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Tourism Forecasting:
Accuracy of Alternative Econometric Models Revisited

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Abstract

This study evaluates the forecasting accuracy of five alternative econometric models in the context of predicting the quarterly international tourism demand in 25 countries/country groupings. Tourism demand is measured in terms of tourist expenditure by inbound international visitors in a destination. Two univariate time series models are included in the forecasting comparison as benchmarks. Accuracy is assessed in terms of error magnitude. Seasonality is an important feature of forecasting models and requires careful handling. For each of the 25 destinations, individual models are estimated over the 1980Q1-2005Q1 period, and forecasting performance is assessed using data covering the 2005Q2-2007Q1 period. The empirical results show that the time-varying parameter (TVP) model provides the most accurate short-term forecasts, whereas the naïve (no-change) model performs best in long-term forecasting up to two years. This study provides new evidence of the TVP model's outstanding performance in short-term forecasting. Through the incorporation of a seasonal component into the model, the TVP model forecasts short-run seasonal tourism demand well.

Keywords: tourism forecasting; econometric models; time series models; forecasting accuracy.

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1 Introduction

The flourishing global economy, enhanced global transport and development of tourist attractions and package holidays over the past fifty years have led to tourism becoming one of the fastest growing service industries. The economic significance of the tourism industry has stimulated a growing interest in forecasting future tourism demand, on which all tourism-related business decisions ultimately rest. Over the last three decades, numerous scholars have carried out research in this area, and a wide variety of tourism demand forecasting techniques have been developed. The majority of the published studies have focused on quantitative modelling techniques, especially econometric and time series methods (for detailed reviews of the tourism demand forecasting literature, see Witt and Witt, 1995; Li *et al.*, 2005; Song and Li, 2008). Many of these approaches have been based on the estimation of various econometric models of inbound and outbound tourism demand and cover almost 90% of recent international tourism flows (Smeral and Witt, 1996; Smeral and Weber, 2000; Smeral, 2004). A number of advanced quantitative forecasting models have been developed in an endeavour to achieve more accurate forecasting of tourism demand, and these have motivated great interest in searching for appropriate modelling approaches through comparison of the accuracy of the models.

Research into tourism forecasting accuracy was initiated by Martin and Witt (1989), who applied seven forecasting techniques to a range of origin country/destination country tourist flows. Annual data were used, and one- and two-year-ahead forecasts were generated. The results showed that the naïve no-change model had the lowest mean absolute percentage error (MAPE) in the case of one-year-ahead forecasts, whereas the more sophisticated traditional econometric model (i.e., least squares regression) performed best in the case of two-year-ahead forecasts. Overall, the no-change model was ranked top, and the least squares regression model was ranked fourth. In a later study, Sheldon (1993) obtained similar results.

The failure of traditional econometric models to outperform simple time series models has been noted in the general forecasting literature. Static regression models suffer from a number of problems, including structural instability, forecasting failure and spurious regression. In a major review of empirical research on tourism forecasting, Witt and Witt (1995, p. 469) suggested that 'the considerable advances in econometric methodology during recent years have largely been ignored. It is essential for future econometric studies of tourism demand to take on board these developments, in particular in the areas of diagnostic checking, error correction models and co-integration'. They concluded, 'It may well be that econometric forecasts, using the most up-to-date methodological developments, would be more accurate' (p. 470). Since then, dynamic specifications such as the autoregressive distributed lag model (ADLM) and error correction model (ECM) have begun to appear in the tourism demand forecasting literature.

A few studies of tourism demand forecasting have incorporated the latest developments in econometric methodology (Kim and Song, 1998; Kulendran and King, 1997; Kulendran and Witt, 2001; Song *et al*., 2000; Song *et al*., 2003). However, the empirical findings are conflicting with regard to whether econometric models or time series models produce more accurate forecasts. Kulendran and King (1997) and Kulendran and Witt (2001) found that econometric models were outperformed by simple univariate time series models. In contrast, Kim and Song (1998), Song *et al*. (2000) and Song *et al*. (2003) found that the forecasting performance of econometric models was superior to that of simple time series models. Relevant studies of the forecasting performance of the econometric and univariate time series models mentioned above are summarised in **Table 1**. The studies are categorised according to the type of econometric models and data used.

(Insert **Table 1** here)

Table 1 shows that among the studies of tourism demand forecasting, that of Song *et al*. (2003), which examined five econometric models including the TVP model, is the most comprehensive. The application of the TVP method to tourism forecasting is rare, as econometric models of tourism demand are usually based on the search for structural stability and a belief that the future will be similar to the past. Such an assumption, however, may be too restrictive and result in econometric models being outperformed by time series models in forecasting comparison. The TVP approach allows for structural instability and is therefore able to improve forecasting accuracy when structural instability is present in tourism demand models. In addition, it has been successfully used in modelling and forecasting other economic activities.

Another possible reason for the conflicting results regarding which is the most accurate type of forecasting model is likely the use of different data frequencies. Kulendran and King (1997) and Kulendran and Witt (2001) found that univariate time series models were more accurate in generating forecasts than were econometric models when quarterly data were used in the modelling process. Researchers who have found that the performance of econometric models is superior often use annual data in their forecasting exercises, perhaps because annual data have fewer unit roots and fewer co-integrating vectors than the same series at a quarterly frequency, and different co-integrating relationships usually lead to different ECMs. The use of seasonal data allows for more precise examination of the lag structure. Because seasonality is an important issue in the tourism context, it deserves closer investigation.

An additional method for improving forecasting accuracy is to consider in time series modelling not only seasonal effects but also calendar effects (e.g., number of weekends per months, the exact dates of national, Easter and Whitsuntide holidays, etc.) as well as unknown special effects (Smeral and Wüger, 2005; Smeral and Wüger, 2006). These effects can best be captured by using simultaneously the methods of seasonal and calendar adjustments, outlier detection and parameter identification (Darne and Diebold, 2004; Smeral and Wüger, 2005, 2006, 2008). This means that the use of the dummy variable approach alone to capture the exogenous shocks to the time series is not sufficient, as appropriate corrections to the various shocks are missing and the uncorrected outliers affect the model's parameter estimation. Given that tourism time series tend to be even more affected by these shocks, the use of a sophisticated outlier detection approach is crucial for accurate forecasting.

This paper examines the forecasting accuracy of a range of alternative modern econometric approaches based on the work of Song *et al*. (2003). The forecasting accuracy of two univariate time series models is also evaluated for benchmarking purposes. These two time series models are the seasonal integrated autoregressive and moving average (SARIMA) model and naïve no-change model. Although the forecasting accuracy of the above models has been examined previously, this study is different from previous research in two ways. Firstly, the forecasting accuracy of the modern econometric models is assessed using quarterly data instead of annual data. Secondly, individual models are estimated for an extensive range of countries/country groupings, including Australia, Austria, Belgium-Luxemburg, Brazil, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, India, Ireland, Italy, Mexico, The Netherlands, New Zealand, Portugal, Russia, Slovenia, Spain, Sweden, Turkey, the United Kingdom and the United States. Such a large-scale empirical study should generate robust conclusions on the forecasting performance of various tourism demand models.

Furthermore, up to now, most of the discussion on and empirical studies of tourism demand forecasting models have focused on tourist arrivals rather than tourism expenditures/receipts, according to the comprehensive reviews by Witt and Witt (1995) and Li *et al*. (2005).

The contributions of this study, therefore, are twofold. First, this paper presents the most comprehensive comparison of the forecasting performance of econometric models within a tourism context using quarterly data. Although the forecasting accuracy of some of the modern econometric models included in this paper has been investigated previously, these models were often estimated using annual data. In contrast to annual data, quarterly economic time series data often exhibit substantial seasonal variation. Therefore, considerable care has to be taken when generating seasonal tourism demand forecasts.

The second contribution of this study is the testing of the accuracy of various econometric and time series models in forecasting tourist expenditures. Compared with tourist arrivals, forecasts of tourist expenditures/receipts are of great importance for economic planners in assessing the economic impacts of tourism on the destination economies.

The remainder of this paper is organised as follows. Section 2 discusses the specifications of the forecasting models used in the accuracy comparison. Section 3 introduces the measures of forecast accuracy. In Section 4, the properties of the data set used in this study are examined. The assessment of forecasting performance is presented in Section 5, and Section 6 concludes the study.

2 Model specifications

The selection of the forecasting models used in this study is based on the popularity of the forecasting models used in past tourism forecasting research (Li *et al*., 2005). All of the forecasting models evaluated are special cases of the general ADLM:

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

where p is the lag length, which is determined by the type of data used, k is the number of explanatory variables and ε_t is the error term, which is assumed to be white noise. As quarterly data are used in this study, a lag length of four is adopted.

2.1 Error correction model

Equation (1) can be re-parameterised into an ECM of the following form (Song and Witt, 2000, pp. 73-4):

$$\Delta y_t = (\text{current and lagged } \Delta x_{jt}s, \text{ lagged } \Delta y_t s) - (1-\phi_1)[y_{t-1} - \sum_{j=1}^{k} \beta_j x_{jt-1}] + \varepsilon_t \,. \quad (2)$$

Based on the residuals from the long-run co-integrating models estimated using OLS, the ECM presented by Equation (2) can be estimated through various procedures.

