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Search query and tourism forecasting during the pandemic: When and where can digital footprints be helpful as predictors?☆

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ABSTRACT

During the COVID-19 pandemic, daily tourism demand forecasting provides actionable insight on tourism operations amid intense uncertainty. This paper applies the lasso method to predict daily tourism demand across 74 countries in 2020. We evaluate the usefulness of online search queries in boosting forecasting accuracy. The lasso method is used to select appropriate predictors and their lag orders. Results indicate that, in general, no evidence supports the usefulness of Google Trends data in generating more accurate forecasts. However, in some countries, the data can be useful for reducing the forecasting errors. Regression analysis further demonstrates that the relative usefulness of online search queries is associated with pandemic severity, the dominance of inbound tourism, and island geography. Lastly, implications are provided.

Introduction

The outbreak of COVID-19, a contagious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has significantly affected the global tourism and travel industry. Declared a Public Health Emergency of International Concern on January 30, 2021, the pandemic has led to 180,817,269 confirmed cases and 3,923,238 deaths as of June 28, 2021 (WHO, 2021). Tourism and travel involve human movement and interaction and may contribute to the spread of disease (Farzanegan et al., 2021). Therefore, many countries have shut down their borders and enforced mobility restrictions; these policies dealt a devastating blow to the global tourism industry. As demand plummeted, many tourism businesses, such as airlines, hotels, and attractions, laid off and furloughed employees. A supply shrink followed. According to UNWTO statistics, the pandemic led to a loss of US $910 billion to US $1.2 trillion from tourism exports and was projected to reduce global GDP by 1.5% to 2.8% in 2020 (UNWTO, 2021).

During this highly uncertain time, tourism forecasting has come to play a more important role than ever in informing decisions among government personnel, industry professionals, and other tourism stakeholders. First, forecasting allows for tourism recovery predictions and can provide valuable insight for tourism policy design and implementation. Second, as demand has been volatile during the pandemic, accurate forecasts can help industry players better allocate their resources (e.g., inventory and staffing) to serve incoming demand. In addition to industry forecasting reports, tourism researchers have striven to develop and evaluate

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multiple forecasting methods to predict tourism demand at different levels (Kourentzes et al., 2021; Liu et al., 2021; Qiu et al., 2021). Various forecasting methods have since been leveraged and compared in terms of forecasting accuracy. Examples include time series models (Wickramasinghe & Ratnasiri, 2021), artificial neural network (ANN) models (Polyzos et al., 2021), stacking models (Qiu et al., 2021), forecasting combinations (Kourentzes et al., 2021), and the scenario-based mixed judgmental forecasting method (Liu et al., 2021).

Many tourism studies have highlighted the importance of big data indicators in enhancing tourism forecasting accuracy (Tian et al., 2021). Digital footprints, such as online search queries, web traffic, and social media posts, reflect prospective travelers' tourism interests and can reasonably predict tourism demand. Customer information processing theory suggests that consumers' path to purchase entails a funnel-like process from search to purchase. Digital footprints can reflect information about consumers' potential choices, some of which will be bought. Empirical studies have confirmed the usefulness of these footprints in improving tourism forecasting accuracy in various contexts (Pan et al., 2012; Pan & Yang, 2017a, 2017b); however, it remains unclear whether this usefulness applies in the COVID-19 era due to the volatility of tourism demand and travelers' unique information search behavior during this crisis.

