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Research article

Adaptive nowcasting of arrivals during health crises

Juan L. Eugenio-Martin [a,*], José M. Cazorla-Artiles [a], Adela Moreda [b], Juan M. Murguia [b]

[a] Universidad de Las Palmas de Gran Canaria, Departamento de Análisis Económico Aplicado, C/ Saulo Torón, s/n, Las Palmas de Gran Canaria, CP. 35017, Spain
[b] Inter-American Development Bank, 1300 New York Avenue, N.W., Washington, D.C. 20577, USA

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A B S T R A C T

This paper develops a new methodology to nowcast the number of arrivals during health-related crises such as Covid-19. The methodology is adaptive, so that the relevance of different determinants varies over time by employing hurdles that work as 'necessary travelling conditions'. It starts with a baseline series built upon a pre-Covid-19 trend. This series is adjusted by each hurdle. The first hurdle is the market closure; epidemiological models are applied to anticipate the dates of re-opening. The second hurdle deals with key travelling determinants such as the income effect. The third hurdle is the lack of confidence; this depends on the length of the recovery, and the expected path to follow.

Introduction

In recent decades the tourism industry has been shaken due to different kinds of crises. Tourism crises vary in nature, length, and severity. They can be related to economic recessions, energy, political issues, natural disasters, or health issues (Hall, 2010). Among these, the severity and length of health-related crises are the most difficult to anticipate. These occur when unknown new diseases arise, because they may trigger fear, depending on the risk of infection, morbidity, and mortality. Such fear is also extended to organisations and policymakers who need to respond to the new situation. Firms need to adjust supply and prices, whereas policymakers need to assess the need for market intervention. Their response requires understanding of the expected evolution of tourism demand. However, such evolution is subject to structural breaks and huge uncertainty, which impede the application of traditional forecasting methods.

In health-related crises, a key determinant of the evolution of tourism demand is the dynamics of the epidemic. However, traditional econometric models cannot incorporate information of this kind. For instance, autoregressive distributed lag models can identify the dynamics of the demand under changes in variables, such as income or price (Song, Wong, & Chon, 2003). This is based on the past, and as long as the future behaves within the expected framework, it should work well. However, the dynamics of any epidemic, or confidence in travelling, are new variables that did not exist, and cannot be incorporated into econometric models. Time varying models can also deal with stochastic parameters that adjust themselves over time (Li, Wong, Song, & Witt, 2006), but they are not capable of dealing with a severe exogenous structural break (Liu, Lin, Li, & Song, 2022). Univariate

* Corresponding author.
E-mail addresses: juanluis.eugenio@ulpgc.es (J.L. Eugenio-Martin), josemanuel.cazorla@ulpgc.es (J.M. Cazorla-Artiles), adelam@iadb.org (A. Moreda), juanmu@iadb.org (J.M. Murguia).

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time series models are not exempt of problems, as they are based on trends or lag structures that are expected to follow a stable growth pattern. The structural break may be overcome by structural time series models ex-post (Eugenio-Martin, Sinclair, & Yeoman, 2005), but they cannot anticipate them ex-ante, since they are based on the recent values of level and slope.

Hence, new ex-ante approaches are required when forecasting tourism demand under a health-related crisis (Liu et al., 2022). This paper is concerned with the recent Covid-19 pandemic which disrupted the tourism industry dramatically, especially after March 2020. The post-Covid-19 tourism demand series has been characterised by a massive drop in arrivals followed by recovery periods and setbacks depending on the behaviour of the pandemic dynamic. Such behaviour has been conditioned by the introduction of several structural breaks due to new virus mutations, effective vaccines, several epidemic waves, as well as varying government severity regulations. Thus, forecasts may change dramatically depending on such issues. Hence, it seems appropriate that epidemic dynamics should be embedded within the tourism demand forecasting method, and that the forecasts should often be updated.

Tourism policymakers need to identify and prioritise target markets under such uncertainty. Some measures may be related with airlines' support agreements, or marketing campaigns at certain destinations; however, the success of such initiatives depends upon a solid understanding of the expected demand. For these reasons, a new nowcasting method is developed in this paper. Nowcasting is a term employed when we are interested in anticipating the value that certain variable may take at the present. It is particularly important when timely information is required, especially when there is a marked lag between the moment when any statistics are officially released and when the outbreak occurred.

A new nowcasting method has been developed to anticipate the expected series of arrivals by distinguishing the main source markets and to update the information daily and automatically. Moreover, the nowcasting model had to be adaptive, so that it may switch automatically from a certain stage where the epidemic dynamics is crucial, to another stage where recovery in confidence is the most relevant factor. This is achieved by applying a hurdles method. The hurdles work as a necessary condition to reach the pre-Covid-19 expected series.

The first hurdle deals with the market closure. This happens either when the destination considers tourists from a certain origin to be a danger or when the origin country perceives travelling to the destination to be a risk. Such decisions are usually taken by governments, depending on indicators of the epidemic's expected evolution. They are estimated by employing the Susceptible-Infected-Recovered epidemic model. The second hurdle 'tunes' the intensity of the arrivals flow by considering any shock on any key determinant. It employs a generalised least squares panel data model to estimate the elasticities of such underpinnings by distinguishing the origin-destination pair. Finally, provided tourists can travel between the origin-destination pair, and have sufficient income to do so, they also need to feel confident to travel. Thus, the third hurdle deals with the dynamics of the confidence, which depends on the expected date of the epidemic recovery, as well as the level and slope of the confidence recovery path. It is estimated with random effects panel data Tobit regressions.

This paper illustrates the adaptive nowcasting methodology developed for 17 Latin American and Caribbean countries. All the data and methodology were integrated into a publicly available on-line platform developed in R and uploaded via Shinyapps servers. Thus, users can enter the platform to see the expected tourism demand by different origin markets in the following months. For simplicity, the case of Barbados is fully illustrated in the paper.

Literature review

Health-related tourism crises

This century the tourism sector has been affected by several health-related crises. The first was the outbreak of Foot-and-mouth disease, which emerged in the UK in the spring and summer of 2001. This was an infectious and sometimes fatal viral disease that affected cloven-hoofed animals. It caused severe falls in bookings in many rural areas across the UK (Blake, Sinclair, & Sugiyarto, 2003). In 2003, the severe acute respiratory syndrome outbreak triggered a series of specific warnings against travel to Hong Kong, China, Toronto, and Taiwan. According to McKercher and Chon (2004), the market over-reacted because the intervention led to a drop of about 70 % of arrivals when according to World Health Organization, about 8096 people worldwide were infected and about 774 died. Wang (2009) compared the effects of four kinds of crises in Taiwan, i.e. economic crisis (Asian financial crisis in 1997), natural disaster (21st September 1999 earthquake), terrorism attack (11th September 2001) and severe acute respiratory syndrome. Wang concluded that inbound tourism demand suffered the greatest decline due to the latter, which proved how sensitive tourists are in relation to health and safety, as compared to any other kinds of crises.

In October 2005, the media echoed the spread of Avian Influenza, which interest was related to the impact on poultry as a food source and the potential of the virus to mutate and trigger a pandemic (Page, Yeoman, Munro, Connell, & Walker, 2006). According to World Health Organization, the number of cases was about 256, resulting in 152 deaths, especially affecting Vietnam and Indonesia. Kuo, Chen, Tseng, Ju, and Huang (2008) studied the impact of severe acute respiratory syndrome and avian flu on international tourism demand. They found the former to be highly significant. In March 2009, the H1N1 influenza virus, or swine flu outbreak occurred in Mexico. It was spread over the Americas and Europe. Page, Song, and Wu (2012) estimated a loss of about 1.6 million visitors in 2009Q2 in the UK, who were discouraged from travelling due to warnings against travel to infected areas.

The Ebola outbreak occurred in December 2013 in Guinea. The most affected countries were Guinea, Liberia and Sierra Leone. The epidemic escalated until January 2015, and arrived at countries beyond Africa. In June 2015, it reached the lowest number of confirmed cases since May 2014 (Novelli, Burgess, Jones, & Ritchie, 2018). Deaths from Ebola were low: Nigeria (8), Mali (6), Spain (2), Germany (1), and USA (1). Despite such low figures, half of the respondents in a US survey stated that they had concerns regarding Ebola during air travel (Cahyanto, Wiblishauer, Pennington-Gray, & Schroeder, 2016. Moreover, Novelli et al. (2018) show that despite countries such as The Gambia being unaffected by Ebola, the perception and images portrayed in the world media generated a negative impact to the whole African continent. They suggest that prompt and accurate information regarding the spread of the epidemic is necessary to improve the confidence of potential visitors.

