**Forecasting US Overseas Travelling with Univariate and Multivariate Models**

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ABSTRACT

This study makes use of specific econometric modelling methodologies to forecast US outbound travelling flows to certain destinations: Europe, Caribbean, Asia, Central America, South America, Middle East, Oceania, and Africa, spanning the period 2000-2019 on a monthly basis. Both univariate (jointly with business conditions) and multivariate models are employed, while out-of-sample forecasts are generated and the results are compared based on popular forecasting performance criteria. These criteria show that in the case of univariate models, the largest forecasting gains are obtained when the modelling process follows the KS-AR(1) model with the business cycles being measured as the coincident indicator. In the case of multivariate models, the largest forecasting gains occur with the standard VAR model for very short forecasting horizons, and with the Bayesian VAR for longer horizons. The results are robust to both total and individual destinations. The findings allow interested stakeholders to gain insights into near-future US outbound tourism to popular diversified international destinations, as well as to better understand its positive and negative impacts for strategic planning and destination adaptation purposes.

KEY WORDS: out-of-sample forecasting; US outbound travelling; univariate and multivariate models

INTRODUCTION

For many countries, tourism provides for the acquisition of foreign exchange, the generation of income from the consumption of goods and services by tourists, employment in the tourism and related service sectors, and tax revenues from tourist expenditures and businesses within the tourism industry. Over the recent decades, the global tourism market has experienced huge growth and deepening diversification, making it one of the world’s fastest growing economic sectors. International tourist arrivals have grown steadily from 25 million in 1950 to a total of 1.395 billion arrivals in 2019. This growth is projected to continue. According to World Tourism Organization (UNWTO) forecasts, international tourist arrivals will increase to 1.8 billion by 2030 (WTO, 2018). The reason of forecasting various variables in tourism is to envisage the success of the destination by ensuring that visitors are hosted in a way that maximises the benefits to certain stakeholders with minimal negative effects, costs and impacts (Edgell et al., 2008; Mason, 2015). More specifically, a number of stakeholders are interested in tourism forecasting for the following reasons.

First, firms, such as airlines, ferry operators, tour operators, hotels, casinos, other recreation facilities providers, and shop owners are interested in the demand for their products by tourists. The success of many businesses depends largely on the state of tourism demand, and ultimate management failure is quite often due to the failure to meet market demand. Because of the key role of demand as a determinant of business profitability, estimates of expected future demand constitute a very important element in all planning activities. Accurate forecasts of tourism flows are essential for efficient planning by tourism-related businesses, particularly given the perishability of the tourism product. Empty airline, ferry, bus and restaurant seats, and unused hire cars, hotel rooms, rental apartments, cruise ship rooms, holiday tour packages and tourist entertainment facilities cannot be stockpiled – once the potential sale is lost it is lost forever. Secondly, flows of tourism travelling forecasting is important because tourism investment, especially investment in destination infrastructures, such as airports, highways and rail-links, requires long-term financial commitments from public finances and the expected net returns on the investment would not be achieved if insufficient tourism demand materialises to fully utilize the designed capacities of the investment projects. The prediction of long-term demand for tourists flows related infrastructures often forms an important part of project appraisals. Thirdly, governments’ macroeconomic policies depend largely on the relative importance of individual sectors within the economy. Hence, accurate forecasts of the demand situation in the tourism sector of the economy will substantially help governments in formulating and implementing appropriate medium-long term tourism strategies.

The importance of tourism forecasting in tourism planning and tourism policy formulation has been widely documented in certain studies as Frechtling (1996) and Wong and Song (2003). International originations, i.e. Pacific Asia Travel Association (PATA) and World Travel and Tourism Council (WTTC) together with Oxford Econometrics (OE) regularly publish forecasts of tourism demand for various countries (Turner and Witt, 2003 and 2004). In the mid-1990s, dynamic modelling, such as the autoregressive distributed lag model (ADLM) and error correction model (ECM) began to gain significant ground in the tourism literature. Kim and Song (1998), Vogt and Wittayakorn (1998), Kulendran and King (1997), and Syriopoulos (1995) were among the first who applied the cointegration and error correction methods to tourism forecasting. Following these studies, there has been a surge in the application of modern econometric approaches to tourism demand modelling and forecasting (Webber, 2001; Huybers, 2003; Kulendran and Witt, 2003; Song et al., 2003). Although, total tourist arrivals is the most frequently used tourist variable to be forecasted, followed by tourist expenditure, our approach here is to alternatively consider total overall tourist travelling for the case of US tourist outflows. More importantly, the Vector Auroregressive (VAR) methodology has been frequently employed, along with the multivariate cointegration analysis (Song et al, 2003; Witt et al., 2003 and 2004). Sheldon and Var (1985) offer a nice review on publications on tourism forecasting. The forecasting methods discussed include time series models, econometric causal models, the gravity model and expert-opinion techniques. They conclude that time series models are the simplest and least costly (and therefore most appropriate for practitioners), while the gravity model is best suited to handle international tourism demand flows (and will be most useful to governments and tourism agencies). Finally, expert-opinion methods are useful when data are unavailable.

