https://doi.org/10.1016/j.tourman.2014.04.005

A META-ANALYSIS OF INTERNATIONAL TOURISM DEMAND FORECASTING AND IMPLICATIONS FOR PRACTICE

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Abstract: Numerous studies on tourism forecasting have now been published over the past five decades. However, no consensus has been reached in terms of which types of forecasting models tend to be more accurate and in which circumstances. This study uses meta-analysis to examine the relationships between the accuracy of different forecasting models, and the data characteristics and study features. By reviewing 65 studies published during the period 1980-2011, the meta-regression analysis shows that the origins of tourists, destination, time period, modelling method, data frequency, number of variables and their measures and sample size all significantly influence the accuracy of forecasting models. This study is the first attempt to pair forecasting models with the data characteristics and the tourism forecasting context. The results provide suggestions for the choice of appropriate forecasting methods in different forecasting settings.

Keywords: forecasting accuracy, international tourism demand, meta-analysis

INTRODUCTION

Since international tourism has become increasingly important to worldwide economic development, both the public and private sectors have channelled a significant amount of resources and investment into the industry. As both governments and businesses need accurate forecasting to develop efficient public policy and make good business decisions, considerable efforts have been made to improve the accuracy of tourism demand forecasting. Before the 1990s, traditional regression approaches dominated the tourism forecasting and modelling literature. 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).

Other quantitative methods, such as gravity models, artificial neural networks (ANN), and univariate time series models, have also played important roles in tourism demand forecasting. However, conflicting conclusions still exist in terms of which models generate the most accurate forecasts under different conditions. Each method has its own advantages in dealing with a particular problem, but none has been shown to be universally superior.

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, Witt and Witt (1995) found that it is not possible to build a single econometric model that is appropriate for all origin-destination pairs. They also showed that the performance of forecasting models varies according to the time interval of the data, the destination-origin pair, and the forecasting horizon. However, until now, little effort has been made to identify optimal forecasting models according to the data characteristics and study features or forecasting contexts, by learning comprehensively from the lessons of this now large body of work. Meta-analysis is a statistically rigorous technique for synthesing the empirical findings from previous studies. Its aim is to explain what data or study features best account for differences in study findings. Through a comprehensive review and integration of 65 articles and 3,198 estimates of tourism demand forecasting accuracy measures over the period 1980-2011, this study sets out to identify such explanations of international tourism demand forecasting accuracy. Where explanations are found, superior forecasting models can be identified, based on the characteristics of the study and the data used in the model, to assist practitioners in making better choices for forecasting methodology, leading to more effective policy and business decisions.

REVIEW OF QUANTITATIVE TOURISM FORECASTING METHODS

Time series models, econometric approaches, and artificial intelligence (AI) models are three main categories of quantitative forecasting methods. Time series methods extrapolate from previous data in the series to predict future trends, which require no more than one data series. According to the complexities of the models, time series forecasting methods can be further subdivided into basic and advanced subcategories. 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.

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. From this perspective, then, econometric models are superior (Song, Witt, & Li, 2009a). Rather than relying on extrapolation, econometric approaches seek to find dependent relationships between tourism demand and a set of explanatory variables. Tourism forecasts can then be produced as a function of the values taken by these explanatory variables in the future. This approach permits forecasting for different scenarios (e.g., different exchange rate outcomes).

***Basic Time Series Methods*[1].** The *Naive 1 (or no change)* model is the simplest method and has often been shown to generate more accurate one-year-ahead forecasts than other more sophisticated models (Martin & Witt, 1989; Witt, Witt, & Wilson, 1994). However, the performance of the Naive 1 model declines when it has to deal with sudden structural change and longer-term forecasting (Witt, Witt, & Wilson, 1994; Chan, Hui, & Yuen, 1999). The *Naive 2 (or constant change)* model is another widely used but simple model employed when there is a constant trend present in the data. Chan, Hui, and Yuen (1999) use the Gulf War as an example of a sudden shock and show that the Naive 2 model performs better than the autoregressive integrated moving average (ARIMA), exponential smoothing (ES), and quadratic trend curve models when dealing with unstable data.

The *SMA* model allows the past values of a variable to determine the forecast values with equal weights assigned to the former. If a time series shows wide variations around a trend, including more lagged observations, the SMA approach 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

[1] Our use of two categories for classification of the time series models into *basic* and *advanced time series* models is based on the three categories of Frechtling (1996). For the purpose of parsimony, however, we collapsed these to two categories in order to maintain a tractable number of explanatory variables in the meta-analysis.

of a time series. Therefore, the SMA method normally generates more accurate forecasts where the time series is less volatile (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, Chen, & McChain, 2004; Lim & McAleer, 2008).

The *SES* model is used to forecast a time series when there is no trend or seasonal pattern. According to Chen, Bloomfield, and Cubbage (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 relatively lower error magnitudes than the Naive 1 model for domestic tourism demand, which is less volatile than international tourism demand.

Advanced time-series methods. *Brown's DES* model (Brown, 1963) was developed to deal with time series with linear trends. Geurts and Ibrahim (1975) were the first to apply the Brown's DES model to forecast tourist arrivals in Hawaii and suggest that it is cheaper and easier to use than the Box-Jenkins approach for forecasting domestic tourism demand. Sheldon (2008) shows that the Brown's DES and Naive 1 models also perform well in forecasting international tourism expenditure. The disadvantage of 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 (Holt, 1957) is more flexible in selecting the smoothing constants (Makridakis, Wheelwright, & Hyndman, 1998). However, according to Chen, Bloomfield, and Cubbage (2008), Brown's DES models outperform Holt's model based on mean absolute percentage error (MAPE) in forecasting tourist arrivals to US national parks. Holt-Winter's model (the triple ES method) adds seasonal variation to Holt's model, which captures both the seasonal pattern and trend of the time series and usually outperforms other ES methods (Lim & McAleer, 2001). Grubb and Mason (2001) prove that adding a damped trend to Holt-Winter's method greatly improves long-run forecasts compared with the Box-Jenkins and BSM in the case of UK air passengers.

The *Box-Jenkins* model, with the *ARMA* process as its basic form is the most frequently used time series approach in tourism demand forecasting. Researchers' evaluations of the Box-Jenkins models are mixed. Makridakis and Hibon (1979) argue that they produce little improvement in forecasting accuracy, and Kim et al. (2011) conclude that the Seasonal ARIMA (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 does not exhibit structural breaks (see for example, Gustavsson & Nordstrom, 2001; Goh & Law, 2002; Chu, 2008). Preez and Witt (2003) show that the ARIMA approach performs best in terms of forecasting accuracy and goodness of fit.

The BSM model is constructed by decomposing a time series into its trend, seasonal, cyclical, and irregular components. Greenidge (2001) successfully applied BSM to forecasting tourist arrivals to Barbados, and showed that it offered valuable insights into the understanding of tourist behaviour. Exogenous variables can be included in BSM to form a *structural time series model (STSM)* with explanatory variables (Harvey, 1990; Gonzalez & Moral, 1995). However, according to Turner and Witt (2001) 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 model.

Static econometric models. The traditional regression method, gravity models, and the static almost-ideal demand system (AIDS) are examples of static econometric models.

The *Traditional Regression Approach* explicitly addresses the causal relationships between tourism demand and the factors influencing it, which is useful for the assessment of policies and business plans, and it provides several statistics to measure accuracy and validity (Frechtling, 1996). However, a regression model that contains a trended series tends to generate a spurious relationship between dependent and independent variables which invalidates the model's diagnostic statistics. It cannot take dynamic changes in tourists' behaviour into consideration when estimating, which is restrictive and unnecessary. Furthermore, there is no clear procedure to be followed for estimating the model specification, and it is very likely that different researchers with the same dataset will generate completely different models (Song, Witt, & Li, 2009a).