The Zika virus outbreak was reported in 2015 in Brazil. The Brazilian Ministry of Health reported neurological abnormalities among babies born to pregnant Zika virus infected women (Gallivan, Oppenheim, & Madhav, 2019). A tenfold increase in the number of babies born with microcephaly (abnormal smallness of a newborn baby's head) was reported. Gallivan et al. (2019) explore tweets related with #babymoon that is associated with travelling pregnant women and their partners. They found out a marked decline in travelling to Zika-affected locations.

Ex-ante tourism demand forecasting

Until the spread of the Covid-19 virus, all tourism demand studies concerning the impact of health-related crises were ex-post. The relevance of the Covid-19 crisis awakened the interest of academics in the ex-ante analysis of tourism demand (Liu et al., 2022). One of the first key papers on forecasting tourism demand amid Covid-19 was that written by Zhang, Song, Wen, and Liu (2021), who suggest combining econometric and judgmental methods. They estimate a baseline series applying the autoregressive distributed lag-error correction model. Zhang et al. (2021) employ quarterly series of arrivals and regress it with GDP, consumer price index and exchange rate to forecast the series between 2020Q1 and 2024Q4. They adapt such series applying Delphi-scenario techniques, which considers the opinion of 17 experts in two rounds in June 2020 and July 2020.

In a similar fashion, Liu, Vici, Ramos, Giannoni, and Blake (2021) also apply a two-stage estimation process. However, for the first stage, they dislike applying econometric models, such as that proposed by Zhang et al. (2021). They state that “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” (Liu, Liu, et al., 2021, p. 3). Instead, they propose averaging a combination of time series and artificial intelligence models. For the second stage, they propose a judgemental adjustment based on researchers' point of view. They construct a Covid-19 risk exposure index, which is based on a combination of an accessibility risk and self-protecting country's measures sub-indices. Additionally, Qiu et al. (2021) and Kourentes et al. (2021) apply a similar two-stage approach, taking part in a forecasting competition (Song, Li, & Cai, 2022).

The problem of applying judgmental methods for forecasting tourism demand amid Covid-19 was that they soon became obsolete. This is a concern identified by most of these papers. Kourentes et al. (2021) advise on potential changes due to mutations of the virus. Liu, Vici, et al. (2021) also state that the success of the various scenarios depends on external events, such as the development of an effective vaccine or the capacity of governments to deal efficiently with the pandemic dynamics. Finally, Qiu, Liu, Stienmetz, and Yu (2021) also recognise that “in a matter of weeks, the mild scenario has now become much less probable, after a second wave of infections which have suddenly been more difficult to manage, at the time of writing” (p.14).

Liu et al. (2022) explore multiple ex-ante models. They conclude that the role of the pair of origin-destination, GDP, lagged variables and the method itself matters on the accuracy of the forecasts. Gunter, Smeral, and Zekan (2023) consider GDP as a key variable for ex-ante forecasting of tourism imports after the Covid-19 crisis. They employ panel data methods combined with different scenarios.

Instead of employing arrivals series, Choi and Varian (2012) suggested employing Google Trends data to predict the total monthly visitors to Hong Kong. According to Artola, Pinto, and de Pedraza (2015) this approach faces two caveats: i) the tourists who employ Google to search for information concerning their trip represents a fraction of all tourists, ii) Google provides an index which is relative to the peak of the series, so that “a decline in the index value for a particular keyword does not necessarily mean that the absolute volume of searches on that particular keyword has declined”. They showed that there is valuable information in online searches, especially in the short term, but they realised that the results worsen in the following years. The relationship between internet searches and actual purchases seems to be blurred for longer terms. This makes sense, since the search is undated and the actual travel date is unknown.

Instead of employing Google Trends, Gallego and Font (2021) suggest the use of flight searches in specialised flight booking sites. This overcomes one of the aforementioned caveats since it applies year-on-year variation rates. However, since the booking searches are undated, they may not be sufficiently correlated with demand over time during a health-related crisis. For instance, searches may be concentrated in periods of higher confidence for a wider than usual time frame. This may displace the role of last-minute bookings or increase the time scale for future bookings. Hence, the longer term blurred effect seems to persist with this method, especially under a health-related crisis. Yang, Fan, Jiang, and Liu (2022) studied short-term (up to 7 days ahead) forecasting accuracy comparing models with and without Google Trends indicators amid Covid-19. They showed that forecasting models with Google trends data improved the accuracy only in 43.1 % of the cases, whereas the remaining 56.9 % obtained worse accurate forecasts with such information. They concluded that “insufficient evidence is available to support the usefulness of these data across countries” (Yang et al., 2022, p.12).

Polyzos, Samitas, and Spyridou (2021) employed data from the 2003 severe acute respiratory syndrome outbreak to train a deep learning artificial neural network, and then calibrated the network to the characteristics of the Covid-19 pandemic. They concluded that it would take about 18 months for arrivals to catch up with the pre-crisis level. Fotiadis, Polyzos, and Huan (2021) extended the study to consider other training sets, such as the 2007 financial crisis and 2012 Middle East respiratory syndrome epidemic. They showed that each training set provided predictions that vary greatly, and that is often overlooked by the literature. This is understandable, because two different kinds of tourism crises do not need to share a common recovery pattern.

Castle, Fawcett, and Hendry (2009) suggest employing nowcasting models under the presence of structural breaks, especially when the break affects both the level and slope of the series. This is the case of the series of arrivals amid Covid-19. The nowcasting tourism demand approach has received increasing attention in the tourism literature recently (Hirashima, Jones, Bonham, & Fuleky, 2017; Lourenço, Gouveia, & Rua, 2021; Wen, Liu, Song, & Liu, 2021; Liu, Liu, Li, & Wen, 2021). Hirashima et al. (2017) used mixed data sampling to employ high frequency variables to nowcast low frequency variables such as tourist arrivals. Liu, Liu, et al. (2021) proved that web search engines could enhance nowcasting model accuracy. They employed a model to reduce the dimensionality offered by the search engine and synchronised the different data frequency provided by daily searches and traditional monthly data. They proved that for the case of Chinese tourists travelling to Hong Kong between 2011 and 2019, the search engine dataset improved the accuracy of the nowcasts. However, the Covid-19 period was not covered by the study. It remains unknown whether this method is equally useful during health-related crises, or if weaknesses might come to light when tested with other origin-destination pairs, as suggested by Yang et al. (2022).

Impact of Covid-19 on tourists' behaviour

Among the extensive literature on the Covid-19 crisis, some additional findings are worth mentioning for the context of this paper. Li, Gong, Gao, and Yuan (2021) found that tourists' behaviour was changed during the pandemic since tourists preferred travelling to closer destinations as well as to places with a low level of Covid-19 cases. It was related with the fear to travel (Zheng, Luo, & Ritchie, 2021), which contributed to the resilience of domestic tourism, as shown for the Spanish case by Boto-García and Mayor (2022). It reshaped the concept of "distance", since tourists were less sensitive to economic distances and price differences during the pandemic (Lin, Qin, Li, & Jiang, 2022).

Moreover, further research showed that tourists preferred non-crowded destinations for travelling (Park, Kim, Kim, Lee, & Giroux, 2021) and that women and elderly people were more affected than men during the first wave of the pandemic (Yu, Zhao, Tang, & Pang, 2023). All these behavioural changes are tried to be understood by Karl, Kock, Ritchie, and Gauss (2021) by employing affective forecasting. It considers an experimental research design to simulate different behavioural changes, so that it can provide valuable information during health-related crises. All the distress caused by the pandemic was studied by Qiu, Park, Li, and Song (2020) who quantified the hypothetical willingness to pay of the residents to get over the situation.

Methodology

Adaptive nowcasting model with hurdles

The rationale of the methodology is that during a crisis, the number of arrivals will not reach the ex-ante expected series. Thus, it is a matter of obtaining the right percentage adjustment with respect to that baseline series. The number of arrivals (A) from origin o to destination d at each period t is the result of adjusting the baseline series (B) with different parameter factors k. So that:

$$A_{odt} = B_{odt}k_{1odt}k_{2odt}k_{3odt} \tag{1}$$

According to Eq. (1), $A_{odt} = B_{odt}$ when all parameter factors $k_{iodt} = 1$. That situation is defined as pre-crisis, i.e., the expected number of arrivals as if the health crisis never occurred. However, once the health-related crisis begins, the disease may affect either the destination, the origin or both. It may condition the closure of borders, affect key determinants for travelling, and may reduce confidence in travelling.

