Annals of Tourism Research 88 (2021) 103155

Contents lists available at ScienceDirect

Annals of Tourism Research

journal homepage: https://www.journals.elsevier.com/annals-of-tourism-research

Visitor arrivals forecasts amid COVID-19: A perspective from the Asia and Pacific team

Richard T.R. Qiu [a,*], Doris Chenguang Wu [b,*], Vincent Dropsy [c], Sylvain Petit [c,d,e], Stephen Pratt [f], Yasuo Ohe [g]

[a] *Department of Integrated Resort and Tourism Management, Faculty of Business Administration, University of Macau, Taipa, Macao, China*
[b] *Business School, Sun Yat-sen University, Guangzhou, China*
[c] *Center for Research on Tourism in Oceania Pacific (CETOP), Governance and Insular Development (GDI, EA 1384) Research Center, University of French Polynesia, French Polynesia*
[d] *CRISS (EA 4343), Polytechnic University Hauts-de-France, France*
[e] *CRESEM (EA 7397) University of Perpignan, Via Dominitia, France*
[f] *School of Tourism & Hospitality Management, University of the South Pacific, Fiji*
[g] *Department of Agribusiness Management, Faculty of International Agriculture and Food Studies, Tokyo University of Agriculture, Tokyo, Japan*

ARTICLE INFO

Article history:
Received 7 November 2020
Received in revised form 20 January 2021
Accepted 21 January 2021
Available online 28 January 2021

Associate editor: Gang Li

Keywords:
COVID-19
Tourism forecasting competition
Stacking models
Recovery scenarios
Judgmental-adjusted forecasting

ABSTRACT

It is important to provide scientific assessments concerning the future of tourism under the uncertainty surrounding COVID-19. To this purpose, this paper presents a two-stage three-scenario forecast framework for inbound-tourism demand across 20 countries. The main findings are as follows: in the first-stage ex-post forecasts, the stacking models are more accurate and robust, especially when combining five single models. The second-stage ex-ante forecasts are based on three recovery scenarios: a mild case assuming a V-shaped recovery, a medium one with a V/U-shaped, and a severe one with an L-shaped. The forecast results show a wide range of recovery (10%–70%) in 2021 compared to 2019. This two-stage three-scenario framework contributes to the improvement in the accuracy and robustness of tourism demand forecasting.

Introduction

Covid-19 has had devastating effects on many facets of society and the economy of all countries in the world. The impact has been particularly felt in the tourism and hospitality sector. To reduce the spread of the virus, nations closed their borders and limited the mobility of their residents. This resulted in a drastic economic and social crisis. Hotels and restaurants closed, airlines cancelled flights and grounded planes, travel agencies and tour operators ceased operation, and tourist attractions shut their doors. These all happened within a few weeks, if not days when countries realized the gravity of the pandemic. The downturn in the global economy has been far more reaching and far deeper than other shocks in the recent past, such as the September 11 terrorist attacks of 2001, the SARS outbreak in 2003, and the global financial crisis of 2008/9. Several studies have sort to estimate the economic impact of COVID-19 (see Farzanegan et al., 2020; Mariolis et al., 2020; Qiu et al., 2020; Yang et al., 2020) yet few studies have sought to model a geographically comprehensive, methodologically rigorous post-COVID-19 recovery. The need for this research is important, given that tourism destinations and tourism and hospitality businesses need to plan when and how

* Corresponding authors.
E-mail addresses: richardtrqiu@um.edu.mo, (R.T.R. Qiu), wucheng@mail.sysu.edu.cn, (D.C. Wu), vincent.dropsy@upf.pf, (V. Dropsy), sylvain.petit@upf.pf, (S. Petit), stephen.pratt@usp.ac.fj, (S. Pratt), yo207358@nodai.ac.jp. (Y. Ohe).

https://doi.org/10.1016/j.annals.2021.103155
0160-7383/

to re-open. This has significant implications for the well-being of residents as businesses decide to re-employ staff. At the time of writing, the pandemic is still ongoing. Some countries have opened their borders again, some remained fully closed and others lay somewhere in between. How and when the tourist and hospitality market will recover remains unknown. However, accurate forecasting of the impact of COVID-19 on the tourism industry and its recovery is critical for strategic planning of tourist destinations and tourism-related businesses.

The evidence of the importance of forecasting tourism demand can be seen by the way of considerable attention it has received in the various literature. Numerous review papers have been published summarizing research published to date. These reviews include Crouch (1994), Witt and Witt (1995), Lim (1997, 1999), Li et al. (2005), Song and Li (2008), and more recently Wu et al. (2017) and Song et al. (2019). As noted by Song and Li (2008, p. 217) "It is crucial for researchers to develop some forecasting methods that can accommodate unexpected events in predicting the potential impacts of these one-off events through scenario analysis."

Tourism demand forecasting under crisis has been studied in the existing literature from different perspectives. For example, Page et al. (2012) assess the effects of both the global economic crisis and swine flu pandemic on the demand for the U.K. by forecasting and comparing tourism demand under no-impact and economic-impact scenarios. Based on a TVP-PVAR model, Wu et al. (2020) predict the probabilities of four scenarios for tourism development in the future of 25 destinations. Four scenarios include: both economic growth and tourism growth accelerate, economic growth decelerates whereas tourism growth accelerates, both economic and tourism growth decelerate, and economic growth accelerates but tourism growth decelerates. These investigations provide the industry with abundant information on not only the impact of the various crises but also the potentials of the tourism industry in different scenarios.

According to Wu et al. (2020), there are two main types of scenario forecasting, with one forecasts the tourism demand given certain conditions or scenarios, and the other aims to predict the probability of a given scenario or condition. This research focuses on the first type and provides the forecasts and evaluations of the impact of COVID-19 on tourism by generating forecasts under mild, medium, and severe scenarios.

The objectives of this research are two-fold: 1) to advance a methodological framework of tourism forecasting under the context of unexpected crisis such as COVID-19 and contribute to the development of tourism forecasting research, and 2) to inform the tourism industry and destination management and marketing organizations of the good forecasting practice and the predicted impact of COVID-19 on tourism.

To achieve the research objectives and as will be elaborated further as below, we undertake a tourism forecasting competition, along the lines of Athanasopoulos et al. (2011). This 'competition' is a contest among various methods for the 'best' forecast of post-COVID-19 tourism demand. There are two stages to the forecasting. The first stage involves ex-post forecasting of international visitor arrivals before COVID-19, which is to identify the most accurate forecasting method(s) during this period. In the second stage, ex-ante judgemental-adjusted scenario forecasting of visitor arrivals during and after COVID-19 is made up until the end of 2021. The purpose of this two-stage forecasting procedure is to identify an effective forecasting framework and evaluation procedures in a crisis.

Regarding the forecasting techniques, 11 single models, which cover time series, econometric, and AI-based techniques, and 26 stacking models are adopted for forecasting accuracy competition. Stacking models, as a type of machine learning method, have proved effective in improving forecast accuracy and robustness by combining forecasts from different models (Jaganathan & Prakash, 2020). This study, therefore, adopts different stacking models for this forecasting competition.

There are numerous measures to assess the accuracy of forecasts. Hyndman and Koehler (2006) advocate for using the Mean Absolute Scaled Error (MASE) above others. They argue that this measure is less sensitive to outliers and it is independent of the scale of the data. An additional benefit is the ease of interpretation: if MASE is greater than one, it is a poorer forecast than the average one-step naïve forecast computed in-sample. Conversely, if MASE is less than one it signifies an improved forecast than the average one-step naïve forecast computed in-sample.

The remainder of the paper is structured as follows: the next section describes the modelling strategies of both stages while the subsequent section presents and discusses the results. The final section concludes the paper, highlighting the methodological and theoretical contributions of the research and the policy implications of the work.

Modelling strategies

The data used in the present competition is collected from 20 tourist destinations across the world, which covers all UNWTO regions (see Table 2 for a complete list). For each destination, the total volume of international visitor arrivals[1] and visitor arrivals from five key source markets are collected as measures of tourism demand (Song et al., 2019). A total of 120 time-series are adopted for the forecasting practice. Quarterly data is used to the end of 2019 (2019Q4), representing the most frequently modelled time interval (Song & Li, 2008). Quarterly data has the advantage of being long enough to help policymakers assess trends and not overreact to random fluctuations but short enough to help policymakers see the effects of their decisions. The starting points of the tourism demand series vary from 1991Q1 to 2010Q1, resulting in the longest series having 116 observations

[1] Due to the differences in the statistical caliber of these governments, the tourism demand series are measured differently in terms of volume of international visitor arrivals (Australia, Bulgaria, Canada, Chile, Indonesia, Japan, South Korea, Malaysia, Mexico, New Zealand, Singapore, Thailand, the UK, and the USA), international tourist arrivals (Finland, Mauritius, South Africa, and Tunisia), and number of hotel nights (Czech Republic and Sweden). For simplicity, all the tourism demand series are referred as "visitor arrivals" in the present paper.

and the shortest series with 40 observations.

To incorporate the influence of external factors, economic variables, such as GDP, CPI, and exchange rates of relevant countries/regions (markets hereafter), are collected from the Global Economic Monitor (GEM) database of the World Bank and the International Financial Statistics (IFS) database of IMF. To facilitate forecast adjustments of the COVID-19 pandemic, the cumulative number of cases and deaths of each relevant markets are collected from Coronavirus Disease COVID-19 Dashboard (WHO, 2020), and the travel ban (border control) information is collected from the Coronavirus Government Response Tracker (University of Oxford, 2020) and the Policy Responses to the Coronavirus Pandemic (Our World in Data, 2020a).

