bakalis	Modelling Tourism Flows from Europe to Australia	1995	7
Mutti and Murai	Airline Travel on the North Atlantic: Is Profitability Possible?	1977	11
Narayan	A Tourism Demand Model for Fiji, 1970-2000	2002	3
Narayan	Determinants of Tourist Expenditure in FIJI, A Cointegration Approach	2003	3

Author	Title	Year	Estimates
Njegovan	Elasticities of Demand for Leisure Air Travel: A System Modelling Approach	2006	2
O’Hagan and Harrison	U.K. and U.S. Visitor Expenditure in Ireland: Some Econometric Findings	1984b	2
O'Hagan and Harrison	Market Shares of U.S. Tourist Expenditure in Europe, An Econometric Analysis	1984a	15
Oliver	The Effectiveness of the UK Travel Allowance	1971	2
Ordóñez, Ordóñez and Torres	Distance Matters: An Assessment of International Tourism Demand in Spain	2010	6
Ouerfelli	Analysis of European Tourism Demand for Tunisia: A New Approach	2010	1
Ouerfelli	Co-integration Analysis of Quarterly European Tourism Demand in Tunisia	2008	6
Papadopoulos and Witt	A Marketing Analysis of Foreign Tourism in Greece	1985	24
Papanikos and Sakellariou	An Econometric Application of the Almost Ideal Demand System Model to Japan's Tourist Demand for ASEAN Destinations	1997	5
Payne and Mervar	A Note on Modelling Tourism Revenues in Croatia	2002	1
Phakdisoth and Kim	The Determinants of Inbound Tourism in Laos	2007	9
Phillips and Hamal	Modelling Australian Outbound Travel Demand	2000	14
Qu and Zhang	Determinants of Tourist Arrivals and Expenditures in Canada	1995	12
Quayson and Var	A Tourism Demand Function for the Okanagan, BC	1982	3
Rey,Myro and Galera	Effect of Low-cost Airlines on Tourism in Spain. A Dynamic Panel Data Model	2011	6
Rosselló, Aguiló and Riera	Modeling Tourism Demand Dynamics	2005	4
Rudez	The GDP Impact on International Tourism Demand: A Slovenia Based Case	2008	1
Rugg	The Choice of Journey Destination: A Theoretical and Empirical Analysis	1973	13
Saayman and Saayman	Determinants of Inbound Tourism to South Africa	2008	3
Salleh	An ARDL Model of Tourism Demand for Malaysia	2007	4
Salleh et al.	Asian Tourism Demand For Malaysia: A Bound Test Approach	2008	4
Salleh, Othman and Ramachandran	Malaysia’s Tourism Demand from Selected Countries: The ARDL Approach to Cointegration	2007	3
Santana-Gallego, Ledesma-Rodriguez and Perez-Rodriguez	Exchange Rate Regimes and Tourism	2010	6
Santana-Jiménez and Hernández	Estimating the Effect of Overcrowding on Tourist Attraction: The Case of Canary Islands	2011	13
Schiff and Becken	Demand Elasticity Estimates for New Zealand Tourism	2011	13