The first effect is the closure of the market, which is controlled by the binary parameter factor k_{1odt}, so that $k_{1odt} = 0$, and hence $A_{odt} = 0$, if the market is closed with respect to origin o from destination d at time t. This functions as a first hurdle, once the market re-opens $k_{1odt} = 1$ and the following effects take place. The second effect is the shock on any key determinant. Let's take as an example an income shock. k_{2odt} is a continuous and fixed parameter factor that adjusts the expected number of arrivals considering how sensitive tourists from origin o are in terms of travelling to the destination in the context of a negative income shock. This works with the income elasticity of each origin-destination pair. The same procedure may be applied for any other key determinant under shock conditions. The third effect is the confidence shock. k_{3odt} is a continuous parameter factor that varies over time. It takes low values soon after a destination has re-opened, and it grows when confidence recovers.

Eq. (1) allows for an automatic adaptive nowcasting modelling, so that at the beginning of an epidemic, k_{1odt} is the most relevant factor, whereas at the end of the epidemic, k_{3odt} is more important.

Baseline scenario (B_{odt})

The baseline scenario is built upon a forecasting model with a pre-crisis tourism series. Athanasopoulos, Hyndman, Song, and Wu (2011) showed that the pure time series approaches provide consistently better accurate forecasting methods than econometric models. The same conclusion is recently found in forecasting competitions run by Liu, Vici, et al. (2021) and Kourentes et al. (2021), who identified exponential smoothing model and auto regressive integrated moving average model among the best forecasting methods. In this paper, we have also considered structural time series modelling as a time series alternative way for forecasting (Eugenio-Martin et al., 2005).

Structural time series modelling relies on unobserved components that vary over time, so that it is sufficiently flexible to cope with structural breaks. Such components - level, slope, cyclical, seasonal and irregular - are easy to interpret. Moreover, they can have a stochastic behaviour or be fixed, depending on how much they vary over time. Structural time series modelling provides further advantages, such as the ability to endow recent observations with greater weight. It does not require the series to be stationary and they can accommodate flexible model specifications such as univariate or multivariate settings. In the latter case, cointegration can also be accommodated with common levels and/or common slopes among the series involved (Commandeur & Koopman, 2007).

Structural time series modelling works according to the following equations (Harvey, 1989):

$$B_{odt} = \mu_t + \gamma_t + \varepsilon_t, \text{with } \varepsilon_t \sim NID\left(0, \sigma_\varepsilon^2\right) \tag{2}$$

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \text{with } \eta_t \sim NID\left(0, \sigma_\eta^2\right) \tag{3}$$

$$\beta_t = \beta_{t-1} + \varsigma_t, \text{with } \varsigma_t \sim NID\left(0, \sigma_\varsigma^2\right) \tag{4}$$

where Eq. (2) represents the measurement equation, B_{odt} denotes the number of arrivals, μ_t denotes the level component, γ_t denotes the seasonal component, and Eqs. (3) and (4) represent the transition equations, where β_t denotes the slope component. NID$(0, \sigma^2)$ denotes that the error follows a normally and identically distributed function with zero mean and variance σ^2. The next section shows the goodness of fit of seasonal auto regressive integrated moving average model, structural time series model and exponential smoothing model for the period and countries of interest for this study.

First hurdle (k_{1odt}): market closure

A health-related crisis may be a concern for the origin, the destination, or both, depending on the spread of the epidemic. On the one hand, international tourists may be concerned by an epidemic at destination. Moreover, the origin country may advise against travelling to certain destinations, or even forbid travelling. On the other hand, international tourist arrivals represent a threat in terms of spreading the epidemic at destination. At the same time, they may represent a source of wealth for the region, so destinations face a trade-off between closing a route or leaving it open. This is a critical decision for the sustainability of the tourism sector in the short and medium terms.

Overall, the countries may opt for the following measures: i) No restrictions, ii) Screening arrivals, iii) Quarantine arrivals from some or all regions, iv) Ban arrivals from some regions, v) Ban on all regions, or total border closure. Such measures may vary among countries and over time. It is difficult to predict when and which measures will be applied by a country. However, once such measures are in place, indicators of epidemic dynamics can be invaluable in estimating the length of time of a market closure.

For instance, during the Covid-19 crisis, most countries applied a mitigation strategy by setting up a flexible system. This allowed entry from certain origins, depending on the evolution of the epidemic. Green zoning strategy (Oliu-Barton & Pradelski, 2021) became popular after the first wave, as it distinguished between green and red zones depending on the incidence of Covid-19. Thus, the origin countries may advise against travelling to red zones and/or destination countries may forbid the entry of tourists from red zones. Therefore, market closure may occur either because the destination or origin decide to close the market to control the spread of the epidemic.

Hence, it became clear that the nowcasting tourism demand model had to embed the epidemic evolution within the methodology. More precisely, interest lies in the expected evolution of the incidence rate. This is a measure of the frequency with which a disease occurs over certain time period. For this purpose, a Susceptible-Infected-Recovered model was implemented. In the classic Susceptible-Infected-Recovered model, the whole population is susceptible, and all the parameters are constant over the epidemic. However, during the Covid-19 pandemic, the lockdown implied that only a part of the population was susceptible. Moreover, not all infected people were properly accounted for, either due to the existence of asymptomatic cases or due to accounting failures or limitations. Parameter α considers the percentage of population (N) that is susceptible (S): $\alpha = S/N$, and is a key parameter because it conditions the size of the epidemic's peak.

The susceptible population is consistently infected over time. The epidemic's speed depends on the probability that an infected person $I(t)$ in period t will infect a susceptible person (per day) (β). Once this happens, the susceptible population decreases by that amount, so that:

$$\frac{dS(t)}{dt} = -\beta I(t) \frac{S(t)}{N} \tag{5}$$

Members of the infected population can recover or die. In any case, they represent a proportion of the infected population, and it happens with probability γ_1 for the recovered population, and γ_2 for the deceased people, so that:

$$\frac{dR(t)}{dt} = \gamma_1 I(t) + \gamma_2 I(t) \tag{6}$$

Hence, the dynamics of the infected population depends on the dynamics of susceptible and recovered people, such that:

$$\frac{dI(t)}{dt} = \beta I(t)\frac{S(t)}{N} - \gamma_1 I(t) - \gamma_2 I(t) \tag{7}$$

Reordering this expression, we can obtain the value of β, so that:

$$\beta_t = \left[\frac{N_t}{S_t I_t}\frac{dI_t}{dt} + \frac{N_t I_t}{S_t}(\gamma_1 + \gamma_2)\right] \tag{8}$$

Decision rules

Once the Susceptible-Infected-Recovered model is performed, the dynamics of infected people can be revealed. It allows for understanding the expected evolution of key indicators such as the incidence rate, which was chosen as a criterion by many countries to define green or red areas. For instance, in January 2021, Germany established a seven-day incidence rate threshold at 200 to identify a 'high-risk' red zone destination (or origin). In this case, the first hurdle is overcome depending on the following rule:

$$k_{1dt} = 1 \text{ if } \frac{\sum_{t=1}^{7} E[I(t)]/7}{N} \times 100,000 \ < \ 200$$

So that k_{1dt} depends on the expected number of infected people averaged for the last 7 days with respect to the population. The evolution of such expectation is provided by the Susceptible-Infected-Recovered model. It permits revealing the expected dates when k_{1dt} may change its value from 0 to 1 or viceversa. More precisely, since the market closure depends on both government decisions, the origin, and the destination, we can decompose k_{1odt} into two components, so that:

$$k_{1odt} = k_{1ot} k_{1dt}$$

where $k_{1ot} = 1$ if the origin country has an incidence rate below the threshold defined by the destination country, and $k_{1dt} = 1$ if the destination has got an incidence rate below the threshold defined by the origin country. Moreover, if either the destination, or the origin, does not take the incidence rate into account, it can be fixed to 1 indefinitely, and that hurdle will always be overcome. Eventually, when this hurdle is overcome, the route is expected to be open, and two additional constraints are in place, i.e., the economic impact and the confidence in travelling as explained below.

Second hurdle (k_{2odt}): shocks on key determinants

Any crisis can imply additional shocks on key determinants. For instance, the Covid-19 crisis also implied an income shock. According to the International Monetary Fund (2022), World GDP was expected to decrease dramatically in 2020, and recover partially in 2021. For instance, it was expected that the UK decreased its GDP by 10.2 %. Hence, once the source market is reopened, some frequent tourists will still not travel due to this income shock (Eugenio-Martin & Campos-Soria, 2014). To estimate the impact, it is necessary to estimate the income elasticity for each pair of origin – destination.

A comprehensive aggregate model of destination choice is employed to understand the relevance of the main determinants of travelling. The determinants of destination choice are based on a gravity model (Morley, Rosselló, & Santana-Gallego, 2014) that considers distance, contiguity, relative prices, origin income, destination income (as a proxy for development), origin population (as a control variable for origin size), destination population (as a control variable for destination size), common language, and alternative specific constants (as quality proxies). A survey on gravity models applied to the context of tourism demand analysis can be found in Rosselló and Santana-Gallego (2022).