To bridge this knowledge gap, we adopted the lasso method to forecast daily tourism demand across 74 countries in 2020. The lasso method is particularly useful when selecting variables from high-frequency, high-dimensional predictors of tourism demand (Tian et al., 2021). Different predictors were incorporated into our model to improve forecasting accuracy. More specifically, we compared the forecasting performance of a model with and without Google search query data. Doing so enabled us to examine the effectiveness of digital footprints in reducing forecasting error during the pandemic. Following our forecasting performance comparison, we employed regression analysis to understand when and where Google search query data were most helpful in improving forecasting accuracy. Results make at least three major contributions to the literature. First, we evaluated models' forecasting performance for daily tourism demand during the COVID-19 pandemic, providing guidelines for model and predictor selection in a time of great uncertainty. Our findings, based on a global sample, offer generalizable implications for academics and practitioners. Second, we scrutinized whether Google search query data (as a typical form of digital footprints) can improve forecasting accuracy across different forecasting horizons. Our conclusions helped evaluate the potential usefulness of digital footprints in tourism forecasting during this chaotic time. Last but not least, we systematically assessed factors explaining the effectiveness of Google search query data in tourism forecasting via rigorous regression analysis of results from 11,396 forecasting models. Although previous meta-analyses addressed potential determinants of forecasting accuracy (Kim & Schwartz, 2013; Peng et al., 2014), no single study has systematically evaluated these contributions in a context allowing for large-scale model comparison. Our findings thus clarify predictors' applicability in tourism forecasting.

Literature review

Tourism demand forecasting

Many forecasting methods have been applied in tourism demand analysis, spanning quantitative and qualitative approaches (Law et al., 2019). Among qualitative methods, Delphi and consensus approaches are commonly adopted to forecast tourism demand; these methods rely on qualitative insight from experts in specific tourism markets. Qualitative methods' inherent constraints, such as limited generalizability (Witt & Witt, 1995), have led researchers to become more interested in quantitative means of estimating relationships among factors in tourism data. According to Law et al. (2019), two main strategies are usually adopted to enhance quantitative methods' performance: (1) incorporating additional potentially relevant variables and (2) developing more sophisticated models to better generalize results. Major quantitative approaches used in tourism demand analysis include time series analysis, econometric analysis, and artificial intelligence (AI) methods (Song & Li, 2008). Time series analysis is the most popular way to forecast tourism demand (Yang et al., 2014); it attempts to identify trends, seasonality, and cycles based on data measured at routine intervals (Yang & Zhang, 2019). Across such models, the autoregressive moving average (ARIMA) model depends on the autoregressive moving average parts of stationary data (Kulendran & Wong, 2005). The generalized autoregressive conditional heteroskedasticity model captures conditional variance to internalize the effects of external shocks (Dutta et al., 2020). The structural time series model estimates multiple components for time series analysis (Jackman & Greenidge, 2010). The long-memory model reflects the long-range dependence in time series (Gil-Alana et al., 2014).

Econometric models are intended to calibrate cause-and-effect relationships between variables (Song et al., 2019). Popular econometric approaches include the autoregressive distributed lag model, error correction model, vector autoregressive model, time-varying parameter model, and almost ideal demand system model (Wu et al., 2017). Many researchers have compared time-series and econometric models and found that the forecasting results can vary contextually (Peng et al., 2014). AI methods, another means of tourism forecasting, deploy algorithms for data mining to discover generic patterns or correlations in large datasets. Typical AI models for this purpose include random forest, support vector machines, and artificial neural networks (Jiao & Chen, 2019; Law et al., 2019). AI approaches possess two key advantages over competitors, namely in their calculation capacity and ability to discern nonlinearity with big data (Zhang et al., 2020). However, no particular approach consistently outperforms others, and forecasting accuracy hinges on the assumption that historical patterns can reasonably project the future (Yang et al., 2014). Forecast pooling or combination has thus become popular. These approaches synchronize forecasts from different models to generate more reliable and robust predictions than any individual model alone (Coshall & Charlesworth, 2011).