Author	Title	Year	Estimates
Seetanah,Durbarry and Ragodoo	Using The Panel Cointegration Approach to Analyse The Determinants of Tourism Demand in South Africa	2010	5
Seetaram	Use of Dynamic Panel Cointegration Approach to Model International Arrivals to Australia	2010	7
Seetaram and Dwyer	Immigration and Tourism Demand in Australia: A Panel Data Analysis	2009	1
Smeral	Impacts of the World Recession and Economic Crisis on Tourism: Forecasts and Potential Risks	2010	6
Smeral	International Tourism Demand and The Business Cycle	2012	5
Smeral	The Impact of the Financial and Economic Crisis on European Tourism	2009	2
Smeral	Tourism Demand, Economic Theory And Econometrics: An Integrated Approach	1988	16
Song and Witt	Tourism Forecasting: The General-to-Specific Approach	2003	15
Song and Wong	Tourism Demand Modeling: A Time-Varying Parameter Approach	2003	6
Song et al.	Forecasting Tourist Arrivals Using Time-varying Parameter Structural Time Series Models	2011a	4
Song et al.	Impact of Financial/Economic Crisis on Demand for Hotel Rooms in Hong Kong	2011b	36
Song et al.	Tourism Demand Modelling and Forecasting: How Should Demand Be Measured?	2010	8
Song, Witt and Li	Modelling and Forecasting the Demand for Thai Tourism	2003b	21
Song, Romilly and Liu	An Empirical Study of Outbound Tourism Demand in the UK	2000	24
Song, Witt and Jensen	Tourism Forecasting: Accuracy of Alternative Econometric Models	2003c	12
Song, Wong and Chon	Modelling and Forecasting the Demand for Hong Kong Tourism	2003a	14
Sriboonjit et al.	Economic Determinants of Long-Term Equilibrium in Malaysian Tourist Arrivals to Thailand, Implications for Tourism Policy	2010	4
Straszheim	Airline Demand Functions in the North Atlantic and Their Pricing Implications	1978	2
Stronge	The Overseas Demand for Tourism in the United States	1982	8
Stronge and Redman	U.S. Tourism in Mexico: An Empirical Analysis	1982	1
Summary	Estimation of Tourism Demand by Multivariable Regression Analysis：Evidence from Kenya	1987	6
Surugiu, Leitão and Surugiu	A Panel Data Modelling of International Tourism Demand: Evidences for Romania	2011	2
Tan and Wong	Structural Change in Hong Kong's Inbound Tourism Demand Model: The Impact of The Asian Financial Crisis	2003	4
Tan, McCahon and Miller	Stability of Inbound Tourism Demand Models for Indonesia and Malaysia: The Pre-and Postformation of Tourism Development Organizations	2002b	6

Author	Title	Year	Estimates
Tan, McCahon and Miller	Modeling Tourist Flows to Indonesia and Malaysia	2002a	4
Thompson	Terrorism and Tourism in Developed Versus Developing Countries	2011	1
Thompson and Thompson	The Exchange Rate, Euro Switch and Tourism Revenue in Greece	2010	1
Toh,Khan and Goh	Japanese Demand for Tourism in Singapore: A Cointegration Approach	2006	1
Tremblay	Pooling International Tourism in Western Europe	1989	15
Truett and Truett	The Response of Tourism to International Economic Conditions: Greece, Mexico, and Spain	1987	9
Uysal and Crompton	Determinants of Demand for International Tourist Flows to Turkey	1984	16
Uysal and El Roubi	Artificial Neural Networks versus Multiple Regression in Tourism Demand Analysis	1999	1
Vanegas	Box-Cox Estimation of International Tourism Demand for Nicaragua	2010	29
Vanegas	Tourism Demand Response by Residents of Latin American Countries	2009	8
Vanegas and Croes	Evaluation of Demand, US Tourists to Aruba	2000	5
Var, Mohammad and Icoz	Factors Affecting International Tourism Demand for Turkey	1990	14
Veloce	Forecasting Inbound Canadian Tourism: An Evaluation of Error Corrections Model Forecasts	2004	4
Webber	Exchange Rate Volatility and Cointegration in Tourism Demand	2001	10
White	An International Travel Demand Model US Travel to Western Europe	1985	7
White and Walker	Trouble in The Travel Account	1982	4
Witt	An Abstract Mode–Abstract (Destination) Node Model of Foreign Holiday Demand	1980a	3
Witt	An Econometric Comparison of UK and German Foreign Holiday Behaviour	1980b	6
Witt and Martin	Econometric Models for Forecasting International Tourism Demand	1987	40
Wu, Li and Song	Analyzing Tourist Consumption: A Dynamic System-of-Equations Approach	2011	24
Yang, Lin and Han	Analysis of International Tourist Arrivals in China: The Role of World Heritage Sites	2010	10
Zhang,Kulendran and Song	Measuring Returns on Hong Kong’s Tourism Marketing Expenditure	2010	4
Total			**1633**