The *Gravity Model* derives its name from the fact that it examines the effects of variables such as distance and population size (representing the attraction of 'mass') on tourism demand. Guo (2007) employs the gravity model it to analyze inbound tourism demand to China, and Khadaroo and Seetanah (2008) use it to investigate the effect of transportation infrastructure on tourism flows. 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, originally introduced by Deaton and Muellbauer (1980), is one of the most popular system-of-equation methods. Empirical studies show that the AIDS model is a popular technique for analyzing the market share of tourism demand, and provides a range of information about the sensitivity of such demand to price and expenditure changes (Syriopoulos & Sinclair, 1993; De Mello, Pack, & Sinclair, 2002; Han, Durbarry, & Sinclair, 2006).

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 co-integration (CI) relationships and short-run dynamics (Song, Witt, & Li, 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 such influences as the effect of “word-of-mouth” (WOM), changing travel tastes or fashions, or the maturing/evolution of tourism preferences over time, which ensure that demand elasticities vary rather than remain constant over relatively long periods of time. Furthermore, the static models ignore the stationarity properties of the variables, so spurious regression is very likely to occur (Li, 2009).

Dynamic econometric models. The adoption of advanced techniques, such as the vector autoregressive (VAR), time varying parameter (TVP), and the error correction models (ECM), has improved the performance of econometric forecasting models.

These dynamic models permit the capture of temporal changes in consumer preference, and the inclusion of the causal variables thereby increases their explanatory power.

The *Autoregressive Distributed Lag model (ADLM)* 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 specification of the general model (Song & Witt, 2003).

The *ECM* and *CI* model are bi-directional transformations, which are useful when both long-run equilibrium and short-run disequilibrium relationships are of interest (Dritsakis, 2004; Choyakh, 2008; Halicioglu, 2010). ECM 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. It also reduces the problem of data mining during estimation (Song, Witt, & Li, 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.

The *VAR* models have been proven to be capable of producing accurate medium- to long-term tourism forecasts (Song & Witt, 2006). It is superior to the single equation for the following reasons (Wong, Song, & Chon, 2006): Firstly, the VAR models do not require an implicit theoretical framework for their construction and estimation. Secondly, it does not require forecasts of the explanatory variables to be produced first, in order to subsequently generate the forecasts of the dependent variable. 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). According to Song, Witt, and Li (2009a), 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, Song, and Louvieris (2003) state that the TVP model performs consistently well for one-year-ahead forecasting.

The *Dynamic AIDS* model is the error-correction form of the AIDS (EC-AIDS) model. 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, Song, and Witt (2004) use the EC-AIDS model to evaluate the international tourism competitiveness of five western European countries and show that the dynamic AIDS model performs better than the static 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 providing 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. 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.

The *Artificial Neural Network (ANN)* model is the most widely used AI method in tourism demand forecasting as it overcomes the restrictions of multiple regression analysis enabling the computation of nonlinear threshold functions. ANN models can 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 learning process of the hidden layers in this approach needs a large amount of data. Additionally, the model cannot generate the impact of explanatory variables on tourism demand (Wu, 2010).

The *Rough Sets Approach* was first used to forecast demand for hotel rooms in Hong Kong by Law and Au (1998). 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). However, 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 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 to 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 models. The results suggest that the GA-SVR approach generated more precise forecasts than both of the other models.

The *Fuzzy Time Series Method* uses linguistic variables (i.e., groups the time series values according to linguistic rules such as Low, Middle or High) to produce forecasts. Its main assumption is that variations from one year to the next follow 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). 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. 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, which can be constructed based on a very short time series, even as few as four observations (Chiang et al., 1998). Both the grey and fuzzy time series models use linguistic variables 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, time-consuming to implement, and not available through most of the commercial statistical packages.

Forecasting Competition. As well as improving accuracy by using different models, a number of studies have tried to compare the performance of various models. Oh and Morzuch (2005) compare the within- and post-sample forecasting accuracy of several time series models of tourism demand in Singapore and suggest that two ARIMA models provide consistent and reliable forecasts across different horizons. Chen, Bloomfield, and Cubbage (2008) compare the accuracy of several models related to three US national parks and show that each of the ARIMA, SES, Naive 1, time series analysis with explanatory variables, Holt's, and SMA models were respectively found to be the most accurate in six different situations. Goh and Law (2011) show that the more advanced econometric methods, such as CI, ECM, and TVP, produce better results than the traditional regression models. Song, Romilly, and Liu (2000) compare the forecasting performance of ECM with that of the auto regression (AR), ARIMA, and VAR models using UK outbound tourism demand data. They show that ECM is superior to all other competitors. Song, Witt, and Jensen (2003) compare six alternative econometric models including a static regression, two ECMs, an ADLM, an unrestricted VAR, and a TVP model, in the context of demand for international tourism in Denmark. Their empirical findings show that the TVP and static models 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) carried out a competition between time series approaches and econometric models, and concluded that the former forecasts tourism demand more accurately. 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 estimates.

These mixed findings show that the performance of models varies considerably depending on the forecast error measurement, forecasting horizon, data frequency, destination-origin pairs, and the competiting techniques included in the comparison. The question therefore arises whether there is any pattern to these findings about which methods are more accurate, when and under what conditions? Can some of the variation in findings of accuracy from study to study be explained? Or is the variation entirely stochastic and therefore unexplainable? The most appropriate method for seeking answers to these questions is known as meta-analysis. After proposing several hypotheses, the meta-analytic approach is explained.

HYPOTHESES

To achieve the research objectives, a series of hypotheses will be developed to explore the effects of data and study characteristics on forecasting accuracy. These include source markets, destinations, modelling methods, time period of the data covered, data frequency, measures of tourism demand, omissions of potential explanatory variables, and other related factors.

As reviewed above, different models perform significantly differently across the published studies. Therefore, we suggest that *the forecasting accuracy of international tourism demand depends on the modelling method employed* (H_1).

The volatility in the forecast time series may affect the performance of forecasting models. It is much easier to forecast worldwide total tourism demand than to predict demand from a specific region. 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. Therefore, it is hypothesized that *the forecasting accuracy of international tourism demand depends on the source market concerned* (H_2).

The destination itself may influence the performance of forecasting models in three possible ways. First, forecasting tourism demand for a mature tourism destination is usually easier than for a developing destination that is changing more rapidly and which is potentially more susceptible to external shocks. Second, forecasting accuracy may be higher for a unique destination than one with many potential substitutes, since uniqueness provides a basis for a more sustainable competitive advantage. Third, since social and political risks may influence the demand for a destination, forecasting accuracy should be better for destinations where such risks do not blight the tourism sector. Therefore, we hypothesize that *the forecasting accuracy of international tourism demand depends on the destination involved (H_3).*

We also hypothesize that *the forecasting accuracy of international tourism demand depends on the time period of the data covered (H_4).* Forecasting errors may increase when the study was conducted over an historical period of fluctuating demand. The tourism industry is also strongly affected by seasonality. Compared to monthly and quarterly data, annual data is usually much smoother. It is more difficult for forecasters to capture the seasonal patterns of tourism products. Therefore, we also believe that *the forecasting accuracy of international tourism demand depends on the data frequency employed (H_5).* Monthly and quarterly demand will be more difficult to predict than annual data.

