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Visitor arrivals forecasts amid COVID-19: A perspective from the Europe team☆

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ABSTRACT

In a context in which the tourism industry is jeopardised by the COVID-19 pandemic, and potentially by other pandemics in the future, the capacity to produce accurate forecasts is crucial to stakeholders and policy-makers. This paper attempts to forecast the recovery of tourism demand for 2021 in 20 destinations worldwide. An original scenario-based judgemental forecast based on the definition of a Covid-19 Risk Exposure index is proposed to overcome the limitations of traditional forecasting methods. Three scenarios are proposed, and *ex ante* forecasts are generated for each destination using a baseline forecast, the developed index and a judgemental approach. The limitations and potential developments of this new forecasting model are then discussed.

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Introduction

The unprecedented situation that the world of tourism finds itself in as it looks to recover from the sudden and extreme limitations of mobility during the COVID-19 pandemic, requires some guidance on how quickly different destinations are going to recover, and by how much. The high sensitivity to risk events makes tourism industry particularly fragile when pandemics occur (Novelli et al., 2018). Pandemics often lead tourists to change their travel plans or even to reduce travels due to concerns on perceived risks (Page et al., 2012; Wilks & Page, 2003). This has been the case in 2020, as the total number of international tourist arrivals has dropped by 65% between January and June, as a result of the COVID-19 outbreak (UNWTO, 2020).

Pandemics and their effects are not new in the tourism literature. Choe et al. (2020) explored the impact of MERS on inbound tourism demand in South Korea by adopting several forecasting methods (e.g. the autoregressive integrated moving average - ARIMA model, exponential smoothing model, and stepwise autoregressive model). Shi and Li (2017) assessed the impact of MERS on the Chinese tourist flows to Korea by using an autoregressive distributed lag model (ADLM), whereas Song (2016) estimated a seasonal ARIMA (SARIMA) model to analyse MERS effects on tourists visiting Jeju Island. All these studies showed

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the detrimental effects of MERS on international tourism. Other papers, such as Zeng et al. (2005) and Yang and Chen (2009) analysed the impact of SARS on international tourism. Kuo et al. (2008) and McAleer et al. (2010) explored both the effects of Avian Flu and SARS, on tourist arrivals in Asian countries. While SARS significantly decreased tourist demand, moderate impact emerged due to Avian Flu. Blake et al. (2003), Rodway-Dyer and Shaw, (2005) and Irvine and Anderson (2005) assessed the impact of the foot and mouth disease in the tourism and other UK sectors. Rosselló et al. (2017) studied several disease effects on infected countries' tourism demand (e.g. Malaria, Yellow Fever, Dengue, and Ebola). Page et al. (2012) adopted a time-variant parameter (TVP) approach to assess and disentangle the simultaneous effects of the global economic crisis and the swine flu pandemic on inbound tourism to UK.

Although based only on how a small number of countries have confronted previous pandemics, two lessons can be inferred from their recoveries. Firstly, tourist arrivals did start to recover even before the pandemic was completely eradicated, but recovery was slow. Secondly, once the outbreaks of both SARS and MERS were contained, recovery to normal levels took a matter of months, and soon grew to above pre-outbreak levels. However, the current situation is pretty different: COVID-19 has not only infected a bunch of countries but nearly 190 countries, causing a global unparalleled crisis, with detrimental impacts to both the health and economic systems. Gössling et al. (2020), in comparing COVID-19 crisis with different types of shocks which affected the tourism industry, predict very negative scenarios. Among other pandemics and epidemics, COVID-19, followed by SARS, remains the external shock that most severely impacted the tourism sector (Ying et al., 2020). Studying tourism data performance when pandemics occur is crucial to help policy makers in designing smart measures, reactions and restriction plans (Ying et al., 2020), particularly when events are unpredictable (Faulkner, 2001), as COVID-19 is. However, given that most previous pandemics only had minor or moderate impacts on travel and tourism growth (Gallego & Font, 2020), the tourism sector may have not been sufficiently prepared for pandemics of such dimension as COVID-19 (Gössling et al., 2020).

The current COVID-19 crisis is characterized by a high degree of uncertainty. The future behaviour of most variables of socio-economic interest, including tourism, depends on the evolution of the pandemic, which cannot be anticipated by any degree of confidence. While accurate forecasting exercises in normal times are crucial and are important planning tools for policy makers (Witt & Song, 2001), more research is needed when external unpredictable shocks occur. In fact, strategies planned before a crisis result in more effective crisis management plans (Ritchie, 2004; Page et al., 2006; Kuo et al., 2008). Under these circumstances, adopting conventional forecasting methods (based on past dynamics of variables and/or their determinants) is not appropriate, as the massive estimation error would make the forecasts useless. In other words, conventional forecasting techniques provide a central estimate under the assumption that there is an estimation interval based on the statistical behaviour of the variables in the past. After an unexpected shock, particularly as relevant as the current one, providing central values with an enormous interval error is not informative.

Given the above considerations, an appropriate alternative is to provide forecasts based on different scenarios. Scenarios should consider the uncertainty root, such as the evolution of the pandemic in the current crisis. Although international institutions such as UNWTO already issued tourism recovery scenarios for the months to come, such exercise is challenging in a global crisis context. The dramatic change in global tourism trends, on one hand, and the profound uncertainty related to the evolution of the outbreak, on the other hand, imply the need to define a tailored forecasting method. However, in the tourism demand forecasting literature, the *ex ante* forecast is limited with a few exceptions such as Song et al. (2011), Athanasopoulos et al. (2011), Liu et al. (2020). To our best knowledge, Polyzos et al. (2020) and Zhang et al. (2021) are the only studies using *ex ante* forecast to predict the demand recovery from COVID-19, but these are both based on a single destination. The forecast of recovery from a global perspective has been overlooked in the tourism demand forecasting literature.