According to the review of Li *et al*. (2005), four ECM estimation methods have been used in previous tourism demand forecasting studies: the Engle and Granger two-stage approach (EG), the Wickens and Breusch one-stage approach (WB), the ADLM approach and, most frequently, the Johansen-Maximum-Likelihood (JML) approach. Unlike the other methods, the JML approach can detect more than one co-integration relationship among the dependent and explanatory variables. In addition, Song *et al*. (2003) found that the magnitudes of the estimated coefficients calculated using the WB approach vary widely compared with those estimated using the JML approach. Song and Witt (2000) recommended that the JML method be used whenever possible because it gives more reliable estimates of the long-run coefficients and generates more accurate forecasts. Therefore, the JML method is used in this study.

The JML-ECM, also known as the vector error correction model (VECM), results from the Johansen co-integration procedure, which is an extension of the univariate Dickey-Fuller test to a multivariate vector autoregressive (VAR) framework. The JML-ECM in this study can be formulated as

$$\nabla S(B) Y_t = \sum_{i=1}^{p-1} \Phi_i \nabla S(B) Y_{t-i} + \Phi \nabla S(B) Y_{t-p} + \Psi D_t + U_t \,, \quad (3)$$

where $\nabla = (1-B)$ denotes the first difference operator, $S(B)$ is the seasonal filter mentioned above, Y_t is a $(k \times 1)$ vector of k potential endogenous variables, Φ is a $(k \times k)$ matrix of parameters, D_t is a vector of deterministic variables (such as intercept, trend and seasonal dummies) and U_t is a $(k \times 1)$ vector of errors. The error correction term is embodied in $\Phi\Delta Y_{t-p}$. The parameter matrices Φ_i and Φ are the short-run and long-run adjustments to the change in Y_t, respectively.

2.2 Reduced ADLM

The dynamic econometric modelling technique advocated by Hendry (1986), known as the general-to-specific approach, is used in this study. In the initial specification of the general ADLM shown by Equation (1), all possible variables are included and the lag length is set equal to four. The least significant explanatory variable is deleted from the model, and then the simplified model is re-estimated. This process is repeated until the coefficients of all of the remaining explanatory variables are statistically significant at the 5% level (one-tailed). The final specific model should be simple in structure and possess the desirable statistical properties. That is, the final model should display no autocorrelation, heteroscedasticity, misspecification, forecasting failure or non-normality.

2.3 Time varying parameter model

The time-varying-parameter (TVP) model was developed to allow the elasticities in log-linear regression to change over time. This method is more adaptable when the assumption of constant coefficients is not valid, and structural changes in econometric models need be tackled. The TVP approach has been successfully applied in modelling and forecasting other economic activities (Brown *et al*., 1997; Riddington, 1993; Song *et al*., 1996, Song *et al*., 1997; Song *et al*., 1998; Stock and Watson, 1996; Swamy *et al*., 1989). However, the TVP method has not received adequate attention in the tourism forecasting research. The published studies include those of Li *et al*. (2006a, 2006b), Riddington (1999), Song and Witt (2000), Song et al. (2003), Song and Wong (2003) and Witt *et al*. (2003).

The TVP approach uses a recursive estimation process in which the more recent information is weighted more heavily than the information obtained in the distant past. With the restriction *p* = 0 imposed on the coefficients in Equation (1), the TVP model is rewritten as a state space form as follows:

$$y_t = x_t \beta_t + \varepsilon_t \tag{4}$$

$$\beta_t = \Phi \beta_{t-1} + \omega_t , \tag{5}$$

where y_t is a vector of tourism demand, x_t is a matrix of the explanatory variables, β_t is the regression coefficients, ε_t refers to a vector of temporary disturbances, ω_t is a matrix of permanent disturbances and Φ is a matrix initially assumed to be known. Equation (4) is called the *measurement equation* or *system equation*, while Equation (5) is known as the *transition equation* or *state equation*, which is used to simulate how the parameters in the system equation evolve over time. If the components of the matrix Φ in Equation (5) equal unity, then each component (β_{jt}) of the transition equation becomes a random walk (RW) process:

$$\beta_{jt} = \beta_{jt-1} + \omega_{jt} \qquad (j = 1, 2, \ldots). \tag{6}$$

In most cases, the RW process is adequate to capture the parameter changes in various economic models (see, for example, Bohara and Sauer, 1992; Kim, 1993; Greenslade and Hall, 1996; Song and Witt, 2000). In this study, based on the RW process, a seasonal component (β_{0t}) is incorporated into the state equation to capture the seasonal fluctuation that is due to the seasonal variations in the parameters. The seasonal component is specified as follows:

$$\beta_{0t} = \beta_{0t-4} + \omega_{0t}\,. \tag{7}$$

The rationale behind this structure is that the seasonal pattern and the fluctuation of the parameters can be captured by such a specification. As shown in Equation (7), the lag period of the intercept term β_{0t} is set to four quarters, to identify the seasonal pattern of tourism demand from the same season of the previous year. To capture the variations in the parameters in the inter-temporal relationship, the parameters of the other explanatory variables are assumed to be determined by their values in the previous season and the external shocks.

The TVP model can be estimated using the Kalman filter algorithm (for details of the estimation procedure, see Kalman, 1960; Harvey, 1989).

2.4 Vector autoregressive model

The vector autoregressive (VAR) method is a system estimation technique that was first suggested by Sims (1980). In contrast to the above models, which depend heavily on the assumption that the explanatory variables are exogenous, the VAR method treats all of the variables as endogenous. The VAR approach has been widely used in macroeconomic modelling and forecasting. Witt *et al*. (2003) and Song and Witt (2006) have successfully applied this technique to tourism demand forecasting. It is important to include an appropriate lag structure in the specification of a VAR model as too few lags will result in the model being unable to fully represent the data generating process (DGP), whereas too many lags will result in over-parameterisation and lack of degrees of freedom. The criteria used for determining the lag length are the Akaike information criterion (AIC) and Schwarz Bayesian criterion (SBC) (Song and Witt, 2000, pp. 93-94).

2.5 Univariate time series models

If none of the explanatory variables plays a statistically significant role in explaining the variations in the dependent variable, then the general ADLM presented by Equation (1) is reduced to a simple autoregressive (AR) model, or an integrated autoregressive and moving average (ARIMA) model if the residuals of the AR model can be used to explain the variations in the dependent variable. Both the AR models (and naïve models) and ARIMA models are considered to be able to generate better forecasts of economic variables than econometric models (Ashley, 1988; Makridakis, 1986; Martin and Witt, 1989; McNees, 1986). A seasonal ARIMA model and naïve model are therefore included in this study as benchmarks for the forecasting accuracy comparison. The standard Box-Jenkins approach (Box and Jenkins, 1976) is followed to fit seasonal ARIMA models for each of the 25 destinations. In general, a seasonal ARIMA model is denoted by SARIMA$\left(p,\ d,\ q\right)\left(P,\ D,\ Q\right)^{s}$. A multiplicative seasonal ARIMA model can be written as

$$\varphi_p(B)\Phi_P(B^s)\nabla^d\nabla_s^D y_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t\,, \tag{8}$$

where B is the backward shift operator, $\varphi_p(B)$, $\theta_q(B)$, $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ are polynomials in B or B^s of non-seasonal and seasonal orders *p*, *q*, *P* and *Q*, respectively, and ε_t is the white noise term. The orders *p*, *q*, *P* and *Q* are determined by the partial autocorrelation function (PACF) and autocorrelation function (ACF), respectively. The number of seasonal differences (∇_s), *D* and the number of regular differences (∇), *d*, are used to reduce the series to stationarity so that an ARIMA model can be fitted. A comprehensive explanation of the multiplicative seasonal ARIMA model-building approach can be found in Chu (1998).

To duplicate the seasonal pattern of the previous year, the naïve model used in this study assumes that the forecast for period t equals the number in period *t*-4:

$$\tilde{y}_t = y_{t-4}\,. \tag{9}$$

3 Measures of forecasting performance

To assess the overall forecasting performance of each of the above models, one-, two-, three-, four- and eight-quarter-ahead forecasts are calculated and compared with the actual values of the series. The measures used for comparing the forecasting accuracy are the mean absolute percentage error (MAPE) and root mean square percentage error (RMSPE), which are defined as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{y_t}\times 100 \tag{10}$$

$$RMSPE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\frac{e_t}{y_t}\right)^2}\times 100\,, \tag{11}$$

where n is the length of the forecasting horizon, $e_t = \hat{y}_t - y_t$ is the forecasting error and $\hat{y}_t$ and y_t are the forecast value and actual value of the dependent variable, respectively.

The most commonly used accuracy measures, the MAPE and RMSPE do not depend on the magnitudes of the demand variables being predicted. Therefore, forecasting performance can be compared not only between different forecasting techniques but also across different countries (units) (for detailed discussion of accuracy measures, see Martin and Witt, 1989; Witt and Witt, 1992).