Accurate tourism forecasts require the identification of determinants for tourism demand. These determinants can be broadly categorized into economic and non-economic factors. Based on conventional economic theories such as demand theory, utility theory, and consumption behavior theory, both quantitative factors (e.g., macroeconomics) and qualitative factors (e.g., political policies) influence tourism demand (Goh & Law, 2002). Turner et al. (1998) discussed several economic factors often associated with tourism demand: population, personal disposable income, the cost of living for tourists in (substitute) destinations, transport costs, and the trade volume (of imports and exports) between destination and origin countries. Non-economic factors include tourists' mood and leisure time (Martins et al., 2017), policy uncertainty (Işık et al., 2020), the quality of natural resources (Meleddu & Pulina, 2016), and weather-related factors (Goh et al., 2008).

Many scholars have sought to offer guidelines for improving forecasting accuracy. Pan et al. (2012) noted that model complexity does not necessarily boost forecasting accuracy, while Kim and Schwartz (2013) discovered that a causal econometric model surpassed the forecasting accuracy of pure time series models. In a meta-analysis, Peng et al. (2014) indicated that the dynamic econometric model had the best accuracy among numerous forecasting models; Li et al. (2005) came to the same conclusion. Despite the lack of definitive answers to some of the above questions, valuable lessons can be drawn from prior studies on forecasting comparison/competition. First, although no lone model appears superior to others across scenarios, forecasting accuracy can presumably be improved by adopting the best model among diverse options (Kim & Schwartz, 2013; Peng et al., 2014). Second, incorporating external predictors can enhance accuracy and strengthen findings' robustness. Researchers can thus refer to rich sources of big data such as search engine queries (Pan & Yang, 2017a).

Search engine queries and tourism forecasting

Along with the growing penetration of modern information and communication technologies, a large amount of data is now available to predict customer behavior. Search engine queries cover customers' digital footprints and appear especially useful in forecasting customer demand and behavior (Pan & Yang, 2017b). The study from Ettredge et al. (2005) on unemployment forecasting represents a pioneering effort to embrace search engine queries in economic forecasting. Many scholars have since integrated web search data in their fields. For instance, Ginsberg et al. (2009) found that online search query data could reasonably predict the incidence of influenza. Yet not until the early 2010s did tourism researchers begin to acknowledge the value of search engine queries for tourism demand forecasting (i.e., Choi & Varian, 2012; Yang et al., 2015). Fesenmaier et al. (2010) stated that, because the vast majority of tourists use search engines to obtain trip-related information before traveling, search engines have become the “first step” of travel planning. As tourists move along their path to purchase, search engine query volume serves as an effective demand predictor.

Online information searches are becoming increasingly popular. With this ubiquity comes a massive body of search engine queries revolving around destinations of interest, hotel options and airfare, and planned activities (Law et al., 2019; Pan et al., 2012). Search query data reflect travelers' attention and have been introduced into forecasting models to project tourism demand. For instance, Choi and Varian (2012) forecasted Hong Kong's tourism demand using Google Trends data and confirmed the usefulness of search query data. Blal and Sturman (2014) found that hotel sales could be forecasted more accurately with online search data. More recently, Pan and Yang (2017a) reconfirmed the effectiveness of search query data for hotel demand forecasting. Overall, studies indicate that search query data can offer meaningful insight into tourists' interests, intentions, preferences, and opinions. These data also serve as powerful predictors of tourism demand (Li et al., 2017; Yang et al., 2014).

To leverage search engine query data more effectively, scholars have adapted multiple forecasting models. For instance, Pan et al. (2012) compared the forecasting performance of an autoregressive integrated moving average with exogenous input (ARIMAX) model and ARMA family models. Findings showed that ARIMAX with Google search queries led to greater forecasting accuracy than other methods. Volchek et al. (2019) included Google Trends in their time series, econometric, and AI models and enjoyed enhanced museum demand forecasting. Sun et al. (2019) demonstrated greatly improved forecasting performance when including Google and Baidu indexes in their developed kernel extreme learning machine model. Wen et al. (2019) stated that their hybrid ARIMA-ANN model was improved by integrating the Baidu index for tourism demand forecasting. One year later, the performance of their improved mixed data sampling seasonal ARIMA model again exceeded that of traditional models (Wen et al., 2021). Li and Law (2020) developed an ensemble empirical decomposition method that deconstructed search engine queries from Google into more specific components with simplified data series. Their results showed that this methodology outperformed the benchmark model in a forecasting evaluation.