With the above considerations in mind, we propose a novel scenario-based two-steps mixed method to forecast worldwide international tourism recovery up to 2021. We estimated tourist arrivals for 20 countries covering the four UNWTO regions and representing different tourism destinations' typologies. For each destination, tourism demand is proxied by the volume of international tourist arrivals. Our estimates considered both, total tourist arrivals, and arrivals from the main five source markets.

Our approach combines advanced tourism demand forecasts, a COVID-19 Risk Exposure (CORE) index and judgmental forecasting technics. We applied 14 alternative forecast specifications covering various time series and artificial intelligence (AI) models, and its hybrid and combined approaches. The second *ex ante* forecast faced the challenge of creating scenarios for 20 worldwide destinations around the globe. Given the vast amount of general information, we proposed a synthetic index, CORE, that provides an objective measure of the risk exposure of each destination. This index includes quantitative information on accessibility and the restrictive measures adopted by economies to inhibit the virus spread. A two steps cluster analysis is used to segment countries' policy reactions. Afterwards, CORE index is used to inform a judgmental approach process which leads to consider three scenarios of COVID-19 impacts.

This paper significantly contributes to the literature in several ways. First, we propose an innovative composite method for scenario building, based on the concurrent use of advanced demand modelling, a composite index, and judgmental approach. Second, most previous studies estimated pandemics' impact based on *ex post* demand modelling. This study is one of the few implementing *ex ante* tourist arrivals forecast and predicting the market recovery from a crisis. Third, this paper adds to the scant literature forecasting the inbound tourism effects of a pandemic affecting most origins and destinations in the world. We estimated country-specific scenarios for 20 countries representing all continents.

The rest of the paper is organised as follows. Section 2 describes the two steps modelling strategy. First, advanced time-series techniques are implemented to calibrate and test a baseline model through *ex post* recent tourist arrivals' forecasting. Then,

scenario writing based on judgmental approach is used to produce *ex ante* forecasts to the end of 2021. Section 3 presents and discusses the results of this modelling exercise. Finally, Section 4 provides conclusions.

Modelling strategies

The forecast of the recovery of international visitors to the 20 selected destinations is composed of two stages. In the first stage, quarterly data of five selected source markets and the total arrivals are used to generate the *ex post* forecast of 2019 visitor arrivals for each destination. The sampling period is from the earliest available period to the end of 2018. Rolling forecasts of one-, two-, three- and four-quarters-ahead are generated. The forecasting accuracy is measured by the mean absolute scaled error (MASE) proposed by Hyndman and Koehler (2006). The most accurate method will be selected to generate the baseline forecast for international visitor arrivals to 2021. This baseline is a forecast of what would have happened if the COVID-19 pandemic had not occurred. Then, in the second stage, CORE index and judgmental approach are combined to obtain adjustment coefficients. These coefficients are used to present three scenarios (mild, medium and severe) for 2021 forecast based on the 2019 visitor arrivals. Fourteen out of the 20 selected destinations measure the inbound tourism demand by visitor arrivals, whereas Finland, the Mauritius, South Africa and Tunisia by tourist arrivals and Czech Republic and Sweden by hotel nights.

Strategy of the first stage

Econometric, time series and AI models are the main forecasting approaches in the tourism and hospitality literature and forecasting practice (Song et al., 2019). Unreliable predictions of explanatory variables will affect the forecasting accuracy of econometric models. In fact, this is one forecasting challenges associated with COVID-19 crisis. It is unlikely to obtain credible forecasts of the conventional independent variables, such as source markets' income or real prices, to generate *ex ante* forecasts. Thus, econometric models are excluded from this study. Time series, AI, the hybrid of the two approaches and combined models are adapted to generate the first stage forecasts.

Time series models

The seasonal naïve (Snaïve) model, SARIMA model, exponential smoothing (ETS) model, and seasonal and trend decomposition using Loess (STL) model, which are four frequently used time series models, are selected to implement the *ex post* forecast in the first stage. The Snaïve assumes that a quarter's forecast equals the previous year same quarter value. It is usually used as the benchmark model in tourism demand forecasting literature (Song et al., 2019). The SARIMA model belongs to the autoregressive moving average (ARMA) family. Although it has been developed over the past five decades, it is popular in tourism demand forecasting literature, and its performance has a good track record (Song et al., 2019). Snaïve and SARIMA are respectively estimated by the snaive () and auto.arima () functions of the "forecast" package in R (a commonly used software package). Lag orders in SARIMA are automatically selected by the Box-Jenkins approach.

The original ETS method was proposed in the 1950s and has been continuously improved since then (Hyndman & Athanasopoulos, 2018). This model decomposes the time series into level, trend and seasonality, and then estimates each component by various smoothing (average) methods with exponentially decreasing weights. ETS is estimated by the es () function in the "smooth" package of R. The type of level, trend and seasonality are automatically optimised by Akaike Information Criteria (AIC) and estimated accordingly.

The STL model also decomposes the data into trend, seasonal and irregular components. In normal forecasting practice, the three decomposed time series are estimated by other time series methods and then the decomposed forecasts are aggregated. In the current study, the STL model is estimated by the stlm () function in the "forecast" R package. The seasonal trend is estimated by the Snaïve model and the other two components are combined first and then estimated by ETS method. Finally, the seasonal and the combined trend and irregular components are aggregated.