Appendix B: Articles on Price Elasticity of International Tourism Demand

Author	Title	Year	Estimates
Aguilo, Riera and Rossello	The Short-term Price Effect of A Tourist Tax Through A Dynamic Demand Model. The case of the Balearic Islands	2005	4
Akis	A Compact Econometric Model of Tourism Demand for Turkey	1998	15
Algieri	An Econometric Estimation of the Demand for Tourism: the Case of Russia	2006	1
Algieri	International Tourism Specialisation of Small Countries	2006	1
Algieri and Kanellopoulou	Determinants of Demand for Exports of Tourism: An Unobserved Component Model	2009	4
Anastasopoulos	The U.S. Travel Account: the Impact of Fluctuations of the U.S. Dollar	1989	6
Bankole and Babatunde	Elasticities of Demand for Tourism in Nigeria: An Ardl Approach	2010	1
Botti et al.	An Econometric Model of Tourism Demand in France	2007	5
Brakke	International Tourism, Demand, and GDP Implications: A Background and Empirical Analysis	2005	1
Brida and Risso	A Dynamic Panel Data Study of the German Demand for Tourism in South Tyrol	2009	1
Campbell and Mitchell	Determinants of Outbound Holiday Travel for Barbados	2007	2
Carey	Tourism Development in LDCs: Hotel Capacity Expansion with Reference to Barbados	1989	2
Cedwyn and Ajit V	Estimating Elasticity of Demand for Tourism in Dubai	2010	2
Chadee and Mieczkowski	An Empirical Analysis of the Effects of the Exchange Rate on Canadian Tourism	1987	1
Chaiboonsri and Chaitip	Thailand's International Tourism Demand: The ARDL Approach to Cointegration	2009	10
Chaiboonsri,Chaitip and Rangaswamy	A Panel Unit Root and Panel Cointegration Test of The Modeling International Tourism Demand in India	2008	18
Chaiboonsri,Chaitip and Rangaswamy	Modelling International Tourism Demand in Thailand	2009	2
Chon et al.	Recovery of Tourism Demand in Hong Kong From the Global Financial and Economic Crisis	2010	7
Choyakh	A Model of Tourism Demand for Tunisia: Inclusion of the Tourism Investment Variable	2008	10

Author	Title	Year	Estimates
Cigliano	Price and Income Elasticities for Airline Travel the North Atlantic Market	1980	6
Cortés-Jiménez and Blake	Tourism Demand Modeling by Purpose of Visit and Nationality	2010	25
Cortés-Jiménez,Durbarry and Pulina	Estimation of Outbound Italian Tourism Demand: A Monthly Dynamic EC-LAIDS Model	2009	4
Croes and Vanegas	An Econometric Study of Tourist Arrivals in Aruba and Its Implications	2005	3
Crouch,Schultzb and Valerio	Marketing international tourism to Australia: A regression analysis	1992	11
Daniel and Ramos	Modelling Inbound International Tourism Demand to Portugal	2002	6
Day	Impact of Exchange Rates on Air Travel	1986	19
De Mello and Fortuna	Testing Alternative Dynamic Systems for Modelling Tourism Demand	2005	9
De Mello and Nell	The Forecasting Ability of A Cointegrated VAR System of the UK Tourism Demand for France, Spain and Portugal	2005	3
Divisekera	Economics of Tourist’s Consumption Behaviour: Some Evidence From Australia	2010	25
Divisekera	Ex Post Demand for Australian Tourism Goods and Services	2009	55
Divisekera and Kulendran	Economic Effects of Advertising on Tourism Demand: A Case Study	2006	8
Dritsakis	Cointegration Analysis of German and British Tourism Demand for Greece	2004a	2
Dritsakis and Gialetaki	Seasonal Tourism Demand Models from USA to Greece	2004b	2
Durbarry	Tourism Taxes: Implications for Tourism Demand in the UK	2008	6
Durbarry and Sinclair	Market Shares Analysis: The Case of French Tourism Demand	2003	3
Durbarry， Nicolas and Seetanah	The Determinants of Tourism Demand in South Africa Using A Dynamic Panel Data Approach	2009	8
Duval and Schiff	Effect of Air Services Availability on International Visitors to New Zealand	2011	6
Eita,Jordaan and Jordaan	An Econometric Analysis of the Determinants Impacting on Businesses in the Tourism Industry	2011	3
Eryigvit,Kotil and Eryigvit	Factors Affecting International Tourism Flows to Turkey: A Gravity Model Approach	2010	1
Fildesa, Weib and Ismailc	Evaluating the Forecasting Performance of Econometric Models of Air Passenger Traffic Flows Using Multiple Error Measures	2011	6
Fourie and Santana-Gallego	The Impact of Mega-sport Events on Tourist Arrivals	2011	6