4 Preliminary data analysis

As mentioned, tourism demand in this paper is measured by tourist expenditure, which is described as expenditures of international inbound visitors excluding transport payments. The economic conditions that are relevant to tourist expenditures include income and tourism prices adjusted by exchange rates. The general tourism demand function takes the form

$$Q_{it} = f\,(Y_{it}, P_{it}, P_{ist}, Dummy\ Variables)\,, \tag{12}$$

where Q_{it} is the real expenditure of inbound international visitors in country *i* at 2000 prices in US dollars. Y_{it} is the average income level of country *i*'s major source markets, and is measured by the weighted average GDP of the key source markets (tourist arrivals from which accounted for 70% of total tourist arrivals to country *i*) at 2000 prices in US dollars. Because of data unavailability, the tourist arrivals variable (rather than the tourist expenditures variable) is used for the selection of the major source markets. P_{it} represents the cost of living for tourists in country *i*, and is measured by the CPI of country *i* (2000 = 100), adjusted by the relevant exchange rate. P_{ist} represents tourism prices in substitute destinations adjusted by relevant exchange rates and is measured by a weighted average price index of a set of alternative destinations for country *i*. The alternative destinations are chosen by comparing the arrivals by country of residence in 2004. When comparing the two destinations, if most of the main source markets are the same, then they are chosen as the alternative destinations. The dummy variables comprise a Gulf War dummy (DGULF = 1 in 1990Q3-91Q1, and 0 otherwise), a dummy for the introduction of the euro (DEURO = 1 in 1999Q1, and 0 otherwise), a dummy for the 9/11 terrorism attack in 2001 (D911 = 1 in 2001Q4-2002Q1, and 0 otherwise), a dummy for the SARS epidemic in early 2003 (DSARS = 1 in 2003Q1-Q2, and 0 otherwise), a dummy for the avian flu outbreak in 2004 (DFLU = 1 in 2004Q1, and 0 otherwise) and seasonal dummies.

The sample covers the period from 1980Q1 to 2007Q1.[2] The data period 1980Q1-2005Q1 is used to estimate the individual forecasting models and the subsequent period for forecasting performance evaluation. Most of the data are extracted from the *Yearbook of Tourism Statistics* published by the United Nations World Tourism Organization (UNWTO) and the International Financial Statistics Online Service website of the International Monetary Fund (IMF). The missing data are generated through extrapolation. As a standard practice, a static log-linear function is adopted for modelling tourism demand for the 25 destinations:

$$q_{it} = \alpha_0 + \alpha_1 y_{it} + \alpha_2 p_{it} + \alpha_3 p_{ist} + Dummies + u_{it}, \qquad (13)$$

where the lower case letters represent the corresponding variables in Equation (12) in logarithmic form.

Before any relationships are estimated, the properties of the data set used are examined. The test proposed by Hylleberg, Engle, Granger and Yoo (1990) (HEGY) is used to test for both seasonal and non-

[2] Because of unavailability of data, the sample range is adjusted for some destinations.

seasonal unit roots. Regressions using non-stationary variables may be subject to the spurious regression problem. An important exception is where the non-stationary variables are integrated of order one, and the linear combinations of these *I*(1) variables are stationary, that is, these series are co-integrated. The next step is to determine which of the regressors discussed above should be included in the co-integration regressions.

For a series $\{y_t\}$, the HEGY test involves various *t* and *F* tests of the coefficients of the regression

$$z_{4t} = \mu_t + \pi_1 z_{1t-1} + \pi_2 z_{2t-1} + \pi_3 z_{3t-2} + \pi_4 z_{3t-1} + \varepsilon_t \, , \qquad (14)$$

where $z_{1t} = (1 + B + B^2 + B^3) y_t$, $z_{2t} = -(1 - B + B^2 - B^3) y_t$, $z_{3t} = -(1 - B^2) y_t$ and $z_{4t} = (1 - B^4) y_t$ in which B is a lag operator. The deterministic component μ_t may include seasonal dummies, a trend and a constant term. Equation (14) is estimated by ordinary least squares with additional lags of z_{4t} included as necessary to ensure that the error term ε_t satisfies the white noise assumption. The rejection of the null hypothesis $\pi_1 = 0$ means that the series y_t does not have a zero-frequency unit root. The rejection of the null hypothesis $\pi_2 = 0$ suggests that the series y_t does not have semi-annual seasonal unit roots. The rejection of the null hypothesis $\pi_3 = \pi_4 = 0$ suggests that the series y_t does not possess annual unit roots. The hypotheses $\pi_1 = 0$, $\pi_2 = 0$ and $\pi_3 = \pi_4 = 0$ are tested separately. If individual *t* tests reject $\pi_1 = 0$ and $\pi_2 = 0$, and a joint *F* test rejects $\pi_3 = \pi_4 = 0$, then there is no zero-frequency unit root and no seasonal unit root, and the order of integration of the series is *I*(0,0,0), that is, the series is stationary. If only $\pi_2 = 0$ and $\pi_3 = \pi_4 = 0$ are rejected, then the order of integration of the series is *I*(1,0,0), indicating that there is a zero-frequency unit root but no seasonal unit root. *I*(1,1,1) suggests that none of the coefficients should be significantly different from zero.

(Insert **Table 2** here)

The results of the HEGY unit root tests of the dependent and explanatory variables for each of the 25 destinations are presented in **Table 2**. It can be seen that all of the time series have a unit root at zero frequency, which implies that these time series have non-stationary stochastic trends. Therefore, there could be some common stochastic trends between the dependent and explanatory variables. The order of integration of tourist expenditures in Finland, Italy and Russia is *I*(1,1,1), suggesting that these series have a unit root at zero frequency and unit roots at seasonal semi-annual and annual frequencies. Before any relationships can be estimated, all of the variables need to have the same order of integration, namely, $I(1)$, so the seasonal unit roots at the semi-annual and annual frequencies need to be removed. This is achieved by applying the filter $S_1(B) = (1 + B + B^2 + B^3)$ to these series. The order of integration of tourist expenditures in the Czech Republic, France and Slovenia is $I(1,1,0)$, which means that the series have a unit root at zero frequency and a unit root at seasonal semi-annual frequency. To perform a standard co-integration test at zero frequency, the seasonal unit root at semi-annual frequency needs to be removed, so the filter $S_2(B) = (1 + B)$ is applied to these series. The order of integration of tourist expenditures in Austria, Australia, Belgium and Luxembourg, Canada, Greece and Ireland is $I(1,0,1)$, implying that the series have a unit root at zero frequency and a unit root at seasonal annual frequency. To perform a standard co-integration test at zero frequency, the seasonal unit root at annual frequency needs to be removed, so the filter $S_3(B) = (1 + B^2)$ is applied to these series.

To see whether there is any relationship between the explanatory variables and the dependent variable we first estimate Equation (13) using the data from 1980Q1 to 2005Q1 for each of the 25 destinations with all of the explanatory variables included. The model for each country is estimated using OLS. The variables included in each equation are all co-integrated. Therefore, the regression relationships are non-spurious, residuals are stationary and inferences drawn from the F and t-statistics are reliable.[3]

As discussed earlier, the JML method is used in this study to test for the long-run co-integrating relationships in the 25 models. It is assumed that the time series have deterministic trends but that the co-integration equations have only intercepts. This assumption has been found to be the most commonly used specification in economics and tourism demand modelling (Song and Witt, 2000). The intervention dummy variables and orthogonalised seasonal dummy variables are included in the test for co-integration relationships using the JML approach. According to the calculated maximal eigenvalue and trace statistics, only one co-integration relationship is detected in each model apart from the cases of Mexico, Turkey, the United Kingdom and the United States, in each of which two co-integration relationships are found.

[3] The estimation results are not presented because of space constraints, but are available from the authors upon request.

5 Empirical results

All six of the models discussed in Section 2 plus the static regression model discussed in Section 4 are estimated based on the quarterly data of 1980Q1-2005Q1, and *ex post* forecasts are generated for the 2005Q2-2007Q1 period. The forecasting performance of the seven models is examined here for each time horizon by ranking the methods in order of both the MAPE and RMSPE for each of the 25 destinations. A summary of the empirical results is presented in **Table 3**.

(Insert **Table 3** here)

For the one-, two- and three-quarter-ahead forecasts, the results show that in terms of both the MAPE and RMSPE, the TVP model is the most accurate forecasting model, followed by the SARIMA model for one-quarter-ahead forecasts and the naïve no-change model for two- and three-quarter-ahead forecasts. The least accurate one-, two- and three-quarter-ahead forecasts are generated by the static regression model, followed by the VAR model, reduced ADLM and JML-ECM.

When lengthening the forecasting horizon to four and eight quarters ahead, the ranking of the naïve model tends to go up, whereas that of the TVP model moves in the reverse direction. The conclusion is that the naïve model generates the most accurate long-term forecasts, followed by the TVP and SARIMA models. As with the short-term forecasts, the static regression model generates the least accurate forecasts, and the reduced ADLM, VAR model and JML-ECM are always ranked below average.

In general, the TVP model provides the most accurate short-term forecasts, whereas the naïve model provides the best long-term forecasts.

To determine whether there is any significant difference in the forecast accuracy between the models, the Morgan-Granger-Newbold (MGN) and Harvey-Leybourne-Newbold (HLN) tests are applied (Diebold and Mariano, 1995; Granger and Newbold, 1977; Harvey *et al*., 1997; Newey and West, 1987, 1994). The MGN test is applicable to one-step-ahead forecasts only, whereas the HLN test can be employed for multiple-step-ahead forecasts. **Table 4** summarises the results of the HLN test between the top two models (i.e., TVP and naïve no-change models) and the other competitors, respectively. These results provide statistical evidence of the superior forecasting performance of the TVP and naïve no-change models. In particular, the TVP model significantly outperforms all of the other competing models at least at the 5% significance level. The MGN test confirms this finding.[4]

(Insert **Table 4** here)

The superior performance of the TVP model over its competitors in short-term forecasting suggests that it is essential to take structural instability into account when generating tourism demand forecasts (Song and Witt, 2000). This empirical result is consistent with the findings of the previous research on international tourism forecasting, which uses annual data to assess forecasting accuracy and in which the TVP model outperforms its competitors in the short run (see, for example, Song and Witt, 2000; Song *et al*., 2003). This finding suggests that, with the proper treatment of seasonality (i.e., by incorporating a seasonal component into the state equation), the TVP model can accurately forecast seasonal tourism demand.