AI models

Three frequently adapted AI models, namely neutral network (NN), random forest (RF) and support vector machine (SVM) are used to generate the *ex post* forecasts. In this study, the NN model takes the lagged dependent variable and seasonal dummies as inputs, and establishes a non-linear relationship between inputs and the output by a hidden layer. The model is estimated by the nnetar () function in the package "forecast" of R. The lagged order is determined by AIC, and the number of nodes in the hidden layer is selected by a grid search, ranging from 1 to 20. The model with the least absolute forecasting error is used to present the NN forecasting result.

RF is an ensemble learning method which builds multitude decision trees using the training dataset, and uses the mean prediction of individual trees as the forecasting output. Seasonal dummies are also considered as inputs into the model. Two hyperparameters need to be determined for the estimation. The first one is the number of trees. Breiman (2001) proved that the generalization error converged as the number of trees increased. Thus, the number of trees in this study is set to 1000, which is large enough to limit the generalization error (ibid). The second hyperparameter is the number of randomly selected features. As a rule of thumb, it should be smaller than log (N + 1), where N is the sample size (ibid). Since the largest sample size of this research is 96, a grid search from 1 to 3 is used to explore the most accurate NN model for each origin-destination pair. The RF model is estimated by the function random Forecast in the "randomForecast" package of R.

SVM is another classical machine learning method which uses different algorithms to map and divide observations into groups in a space and then map new observations into the developed groups. In addition to the traditional linear classification, a polynomial method is adapted to map the inputs into a high-dimensional feature space (Goldberg & Elhadad, 2008). Seasonal dummies are defined as model inputs. According to Meyer et al. (2019), four hyperparameters need to be tuned in order to identify the most accurate model. Details of the four hyperparameters can be found in Meyer et al. (2019). The SVM model is estimated by the tune.svm () function in the "e1071" package of R.

Hybrid models and forecast combination

Three hybrid models are proposed in this research. In the hybrid models, the trend and seasonal components are estimated by the STL model using ETS and Snaïve methods, while the irregular component is estimated by NN, NF and SVM, using the same procedure discussed in the previous section to optimise hyperparameters. The three hybrid models are named as STL-NN, STL-NF and STL-SVM.

Compared with a single forecasting method, a combination forecast can provide more robust results (Li et al., 2019), because there is no forecasting model that can always beat other models (Song et al., 2019). In this paper, simple average forecast combination is used to generate four combined models including the combination of the four time series models (C_TS), the combination of the three AI models (C_AI), the combination of the three hybrid STL and AI models (C_Hybrid) and the combination of all the above 10 models (C_10). In total, 14 models are used to generate the *ex post* forecast in the first stage. The optimal model in Stage 1 is used to generate the baseline forecast without the consideration of COVID-19. It is assumed that no origin-destination pair can recover to a level beyond the baseline forecast. The 2020 arrivals are a mix of real data and the seasonal mean between 2020 lowest number and the 2021 forecast in the same quarter.

Strategy of the second stage: judgmental forecasting and COVID-19 risk exposure (CORE) index

Scenario-based judgmental forecasting

A scenario-based judgmental forecasting is used to predict the recovery of tourism demand in 2021. Scenario writing is particularly appropriate when there is low predictability regarding the future evolution of some relevant variables or events (Önkal et al., 2013; Wright & Goodwin, 2009). This is usually applied in crises management (Pearson & Clair, 1998) and intelligence analysis (Wicke et al., 2019). Scenario writing has also been incorporated in previous tourism research. Prideaux et al. (2003), used the case of Indonesia in the late 1990's and early 2000's to stress that traditional forecasting methods are not adequate in times of crises. They propose to "bring together the quantitative elements of forecasting plus less frequently used qualitative methods to produce a series of scenarios." Song et al. (2008) combine the use of both judgmental forecasting and scenario writing. They defend that scenarios are particularly useful to incorporate different relevant variables' values under uncertainty.

Judgmental forecasting aims at incorporating experts' knowledge into a predicting context. The objective is to enrich forecasting process incorporating experts' contextual information which was not included in the statistical modelling (Lawrence et al., 2006). Judgmental forecasting can be a "pure judgmental" exercise, as in Dovern and Weisser (2011), in which experts provide macroeconomic forecasts. Or it can be an adjustment process: first, statistical models are applied; afterwards, experts adjust initial forecast incorporating contextual knowledge (Lin et al., 2014). There is considerable literature indicating that this approach provides more accurate estimates (Fildes et al., 2006; Fildes et al., 2009; Goodwin, 2005). Dijk and Franses (2019) used statistical properties to technically prove why combined expert adjustment improves forecasts accuracy. They indicate that the experts' different interpretation of news might explain a negative covariance that leads to better combined adjusted forecasts. In this sense, we used experts from five different origins to incorporate different contextual interpretation of the COVID-19 effects.

Judgmental two-steps adjustment was already used in the tourism literature 40 year ago (Edgell et al., 1980). More recently Song et al. (2008) propose a web-based system with two steps: first, econometric models are used to forecasts Hong Kong's inbound tourism; then, a panel of experts adjusts the results through a Delphi type revision process. Croce and Wöber (2011) applies user intervention at the European tourism context in what is labelled as "system supporting collaborative forecasting". They allow for both "pure judgmental" and judgmental adjustment. Lin et al. (2014) applies a similar approach, but they improved the tourism demand forecasting system mainly by considering more advanced econometric models (ARDL-ECM), and by providing accuracy quantification. In their research, they concluded that the two-steps process on average improved accuracy and was unbiased, although the adjustments were biased for some individual source markets. Delphi type methods are often used to generate consensus in forecasters groups. Lin and Song (2015) reviewed its applications in tourism and indicated its usefulness in situations similar to the current COVID-19 effects: insufficient data, change in trends and new events that interfere with the forecast.