 Overall, a review of the existing literature shows that, to the best of my knowledge, there have been no published studies in academic journals concerning the forecasting of travelling flows abroad. The empirical goal of this study is to identify a model that best describes and forecasts US travelling flows abroad. Given the high number of the outbound US tourist flows (US is the second of the world's largest source market for international tourists-UNWTO, 2018), this will allow interested stakeholders to gain insights into near-future US outbound tourism to popular diversified international destinations, as well as to better understand its positive and negative impacts for strategic planning and destination adaptation purposes. The tourism industry tends to be substantially vulnerable to external environmental changes and crisis events, and recovery could be fast or slow pertinent to a sophisticated interaction among source country, destination and event characteristics. A successful forecasting performance will allow the assessment of how crisis events may receive significant attention that enhances concerns travelling to a particular destination where the crisis occurs. Moreover, international tourists perceive the influence of natural disasters and travel risks on their travel differently (Park and Reisinger, 2010). Hence, destinations must develop strategies in marketing and service to reduce target groups’ concerns. Moreover, tourism is relatively resilient to economic downturns. The literature has discussed how the tourism industry could prepare and respond to such crises, with the focus on crisis and risk management (Anderson, 2006), impact estimation (Dwyer et al., 2006), forecasting (Lean et al., 2008), recovery strategies (Scott et al., 2007) and security (Hall et al., 2004). The current body of literature on crisis events focuses on economic and financial crisis, natural disasters, environmental problems, pandemics and diseases, and terrorism (Hall, 2010). Therefore, to provide policy-making suggestions, tourism industry and academics should forecast tourist outbound flows. Finally, the findings are expected to potentially assist the inbound countries to plan better their tourism strategies. In particular, since the needs of US tourists could be significantly different from those from other origin countries/regions, the business sectors in the host countries need to pay considerable attention to catering for the needs of US tourists.

The employment of outbound flows is in contrast to many other tourism studies that focus on tourism demand from a number of tourism-generating country destinations. The only potentially close study is that by Furmanov et al. (2016) who explore the forecasting of trips outflows made by Russian tourists to Mediterranean destinations using the well-known autoregressive integrated moving average (ARIMA) class of univariate time-series models, along with the multivariate, joint model for several destination countries.

METHODOLOGY

The empirical analysis will make use of different univariate and multivariate models to generate monthly forecasts for US overseas travelling. More specifically, it will consider both univariate and multivariate models with and without exogenous variables, as well as potential combinations of such models. All of them will be compared with a benchmark autoregressive model of order one.

 In terms of univariate modelling, the analysis applies a linear regression approach that involves certain lags of the dependent variable, as well as certain drivers. This type of model is known as the ‘kitchen sink’ (KS) modelling. The four univariate models are an AR(1) autoregressive model of order one (explicitly used as the benchmark model), a Seasonal ARIMA(p, q) (SARIMA) model, the SARIMA model modified with Fourier series (Hsu, 2003; Guo et al., 2005; Kan et al., 2010; Askari and Fetanat, 2011), and the ‘kitchen sink’ (KS) modelling specification that extends the AR(1) model by considering the linear multiple regression which involves potential drivers of the dependent variable. The model we consider is the following predictive regression model:

yt+1 = x’tβ + εt+1 (1)

where y denotes tourist outbound travelling, x’t is a (N + 1) x 1 vector of predictors which contain the lagged (one-month) travelling flows, and β is a (N+1) x 1 vector of parameters. The model includes all N predictive variables as separate regressors in addition to current values of travelling flows and is widely known as the Kitchen Sink (KS) model (Goyal and Welch, 2008). Rapach et al. (2010) provide evidence that the KS model performs no shrinkage, as opposed to the simple mean combination scheme that shrinks forecasts by a factor of 1/N. To this end, the analysis considers shrinking the estimated parameters of model (1) through bootstrap aggregating (bagging), along the lines proposed by Inoue and Kilian (2008). Bagging, introduced by Breiman (1996), is performed via a moving-block bootstrap, where a large number (B) of pseudo samples of size t for the left-hand-side and right-hand-side variables in (KS) are generated by randomly drawing blocks of size m (with replacement) from the observations of these variables available from the beginning of the sample through time t. For each pseudo-sample, the analysis estimates (KS) using the pseudo-data, the model is re-estimated using the pseudo-data, and a forecast of yt+1 is formed by plugging the actual included yt+1 values and tourist outflowst values into the re-estimated version of the forecasting model (again setting the error term equal to its expected value of zero). The bagging model forecast corresponds to the average of the B forecasts for the bootstrapped pseudo samples. Stock and Watson (2012) provide evidence that bagging reduces prediction variance and asymptotically can be represented in shrinkage form. Finally, the analysis evaluates the forecasting of out-of-sample performance by utilizing the rolling estimation to produce a one-step-ahead prediction of US overseas travelling.

 In terms of the multivariate modelling, the empirical part of the paper will apply a vector autoregressive (VAR) estimated model that includes both the dependent variable and the potential drivers of it, as well as a Bayesian vector autoregressive model. VARs models have been extensively applied in financial and macroeconomic forecasting (Lutkepohl, 2007; Koop and Korobilis, 2010); the same is also true for the case of Bayesian VAR (BVAR) specifications (Koop, 2003). In the case of the Bayesian VAR modelling process, the method follows Karlsson and Österholm (2020) to choose priors that match the scale and variation of the data. A diffuse prior is chosen for the initial conditions in relevance to the parameter vector, which is described by a normal prior. Defining the vector of dependent variables as y’t = (real exchange rate, disposable income per capita, geopolitical risk, US economic policy uncertainty, global economic policy uncertainty), the analysis specifies the BVAR in its most general form and considers drifting parameters and stochastic volatility. This form is the most general specification of the BVAR. The model is given as:

B0t yt = γt + B1t yt-1 + … + Bpt yt-p + εt (2)

where B0t is a 2×2 lower triangular matrix with ones on the diagonal. The 2×1 vector γt contains the intercepts and the 2×2 matrices B1t, ..., Bpt describe the dynamics of the model. Lag length is in all cases set to p=2 (this is a common choice in the related literature, Cogley and Sargent, 2005; Primiceri, 2005). The disturbances are multivariate normal εt∼N(0,Σt), where Σt=diag(exp(h1t), exp(h2t)). The free parameters of γt and Bit are collected in the vector θt which is assumed to evolve as a random walk, as are the log volatilities:

θt = θt-1 + ηt (3)

ht = ht-1 + ζt (4)

where ηt∼N(0,Σθ) and ζt∼N(0,Σh). The model’s prior is chosen to match the scale and volatility of the data and follow the approach used by Karlsson and Österholm (2019). In order to establish whether the relation between US travelling abroad and the drivers has been constant, the analysis estimates the model based on marginal likelihoods (the marginal likelihood is the appropriate measure of how well the model and prior agree with the data and the model with the highest marginal likelihood should be selected). However, calculating the marginal likelihood for VAR models with drifting parameters and/or stochastic volatility is non-trivial. The analysis relies on the developed methods of Chan and Eisenstat, 2018). In both multivariate modelling approaches, the forecasting analysis evaluates the forecasting performance by utilizing the rolling estimation to generate a one-step-ahead prediction of US overseas travelling.

In the standard VAR modelling, the potential drivers identified by the literature are the real effective exchange rate (Webber, 2001; Kuo et al., 2009; Nowjee et al., 2012), real personal disposable income per capita (Lee et al., 2015), the geopolitical risk index (Antonakakis et al., 2017; Bassil et al., 2019; Lanouar and Goaied, 2019), the U.S. economic policy uncertainty (Gozgor and Ongan, 2017; Balli et al., 2018; Sharma, 2019), and global economic policy uncertainty (Akadiri et al. 2019; Wu and Wu, 2020; Liu et al., 2020; Nguyen et al., 2020).

 The performance of the forecasts will be assessed based on certain metrics. More specifically, the analysis will use the mean squared errors (MSE) for each of the forecast horizons considered. In terms of both the univariate and multivariate models, this metric will be computed separately for the total travelling, as well as for each geographical destination. In addition, the assessment procedure will report the ratio of each model’s MSE to that of the baseline. Values less than one signify that this particular model yields forecasts characterized as more accurate than those from the baseline model. Furthermore, the differences across the models will be assessed statistically through the Diebold and Mariano (1995) t-test for equality of the average loss (i.e., loss is defined as the squared error and negative log score) of each model against the benchmark AR(1) model. In addition, the analysis makes use of the model confidence set procedure offered by Hansen et al. (2011), so as to compare all forecasting jointly. The differences are tested separately for each horizon.

DATA

The analysis uses monthly data from 2000:1 to 2019:10. Data on U.S. citizens overseas air passenger travel in total (OST) and by eight regional destinations (Europe, EUR; Caribbean, CAR; Asia, ASI; Central America, CAM; South America, SAM; Middle East, MID; Oceania, OCE; and Africa, AFR) were obtained from the U.S. Department of Commerce, International Trade Administration, Office of Travel and Tourism Industries. U.S. citizens air passenger travel outside of North American (excludes Canada and Mexico). Note the data on US citizens air passenger travel overseas ends in 2019:10, and as such data during the COVID-19 pandemic are not available.

Data for the broad real effective exchange rate (ER) and real personal disposable income per capita (PY) are drawn from the St. Louis Federal Reserve Bank database, FRED II. The geopolitical risk index (GPR) along with the U.S. (USEPU) and global (GEPU) economic policy uncertainty indices are accessed from the website, [www.policyuncertainty.com](http://www.policyuncertainty.com). All variables are converted to growth rates based on first-difference of the natural logarithms of the variables. ADF-GLS unit root tests below document that the growth rates of the respective variables are integrated of order zero, I(0). Table I offers certain summary statistics. These statistical findings illustrate that US travelling was mostly destined to Europe followed by the Caribbean and Asian destinations.

Table I. Summary statistics

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Variables Mean SD Min Max

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TOTOVR 2,541,048 648,864.8 1,422,363 5,131,219

EUR 1,066,586 380,786.9 414,958 2,566,724

CAM 200,370 64,281.6 73,723 364,499

CAR 518,367 161,880.9 220,141 1,006,030

SAM 167,881 37,327.3 99,264 290,232

AFR 25,886 9,988.9 6,956 61,360

MIDE 101,549 65,222.6 13,434 256,427

ASIA 399,548 82,794.8 176,244 611,415

OCE 60,861 13,956.7 35,157 108,323

GPR 104 70.7 27 545

GEPU 121 51.6 48 307

USEPU 125 48.4 45 284

BREER 110 9.6 93 129

COIN 103 12.2 86 129

PYPC 38,711 3,213.9 33,112 45,809

INDPR 100 5.6 87 111

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SD = standard deviation

EMPIRICAL ANALYSIS

**Integration analysis**

In the first part of the empirical analysis, we test for the presence of unit root through the test recommended by Elliot et al. (1996), known as the ADF-GLS test, which has superior power properties over the traditional ADF test. The results are reported in Table II and clearly document that we can reject the null hypothesis of a unit root at 1% across all first differenced series considered, implying that they all are stationary.

Table II. Unit root tests

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Variables ADF-GLS test

 Levels First differences

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TOTOVR -1.36(4) -7.54(3)\*\*\*

EUR -1.28(5) -7.13(3)\*\*\*

CAM -1.33(4) -6.58(3)\*\*\*

CAR -1.38(5) -7.19(4)\*\*\*

SAM -1.26(5) -7.81(4)\*\*\*

AFR -1.34(3) -6.42(2)\*\*\*

MIDE -1.38(6) -6.58(4)\*\*\*

ASIA -1.16(5) -8.34(4)\*\*\*

OCE -1.42(5) -6.38(3)\*\*\*

GPR -1.31(4) -6.74(3)\*\*\*

GEPU -1.46(5) -6.26(4)\*\*\*

USEPU -1.42(6) -6.39(5)\*\*\*

BREER -1.35(5) -6.78(4)\*\*\*

COIN -1.24(6) -7.13(4)\*\*\*

PYPC -1.26(5) -7.46(4)\*\*\*

INDPR -1.30(5) -7.24(3)\*\*\*

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Figures in parentheses denote p-values. \*\*\*: p≤0.01.