The inclusion of more and relevant variables would be helpful to explain the variation in demand and reduce forecasting errors. As long as there is some association between tourism demand and a potential explanatory variable, the addition of such a variable will increase the explanatory power of the model. However, in *ex ante* forecasting, before a forecast of demand can be made, it is necessary to predict the values that each explanatory variable will take through the forecast period. Estimation errors of these explanatory variables will, in turn, produce errors in the forecast dependent variable. There is therefore both a benefit and a price to be paid with the inclusion of additional explanatory variables. Therefore, it is likely that *the forecasting accuracy of international tourism demand depends on the number of explanatory variables included in the model (H_6).*

The effect of an explanatory variable, such as changes in currency exchange rates, does not result in an immediate impact on demand. It takes a little time for tourism markets to respond to such changes. In some cases this lag effect may be relatively long. For example, travel during peak seasonal periods typically requires planning and travel decisions well in advance of the trip compared to travel during low-demand seasons. Longer lag effects tend to buffer fluctuations in demand, or limit the ability of travel consumers to alter their travel decisions already made. Additionally, the lag length of the demand model may also reflect the loyalty displayed by tourists toward a destination. The longer the lag length of the dependent variables, the more likely it is that tourists are loyal. For such a destination, the demand series may be much smoother and easier to predict. Therefore, it is hypothesized that *the forecasting accuracy of international tourism demand depends on the lag length of the dependent variable in the model (H_7).*

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. As a luxury product, long-haul tourism is more sensitive to economic fluctuations. As a result, demand for long-haul travel will be more difficult to model and thus to predict accurately. Thus, we suspect that *the forecasting accuracy of international tourism demand depends on travel distance involved (H_8).*

Different measures of tourism demand may also influence the forecasting performance of the models. Demand measured as expenditure on international tourism, or as the number of visitor-nights, is likely to be more sensitive to changes in affordability than demand measured as the number of visitors, since travellers are more likely to vary their budget before they alter their decision to travel. Expenditure per trip or the length-of-stay, are likely to reduce in response to financial and economic crises, making these more difficult to model and forecast than total arrivals. That is to say, we suggest that *the forecasting accuracy of international tourism demand is lower when demand is measured by expenditure and receipts than by other means (H_9).*

Some studies focus on modelling demand at the destination level, while others analyze the demand of specific products such as business travel, VFR, or holiday tourism. It is expected, therefore, that *the forecasting accuracy of international tourism demand depends on the level of aggregation in international tourism demand measurement (H_{10}).* Turner, Kulendran, and Pergat (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 or market segments.

The year in which a research study is published may be viewed as representing a time trend in the evolution and sophistication of international tourism demand modelling and forecasting studies. Modelling techniques have improved in recent years. Such advances ought, themselves, to have led to a reduction in forecasting errors over time. Thus, we hypothesize that *the forecasting errors of international tourism demand may be negatively associated with the year of publication of the study (H_{11}).*

We further hypothesize that *the forecasting accuracy of international tourism demand depends on the sample size (H_{12}).* For example, Markham and Rakes (1998) find that the performance of ANNs for linear regressions depends on sample size and noise level. A large sample is needed to build up a successful ANN model (Zhang, 2003). Finally, it is likely that *the forecasting accuracy of international tourism demand declines with the increase of forecasting horizon (H_{13}).* 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.

METHODOLOGY

Meta-analysis, as a statistical method which combines the empirical results of published studies, is applied in this research. Compared to single studies, meta-analysis has the power to generate a true effect size through a comprehensive and systematic review of the findings from past studies. The method was first applied in medical research as a means of explaining varying results from experiments of the effectiveness of drugs and other medical procedures. The method has now been used very widely in many fields, including in the social sciences, wherever an explanation of the reason for different findings or effects across different studies was needed. The application of meta-analysis in tourism demand analysis has so far been fairly limited with the exceptions of Crouch (1992, 1995, 1996); Lim (1997, 1999) and Brons et al. (2002).

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 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, referencing and footnote chasing was also used to ensure the comprehensiveness of the articles searched.

After identifying potential sources, some studies were rejected according to the following criteria: 1) the article did not report tourism forecasting accuracy measures; 2) the article was not written in English; or 3) the article reported empirical results that have been included in other studies.

For the purpose of our meta-analysis, regression analysis was used to identify and evaluate the effects of data characteristics and study features on the forecasting accuracy. The single log-linear regression model suggested by Sargan (1964) is selected to analyse the data:

$$logY = \beta \quad X \quad + C + \mu$$

where Y refers to a vector of reported measures of international tourism demand forecasting accuracy (usually either MAPE or RMSPE measures); X is a matrix of explanatory variables (discussed below); β is the vector of parameters to be estimated, and which indicates the fractional change of Y in response to one unit change in X; C is the constant term; and μ refers to the vector of residuals.

The explanatory variables for the meta-analytical regressions include a set of continuous variables as well as a set of dummy variables. The variables that were modelled in a continuous form included: the year of publication, the number of variables included in each of the previous studies, the length of the lag inherent in the dependent variable(s) used in each study, the study sample size, and the length of the forecasting time horizon. The variables that were modelled in the form of dummy variables involved the different levels (values) of that variable being assigned the value of either 0 or 1. Assigning the value of zero to the level of a dummy variable causes that variable to be dropped so that the levels assigned the dummy value of 1 can be interpreted as the change in forecasting accuracy arising from the dummy variable taking a different level from the level dropped. Such dummy variables were employed to model the effects of the following:

a. the following tourism source markets as well as destination regions (set to 1 if the origin/destination country in the past study involved is in either of Europe, America, Australia, Asia, or Africa, and 0 otherwise)

b. the time period/years of data covered in the past study (set to 1 if the study covered the 1970s, 1980s, 1990s, or 2000s, and 0 otherwise)

c. the frequency of the data (set to 1 if the study used either monthly or quarterly data, and 0 otherwise)

d. the type of forecasting model employed (set to 1 if the study used either of the advanced time series, static econometric, dynamic econometric, or AI models, and 0 otherwise)

e. the travel distance/length of haul (set to 1 if the study focused on cross-continental tourism demand analysis, and 0 otherwise)

f. the measurement of demand used in the forecasting model (set to 1 if demand is measured using tourist expenditure/receipts, and 0 otherwise), and

g. the level of aggregation of tourism demand (set to 1 if the study addresses disaggregated demand and 0 otherwise).

β_S measure the effect of each individual variable on the forecasting accuracy when other factors are held constant.

The meta-regression estimations follow the general-to-specific estimation procedure (see the detailed explanation in Song & Witt, 2003), in which variables that are insignificant are removed from the model until all the coefficients in the models are significantly different from zero at the 5% significance level. To avoid the potential heteroskedasticity problem, the weighted least squares method was used the model estimation.

DATA DESCRIPTION

A comprehensive search of the literature generated 702 articles on international tourism demand forecasting. Based on the selection criteria set out above, 5,431 forecasting accuracy measures were coded. In the past studies, forecasting accuracy measures such as MAPE (47.6%), Theil's U (16.0%), RMSE (16%), and RMSPE (11.3%) have been most commonly used. For the reason of comparability (i.e., they are unit-free measures), only MAPE and RMSPE are included in the meta-regression. Finally, a total of 3,198 estimates of forecasting accuracy from 65 articles were used, of which 2,584 were MAPEs, and 614 were RMSPEs (These 65 articles are listed in Tables 1).

(Insert Tables 1-2 here)

Improving forecasting performance by searching for the best models has been the main focus of the previous studies. Advanced time series models have been the most popular methods used. Among the 65 articles which use MAPE to evaluate forecasting accuracy, 47 (1,471 estimates, 56.9%) used such methods (see Tables 1 and 2). AI and dynamic econometrics models are the two currently emerging techniques in tourism forecasting, having developed very quickly in recent years.

Most previous studies have focused on forecasting international tourist arrivals (2,371 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, Asia and Europe are the two most frequently studied regions. In particular, 24.8% (642) of forecasts are for Asian and 33.0% (853) forecasts are for European origin countries (both using MAPE). Asian countries are the most popular of the destinations studied 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 has been the main focus of the previous studies, accounting for 66.6% of the forecasts (MAPE). Among those disaggregated products studied, forecasts of business (11.9%) and leisure (13.6%) travel have attracted the most attention. Only two studies (eight estimates) forecast demand for hotel rooms. Since research on forecasting at the product level is very limited, the RMSPE measures are not reported in this study.

RESULTS OF THE META-REGRESSION MODELS

In the case of the dummy-coded categorical variables, the category selected as a comparator within each subgroup (i.e., coded as zero) is labelled as the 'benchmark' in the tables reporting that set of regression results. Tables 3 shows the estimated coefficients of the meta-regressions (with log(MAPE) and log(RMSPE) as the dependent variables) for international tourism demand forecasting. The adjusted R^2 values show that the meta-regression models are successful in explaining 31.9% of the variation in log(MAPE) and 76.7% in log(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 log(RMSPE) should be viewed as a supplement to the log(MAPE) regression.

