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VISITOR ARRIVAL FORECASTS AMID COVID-19: A perspective from the Asia and Pacific team

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-based algorithms 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-shape recovery, a medium one with a V/U-shape, and a severe one with an L-shape. The forecast results show a wide range of recovery (10%-70%) in 2021 compared to 2019. This two-stage three-scenario framework contributes to improvement in the accuracy and robustness of tourism demand forecasting.

Keyword: COVID-19, tourism forecasting competition , stacking-based algorithms, recovery scenario, judgemental-adjusted forecasting

INTRODUCTION

Covid-19 has had devastating effects on many facets of society and the economy of every country 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 limit the mobility of its 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. This 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; Yang *et al.*, 2020) yet few studies have sort 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 to re-open. This has significant implications for the wellbeing of residents as businesses decide to reemploy staff. At the time of writing, the pandemic is still ongoing. Some countries have opened again, some remain fully closed and others lie 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 tourism demand forecasting has received considerable attention in the literature. Numerous review papers have been published summarizing research published to date. These reviews include Crouch (1994), Witt & Witt (1995), Lim (1997, 1999), Li *et al.* (2005), Song & Li (2008), and more recently Wu *et al.* (2017) and Song *et al.* (2019). As noted by Song & 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.” According to Wu *et al.* (2020), there are two main types of scenario forecasting. The first one forecasts tourism demand given certain conditions/scenarios, such as optimistic or pessimistic scenarios. The second type of scenario forecasting aims to predict the probability of a given scenario/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 three scenarios in 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 on 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, 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 are made up until the end of 2021. The purpose of this two-stage forecasting procedure is to identify effective forecasting framework and evaluation procedures in a crisis.

There are numerous measures to assess the accuracy of forecasts. Hyndman & 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, and highlights 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. They are Australia, Bulgaria, Canada, Chile, Czech, Finland, Indonesia, Japan, South Korea, Malaysia, Mauritius, Mexico, New Zealand, Singapore, South Africa, Sweden, Thailand, Tunisia, UK, and USA. For each destination, the total volume of international visitor arrivals 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 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, with the data until the end of 2019 as training and data of 2019 as testing. 11 single models and 26 stacking models are examined and compared. In the second stage, judgmental adjusted forecasting under three recovery scenarios and one set of baseline forecasting which assumes there is no COVID-19 are generated separately to estimate the impact of the COVID-19 on tourism demand. Figure 1 illustrates this framework.

[Figure 1 about here]

First Stage –ex post forecasting before COVID-19

Individual forecasting models

The difficulty of the first stage forecast is in trying to find one algorithm that not only provides accurate forecasts of the tourism demand series but also in finding an algorithm that performs stably across various origin-destination pairs and different time horizons. Ensemble methods have proved effective in improving the forecast accuracy of constituent methods (Jaganathan & Prakash, 2020). In particular, bagging, boosting, and stacking techniques have emerged to provide outstanding forecasts in tourism demand analysis (e.g. Athanasopoulos, Song, & Sun, 2018; Cankurt, 2016). For the present competition, stacking-based algorithms are examined and compared, and the best algorithm is proposed for forecasting the 120 time-series of international visitor arrivals. 11 preliminary single models are adopted to generate forecasts of the tourism demand series, namely *seasonal Naïve (SN)*, *seasonal autoregressive integrated moving average (SARIMA)*, *exponential smoothing (ETS)*, *seasonal and trend decomposition using Loess (STL)*, *exponential smoothing state space model with Box-Cox transformation, ARMA errors, trend, and seasonal components (TBATS)*, *autoregressive distributed lag (ARDL)*, *static regression with time-varying parameter (SR-TVP)*, *univariate multilayer perceptron (MLP)*, *multivariate multilayer perceptron (MLPX)*, *univariate extreme learning machine (ELM)*, and *multivariate extreme learning machine (ELMX)*. These models cover the three major families of quantitative forecasting approaches commonly adopted in tourism demand forecasts: time series methods;

econometric models; and AI-based techniques (Song, *et al.*, 2019). These models include both univariate and multivariate methods, which ensure both historical patterns of tourism demand series and the influence of economic factors are covered.

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 & Khandakar, 2008; Hyndman, *et al.*, 2020). The imputation of missing values provides a complete time series for model estimation while preserving the characteristics of the original time series. 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 original information.

The estimations of the 11 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 (Natsiopoulous & 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 (i.e. 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.

Stacking models

To train the eleven preliminary single models as well as the stacking-based algorithms. 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.

The 11 preliminary single models are stacked in 26 different ways to explore the best stacking algorithm 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 11 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 algorithms, using MAPE, RMSE, or MASE as criteria, and combine these algorithms 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 algorithms above and allows different stacking algorithms to forecast different quarters.

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

$$ASE = \frac{|e_{d,j}|}{\frac{1}{T-1} \sum_{t=2}^T |Y_{d,t} - Y_{d,t-m}|},$$

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 , and m is the seasonal period. 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 algorithm among all 37 algorithms (11 preliminary single models and 26 stacking-based algorithms).

Second Stage – ex ante scenario forecasting under COVID-19

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 quarter 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 gradually reopen and travel restrictions are lifted. A recovery of international tourism 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 taking into account national specificities.

- 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 shape 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 (2020a)
- 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; International Monetary Fund; Travel Off Path; U.S. Department of State; World Nomads.
- 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 tourism 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.

The following figure illustrates the adjustment process.

[Figure 2 about here]

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 algorithms. 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. Amongst these 37 models, regression stacking based on all 11 single models performs extremely poor 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 algorithm 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.