Author	Title	Year	Estimates
Garın-Munoz	Inbound International Tourism to Canary Islands: A Dynamic Panel Data Model	2006	4
Gar ń-Mu ñoz	Madrid as a Tourist Destination: Analysis and Modelization of Inbound Tourism	2004	5
Gar ń-Mu ñoz and Montero-Martın	Tourism in the Balearic Islands: A Dynamic Model for International Demand Using Panel Data	2007	1
Gonzailez and Moral	An Analysis of the International Tourism Demand in Spain	1995	2
Greenidge	Forecasting Tourism Demand: An STM Approach	2001	2
Guizzardi and Mazzocchi	Tourism Demand for Italy and The Business Cycle	2010	1
Habibi, Rahim and Ramchandran	Dynamic Model for International Tourism Demand for Malaysia: Panel Data Evidence	2009	1
Haitovsky,Salomon and Silman	The Economic Impact of Charter Flights on Tourism to Israel: An Econometric Approach	1987	3
Halicioglu	An ARDL Model of Aggregate Tourism Demand for Turkey	2004	4
Halicioglu	An Econometric Analysis of The Aggregate Outbound Tourism Demand of Turkey	2010	4
Hamal	Australian Outbound Holiday Travel Demand: Long-haul Versus Short-haul	1998	6
Hana,Durbarry, and Sinclair	Modelling US Tourism Demand for European Destinations	2006	4
Hanafiah, Harun and Jamaluddin	Bilateral Trade and Tourism Demand	2010	1
Hao,Var and Chon	A Forecasting Model of Tourist Arrivals From Major Markets to Thailand	2003	3
Hiemstra and Wong	Factors Affecting Demand for Tourism in Hong Kong	2002	4
Ibrahim	The Determinants of International Tourism Demand for Egypt: Panel Data Evidence	2011	1
Idowu and Bello	What Are the Factors Determining Tourists Destinations in Africa?	2010	2
Jud and Joseph	International Demand for Latin American Tourism	1974	9
Ketenci	Cointegration Analysis of Tourism Demand for Turkey	2010	74
Ketenci	The ARDL Approach to Cointegration Analysis of Tourism Demand in Turkey with Greece As The Substitution Destination	2009	13
Khadaroo and Seetanah	The Role of Transport Infrastructure in International Tourism Development: A Gravity Model Approach	2008	9
Khadaroo and Seetanah	Transport Infrastructure and Tourism Development	2007	8

Author	Title	Year	Estimates
Kim and Song	Analysis of Inbound Tourism Demand in South Korea: A Cointegration and Error Correction Approach	1998	4
Kim, Park and Sakai	Forecasting International Tourism Demand from Japan to Korea	2002	6
Kliman	A Quantitative Analysis of Canadian Overseas Tourism	1981	12
Kraipornsak	The World Economy, Competition, External Shocks and Demand for International Tourist Arrivals in Thailand	2011	3
Kulendran	Australian Tourism Marketing Expenditure Elasticity Estimates	2006	8
Kulendran	Modelling Quarterly Tourist Flows to Australia Using Cointegration Analysis	1996	6
Kulendran and Divisekera	Measuring the economic impact of Australian tourism marketing expenditure	2007	9
Kulendran and Dwyer	Measuring the Return from Australian Tourism Marketing Expenditure	2009	3
Kulendran and Wilson	Modelling Business Travel	2000	1
Kulendran and Witt	Cointegration Versus Least Squares Regression	2001	6
Kulendran and Witt	Forecasting the Demand for International Business Tourism	2003	1
Kwack	Effects of Income and Prices on Travel Spending Abroad, 1960 III-1967 IV	1972	3
Lathiras and Siriopoulos	The Demand for Tourism to Greece: A Cointegration Approach	1998	8
Ledesma-Rodríguez,Navarro-Ibáñez and Pérez-Rodríguez	Panel data and Tourism: A Case Study of Tenerife	2001	8
Leitao	Does Trade Help to Explain Tourism Demand? The Case of Portugal	2010	3
Lelwala and Guanratne	Modelling Tourism Demand Using Cointegration Analysis: A Case Study for Tourists Arriving from United Kingdom to Sri Lanka	2009	2
Li et al.	Tourism Demand Forecasting: A Time Varying Parameter Error Correction Model	2006	15
Li,Song and Witt	Modeling Tourism Demand: A Dynamic Linear AIDS Approach	2004	10
Lim	The Major Determinants of Korean Outbound Travel to Australia	2004	2
Lim and McAleer	A Cointegration Analysis of Annual Tourism Demand by Malaysia for Australia	2002	6
Little	International Travel in the U.S.: Balance of Payments	1980	11
Loeb	International Travel to The United States An Econometric Evaluation	1982	7