(Insert Table 3 here)

The regression results show that the forecasting accuracies of the different models vary significantly. Compared to the basic models, the estimated β coefficients for the dynamic econometric, advanced time series, and AI models produce more accurate forecasts indicated by the fact that the coefficient has a negative sign which is evidence that the use of such models tends to reduce forecasting error. Among them, the highly statistically significant results indicate that the dynamic econometrics model is the most precise of the techniques.

The regression results show that forecasting international tourism demand for a specific region is more difficult than predicting the aggregated demand of all regions. The different magnitudes of the coefficients indicate different levels of difficulty in forecasting demand for different continents, which supports our Hypothesis 2 that the forecasting accuracy depends on the source market. For mature markets such as the North America, where demand is relatively stable, the forecasting errors are lower than those for other source markets (see the estimation results of log(RMSPE) in Table 3).

The meta-regression results also show that the forecasting accuracy depends on the destination being forecast. For African destinations, forecasting accuracy is higher overall. This may have arisen because international tourist flows in this case are relatively stable because of the uniqueness of this destination, which may insulate it from external factors leading to better predictability (see the estimation results of log(MAPE) in Table 3). In contrast, tourism demand forecasting errors for European countries are significantly higher. As most international tourism in Europe derives from neighbouring countries, tourists in these origin markets tend to be well informed about the changing fortunes of their neighbours, and therefore more sensitive to such variations. Moreover, higher tourism prices in Europe may magnify fluctuations in demand during periods of economic uncertainty. The results for Asian destinations are mixed, perhaps reflecting the complexity and diversity of Asia. As a category, Asia is perhaps too large and diverse to expect to find some consistency in the results. There are also many destinations within Asia, which are at very different stages of economic as well as tourism development. For developed tourist countries such as Singapore and South Korea, international tourism demand is relatively stable and therefore easier to predict. However, for the countries where the industry is rapidly developing, such as China, inbound tourism demand is growing rapidly making forecasting considerably more difficult.

The dummy variables used to categorize the data decade all had a significant influence on forecasting accuracy. The results suggest that overall forecasting accuracy was better during 1970s, 1980s and 2000s but worse during the 1960s and 1990s.

The regressions also support the hypothesis that forecasting accuracy depends on data frequency. Monthly and quarterly data have significant negative effects on log(MAPE); that is to say, it is more difficult to forecast monthly and quarterly than annual demand. The addition of seasonality introduces greater volatility and therefore an extra challenge to forecasting accuracy. Forecasting errors in cross-continental or long-haul demand are significantly higher than for shorter-haul or within-continent tourism. This finding is consistent with predictions that, since long-haul tourism is usually considered to be a luxury product, demand is more likely to fluctuate.

Contrary to our expectation, no significant difference in forecasting difficulty across different measures of demand was found. However, the meta-regressions show it is easier to forecast total demand for a whole destination than for specific product/market segments, supporting the hypothesis that forecasting accuracy varies according to the level of aggregation. Larger sample sizes ought to reduce estimation error of the model coefficients. The results found, however, that this did not necessarily translate to improved forecasting accuracy as, in most cases, increasing the sample size did not improve log(MAPE) or log(RMSPE).

However, the estimated coefficients for the number of variables and the lag length of dependent variable are significantly negative. The inclusion of more explanatory variables clearly reduces forecasting error, and forecasting tends to be better when lag effects are taken into account. The year of publication, as a proxy variable representing a time-dependent trend in technique development, has a significant negative relationship with log(MAPE) and log(RMSPE). This would suggest that forecasting accuracy has improved over time even over and above developments in forecasting methodologies employed. This may indicate that the 'art' of tourism forecasting has improved as experience has accumulated and choices about methodology, data, and explanatory variables have progressed. The coefficients of the forecasting horizon have a positive sign which confirms that the longer the forecasting horizon, the more uncertainty involved and the less accurate the forecast.

To establish the reliability of the regression models, a set of collinearity diagnostics were performed. The correlation matrices between observed variables show that none of the bivariate correlation indexes are larger than 0.8, which indicates no strong linear association between any two variables (Mason and Perreault, 1991) and the VIF indices indicate no serious multicollinearity for the regression models.

RESEARCH FINDINGS

The meta-regression results showed that various data characteristics and features of the forecasting models and techniques helped to explain a significant portion of the variability in forecasting accuracy across the different studies. Therefore, matching the forecasting model and technique to the particular circumstances involved is one way to improve forecasting performance. In this section, previous studies of forecasting are synthesized 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.

Consistent with previous research, the dynamic econometric models performed best overall, while the static econometric models were the poorest (see Table 5). 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. 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 as the measure of demand (see Table 6). The static econometric models performed very well (ranked first) when demand is measured by expenditure. The advanced time series models perform poorly in forecasting expenditure.

Previous studies imply that the dynamic econometric models rank first when forecasting annual tourism demand (see Table 7). Errors increase significantly when quarterly demand is used, where the AI approach seems to be the best choice. The static econometric and advanced time-series models are the best options for forecasting monthly demand.

(Insert Tables 5-7 here)

Tables 8 & 9 summarize the rankings of forecasting performance by the different models as a function of the different origins, destinations and products analyzed. The dynamic econometric model is the top performer (four out of five cases) when origin is considered. In contrast, however, this method does not seem to perform as well in comparison to time series models when considering forecasting performance as a function of the destination to be modelled. In three cases where accuracy was assessed according to destination, the Naive models outperformed the dynamic econometric methods. Specifically, when the forecasts concern Asia as both an origin and destination, and Europe as a destination, the dynamic econometric models perform best. It is interesting to note also that the Naive models perform reasonably well when a destination is the basis for evaluating forecasting accuracy. After comparing the forecasting accuracy of different models across product/market segments, we find that the dynamic econometric models perform best at forecasting aggregated demand (see

Table 9), but that the Naive model performed better in the case of certain travel segments and AI methods were more accurate for business tourism.

(Insert Tables 8-10 here)

The forecasts for less than 5 years in previous studies are synthesized (in total of 2537 estimates). Generally speaking, as noted above, the accuracy of all models tends to decline with a longer forecasting horizon. However, some models did perform better than others when this factor is considered. Not surprisingly, the advanced time series models provided the most accurate forecasts when forecasting for the short-term (less than one year), while the dynamic econometric models were better for longer horizons (see Table 10).

CONCLUSION AND FUTURE RESEARCH DIRECTION

This study uses meta-analysis to examine the relationships between the accuracy of forecasting models, and the data characteristics and study features. By reviewing 262 studies published during the period 1961-2011, the meta-regression shows that origin, destination, time period, modelling method, data frequency, demand variables and their measures, and sample size all significantly influence forecasting accuracy. This study is the first attempt to pair tourism forecasting models with specific datasets and forecasting contexts. Superior forecasting models are 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 investment decisions. The research also summarises the progress of tourism demand forecasting research, and identifies future research directions for this important topic.

Due to time constraints, only published articles (journal papers, book chapters, and conference proceedings) were included in this analysis. Such a publication bias could be a possible limitation of the study. Since published articles are less likely to report estimates that are either statistically insignificant or contrary to theoretically expectations, this potential bias can influence conclusions arising from 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. There is a view that unpublished studies may be less reliable than published studies which have passed through rigorous reviewing procedures. This need not be a problem if features and characteristics of the methodology and data are appropriately coded in the meta-analysis as potential explicators of the effect size of interest. Due to the constraints of the sample, only the effects of origins and destinations at the continental level were evaluated in the regression analysis. Over time, with an increase in the number of relevant studies in the future, it may be possible to evaluate effects at a single country level. Similarly, the forecasting techniques employed were grouped into five categories for the purpose of this study, but the analysis could be carried out on additional subcategories of methodology if the sample increases significantly in future. Further, since interval forecasting studies are still quite limited in number (except for Song & Lin, 2010; Kim et al., 2011), this research is focused only on point forecasts. Future studies could consider more applications of interval or range forecasts, should these types of forecasting studies grow considerably in number, to reduce the risk of complete forecasting failure.