The finding of the excellent forecast accuracy of the naïve no-change model in the long run confirms the empirical results obtained by Martin and Witt (1989), Song and Witt (2000), Kulendran and Witt (2001) and Song *et al*. (2003). Furthermore, the empirical finding that the naïve no-change model generates more accurate long-term tourism demand forecasts than does the SARIMA model partially supports the findings of Chan (1993), Kulendran and Witt (2001) and Song *et al*. (2003).

However, it is shown that a model that simultaneously considers seasonal and calendar effects, (unknown) outliers and parameter identification, in this study, the TVP model, consistently generates excellent results for one- to three-quarter ahead forecasts, which confirms the findings of Smeral and Wüger (2005, 2006).

The static regression model tends to generate relatively inaccurate forecasts of international tourism demand for all forecasting horizons. The main reason for its poor forecasting performance is that the model does not have a dynamic structure. It is unable to adequately capture fluctuations in quarterly tourism demand series, which are likely to be more evident than those in annual time series.

As might be expected and has been observed by many researchers (see, for example, Witt and Witt, 1995; Kulendran and King, 1997), the performance of a forecasting model depends, to a certain extent, on the

[4] The results are not presented because of space constraints, but are available from the authors upon request.

demand for and supply of tourism products/services in the destination concerned, seasonal, calendar and holiday structures and forecasting horizons.

The destination-specific forecasting results (see **Tables 5-9**) show that no single forecasting method outperforms the others on all occasions, which confirms the findings of Li *et al*. (2005) and Song and Li (2008). For instance, with regard to one-quarter-ahead forecasts, the TVP model delivers below-average performance for countries including Austria, Denmark, the Netherlands, New Zealand and the United States, whereas the JML-ECM, static regression model, VAR model, reduced ADLM and SARIMA model perform best in the cases of Austria, Denmark, the Netherlands, New Zealand and the United States. Similarly, the longer term forecast deviations from the general trend can also be found in terms of the best performing model. This implies that to choose the optimal forecasting model, the specific structure of the tourism industry in a destination country should be considered.

(Insert **Tables 5-9** here)

The frequencies of the top-performing models across various horizons are summarised in the bottom rows of **Tables 5-9**. It can be seen that for one- and two-quarter-ahead forecasts, the TVP model takes the top position most frequently among the 25 destination cases. However, although the average performance of the naïve model appears to be the best for longer term forecasting (as shown in **Table 4**), it does not beat that of the reduced ADLM or SARIMA model in terms of the frequency of its top destination-specific performance. This indicates that the TVP model adapts better to different market structures and is less sensitive to different data generating processes. Therefore, its forecasting performance is both superior and more consistent.

6 Summary and conclusions

The relative forecasting accuracy of five econometric models has been evaluated in this study using quarterly data. These models comprise a static regression model, an ECM based on the JML approach, a reduced ADLM, an unrestricted VAR model and a TVP model. In addition, two univariate time series models—a SARIMA model and a naïve no-change model—have been included in the comparison. The forecasting performance of the various models has been assessed using international tourism demand data in terms of aggregate tourist expenditures in 25 countries/country groupings.

For the short-term (one-, two- and three-quarter-ahead) forecasts, the results show that in terms of both the MAPE and RMSPE, the TVP model is the most accurate forecasting model, followed by the SARIMA model for one-quarter-ahead forecasts and the naïve model for two- and three-quarter-ahead forecasts. The least accurate one-, two- and three-quarter-ahead forecasts are those generated by the static regression model, followed by those of the VAR model, reduced ADLM and JML-ECM.

When lengthening the forecasting horizon, the ranking of the naïve model tends to go up, whereas that of the TVP model moves in the reverse direction. The conclusion is that the naïve model generates the most accurate long-term forecasts (up to two years ahead), followed by the TVP and SARIMA models. As with the short-term forecasts, the static model generates the least accurate forecasts, and the reduced ADLM, VAR model and JML-ECM are always ranked below average.

The superior performance of the TVP model for short-term forecasting suggests that it is essential to take structural instability and seasonal fluctuations into account when generating tourism demand forecasts.

The destination-specific forecasting results of the various models confirm the findings in the literature that no single model can outperform other models on all occasions. Therefore, in the selection of the optimal forecasting model, the specific market conditions of a destination should be considered. The frequency of the top performance of the destination-specific models suggests that the TVP model consistently performs well across different market conditions.

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Table 1: Forecasting performance literature

Authors	Econometric Models	Data Frequency	Most Accurate Method
Martin and Witt (1989)	TLS	Annual	Univariate time series
Kulendran and King (1997)	ECM	Quarterly	Univariate time series
Kim and Song (1998)	ECM VAR	Annual	Econometric (ECM)
Song, Romilly and Liu (2000)	ECM VAR	Annual	Econometric (ECM)
Kulendran and Witt (2001)	TLS ECM	Quarterly	Univariate time series
Song, Witt and Jensen (2003)	TLS ADLM ECM VAR TVP	Annual	Econometric (TVP)

Note: TLS = traditional least squares regression model; VAR = vector autoregressive model; TVP = time-varying parameter approach.

Table 2: Unit root tests

Destination	Variable			
	LnQ_{it}	LnY_{it}	LnP_{it}	LnP_{ist}
Australia	$I(1,0,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Austria	$I(1,0,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Belgium and Luxembourg	$I(1,0,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Brazil	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Canada	$I(1,0,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Czech Republic	$I(1,1,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Denmark	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Finland	$I(1,1,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
France	$I(1,1,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Germany	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Greece	$I(1,0,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
India	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Ireland	$I(1,0,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Italy	$I(1,1,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Mexico	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
The Netherlands	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
New Zealand	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Portugal	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Russia	$I(1,1,1)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Slovenia	$I(1,1,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Spain	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Sweden	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
Turkey	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
UK	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$	$I(1,0,0)$
USA	$I(1,0,0)$	$I(0,0,0)$	$I(1,0,0)$	$I(1,0,0)$

Table 3: Summary of forecasting accuracy

Method	Measure	Forecasting horizon									
		1 quarter		2 quarters		3 quarters		4 quarters		8 quarters	
Static regression	MAPE	16.986	(7)	17.351	(7)	17.502	(7)	17.419	(7)	17.748	(7)
	RMSPE	18.738	(7)	19.068	(7)	19.217	(7)	19.001	(7)	17.748	(7)
JML-ECM	MAPE	6.959	(4)	7.616	(4)	8.705	(4)	8.935	(5)	14.542	(4)
	RMSPE	8.506	(4)	9.486	(4)	10.150	(4)	10.296	(4)	14.542	(4)
Reduced ADLM	MAPE	7.623	(5)	8.723	(5)	9.243	(6)	9.646	(6)	15.708	(5)
	RMSPE	9.114	(5)	10.355	(5)	10.977	(6)	11.091	(6)	15.708	(5)
TVP	MAPE	5.211	(1)	5.709	(1)	6.135	(1)	6.858	(2)	9.674	(2)
	RMSPE	6.564	(1)	6.973	(1)	7.346	(1)	7.793	(2)	9.674	(2)
VAR	MAPE	7.929	(6)	9.718	(6)	8.934	(5)	8.677	(4)	16.600	(6)
	RMSPE	9.531	(6)	11.459	(6)	10.452	(5)	10.303	(5)	16.600	(6)
SARIMA	MAPE	6.174	(2)	6.379	(3)	6.809	(3)	7.655	(3)	10.472	(3)
	RMSPE	7.441	(2)	7.651	(3)	8.085	(3)	8.560	(3)	10.472	(3)
Naïve	MAPE	6.491	(3)	6.271	(2)	6.408	(2)	6.357	(1)	8.469	(1)
	RMSPE	7.697	(3)	7.444	(2)	7.532	(2)	7.335	(1)	8.469	(1)

Note: The values in parentheses are rankings.

Table 4: HLN tests for equal forecast accuracy

Competing models	1 quarter ahead		2 quarters ahead		3 quarters ahead		4 quarters ahead	
	TVP	Naïve	TVP	Naïve	TVP	Naïve	TVP	Naïve
Static regression	5.135***	4.591***	4.679***	4.466***	4.544***	4.418***	4.070***	4.060***
JML-ECM	2.511**	0.429	1.982**	1.550	2.138**	2.001**	1.525	1.753*
Reduced ADLM	3.734***	1.031	3.340***	2.210**	2.783***	2.285**	2.067**	2.231**
VAR	3.475***	1.250	2.671***	1.915*	2.033**	1.702*	1.611	1.927*
SARIMA	2.291**	–0.882	1.592	–0.143	1.179	0.281	1.082	1.518
TVP	—	–2.366**	—	–1.310	—	–0.898	—	1.509
Naïve	2.366**	—	1.310	—	0.898	—	–1.509	—

Note: ***, ** and * indicate the 1%, 5% and 10% significance levels, respectively. The positive statistics suggest that the TVP or naïve models (in columns) outperform the competing models (in rows). Because of the extremely small number of eight-quarter-ahead forecasts, the HLN test was not conducted.