This model allows the elasticities to be estimated, which are very useful to quantify the relevance of shocks. In terms of Eq. (1), $k_{2odt} = 1 + \varepsilon_{od}\frac{\dot{y}_{ot}}{y_{ot-1}}$, where ε_{od} denotes the income elasticity of origin market o, with respect to travelling to destination d, $\dot{y}_{ot}$ denotes per capita GDP changes in origin o, with respect to the previous period, so that $\frac{\dot{y}_{ot}}{y_{ot-1}}$ is the percentage change in per capita GDP.

Third hurdle (k_{3odt}): lack of confidence

Assaf and Scuderi (2020) argue that confidence in travelling, and risk perception, will affect the speed of the industry's recovery. This effect considers the progressive recovery of travellers' confidence. The confidence in travelling between origin o and destination d at time t depends on the parameter k_{3odt}, which lies between 0 and 1. If $k_{3odt} = 1$ means that the confidence has been fully recovered, i.e., 100 % of the usual tourists will keep travelling. Lower values of k_{3odt} imply a smaller share of tourists willing to travel due to the lack of confidence. The dynamics of the parameter is characterised by three elements, i.e., the starting value of the level of the parameter, the recovery path, and the length of the recovery.

Stage 1: modelling the confidence recovery path with limited information

At the start of a health-related crisis, most of these characteristics are unknown. By that time, we could employ two sources of information. On the one hand, we could employ the characteristics of similar health-related crises, such as the evolution of the lack of confidence parameter after severe acute respiratory syndrome recovery. For instance, for USA and Canada, in this case, the starting value of the level of the parameter was about 0.5 for both countries with a similar recovery length of about 17 months, but slightly different recovery paths, since USA showed an earlier non-linear recovery. However, the circumstances may be different for Covid-19. On the other hand, we could employ surveys that could reveal the willingness to travel. International Air Transport Association (2020) ran five waves of surveys concerning confidence in travelling. The descriptive analysis of this question provides anchor values to deduct the recovery path for the confidence factor. Moreover, two alternative naïve paths may be considered, a linear path and a log-linear path, which are useful when no prior information is available. The log linear path can be represented by a confidence function $c(t) = \log_b(t + \bar{c})$, where b and $\bar{c}$ may be calibrated depending on the characteristics of the crisis. For instance, when $b = 20$ and $\bar{c} = 3/2$ then the confidence parameter starts with $k_{3odt} = 0.20$ and it reaches 1 after 17 months. Alternative values can be provided to shift the figure upwards or to extend the right-hand side tail. Hence, by taking all this into account, a time varying confidence factor can be built, as depicted in Fig. 3.

Stage 2: modelling the confidence recovery path with information

Over time, the current data of arrivals are revealed, so that the first values of the confidence recovery series may also be eventually obtained for each pair of origin-destination. The challenge is to estimate the determinants of such recovery series and nowcast the remaining recovery path until $k_{3odt} = 1$. For this purpose, we employ random effects panel data regressions to estimate them. Moreover, since $k_{3odt} \in [0, 1]$, then a censored Tobit panel data regression is considered, so that the lower limit of the censor is set to be 0 and the upper limit to be 1.

We consider different kinds of determinants for the model specification. We take into account the role of vaccines in the confidence recovery process, both at the origin and at the destination. Moreover, we consider a linear and non-linear time trend and dummy variables of destinations and origins. More precisely, we test alternative models of the following expression:

$$k_{3odt} = C + \sum_{od} \beta_{od} t + \sum_{od} \beta_{2od} t^2 + \beta_{vo} V_{ot} + \beta_{2vo} V_{ot}^2 + \beta_{vd} V_{dt} + \beta_{2vd} V_{dt}^2 + \sum_{o} \beta_o d_o + \sum_{d} \beta_d d_d + u_{od} + \varepsilon_{odt}$$

where C denotes a constant term, o denotes origin, d denotes destination, t denotes time, V denotes the percentage of vaccinated population as obtained from (Mathieu et al., 2021), d denotes origin or destination dummy variables, u_{od} denotes the random effects that are assumed to be *i.i.d.*, $N(0, \sigma_u^2)$ and ε_{odt} denotes the error term that is assumed to be *i.i.d.* $N(0\sigma_\varepsilon^2)$ and independent of u_{od}.

Model calibration and estimates

The different hurdles are applied to Latin American and Caribbean countries, which requires of proper calibration and specific estimates. They are shown below for the different hurdles.

Baseline model alternatives

The goodness of fit of the alternative baseline models for year 2019 was assessed according to the mean absolute percentage error, which results were 13.31 % for seasonal auto regressive integrated moving average model, 11.64 % for structural time series model and 15.06 % for exponential smoothing model. The details are shown in Table 1 below. Hence, structural time series modelling is employed to forecast arrivals, as recommended by Harvey (1989: 93–95).

Susceptible-infected-recovered model

During the Covid-19 pandemic β_t was not constant due to changes in mobility, lockdown, mitigation measures, vaccination, and the entry of new variants, such as Omicron (reported on 24th November 2021 to World Health Organization from South Africa). All these changes vary β_t. Hence, β_t had to be re-estimated daily. However, at country level, many data issues made its measurement unstable. For instance, the aggregation of the regional data may not have happened continuously over a week.

Table 1
Time series competition. Mean absolute percentage error for 2019.

	Seasonal auto regressive integrated moving average	Structural time series	Exponential smoothing
Argentina	3.85 %	3.56 %	3.61 %
Bahamas	5.71 %	4.18 %	4.20 %
Barbados	4.32 %	5.05 %	6.51 %
Belize	13.19 %	10.43 %	6.97 %
Bolivia	15.82 %	14.72 %	16.31 %
Chile	18.21 %	21.16 %	24.21 %
Colombia	3.94 %	4.61 %	4.33 %
Costa Rica	3.27 %	4.60 %	3.45 %
Ecuador	48.73 %	33.17 %	32.87 %
El Salvador	6.02 %	4.86 %	5.51 %
Jamaica	3.01 %	3.78 %	2.94 %
Nicaragua	43.74 %	35.57 %	83.44 %
Panama	12.83 %	12.83 %	9.54 %
Paraguay	20.55 %	13.56 %	26.66 %
Dominican Republic	11.56 %	11.32 %	12.00 %
Trinidad and Tobago	7.87 %	10.80 %	10.00 %
Peru	3.70 %	3.71 %	3.55 %
Average	13.31 %	11.64 %	15.06 %

This causes a certain volatility on the infected series, which also affects the daily re-estimation of the tourism demand nowcasts. To provide stability, the 14-day moving median of β_t was employed instead.

Fig. 1 shows the evolution of β_t for the UK between March 2020 and July 2022. It shows that at the beginning of the epidemic when there was poor knowledge of the disease the parameter was over 0.25. Fig. 1 shows how it decreased after the introduction of the lockdowns on 23 March 2020. The restrictions were steadily eased by early summer, which increased the spread of the disease as also shown by the evolution of β_t. Similar ups and downs kept occurring due to different events, such as mobility restrictions (labelled as 'tiers' in the UK), vaccination, new variants, or holidays.

The parameters γ_1 and γ_2 control for the probability of recovering or dying after being infected. γ_1 is calibrated by estimating the relationship between the number of infected people and the number of recovered people in the previous two months. Such a relationship is estimated daily by regression, applying ordinary least squares. Thus, it is estimated by a daily 2-month moving regression, which allows for a smooth adaptation, especially after vaccinations began. The same procedure is applied to γ_2. The last parameter to be calibrated is α. It should be noted that its value conditions the height of the curve. To understand the calibration strategy, it is useful to distinguish several stages in the epidemic dynamics. Fig. 2 shows the stages of the Susceptible-Infected-Recovered model; however, in practice, many curves (known as 'waves') like this were produced over time. Thus, the events may create new waves, meaning that the height of the curves needs to be adjusted.