Although this study covered 262 published studies on tourism demand modelling and forecasting, a large proportion of them did not actually report the forecasting error measures such as MAPE and RMSPE. Future researchers in the area of tourism demand forecasting are encouraged to report various forecasting error measures other than just MAPE and RMSPE, which may suffer from skewed distributions when the forecasts of the dependent variable are close to zero (Hyndman & Koehler, 2006).

One of the limitations of the study is that it did not consider the influence of different forecasting methods (iterative or direct forecasting) on the forecasting accuracy. Future studies should also take this into consideration, as the use of such different approaches in generating forecasts can also lead to variations in forecasting accuracy (Chevillion & Hendry, 2005). A further limitation is that we did not look at the influence of aggregation (i.e., use of monthly or quarterly data to generate annual forecasts) on the forecasting performance. Future studies could address this issue as well.

References

Álvarez-Díaz M., and J. Rosselló-Nadal (2010). Forecasting British Tourist Arrivals in the Balearic Islands Using Meteorological Variables. *Tourism Economics*, 16(1): 153-168.

Athanasopoulos G., R.J. Hyndman, H. Song and D.C. Wu (2011). The Tourism Forecasting Competition. *International Journal of Forecasting*, 27(3): 822-844.

Andrawis R.R., A.F. Atiya and H. El-Shishiny (2011). Combination of Long Term and Short Term Forecasts, with Application to Tourism Demand Forecasting. *International Journal of Forecasting*, 27(3): 870-886.

Athiyaman A. and R. W. Robertson (1992). Time Series Forecasting Techniques: Short-term Planning in Tourism. *International Journal of Contemporary Hospitality Management*, 4(4): 8-11.

Au N. and R. Law (2002). Categorical Classification of Tourism Dining. *Annals of Tourism Research*, 29(3): 819-833.

Bach M.P. and Z. Gogala (1997). Forecasting Tourism Demand: An Illustration Using Time Series and Bayesian Forecasting Model. *Acta Turistica*, 9(2): 155-170.

Brida, J.G. and W.A. Risso (2011). Tourism Demand Forecasting with SARIMA Models–The Case of South Tyrol. *Tourism Economics,* 17(1): 209-221.

Brons M., E. Pels, P. Nijkamp and P. Rietveld (2002). Price Elasticities of Demand for Passenger Air Travel: A Meta-analysis. *Journal of Air Transport Management*, 8(3): 165-175.

Brown R.G. (1963). *Smoothing, Forecasting and Prediction of Discrete Time Series.* Englewood Cliffs, N.J.: Prentice-Hall, 1963.

Burger C.J.S.C., M. Dohnal, M. Kathrada and R. Law (2001). A Practitioners Guide to Time-series Method for Tourism Demand Forecasting—A Case Study of Durban, South Africa. *Tourism Management*, 22(4): 403-409.

Cang S. and N. Hemmington (2010). Forecasting U.K. Inbound Expenditure by Different Purposes of Visit. *Journal of Hospitality & Tourism Research,* 34(3): 294-309.

Chan Y., T. Hui and E. Yuen (1999). Modeling the Impact of Sudden Environmental Changes on Visitor Arrival Forecasts: The Case of the Gulf War. *Journal of Travel Research*, 37(4): 391-394.

Chang Y. and M. Liao (2010). A Seasonal ARIMA Model of Tourism Forecasting: The Case of Taiwan. *Asia Pacific Journal of Tourism Research*, 15(2): 215-221.

Che Y.B. (2004). An Approach to Modeling Regional Tourist Attraction. *Resource Development & Market*, 20(3): 163-165.

Chen R.J.C (2005). Before and After the Inclusion of Intervention Events, An Evaluation of Alternative Forecasting Methods for Tourist Flows. *Tourism Analysis*, 10(3): 269-276.

Chen R.J.C, P. Bloomfield and F.W. Cubbage (2008). Comparing Forecasting Models in Tourism. *Journal of Hospitality & Tourism Research,* 32(1): 3-21.

Chen K.Y. and C.H. Wang (2007). Support Vector Regression with Genetic Algorithms in Forecasting Tourism Demand. *Tourism Management*, 28(1): 215-226.

Chevillion, G. D. F. Hendry (2005). Non-parametric Direct Multistep Estimation for Forecasting Economic Process. *International Journal of Forecasting, 21 (2), 201-208.*

Chiang J.S., P.L. Wu, S.D. Chiang, T.J. Chang, S.T. Chang and K.L. Wen (1998). *Introduction of Grey Theory*. Taiwan: Gao-Li.

Cho V. (2001). Tourism Forecasting and Its Relationship with Leading Economic Indicators. *Journal of Hospitality and Tourism*, 25(4): 399-420.

Cho V. (2003). A Comparison of Three Different Approaches to Tourist Arrival Forecasting. *Tourism Management*, 24(3): 323-330.

Cho, V. (2009). A Study on the Temporal Dynamics of Tourism Demand in the Asia Pacific Region. *International Journal of Tourism Research*, 11(5): 465-485.

Choy D.J.L. (1984). Forecasting Tourism Revisited. *Tourism Management,* 5(3): 171-176.

Choyakh H. (2008). A Model of Tourism Demand for Tunisia: Inclusion of the Tourism Investment Variable. *Tourism Economics*, 14(4): 819-838.

Chu F. (1998a). Forecasting Tourists Arrivals: Nonlinear Sine Wave or ARIMA? *Journal of Travel Research,* 36(3): 79-84.

Chu F. (1998b). Forecasting Tourism: A Combined Approach. *Tourism Management*, 19(6): 515-520.

Chu, F. (2004). Forecasting Tourism Demand: A Cubic Polynomial Approach. *Tourism Management,* 25(2): 209-218.

Chu F. (2008). A Fractionally Integrated Autoregressive Moving Average Approach to Forecasting Tourism Demand. *Tourism Management*, 29(1): 79-88.

Chu F. (2011). A Piecewise Linear Approach to Modeling and Forecasting Demand for Macau Tourism. *Tourism Management, 32*(6): 1414-1420.

Coshall J.T. (2009). Combining Volatility and Smoothing Forecasts of UK Demand for International Tourism. *Tourism Management*, 30(4): 495-511.

Crouch G.I. (1992). Effect of Income and Price on International Tourism. *Annals of Tourism Research*, 19(4): 643-664.

Crouch G.I. (1995). A Meta-analysis of Tourism Demand. *Annals of Tourism Research*, 22(1): 103-118.

Crouch G.I. (1996). Demand Elasticities in International Marketing: A Meta-Analytical Application to Tourism. *Journal of Business Research*, 36(2): 117-136.

Deaton A. S. and J. Muellbauer (1980). An Almost Ideal Demand System. *American Economic Review,* 70(3): 312–326.De Mello M.M. and A. Pack and M.T. Sinclair (2002). A System of Equations Model of UK Tourism Demand in Neighbouring Countries. *Applied Economics,* 34(4): 509-521.

De Mello M. M. and K. S. Nell (2005). The Forecasting Ability of A Cointegrated VAR System of the UK Tourism Demand for France, Spain and Portugal. *Empirical Economics,* 30(2): 277-308.