[Table 1 about here]

The results of the rest 36 models are further shown in Figure 3, in which the blue line refers to the MASEs and the orange dashed line refers to the standard deviations of these MASEs. From the figure, it is seen that overall stacking algorithms outperform the single models on average. The average MAPEs for the 11 single models and the 25 stacking algorithms are 1.4287 and 1.0122 respectively, and the average MASE standard deviations for the 11 single models and the 25 stacking algorithms are 1.3462 and 0.9406 respectively (see Table 1). Therefore, stacking algorithms are more effective in generating more accurate and more robust forecasts of tourism demand. This conclusion is consistent with the existing studies that 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 Figure 3 it is also observed that stacking models exhibit less variation whereas the performance of the 11 single models varies more widely.

[Figure 3 about here]

Table 1 also shows that among the 11 single models, five single models of 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 the benchmark of SNAIVE. These models are SARIMA, ETS, and STL (Figure 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.

[Figure 4 about here]

Where stacking algorithms are concerned, Figure 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 algorithms outperform the benchmark for both MASEs and their standard deviations. Amongst these algorithms, four stacking algorithms, namely bn5rs, bn5re, bn5r2, and bn5rc perform best, having both the smallest MASEs and the smallest MASE standard deviations. We therefore conclude that the optimal number of single models to be combined in this study is five.

[Figure 5 about here]

Table 2 reports the forecasting accuracy of the stacking algorithm “bn5re”, which combines the five best single models by minimising the RMSE, for each destination. The stacking algorithm “bn5re” is the best performed one among 11 single models and 26 stacking algorithms, 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) (The results for destinations are available upon request). This observation is consistent with the existing studies (Song, *et al.*, 2019; Wu, *et al.*, 2017).

[Table 2 about here]

In conclusion, this stage focuses on the forecasting competition before COVID-19 based on 11 single models and 25 stacking-based algorithms. 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-based algorithms 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-based algorithms. These findings provide helpful information for future tourism demand forecasting practices.

Empirical Results from the Second Stage

The COVID-19 pandemic spreads first in 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.

[Table 3 about here]

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 to COVID-19 (IMF, 2020) 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 to 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). 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.

We select the following five destinations, Australia, Sweden, Thailand, Tunisia, and the USA, to demonstrate our results.

Australia

Australia is one of the destinations that has implemented a continuous ban of international tourism 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, a very low-risk country, starting from October 16th, 2020. Australia also indicated 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.

[Figure 6a about here]

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, forecasted tourism arrivals in Sweden show a rapid and strong rebound, where recovery rates are some of the highest, i.e. 70% for scenario 1 (red line), 45% for scenario 2 (blue line), and 23% for scenario 3 (green line).

[Figure 6b about here]

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 tourists from coming to Thailand. The graphs related to forecasted tourism flows to Thailand show recovery starting in 2021, 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).

[Figure 6c about here]

Tunisia

Tunisia also reopened its borders to international tourists 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.

[Figure 6d about here]

The United States

The United States closed its borders to tourists from Canada, China, Europe, and Mexico in 2020. A gradual recovery is expected in 2021, as shown on the six corresponding US graphs, 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.

[Figure 6e about here]

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 tourists 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 unseen. 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 forecasting before COVID-19 and ex ante forecasting post-COVID-19.

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

Regarding the second stage ex ante forecasting, 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-shape, 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 tourism 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.

Finally, the COVID-19 pandemic is unprecedented so generating accurate and robust forecasts is a most challenging task for economists. Nevertheless, this paper has used state-of-the-art forecasting techniques to provide policymakers and tourism businesses with the tourism demand forecasts under different scenarios, with the available information at the time and forecasting competition results.. This framework is also particularly useful for impact evaluation of crises on tourism demand and its recovery estimation.

Once a vaccine is found and tourism has converged to its new normal, further research could analyse international arrivals and improve their forecasts by integrating models based on its fundamental long-term determinants (such as gravity models), which are of little use for the short-term forecasting exercise in this paper, but could become again valuable tools for future investigations. Another direction for research could be an analysis of the impact of greater

uncertainty on confidence intervals in forecasts, due to exogenous shocks such as the pandemic and its evolution as a result of various policies. Indeed, in a matter of weeks, the mild scenario has now become much less probable, after a second wave of infections which appears to be suddenly more difficult to manage than expected, as the time of writing (October 2020).

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

	MASE	Std. Deviation of MASEs		MASE	Std. Deviation of MASEs
<i>11 single models</i>			<i>26 stacking models</i>		
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
<i>Average</i>	<i>1.4287</i>	<i>1.3462</i>	<i>Average</i>	<i>1.0122</i>	<i>0.9406</i>

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 algorithms (p – MAPE, r – RMSE, a – MASE), and the fifth digit representing the method of combining the selected algorithms (s – simple average, e – error weighting, 2 – squared error weighting, c – selection criteria based weighting).

Table 2 Forecasting performance (MASE) for all destinations

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

Table 3. Stage 2 forecast summary

Destination	Indicator	Scenario 1	Scenario 2	Scenario 3
UK	Deepest impact	-95,70%	-95,70%	-95,70%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 Recovery rate	69,20%	44,19%	22,12%
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%	-96%	-96%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 Recovery rate	69,99%	45%	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%
Bulgaria	Deepest impact	-77,81%	-92,60%	-96,45%
	Bottom time	2020Q3	2020Q3	2020Q3
	2021 Recovery rate	69,37%	44,21%	21,73%
Japan	Deepest impact	-99,90%	-99,90%	-99,90%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 Recovery rate	55,66%	30,95%	10,68%
South Korea	Deepest impact	-97.90%	-97.90%	-97.90%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 Recovery rate	56.05%	31.31%	9.63%
Thailand	Deepest impact	-100%	-100%	-100%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 Recovery rate	58.33%	33.40%	11.28%
Singapore	Deepest impact	-99.90%	-99.90%	-99.90%
	Bottom time	2020Q3	2020Q3	2020Q3
	2021 Recovery rate	57.33%	32.46%	9.18%
Malaysia	Deepest impact	-99.70%	-99.70%	-99.70%
	Bottom time	2020Q2	2020Q2	2020Q2
	2021 Recovery rate	66.03%	40.21%	12.20%
Indonesia	Deepest impact	-88,41%	-89,74%	-95,08%
	Bottom time	2020Q3	2021Q1	2021Q1
	2021 Recovery rate	55,77%	31,06%	10,79%
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%

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%
USA	Deepest impact	-95,16%	-95,16%	-95,16%
	Bottom time	2020Q3	2020Q3	2020Q3
	2021 Recovery rate	56,45%	31,62%	10,95%
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%

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.