The main framework of the forecasts is a two-stage-process. In the first stage, ex-post forecasting of international visitor arrivals before COVID-19 is examined and evaluated. We use data up until the end of 2019, and trained multiple preliminary single models and stacking models to capture the characteristics of the demand series for both the historical patterns of the series and the influences from external factors. In the second stage, one baseline forecast assuming the absence of COVID-19 and judgmental-adjusted forecasts under three recovery scenarios are generated separately to estimate the impact of the COVID-19 on tourism demand. Fig. 1 illustrates this framework.

First stage – statistical baseline

The difficulty of the first stage in forecasting is in trying to find one model that not only provides accurate forecasts of the tourism demand series but also manages to perform stably across various origin-destination pairs and different time horizons. To achieve these objectives, 11 single models and 26 stacking models are adopted and examined respectively. In particular, five out of 11 single models are univariate time series models, namely *seasonal Naïve* (SN), *seasonal autoregressive integrated moving average* (SARIMA), *exponential smoothing* (ETS), *seasonal and trend decomposition using Loess* (STL), and *exponential smoothing state space model with Box-Cox transformation*, *ARMA errors*, *trend*, *and seasonal components* (TBATS). The first three models are often used in tourism forecasting exercises as benchmarks and the other two models are more advanced and capable of capturing the characteristics of different components of tourism demand. These models forecast tourism demand by tracing the historical trends and patterns in the data series. Two multivariate econometric models are adopted, namely *autoregressive distributed lag* (ARDL) model and *static regression with time-varying parameter* (SR-TVP), due to their popularity, satisfactory forecasting performance, and capability of integrating the influence of economic factors into the forecasting process (Song et al., 2019; Wu et al., 2017). Finally, four AI-based models are adopted and expected to generate accurate forecasts due to their nonlinearity modelling process: *univariate multilayer perceptron* (MLP), *multivariate multilayer perceptron* (MLPX), *univariate extreme learning machine* (ELM), and *multivariate extreme learning machine* (ELMX).

As discussed previously, a stacking model is further adopted for its capability of integrating forecasts from different models. A number of stacking models are examined and compared in the present competition, and the best-performed model is proposed for forecasting the 120 time-series of international visitor arrivals. The 11 preliminary single models are stacked in 26 different ways to explore the best stacking model in the current context. In particular, one regression-based stacking, 24 "best n" stacking, and a "seasonal naïve" stacking are considered. The regression-based stacking takes the forecasts of the eleven preliminary single models as explanatory variables and fits them to the actual tourism demand. The preliminary single models with statistically significant coefficients are chosen and weighted by their standardized coefficients. The preliminary single models with insignificant coefficients are ignored in the weighing process. If no preliminary single model has significant coefficients, the regression-based stacking does not generate a forecast. The "best n" type stacking selects several preliminary single models according to certain criteria and combines the selected models using different averaging methods. In the present competition, we consider the selection of three and five models, using MAPE, RMSE, or MASE as criteria, and combine these models using simple average, error weighted average, square-error weighted average, and accuracy measure weighted average. Therefore, a total of 24 (two by three by four) "best n" type of stacking are generated. The "seasonal naïve" examines all 25 stacking models above and allows different stacking models to forecast different quarters.

Both the tourism demand series and the economic factor series are pre-processed before the model estimation. Missing values in the middle of the time series are imputed using Kalman Smoothing on structural time series models (Harvey, 1990) with the "na_kalman" function of "imputeTS" package in R (Moritz & Bartz-Beielstein, 2017). Missing values at the end of the time series (i.e. series end earlier than 2019Q4) are extended by exponential smoothing using the "ets" function of "forecast" package in R (Hyndman et al., 2020; Hyndman & Khandakar, 2008). The imputation of missing values provides a complete time series for model estimation while preserving the characteristics of the original time series, and the methods adopted are widely accepted as effective tools in dealing with seasonal data (Hyndman & Athanasopoulos, 2018). In statistical analysis, extreme values and outliers may have a significant influence on model estimation. In the tourism demand context, these extreme values and outliers are usually caused by one-off events or sudden fluctuations in the model variables. These disturbances are usually treated by incorporating dummy variables into the statistical model, but their treatment can be subjective and inflexible. Furthermore, in a large-scale forecast project like the present competition, it is extremely costly to implement such treatments. In contrast, we adopt an outlier smoothing process. The extreme values in both tourism demand series and economic variables are firstly identified by "tsoutlier" function of "forecast" package in R. The identified outliers remain in the time series in multivariate model estimations if the fluctuations of tourism demand series and economic variables happen simultaneously. In the single variate model estimations, or in the case that identified outliers in the tourism demand series and the economic variables do not occur simultaneously, extreme values are replaced by STL decomposition smoother. This process removes extreme values in the data while preserving the most out of the original information.

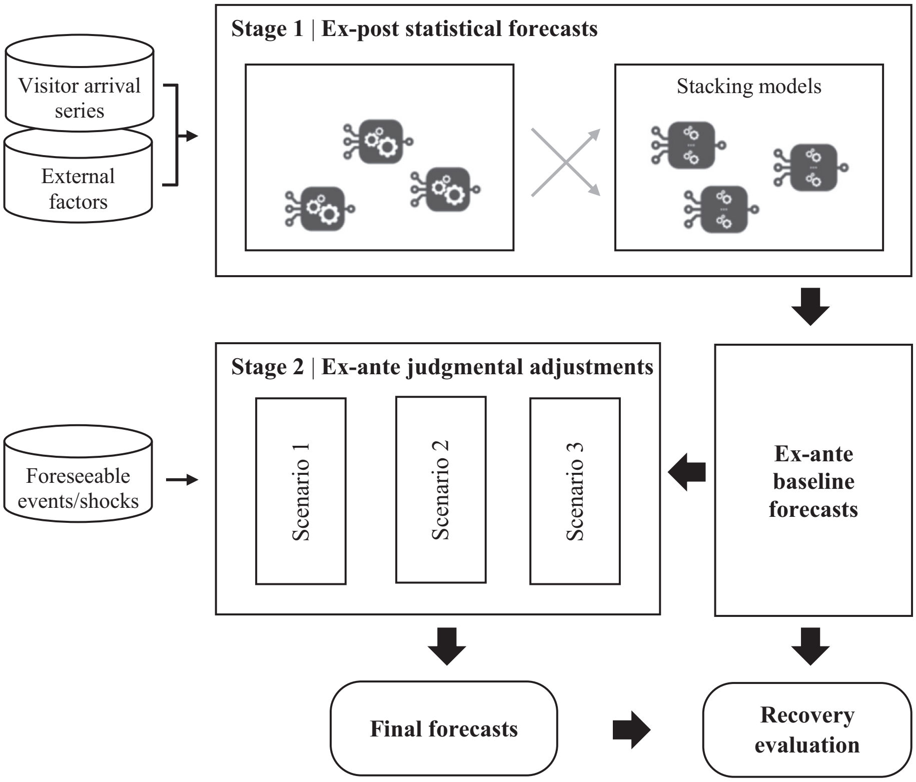


Fig. 1. Framework of the study.

The estimations of the eleven preliminary single models are performed in R. The time series models (SN, SARIMA, ETS, STL, and TBATS) are estimated by functions of "forecast" package ("snaive", "auto.arima", "ets", "stlm", and "tbats", respectively). All the time series methods, except for SN, are optimized within the family. For example, SARIMA models with different AR lags and MA lags are considered and compared using the Akaike information criterion (AIC). Estimations of economic models are conducted on tourism demand series whenever the corresponding economic variables available. The ARDL model is estimated using "auto_ardl" function of "ARDL" package in R (Natsiopoulos & Tzeremes, 2020). The lag of each variable in the ARDL model is derived automatically through an AIC comparison with the maximum of lags set to eight (two years in the current context). The optimal ARDL models are also selected so that the correct signs correspond with the coefficients of economic variables. That is, in the current context, positive for income (GDP) and negative for prices (exchange rate adjusted CPIs). The SR-TVP model is estimated using "tvLM" function of "tvReg" in R (Casas & Fernandez-Casal, 2019, 2020). Both of the AI-based techniques are trained with "nnfor" package in R (Kourentzes, 2019), using "mlp" function for MLP and MLPX, and "elm" function for ELM and ELMX.

To train the eleven preliminary single models as well as the stacking models, each tourism demand series is divided into two training sets and one testing set. The testing set of every tourism demand series has identical timeframes, from 2019Q1 to 2019Q4. The division of two training sets varies according to the starting point of the particular tourism demand series. The estimation of each preliminary single model uses the data of the first fold of the training set as the inputs and the width of the second fold of training data as the rolling window. Multiple forecasts generated through rolling are used as the basis of stacking in the following steps.

For each origin-destination pair, 10 absolute scaled errors (ASE) are calculated as

$$\mathrm{ASE} = \frac{\left|e_{d,j}\right|}{\frac{1}{j-h-m}\sum_{t=m+1}^{j-h}\left|Y_{d,t}-Y_{d,t-m}\right|},$$

where $e_{d,\ j}$ is the difference between the forecast value and the actual value of international visitor arrivals of origin-destination pair d at time j; $Y_{d,\ t}$ represents the actual value of international visitor arrivals of origin-destination pair d at time t, m is the seasonal period, and h is the forecast horizon. The 10 ASEs correspond to 1-step-ahead forecasts of 2019Q1, 2019Q2, 2019Q3, and 2019Q4, 2-step-ahead forecasts of 2019Q2, 2019Q3, and 2019Q4, 3-step-ahead forecasts of 2019Q3 and 2019Q4, and 4-step-ahead forecast of 2019Q4. The arithmetic average of these 10 ASEs comprises the mean absolute scaled error (MASE) of the specific origin-destination pair. The arithmetic average and the standard deviation of origin-destination specific MASE are used as the standard to select the best model among all 37 models (11 preliminary single models and 26 stacking models).