**Model selection**

Next, we estimate the appropriate lagged models of each of the US overseas travel variable and in the case of univariate models. The results, reported in Table III and based on the Ljung-Box Q statistic for the cases of the SARIMA and SARIMA-F models, recommend the selected models and the number of lags in the case of the KS model. The selection of the best KS model is based on the Akaike informational criterion and the figures indicate that the smallest AIC criterion values are reached at the first lag order, with the results remaining consistently similar across all travelling variables, as well as across all types of models based on which business cycle variable is introduced.

Table III. Model statistics: univariate models

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Variables Models: SARIMA SARIMA-F

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TOTOVR (1, 0, 1)(1, 1, 1,)12 (1, 0, 1)(1, 1, 1,)12

Ljung-Box Q: 9.438[0.75] 7.662[0.83]

EUR (2, 0, 1)(1, 1, 1,)12 (2, 0, 1)(1, 1, 1,)12

Ljung-Box Q: 11.296[0.62] 9.114[0.72]

CAM (2, 0, 1)(1, 1, 1,)12 (2, 0, 1)(1, 1, 1,)12

Ljung-Box Q: 10.079[0.71] 8.128[0.76]

CAR (1, 0, 1)(1, 1, 1,)12 (1, 0, 1)(1, 1, 1,)12

Ljung-Box Q: 10.264[0.70] 8.559[0.75]

SAM (1, 0, 1)(1, 1, 1,)12 (1, 0, 1)(1, 1, 1,)12

Ljung-Box Q: 11.006[0.64] 8.915[0.74]

AFR (1, 0, 2)(1, 1, 1,)12 (1, 0, 2)(1, 1, 1,)12

Ljung-Box Q: 10.563[0.66] 8.692[0.73]

MIDE (1, 0, 2)(1, 1, 1,)12 (1, 0, 2)(1, 1, 1,)12

Ljung-Box Q: 9.196[0.78] 8.354[0.74]

ASIA (1, 0, 1)(1, 1, 1,)12 (1, 0, 1)(1, 1, 1,)12

Ljung-Box Q: 9.005[0.80] 8.127[0.77]

OCE (1, 0, 0)(1, 1, 1,)12 (1, 0, 0)(1, 1, 1,)12

Ljung-Box Q: 10.396[0.67] 8.751[0.72]

KS1 model KS2 model KS3 model

 Akaike criterion

Variables

TOTOVR 1 lag: -3.409 1 lag: -3.196 1 lag: -2.985

EUR 1 lag: -2.784 1 lag: -2.695 1 lag: -2.673

CAM 1 lag: -3.108 1 lag: -3.006 1 lag: -2.875

CAR 1 lag: -3.561 1 lag: -3.299 1 lag: -3.083

SAM 1 lag: -3.228 1 lag: -2.960 1 lag: -2.784

AFR 1 lag: -3.127 1 lag: -3.026 1 lag: -2.963

MIDE 1 lag: -3.342 1 lag: -3.119 1 lag: -2.895

ASIA 1 lag: -3.784 1 lag: -3.439 1 lag: -3.138

OCE 1 lag: -4.326 1 lag: -3.648 1 lag: -3.227

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SARIMA denotes a seasonal ARIMA model, SARIMA-F is a modified SARIMA model with Fourier series, KS denotes the ‘kitchen sink’ model. KS1 is the KS model with the coincident indicator, KS2 is the KS model with PYPC, and KS3 is the KS model with industrial production. Figures in brackets denote p-values.

Next, we repeat the process for the case of multivariate model. The VAR model contains the corresponding US overseas travelling variable, along with either business cycles variable, the geopolitical risk index, the global economic policy uncertainty index, the US economic policy uncertainty index, and the U.S. Broad Real Effective Exchange Rate index; the new findings are displayed in Table IV. The selection of the best VAR model is based (again) on the Akaike informational criterion and the figures indicate that the smallest AIC criterion values are reached at the first lag order, with the results remaining consistently similar across all travelling variables, as well as across all types of models based on which business cycle variable is introduced. The only exception is in the case of the total overseas travelling where in all cases the criterion selected two lags as the optimal selection. Similar results are reached for the case of the Bayesian VAR model, but in this case the selection criterion is based on the Chan and Eisenstat (2018) method to find marginal likelihoods for VARs which allows stochastic volatility to be included to account for heteroscedasticity.

Table IV. Model statistics: multivariate models

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Variables Models: VAR Bayesian VAR

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**with COIN Akaike Criterion Log Marginal Likelihood**

TOTOVR -5.439(2) 413.359(2)

EUR -5.127(1) 462.875(1)

CUM -6.703(1) 405.662(1)

CAR -5.459(1) 539.083(1)

SAM -6.002(1) 476.836(1)

AFR -5.581(1) 490.431(1)

MIDE -4.886(1) 532.784(1)

ASIA -4.905(1) 488.504(1)

OCE -6.538(1) 561.239(1)

**with PYPC Akaike Criterion Log Marginal Likelihood**

TOTOVR -4.955(2) 452.084(2)

EUR -4.804(1) 438.771(1)

CUM -5.883(1) 424.189(1)

CAR -5.006(1) 496.295(1)

SAM -5.491(1) 484.614(1)

AFR -5.377(1) 465.918(1)

MIDE -4.549(1) 499.452(1)

ASIA -4.681(1) 476.437(1)

OCE -5.854(1) 513.806(1)

**with INDPR Akaike Criterion Log Marginal Likelihood**

TOTOVR -5.218(2) 516.477(2)

EUR -4.893(1) 469.248(1)

CUM -5.429(1) 454.920(1)

CAR -5.199(1) 562.513(1)

SAM -4.907(1) 542.444(1)

AFR -5.033(1) 486.824(1)

MIDE -4.422(1) 538.223(1)

ASIA -4.176(1) 489.745(1)

OCE -5.430(1) 538.074(1)

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VAR denotes a vector autoregressive model. Figures in parentheses denote the optimal number of lags.