Development of CORE index

In this study, the CORE index is developed on the basis of a set of objective measures. A Delphi method was implemented to collect opinions among the authors of this study about adjustment coefficients for 2021 forecast based on the 2019 visitor arrivals to the destinations. The construction of the CORE procedure followed the following steps: First, researchers participate in several rounds of consultation to define the list of objective variables that could measure destinations' COVID-19 risk exposure at international level. The following paragraphs of this section describe the index construction. Second, researchers were informed about the CORE results, and they were asked to anonymously provide maximum and minimum percentage impacts for the countries with higher and lower values CORE, for each of the mild, medium and severe scenarios. Then the relationship between the

generated adjustment coefficient and the index was established. To ensure consistency, the adjustment coefficients of the other 18 destinations are predicted by their position in the CORE index relative to the highest and lowest values.

Considering specifically the construction of CORE, the index combines two quantitative elements that determined the evolution of tourism after COVID-19 at the different destinations: the accessibility risk (AR), and the country's self-protecting measures (SP). These two measures are country specific.

$$\text{CORE index} = f(AR, SP)$$

Accessibility risk sub-index (AR). The negative impact of COVID-19 on the tourism industry operates through different channels of policy regulations and demand and supply reactions. However, the pandemic's impact on mobility has been particularly relevant. Mobility is the essence of tourism as captured by its official definition: tourism "entails the movement of people to countries or places outside their usual environment" (UNWTO, 2008). The AR sub-index aims at capturing that the impact of COVID-19 on international mobility is moderated by distance. Therefore, AR sub-index, classify each inbound tourism market into three groups:

AR-a) Feasible land and water transport

AR-b) Short-haul flight

AR-c) Long-haul flight

There are different academic approaches for short-haul or long-haul classification considering both, distance and travel time (Bianchi et al., 2017; Fang & McKercher, 2008; Ho & McKercher, 2014; Wilkerson et al., 2010). The procedure followed in this paper was that for each pair of origin-destination, we considered the closest international airports with relevance for tourism. If the flight time between those airports was less than 3 h, the pair was considered in category b, while it was assigned to category c for longer flights. Also, countries that were connected by existing land or boat routes in less than 6 h were assigned to category a. Afterwards, judgmental approach was used to allocate values to each destination group, considering that a higher value indicates a higher exposure of its tourism sector to COVID-19 due to accessibility risks. The AR sub-indexes for each destination's specific origin markets were then combined through a weighted average into a single AR sub-index (See Table 1). The weights were assigned based on the most recent market share data.

The second column of Table 1 presents the normalized AR. Therefore, Australia, due to its dependence on long-haul markets, presents an accessibility risk that is 34% higher than the 20 destinations' average. Differently, Mexico presents only half accessibility risk compared with the 20 destinations' average, as 80% of its inbound tourism comes from the US. It is obvious that in the case of large origin-destination pairs, such as US-Mexico, most tourists will not come by land or boat transportation. However, the assumption adopted in the paper is that the vicinity effect is still persistent and relevant for the COVID-19 -travel effects. Visitors are assumed to value positively the fact that they are close to their country, and they could avoid getting "trapped" at the destination. Additionally, there is a degree of substitution of long-haul trips favouring short-distance destinations.

Self-protecting country's measures sub-index (SP). The impact of the COVID-19 outbreak on inbound tourism has been deeply affected by the magnitude of self-protecting country's measures. There has been a huge variability in the type of policies and their speed of implementation.

Table 1
Weights of the CORE index.

Destination	Normalized AR	Normalized SP	AR & SP
Australia	1.34	1.29	1.73
Bulgaria	1.17	0.32	0.38
Canada	0.64	1.29	0.82
Chile	1.10	0.97	1.07
Czech Republic	1.05	0.97	1.01
Finland	1.07	0.97	1.04
Indonesia	1.04	1.29	1.34
Japan	1.05	0.97	1.01
Malaysia	0.65	0.97	0.63
Mauritius	1.36	1.29	1.76
Mexico	0.51	0.97	0.50
New Zealand	1.20	1.29	1.54
Singapore	1.16	0.32	0.37
South Africa	0.90	1.29	1.16
South Korea	1.06	0.97	1.03
Sweden	0.84	0.97	0.81
Thailand	1.10	1.29	1.42
Tunisia	0.77	1.29	0.99
UK	1.14	0.32	0.37
USA	0.85	0.97	0.83

To control for countries' policy reactions, we used the Hale et al.'s (2020) coronavirus Government Response Tracker (OxCGRT) provided by the Blavatnik School of Government at the University of Oxford. In particular, we considered the number of days (between January 1st and August 31st) in which countries imposed international travel controls. There is a ranking of policy reactions regarding international mobility ranging from a) no measures; to different limitations such as: b) quarantine on arrival from high-risk regions; c) ban on high-risk regions; or d) total border closure.

Given that some countries may have substituted international travel controls through airports' closure, or by simply shrinking air traffic flows, we also considered the reduction of flight departures for our analysis. ICAO (2020) data have been used to count the number of days in which the countries have registered a number of flight departures 20% lower than the pre-COVID-19 average.

The four typologies of travel restrictions (three restrictive policies, and air traffic below 20%) have been used to classify the destinations in groups. Methodologically, a mixed two-steps cluster analysis has been adopted to segment countries into homogeneous groups. Although the most common cluster techniques are hierarchical or non-hierarchical methods, they are both weak in terms of cluster set selection and outlier (noise) detection (Tan et al., 2006). The mixed approach is recommended as it provides accurate solutions, while controlling for outliers (Hair et al., 2010). In the first step, a hierarchical algorithm (i.e. complete linkage) has been adopted to identify the best partition, while the squared Euclidean distance has been used to measure dissimilarities. Two types of stopping rules (the Calînski and Harabasz pseudo-F index and the Duda–Hart test) have been used to detect the optimal partition. In the second step, a non-hierarchical K-means method has been adopted by imposing the number of clusters identified in the first step.