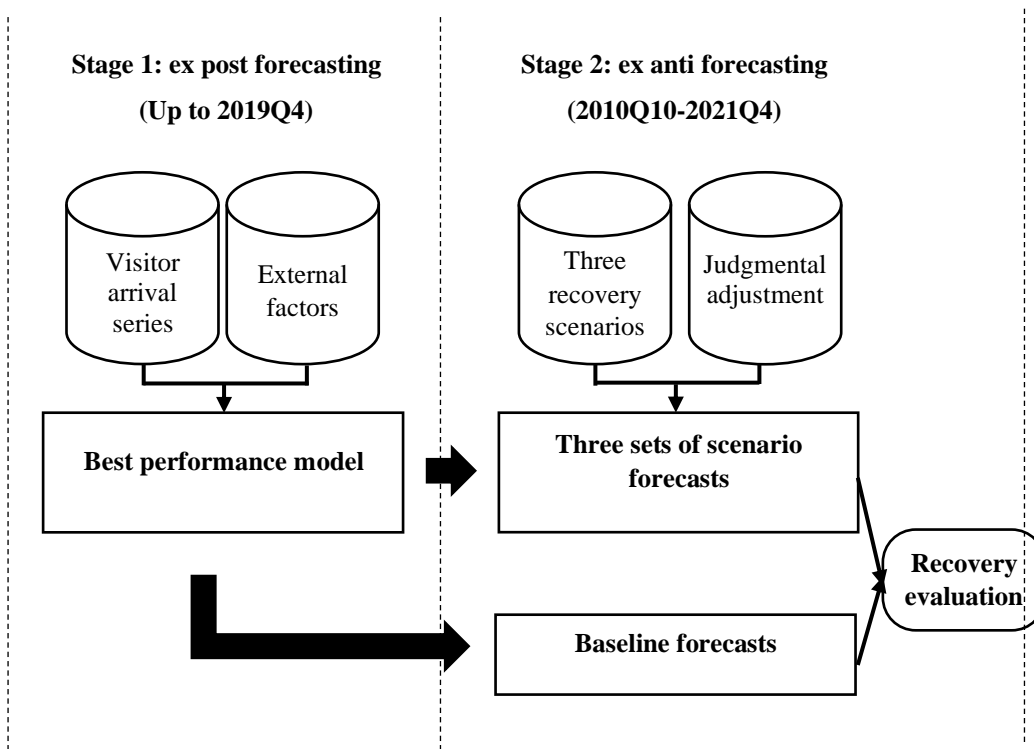
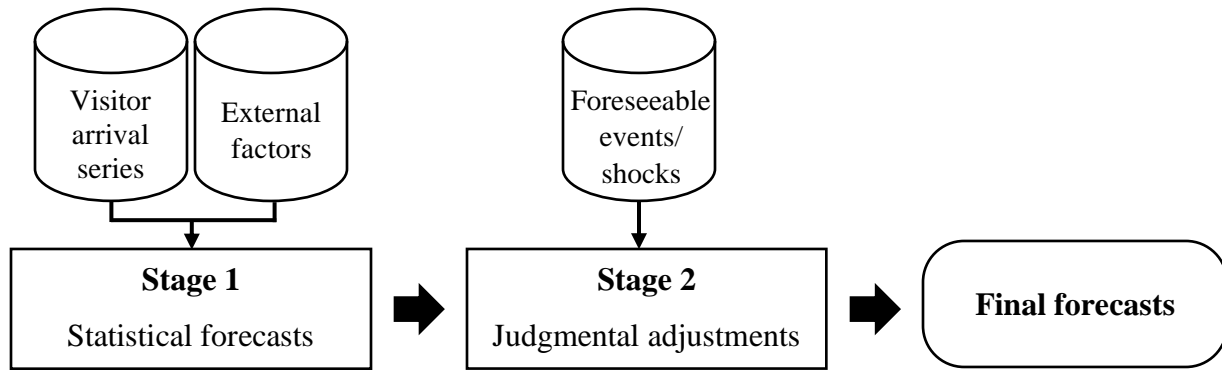
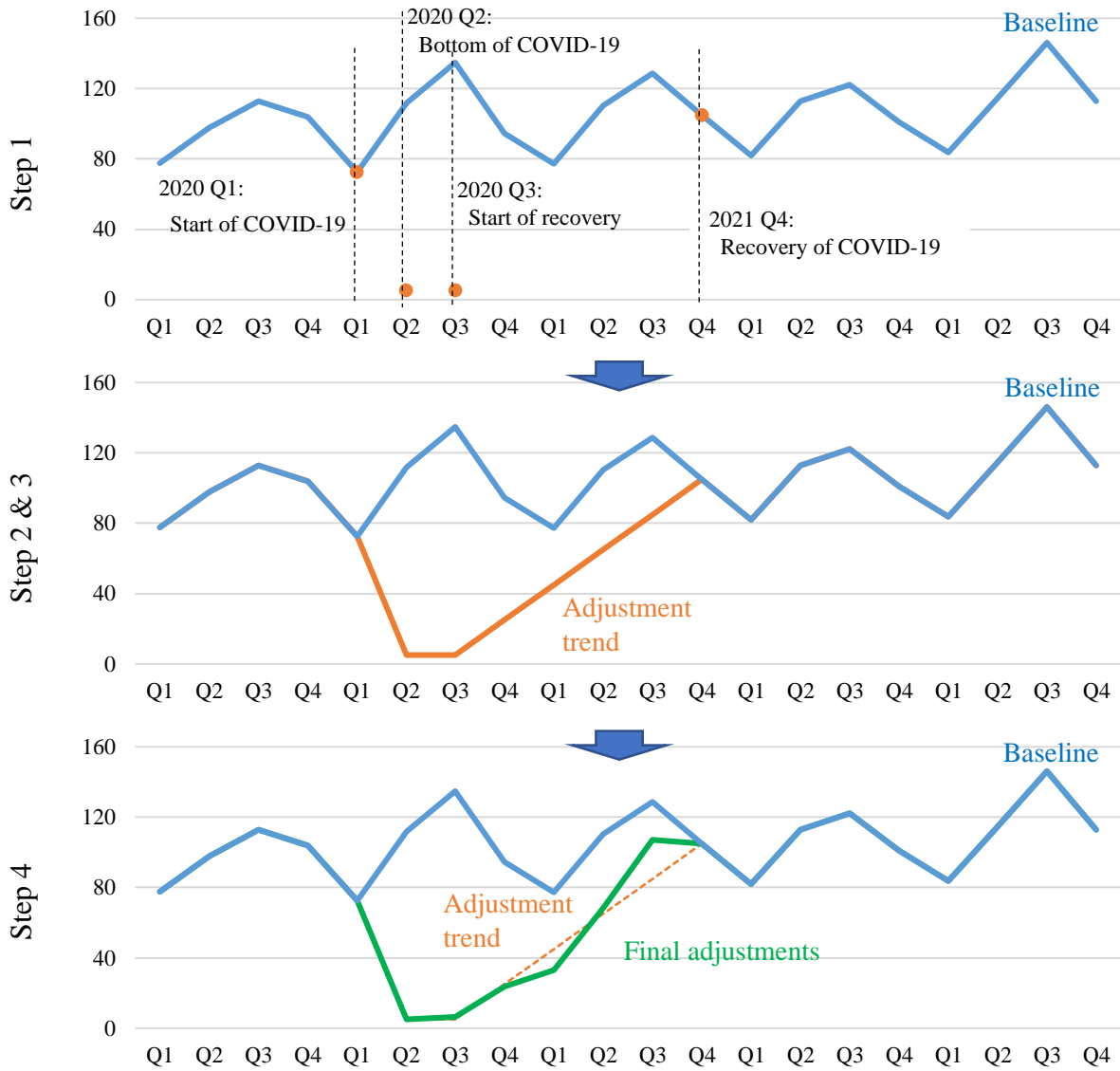