De Mello M.M. and N. Fortuna (2005). Testing Alternative Dynamic System for Modelling Tourism Demand. *Tourism Economics*, 11(4): 517-537.
Dritsakis N. (2004). Cointegration and Analysis of German and British Tourism Demand for Greece. *Tourism Management*, 25(1): 111-119.
Durbarry R. and M.T. Sinclair (2003). Market Shares Analysis: The Case of French Tourism Demand. *Annals of Tourism Research*, 30 (4): 927-941.
Frechtling D.C. (1996). *Practical Tourism Forecasting*. Oxford: Butterworth-Heinemann.
Geurts M.D. and I.B. Ibrahim (1975). Comparing the Box-Jenkins Approach with the Exponentially Smoothed Forecasting: Model Application to Hawaii Tourists. *Journal of Marketing Research*, 12(2): 182-188.
Goh C. and R. Law (2002). Modeling and Forecasting Tourism Demand for Arrivals with Stochastic Nonstationary Seasonality and Intervention. *Tourism Management*, 23(5): 499-510.
Goh C. and R. Law (2003). Incorporating the Rough Sets Theory into Travel Demand Analysis. *Tourism Management*, 24(5): 511-517.
Goh C., R. Law and H.M.K. Mok (2008). Analyzing and Forecasting Tourism Demand: A Rough Sets Approach. *Journal of Travel Research*, 46(3): 327-338.
Goh C. and R. Law (2011). The Methodological Progress of Tourism Demand Forecasting: A Review of Related Literature. *Journal of Travel & Tourism Marketing*, 28(3): 296-317.
Gonzalez P. and P. Moral (1995). An Analysis of the International Tourism Demand in Spain. *International Journal of Forecasting*, 11(2): 233-251.
Greenidge K. (2001). Forecasting Tourism Demand: An STM Approach. *Annals of Tourism Research*, 28(1): 98-112.
Grubb H. and A. Mason (2001). Long Lead-time Forecasting of UK Air Passengers by Holt-Winters Methods with Damped Trend. *International Journal of Forecasting*, 17(1): 71-82.
Gustavsson P. and J. Nordström (2001). The Impact of Seasonal Unit Roots and Vector ARMA Modelling on Forecasting Monthly Tourism Flows. *Tourism Economics*, 7(2): 117-133.
Guthrie H.W. (1961). Demand for Tourists' Goods and Services in a World Market. *Papers and Proceedings of the Regional Science Association*, 7: 159-175.
Guo W. (2007). Inbound Tourism, An Empirical Research Based on Gravity Model of International Trade. *Tourism Tribune*, 22(3): 30-34.
Hadavandi E., A. Ghanbari, K. Shahanaghi and S. Abbasian-Naghneh (2011). Tourist Arrival Forecasting by Evolutionary Fuzzy Systems. *Tourism Management*, 32(5): 1196-1203.
Halicioglu F. (2010). An Econometric Analysis of the Aggregate Outbound Tourism Demand of Turkey. *Tourism Economics*, 16(1): 83-97.
Han Z., R. Durbarry and M.T. Sinclair (2006). Modelling US Tourism Demand for European Destinations. *Tourism Management*, 27(1): 1-10.

Harvey A. (1990). *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge: Cambridge University Press.

Holt C.C. (1957). Forecasting trends and seasonals by exponentially weighted moving averages. *ONR Memorandum, 52*. Pittsburgh, PA: Carnegie Institute of Technology.

Hong W. (2006). The Application of Support Vector Machines to Forecast Tourist Arrivals in Barbados: An Empirical Study. *International Journal of Management*, 23(2): 375-385.

Hong W., Y. Dong, L. Chen and S. Wei (2011). SVR with Hybrid Chaotic Genetic Algorithms for Tourism Demand Forecasting. *Applied Soft Computing*, 11(2): 1881-1890.

Hsu L.C. and C.H. Wang (2008). Applied Multivariate Forecasting Model to Tourism Industry. *Tourism(Zagreb)*: 56(2): 59-172.

Hu C., M. Chen and S.C. McChain (2004). Forecasting in Short-Term Planning and Management for a Casino Buffet Restaurant. *Journal of Travel & Tourism Marketing*, 16(2): 79-98.

Hyndman, R. J. and A. B. Koehler (2006). Another Look at Measures of Forecast Accuracy. *International Journal of Forecasting*, 22: 679-688.

Khadaroo J. and B. Seetanah (2008). The Role of Transport Infrastructure in International Tourism Development: A Gravity Model Approach. *Tourism Management*, 29(5): 831-840.

Kim J.H., K. Wong, G. Athanasopoulos and S. Liu (2011). Beyond Point Forecasting: Evaluation of Alternative Prediction Intervals for Tourist Arrivals. *International Journal of Forecasting*, 27(3): 887-901.

Kon S.C. and L.W. Turner (2005). Neural Network Forecasting of Tourism Demand. *Tourism Economics*, 11(3): 301-328.

Kulendran N. and K. Wilson (2000). Modelling Business Travel. *Tourism Economics*, 6(1): 47-59.

Kulendran N. and K.K.F. Wong (2005). Modeling Seasonality in Tourism Forecasting. *Journal of Travel Research*, 44(2): 163-170.

Kulendran N. and S.F. Witt (2001). Cointegration versus Least Squares Regression. *Annals of Tourism Research*, 28(2): 291-311.

Kulendran N. and S.F. Witt (2003a). Leading Indicator Tourism Forecasts. *Tourism Management*, 24(5): 503-510.

Kulendran N. and S.F. Witt (2003b). Forecasting the Demand for International Business Tourism. *Journal of Travel Research*, 41: 265-271.

Lai S.L. and W. Lu (2005). Impact Analysis of September 11 on Air Travel Demand in the USA. *Journal of Air Transport Management*, 11(6): 455-458.

Law R. (2000). Back-propagation Learning in Improving the Accuracy of Neural Network-based Tourism Demand Forecasting. *Tourism Management*, 21(4): 331-340.

Law R. (2001). The Impact of the Asian Financial Crisis on Japanese Demand for Travel to Hong Kong: A Study of Various Forecasting Techniques. *Journal of Travel & Tourism Marketing*, 10 (2-3): 47-65.

Law R. and N. Au (1998). A Rough Set Approach to Hotel Expenditure Decision Rules Induction. *Journal of Hospitality & Tourism Research,* 22(4): 359-375.

Law R. and N. Au (1999). A Neural Network Model to Forecasting Japanese Demand for Travel to Hong Kong. *Tourism Management*, 20: 89-97.

Li G. (2009). Tourism Demand Modelling and Forecasting: A Review of Literature Related to Greater China. *Journal of China Tourism Research,* 5(1): 2-40.

Li G., H. Song and S.F. Witt (2004). Modelling Tourism Demand: A Dynamic Linear AIDS Approach. *Journal of Travel Research*, 43(2): 141-150.

Li, G., H. Song and S.F. Witt (2006). Time Varying Parameter and Fixed Parameter Linear AIDS: An Application to Tourism Demand Forecasting. *International Journal of Forecasting*, 22(1): 57-71.

Lim C. (1997). Review of International Tourism Demand Models. *Annals of Tourism Research,* 24(4):835-849.

Lim C. (1999). A Meta-Analytic Review of International Tourism Demand. *Journal of Travel Research*, 37(3): 273-284.

Lim C. and M. McAleer (2001). Forecasting Tourist Arrivals. *Annals of Tourism Research*, 28(4): 965-977.

Lim C. and M. McAleer (2008). Analysing Seasonal Changes in New Zealand's Largest Inbound Market. *Tourism Recreation Research*, 33(1): 83-91.

Lin C.J., H.F. Chen and T.S. Lee (2011). Forecasting Tourism Demand Using Time Series, Artificial Neural Networks and Multivariate Adaptive Regression Splines: Evidence from Taiwan. *International Journal of Business Administration, 2*(2): 14-24.

Loganathan, Nanthakumar and Y. Ibrahim (2010). Forecasting International Tourism Demand in Malaysia Using Box Jenkins Sarima Application. *South Asian Journal of Tourism and Heritage*, 3(2): 50-60.

Louvieris P. (2002). Forecasting International Tourism Demand for Greece: A Contingency Approach. *Journal of Travel & Tourism Marketing,* 13(1-2): 21-40.

Makridakis S. and M. Hibon (1979). Accuracy of Forecasting: An Empirical Investigation. *Journal of the Royal Statistical Society A*, 142(2): 97-145.

Makridakis S., S.C. Wheelwright and R.J. Hyndman (1998). *Forecasting: Methods and Applications* (3rd ed.). New York: John Wiley.