The two-steps cluster analysis suggests to group countries in three clusters: the group of very restrictive countries that imposed a total closure of borders and completely or severe air traffic reduction (group 3), which includes 10 countries (Mauritius, South Africa, Canada, Tunisia, Thailand, Indonesia, New Zealand, Australia); another group of 9 countries (Mexico, Sweden, Chile, Finland, USA, Republic of South Korea, Japan, Malaysia, Czech Republic) that adopted slightly less restricting travel limitations by banning journeys from high-risk regions, while reducing flights from other areas (group 1); a final group of 3 countries (UK, Bulgaria, Singapore) which imposed softer travel restriction policies and weaker flight controls (group 2). The matrix

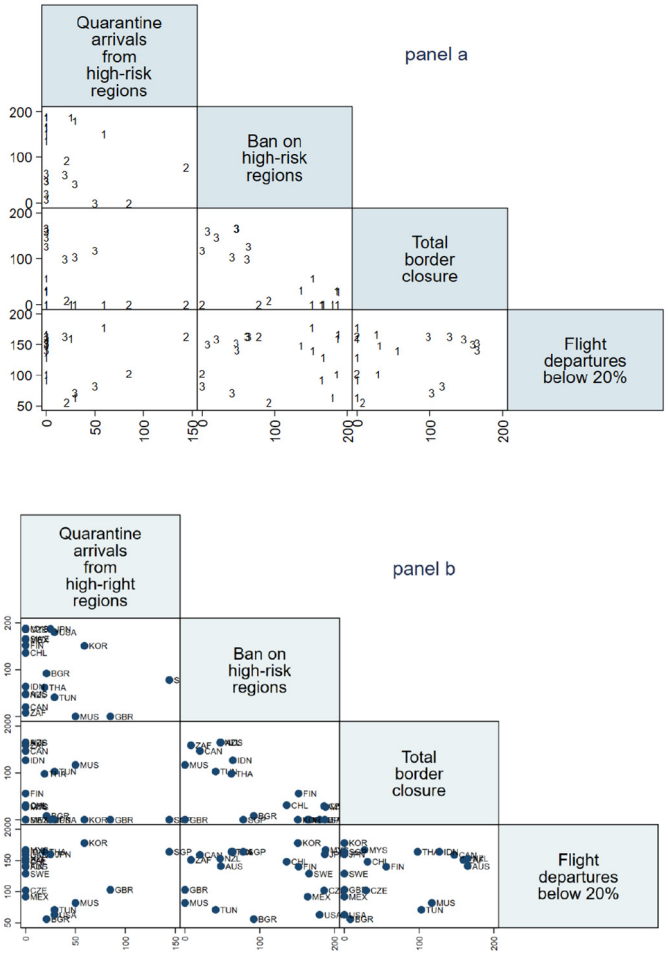

Fig. 1. Pairwise plot of the travel restriction measures with identification of clusters (panel a) or country codes (panel b).

scatter plot (Fig. 1, panel a) shows the pairwise links between the four measures used to cluster countries in homogeneous groups and visually highlights the specific behaviour of the different clusters with respect to these four variables. For example, the first plot (from the top) shows for each country the number of days it imposed a quarantine to arrivals from high-risk regions (horizontal axis) and the number of days it banned tourists from high-risk regions (vertical axis) in the time span analysed. Countries belonging to group 1 mainly banned tourists from high-risk regions, while nearly never imposed quarantine to arrivals (with some exceptions). The opposite occurred to the countries belonging to group 2. Fig. 1, panel b, presents complementary information. In this sense, instead of displaying the group, the graph presents the countries' acronyms. In other words, panel b identifies each destination and positions it with respect to the four measures. So, for example, panel b shows where South Korea is located and, comparing it to panel a, it is clear it belongs to group 1.

In a parallel way as for AR, a global SP has been obtained providing different values for the three groups described above. A similar normalization has been applied to compute the third column of Table 1. The values capture the percentage change compared with the average behaviour of the 20 destinations.

The two normalized indexes were multiplied, generating the Table 1's fourth column. Note that this column indicates the country-specific accessibility and response related with COVID-19. Higher values indicate higher exposure to COVID-19. Mauritius, with a value of 1.75 ranks as the destination for which tourism is more at risk of being substantially affected by COVID-19, closely followed by Australia. On the other side of the distribution, the UK, with a value of 0.36, is the country with the smallest combined index.

Results and discussion

First stage results

Table 2 presents the MASE values of the 14 forecasting methods across the first stage four rolling periods. The last column indicates the overall performance, which is computed as the simple average mean across the four-steps ahead forecasts. Overall, C_TS, which combines the four time series models can outperform all the other 13 models including the four single times series models, three single AI models, the hybrid models and the other three combined models. Thus, this method is the best among the 14 proposed methods. In terms of the 10 single methods, time series models outperformed all AI and hybrid models. In the overall performance, the combination of all the 10 models can outperform all single models except SARIMA and ETS. As argued by Song et al. (2019) and Wu et al. (2017), although SARIMA and ETS are traditional methods that have been used for decades, their performance is well acknowledged in the literature. The full results of Stage 1 including the MASE values of 120 origin-destination pairs across the four rolling periods generated by different methods are available upon request.