Author	Title	Year	Estimates
Lyssiotou	Dynamic Analysis of British Demand for Tourism Abroad	2000	4
Mangion, Durbarry and Sinclair	Tourism Competitiveness: Price and Quality	2005	3
Martin and Witt	Accuracy of Econometric Forecasts of Tourism	1989b	5
Martin and Witt	Substitute Prices in Models of Tourism Demand	1988	26
Martin and Witt	Tourism Demand Forecasting Models	1987	8
McDermott and Jackson	The Economic Determinants of Tourist Arrivals in Australia and New Zealand	1985	7
Morley	A Dynamic International Demand Model	1998	11
Morley	An Evaluation of the Use of Ordinary Least Squares for Estimating Tourism Demand Models	1997	11
Morris, Wilson and Bakalis	Modelling Tourism flows from Europe to Australia	1995	5
Munoz	German Demand for Tourism in Spain	2007	2
Mutti and Murai	Airline Travel on the North Atlantic: Is Profitability Possible?	1977	11
Narayan	A Tourism Demand Model for Fiji, 1970-2000	2002	3
Narayan	Determinants of Tourist expenditure in FIJI, A Cointegration Approach	2003	3
Njegovan	A Leading Indicator Approach to Predicting Short-Term Shifts in Demand for Business Travel by Air To and From the UK	2005	2
Njegovan	Elasticities of Demand for Leisure Air Travel: A System Modelling Approach	2006	2
O’Hagan and Harrison	U.K. and U.S. Visitor Expenditure in Ireland: Some Econometric Findings	1984b	2
O'Hagan and Harrison	Market Shares of U.S. Tourist Expenditure in Europe, An Econometric Analysis	1984a	14
Ordóñez, Ordóñez and Torres	Distance Matters: An Assessment of International Tourism Demand in Spain	2010	6
Ouerfelli	Analysis of European Tourism Demand for Tunisia: A New Approach	2010	1
Ouerfelli	Co-integration Analysis of Quarterly European Tourism Demand in Tunisia	2008	6
Papadopoulos and Witt	A Marketing Analysis of Foreign Tourism in Greece	1985	15
Papanikos and Sakellariou	An Econometric Application of the Almost Ideal Demand System Model to Japan's Tourist Demand for ASEAN Destinations	1997	5
Phakdisoth and Kim	The Determinants of Inbound Tourism in Laos	2007	9
Phillips and Hamal	Modelling Australian Outbound Travel Demand	2000	9
Qu and Zhang	Determinants of Tourist Arrivals and Expenditures in Canada	1995	7

Author	Title	Year	Estimates
Quayson and Var	A Tourism Demand Function for the Okanagan, BC	1982	3
Rey,Myro and Galera	Effect of Low-cost Airlines on Tourism in Spain. A Dynamic Panel Data Model	2011	1
Rosselló, Aguiló and Riera	Modeling Tourism Demand Dynamics	2005	2
Saayman and Saayman	Determinants of Inbound Tourism to South Africa	2008	1
Salleh	An ARDL Model of Tourism Demand for Malaysia	2007	5
Salleh et al.	Asian Tourism Demand For Malaysia: A Bound Test Approach	2008	5
Salleh, Hanim and Othman	Malaysia's Tourism Demand from Selected Countries: The ARDL Approach to Cointegration	2007	4
Schiff and Becken	Demand Elasticity Estimates for New Zealand Tourism	2011	15
Seetanah, Durbarry and Ragodoo	Using The Panel Cointegration Approach to Analyse The Determinants of Tourism Demand in South Africa	2010	5
Seetaram	Use of Dynamic Panel Cointegration Approach to Model International Arrivals to Australia	2010	7
Seetaram and Dwyer	Immigration and Tourism Demand in Australia: A Panel Data Analysis	2009	1
Smeral	Impacts of the World Recession and Economic Crisis on Tourism: Forecasts and Potential Risks	2010	6
Smeral	International Tourism Demand and The Business Cycle	2012	5
Smeral	The Impact of the Financial and Economic Crisis on European Tourism	2009	2
Smeral	Tourism Demand, Economic Theory And Econometrics: An Integrated Approach	1988	16
Song and Witt	Tourism Forecasting: The General-to-Specific Approach	2003	16
Song and Wong	Tourism Demand Modeling: A Time-Varying Parameter Approach	2003	6
Song et al.	Forecasting Tourist Arrivals Using Time-varying Parameter Structural Time Series Models	2011a	4
Song et al.	Impact of Financial/Economic Crisis on Demand for Hotel Rooms in Hong Kong	2011b	35
Song et al.	Tourism Demand Modelling and Forecasting: How Should Demand Be Measured?	2010	7
Song, Witt and Li	Modelling and Forecasting the Demand for Thai Tourism	2003b	28