Table 5: One-quarter-ahead forecasts for each destination

Destination	Measure	Static regression	JML-ECM	Reduced ADLM	TVP	VAR	SARIMA	Naïve
Australia	MAPE	3.401 (5)	3.713 (6)	3.189 (4)	1.839 (2)	3.018 (3)	1.800 (1)	4.088 (7)
	RMSPE	4.184 (5)	4.921 (6)	3.701 (3)	2.291 (2)	3.976 (4)	2.274 (1)	5.015 (7)
Austria	MAPE	13.909 (7)	4.846 (1)	6.890 (3)	7.153 (4)	5.441 (2)	7.440 (5)	7.502 (6)
	RMSPE	16.486 (7)	7.208 (1)	9.687 (6)	8.613 (4)	7.615 (2)	9.042 (5)	8.572 (3)
Belgium and Luxembourg	MAPE	37.453 (7)	5.262 (4)	4.276 (2)	5.221 (3)	3.623 (1)	5.737 (6)	5.672 (5)
	RMSPE	37.827 (7)	6.289 (4)	5.551 (2)	6.135 (3)	4.586 (1)	6.816 (5)	7.480 (6)
Brazil	MAPE	51.476 (7)	9.609 (4)	10.202 (5)	6.180 (1)	21.310 (6)	6.248 (2)	6.932 (3)
	RMSPE	51.810 (7)	9.999 (4)	12.341 (5)	7.008 (1)	23.371 (6)	8.073 (2)	8.721 (3)
Canada	MAPE	15.629 (7)	4.120 (3)	8.065 (6)	3.288 (1)	7.430 (5)	4.109 (2)	4.311 (4)
	RMSPE	19.341 (7)	5.141 (4)	9.517 (6)	3.595 (1)	8.555 (5)	4.677 (2)	4.693 (3)
Czech Republic	MAPE	7.153 (7)	5.210 (3)	6.486 (6)	5.469 (4)	5.642 (5)	4.746 (2)	4.368 (1)
	RMSPE	8.647 (7)	6.877 (4)	7.730 (6)	6.277 (3)	6.986 (5)	5.716 (2)	4.698 (1)
Denmark	MAPE	4.229 (1)	4.370 (2)	5.642 (4)	6.043 (6)	5.312 (3)	5.790 (5)	6.975 (7)
	RMSPE	4.629 (1)	5.587 (2)	7.318 (5)	7.526 (6)	6.322 (3)	7.055 (4)	9.474 (7)
Finland	MAPE	13.487 (7)	4.498 (3)	5.940 (4)	3.043 (1)	6.019 (6)	3.493 (2)	6.001 (5)
	RMSPE	15.604 (7)	6.261 (3)	6.984 (5)	4.722 (1)	7.898 (6)	5.272 (2)	6.973 (4)
France	MAPE	11.105 (7)	5.947 (2)	9.725 (5)	6.713 (3)	10.207 (6)	7.684 (4)	4.528 (1)
	RMSPE	14.466 (7)	7.177 (2)	11.167 (5)	8.297 (3)	12.097 (6)	8.891 (4)	5.635 (1)
Germany	MAPE	5.608 (3)	5.795 (4)	6.824 (7)	3.786 (1)	6.773 (6)	4.107 (2)	6.050 (5)
	RMSPE	6.984 (4)	6.514 (3)	8.008 (7)	5.988 (2)	7.905 (6)	5.683 (1)	7.240 (5)
Greece	MAPE	32.368 (7)	8.251 (3)	16.666 (5)	7.510 (2)	20.270 (6)	9.284 (4)	6.101 (1)
	RMSPE	36.969 (7)	10.162 (4)	20.584 (5)	8.769 (1)	24.402 (6)	9.886 (3)	9.119 (2)
India	MAPE	32.047 (7)	14.656 (4)	14.778 (5)	9.556 (1)	16.296 (6)	13.759 (3)	11.881 (2)
	RMSPE	34.581 (7)	17.531 (5)	16.916 (4)	11.482 (1)	20.202 (6)	14.039 (3)	12.438 (2)
Ireland	MAPE	17.333 (7)	5.317 (6)	3.799 (2)	4.571 (3)	2.804 (1)	5.106 (5)	4.667 (4)
	RMSPE	21.178 (7)	7.254 (6)	4.241 (2)	5.418 (3)	3.097 (1)	5.546 (4)	5.705 (5)
Italy	MAPE	25.682 (7)	6.386 (4)	13.651 (6)	3.412 (1)	9.876 (5)	4.366 (2)	4.547 (3)
	RMSPE	27.194 (7)	7.538 (4)	15.227 (6)	4.717 (1)	11.507 (5)	5.409 (3)	5.279 (2)
Mexico	MAPE	5.414 (4)	6.280 (5)	4.938 (1)	5.113 (2)	5.161 (3)	6.492 (6)	8.723 (7)
	RMSPE	6.212 (1)	8.532 (6)	6.805 (2)	7.342 (3)	7.803 (4)	8.276 (5)	10.932 (7)
The Netherlands	MAPE	12.223 (7)	5.713 (2)	6.608 (4)	7.411 (5)	5.525 (1)	8.490 (6)	5.736 (3)
	RMSPE	13.824 (7)	6.907 (2)	7.897 (3)	9.752 (5)	6.533 (1)	10.821 (6)	8.514 (4)
New Zealand	MAPE	5.121 (4)	5.623 (5)	4.083 (1)	8.751 (7)	4.228 (2)	7.766 (6)	4.264 (3)
	RMSPE	5.708 (4)	6.148 (5)	5.267 (3)	9.998 (7)	4.887 (2)	9.077 (6)	4.729 (1)
Portugal	MAPE	10.853 (7)	5.146 (5)	5.553 (6)	3.201 (2)	4.892 (3)	2.864 (1)	5.022 (4)
	RMSPE	11.052 (7)	5.976 (3)	6.210 (6)	3.393 (2)	6.038 (5)	3.075 (1)	5.980 (4)
Russia	MAPE	9.050 (5)	20.674 (7)	7.095 (3)	5.093 (1)	7.378 (4)	6.843 (2)	12.020 (6)
	RMSPE	10.691 (5)	24.487 (7)	9.152 (3)	7.797 (1)	8.666 (2)	9.599 (4)	12.728 (6)
Slovenia	MAPE	18.185 (7)	3.562 (3)	8.624 (5)	2.925 (1)	9.794 (6)	3.540 (2)	5.333 (4)
	RMSPE	19.004 (7)	5.048 (3)	10.145 (5)	3.349 (1)	11.743 (6)	4.226 (2)	6.167 (4)
Spain	MAPE	9.500 (7)	6.239 (6)	5.645 (4)	4.780 (3)	5.772 (5)	4.667 (2)	3.784 (1)
	RMSPE	10.686 (7)	7.629 (6)	6.417 (2)	6.959 (5)	6.826 (3)	6.853 (4)	4.932 (1)
Sweden	MAPE	24.822 (7)	7.138 (3)	7.718 (4)	6.370 (2)	8.012 (5)	6.352 (1)	18.372 (6)
	RMSPE	26.416 (7)	9.854 (4)	9.283 (3)	8.184 (2)	11.002 (5)	7.490 (1)	18.849 (6)
Turkey	MAPE	27.058 (7)	16.447 (6)	14.416 (4)	5.092 (1)	13.426 (3)	16.408 (5)	6.329 (2)
	RMSPE	31.951 (7)	19.211 (6)	16.247 (4)	6.712 (1)	15.082 (3)	19.075 (5)	7.924 (2)
UK	MAPE	10.776 (7)	5.836 (4)	6.015 (5)	4.346 (1)	6.747 (6)	4.637 (2)	5.410 (3)
	RMSPE	11.796 (7)	6.275 (4)	7.208 (5)	5.431 (1)	7.470 (6)	6.105 (2)	6.150 (3)
USA	MAPE	20.769 (7)	3.340 (3)	3.739 (6)	3.404 (4)	3.258 (2)	2.629 (1)	3.653 (5)
	RMSPE	21.220 (7)	4.124 (3)	4.248 (4)	4.339 (5)	3.715 (2)	3.057 (1)	4.469 (6)
Frequency of top performance (out of 50)		3	2	2	20	6	9	8

Note: MAPE and RMSPE represent the mean absolute percentage error and root mean square percentage error, respectively. The values in parentheses are rankings.