**Univariate forecasting results**

For out-of-sample forecast, the analysis uses the rolling estimation method to generate a one-step-ahead forecasting value for the various samples of US overseas travelling. In that sense, the whole T-observation sample of US overseas travelling series are divided into two parts, where the T-M observations are used for the out-of-sample. Based on Ritchie et al. (2010), the economic and financial crisis seems to be a significant threshold point affecting US travelling for tourism reasons. Therefore, the out-sample forecasting is implemented from 2008:9 (the turning point associated with the collapse of Lehman Brothers). Table V reports MSEs for predicting the US travelling overseas using univariate models over specific monthly forecasting horizons, i.e. 1, 6, 8, and 12, after 2008:9. More specifically, the information provided shows the MSE for the benchmark model and the ratio of the MSE of the other models to that of the benchmark. Values in bold illustrate the rejection of the null hypothesis of equal predictive ability between each model and the benchmark based on the Diebold–Mariano test at 5% significance. For instance, in the case of total US overseas travelling (TOTOVR) the largest gains occur when the modelling process follows the KS-AR(1) model and the business cycles are measured through the U.S. coincident indicator (COIN). Across all US overseas travelling variables, in most of the cases, when the monthly forecast horizon increases, the forecast accuracy follows the same route, while the models considered provide better predicting accuracy over short horizons, i.e. from 1 to 6 or 8 months.

Table V. Mean squared errors (MSE): univariate models

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Forecasting horizon (h): 1 6 8 12

Model

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**TOTOVR**

Benchmark AR(1) 16.24 16.71 16.94 17.06

SARIMA **0.95** **0.99** 1.06 1.04

SARIMA-F **0.83** **0.87** **0.94** 1.03

KS-AR(1) with COIN **0.79** **0.84** **0.92** 1.01

KS-AR(1) with PYPC  **0.84** **0.82** **0.97** 1.03

KS-AR(1) with INDPR **0.93** **0.98** 1.04 1.02

**EUR**

Benchmark AR(1) 19.73 20.37 20.65 20.82

SARIMA **0.92** **0.96** 1.01 1.11

SARIMA-F **0.80 0.84 0.81 0.87**

KS-AR(1) with COIN **0.76 0.81 0.87 0.94**

KS-AR(1) with PYPC **0.88 0.96** 1.05 1.04

KS-AR(1) with INDPR  **0.96**  1.07 1.15 1.19

**CUM**

Benchmark AR(1) 17.08 17.53 17.91 18.02

SARIMA **0.97** 1.04 1.06 1.16

SARIMA-F **0.87** **0.89 0.98** 1.07

KS-AR(1) with COIN **0.84 0.88 0.85 0.89**

KS-AR(1) with PYPC **0.89 0.97** 1.06 1.14

KS-AR(1) with INDPR **0.98** 1.06 1.12 1.11

**CAR**

Benchmark AR(1) 15.35 15.64 15.86 15.82

SARIMA **0.90 0.96** 1.01 1.08

SARIMA-F **0.81 0.86 0.90 0.97**

KS-AR(1) with COIN **0.74 0.79 0.75 0.80**

KS-AR(1) with PYPC  **0.87 0.94** 1.02 1.09

KS-AR(1) with INDPR **0.96**  1.04 1.13 1.11

**SAM**

Benchmark AR(1) 20.75 20.86 20.98 21.13

SARIMA **0.93** 1.01 1.09 1.16

SARIMA-F  **0.88 0.92 0.98** 1.07

KS-AR(1) with COIN **0.82 0.86 0.83** 0.91

KS-AR(1) with PYPC **0.89 0.96**  1.05 1.22

KS-AR(1) with INDPR  **0.95** 1.03 1.09 1.13

**AFR**

Benchmark AR(1) 24.52 24.88 25.09 25.07

SARIMA 1.08 1.15 1.24 1.27

SARIMA-F **0.91 0.98** 1.06 1.14

KS-AR(1) with COIN **0.86 0.81 0.88** 1.02

KS-AR(1) with PYPC **0.93** 1.02 1.09 1.15

KS-AR(1) with INDPR **0.99**  1.07 1.14 1.18

**MIDE**

Benchmark AR(1) 18.47 18.43 18.82 18.95

SARIMA  **0.90 0.97**  1.04 1.12

SARIMA-F  **0.77 0.82 0.79 0.87**

KS-AR(1) with COIN **0.73 0.78 0.85 0.89**

KS-AR(1) with PYPC **0.87 0.95**  1.04 1.03

KS-AR(1) with INDPR **0.91** 1.02 1.09 1.17

**ASIA**

Benchmark AR(1) 15.63 15.84 15.78 15.93

SARIMA **0.91 0.95** 1.02 1.08

SARIMA-F **0.81 0.84 0.79 0.87**

KS-AR(1) with COIN  **0.75 0.81 0.88 0.93**

KS-AR(1) with PYPC **0.82 0.87 0.83** 1.01

KS-AR(1) with INDPR  **0.90 0.99** 1.06 1.18

**OCE**

Benchmark AR(1) 27.82 27.75 28.12 28.27

SARIMA 1.02 1.08 1.14 1.20

SARIMA-F **0.96** 1.05 1.09 1.15

KS-AR(1) with COIN **0.88 0.95**  1.03 1.09

KS-AR(1) with PYPC **0.86 0.82 0.89**  1.01

KS-AR(1) with INDPR **0.96** 1.04 1.03 1.15

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The findings are relative to the benchmark specification AR(1), for which the absolute score is reported. Values in bold indicate the rejection of the null hypothesis of equal predictive ability between each model and the benchmark based on the Diebold–Mariano test at 5% significance.