Second stage – judgmental adjustments

The best performing model from the first stage is used to generate a baseline *ex-ante* forecast for the period 2020Q1–2021Q4.

The COVID-19 pandemic generated a sudden sharp shock to world travel and tourism in 2020. The most recent data available, as of September 15th (UNWTO, 2020a,b), show that international visitor arrivals decreased by 65% in the first half of 2020 over to the same period last year and that a bottom occurred during the second quarter of 2020 with a 95% decline relative the same quarter in the previous year.

By comparison, world visitor arrivals had declined by only −0.4% in 2003 because of the SARS epidemic, and by −4.0% in 2009 because of the global economic crisis (UNWTO, 2020c). As a result, international arrivals took 11 months after SARS and 19 months after the global economic crisis to recover to their pre-crisis levels (UNWTO, 2020d).

There is considerable uncertainty about the magnitude of the COVID-19 impact on world tourism and the speed of its recovery. In the three scenarios presented by the UNWTO (2020d), the decrease in international visitor arrivals in 2020 ranges from −58% to −78%, depending on when (July, September, or December) borders would gradually reopen and travel restrictions are lifted. A recovery of international visitor arrivals to their 2019 level is estimated to take from 2.5 to 4 years, according to the UNWTO (2020a), and up to five years, according to Tourism Economics (2020). A strong rebound in 2021 is "based on the assumption of a reversal of the evolution of the pandemic, significant improvement in traveller confidence and major lifting of travel restrictions by the middle of the year" UNWTO (2020a).

We define three scenarios to reflect mild, medium, and severe impacts based on this recovery while considering national specificities. A V-shaped recovery pattern is defined, which assumes that the recovery emerges shortly after the bottom quarter, similar to the patterns of some other pandemics such as SARS. A medium pattern assumes that the worst situation continues for a while but a significant recovery can still be expected within the forecast period (a deep V/U-shaped pattern), whereas the severe pattern assumes that, no significant recovery appears within the forecasting period (L-shaped pattern). The specific details of each scenario are as follows:

- Scenario 1: Mild (a V-shaped pattern)
  The pandemic fades out at the end of 2020, the international travel of each specific original-destination pair starts to recover as soon as the bilateral travel bans are lifted, and the recovery to the 2019 average level takes 12 quarters (three years).
- Scenario 2: Medium (a deep V/U-shaped pattern)
  The pandemic fades out in the first half of 2021, the recovery of international travel for each specific original-destination pair starts slowly after travel restrictions are removed, and the recovery to the 2019 average level takes 16 quarters (four years).
- Scenario 3: Severe (an L-shaped pattern)
  The influence of the pandemic does not fade away until the vaccine is available to the general public (approaching the end of 2021), international travel for each specific original-destination pair remains at its bottom for two more quarters relative to scenario 2, and the recovery to the 2019 average level takes 16 quarters (four years).

Our forecasting methodology is based on the following steps for each origin-destination pair:

Step 1. Determine important dates (which quarter and number of quarters) for the start of COVID-19, duration of travel restrictions, the start of recovery, and length of recovery:

- The start date for COVID-19 (2020Q1 for all countries): cf. WHO (2020)
- Period of severe travel restrictions, defined by the "international travel controls" index (a component of the Oxford Coronavirus Government Response Tracker: cf. Our World in Data, 2020b) equal to its maximum value on a range from 0 to 4, or from the following sources: France Diplomatie (2020); International Monetary Fund; Travel Off Path (2020); U.S. Department of State (2020); World Nomads (2020).
- The bottom date for COVID-19 (last quarter of severe travel restrictions = start date for COVID-19 + number of quarters in the period of severe travel restrictions)
- The start date for recovery (=bottom quarter + 1)
- Date of recovery to the 2019 average level (=start date for recovery + 11 quarters for scenario 1 or 15 quarters for scenarios 2 & 3)

Step 2. Determine the number of visitor arrivals in 2020Q1 and 2020 Q2, using annual percentage changes (over the same quarter in 2019) for each destination, from the "UNWTO World Tourism Barometer and Statistical Annex, August/September" (2020a), or national sources, if not already available in the original database.

Step 3. Determine the number of arrivals during the period of severe travel restrictions, by replicating the bottom value of bilateral flows for 2020Q2.

Step 4. Determine the number of arrivals during the first two quarters of recovery, by using the following annual percentage changes over the average value for 2019:

- −70.0% for the first quarter, then −40.0% for the second quarter for scenario 1
- −90.0% for the first quarter, then −67.0% for the second quarter for scenario 2

- −95.2% for the first quarter, then −94.0% for the second quarter for scenario 3

  These parameters were calibrated so that the 2019 to 2020 annual percentage changes would be equal to −58% for scenario 1, −70% for scenario 2, −78% for scenario 3 (similar to UNWTO's three scenarios), using the actual annual percentage changes for 2020Q1 (−27,8%), for 2020Q2 (−95,2%), and the values above for 2020Q3 and 2020Q4. For consistency, the results are also compared with two benchmarks (an annual forecast based on a gravity model, and a forecast from Tourism Economics, 2020).

Step 5. Determine the number of arrivals at the date (quarter) of recovery (=start date for recovery + 11 quarters for scenario 1 or 15 quarters for scenarios 2 & 3), to be equal to its average value for 2019.

Step 6. Determine the number of arrivals during the period of recovery, by linearly linking the value of the second quarter of recovery to the value of the date of recovery, to form a trend line of adjustment.

Step 7. Seasonally adjust the trend line with observed values prior to the events. With the data of 2018 and 2019, a seasonal multiplier is constructed for each quarter by seasonal decomposition using Loess. Before applying the trend line adjustments, the multipliers from Q1 to Q4 are standardized to an average of one, so that seasonally adjusted forecasts would provide the same annual volume as the trend (seasonally unadjusted) forecasts.

Fig. 2 illustrates the adjustment process.

Results and discussion

Empirical results from the first stage

Table 1 indicates the performance of all 37 models including 11 preliminary single models and 26 stacking models. The MASE values reflect the forecasting accuracy of each model, and the standard deviations of the MASEs reflect the robustness of the forecasting accuracy for each model. Ideally, the models with smaller MASEs and smaller standard deviations of MASEs are more favourable. Among these 37 models, regression stacking based on all 11 single models performs extremely poorly with the largest MASE and the standard deviation (4.1632 and 23.8915 respectively). After inspections of origin-destination specific forecasts, it is found out that regression stacking is extremely sensitive to the quality and volumes of the data. The model generates unreliable forecasts when the tourism demand series is short (i.e. less data). Given its very poor performance, this model is dropped from the subsequent discussion.

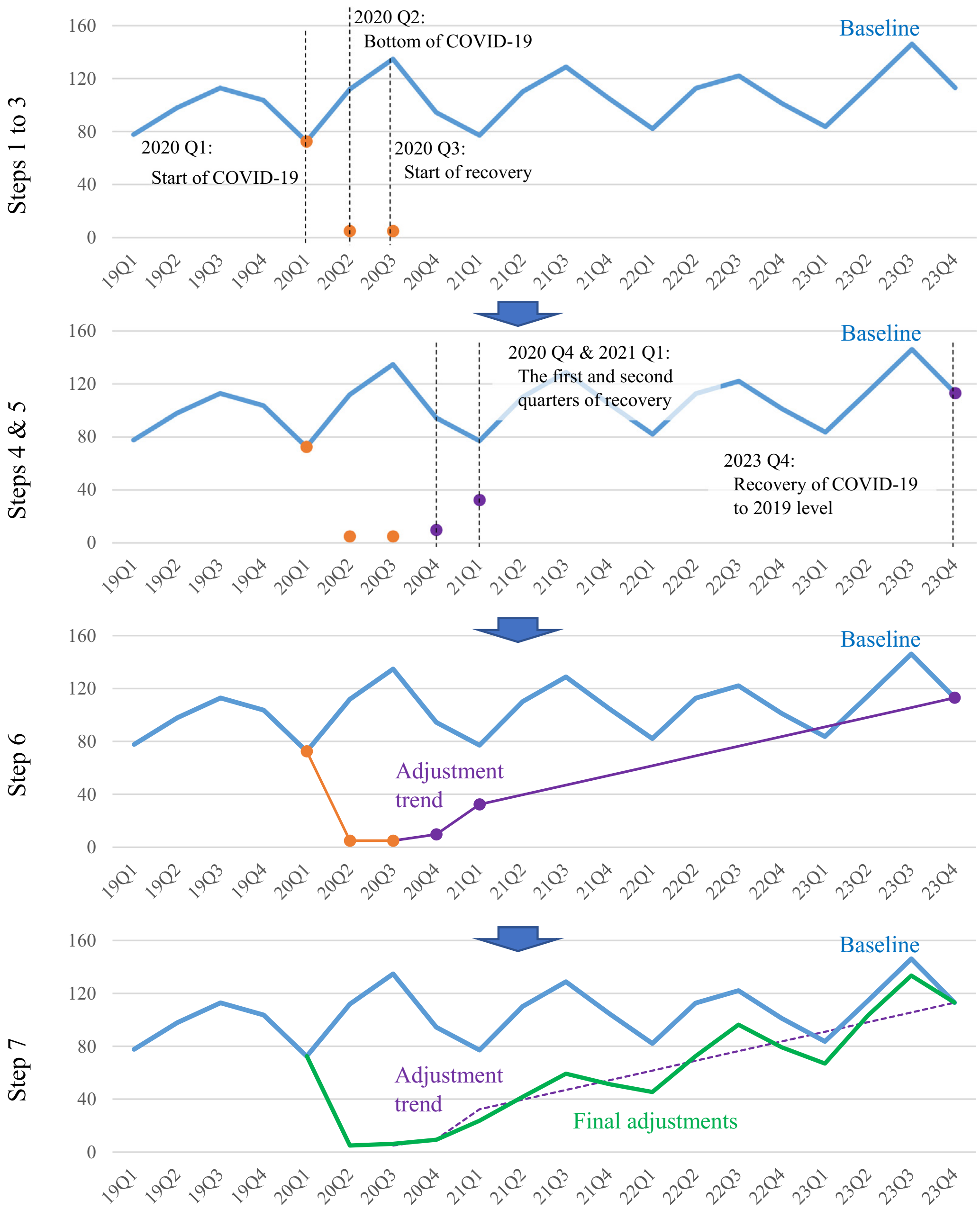
The results of the remaining 36 models are further shown in Fig. 3, in which the blue bars refer to the MASEs and the orange bars refer to the standard deviations of these MASEs. From the figure, it is seen that overall stacking models outperform the single models on average. The average MAPEs for the 11 single models and the 25 stacking models are 1.4287 and 1.0122 respectively, and the average MASE standard deviations for the 11 single models and the 25 stacking models are 1.3462 and 0.9406 respectively (see Table 1). Therefore, stacking models are more effective in generating accurate and robust forecasts of tourism demand. This conclusion is consistent with the existing studies that show combined forecasts, based on a number of single models, often outperform the corresponding single models (see, for example, Li et al., 2019; Song et al., 2019; Wu et al., 2017). In Fig. 3, it is also observed that stacking models exhibit less variation whereas the performance of the 11 single models varies more widely.