Figure 1. Framework of the study



Note: dates and magnitudes are for illustration only.

Figure 2. Procedure of stage two (judgmental) forecast

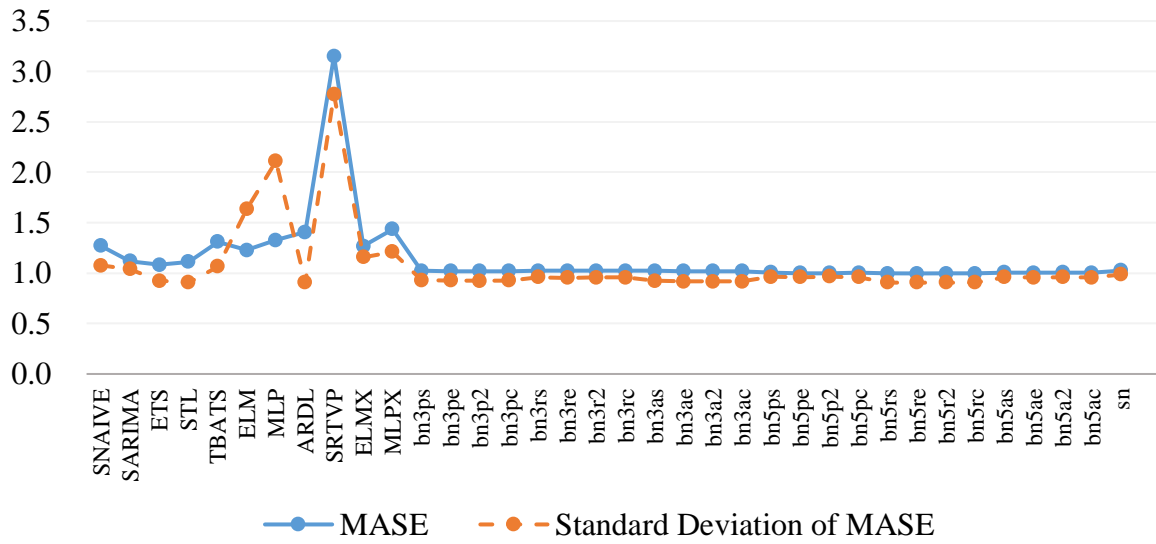


Figure 3. Forecasting performance of all 36 models

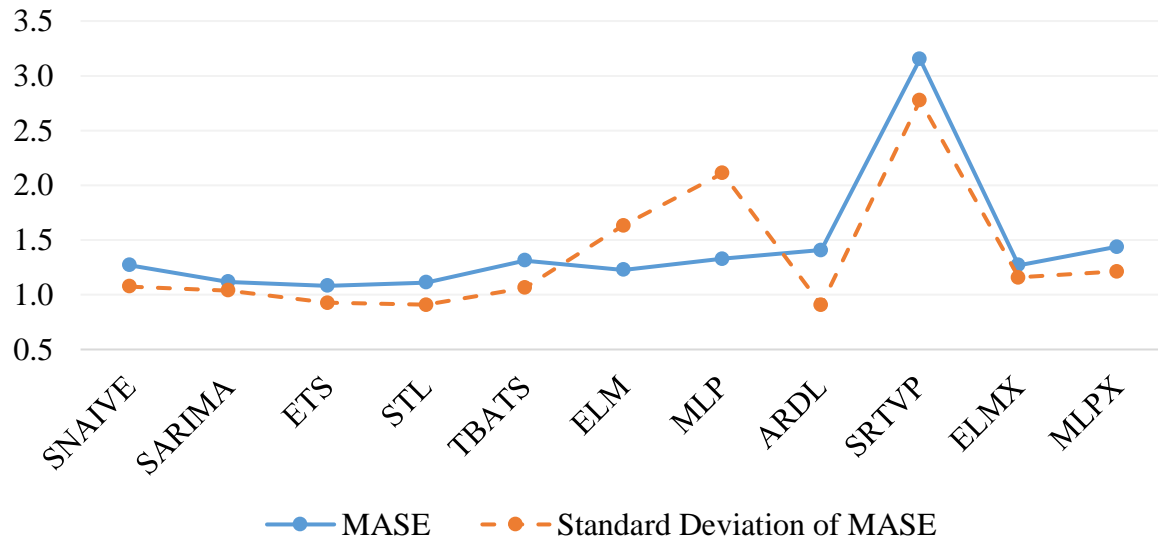


Figure 4. Forecasting performance of 11 single models