Author	Title	Year	Estimates
Song, Romilly and Liu	An Empirical Study of Outbound Tourism Demand in the UK	2000	24
Song, Witt and Jensen	Tourism Forecasting: Accuracy of Alternative Econometric Models	2003c	11
Song, Wong and Chon	Modelling and Forecasting the Demand for Hong Kong Tourism	2003a	13
Sriboonjit et al.	Economic Determinants of Long-Term Equilibrium in Malaysian Tourist Arrivals to Thailand, Implications for Tourism Policy	2010	2
Straszheim	Airline Demand Functions in the North Atlantic and Their Pricing Implications	1978	7
Stronge	The Overseas Demand for Tourism in the United States	1982	7
Summary	Estimation of Tourism Demand by Multivariable Regression Analysis：Evidence from Kenya	1987	4
Surugiu, Leitão and Surugiu	A Panel Data Modelling of International Tourism Demand: Evidences for Romania.	2011	1
Tan and Wong	Structural Change in Hong Kong's Inbound Tourism Demand Model: The Impact of The Asian Financial Crisis	2003	4
Tan, McCahon and Miller	Modeling Tourist Flows to Indonesia and Malaysia	2002	7
Tan, McCahon and Miller	Stability of Inbound Tourism Demand Models for Indonesia and Malaysia: The Pre-and Postformation of Tourism Development Organizations	2002	2
Thompson	Terrorism and Tourism in Developed Versus Developing Countries	2011	1
Toh, Khan and Goh	Japanese Demand for Tourism in Singapore: A Cointegration Approach	2006	1
Tremblay	Pooling International Tourism in Western Europe	1989	12
Truett and Truett	The Response of Tourism to International Economic Conditions: Greece, Mexico, and Spain	1987	9
Uner, Kose and Gokten	An Econometric Model of Tourism Demand and Room Rates: A Study in Belek, Antalya	2008	1
Uysal and Crompton	Determinants of Demand for International Tourist Flows to Turkey	1984	7
Uysal and El Roubi	Artificial Neural Networks versus Multiple Regression in Tourism Demand Analysis	1999	1
Vanegas	Box-cox Estimation of International Tourism Demand for Nicaragua	2010	30
Vanegas	Tourism Demand Response by Residents of Latin American Countries	2009	8
Vanegas and Croes	Evaluation of Demand, US Tourists to Aruba	2000	4

Author	Title	Year	Estimates
Webber	Exchange Rate Volatility and Cointegration in Tourism Demand	2001	10
White	An International Travel Demand Model US Travel to Western Europe	1985	7
White and Walker	Trouble in The Travel Account	1982	4
Witt	An Abstract Mode–Abstract (Destination) Node Model of Foreign Holiday Demand	1980a	3
Witt	An Econometric Comparison of UK and German Foreign Holiday Behaviour	1980b	5
Witt and Martin	Econometric Models for Forecasting International Tourism Demand	1987	37
Wu,Li and Song	Analyzing Tourist Consumption: A Dynamic System-of-Equations Approach	2011	20
Yoon and Shafer	Models of U.S. Travel Demand Patterns for the Bahamas	1996	1
Zhang, Kulendran and Song	Measuring Returns on Hong Kong's Tourism Marketing Expenditure	2010	1
Total			**1200**