Markham I.S. and T.R. Rakes (1998). The Effect of Sample Size and Variability of Data on the Comparative Performance of Artificial Neural Networks and Regression. *Computers & Operations Research*, 25(4): 251–263.

Martin C.A. and S.F. Witt (1989). Forecasting Tourism Demand: A Comparison of the Accuracy of Several Quantitative Methods. *International Journal of Forecasting*, 5(1): 7-19.

Mason C.H. and W.D. Perreault, Jr. (1991). Collinearity, Power, and Interpretation of Multiple Regression Analysis. *Journal of Marketing Research*, 28(3): 268-280.

Medeiros M.C., M. McAleer, D. Slottje, V. Ramos and J. Rey-Maquieira (2008). An Alternative Approach to Estimating Demand: Neural Network Regression

with Conditional Volatility for High Frequency Air Passenger Arrivals. *Journal of Econometrics,* 147(2): 372-383.
Min J.C.H. (2008). Forecasting Japanese Tourism Demand in Taiwan Using an Intervention Analysis. *International Journal of Culture, Tourism and Hospitality Research,* 2(3): 197-216.
Nadal J.R. (2001). Forecasting Turning Points in International Visitor Arrivals in the Balearic Islands. *Tourism Economics*, 7(4): 365-380.
Oh C. and B.J. Morzuch (2005). Evaluating Time-Series Models to Forecast the Demand for Tourism in Singapore: Comparing Within-Sample and Postsample Results. *Journal of Travel Research*, 43(4): 404-413.
Oh C. and R.B. Ditton (2005). An Evaluation of Price Measures in Tourism Demand Models. *Tourism Analysis*, 10(3): 257-268.
Ouerfelli C. (2008). Co-integration Analysis of Quarterly European Tourism Demand in Tunisia. Tourism Management, 29(1): 127-137.
Padhan P.C. (2011). Forecasting International Tourists Footfalls in India: An Assortment of Competing Models. *International Journal of Business and Management*, 6(5): 190-202.
Pai P. and W. Hong (2005). An Improved Neural Network Model in Forecasting Arrivals. *Annals of Tourism Research,* 32(4): 1138-1141.
Petropoulos C., A. Patelis and K. Metaxiotis (2003). A Decision Support System for Tourism Demand Analysis and Forecasting. *Journal of Computer Information Systems*, 44(1): 21-32.
Preez J. and S.F. Witt (2003). Univariate versus Multivariate Time Series Forecasting: An Application to International Tourism Demand. *International Journal of Forecasting*, 19(3): 435-451.
Qu H. and H.Q. Zhang (1996). Projecting International Tourist Arrivals in East Asia and the Pacific to the Year 2005. *Journal of Travel Research,* 35(1): 27-34.
Sargan, J. D. (1964), Wages and Prices in the United Kingdom, *Econometric Analysis for National Economic Planning*. London: Butterworths.
Sheldon P.J. (2008). Forecasting Tourism: Expenditures versus Arrivals. *Journal of Travel Research*, 32(1): 13-20.
Smeral E. (2007). World Tourism Forecasting –Keep it Quick, Simple and Dirty. *Tourism Economics,* 13(2): 309-317.
Smeral E. and M. Wuger (2005). Does Complexity Matter? Methods for Improving Forecasting Accuracy in Tourism: The Case of Australia. *Journal of Travel Research*, 4(1): 100-110.
Song H. and G. Li (2008). Tourism Demand Modelling and Forecasting: A Review of Recent Research. *Tourism Management*, 29(2): 203-220.
Song H., G. Li, S.F. Witt and B. Fei (2010). Tourism Demand Modelling and Forecasting: How Should Demand Be Measured? *Tourism Economics*, 16(1): 63-81.
Song H., G. Li, S.F. Witt and G. Athanasopoulos (2011). Forecasting Tourist Arrivals Using Time-varying Parameter Structural Time Series Models. *International Journal of Forecasting,* 27(3): 855-869.

Song H. and K.K.F. Wong (2003). Tourism Demand Modelling: A Time-Varying Parameter Approach. *Journal of Travel Research*, 42(1): 57-64.

Song H., P. Romilly and X. Liu (1998). The UK Consumption Function and Structural Instability: Improving Forecasting Performance Using a Time Varying Parameter Approach. *Applied Economics*, 30(7): 975–983.

Song H., P. Romilly and X. Liu (2000). An Empirical Study of Outbound Tourism Demand in the UK. *Applied Economics*, 32(5): 611-624.

Song H., S.F. Witt and T.C. Jensen (2003). Tourism Forecasting: Accuracy of Alternative Econometric Models. *International Journal of Forecasting*, 19(1): 123-141.

Song H. and S.F. Witt (2000). *Tourism Demand Modelling and Forecasting: Modern Econometric Approaches*. Pergamon: Oxford.

Song H. and S.F. Witt (2003). Tourism Forecasting: The General-to-Specific Approach. *Journal of Travel Research*, 42(1): 65-74.

Song H. and S.F. Witt (2006). Forecasting International Tourist Flows to Macau. *Tourism Management*, 27(2): 214-224.

Song H., S.F. Witt and G. Li (2009a). *The Advanced Econometrics of Tourism Demand*. Routledge: NewYork & London.

Song H., S.F. Witt, K.F. Wong and D.C. Wu (2009b). An Empirical Study of Forecast Combination in Tourism. *Journal of Hospitality & Tourism Research*, 33(3): 3-29.

Song H. and S. Lin (2010). Impacts of the Financial and Economic Crisis on Tourism in Asia. *Journal of Travel Research*, 49(1): 16-30.

Syriopoulos T.C. and T. Sinclair (1993). An Econometric Study of Toursim Demand: the AIDS Model of US and European Tourism in Mediterranean Countries. *Applied Economics*, 25(12): 1541–1552.

Turner L.W. and A. M.M. Kijagulu (1998). Univariate Periodic and Nonperiodic Modeling of Tourism Time Series Compared. *Tourism Analysis*, 3(3-4): 143-158.

Turner L.W., N. Kulendran and V. Pergat (1995). Forecasting New Zealand Tourism Demand with Disaggregated Data. *Tourism Economics*, 1(1): 51-69.

Turner L.W. and S.F. Witt (2001). Forecasting Tourism Using Univariate and Multivariate Structural Time Series Models. *Tourism Economics*, 7(2):135-147.

Uysal M. and M.S. El Roubi (1999). Artificial Neural Networks Versus Multiple Regression in Tourism Demand Analysis. *Journal of Travel Research*, 38(2): 111-118.

Veloce W. (2004). Forecasting Inbound Canadian Tourism: An Evaluation of Error Corrections Model Forecasts. *Tourism Economics*, 10(3): 262-280.

Vu J.C. (2006). Effect of Demand Volume on Forecasting Accuracy. *Tourism Economics*, 12(2): 263-276.

Vu C.J. and L. Turner (2005). Data Disaggregated in Demand Forecasting. *Tourism & Hospitality Research*, 6(1): 38-52.

Wandner S.A. and J.D. Erden (1980). Estimating the Demand for International Tourism Using Time Series Analysis. In *Proceeding of the International Symposium on Tourism in the Next Decade*. Washington, DC.

Wang C.H. (2004). Predicting Tourism Demand Using Fuzzy Time Series and Hybrid Grey Theory. *Tourism Management*, 25(3): 367-374.

Wang C.H. and L.C. Hsu (2008). Constructing and Applying an Improved Fuzzy Time Series Model: Taking the Tourism Industry for Example. *Expert Systems with Applications*, 34(4): 2732-2738.

Witt S.F. and C.A. Witt (1992). *Modeling and Forecasting Demand in Tourism*. London: Academic Press Ltd.

Witt S.F., C.A. Witt and N. Wilson (1994). Forecasting International Tourists Flow. *Annals of Tourism Research*, 21(3): 612-628.

Witt S.F., G.D. Newbould and A.J. Watkins (1992). Forecasting Domestic Tourism Demand: Application to Las Vegas Arrivals Data. *Journal of Travel Research*, 31(1): 36-41.