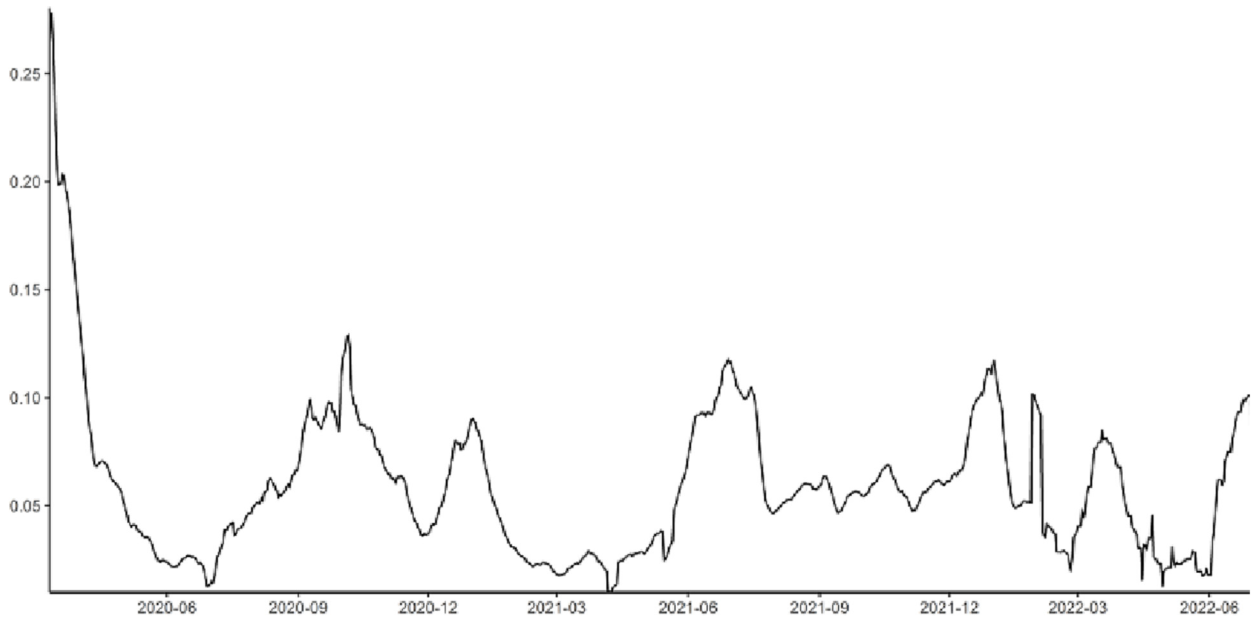

Fig. 1. Beta parameter of the Susceptible-Infected-Recovered model for the United Kingdom (March 2020–July 2022).

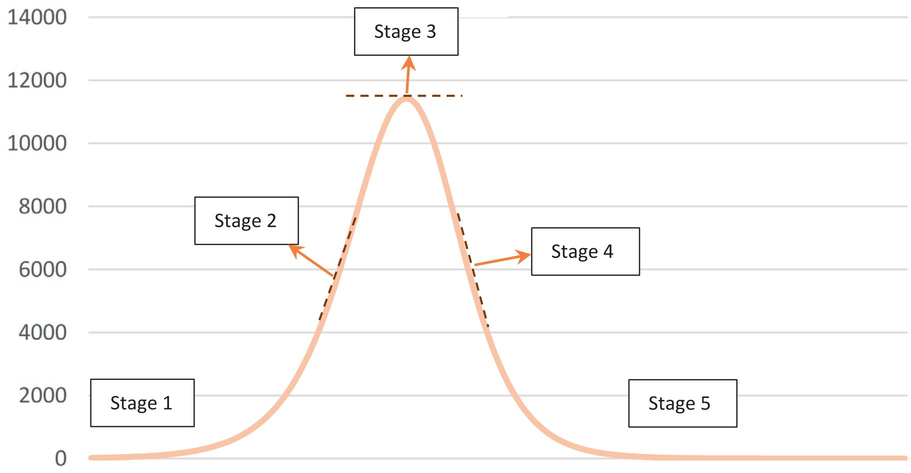

Fig. 2. Stages in the infection curve of a Susceptible-Infected-Recovered model.

Stage 1 is the beginning of the epidemic, or a new wave, and at this stage the height of the curve is uncertain, such that α cannot be calibrated. However, once the epidemic has reached stage 2, it can be calibrated. The reason for this is because after stage 2, the speed of the epidemic slows down. The speed is measured with the first derivative, i.e., dI/dt. In stage 2, it reaches the maximum value of dI/dt and in stage 3, the speed freezes since $\frac{dI}{dt} = 0$. Thus, the curve can be anticipated by analysing dI/dt instead of $I(t)$. Specifically, dI/dt can be forecast applying structural time series modelling so that the date when $\frac{dI}{dt} = 0$ can be anticipated. Hence, the α calibration strategy consists of assuring that the projected curve replicates the current or expected curve peak of stage 3.

Destination choice model

The dataset comprises the choice of 209 origin countries and 188 destination countries between 1995 and 2018. It is based on 16,601 origin-destination pairs with a series of 24 years, which implies 379,915 effective observations. The source of the dataset is United Nations World Tourism Organization, and the kind of arrival data differs by countries. For instance, for some countries the arrivals figure is measured at the borders, whereas other countries consider whether the tourist spend a night or not. For this reason, 8 dummy variables are introduced to control this measurement issue. GDP, prices, and population data are from World Bank; and the dataset of distance, contiguity, and language from Centre D'Études Prospectives et D'Informations Internationales.

The model is estimated employing random effects generalised least squares method to the panel dataset (Eugenio-Martin, Sinclair, & Martin-Morales, 2008). Moreover, the estimates are obtained after applying the Huber/White/sandwich variance co-variance estimator (Arellano, 2003), which produces a consistent estimator when the disturbances are not identically distributed

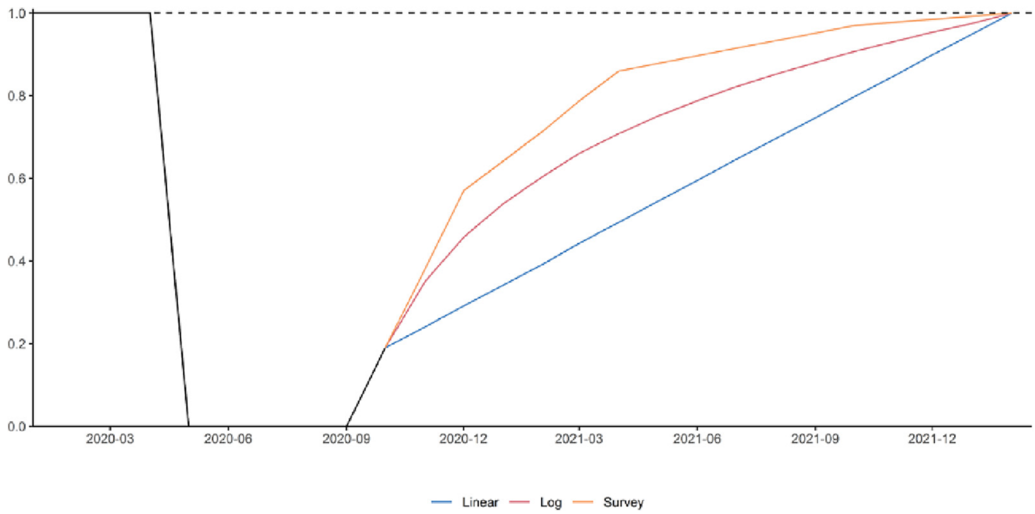

Fig. 3. Time varying confidence factor in travelling with limited information.