Second stage results

The full results of Stage 2 are summarized in Table 3. For each country and scenario, the table indicates: the percentage deepest impact; the quarter in which this deepest impact occurs (bottom quarter of 2020 in column 1); and the recovery rate during 2021. Note that, at the time of estimation (October 2020), tourist arrivals data for the second quarter of 2020 were already available for some countries. In those cases, if the bottom period occurs during this second quarter, the reported deepest impact does not vary among scenarios. In line with previous recoveries from epidemics such as SARS and MERS it is to be expected that when infection rates are low enough and travel bans are lifted, a significant but not complete, recovery in tourism numbers will occur rather than a gradual recovery pattern. The exact time that this will happen cannot be predicted accurately, and is show in the results as a sharp recovery in the first quarter of 2021, which the judgmental forecast deemed the most likely.

For sake of space, we will only discuss in detail the total arrivals' forecasts to five destinations. The choice of the five selected destinations relies on their location in different continents, the different AR and SP values, the COVID-19 overall impact, and the

Table 2
MASE of 15 forecasting methods across four rolling periods.

	One-quarter-ahead	Two-quarters-ahead	Three-quarters-ahead	Four-quarters-ahead	Overall performance
SARIMA	1.17	1.12	1.32	1.39	1.25
STL	1.57	1.68	1.77	1.72	1.69
Snaïve	1.39	1.20	1.28	1.31	1.30
ETS	1.09	1.15	1.31	1.42	1.24
RN	5.54	5.71	6.02	6.41	5.91
NN	1.27	1.42	1.50	1.82	1.46
SVM	2.12	2.04	2.20	2.58	2.24
STL-RN	1.80	1.86	1.95	1.93	1.88
STL-NN	1.59	1.56	1.59	1.90	1.62
STL-SVM	1.48	1.63	1.91	1.85	1.72
C_TS	1.10	1.10	1.26	1.27	1.18
C_AI	1.51	1.58	1.72	2.06	1.70
C_Hybrid	1.57	1.61	1.75	1.84	1.67
C_10	1.19	1.19	1.32	1.37	1.27

Table 3
Summary of the forecasting results in stage 2.

Destination (bottom quarter, 2020)	Indicator	Scenario mild	Scenario medium	Scenario severe
Australia (Q2)	Deepest impact	−99.45%	−99.45%	−99.45%
	2021 recovery rate	70.98%	41.58%	12.26%
Bulgaria (Q2)	Deepest impact	−79.99%	−97.34%	−98.41%
	2021 recovery rate	70.98%	41.58%	12.26%
Canada (Q2)	Deepest impact	−82.58%	−97.55%	−98.53%
	2021 recovery rate	77.44%	49.43%	22.84%
Chile (Q1)	Deepest impact	−90.67%	−99.14%	−99.47%
	2021 recovery rate	88.76%	63.51%	27.12%
Czech Republic (Q2)	Deepest impact	−82.94%	−97.52%	−98.50%
	2021 recovery rate	92.95%	62.98%	27.42%
Finland (Q3)	Deepest impact	−76.47%	−95.16%	−97.58%
	2021 recovery rate	82.01%	59.11%	25.54%
Indonesia (Q1)	Deepest impact	−91.51%	−98.51%	−99.50%
	2021 recovery rate	79.37%	50.83%	19.38%
Japan (Q2)	Deepest impact	−99.92%	−99.92%	−99.92%
	2021 recovery rate	66.92%	44.53%	20.29%
Malaysia (Q2)	Deepest impact	−80.42%	−97.55%	−98.53%
	2021 recovery rate	76.21%	49.77%	24.20%
Mauritius (Q2)	Deepest impact	−96.91%	−98.08%	−98.88%
	2021 recovery rate	59.64%	36.32%	10.43%
Mexico (Q1)	Deepest impact	−95.98%	−99.37%	−99.79%
	2021 recovery rate	77.06%	50.23%	25.17%
New Zealand (Q2)	Deepest impact	−99.00%	−99.00%	−99.00%
	2021 recovery rate	62.16%	37.23%	12.62%
Singapore (Q2)	Deepest impact	−99.92%	−99.92%	−99.92%
	2021 recovery rate	93.30%	77.06%	40.17%
South Africa (Q2)	Deepest impact	−90.33%	−98.52%	−99.11%
	2021 recovery rate	71.28%	48.05%	19.81%
South Korea (Q2)	Deepest impact	−97.86%	−97.86%	−97.86%
	2021 recovery rate	79.39%	49.89%	21.60%
Sweden (Q2)	Deepest impact	−82.44%	−97.36%	−98.41%
	2021 recovery rate	69.14%	47.93%	22.53%
Thailand (Q2)	Deepest impact	−84.99%	−97.90%	−98.76%
	2021 recovery rate	73.38%	46.21%	21.33%
Tunisia (Q2)	Deepest impact	−90.00%	−97.39%	−98.52%
	2021 recovery rate	87.34%	55.06%	24.15%
UK (Q2)	Deepest impact	−80.42%	−97.55%	−98.53%
	2021 recovery rate	82.41%	61.36%	31.56%
USA (Q2)	Deepest impact	−84.99%	−97.90%	−98.76%
	2021 recovery rate	73.38%	46.21%	21.33%

quality of the first stage forecasts. In line with these criteria, we selected Australia, Mexico, South Korea, Tunisia and the UK (Fig. 2).

Even though in Australia tourism contributes to 9% of GDP, and 83% of tourism spending derives from domestic tourism (WTTC, 2020), this destination is among those countries that suffered most from tourist arrival losses (−99.45% in the second quarter 2020). This is because around 85% of inbound tourism comes from distant countries (long-haul flight). Australia is among those destinations that adopted tighter measures to limit the virus' spread. It totally closed borders and several airports, and drastically reduced air connections (Fig. 1, panel b). These measures severely affected inbound tourism, as also indicated by the COVID-19 Tourism Index (Yang et al., 2020), falling from 96.8 at the end of January to 23.04 at the beginning of April. Since then, it recovered in part to 35.68 at the end of August (with a positive recovery during June reaching an index value around 45). We forecast that, in the best scenario, Australia will recover 70.98% of tourist arrivals in 2021. However, in the harshest scenario, when new possible waves of virus spread may occur, we forecast a recovery rate of 12.26%.