Witt S.F. and C.A. Witt (1995). Forecasting Tourism Demand: A Review of Empirical Research. *International Journal of Forecasting*, 11(3): 447-475.

Witt S.F., H. Song and P. Louvieris (2003). Statistical Testing in Forecasting Model Selection. *Journal of Travel Research*, 42(2):151-158.

Wong K.K.F., H. Song and K.S. Chon (2006). Bayesian Models for Tourism Demand Forecasting. *Tourism Management*, 27(5): 773-780.

Wong K.K.F., H. Song, S.F. Witt, and D.C. Wu (2007). Tourism Forecasting: To Combine or Not To Combine? *Tourism Management, 28*(4): 1068-1078.

Wu C.G. (2010). Econometric Analysis of Tourist Expenditures. PhD Thesis, The Hong Kong Polytechnic University.

Yu G. and Z. Schwartz (2006). Forecasting Short Time-Series Tourism Demand with Artificial Intelligence Models. *Journal of Travel Research*, 45(2): 194-203.

Zhang G.P. (2003). Time Series Forecasting Using a Hybrid ARIMA and Neural Network Model. *Neurocomputing*, 50: 159–175.

Table 1
The Number and Share of MAPE Observations Across Dimensions

Data Categories	Subgroups	No.	Prop.
Model	Artificial Intelligence	264	0.102
	Advanced Time-series	1471	0.569
	Dynamic Econometrics	223	0.086
	Naïve	481	0.186
	Static Econometrics	145	0.056
Demand Measure	Arrival	2371	0.918
	Arrival/POP	3	0.001
	Expenditure	111	0.043
	Expenditure /POP	99	0.038
Data Frequency	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 Distance	Cross-continent	996	0.385
	Inner-continent	839	0.325
	Others	749	0.290
Total		2584	

Table 2
The Number and Share of RMSPE Observations Across Dimensions

Data Categories	Subgroups	No.	Prop.
Model	Artificial Intelligence	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	

Note: In the data frequency dimension, the daily frequency was not included.

Table 3 Meta-Regression for Tourism Forecasting Accuracy

Variable	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			
other	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			
other	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-squared	**0.319**		**0.00**	**0.767**		**0.00**

Note: ‘Benchmark’ identifies dummy variable levels coded as zero. The empty cesses indicate that the corresponding variables are statistically insignificant.

Table 4 Overall Ranking of Forecasting Models

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

Table 5 Forecasting Model Rankings for Demand Measure

Demand as Arrivals				Demand as Expenditure			
Rank	**Model**	**MAPE**	**N**	**Rank**	**Model**	**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/Total		14.094	2374	Average/Total		9.143	210

Table 6 Forecasting Model Rankings for Data Frequency

Yearly Data				Quarterly Data				Monthly Data			
Rank	**Model**	**MAPE**	**N**	**Rank**	**Model**	**MAPE**	**N**	**Rank**	**Model**	**MAPE**	**N**
1	DE	6.302	146	1	AI	12.96	149	1	SE	6.402	31
2	AT	9.784	61	2	Naive	13.10	320	2	AT	9.769	370
3	AI	11.68	47	3	AT	14.52	1040	3	AI	12.96	44
4	SE	20.82	82	4	DE	18.36	77	4	Naive	16.16	89
5	Naive	28.87	72	5	SE	21.96	32		DE		
Average/Total		14.34	408	Average/Total		14.43	1618	Average/Total		10.90	534

Table 7 Forecasting Model Rankings for Origins

Origin not specified			
Rank	Model	MAPE	N
1	DE	4.499	8
2	AT	8.405	353
3	AI	10.978	72
4	SE	21.579	48
5	Naive	31.238	71
Average/Total		12.767	552

Origin = Asia			
Rank	Model	MAPE	N
1	DE	3.658	17
2	AI	12.521	79
3	Naive	14.281	131
4	SE	15.327	20
5	AT	17.128	395
Average/Total		15.567	642

Origin = America			
Rank	Model	MAPE	N
1	DE	3.554	33
2	Naive	10.946	64
3	AI	11.861	34
4	SE	12.923	8
5	AT	13.068	174
Average/Total		11.496	313

Origin = Europe			
Rank	Model	MAPE	N
1	DE	12.981	157
2	AT	14.412	406
3	Naive	14.426	164
4	AI	16.949	59
5	SE	16.988	67
Average/Total		14.529	853

Origin = Australia			
Rank	Model	MAPE	N
1	AI	6.891	18
2	AT	9.964	134
3	DE	10.085	8
4	Naive	10.574	48
5	SE	12.450	2
Average/Total		9.868	210

Table 8 Forecasting Model Rank for Destinations

Destination not specified			
Rank	Model	MAPE	N
1	AT	12.583	97
2	Naive	13.959	66
3	SE	17.109	16
4	AI	17.901	8
5	DE	18.000	4
Average/Total		13.774	191

Destination = Asia			
Rank	Model	MAPE	N
1	DE	2.337	60
2	SE	9.275	65
3	AT	10.564	711
4	AI	11.296	125
5	Naive	14.031	220
Average/Total		10.798	1181

Destination = America			
Rank	Model	MAPE	N
1	Naive	11.635	14
2	AI	11.870	36
3	AT	12.271	41
4	DE	15.313	9
5	SE	21.548	6
Average/Total		12.834	106

Destination = Europe			
Rank	Model	MAPE	N
1	DE	13.590	134
2	AI	14.676	62
3	AT	15.464	141
4	SE	27.995	57
5	Naive	29.988	86

Destination = Australia			
Rank	Model	MAPE	N
1	Naive	10.065	91
2	DE	10.185	16
3	AI	13.364	28
4	AT	16.457	477
	SE		

Average/Total	18.929	480	Average/Total	15.201	612

Table 9 Forecasting Model Rankings for Tourism Product

Product = Destination			
Rank	**Model**	**MAPE**	**N**
1	DE	7.255	155
2	AT	10.894	931
3	AI	12.759	186
4	SE	17.491	121
5	Naive	17.705	329
Average/Total		12.533	1722

Product = Holiday			
Rank	**Model**	**MAPE**	**N**
1	Naive	13.457	65
2	AI	15.416	36
3	AT	17.178	174
5	DE	20.126	52
6	SE	20.514	24
Average/Total		16.973	351

Product = Business			
Rank	**Model**	**MAPE**	**N**
1	AI	8.461	36
2	DE	10.185	16
3	Naive	10.541	53
4	AT	15.159	202
Average/Total		13.317	307

Product = VFR			
Rank	**Model**	**MAPE**	**N**
1	Naive	12.810	22
2	AT	15.060	101
Average/Total		14.658	123

Product = Other			
Rank	**Model**	**MAPE**	**N**
1	Naive	14.248	12
2	AI	16.742	6
3	AT	25.481	63
Average/Total		23.169	81

Table 10 Forecasting Model Rankings for Forecasting

Horizon <= 1 quarter			
Rank	**Model**	**MAPE**	**N**
1	AT	8.439	331
2	AI	11.323	93
3	Naïve	11.690	102
4	SE	14.229	9
5	DE	14.760	18
Average/Total		9.824	553

Horizon 1 quarter to 1 year			
Rank	**Model**	**MAPE**	**N**
1	AT	10.941	352
2	DE	11.041	80
3	SE	12.308	69
4	Naïve	12.980	205
5	AI	15.481	70
Average/Total		12.021	776

Horizon 1 to 2 years			
Rank	**Model**	**MAPE**	**N**
1	DE	12.730	74
2	AI	13.121	83
3	AT	17.647	491
4	Naïve	23.966	129
5	SE	27.312	53
Average/Total		18.355	830

Horizon 2 to 5 years			
Rank	**Model**	**MAPE**	**N**
1	DE	5.250	37
2	AI	6.433	10
3	SE	13.023	11
4	AT	13.795	276
5	Naïve	17.185	44
Average/Total		13.136	378