Table 1 also shows that among the 11 single models, SARIMA, ETS, STL, ELM, and ELMX outperform the benchmark model of SNAIVE, with lower MASEs. In considering robustness among these five models, three models have smaller standard deviations than SNAIVE. These models are SARIMA, ETS, and STL (Fig. 4). The favourable performance of these three models provides empirical evidence for the adoption of these models in the tourism demand forecasting using single models.

Where stacking models are concerned, Fig. 5 shows that the MASEs do not vary much across models. Their standard deviations are also quite similar. The MASEs vary between 0.997 and 1.027, and the standard deviations vary between 0.906 and 0.985 for 25 stacking models (see Table 1). Compared to the benchmark model of SNAIVE, all 24 “best *n*” stacking models outperform the benchmark for both MASEs and their standard deviations. Among these models, four stacking models, namely bn5rs, bn5re, bn5r2, and bn5rc perform the best, having both the smallest MASEs and the smallest MASE standard deviations. We conclude that the optimal number of single models to be combined in this study is five.

Table 2 reports the forecasting accuracy of the stacking model “bn5re”, which combines the five best single models by minimising the RMSE, for each destination. The stacking model “bn5re” is the best performed one among 11 single models and 26 stacking models, with the lowest MASE of 0.9969 (see Table 1). It is observed that on average the forecasts are more accurate for lower forecasting horizons. In addition, the forecasting accuracy varies over origin-destination pairs. For example, when the one quarter ahead forecasting is concerned, the MASEs vary from 0.2198 (the case of South Africa) to 2.6232 (the case of Chile). This observation is consistent with the existing studies (Song et al., 2019; Wu et al., 2017).

In conclusion, this stage focuses on the forecasting competition before COVID-19 based on 11 single models and 25 stacking models. Some interesting findings are discovered. Firstly, the forecasting performance of the 11 single models varies. Further, SARIMA, ETS, and STL perform best taking into consideration both forecasting accuracy and robustness. Secondly, compared to single models, the stacking models provide more accurate and more robust forecasts on average. Thirdly, the optimal number of stacked single models is five. Fourthly, RMSE is the best criteria in selecting the single models to be included in the stacking models. These findings provide helpful information for future tourism demand forecasting practices.



Note: Dates and magnitudes are for illustration only; only one scenario is illustrated in the figure.

Fig. 2. Procedure of stage two (judgmental) forecast.

Empirical results from the second stage

The COVID-19 pandemic spreads first in the Asia Pacific (China, South Korea, Japan, Thailand, Australia, Indonesia, Malaysia, New Zealand, Singapore), then to North America (USA, Canada, Mexico, Chile), then to Europe (UK, Bulgaria, Sweden, Finland, Czech Republic), and finally Africa (Mauritius, South Africa, Tunisia), in the order of first confirmed COVID-19 deaths all occurring in the first quarter of 2020 (WHO).

Table 3 provides a summary of second stage forecast indicators (deepest impact, bottom date, 2021 recovery rate) for the three scenarios across the 20 nations.

Almost all destinations closed their borders (or banned travellers from high-risk regions, for Japan, Mexico, Singapore, South Korea, Sweden, the UK, and the USA) by the end of March 2020 (Our World in Data, 2020b). However, these policy responses

Table 1
MASEs and standard deviation of MASEs for all models.

11 single models	MASE	Std. Deviation of MASEs	26 stacking models	MASE	Std. Deviation of MASEs
SNAIVE	1.2717	1.0761	Regression	4.1632	23.8915
SARIMA	1.1172	1.0384	bn3ps	1.0229	0.9313
ETS	1.0811	0.9252	bn3pe	1.0206	0.9275
STL	1.1113	0.9088	bn3p2	1.0199	0.9253
TBATS	1.3115	1.0644	bn3pc	1.0211	0.9275
ELM	1.2286	1.6337	bn3rs	1.0236	0.9593
MLP	1.3285	2.1095	bn3re	1.0220	0.9543
ARDL	1.4069	0.9062	bn3r2	1.0242	0.9567
SRTVP	3.1527	2.7749	bn3rc	1.0232	0.9581
ELMX	1.2690	1.1581	bn3as	1.0215	0.9224
MLPX	1.4367	1.2125	bn3ae	1.0206	0.9184
			bn3a2	1.0206	0.9181
			bn3ac	1.0211	0.9182
			bn5ps	1.0047	0.9641
			bn5pe	1.0009	0.9602
			bn5p2	1.0002	0.9665
			bn5pc	1.0019	0.9599
			bn5rs	0.9980	0.9059
			bn5re	0.9969	0.9062
			bn5r2	0.9980	0.9059
			bn5rc	0.9972	0.9062
			bn5as	1.0062	0.9612
			bn5ae	1.0040	0.9579
			bn5a2	1.0050	0.9609
			bn5ac	1.0043	0.9578
			sn	1.0269	0.9851
Average	1.4287	1.3462	Average	1.0122	0.9406

Note: The first two digits, "bn", stand for "best n" type of stacking methods, with the third digit representing the number of preliminary single models used in stacking, the fourth digit representing the criteria of selecting the best models (p – MAPE, r – RMSE, a – MASE), and the fifth digit representing the method of combining the selected models (s – simple average, e – error weighting, 2 – squared error weighting, c – selection criteria based weighting).

to COVID-19 (IMF, 2020a) differed across the countries in the sample. Most European nations (and Mauritius) opened their borders to travel in July 2020 (i.e. bottom date = 2020Q2) to generate some tourism revenues from Northern Hemisphere summer vacationers, whereas South Africa and Malaysia plan to relax their travel restrictions in 2020Q4, and the remainder of the destinations are waiting for 2021Q1 to do so. This bottom date is often the same for all origin countries for a given destination, but in some cases, tourists from high-risk regions are not permitted to enter a destination (e.g. visitors from the USA to Europe) while other source markets are permitted.

The overwhelming majority of destinations experienced an almost total collapse of their international tourists during 2020Q2 (their deepest impact ranging from −95% to −100%); the exception being Bulgaria, Indonesia, Mexico, and Sweden. The latter is a special case in Europe since the Swedish government decided not to resort to a lockdown in the first place and have relied on voluntary social distancing and a few other light constraints, in response to COVID-19.

The 2021 recovery rate ranges from 53% to 70% for the mild scenario 1 (after a 58% fall in 2020), from 29% to 45% for the medium scenario 2 (after a 70% decline in 2020), and only from 9% to 23% for the severe scenario 3 (after a 78% collapse in 2020).

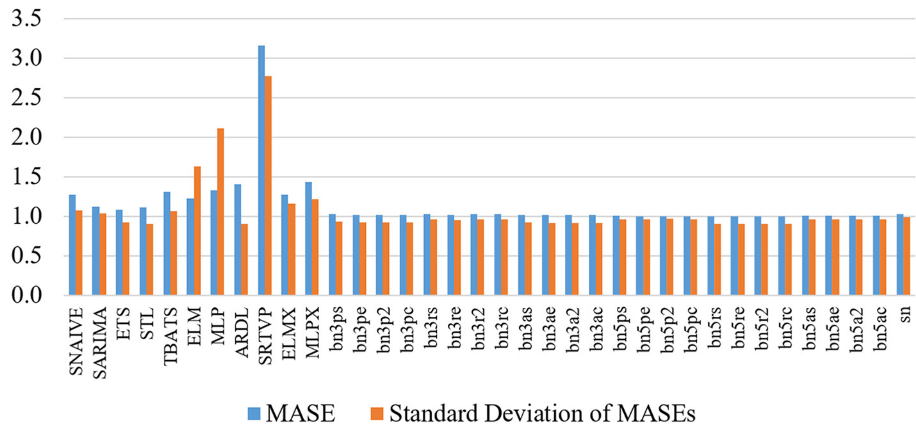


Fig. 3. Forecasting performance of all 36 models.