Mexico heavily relies on international tourist arrivals since, before the COVID-19 outbreak, only 6% of total tourism spending was due to domestic tourism, while tourism receipts represented 15.8% of GDP (WTTC, 2020). Starting from 94.71, its COVID-19 Tourism index (Yang et al., 2020) plunged to 14.07 in March 2020, and reached 34.83 by August. Mexico belongs to the group of countries who tried to preserve both their safety and their tourism competitiveness. It implemented protective but flexible measures such as high-risk countries' ban and flights' limitations. We forecast the deepest tourist arrivals fall in the second quarter 2020, ranging from −93.18 in the mildest scenario to −99.45% in the worst scenario. Nonetheless, Mexico could benefit from its moderate self-protecting policy on the one hand, and its proximity to United States, its main origin market. Before the outbreak, the USA accounted for 80% of tourist flows and, provided that the border reopened soon, the recovery of Mexico could be strong enough. In the best scenario, we expect a 77.06% recovery for 2021 compared to 2019, while it will only achieve 25.17% recovery in the worst scenario.

In South Korea, the tourism industry contributes by 26.3% to GDP (WTTC, 2020), mainly due to international tourism (only 22% of tourism spending is attributable to domestic market). South Korea is among those destinations that reacted immediately

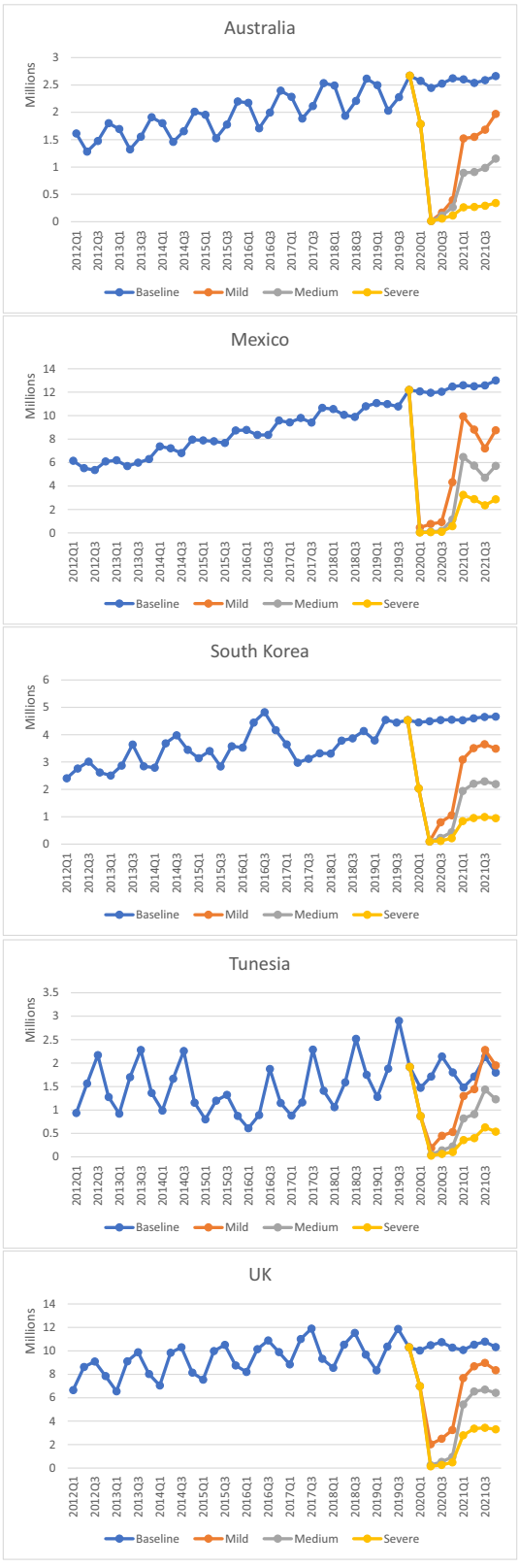

Fig. 2. Scenario forecasts of selected destinations.

to limit COVID-19 outbreak, given its previous experience in limiting pandemic spreads and losses (MERS, H1N1, etc.). It banned journeys from high-risk countries and imposed quarantines from other regions; moreover, it registered a high reduction in air traffic. 63% of its inbound tourism flows originate in relatively close destinations, and this can have helped in limiting losses. In the second quarter 2020, it lost around 98% of its usual inbound tourist flows. The COVID-19 tourism index (Yang et al., 2020) fell from 95.52 before the virus outbreak to 20.34 in April. This index slightly improved, but now it fluctuates around a value of 30. We forecast that, in the most optimistic scenario, South Korea will recover 79.39% of previous tourist arrivals in 2021. However, in the most pessimistic scenario, the recovery rate is forecasted to be 21.60%.

Before COVID-19 outbreak, tourism accounted for 8% of GDP in Tunisia, and tourism spending was mostly domestic, 76% of the total according to WTTC (2020). The COVID-19 Tourism index considers that the country has fallen from a score of 95.03 in the early 2020 to a minimum of 7.75 in April, before rising back to 55.32 in August (Yang et al., 2020). Tunisia has implemented strict self-protecting measures; its SP index score is among the highest and this has a clear impact on frequentation. According to our forecasts, the visitors' drop for 2020Q2 ranges between −90% and −98.5%. Nonetheless, we believe that Tunisia benefits from the fact that its main source markets are neighbours or short-haul destinations, and this could favour the recovery for 2021. We forecast a strong recovery of 87.34% in the best scenario and 55.06% in the medium scenario.