Appendix C: Articles Report MAPE of International Tourism Demand Forecasting

Author	Title	Year	Estimates
Akal	Forecasting Turkey's tourism revenues by ARMAX model	2004	28
Álvarez-Díaz and Rosselló-Nadal	Forecasting British Tourist Arrivals in The Balearic Islands Using Meteorological Variables	2010	4
Athiyaman and Robertson	Time Series Forecasting Techniques: Short-term Planning in Tourism	1992	7
Bach and Gogala	Forecasting Tourism Demand: An Illustration Using Time Series and Bayesian Forecasting Model	1997	30
Brida and Risso	Tourism Demand Forecasting with SARIMA Models–The Case of South Tyrol	2011	2
Burger, Dohnal, Kathrada and Law	A practitioners guide to time-series methods for tourism demand forecasting-- a case study of Durban, South Africa	2001	14
Cang and Hemmington	Forecasting U.K. Inbound Expenditure by Different Purposes of Visit	2010	15
Chaitip, Chaiboonsri and Rangaswamy	Forecasting with X-12-ARIMA: International Tourist Arrivals to India	2009	20
Chang and Liao	A Seasonal ARIMA Model of Tourism Forecasting: The Case of Taiwan	2010	4
Chen	Before and After the Inclusion of Intervention Events, An Evaluation of Alternative Forecasting Methods for Tourist Flows	2006	20
Chen and Wang	Support Vector Regression with Genetic Algorithms in Forecasting Tourism Demand	2007	3
Cho	A Comparison of Three Different Approaches to Tourist Arrival Forecasting	2003	18
Cho	A Study on the Temporal Dynamics of Tourism Demand in the Asia Pacific Region	2009	84
Cho	Tourism Forecasting and Its Relationship with Leading Economic Indicators	2001	48
Choy	Forecasting Tourism Revisited	1984	24
Chu	A Fractionally Integrated Autoregressive Moving Average Approach to Forecasting Tourism Demand	2008	204
Chu	A Piecewise Linear Approach to Modeling and Forecasting Demand for Macau Tourism	2011	16
Chu	Forecasting Tourism Demand: A Cubic Polynomial Approach	2004	22

Author	Title	Year	Estimates
Chu	Forecasting Tourists Arrivals: Nonlinear Sine Wave or ARIMA?	1998b	6
De Mello and Nell	The Forecasting Ability of A Cointegrated VAR System of the UK Tourism Demand for France, Spain and Portugal	2005	12
Goh and Law	Modeling and Forecasting Tourism Demand for Arrivals with Stochastic Nonstationary Seasonality and Intervention	2003	95
Guizzardi and Mazzocchi	Tourism Demand for Italy and The Business Cycle	2010	6
Hadavandi et al.	Tourist Arrival Forecasting by Evolutionary Fuzzy Systems	2011	3
Hong	The Application of Support Vector Machines to Forecast Tourist Arrivals in Barbados: An Empirical Study	2006	4
Hong et al.	SVR with Hybrid Chaotic Genetic Algorithms for Tourism Demand Forecasting	2011	2
Hsu and Wang	Applied Multivariate Forecasting Model to Tourism Industry	2008	15
Kon and Turner	Neural Network Forecasting of Tourism Demand	2005	270
Kulendran and Shan	Forecasting China's Monthly Inbound Travel Demand	2002	10
Kulendran and Wilson	Modelling Business Travel	2000	12
Kulendran and Witt	Cointegration Versus Least Squares Regression	2001	92
Kulendran and Witt	Forecasting the Demand for International Business Tourism	2003	84
Kulendran and Wong	Modeling Seasonality in Tourism Forecasting	2005	152
Kulendrana and Witt	Leading Indicator Tourism Forecasts	2003	48
Lai and Lu	Impact Analysis of September 11 on Air Travel Demand in the USA	2005	3
Law	Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting	2000	6
Law and Au	A neural network model to forecast Japanese demand for travel to Hong Kong	1999	5
Li, Song and Witt	Time Varying Parameter and Fixed Parameter Linear AIDS: An Application to Tourism Demand Forecasting	2006	24
Lin, Chen and Lee	Forecasting Tourism Demand Using Time Series, Artificial Neural Networks and Multivariate Adaptive Regression Splines: Evidence from Taiwan	2011	2