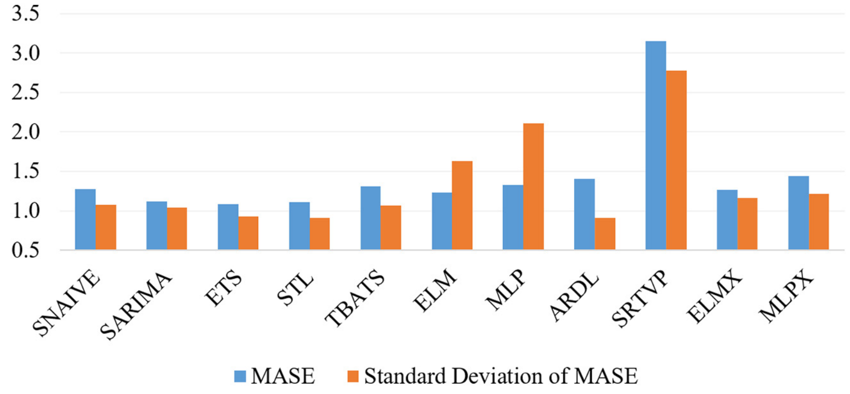


Fig. 4. Forecasting performance of 11 single models.

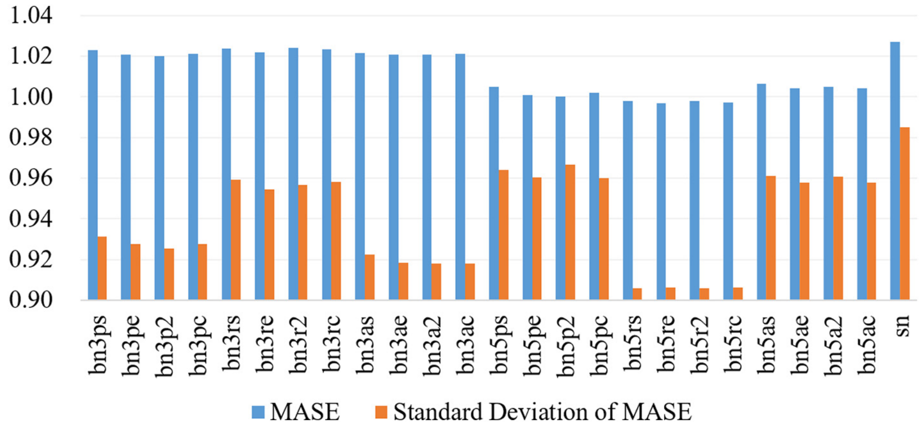


Fig. 5. Forecasting performance of 25 stacking models.

Table 2
Forecasting performance (MASE) for all destinations.

	1Q-ahead	2Q-ahead	3Q-ahead	4Q-ahead
Africa				
Mauritius	1.1529	1.1363	1.3825	1.4843
South Africa	0.2198	1.1358	0.9472	0.7696
Tunisia	0.4068	0.8598	1.4806	0.6688
The Americas				
Canada	1.1054	1.2251	2.1464	1.8193
Chile	2.6232	1.7403	1.4582	1.8180
Mexico	0.8510	0.6409	0.6064	0.7628
USA	0.2944	0.5090	0.5238	0.6737
Asia				
Indonesia	0.8908	1.1560	0.8358	1.5825
Japan	1.2069	2.0178	1.6670	1.4687
Malaysia	1.1541	0.9210	0.7220	0.8479
Singapore	0.7303	0.5787	0.8325	0.9167
South Korea	0.5486	0.6263	1.4568	0.9181
Thailand	0.2597	0.5225	0.4272	0.8387
Europe				
Bulgaria	0.5535	0.6797	0.6734	3.0527
Czech	0.7521	0.8005	0.7496	0.6241
Finland	0.9505	0.7558	1.5307	1.1113
Sweden	0.5929	0.7497	1.5836	1.3647
UK	1.2188	1.1081	0.9035	0.9434
The Pacific				
Australia	0.6456	0.4715	0.5475	0.6310
New Zealand	0.4812	0.7479	0.9676	0.9961
Overall	0.8319	0.9191	1.0721	1.1646

Table 3
Stage 2 forecast summary.

Destination	Indicator	Scenario 1	Scenario 2	Scenario 3
Africa				
Mauritius	Deepest impact	−99.99%	−99.99%	−99.99%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	70.12%	45.11%	22.99%
South Africa	Deepest impact	−100%	−100%	−100%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	66.05%	40.24%	16.16%
Tunisia	Deepest impact	−99.23%	−99.23%	−99.23%
	Bottom time	2020Q4	2020Q4	2020Q4
	2021 recovery rate	58.64%	33.40%	11.43%
The Americas				
Canada	Deepest impact	−98.42%	−98.42%	−98.42%
	Bottom time	2020Q4	2020Q4	2020Q4
	2021 recovery rate	57.83%	32.88%	10.87%
Chile	Deepest impact	−99.75%	−99.75%	−99.75%
	Bottom time	2020Q3	2020Q3	2020Q3
	2021 recovery rate	53.63%	29.39%	10.62%
Mexico	Deepest impact	−76.92%	−89.71%	−95.06%
	Bottom time	2020Q4	2021Q1	2021Q1
	2021 recovery rate	55.08%	30.52%	10.73%
USA	Deepest impact	−95.16%	−95.16%	−95.16%
	Bottom time	2020Q3	2020Q3	2020Q3
	2021 recovery rate	56.45%	31.62%	10.95%
Asia				
Indonesia	Deepest impact	−88.41%	−89.74%	−95.08%
	Bottom time	2020Q3	2021Q1	2021Q1
	2021 recovery rate	55.77%	31.06%	10.79%
Japan	Deepest impact	−99.90%	−99.90%	−99.90%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	55.66%	30.95%	10.68%
Malaysia	Deepest impact	−99.70%	−99.70%	−99.70%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	66.03%	40.21%	12.20%
South Korea	Deepest impact	−97.90%	−97.90%	−97.90%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	56.05%	31.31%	9.63%
Singapore	Deepest impact	−99.90%	−99.90%	−99.90%
	Bottom time	2020Q3	2020Q3	2020Q3
	2021 recovery rate	57.33%	32.46%	9.18%
Thailand	Deepest impact	−100%	−100%	−100%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	58.33%	33.40%	11.28%
Europe				
Bulgaria	Deepest impact	−77.81%	−92.60%	−96.45%
	Bottom time	2020Q3	2020Q3	2020Q3
	2021 recovery rate	69.37%	44.21%	21.73%
Czech	Deepest impact	−95.70%	−95.70%	−95.70%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	69.87%	44.85%	22.75%
Finland	Deepest impact	−96.00%	−96.00%	−96.00%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	69.99%	45.00%	22.95%
Sweden	Deepest impact	−88.50%	−90.45%	−95.24%
	Bottom time	2020Q2	2020Q3	2020Q3
	2021 recovery rate	69.98%	44.99%	22.92%
UK	Deepest impact	−95.70%	−95.70%	−95.70%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 recovery rate	69.20%	44.19%	22.12%
The Pacific				
Australia	Deepest impact	−99.48%	−99.48%	−99.48%
	Bottom time	2020Q3	2020Q3	2020Q3
	2021 recovery rate	55.51%	30.96%	11.18%
New Zealand	Deepest impact	−99.48%	−99.48%	−99.48%
	Bottom time	2020Q4	2020Q4	2020Q4
	2021 recovery rate	54.16%	29.89%	10.96%

Note: "Deepest impact" refers to the deepest decline of visitor arrivals in percentage against the same quarter in 2019; "Bottom time" is the quarter when the deepest impact takes place; "2021 recovery rate" refers to the ratio of the predicted annual total visitor arrivals in 2021 against the annual visitor arrivals in 2019.

The latest UNWTO World Tourism Barometer August/September 2020 issue, which was published on September 15th, comments: "current trends point to a decline in international arrivals closer to 70% for 2020" (UNWTO, 2020b). Yet, a great deal of uncertainty remains about the evolution of the pandemic and thus the most likely scenario.

Due to the space constraint, one destination is chosen from each continent, namely Australia from the Pacific, Sweden from Europe, Thailand from Asia, Tunisia from Africa, and the USA from the Americas, to demonstrate our results. The selection is based on the importance of tourism industry in its economy, the severity of the pandemic, and the coronavirus policy. The corresponding quarterly forecasts of these destinations in baseline and three scenarios are presented in Fig. 6.

Australia

Australia is one of the destinations that has implemented a continuous ban of international visitor arrivals since March 2020 to significantly reduce the likelihood of importing COVID-19 cases. The Australian Government (2020) is nevertheless establishing a safe travel zone with New Zealand, which is a very low-risk country, starting from October 16th, 2020. Australia also indicated that they would gradually lift other travel restrictions in 2021, notably for international students. The following six graphs clearly show the absence of international arrivals for the last three quarters of 2020, and the beginning of a soft recovery in 2021, where rates are equal to 55% for scenario 1 (red line), 31% for scenario 2 (blue line), and 11% for scenario 3 (green line), respectively (Fig. 6A).