**Multivariate forecasts**

Once again, for the out-of-sample forecast, the analysis generates a one-step-ahead forecasting value for the various samples of US overseas travelling, with the out-sample forecasting being explored from 2008:9 (the turning point associated with the collapse of Lehman Brothers).Table VI reports the MSEs and the predictive ratios for the two multivariate models. The evidence is clearly supportive to the standard VAR model, as opposed to the Bayesian VAR model, that provides statistically superior point forecasts at short horizons (i.e., 1 to 6 months). By contrast, the Bayesian VAR seems to provide better forecasting performances over longer horizon, i.e. 8 to 12 months. Once again, the significant improvements are indicated by the figures in bold.

Table VI. Mean squared errors (MSE): multivariate models

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Forecasting horizon (h): 1 6 8 12

Model

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**TOTOVR**

Benchmark AR(1) 19.74 19.95 20.47 20.65

*COIN*

VAR 0.86 0.94 1.04 1.12

Bayesian VAR 1.02 1.09 0.98 0.99

*PYPC*

VAR 0.95 1.03 1.08 1.13

Bayesian VAR 1.03 1.01 0.95 1.03

*INDPR*

VAR 0.92 0.97 1.06 1.17

Bayesian VAR 1.05 1.03 0.98 0.94

**EUR**

Benchmark AR(1) 17.26 17.49 17.83 18.01

*COIN*

VAR 0.83 0.89 0.94 1.09

Bayesian VAR 1.05 1.06 0.96 1.01

*PYPC*

VAR 0.99 1.06 1.05 1.10

Bayesian VAR 1.07 1.03 0.98 1.04

*INDPR*

VAR 0.90 0.94 1.05 1.14

Bayesian VAR 1.02 1.01 0.95 0.92

**CUM**

Benchmark AR(1) 23.62 23.94 24.48 25.09

*COIN*

VAR 0.87 0.93 1.04 1.07

Bayesian VAR 1.06 1.03 0.93 0.90

*PYPC*

VAR 0.97 1.04 1.12 1.08

Bayesian VAR 1.08 1.02 0.97 1.06

*INDPR*

VAR 0.89 0.92 0.98 1.10

Bayesian VAR 1.06 1.03 1.01 0.96

**CAR**

Benchmark AR(1) 22.51 22.75 22.97 23.16

*COIN*

VAR 0.88 0.97 1.05 1.11

Bayesian VAR 1.07 1.02 0.98 0.94

*PYPC*

VAR 0.98 1.05 1.03 1.12

Bayesian VAR 1.09 1.05 0.99 1.06

*INDPR*

VAR 0.93 0.99 1.07 1.16

Bayesian VAR 1.05 1.02 0.97 0.91

**SAM**

Benchmark AR(1) 25.37 25.63 26.32 27.09

*COIN*

VAR 0.87 0.95 1.09 1.15

Bayesian VAR 1.08 1.03 0.98 0.95

*PYPC*

VAR 1.03 1.07 1.04 1.15

Bayesian VAR 1.08 1.04 1.03 1.06

*INDPR*

VAR 0.94 0.99 1.08 1.17

Bayesian VAR 1.07 1.03 0.96 0.99

**AFR**

Benchmark AR(1) 28.34 28.72 29.70 30.19

*COIN*

VAR 0.92 1.04 1.10 1.18

Bayesian VAR 1.08 1.05 0.99 1.07

*PYPC*

VAR 0.97 1.12 1.16 1.14

Bayesian VAR 1.10 1.06 1.02 1.05

*INDPR*

VAR 0.93 0.99 1.08 1.18

Bayesian VAR 1.07 1.03 0.97 0.99

**MIDE**

Benchmark AR(1) 21.74 22.13 22.94 23.26

*COIN*

VAR 0.90 0.96 1.06 1.15

Bayesian VAR 1.08 1.03 0.94 0.98

*PYPC*

VAR 0.97 1.08 1.06 1.17

Bayesian VAR 1.12 1.07 1.03 1.06

*INDPR*

VAR 0.93 0.97 1.11 1.23

Bayesian VAR 1.09 1.04 0.97 0.90

**ASIA**

Benchmark AR(1) 15.74 15.98 16.55 17.04

*COIN*

VAR 0.81 0.86 0.99 1.12

Bayesian VAR 1.09 1.05 0.92 0.96

*PYPC*

VAR 0.96 1.05 1.08 1.06

Bayesian VAR 1.12 1.06 0.95 0.92

*INDPR*

VAR 0.85 0.91 1.09 1.19

Bayesian VAR 1.10 1.15 0.94 0.99

**OCE**

Benchmark AR(1) 29.35 29.86 30.63 31.17

*COIN*

VAR 0.93 1.04 1.12 1.19

Bayesian VAR 1.11 1.14 0.98 1.07

*PYPC*

VAR 0.96 1.13 1.15 1.12

Bayesian VAR 1.13 1.16 1.09 1.19

*INDPR*

VAR 0.94 0.97 1.10 1.17

Bayesian VAR 1.13 1.06 0.98 1.09

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The findings are relative to the benchmark specification AR(1), for which the absolute score is reported. Values in bold indicate the rejection of the null hypothesis of equal predictive ability between each model and the benchmark based on the Diebold–Mariano test at 5% significance.