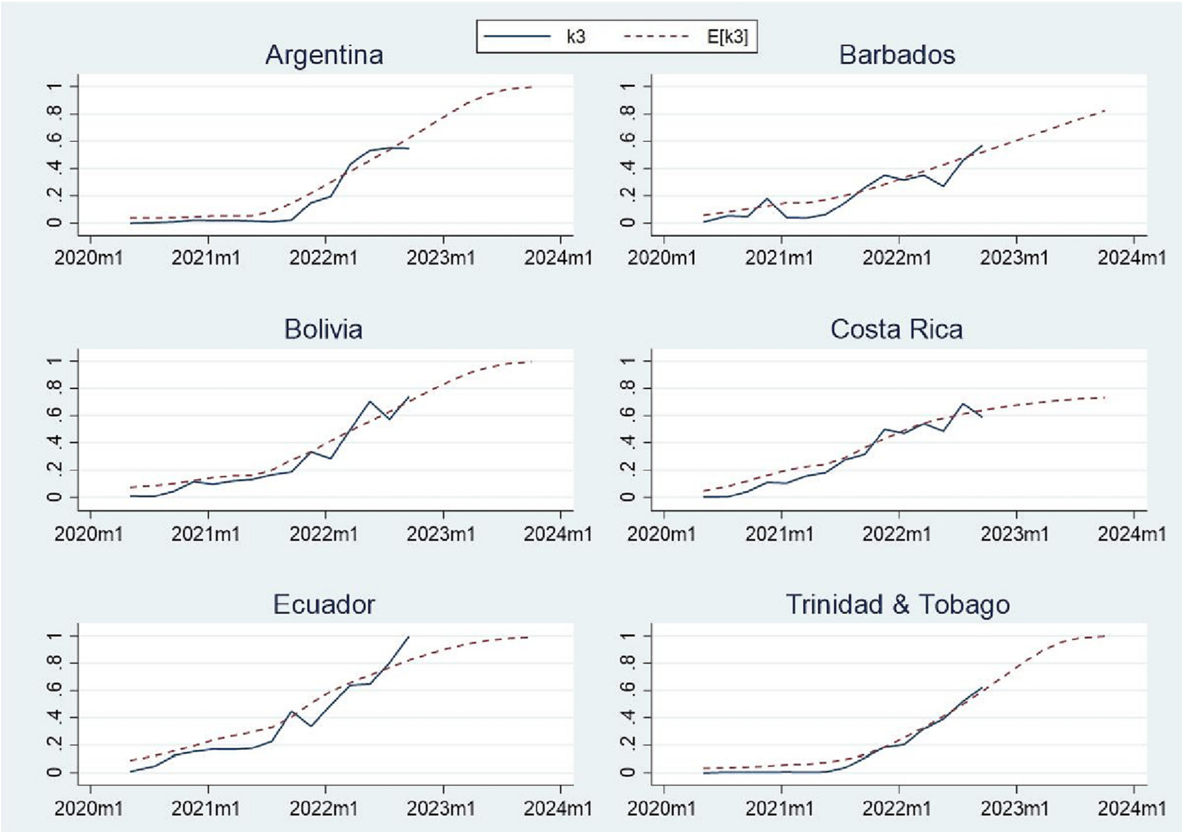

Fig. 4. Estimated confidence recovery paths (2020—2023).

over panels, or there is serial correlation. The results are shown in Table 2. They are all significant determinants with the expected signs. In particular, the results show elasticities of continuous variables because they are specified in a double log fashion.

Overall, the worldwide income elasticity is 1.117. This means that if income increases by 1 %, the number of arrivals is expected to increase by 1.117 %. This is an average result for the whole world, but it varies by origins and furthermore by pairs

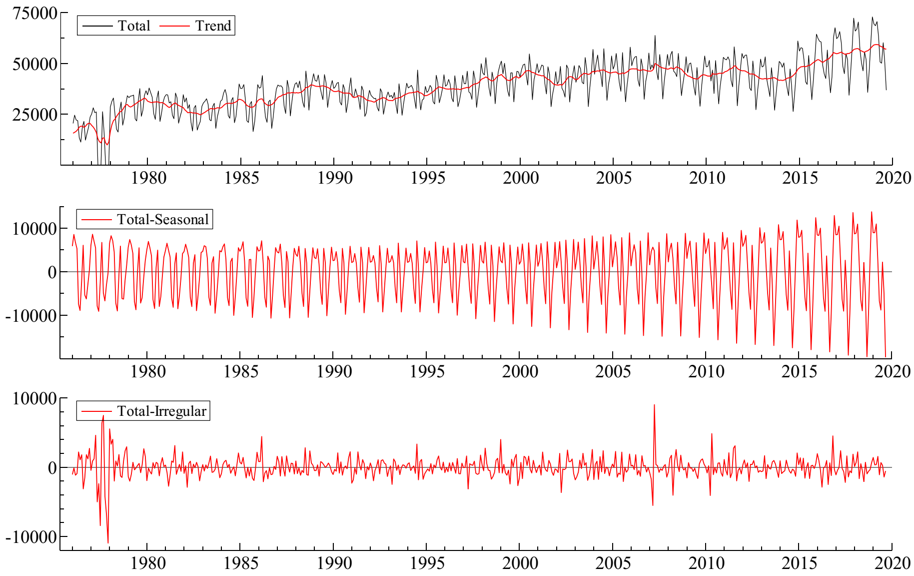

Fig. 5. Structural time series model of air passengers' series to Barbados (1976–2019).

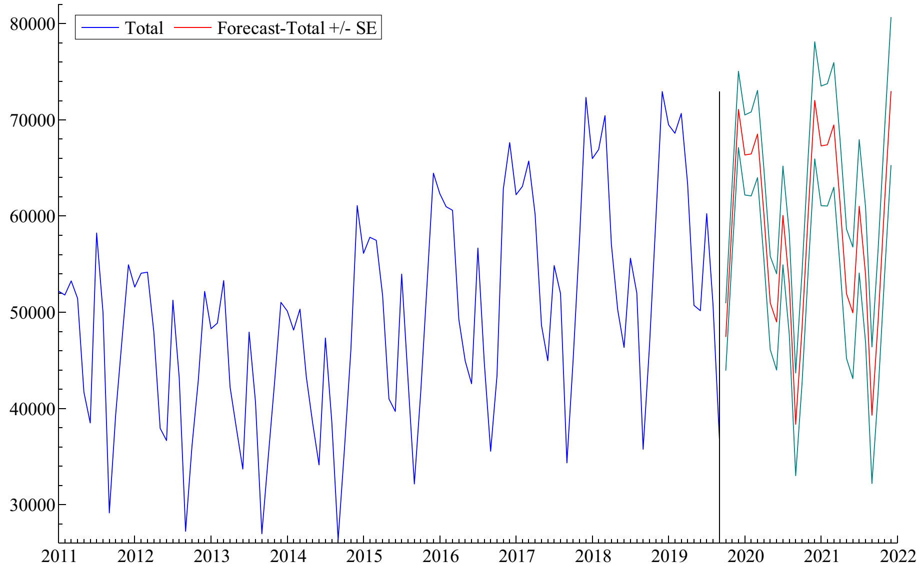

Fig. 6. Expected pre-Covid-19 inbound tourism demand to Barbados. Baseline scenario (2020−2021).

of origin - destination. They can be estimated employing multiplicative dummy variables that can shift the 1.117 coefficient upwards or downwards depending on how sensitive it is for each pair.

Confidence recovery model

The results of four different model specifications are shown in Table 3. Model 1 considers non-linear explicative variables with common trend effects. Model 2 disentangles the trend effects by destinations in a linear way, whereas Model 3 also considers non-linear trend effects that vary by destinations. Finally, Model 4 deals with different trends effects by pair of origin-destination.

Table 3 also shows that Model 3 is the preferred specification in terms of mean absolute percentage error and Bayesian information criterion. It should be noted that for Model 3 the overall (σ_ε^2) and panel-level (σ_u^2) variance components are significantly different from zero. Thus, $\rho = \sigma_u^2/(\sigma_\varepsilon^2 + \sigma_u^2)$ is greater than zero. It is employed to compare a pooled estimator (Tobit) with the panel estimator. In this case, we reject the null hypothesis that there are no panel-level effects.

Fig. 4 shows the expected confidence recovery path (dash line) for certain countries that had available data up to the end of 2022. Overall, the expected path presents a sinusoid shape with a marked threshold once the vaccination took place.

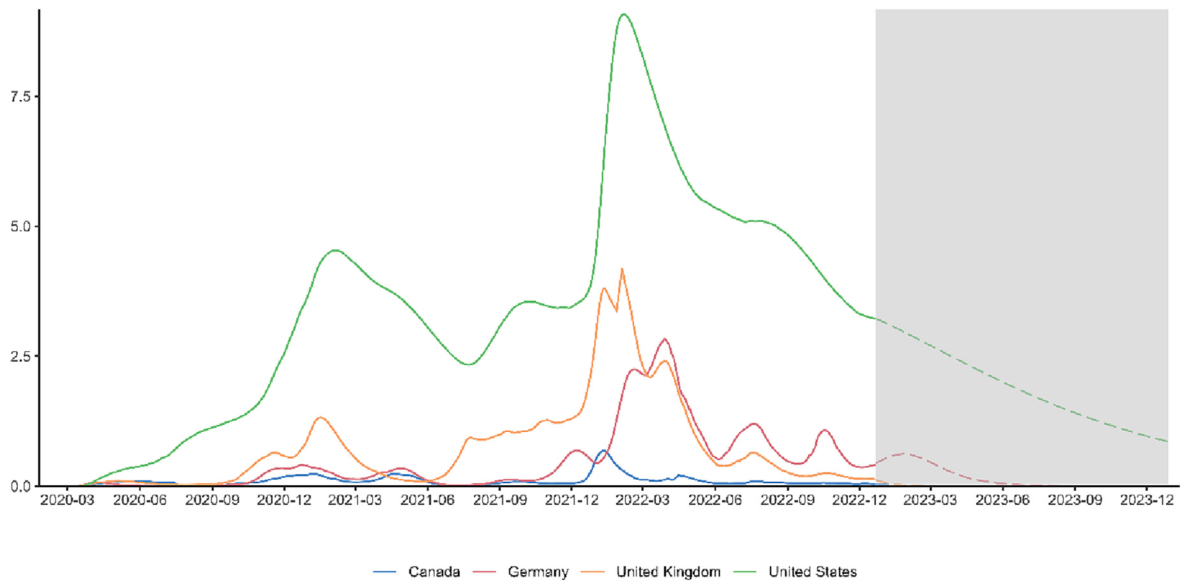

Fig. 7. Probability of infected tourists by country of origin (percentage, 2020–2023).