Sweden

Sweden is also a special case due to its unique strategy of pursuing herd immunity without any lockdown or strict sanitary measures. Contrary to most of its European neighbours, Sweden experienced an early wave of infection in June and July 2020, in which COVID-19 almost disappeared, in contrast to a second wave of infections appearing in the rest of the European Union. As a result, predicted visitor arrivals in Sweden show a rapid and strong rebound, where recovery rates are some of the highest (Fig. 6B), i.e. 70% for scenario 1 (red line), 45% for scenario 2 (blue line), and 23% for scenario 3 (green line).

Thailand

Thailand is one of the hardest-hit economies due to its dependence on tourism revenues. The IMF (2020b) concludes that "in Thailand, a decrease in tourism due to COVID-19 could bring the country's overall exports down by eight percentage points of GDP and have a direct net impact of about six percentage points of GDP on its current account balance in 2020. That could erode part of the seven percent overall current account surplus the country had in 2019". Since October 1st, Phuket has reopened its tourism, but under strict rules such as a 14-day hotel quarantine, which will discourage many visitors from coming to Thailand. The graphs related to forecasted tourism flows to Thailand show recovery starting in 2021 (Fig. 6C), whose rates are equal to a meager 58% for scenario 1 (red line), 33% for scenario 2 (blue line), and 11% for scenario 3 (green line).

Tunisia

Tunisia also reopened its borders to international visitors at the end of June 2020, but a color-coded system based on COVID-19 risk (green for low risk; orange for medium risk; red for high risk). Low risk involves completing a form. Medium risk requires a negative PCR test to enter Tunisia while high risk necessitates a mandatory 14-day quarantine at a public center. As a result, tourism is likely to recover slowly in 2021, with a moderate recovery of 58% for scenario 1 (red line), 33% for scenario 2 (blue line), and 11% for scenario 3 (green line), and with strong seasonality, as shown on the six graphs related to this destination (Fig. 6D).

The United States

The United States closed its borders to visitors from Canada, China, Europe, and Mexico in 2020. A gradual recovery is expected in 2021, as shown on the six corresponding US graphs (Fig. 6E), with rates of 56% for scenario 1 (red line), 32% for scenario 2 (blue line), and 11% for scenario 3 (green line). The US elections will probably play a role in the policies to be implemented against COVID-19 in 2021, and this will also affect recovery.

In conclusion, these second-stage forecasts are highly dependent on the policies implemented by countries regarding the pandemic and its evolution. There is a great deal of uncertainty regarding these policies including the timing of a vaccine and the extent to which visitors will regain confidence in international travel.

Conclusions

Being totally unanticipated, COVID-19 brought international travel to an immediate halt, severely impacting the global economy and in particular, the tourism and hospitality sector. The impact is far-reaching. Both private and public sectors have instituted various countermeasures, both travel-related as well as health- and safety-related, to combat the spread of the contagious virus. At the time of writing (October 2020), the full effects of these measures remain to be seen. Thus, it is important for tourism economists to estimate evidence-based forecasts in how the tourism and hospitality industry will recover. In this paper, we forecast inbound tourism demand for 20 countries using a two-stage forecast framework: ex-post forecasts before COVID-19 and ex-ante forecasts post-COVID-19.

The main findings are as follows: regarding the first stage ex-post forecast models, SARIMA, ETS, and STL performed well in terms of accuracy and robustness among the preliminary single models. Nonetheless, the stacking models provide more accurate

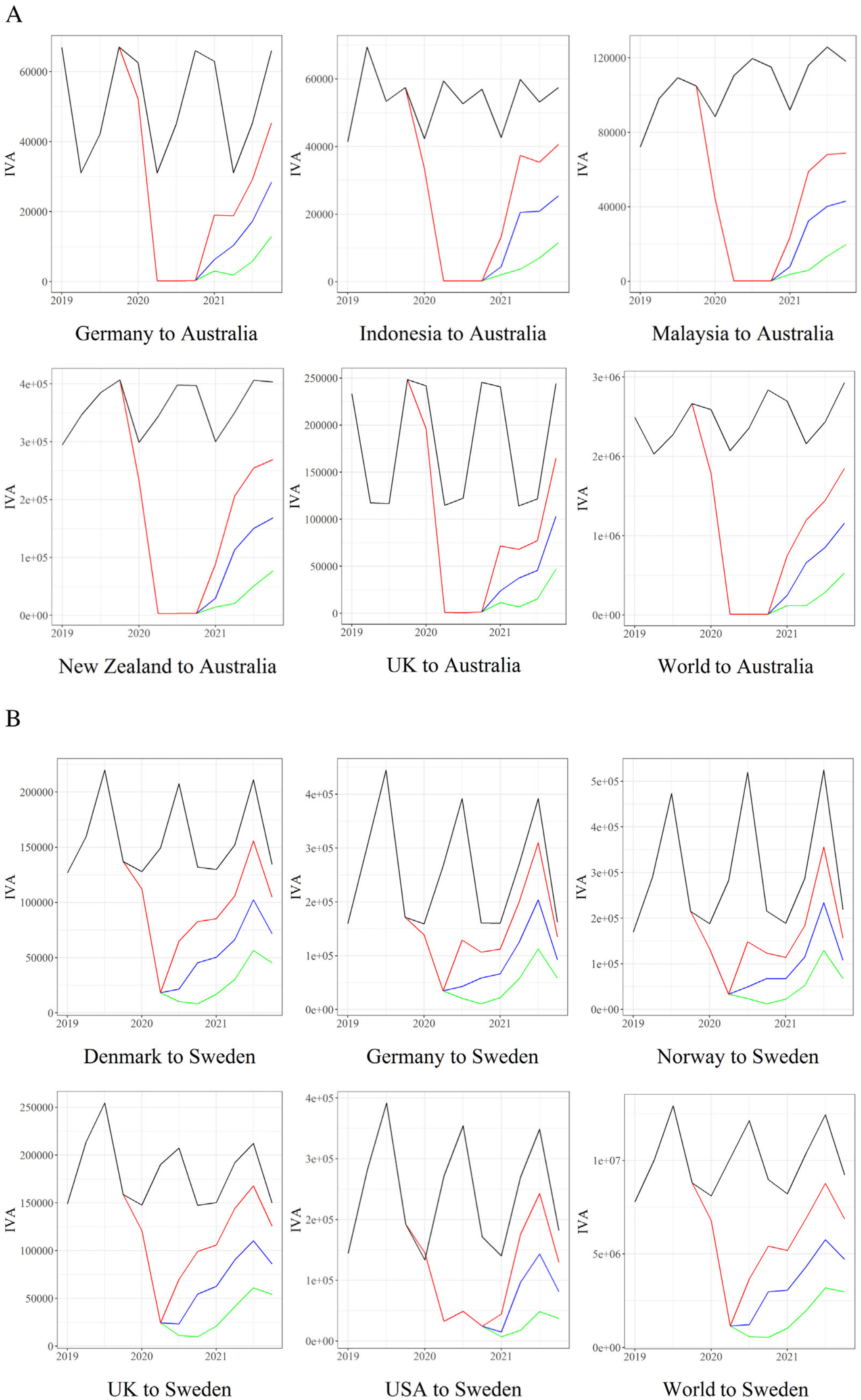
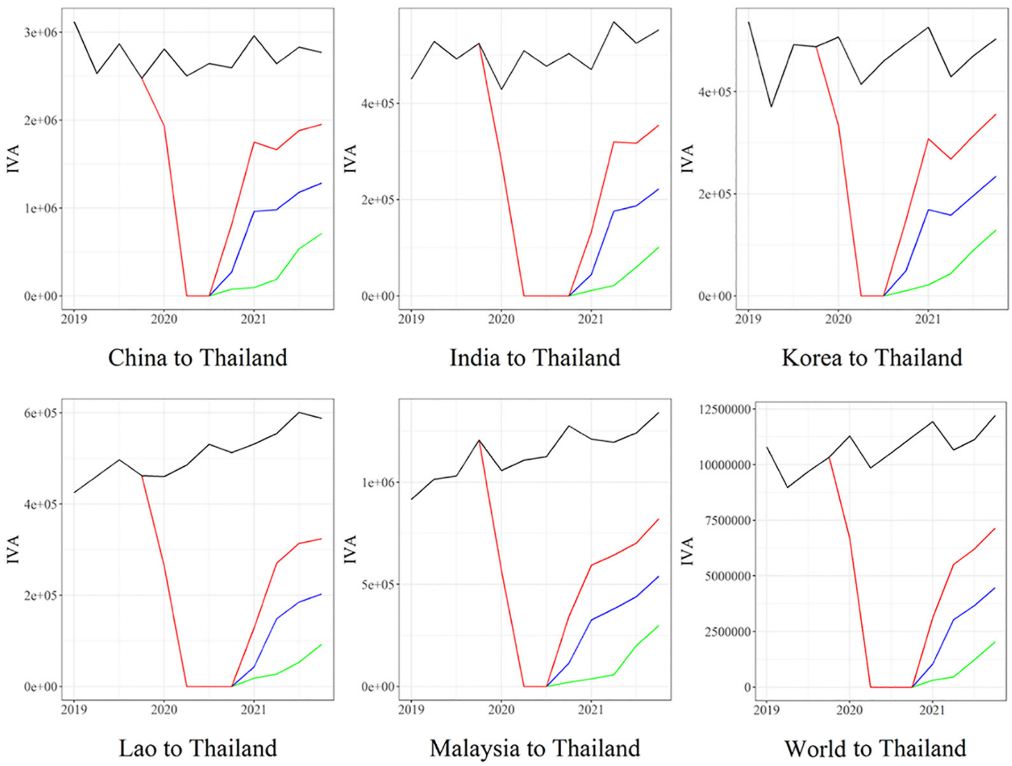


Fig. 6. a. Forecasts for Australia. b. Forecasts for Sweden. c. Forecasts for Thailand. d. Forecasts for Tunisia. e. Forecasts for the United States.