Table 6: Two-quarter-ahead forecasts for each destination

Destination	Measure	Static regression	JML-ECM	Reduced ADLM	TVP	VAR	SARIMA	Naïve
Australia	MAPE	3.728 (5)	4.221 (7)	3.134 (3)	2.726 (1)	3.540 (4)	2.957 (2)	4.200 (6)
	RMSPE	4.453 (4)	5.146 (5)	4.192 (3)	3.419 (2)	5.268 (7)	3.364 (1)	5.213 (6)
Austria	MAPE	14.493 (7)	5.824 (1)	7.679 (5)	7.193 (3)	6.200 (2)	8.405 (6)	7.538 (4)
	RMSPE	17.228 (7)	7.539 (1)	10.638 (6)	8.468 (3)	8.164 (2)	9.200 (5)	8.745 (4)
Belgium and	MAPE	37.963 (7)	4.527 (2)	5.289 (4)	5.648 (5)	4.081 (1)	5.193 (3)	5.994 (6)
Luxembourg	RMSPE	38.358 (7)	5.878 (2)	6.491 (3)	6.897 (5)	5.099 (1)	6.635 (4)	7.891 (6)
Brazil	MAPE	52.885 (7)	10.440 (4)	17.208 (5)	6.445 (3)	32.664 (6)	5.340 (1)	5.808 (2)
	RMSPE	53.108 (7)	13.102 (4)	18.968 (5)	6.953 (2)	35.449 (6)	6.499 (1)	7.460 (3)
Canada	MAPE	16.697 (7)	5.558 (3)	13.111 (6)	3.950 (1)	9.341 (5)	5.928 (4)	4.270 (2)
	RMSPE	20.446 (7)	7.425 (4)	13.927 (6)	4.618 (1)	9.839 (5)	6.732 (3)	4.706 (2)
Czech Republic	MAPE	7.977 (5)	6.898 (4)	8.808 (6)	6.313 (3)	8.873 (7)	5.457 (2)	4.116 (1)
	RMSPE	9.229 (5)	7.771 (4)	10.007 (7)	6.695 (3)	9.895 (6)	6.048 (2)	4.455 (1)
Denmark	MAPE	4.530 (1)	4.804 (2)	8.111 (7)	7.721 (6)	7.150 (4)	7.180 (5)	5.325 (3)
	RMSPE	4.883 (1)	6.112 (2)	9.931 (7)	8.119 (5)	7.792 (4)	8.428 (6)	7.319 (3)
Finland	MAPE	14.711 (7)	5.285 (3)	6.028 (4)	4.127 (1)	6.078 (5)	4.994 (2)	6.348 (6)
	RMSPE	16.577 (7)	6.494 (3)	7.190 (4)	5.565 (1)	7.381 (6)	6.238 (2)	7.332 (5)
France	MAPE	12.406 (7)	5.702 (4)	10.062 (6)	4.488 (2)	8.574 (5)	4.390 (1)	4.994 (3)
	RMSPE	15.446 (7)	7.473 (4)	12.229 (6)	5.830 (2)	11.544 (5)	5.433 (1)	6.005 (3)
Germany	MAPE	5.826 (6)	4.910 (3)	5.281 (4)	4.854 (2)	5.707 (5)	4.218 (1)	6.131 (7)
	RMSPE	7.305 (6)	5.745 (2)	6.204 (3)	6.757 (4)	7.109 (5)	5.514 (1)	7.458 (7)
Greece	MAPE	30.989 (6)	7.358 (3)	21.053 (5)	6.403 (1)	32.312 (7)	8.843 (4)	6.933 (2)
	RMSPE	36.189 (7)	10.066 (3)	25.840 (5)	9.045 (1)	35.704 (6)	10.622 (4)	9.748 (2)
India	MAPE	30.426 (7)	15.938 (5)	14.473 (4)	9.786 (1)	19.701 (6)	11.323 (3)	11.148 (2)
	RMSPE	33.130 (7)	20.022 (5)	16.486 (4)	10.555 (1)	23.136 (6)	13.787 (3)	11.638 (2)
Ireland	MAPE	19.378 (7)	7.766 (6)	3.949 (3)	3.555 (1)	3.976 (4)	3.559 (2)	4.410 (5)
	RMSPE	22.611 (7)	9.440 (6)	4.336 (1)	4.550 (2)	4.675 (3)	4.870 (4)	5.587 (5)
Italy	MAPE	25.539 (7)	4.462 (4)	16.753 (6)	3.759 (2)	10.321 (5)	3.465 (1)	3.993 (3)
	RMSPE	27.267 (7)	6.531 (4)	18.010 (6)	4.823 (3)	11.454 (5)	4.488 (1)	4.660 (2)
Mexico	MAPE	4.928 (1)	7.968 (4)	5.847 (2)	8.849 (5)	7.854 (3)	10.411 (7)	9.159 (6)
	RMSPE	5.744 (1)	9.884 (4)	8.063 (2)	10.387 (5)	9.728 (3)	12.706 (7)	11.488 (6)
The Netherlands	MAPE	13.854 (7)	4.525 (1)	5.874 (5)	4.714 (3)	5.763 (4)	6.272 (6)	4.685 (2)
	RMSPE	14.776 (7)	5.628 (1)	7.475 (5)	6.508 (2)	7.189 (4)	6.737 (3)	7.638 (6)
New Zealand	MAPE	5.513 (4)	5.444 (3)	4.313 (2)	9.666 (7)	6.937 (5)	8.519 (6)	4.132 (1)
	RMSPE	6.036 (3)	6.814 (4)	5.372 (2)	13.177 (7)	8.453 (5)	10.586 (6)	4.659 (1)
Portugal	MAPE	10.759 (7)	6.510 (4)	6.641 (5)	3.474 (2)	7.034 (6)	3.300 (1)	4.349 (3)
	RMSPE	10.985 (7)	7.607 (4)	8.696 (6)	3.867 (1)	8.455 (5)	3.930 (2)	5.228 (3)
Russia	MAPE	7.856 (2)	32.203 (7)	8.085 (3)	6.847 (1)	13.699 (6)	10.389 (4)	12.197 (5)
	RMSPE	9.344 (2)	36.160 (7)	9.784 (3)	9.089 (1)	15.739 (6)	12.003 (4)	12.983 (5)
Slovenia	MAPE	19.352 (7)	4.807 (3)	12.588 (6)	2.657 (1)	8.091 (5)	4.867 (4)	4.340 (2)
	RMSPE	19.960 (7)	5.690 (4)	13.644 (6)	3.031 (1)	9.791 (5)	5.311 (3)	4.681 (2)
Spain	MAPE	10.405 (7)	2.858 (1)	3.461 (3)	4.102 (6)	3.602 (4)	3.787 (5)	3.262 (2)
	RMSPE	11.361 (7)	3.480 (1)	4.136 (2)	5.682 (6)	4.290 (3)	4.576 (5)	4.460 (4)
Sweden	MAPE	25.280 (7)	8.468 (3)	7.782 (1)	10.470 (5)	9.022 (4)	8.087 (2)	18.285 (6)
	RMSPE	27.032 (7)	12.253 (3)	10.263 (2)	12.371 (4)	13.128 (5)	9.854 (1)	18.831 (6)
Turkey	MAPE	25.756 (7)	17.250 (6)	13.245 (3)	6.175 (1)	14.930 (4)	15.487 (5)	7.115 (2)
	RMSPE	31.303 (7)	22.596 (6)	16.757 (3)	6.682 (1)	18.745 (4)	18.914 (5)	8.465 (2)
UK	MAPE	10.567 (7)	3.453 (1)	5.652 (6)	4.185 (3)	4.172 (2)	4.794 (4)	5.059 (5)
	RMSPE	11.731 (7)	4.092 (1)	6.141 (6)	4.784 (3)	4.422 (2)	5.362 (4)	5.863 (5)
USA	MAPE	21.960 (7)	3.214 (3)	3.641 (5)	4.611 (6)	3.336 (4)	2.308 (1)	2.979 (2)
	RMSPE	22.194 (7)	4.202 (5)	4.089 (4)	6.460 (6)	4.038 (3)	3.430 (1)	3.578 (2)
Frequency of top performance (out of 50)		4	8	2	17	2	13	4

Note: MAPE and RMSPE represent the mean absolute percentage error and root mean square percentage error, respectively. The values in parentheses are rankings.