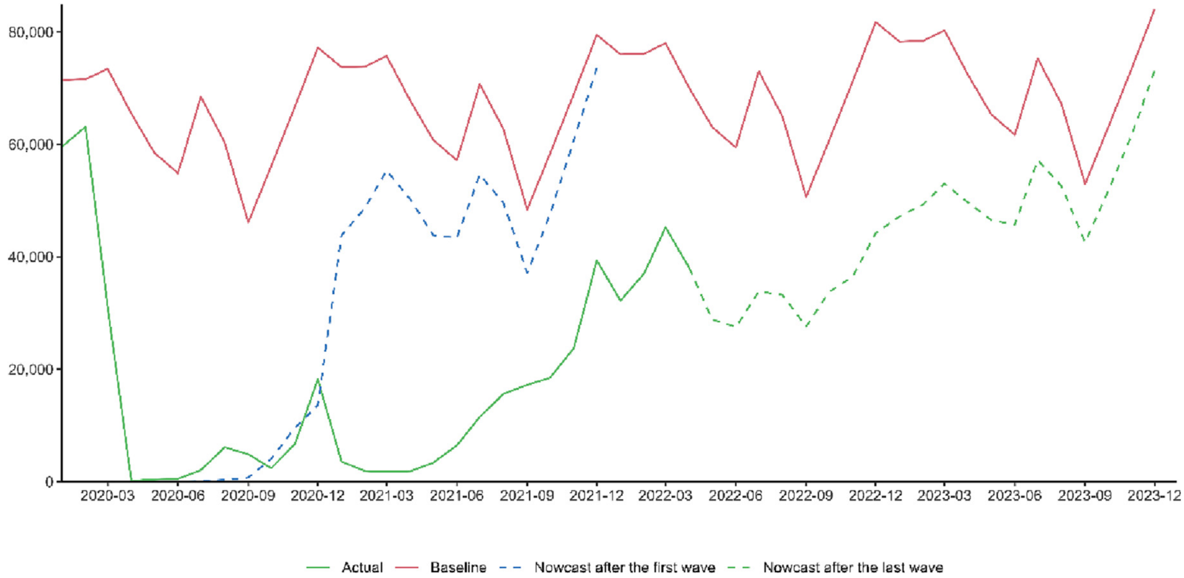

Fig. 8. Nowcasting arrivals in Barbados (2020–2023). Differences between nowcasting after the first wave and the last wave.

Illustration

The paper applies the methodology for the Covid-19 crisis in Barbados as an illustration. For simplicity, only the air passengers are considered. The baseline series for Barbados is constructed with the structural time series model employing a monthly series between January 1976 and December 2019. The model incorporates stochastic level, fixed slope, and stochastic seasonal components. Fig. 5 shows the trend (level and slope); the seasonal component; and the irregular component. This model is employed for forecasting the number of arrivals for air passengers, as shown in Fig. 6.

Understanding the length of closure with epidemic dynamics

During the first wave, the rationale was that both the destination and the origin required a low risk of infection to re-open a route. The epidemic dynamics depends on the dynamics of confirmed recoveries and deaths. During the first wave, the epidemic in Barbados was under control. The authorities were concerned about the epidemic dynamics of incoming tourists, so restrictions were imposed. Once Barbados overcame the epidemics, the next step was to re-open the tourism market with 'safe origin' countries. Here, a balance between

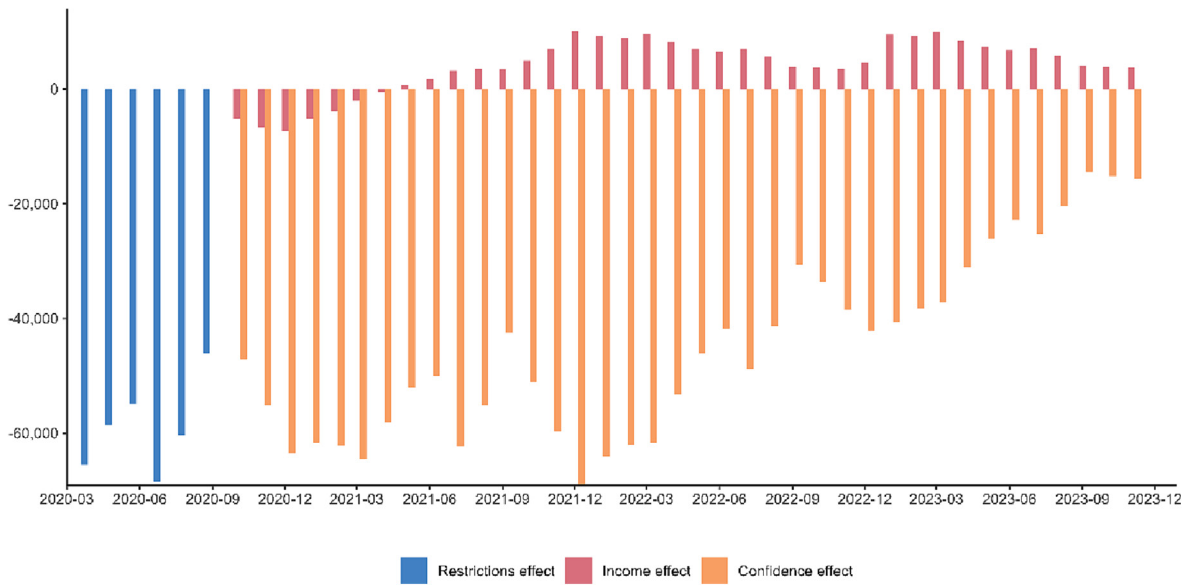

Fig. 9. Decomposing all the effects in the nowcasting model for Barbados (February 2023 version).

Table 2
Destination choice model with random effects panel data model (1995–2018).

Determinant	Coefficient	*p*-Value
Distance	−1.430	[0.000]
Contiguity	1.648	[0.000]
Relative prices	−0.305	[0.000]
Origin GDP per capita	1.117	[0.000]
Destination GDP per capita	2.209	[0.000]
Origin population	0.746	[0.000]
Destination population	1.764	[0.000]
Common language	1.360	[0.000]
Alternative specific constants	(omitted)	
Kind of arrival data	(omitted)	
Goodness of fit		
R^2 within panel	0.147	
R^2 between panels	0.733	
R^2 global	0.559	

risk taken and the number of arrivals achieved is expected. Opening the frontiers to all countries runs the risk of a new outbreak, with a new loss in confidence. However, at the same time it speeds up the economic recovery.

Fig. 7 shows the evolution of such probabilities for USA, the UK, Canada, and Germany. Such probability can be understood as a criterion for targeting markets. Destinations may need to prioritise their promotional budget among alternative origins, and this criterion can help decide. Fig. 7 shows a heterogeneous evolution but also a consistent and different level throughout most periods. USA has consistently been the country with the highest probability, followed by the UK. Germany and Canada have shown low values during 2020 and 2021 in relative terms. This criterion puts them in a better position with respect to the USA or the UK. However, during 2022 the behaviour of Germany has converged with the UK, leaving them as similarly attractive markets to target. More interestingly, Fig. 7 shows the expected evolution of probabilities (dashed line in gray area), so that it provides scope for recovery and a time estimate to anticipate decisions in a more informative way.

Income effect

The results of the income elasticities for each pair of interest are shown in Table 4. The pairs of interest are defined according to the top 10 origin markets in terms of arrivals. They are all highly significant. Table 4 also shows the GDP changes during 2020

Table 3
Random effects panel data censored Tobit regressions of the confidence recovery path.