In the pre-COVID-19 context, the United Kingdom tourism industry generated 8.4% of GDP (according to the WTTC, 2020), with international tourism accounting for 68% of total tourism spending. This country is among those destinations that initially adopted softer travel restrictions (it mainly imposed quarantine on arrivals from high-risk regions), while in part limited flight departures (Fig. 1, panel b). However, the remote origin of a large part of its international tourism demand (68%) exacerbates its COVID-19 risk exposure. The United Kingdom registered its largest tourism decline in the second quarter 2020, when the loss of tourist arrivals ranges between −80.42%, in the mildest scenario and −98.53% in the severest scenario. Its COVID-19 Tourism Index (Yang et al., 2020) fell from 96.18 in pre-COVID-19 periods to 11.34 in April, then started its recovery until the end of August (47.55) when it was stopped by COVID-19 second wave, which led to a stable downturn of the index. Given the laxer reaction of this country to limit travel traffic, our model forecasts that, in the mildest scenario, the UK will register a recovery rate of 82.41% in 2021, whereas in the severest scenario, the unbounded spread of the virus will reduce the recovery rate to 31.56%.

Conclusions

This paper demonstrates a novel forecasting technique to apply existing methodologies to an unprecedented uncertain situation. The combination of advanced forecasting techniques with a scenario-based judgmental approach has been necessary given the uniqueness of the forecasting horizon. Never before has tourism been in a situation of effectively being locked down around the globe, and never before has it needed to recover from such a situation, so traditional forecasting methods alone are not capable of providing reliable forecasts. We are also confronted with uncertainties about the epidemiology of the virus and the timing, or even the possibility, of a vaccine or of lockdown measures leading to a situation where travel is unable to recover.

While data projections are essential tools for policy makers and their strategic planning in normal conditions (Witt & Song, 2001), more research is needed when unpredictable shocks, like COVID-19, occur. Accurate *ex-ante* forecasting may help policy makers in developing effective crisis management plans (Kuo et al., 2008; Page et al., 2006; Ritchie, 2004).

We propose a CORE index, which has been used to apply a novel forecasting procedure to estimate tourist arrivals as destinations recover from the COVID-19 pandemic. In terms of replicability, our proposed approach could be applied to future tourism crises by adapting the synthetic index to the relevant objective measures of the corresponding case.

The originality of the research is the introduction of a two-step scenario-based judgmental forecasting in an *ex ante* forecasting practice. At the first stage, we estimated 14 alternative specifications (including advance time series, AI models, its hybrid and combined versions) modelling tourist arrivals to 20 international destinations. For each of them, we considered total arrivals and the series for their main 5 origin markets. The *ex post* forecasts are evaluated to determine that the combination of the four time series models was the optimal methodology. This has been used to generate an *ex ante* baseline forecast of which would have been the expected tourist arrivals under the assumption of no COVID-19. At the second stage, judgmental forecasting uses CORE index to estimate three alternative *ex ante* scenarios. CORE index synthetizes two determinates of destinations' risk exposure: First, the AR sub-index, examined the accessibility risk, as different modes of transport and different lengths of journeys are likely to recover differently. Second, a self-protecting measures' sub-index (SP), examined how countries implemented measures to protect their citizens from the spread of the virus in early 2020. Countries were segmented through cluster analysis, producing an index that demonstrates government restrictions' risks on their tourism industries. The CORE index has been used to inform judgmental forecasting to produce country specific adjustment coefficients from the baseline forecast. Finally, we used those coefficients to estimate tourist arrivals for three alternative scenarios.

The results demonstrate that in the best-case scenario (mild), where COVID-19 cases will have dramatically dropped, some countries (particularly those that do not rely on long-haul markets) will recover to somewhere near the baseline. This is consistent with past experiences following SARS and MERS. In our central (medium) and worst-case (severe) scenarios, however, the spread of the virus has not been eliminated or contained and may be accelerating in the severe case. Under these assumptions, the forecasted tourist arrivals are far from the baseline, and would still be considered to be in crisis throughout our forecasting period to the end of 2021, and even beyond. The results obtained using our methodology suggest that the speed and intensity of the recovery is going to depend on how much a destination depends on long-haul markets. The less dependent on long-haul, the faster a destination recovers. Beyond the countries considered in the paper, this method could be applied to any

destination upon data availability. The method can also be generalized to forecast the recovery in the future crises given that high uncertainty is a common feature of all crises.

Our analysis is not free of limitations. In the first stage of analysis, we could not estimate econometric forecasting models and compare their performance with the other models because accurate forecasts for the inputs, such as GDP of source markets or consumer price indices, were not available. For future research, if reliable predictions are made available, econometric models can also be tested when defining the best performing approach. Furthermore, the definition of proper scenarios is a challenging task in a context in which the recovery process of the tourism industry crucially depends on a series of external events, such as the development of an effective vaccine or the capacity of governments to implement and coordinate worldwide efficient risk management strategies. Future research could also test whether the accuracy of ex-ante forecasting changes when different measures of tourism demand are considered besides international tourist arrivals (e.g. overnight stays, tourism receipts). As for other pandemics, COVID-19 is going to generate a number of *ex post* impact studies. The use of the CORE is a key contribution of this paper. Future research, confronting forecasts to actual data, is needed in order to assess the validity and the accuracy of this approach. Such validation studies would make it possible to improve the index and apply it to forecast the impact of the next tourism crises.

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.

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