C



D

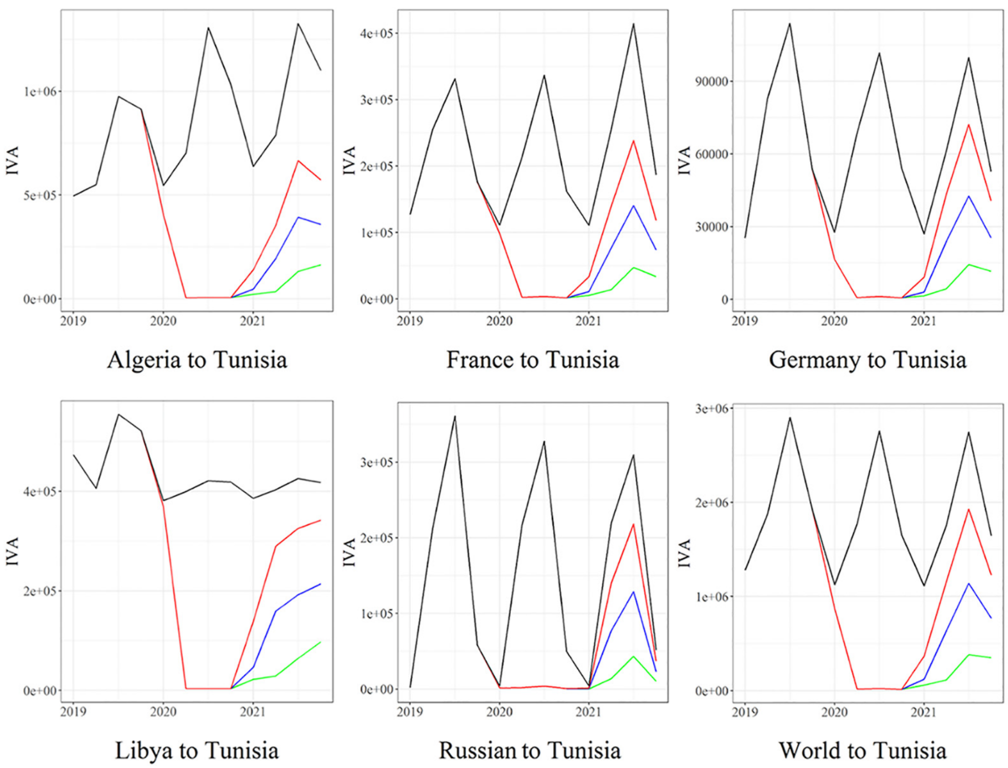


FIg. 6 (*continued*)

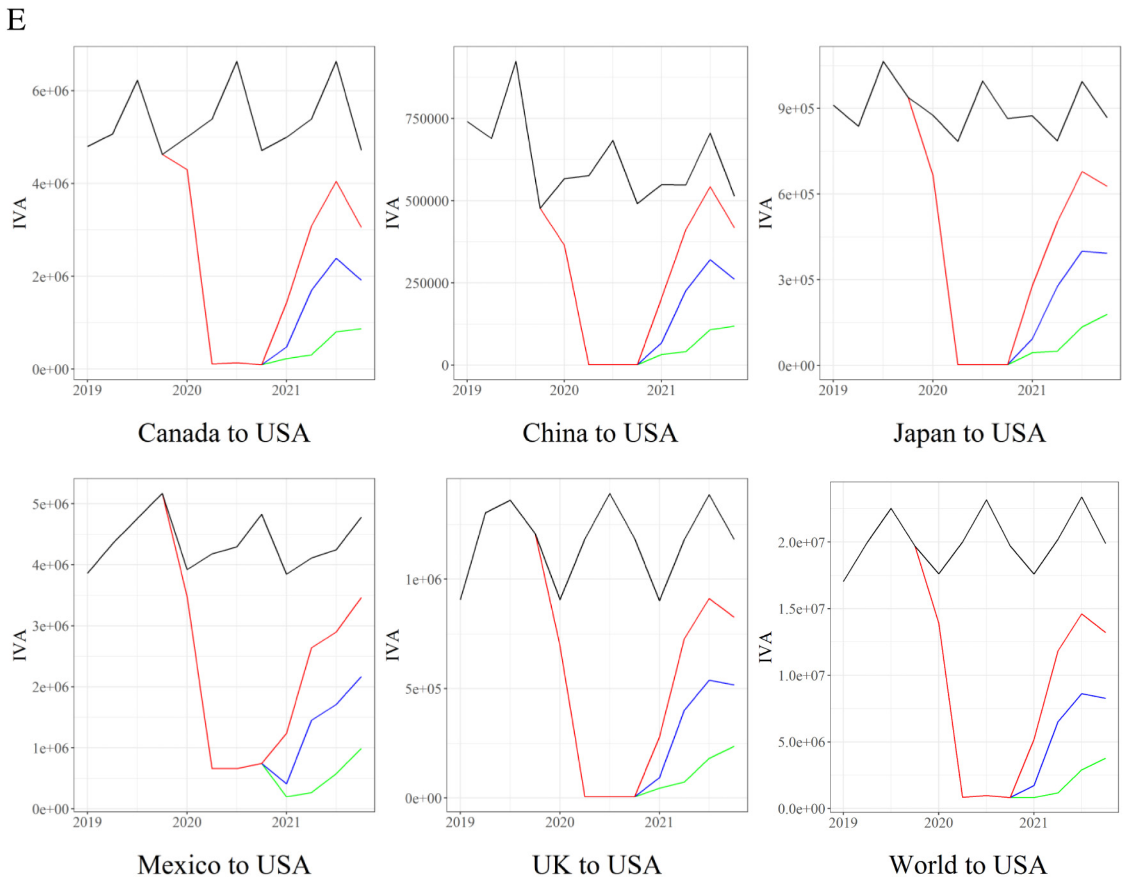


Fig. 6 (*continued*)

and robust forecasts, based on MASEs. The optimal number of single models that could be used for the combination model is five. These methodological findings contribute to constructing a more accurate and robust forecast framework.

Regarding the second stage ex-ante forecast, three scenarios of different patterns of inbound tourism recovery were modelled: a mild scenario displaying a V-shaped rebound; a medium scenario which is a deep V/U-shaped; and a severe scenario showing an L-shaped recovery. These scenarios are adapted for each country-wise situation. The second stage results demonstrate wide variations in the 2021 recovery rates depending on the three scenarios, allowing for country-wise adjustments. Compared to the same quarter in 2019, the mild scenario shows international arrivals ranging from 53% to 70% of the same level over the comparative period. The medium scenario has international arrivals being between 29% and 45% of the previous level while the recovery in the severe scenario forecasts visitor arrivals ranging from 9% to 23% compared to the same quarter in 2019. Although there is considerable uncertainty regarding the likely scenario, a country's travel policies will influence recovery speeds. For instance, Sweden has opted for a unique open-door no-lockdown herd-immunity policy, so may experience faster recovery than those countries with strict travel-control policies.

This study contributes to the tourism forecasting literature in different aspects. Firstly, due to the unprecedented nature of the COVID-19 pandemic, generating accurate and robust forecasts is the most challenging task for economists. This study proposes an innovative methodological framework with state-of-art forecasting techniques for tourism scenario forecasting under the context of unexpected crises such as COVID-19, which provides the tourism industry and destination management and marketing organizations with good forecasting practice. Secondly, 120 origin-destination pairs are forecast for three scenarios in this study, and each of them has different models involved in stacking. The automatic model selection method and self-adapting weighting in the stacking process proposed in this study provides a valuable and effective tool for large scale forecasting exercises when a large number of forecasts are required in a short period of time. Finally, the set of three scenarios sheds new light on the application of scenario forecasting in the tourism context in the future. As Wu et al. (2020) suggested, scenario forecasting provides rich and straightforward information and is easily understood and adopted by decision-makers.

A few limitations exist in this study. Firstly, a linear recovery trend is adopted in the present study to simplify reality. Future studies could investigate the shape of the recovery trend in different destinations under various scenarios. Secondly, only three scenarios are discussed in the present study, which does not cover all possibilities of reality. For example, in a matter of weeks, the mild scenario has now become much less probable, after a second wave of infections which have suddenly been more difficult to manage, at the time of writing (October 2020). Therefore, the *ex-ante* forecasts can be updated in a timely manner, as needed. Thirdly, only point forecasts are provided in this study which overlooks the uncertainty at the given prediction points. Probabilistic forecasting such as interval forecasting is encouraged to capture the uncertainty in the tourism demand system (Li et al., 2019).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Athanasopoulos, G., Hyndman, R. J., Song, H., & Wu, D. C. (2011). The tourism forecasting competition. *International Journal of Forecasting*, *27*(3), 822–844. https://doi.org/10.1016/j.ijforecast.2010.04.009.