Along with the growing use of search engine queries in forecasting models, how to better incorporate search engine queries into forecasting (e.g., through keyword selection) has become increasingly important (Sun et al., 2019). An intuitive strategy involves applying data from Google Trends categories or exact keywords (i.e., Bangwayo-Skeete & Skeete, 2015; Ginsberg et al., 2009; Pan et al., 2012). Some studies have included search-engine-recommended keywords (Huang et al., 2017; Rivera, 2016), whereas other authors have chosen keywords based on correlations among predictive variables (Peng et al., 2017; Yang et al., 2015). Identifying the geographic origin(s) of search data is also essential because tourism activities are unevenly distributed over space: search queries from certain areas can be more relevant and informative than others. Yang et al. (2014) found that a business traveler–focused destination differed from a vacation-focused destination in the planning horizon. Their results suggested the importance of considering the geographic origin of search queries, such that certain models need to be tested based on geographic areas' specific characteristics.

COVID-19 and tourism demand forecasting

Since its emergence around 2020, the COVID-19 pandemic has changed the world in every imaginable respect. It has obliterated tourism industry predictions given this sector's high sensitivity to the crisis. Tourism demand is substantially affected whenever a viral outbreak occurs (Page et al., 2012). Many researchers have begun to examine the pandemic's impact on tourism demand. Gössling et al. (2020) provided a rapid assessment of COVID-19 within the tourism industry and compared this crisis to previous ones. Hao et al. (2020) reviewed the pandemic's overall effects on China's hotel industry, stating that the outbreak has influenced the industry's adoption of digital technology, product design, and investment preferences. Hoque et al. (2020) also measured the impact of COVID-19 on China's tourism industry and found the sector to be heavily affected. Liew (2020) investigated COVID-19's effects on tourism industry share prices using data from Booking.com, Expedia, and Trip.com; findings reflected a rapid decline in tourism industry performance amid the pandemic. Polyzos et al. (2021) considered the anticipated consequences of the COVID-19 outbreak on tourist arrivals by employing data from the SARS outbreak in 2003 to train a deep learning ANN entitled long short-term memory model (LSTM). They asserted that the current pandemic could have notably adverse effects on the tourism industry and adjacent sectors. They further suggested that the recovery of tourist arrivals to pre-crisis levels might take up to a year. Wu et al. (2020) investigated the impact of COVID-19 on Hong Kong's hotel industry. Their results indicated that 4- and 4.5-star hotels were most seriously affected while 5-star hotels were least affected by the pandemic.

Although numerous studies have scrutinized COVID-19's impact on the tourism industry, few have focused on tourism demand forecasting during this time. Korinth (2021) discussed the negative tourism implications of the pandemic in Poland by forecasting time series with ARIMA. A large impact was predicted in central Poland, where passenger air traffic and the proportion of occupied accommodation decreased significantly. Liu et al. (2022) evaluated forecasting errors across different prediction horizons and examined predictors of *ex-ante* forecasting accuracy based on the Pacific Asia Tourism Association's annually published forecasts. The authors recommended a combination of judgmental forecasting methods and econometric models to enhance forecasting accuracy, especially during a catastrophe such as COVID-19. Polyzos et al. (2021) predicted the pandemic's impacts on Chinese tourist arrivals in the United States and Australia; their ANN model indicated that tourist arrivals would resume normal patterns within roughly a year for the United States and half a year for Australia. Wickramasinghe and Ratnasiri (2021) developed disaggregated forecasts via four time series models (i.e., ARMA, ARMAX, SARMA, and SARMAX) for international arrivals in Sri Lanka using Google search query data. They found that the guest night variable could better project the economic consequences of the COVID-19 pandemic. Fotiadis et al. (2021) conducted tourism demand forecasting using a generalized additive model and LSTM neural network. Their findings implied that the decline in tourist arrivals would range from 30.8% to 76.3% during the pandemic. The authors further suggested that this crisis is far from over in the tourism sector. Similarly, Zhang, Song, et al. (2021) assembled *ex-ante* forecasts for post-pandemic tourism demand recovery using a combination of one quantitative model and two qualitative methods. They identified experts' opinions as key indicators that promoted the accuracy of tourism demand forecasting; therefore, they recommended predicting explanatory variables using different methods.