CONCLUSION

This paper provided empirical evidence in forecasting US outbound travelling flows to certain destinations: Europe, Caribbean, Asia, Central America, South America, Middle East, Oceania, and Africa, spanning the period 2000-2019. Both univariate (jointly with business conditions) and multivariate models were employed, while forecasts over a period of 12 months were generated and the results were compared based on popular forecasting performance criteria. The findings documented that in the case of univariate models, the largest forecasting gains were obtained when the modelling process followed the KS-AR(1) model with the business cycles being measured as the coincident indicator. In the case of multivariate models, the largest forecasting gains occurred with the standard VAR model for very short forecasting horizons, and with the Bayesian VAR for longer horizons. The results remained robust to both total and individual destinations. The results carry substantial implications for certain interested stakeholders to gain insights into near-future US outbound tourism to popular diversified international destinations, as well as to better understand its positive and negative impacts for strategic planning and destination adaptation purposes. Provided that the needs of US tourists could be different from those from other origin countries/regions, the business sectors in the destinations under consideration need to pay considerable attention to catering for the needs of US tourists. Therefore, the forecasting guidance will make easier the provision of facilities for travellers to successfully attracting more high-class tourists from the US.

 The results suggest the following potential directions for future research. The procedure can be tested as to whether the findings can be replicated with outbound travelling series from other countries. Secondly, future research could consider expanding outbound travelling forecasting with the use of Neural Networks and fuzzy logic models. The important reason for using fuzzy systems and Neural Networks is their leaming capability as highlighted by Nauck et al. (1997) and they can extract the features of time series data and potentially generate more accurate forecasts (Zhang et al., 1998). Thirdly, further research is needed for different tourism data series, to confirm these findings.

REFERENCES

Akadiri, S.S., Alola, A.A., Uzuner, G. 2019. Policy uncertainty and tourism: evidence from the heterogeneous panel. *Current Issues in Tourism*, forthcoming.

Anderson, B.A. 2006. Crisis management in the Australian tourism industry: preparedness, personnel and postscript. *Tourism Management* **27**: 1290-1297.

Antonakakis, N., Gupta, R., Kollias, C., Papadamou, S. 2017. Geopolitical risks and the oil-stock nexus over 1899-2016. *Finance Research Letters* **23**: 165-173.

Askari, M., Fetanat, A. 2011. Long-term load forecasting in power system: grey system prediction-based models. *Journal of Applied Sciences* **11**: 3034-3038.

Balli, F., Uddin, G.S., Shahzad, S.J.H. 2019. Geopolitical risk and tourism demand in emerging economies. *Tourism Economics* **25**: 997-1005.

Bassil, C., Saleh, A.S., Anwar, S. 2019. Terrorism and tourism demand: a case study of Lebanon, Turkey and Israel. *Current Issues in Tourism* **22**: 50-70.

Breiman, L. 1996. Bagging predictors. *Machine Learning* **24**: 123-140.

Chan, J.C., Eisenstat, E. 2018. Bayesian model comparison for VARs with stochastic volatility. *Journal of Applied Econometrics* **33**: 509-532.

Cogley, T., Sargent, T.J., 2005. Drifts and volatilities: monetary policies and outcomes in the post WWII US. *Review of Economic Dynamics* **8**: 262-302.

Diebold, F., Mariano, R. 1995. Comparing predictive accuracy. *Journal of Business and Economic Statistics* **13**: 253-263.

Dwyer, L., Forsyth, P., Spurr, R., VanHo, T. 2006. Economic effects of the world tourism crisis on Australia. *Tourism Economics* **12**: 171-186.

Elliot, G., Rothenberg, T., Stock, J. 1996. Efficient tests for an autoregressive unit root. *Econometrica* **64**: 813-836.

Frechtling, D. 1996. *Practical Tourism Forecasting*. Butterworth Heinemann: Oxford.

Furmanov K., Balaeva O., Predvoditeleva M. 2016. Forecasting tourism flows from the Russian Federation into the Mediterranean countries. In: Mariani M.M., Czakon W., Buhalis D., Vitouladiti O. (Eds). *Tourism Management, Marketing, and Development*. Palgrave Macmillan, New York.

Goyal, A., Welch, I. 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* **21:** 1455-1508.

Gozgor, G., Ongan, S. 2017. Economic policy uncertainty and tourism demand: empirical evidence from the USA. *International Journal of Tourism Research* **19:** 99-106.

Guo, Z., Song, X., Ye, J. 2005. A Verhulst model on time series error corrected for port throughput forecasting. *Journal of the Eastern Asia Society for Transportation Studies* **6**: 881-891.

Hall, C.M. 2010. Crisis events in tourism: subjects of crisis in tourism. *Current Issues in Tourism* **13**: 401-417.

Hall, C.M., Timothy, D.J., Duval, D.T. 2004. Security and tourism. *Journal of Travel and Tourism Marketing* **15**: 1-18.

Hansen, P.R., Lunde, A., Nason, J.M. 2011. The model confidence set. *Econometrica* **79**: 453-497.

Hsu, L.C. 2003. Applying the grey prediction model to the global integrated circuit industry. *Technological Forecasting and Social Change* **70**: 563-574.

Huybers, T. 2003. Modelling short-break holiday destination choices. *Tourism Economics* **9**: 389-405.

Kan, M.L., Lee, Y.B., Chen, W.C. 2010. Apply grey prediction in the number of Tourist. Paper presented at the fourth international conference on Genetic and Evolutionary computing in Shenzhen, China, 481-484.

Karlsson, S., Österholm, P. 2020. The relation between the corporate bond-yield spread and the real economy: stable or time-varying? *Economics Letters* **186**.