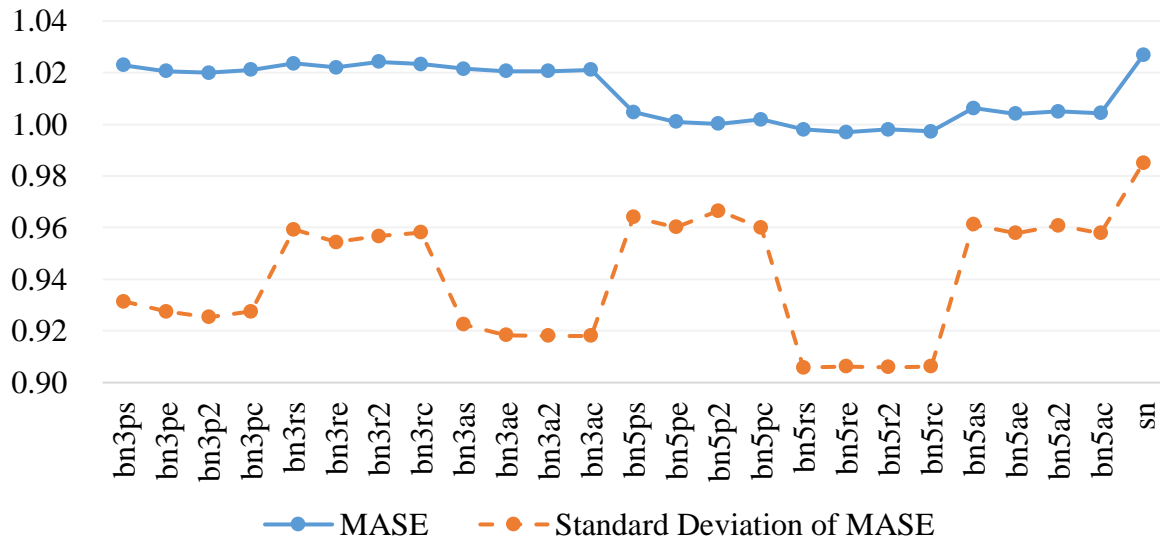


Figure 5. Forecasting performance of 25 stacking models

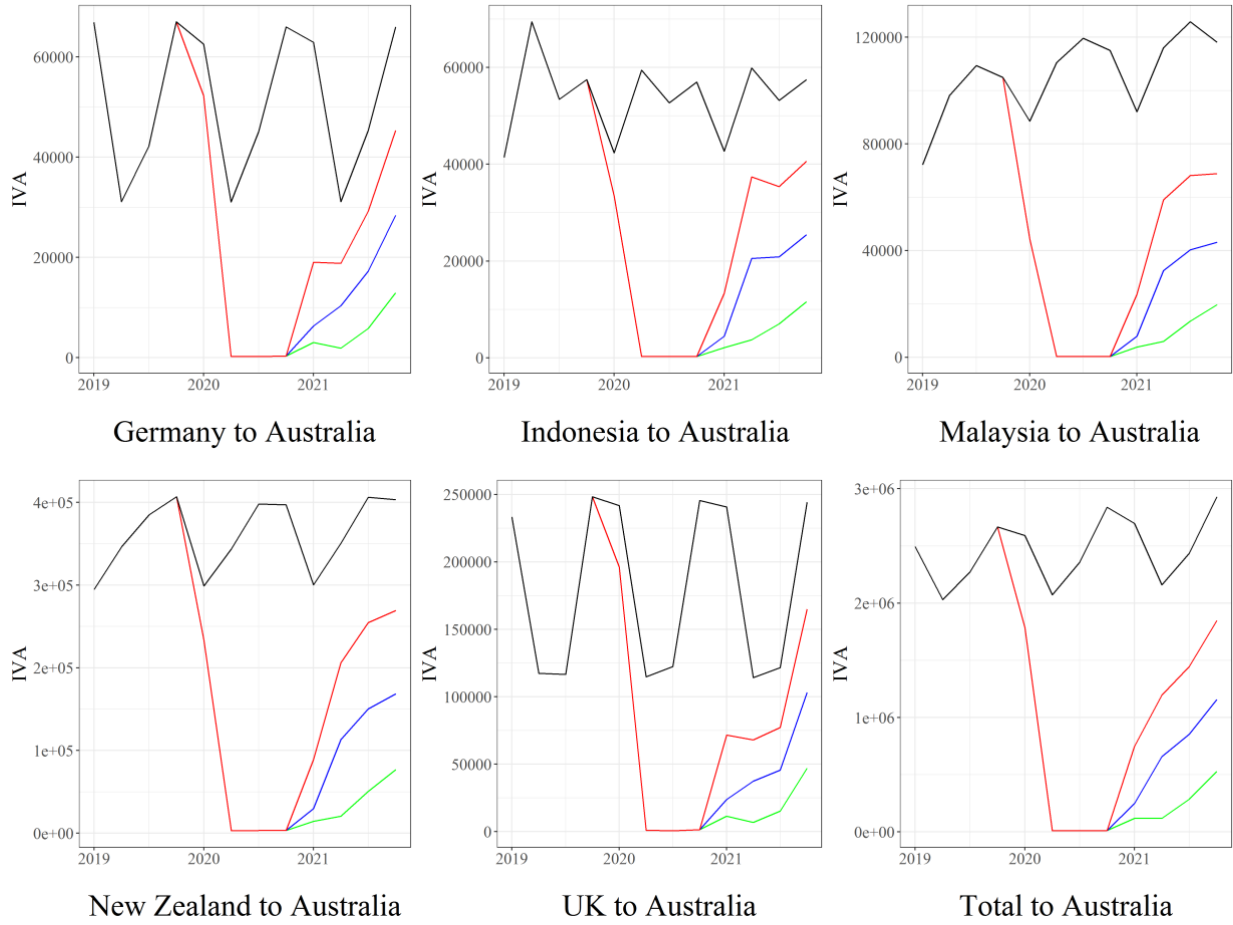