	Model 1 $\beta_1 t + \beta_2 t^2$	Model 2 $\sum_{d=1}^{16} \beta_d t$	Model 3 $\sum_{d=1}^{16} \beta_{1d} t + \beta_{2d} t^2$	Model 4 $\sum_{od=1}^{160} \beta_d t$
t	0.2797***	(…)	(…)	(…)
	[0.001]			
t^2	−0.0001***	–	(…)	–
	[0.002]			
V_o	−0.0046***	−0.0034***	−0.0031***	−0.0035***
	[0.000]	[0.000]	[0.000]	[0.000]
V_o^2	0.00006***	0.00004***	0.00004***	0.00004***
	[0.000]	[0.000]	[0.000]	[0.000]
V_d	−0.0003	−0.0018***	−0.0014*	−0.0017***
	[0.574]	[0.008]	[0.072]	[0.006]
V_d^2	-2.55×10^{-6}	0.00003***	0.00002**	0.00003***
	[0.713]	[0.000]	[0.027]	[0.000]
C	−113.697***	−19.1761***	436.968***	−8.5412***
	[0.000]	[0.000]	[0.000]	[0.000]
d_o	(…)	(…)	(…)	(…)
d_d	(…)	(…)	(…)	(…)
σ_ε^2	0.1705***	0.1534***	0.1477***	0.1427***
	[0.000]	[0.000]	[0.000]	[0.000]
σ_u^2	0.0697***	0.0727***	0.0734***	0
	[0.000]	[0.000]	[0.000]	[1.000]
ρ	0.1433***	0.1835***	0.1980***	0
Log likelihood	542.933	917.360	1021.492	1272.127
Mean absolute percentage error	10.611	8.583	6.286	6.587
Bayesian information criterion	−572.971	−1207.849	−1326.559	−745.050

p-values in brackets.
*** Level of significance 1 %.
** Level of significance 5 %.
* Level of significance 10 %.

Table 4
Income elasticities of Barbados' main origin markets.

Origin market	Income elasticity	2020 variation		2021 variation	
		GDP	Demand	GDP	Demand
UK	1.546	−9.8	−15.15	7.4	11.44
United States	1.265	−3.4	−4.30	5.7	7.21
Canada	1.393	−5.3	−7.38	5.7	7.94
Trinidad and Tobago	1.281	−7.9	−10.12	−0.7	−0.89
Guyana	1.603	43.5	69.73	23.8	38.15
Germany	1.365	−4.6	−6.28	2.6	3.54
St. Vincent and Grenadines	1.416	−3.3	−4.67	0.5	0.70
Jamaica	1.518	−10.0	−15.18	4.6	6.98
Saint Lucia	1.354	−20.4	−27.62	12.2	16.51
Dominica	1.449	−11.0	−15.94	4.8	6.95

and 2021, according to the International Monetary Fund (2022). If we employ the income elasticities, the number of arrivals is expected to vary. It should be noted that even though GDP growth in 2021 is positive, it is still lower than the 2020 decrease, which means that it is still lower than 2019. It implies a net decrease in 2021 with respect to the baseline.

Nowcasting arrivals

The nowcasting arrivals series is updated daily. To illustrate such variations in the paper, we show the expected arrivals during the first wave and during the last wave at the time of writing. The nowcasts are calculated by applying Eq. (1). This is carried out by origin and effect by effect, so that arrivals can be provided by distinguishing the origin country and the effect. The top 10 origin country arrivals are aggregated and weighted to obtain the total number of arrivals by air traffic, as shown in Fig. 8. It shows the baseline series (in red) and the nowcasts of arrivals as expected during the first wave (in blue, dashed). The solid green series show the actual series, whereas the dashed green series is based on the nowcasting model. If we look at the blue series, the nowcasts are like the actual series up to the end of 2020. In January 2021 a new outbreak occurred in Barbados, which delayed the expected recovery. The nowcasting model can recalculate the new series as soon as the new information is updated. Fig. 8 also shows three more waves after September 2021, which delayed the recovery in confidence. That is the main advantage of the nowcasting model, i.e., its ability to adjust the series daily and automatically based on new available data.

Additional waves extended the recovery period, but also the vaccinations improved the travellers' confidence. Fig. 9 disentangles all the effects of the nowcasting model over time. It shows the relevance of market closure during the early days of the crisis. It also shows the relative low impact of the income shocks, which become positive by mid-2021. Finally, it shows the relevance of the confidence effect throughout the whole crisis, and its diminishing relevance by the end of it.

Model performance

To assess the goodness of fit of the nowcasting model, the mean absolute percentage error is calculated ex-post. It is expressed as follows:

$$G_{dt} = \frac{1}{m}\sum_{m}\left|\frac{y_t - \hat{y}_{tm}}{y_t}\right|100$$

where G_{dt} denotes the goodness of fit measure for destination d at time t, y_t denotes the current value and $\hat{y}_{tm}$ denotes the nowcast with m months in advance. m may correspond to 1, 2, 3, or 4 months ahead nowcasts.

As stated earlier, the nowcasting model was applied to 17 countries of Latin America and the Caribbean, but not all the countries have provided current data post Covid-19. In order to report the goodness of fit it is more appropriate to consider as many countries as possible to get a broader view of its capacity. The countries employed are those that have reported more recent current data. Their average mean absolute percentage error values are: Argentina (25.30 %), The Bahamas (15.02 %), Barbados (18.00 %), Bolivia (23.97 %), Colombia (16.77 %), Costa Rica (9.77 %), Dominican Republic (11.27 %), Ecuador (17.01 %), Jamaica (15.83 %), Mexico (10.28 %), Paraguay (15.59 %), Peru (23.28 %), and Trinidad and Tobago (22.07 %). The number of months ahead worsen the results. The average mean absolute percentage error for nowcasts to one month ahead is 15.94 %, whereas for two months ahead is 18.00 % and for three months ahead is 23.67 %. Further details can be provided by the authors upon request.

Overall, the goodness of fit of all nowcasts since November 2021 until September 2022 in terms of mean absolute percentage error was 17.19 %, which is higher than the structural time series modelling results before Covid-19, as expected, but still good given the huge uncertainty during the crisis. Nowcasting arrivals during Covid-19 are very uncertain because airlines can enter or exit the market abruptly and/or closure or re-opening of markets can also happen abruptly. Both issues may cause unexpected shifts in current traffic and induce errors.

Display of the nowcasting model results in real time

The nowcasting model was built to provide up-to-date information for decision makers. We realised that the traditional country reports become obsolete quickly. Thus, we decided to show all the results on a live web platform. For this purpose, we programmed in R software all the required calculations, i.e., all Susceptible-Infected-Recovered model parameters, all regression estimates and all-time series estimates. The code was also written employing the Shiny package (Chang et al., 2021), which is used as a framework for javascript. Daily, the nowcasting model is updated automatically and provides all the results to the users on the web. The epidemic data series are provided by Johns Hopkins Coronavirus Resource Center (Dong, Du, & Gardner, 2020), the GDP series by the International Monetary Fund (2020), and the current arrivals series by the Statistical offices of each country. The alpha parameter of the Susceptible-Infected-Recovered model requires it to be monitored and calibrated at least once per month. The remaining parameters are monitored and updated automatically in real time.

Conclusions

This methodology has proved to be very flexible to manage a dynamic environment such as Covid-19, where multiple waves took place, multiple variants, the rise of vaccinations, lockdowns periods, green-zoning flexibility, and varying mitigation measures, which happened heterogeneously all over the world. Mostly, the beta parameter could handle the majority of these events smoothly, since it was based on a 14-day median average. For this reason, it does not capture rapid changes easily, as expected, but it provides stability to the infected series, which is more important for the stability of the tourist nowcasts series. Moreover, both gamma parameters worked well with automatic regression based on the last 60 days of observations. Finally, the alpha parameter was a bit tricky to handle, especially at the start of a new wave, which required calibration of its value more often.

Overall, the nowcasting model presented in this paper is novel for three main reasons. It can combine several effects simultaneously, the relevance of the effects may vary over time, and it embeds the epidemic dynamics with the nowcasting tourism model. As far as we know, this is the first time that these characteristics are found in a nowcasting model for a health-related crisis. The effects are considered as hurdles to be overcome which tunes the series. The methodology integrates income shock, which is also a great concern as shown in previous economic crises, but it also considers a confidence recovery parameter. The latter is also linked with the epidemic dynamics in a novel way. Moreover, the methodology disentangles the three effects, so that we can see which effect is restricting demand at every moment. Finally, it should be mentioned that the baseline series is assumed to work as a reliable benchmark. However, this may be wrong if a "new normality" happens during and/or after the crisis is over. Further research in this area should improve the accuracy of the modelling.

The nowcasts provided distinguish the origin country, so that destinations can anticipate the demand by market, and can adjust their marketing efforts accordingly. Moreover, the methodology provides information on the probability of receiving infected tourists by origin market and how it is expected to vary over time. Hence, destinations can make informed decisions with both values, i.e., demand and risk, so that the destination can prioritise the key markets to be targeted over time. In order to share the nowcasts in real time, all the modelling calculations were programmed in R and shared on a website via Shinyapps.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.annals.2023.103609.

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Juan L. Eugenio-Martin is interested in tourism demand analysis and the economic impact of tourism.
José M. Cazorla-Artiles is interested in tourism demand analysis and data visualization.
Adela Moreda and **Juan M. Murguia** are interested in sustainable tourism and economic development assessment.