Australian Government (d). Minister for home affairs (2020). Joint statement – Safe travel zone with New Zealand. Media Release (October 2, 2020). Retrieved from https://minister.homeaffairs.gov.au/peterdutton/Pages/safe-travel-zone-with-new-zealand.aspx.

Casas, I., & Fernandez-Casal, R. (2019). tvReg: Time-varying coefficients linear regression for single and multi-equations in R. SSRN. R package version 0.5.3. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3363526.

Casas, I., & Fernandez-Casal, R. (2020). tvReg: Time-varying coefficients linear regression for single and multi-equations. R package version 0.5.3. https://CRAN.R-project.org/package=tvReg.

Crouch, G. I. (1994). The study of international tourism demand: A survey of practice. Journal of Travel Research, 32(4), 41–55. DOI: 10.1177%2F004728759403200408.

Farzanegan, M. R., Gholipour, H. F., Feizi, M., Nunkoo, R., & Andargoli, A. E. (2020). International tourism and outbreak of coronavirus (COVID-19): A cross-country analysis. *Journal of Travel Research*. https://doi.org/10.1177/0047287520931593.

France Diplomatie (2020). Conseils aux Voyageurs Conseils par pays/destination. Retrieved from https://www.diplomatie.gouv.fr/fr/conseils-aux-voyageurs/conseils-par-pays-destination.

Harvey, A. (1990). *Forecasting, structural time series models and the Kalman filter*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9781107049994.

Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-Wild, M., Petropoulos, F., Razbash, S., Wang, E., & Yasmeen, F. (2020). forecast: Forecasting functions for time series and linear models. R package version 8.12. http://pkg.robjhyndman.com/forecast.

Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: Principles and practice, 2nd edition, OTexts: Melbourne, Australia. OTexts.com/fpp2.

Hyndman, R. J., & Khandakar, Y. (2008). Automatic time series forecasting: The forecast package for R. *Journal of Statistical Software*, *26*(3), 1–22. https://doi.org/10.18637/jss.v027.i03.

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, *22*(4), 679–688. https://doi.org/10.1016/j.ijforecast.2006.03.001.

International Monetary Fund (2020a). Policy Responses to COVID-19. Retrieved from https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

International Monetary Fund (2020b). Tourism Trauma and COVID-19. IMF Blog (August 20, 2020). Retrieved from https://blogs.imf.org/2020/08/20/tourism-trauma-and-covid-19/.

Jaganathan, S., & Prakash, P. K. S. (2020). A combination-based forecasting method for the M4-competition. *International Journal of Forecasting*, *36*(1), 98–104. https://doi.org/10.1016/j.ijforecast.2019.03.030.

Kourentzes, N. (2019). nnfor: Time series forecasting with neural networks. R package version 0.9.6. https://CRAN.R-project.org/package=nnfor.

Li, G., Song, H., & Witt, S. F. (2005). Recent developments in econometric modeling and forecasting. Journal of Travel Research, 44(1), 82–99. DOI: 10.1177%2F0047287505276594.

Li, G., Wu, D. C., Zhou, M., & Liu, A. (2019). The combination of interval forecasts in tourism. *Annals of Tourism Research*, *75*, 363–378. https://doi.org/10.1016/j.annals.2019.01.010.

Lim, C. (1997). Review of international tourism demand models. *Annals of Tourism Research*, *24*(4), 835–849. https://doi.org/10.1016/S0160-7383(97)00049-2.

Lim, C. (1999). A meta-analytic review of international tourism demand. Journal of Travel Research, 37(3), 273–284. DOI: 10.1177%2F004728759903700309.

Mariolis, T., Rodousakis, N., & Soklis, G. (2020). The COVID-19 multiplier effects of tourism on the Greek economy. *Tourism Economics*. https://doi.org/10.1177/1354816620946547.

Moritz, S., & Bartz-Beielstein, T. (2017). imputeTS: Time series missing value imputation in R. *The R Journal*, *9*(1), 207–218. https://doi.org/10.32614/RJ-2017-009.

Natsiopoulos, K., & Tzeremes, N. (2020). *ARDL: ARDL, ECM and bounds-test for cointegration. R package version 0.1.0*Department of Economics: University of Thessalyhttps://github.com/Natsiopoulos/ARDL.

Our World in Data (2020a). Coronavirus Pandemic (COVID-19). Retrieved from https://ourworldindata.org/coronavirus.

Our World in Data (2020b). Policy responses to the coronavirus pandemic: International travel controls. Retrieved from https://ourworldindata.org/policy-responses-covid#international-travel-controls.

Page, S., Song, H., & Wu, D. C. (2012). Assessing the impacts of the global economic crisis and swine flu on inbound tourism demand in the United Kingdom. *Journal of Travel Research*, *51*(2), 142–153. https://doi.org/10.1177/0047287511400754.

Qiu, R. T. R., Park, J., Li, S. N., & Song, H. (2020). Social costs of tourism amid COVID-19 pandemic. *Annals of Tourism Research*, *84*, 102994. https://doi.org/10.1016/j.annals.2020.102994.

Song, H., & Li, G. (2008). Tourism demand modelling and forecasting—A review of recent research. *Tourism Management*, *29*(2), 203–220. https://doi.org/10.1016/j.tourman.2007.07.016.

Song, H., Qiu, R. T. R., & Park, J. (2019). A review of research on tourism demand forecasting: Launching the Annals of Tourism Research Curated Collection on tourism demand forecasting. *Annals of Tourism Research*, *75*, 338–362. https://doi.org/10.1016/j.annals.2018.12.001.

Tourism Economics (an Oxford Economics company) (2020). Global travel service - Global highlights & risks - July 2020. Retrieved from https://resources.oxfordeconomics.com/hubfs/Global-Travel-Service-July-2020.pdf.

Travel Off Path (2020). Countries reopening their borders for tourism: The complete list. Retrieved from https://www.traveloffpath.com/countries-reopening-their-borders-for-tourism-the-complete-list/.

U.S. Department of State (2020). COVID-19 country specific information. Retrieved from https://travel.state.gov/content/travel/en/traveladvisories/COVID-19-Country-Specific-Information.html.

UN World Tourism Organization (2020a). UNWTO tourism recovery tracker. Retrieved from https://www.unwto.org/unwto-tourism-recovery-tracker.

UN World Tourism Organization (2020b). UNWTO world tourism barometer and statistical annex, August/September 2020. Retrieved from https://doi.org/10.18111/wtobarometereng.

UN World Tourism Organization (2020c). Impact assessment of the COVID-19 outbreak on international tourism (updated May 2020). Retrieved from https://www.unwto.org/impact-assessment-of-the-covid-19-outbreak-on-international-tourism.

UN World Tourism Organization (2020d). UNWTO world tourism barometer – Special focus on the impact of COVID-19, May 2020. Retrieved from https://doi.org/10.18111/wtobarometereng.

University of Oxford, Blavatnik School of Government (2020). Oxford coronavirus government response tracker (OxCGRT). Retrieved from https://covidtracker.bsg.ox.ac.uk/.
Witt, S. F., & Witt, C. A. (1995). Forecasting tourism demand: A review of empirical research. *International Journal of Forecasting*, *11*(3), 447–475. https://doi.org/10.1016/0169-2070(95)00591-7.
World Health Organization (2020). WHO coronavirus disease (COVID-19) dashboard. Retrieved from https://covid19.who.int/table.
World Nomads (2020). COVID-19 travel alert: Which countries have open borders? Retrieved from https://www.worldnomads.com/travel-safety/worldwide/worldwide-travel-alerts.
Wu, D. C., Cao, Z., Wen, L., & Song, H. (2020). Scenario forecasting for global tourism. *Journal of Hospitality and Tourism Research*. https://doi.org/10.1177/1096348020919990.
Wu, D. C., Song, H., & Shen, S. (2017). New developments in tourism and hotel demand modeling and forecasting. *International Journal of Contemporary Hospitality Management*, *29*(1), 507–529. https://doi.org/10.1108/IJCHM-05-2015-0249.
Yang, Y., Zhang, H., & Chen, X. (2020). Coronavirus pandemic and tourism: Dynamic stochastic general equilibrium modeling of infectious disease outbreak. *Annals of Tourism Research*, *83*, 102913. https://doi.org/10.1016/j.annals.2020.102913.

Richard T. R. Qiu is an assistant professor at the Department of Integrated Resort and Tourism Management, Faculty of Business Administration, University of Macau.
Doris Chenguang Wu is a professor of tourism forecasting in the Business School at the Sun Yat-sen University, China. Her research interests include tourism demand forecasting and tourism impact analysis.
Vincent Dropsy is a professor of economics at the University of French Polynesia, and the co-director of the Center for Research on Tourism in Oceania Pacific (CETOP) within the Governance and Insular Development (GDI) research center.
Sylvain Petit is an associate professor in economics at the Polytechnic University of Hauts de France and is a visiting professor at the University of French Polynesia where he is head of the Law, Economics and Management Department. He is a member of the research teams CRISS (in France) and GDI-CETOP (in Polynesia), as well as an associate researcher in the CRESEM team (University of Perpignan).
Stephen Pratt is a professor and Head of School of Tourism & Hospitality Management at the University of the South Pacific, Fiji.
Yasuo Ohe is a professor at the Department of Agribusiness Management, Faculty of International Agriculture and Food Studies, Tokyo University of Agriculture.