Table 7: Three-quarter-ahead forecasts for each destination

Destination	Measure	Static regression	JML-ECM	Reduced ADLM	TVP	VAR	SARIMA	Naïve
Australia	MAPE	3.821 (4)	4.904 (7)	3.618 (2)	3.796 (3)	4.380 (6)	3.500 (1)	4.311 (5)
	RMSPE	4.633 (4)	5.655 (6)	4.497 (3)	4.296 (2)	5.999 (7)	3.932 (1)	5.443 (5)
Austria	MAPE	13.831 (7)	3.846 (1)	4.710 (3)	5.994 (4)	4.232 (2)	7.041 (6)	6.115 (5)
	RMSPE	17.013 (7)	4.546 (1)	6.869 (4)	7.043 (5)	5.040 (2)	8.373 (6)	6.793 (3)
Belgium and Luxembourg	MAPE	37.528 (7)	4.619 (2)	4.552 (1)	6.826 (5)	4.809 (3)	4.825 (4)	6.847 (6)
	RMSPE	37.976 (7)	5.328 (1)	5.780 (2)	8.001 (5)	5.999 (3)	6.050 (4)	8.516 (6)
Brazil	MAPE	53.730 (7)	14.649 (4)	22.884 (5)	6.955 (2)	36.847 (6)	9.266 (3)	6.223 (1)
	RMSPE	53.939 (7)	17.142 (4)	23.850 (5)	9.159 (2)	40.084 (6)	11.845 (3)	7.943 (1)
Canada	MAPE	16.745 (7)	6.779 (3)	11.944 (6)	4.410 (2)	9.512 (5)	7.457 (4)	4.369 (1)
	RMSPE	21.044 (7)	7.883 (3)	13.289 (6)	5.261 (2)	9.854 (5)	8.294 (4)	4.857 (1)
Czech Republic	MAPE	7.934 (5)	9.814 (6)	10.322 (7)	3.814 (2)	7.481 (4)	3.456 (1)	3.906 (3)
	RMSPE	9.384 (5)	10.522 (6)	11.155 (7)	4.417 (3)	8.753 (4)	4.165 (1)	4.283 (2)
Denmark	MAPE	4.761 (2)	4.419 (1)	9.347 (7)	5.175 (5)	4.997 (3)	6.868 (6)	5.134 (4)
	RMSPE	5.117 (2)	5.098 (1)	11.176 (7)	5.809 (4)	5.217 (3)	8.351 (6)	7.451 (5)
Finland	MAPE	14.591 (7)	6.370 (5)	6.332 (4)	5.317 (1)	6.037 (2)	6.230 (3)	6.925 (6)
	RMSPE	16.761 (7)	7.314 (3)	7.574 (4)	6.455 (1)	7.629 (5)	7.261 (2)	7.831 (6)
France	MAPE	12.222 (6)	5.728 (2)	13.382 (7)	7.432 (4)	7.158 (3)	8.367 (5)	5.228 (1)
	RMSPE	15.746 (6)	7.737 (2)	16.313 (7)	8.800 (3)	9.957 (5)	9.675 (4)	6.318 (1)
Germany	MAPE	5.856 (5)	3.946 (1)	5.390 (3)	6.846 (7)	5.212 (2)	5.649 (4)	6.685 (6)
	RMSPE	7.546 (5)	5.008 (1)	6.410 (2)	7.922 (6)	6.469 (3)	6.517 (4)	7.974 (7)
Greece	MAPE	26.591 (6)	8.583 (4)	23.180 (5)	5.489 (1)	29.003 (7)	5.859 (2)	7.405 (3)
	RMSPE	31.294 (6)	11.166 (4)	28.246 (5)	8.069 (2)	32.272 (7)	7.550 (1)	10.395 (3)
India	MAPE	32.529 (7)	15.949 (5)	12.137 (4)	8.396 (2)	19.374 (6)	7.350 (1)	10.398 (3)
	RMSPE	35.038 (7)	19.011 (5)	15.518 (4)	9.894 (2)	23.634 (6)	8.653 (1)	10.827 (3)
Ireland	MAPE	19.851 (7)	8.545 (6)	3.750 (2)	4.185 (3)	4.721 (4)	3.720 (1)	4.824 (5)
	RMSPE	23.471 (7)	9.954 (6)	4.217 (1)	4.924 (3)	5.685 (4)	4.687 (2)	5.984 (5)
Italy	MAPE	24.460 (7)	4.054 (2)	14.689 (6)	4.660 (4)	6.858 (5)	3.893 (1)	4.385 (3)
	RMSPE	26.393 (7)	5.473 (4)	15.678 (6)	5.459 (3)	7.942 (5)	4.915 (1)	4.988 (2)
Mexico	MAPE	5.250 (1)	7.285 (4)	5.280 (2)	10.817 (6)	6.001 (3)	11.617 (7)	10.672 (5)
	RMSPE	6.083 (1)	8.888 (4)	7.977 (3)	12.473 (6)	7.094 (2)	14.419 (7)	12.409 (5)
The Netherlands	MAPE	15.017 (7)	5.806 (5)	6.902 (6)	4.581 (1)	5.071 (2)	5.494 (4)	5.444 (3)
	RMSPE	15.711 (7)	6.267 (1)	8.220 (5)	7.170 (4)	6.961 (3)	6.641 (2)	8.250 (6)
New Zealand	MAPE	5.444 (4)	6.450 (5)	2.904 (1)	9.370 (7)	3.448 (2)	8.983 (6)	3.951 (3)
	RMSPE	6.054 (4)	7.502 (5)	4.093 (2)	10.546 (7)	4.012 (1)	10.325 (6)	4.559 (3)
Portugal	MAPE	10.305 (7)	5.864 (4)	7.666 (6)	3.629 (1)	6.797 (5)	3.711 (2)	4.847 (3)
	RMSPE	10.511 (7)	6.633 (4)	10.395 (6)	4.623 (1)	7.667 (5)	4.673 (2)	5.620 (3)
Russia	MAPE	6.756 (1)	34.439 (7)	9.105 (3)	8.870 (2)	13.935 (6)	11.584 (4)	11.823 (5)
	RMSPE	8.188 (1)	37.340 (7)	10.537 (3)	10.354 (2)	15.899 (6)	12.712 (4)	12.724 (5)
Slovenia	MAPE	19.331 (7)	6.575 (5)	16.047 (6)	3.163 (1)	3.195 (2)	5.654 (4)	4.176 (3)
	RMSPE	20.039 (7)	7.491 (5)	17.044 (6)	3.450 (1)	3.854 (2)	6.102 (4)	4.565 (3)
Spain	MAPE	9.638 (7)	3.320 (6)	3.249 (5)	2.576 (3)	2.942 (4)	1.996 (1)	2.278 (2)
	RMSPE	10.632 (7)	3.876 (6)	3.787 (5)	3.423 (3)	3.542 (4)	2.291 (1)	3.035 (2)
Sweden	MAPE	27.455 (7)	10.202 (4)	9.089 (2)	13.872 (5)	8.418 (1)	10.005 (3)	18.195 (6)
	RMSPE	28.768 (7)	12.422 (4)	11.196 (2)	15.235 (5)	11.448 (3)	11.046 (1)	18.832 (6)
Turkey	MAPE	29.983 (7)	28.289 (6)	16.129 (4)	8.222 (2)	15.183 (3)	20.383 (5)	7.731 (1)
	RMSPE	33.810 (7)	32.394 (6)	20.873 (4)	8.356 (1)	17.563 (3)	24.343 (5)	9.036 (2)
UK	MAPE	11.105 (7)	3.243 (1)	5.003 (5)	3.599 (2)	3.629 (3)	4.380 (4)	5.632 (6)
	RMSPE	12.311 (7)	3.972 (1)	5.998 (5)	5.403 (3)	4.089 (2)	5.922 (4)	6.298 (6)
USA	MAPE	22.815 (7)	3.946 (4)	3.476 (3)	5.388 (6)	4.112 (5)	2.948 (2)	2.701 (1)
	RMSPE	22.966 (7)	5.124 (5)	3.736 (3)	7.117 (6)	4.646 (4)	3.377 (2)	3.367 (1)
Frequency of top performance (out of 50)		4	10	3	9	2	13	9

Note: MAPE and RMSPE represent the mean absolute percentage error and root mean square percentage error, respectively. The values in parentheses are rankings.