Kim, S., Song, H. 1998. Analysis of tourism demand in South Korea: a cointegration and error correction approach. *Tourism Analysis* **3**: 25-41.

Koop, G. 2003. *Bayesian Econometrics*. Wiley.

Koop, G., Korobilis, D. 2010. Forecasting inflation using dynamic model averaging. *Bayesian Multivariate Time Series Methods for Empirical Macroeconomics* **3**: 267-358.

Kulendran, N., Witt, S.F. 2003. Forecasting the demand for international business tourism. *Journal of Travel Research* **41**: 265-271.

Kulendran, N., King, M. 1997. Forecasting international quarterly tourism flows using error correction and time series models. *International Journal of Forecasting* **13**: 319-327.

Kuo, H-I., Wang, H-C., Hwang, W-Y., Ye, C-Y. 2009. Tourism demand and exchange rates in Asian countries: evidence from a panel data approach. *World Congress on Computer Science and Information Engineering*, 508-512.

Lanouar, C., Goaied, M. 2019. Tourism, terrorism and political violence in Tunisia: evidence from Markov-switching models. *Tourism Management* **70**: 404-418.

Lean, H.H., Smyth, R., Barros, C.P., Matias, Á., Santos, C.M. 2008. Are Malaysia's tourism markets converging? Evidence from univariate and panel unit root tests with structural breaks. *Tourism Economics* **14**: 97-112.

Lee, C.-W., Fu, W.F., Peng, C.J. 2015. To analyze the factors affecting tourism receipts from global travelers: application of random coefficient model. *International Journal of Research in Finance and Marketing* **5**: 164-178.

Liu, H., Liu, Y., Wang, Y. 2020. Exploring the influence of policy uncertainty on the relationship between tourism and economic growth with an MF-VAR model. *Tourism Economics*, forthcoming.

Lutkepohl, H. 2007. *New Introduction to Multiple Time Series Analysis*. Springer Publishing Company, Inc.

Nauck, D., Klawoim, F., Kmse, R. 1997. *Foundations of Neuro-Fuzzy Systems*. John-Wiley & Sons.

Nguyen, C.P., Schinckus, C., Su, T.D. 2020. Economic policy uncertainty and demand for international tourism: an empirical study. *Tourism Economics*, forthcoming.

Nowjee, A., Poloodoo, V., Lamport, M., Padachi, K., Ramdhony, D. 2012. The relationship between exchange rate, tourism and economic growth: evidence from Mauritius. Proceedings of the 2nd International Conference on International Trade and Investment. Mauritius.

Park, K., Reisinger, Y. 2010. Differences in the perceived influence of natural disasters and travel risk on international travel. *Tourism Geographies* **12**: 1-24.

Primiceri, G., 2005. Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies* **72**: 821-852.

Rapach, D., Strauss, J., Zhou, G. 2010. Out-of-sample equity premium prediction: combination forecasts and links to the real economy. *Review of Financial Studies* **23**: 821-862.

Ritchie, J.R.B., Molinar, C.M.A., Frechtling, D.C. 2010. Impacts of the world recession and economic crisis on tourism: North America. *Journal of Travel Research* **49**: 5-15.

Sharma, C. 2019. Testing the asymmetric effects of the economic policy uncertainty on the tourism demand in India. *Tourism Economics*.

Stock, J., Watson, M. (2012). Generalized shrinkage methods for forecasting using many predictors. *Journal of Business and Economic Statistics* **30**: 481-493.

Scott, N., Laws, E., Prideaux, B. 2007. Tourism crises and marketing recovery strategies. *Journal of Travel and Tourism Marketing* **23**: 1-13.

Sheldon, P.J., Var, T. 1985. Tourism forecasting: a review of empirical research. *Journal of Forecasting* **4**: 183-195.

Song, H., Witt, S.F., Jensen, T.C. 2003. Tourism forecasting: accuracy of alternative econometric models. *International Journal of Forecasting* **19**: 123-141.

Syriopoulos, T. 1995. A dynamic model of demand for Mediterranean tourism. *International Review of Applied Economics* **9**: 318-336.

Turner, L.W., Witt, S.F. 2004. Pacific Asia Tourism Forecasts 2004-2006, PATA: Bangkok.

Turner, L.W., Witt, S.F. 2003. Pacific Asia Tourism Forecasts 2003-2005, PATA: Bangkok.

UNWTO 2018. World tourism barometer and statistical. Retrieved from <https://www.eunwto.org/doi/pdf/10.18111/wtobarometereng>.

Vogt, M.G., Wittayakorn, C. 1998. Determinants of the demand for Thailand’s exports of tourism. *Applied Economics* **30**: 711-715.

Webber, A. 2001. Exchange rate volatility and cointegration in tourism demand. *Journal of Travel Research* **39**: 398-405.

Witt, S.F., Song, H., Wanhill, S. 2004. Forecasting tourism generated employment: the case of Denmark. *Tourism Economics* **10**: 167-176.

Witt, S.F., Song, H., Louvieris, P. 2003. Statistical testing in forecasting model selection. *Journal of Travel Research* **42**: 151-158.

Wong, K. F., Song, H., Chon, K. 2003. Tourism forecasting: a Bayesian VAR approach. Working Paper, School of Hotel and Tourism Management, The Hong Kong Polytechnic University.

World Tourism Organization. 2018. Tourism Towards 2030/Global Overview. Madrid.

Wu, T.-P., Wu, H.C. 2020. A multiple and partial wavelet analysis of the economic policy uncertainty and tourism nexus in BRIC. *Current Issues in Tourism* **23**: 906-916.

Zhang, G., Putuwo, B.E., Hu, M.Y. 1998. Forecasting with artificial Neural Networks: the state of the art. *International Journal of Forecasting* **14**: 35-62.