Figure 6a. Forecasts for Australia

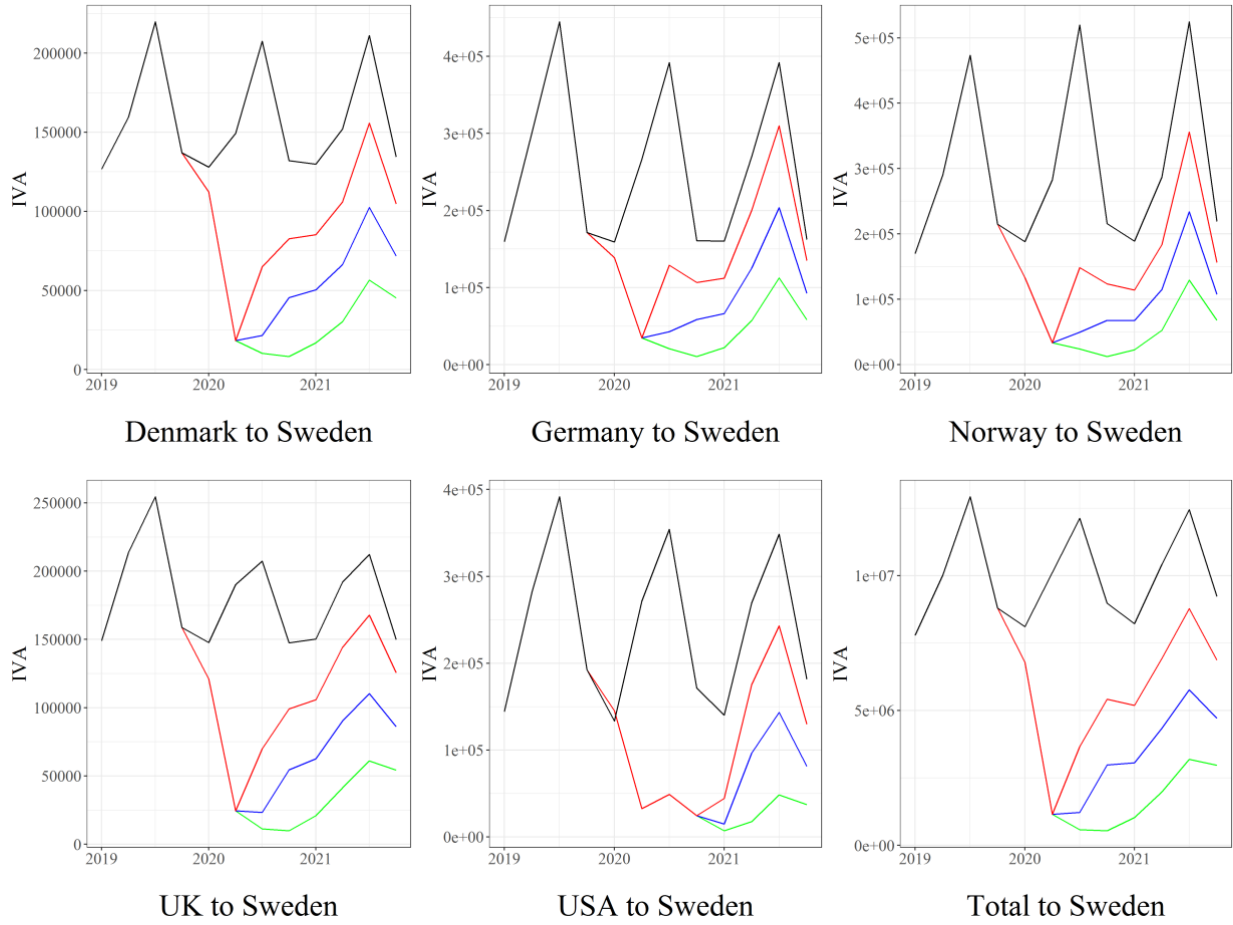


Figure 6b. Forecasts for Sweden

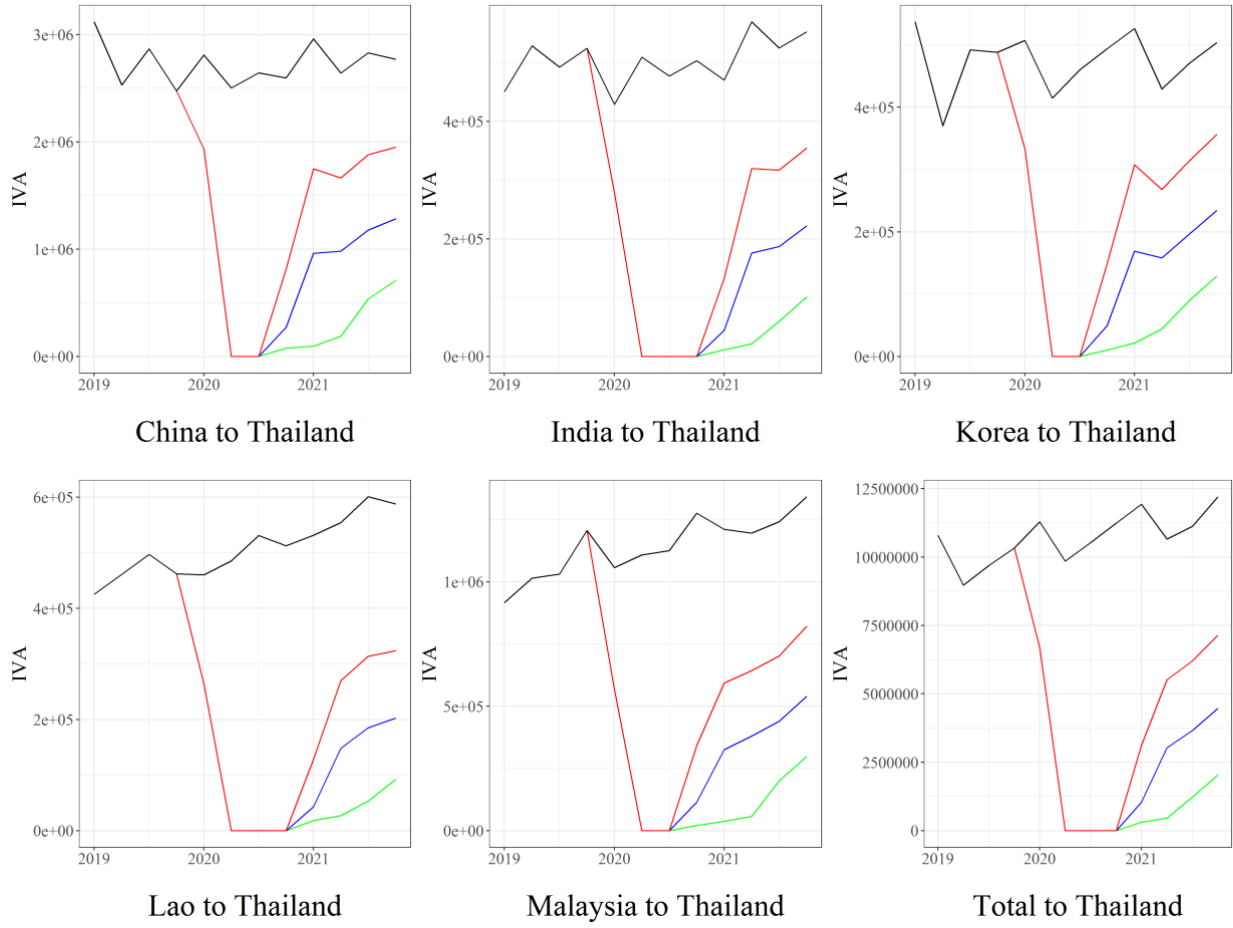


Figure 6c. Forecasts for Thailand