Table 8: Four-quarter-ahead forecasts for each destination

Destination	Measure	Static regression	JML-ECM	Reduced ADLM	TVP	VAR	SARIMA	Naïve
Australia	MAPE	3.353 (1)	4.000 (5)	3.970 (4)	4.903 (7)	3.894 (3)	3.663 (2)	4.677 (6)
	RMSPE	4.262 (2)	4.386 (3)	4.751 (5)	5.346 (6)	4.604 (4)	4.223 (1)	5.858 (7)
Austria	MAPE	10.478 (7)	5.860 (5)	2.619 (1)	5.762 (4)	3.322 (2)	8.288 (6)	5.733 (3)
	RMSPE	12.654 (7)	6.619 (4)	3.173 (1)	6.667 (5)	4.119 (2)	9.179 (6)	6.518 (3)
Belgium and Luxembourg	MAPE	39.514 (7)	6.093 (2)	2.835 (1)	8.773 (6)	6.164 (3)	8.304 (5)	7.834 (4)
	RMSPE	39.728 (7)	6.514 (2)	3.501 (1)	9.877 (6)	7.276 (3)	8.822 (4)	9.289 (5)
Brazil	MAPE	54.448 (7)	10.992 (4)	28.430 (6)	8.052 (2)	20.461 (5)	9.400 (3)	4.291 (1)
	RMSPE	54.667 (7)	12.377 (4)	28.738 (6)	8.978 (2)	22.002 (5)	10.678 (3)	5.025 (1)
Canada	MAPE	14.165 (7)	7.168 (3)	10.430 (6)	4.026 (2)	9.297 (5)	7.830 (4)	3.837 (1)
	RMSPE	18.858 (7)	8.074 (3)	11.579 (6)	4.992 (2)	9.826 (5)	8.429 (4)	4.293 (1)
Czech Republic	MAPE	7.708 (5)	8.666 (6)	10.530 (7)	4.046 (3)	7.468 (4)	3.251 (1)	3.437 (2)
	RMSPE	9.447 (5)	10.063 (6)	11.507 (7)	4.493 (3)	8.012 (4)	3.783 (2)	3.768 (1)
Denmark	MAPE	5.542 (5)	5.411 (4)	12.025 (7)	3.596 (2)	5.259 (3)	9.681 (6)	2.880 (1)
	RMSPE	5.592 (3)	7.027 (5)	13.044 (7)	4.466 (2)	6.223 (4)	10.447 (6)	3.576 (1)
Finland	MAPE	15.671 (7)	6.560 (5)	5.866 (3)	5.501 (1)	5.822 (2)	6.385 (4)	6.767 (6)
	RMSPE	17.895 (7)	7.341 (3)	7.490 (4)	6.645 (1)	7.117 (2)	7.530 (5)	7.854 (6)
France	MAPE	14.310 (6)	6.112 (1)	14.858 (7)	6.457 (3)	7.236 (5)	6.756 (4)	6.197 (2)
	RMSPE	17.230 (6)	7.488 (3)	17.768 (7)	7.352 (2)	8.903 (5)	7.810 (4)	6.919 (1)
Germany	MAPE	6.537 (5)	3.496 (1)	6.008 (4)	7.641 (7)	5.904 (3)	4.859 (2)	7.498 (6)
	RMSPE	8.193 (6)	5.081 (1)	6.813 (3)	8.091 (5)	7.654 (4)	5.895 (2)	8.656 (7)
Greece	MAPE	28.029 (6)	12.725 (4)	26.393 (5)	6.988 (1)	34.053 (7)	8.149 (2)	8.385 (3)
	RMSPE	33.164 (6)	16.867 (4)	32.792 (5)	10.065 (2)	37.538 (7)	8.773 (1)	11.332 (3)
India	MAPE	35.753 (7)	15.895 (5)	13.215 (4)	11.791 (3)	21.021 (6)	6.331 (1)	11.300 (2)
	RMSPE	37.674 (7)	18.863 (5)	16.910 (4)	13.016 (3)	23.876 (6)	7.495 (1)	11.564 (2)
Ireland	MAPE	16.645 (7)	8.568 (6)	3.892 (1)	5.208 (4)	5.519 (5)	4.614 (2)	4.728 (3)
	RMSPE	20.088 (7)	9.997 (6)	4.424 (1)	6.395 (4)	6.492 (5)	5.694 (2)	6.110 (3)
Italy	MAPE	21.228 (7)	2.998 (1)	11.864 (6)	5.797 (4)	7.659 (5)	4.614 (3)	4.499 (2)
	RMSPE	22.492 (7)	4.325 (1)	12.280 (6)	6.070 (4)	8.911 (5)	5.469 (3)	5.191 (2)
Mexico	MAPE	4.294 (3)	4.191 (2)	3.869 (1)	11.308 (6)	9.065 (4)	11.397 (7)	9.530 (5)
	RMSPE	4.928 (2)	4.513 (1)	5.552 (3)	11.820 (6)	11.734 (5)	12.960 (7)	11.449 (4)
The Netherlands	MAPE	14.349 (7)	5.306 (2)	6.797 (6)	6.190 (4)	4.846 (1)	6.396 (5)	5.526 (3)
	RMSPE	15.126 (7)	6.544 (1)	7.994 (4)	8.309 (5)	7.763 (3)	7.469 (2)	8.753 (6)
New Zealand	MAPE	5.023 (4)	10.282 (6)	1.715 (1)	6.947 (5)	3.813 (2)	14.367 (7)	4.496 (3)
	RMSPE	5.707 (4)	11.041 (6)	2.136 (1)	7.782 (5)	4.883 (2)	15.063 (7)	4.964 (3)
Portugal	MAPE	10.338 (7)	4.060 (1)	8.525 (6)	5.679 (3)	5.839 (5)	5.512 (2)	5.680 (4)
	RMSPE	10.583 (6)	5.049 (1)	10.843 (7)	6.002 (3)	7.320 (5)	5.876 (2)	6.149 (4)
Russia	MAPE	5.092 (1)	29.441 (7)	8.237 (2)	9.068 (3)	9.918 (4)	10.898 (6)	10.157 (5)
	RMSPE	5.916 (1)	31.884 (7)	9.691 (2)	9.842 (3)	15.139 (6)	11.633 (5)	10.632 (4)
Slovenia	MAPE	17.779 (6)	4.300 (4)	19.640 (7)	2.828 (2)	2.793 (1)	6.073 (5)	3.431 (3)
	RMSPE	18.306 (6)	5.912 (4)	19.686 (7)	3.001 (2)	2.878 (1)	7.196 (5)	3.540 (3)
Spain	MAPE	9.610 (7)	2.678 (5)	2.366 (1)	2.645 (4)	2.685 (6)	2.506 (3)	2.462 (2)
	RMSPE	10.794 (7)	2.938 (2)	3.130 (3)	3.606 (5)	3.689 (6)	2.790 (1)	3.269 (4)
Sweden	MAPE	29.103 (7)	11.767 (3)	10.096 (1)	17.826 (5)	11.728 (2)	12.795 (4)	18.781 (6)
	RMSPE	30.319 (7)	13.994 (4)	12.680 (1)	19.008 (5)	12.962 (2)	13.738 (3)	19.467 (6)
Turkey	MAPE	33.057 (6)	38.186 (7)	20.495 (4)	10.025 (2)	16.322 (3)	24.309 (5)	8.488 (1)
	RMSPE	36.457 (6)	40.808 (7)	23.050 (4)	10.408 (2)	20.035 (3)	26.755 (5)	9.740 (1)
UK	MAPE	11.348 (7)	3.270 (3)	3.117 (2)	4.597 (5)	3.380 (4)	2.468 (1)	5.075 (6)
	RMSPE	12.741 (7)	3.338 (2)	4.000 (4)	5.211 (5)	3.946 (3)	3.196 (1)	5.782 (6)
USA	MAPE	22.098 (7)	5.354 (5)	3.360 (3)	5.784 (6)	3.448 (4)	2.525 (1)	3.230 (2)
	RMSPE	22.216 (7)	6.352 (5)	3.748 (3)	7.377 (6)	4.669 (4)	3.087 (1)	3.689 (2)
Frequency of top performance (out of 50)		3	9	12	3	3	10	10

Note: MAPE and RMSPE represent the mean absolute percentage error and root mean square percentage error, respectively. The values in parentheses are rankings.

Table 9: Eight-quarter-ahead forecasts for each destination

Destination	Static regression	JML-ECM	Reduced ADLM	TVP	VAR	SARIMA	Naïve
Australia	0.482 (1)	2.904 (3)	5.482 (5)	9.112 (6)	3.796 (4)	2.060 (2)	9.855 (7)
Austria	4.485 (3)	9.487 (5)	0.237 (1)	8.073 (4)	3.879 (2)	13.054 (7)	9.875 (6)
Belgium and Luxembourg	38.535 (7)	2.710 (2)	0.043 (1)	10.201 (6)	4.361 (3)	6.484 (4)	9.436 (5)
Brazil	62.013 (7)	21.066 (4)	43.854 (6)	19.876 (2)	23.307 (5)	20.202 (3)	3.951 (1)
Canada	6.758 (2)	10.606 (4)	13.483 (7)	7.667 (3)	10.861 (5)	12.339 (6)	3.871 (1)
Czech Republic	0.074 (1)	5.626 (6)	7.794 (7)	3.052 (2)	4.356 (5)	3.247 (4)	3.217 (3)
Denmark	6.061 (3)	8.243 (5)	11.962 (6)	3.578 (2)	6.577 (4)	12.123 (7)	2.042 (1)
Finland	28.275 (7)	18.259 (4)	16.991 (2)	17.090 (3)	16.217 (1)	19.164 (5)	19.515 (6)
France	25.264 (6)	12.103 (4)	33.628 (7)	6.186 (3)	21.433 (5)	1.575 (1)	3.398 (2)
Germany	7.821 (6)	2.296 (2)	3.880 (4)	3.595 (3)	9.455 (7)	1.747 (1)	6.227 (5)
Greece	17.109 (4)	28.931 (5)	83.718 (6)	12.997 (2)	131.100 (7)	1.489 (1)	13.649 (3)
India	48.466 (7)	27.328 (4)	25.929 (3)	28.570 (5)	38.940 (6)	14.745 (1)	21.259 (2)
Ireland	12.045 (6)	12.228 (7)	5.148 (2)	6.645 (4)	2.875 (1)	6.403 (3)	6.756 (5)
Italy	13.958 (5)	9.748 (4)	24.190 (7)	2.294 (3)	21.348 (6)	0.186 (2)	0.136 (1)
Mexico	3.102 (3)	8.115 (5)	0.343 (1)	4.678 (4)	16.373 (7)	8.339 (6)	0.728 (2)
The Netherlands	13.755 (7)	6.585 (5)	5.806 (4)	4.288 (3)	3.179 (2)	12.563 (6)	1.081 (1)
New Zealand	7.376 (4)	20.164 (6)	2.758 (1)	8.149 (5)	6.364 (3)	27.242 (7)	4.346 (2)
Portugal	10.063 (5)	3.981 (1)	13.162 (7)	6.403 (3)	10.928 (6)	5.700 (2)	7.337 (4)
Russia	5.962 (3)	37.446 (7)	3.633 (1)	14.501 (4)	4.746 (2)	19.186 (6)	17.753 (5)
Slovenia	12.721 (5)	5.352 (2)	34.285 (7)	5.968 (3)	2.437 (1)	14.539 (6)	8.087 (4)
Spain	8.357 (6)	6.308 (5)	3.497 (3)	3.792 (4)	9.055 (7)	0.360 (1)	2.237 (2)
Sweden	41.591 (7)	37.242 (4)	26.961 (1)	36.579 (3)	38.786 (5)	33.280 (2)	40.250 (6)
Turkey	31.028 (6)	55.066 (7)	18.783 (4)	4.222 (2)	15.485 (3)	21.580 (5)	3.402 (1)
UK	17.048 (7)	5.142 (3)	5.540 (4)	6.061 (5)	3.464 (2)	1.163 (1)	7.203 (6)
USA	21.355 (7)	6.622 (5)	1.587 (1)	8.269 (6)	5.684 (3)	3.033 (2)	6.120 (4)
Frequency of top performance /25	4	2	14	0	6	12	12

Note: MAPE and RMSPE represent the mean absolute percentage error and root mean square percentage error, respectively. The values in parentheses are rankings. The MAPE and RMSPE are the same for the eight-quarter-ahead forecasts because only one forecast value could be calculated for each destination.

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