Author	Title	Year	Estimates
Loganathan, Nanthakumar and Ibrahim	Forecasting International Tourism Demand in Malaysia Using Box Jenkins Sarima Application	2010	3
Louvieris	Forecasting International Tourism Demand for Greece: A Contingency Approach	2002	1
Martin and Witt	Accuracy of Econometric Forecasts of Tourism	1989b	56
Medeiros et al.	An Alternative Approach to Estimating Demand: Neural Network Regression with Conditional Volatility for High Frequency Air Passenger Arrivals	2008	24
Min	Forecasting Japanese Tourism Demand in Taiwan Using An Intervention Analysis	2008	2
Oh and Ditton	An Evaluation of Price Measures in Tourism Demand Models	2005	41
Oh and Morzuch	Evaluating Time-Series Models to Forecast the Demand for Tourism in Singapore : Comparing Within-Sample And Postsample Results	2005	6
Padhan	Forecasting International Tourists Footfalls in India: An Assortment of Competing Models	2011	15
Pai and Hong	An Improved Neural Network Model in Forecasting Arrivals	2005	6
Palmer, Montan˜o and Sese	Designing An Artificial Neural Network for Forecasting Tourism Time Series	2006	28
Petropoulos et al.	A Decision Support System for Tourism Demand Analysis and Forecasting	2003	4
Qu and Zhang	Projecting International Tourist Arrivals in East Asia and the Pacific to the Year 2005	1996	12
Smeral	World Tourism Forecasting –Keep It Quick, Simple and Dirty	2007	12
Smeral and Wüger	Does Complexity Matter? Methods for Improving Forecasting Accuracy in Tourism: The Case of Austria	2005	8
Song et al.	Forecasting Tourist Arrivals Using Time-varying Parameter Structural Time Series Models	2011	20
Song et al.	Tourism Demand Modelling and Forecasting: How Should Demand Be Measured?	2010	12
Song, Witt and Jensen	Tourism Forecasting: Accuracy of Alternative Econometric Models	2003c	96
Turner and Kijagulu	Univariate Periodic and Nonperiodic Modeling of Tourism Time Series Compared	1998	48
Turner and Witt	Forecasting Tourism Using Univariate and Multivariate Structural Time Series Models	2001	150

Author	Title	Year	Estimates
Turner,Kulendran and Pergat	Forecasting New Zealand tourism demand with disaggregated data	1995	200
Uysal and El Roubi	Artificial Neural Networks versus Multiple Regression in Tourism Demand Analysis	1999	2
Vu	Effect of Demand Volume on Forecasting Accuracy	2006	324
Vu and Turner	Data Disaggregation in Demand Forecasting	2005	12
Wandner and Erden	Estimating the Demand for International Tourism Using Time Series Analysis	1980	4
Wang and Hsu	Constructing and Applying an Improved Fuzzy Time Series Model: Taking the Tourism Industry for Example	2008	4
Witt,Witt and Wilson	Forecasting International Tourist Flows	1994	56
Yu and Schwartz	Forecasting Short Time-Series Tourism Demand with Artificial Intelligence Models	2006	24
Total			**2584**

Appendix D:Articles Report RMSPE of International Tourism Demand Forecasting

Author	Title	Year	Estimates
Álvarez-Díaz and Rosselló-Nadal	Forecasting British Tourist Arrivals in The Balearic Islands Using Meteorological Variables	2010	4
Chen	Before and After the Inclusion of Intervention Events, An Evaluation of Alternative Forecasting Methods for Tourist Flows	2006	20
Goh and Law	Modeling and Forecasting Tourism Demand for Arrivals with Stochastic Nonstationary Seasonality and Intervention	2003	95
Kulendran and Shan	Forecasting China's Monthly Inbound Travel Demand	2002	10
Kulendran and Wilson	Modelling Business Travel	2000	12
Kulendran and Witt	Forecasting the Demand for International Business Tourism	2003	84
Law	Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting	2000	6
Li, Song and Witt	Time Varying Parameter and Fixed Parameter Linear AIDS: An Application to Tourism Demand Forecasting	2006	24
Martin and Witt	Accuracy of Econometric Forecasts of Tourism	1989b	56
Oh and Ditton	An Evaluation of Price Measures in Tourism Demand Models	2005	42
Song et al.	Forecasting Tourist Arrivals Using Time-varying Parameter Structural Time Series Models	2011	20
Song et al.	Tourism Demand Modelling and Forecasting: How Should Demand Be Measured?	2010	12
Song, Witt and Jensen	Tourism Forecasting: Accuracy of Alternative Econometric Models	2003c	96
Vu	Effect of Demand Volume on Forecasting Accuracy	2006	108
Yu and Schwartz	Forecasting Short Time-Series Tourism Demand with Artificial Intelligence Models	2006	24
Total			**614**

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