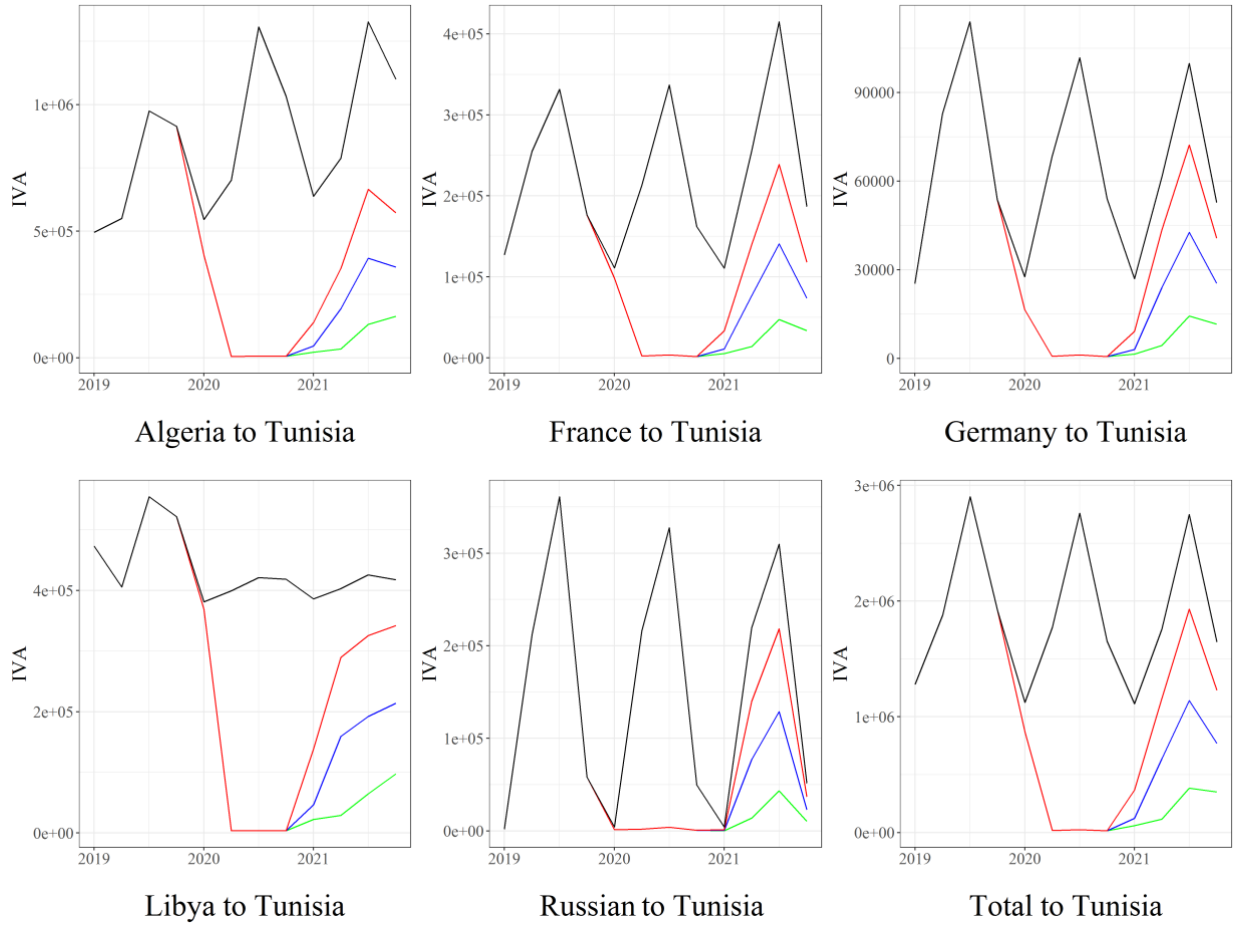


Figure 6d. Forecasts for Tunisia

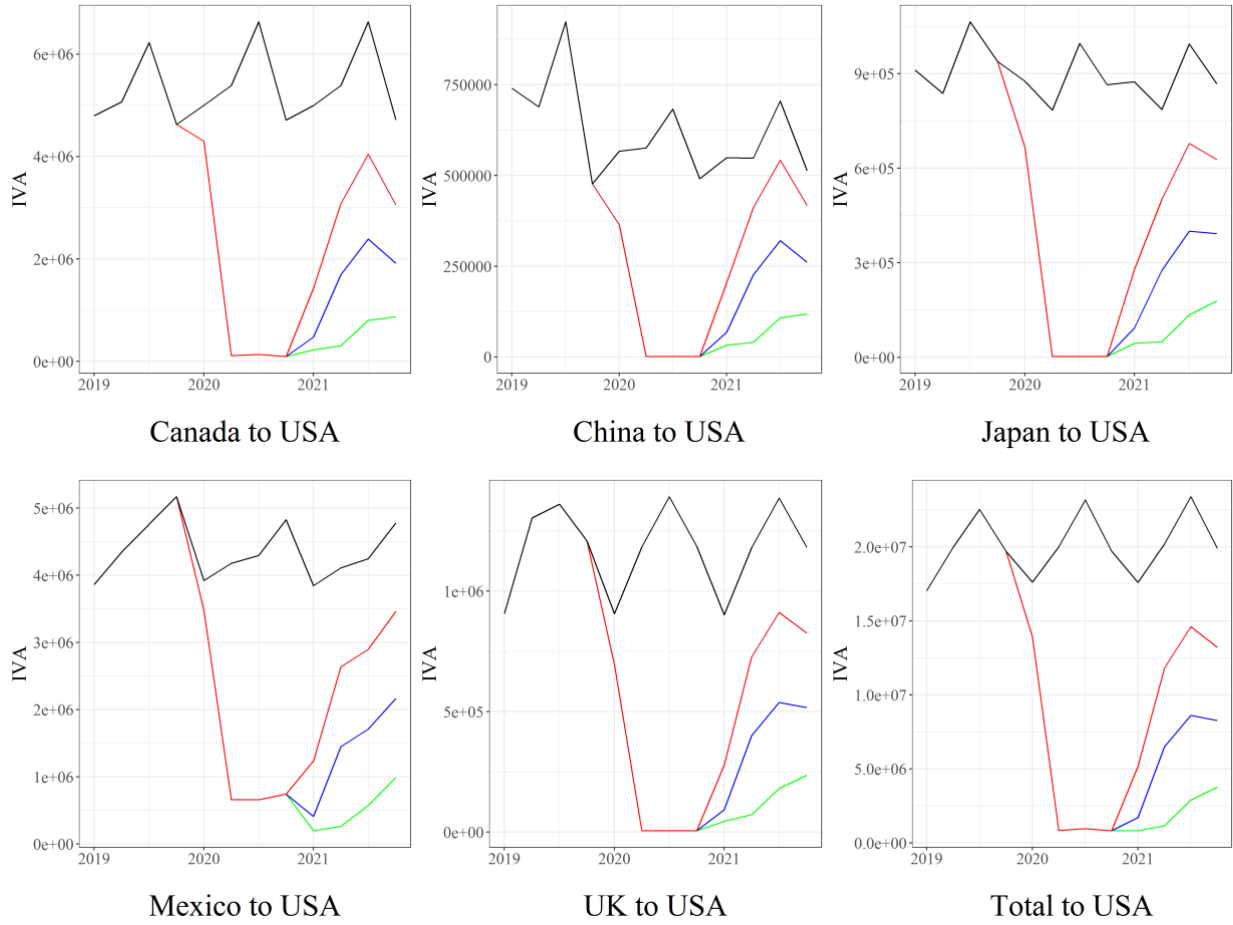


Figure 6e. Forecasts for the United States