Most recently, a competition challenged researchers to employ demand forecasting to identify the most effective forecasting methods in a crisis. Forecasting involved two phases: Phase 1 identified the most accurate method for *ex-post* forecasts of arrivals before COVID-19; Phase 2 generated *ex-ante* forecasts of arrivals during and after COVID-19 using a baseline (assuming no COVID-19) and three pandemic scenarios (mild, moderate, and severe COVID-19 effects). Various forecasting techniques were adopted, including 11 single models (i.e., econometric, AI-based techniques, and time series approaches) and 26 stacking models. Kourentzes et al. (2021) used a combination of methods in Phase 1, including univariate/multivariate time series models, neural networks, and machine learning. Judgmental adjustments were applied to model-based forecasts in Phase 2. Results suggested an average recovery of 80% under the mild scenario, 58% under the moderate scenario, and 34% under the severe scenario, compared with tourist arrivals to 20 destinations in 2019. Qiu et al. (2021) discovered that the stacking models were more accurate for first-phase *ex-post* forecasts. In the second phase, their results showed a recovery of 53–70% compared with tourist arrivals in 20 destinations during 2019 under the mild scenario, 29–45% under the moderate scenario, and 9–23% under the severe scenario. Liu et al. (2021) proposed a scenario-based mixed judgmental forecasting method, indicating that some countries would recover to near baseline in the mild scenario.

It is worth considering the additional value of including search engine queries in forecasting during COVID-19. The sudden outbreak of COVID-19 becomes a considerable uncertainty to the general population about the potential risk to their health. In front of intense health risks associated with travel during the pandemics, tourists adopt different information search strategies to mitigate the potential risks (Haridasan et al., 2021). Compared to the pre-COVID time, tourists are more likely to read product and service information in advance (Zhang, Choi, & Akhmedov, 2021), which involves a certain level of online information search. Humagain and Singleton (2021) indicated that tourists tend to undertake extensive planning and information searching in the presence of various constraints associated with outdoor recreation trips during COVID-19. Although limited tourism literature has addressed this issue, revelations may lie in recent studies from other disciplines. Cousins et al. (2020) investigated how search engine query patterns increase the accuracy of predicting COVID-19 case rates in the United States. They identified a high correlation between predicted and confirmed case rates at the metropolitan level. Yom-Tov et al. (2020) analyzed Bing search queries and regarded abnormal cases in certain regions of the country. They also discerned a significant correlation between searches for "fever" and "cough" and future case counts.

Google Trends data have also been found to be useful in forecasting economic indicators during the COVID-19 pandemic. For example, Petropoulos et al. (2021) used the Google Trends data to predict financial market turbulence with a Deep Learning method, and the usefulness of the data was confirmed for short time forecasts. Nebolsina (2021) forecasted the U.S. business interruption insurance demand based on a related keyword from Google Trends, and a positive relationship was revealed between the Google Trends data and initial claims for unemployment insurance benefits. Likewise, Aaronson et al. (2021) leveraged the Google Trends indexes to forecast unemployment insurance claims during the COVID-19 pandemic, and the model performed well because of the high-frequency information on labor market activity provided by the Google Trends data. To date, however, it remains unclear how much value can be gleaned from incorporating search engine queries into tourism demand forecasting during the pandemic. This lacuna inspired our study.

Research methods

Data sources

We collected daily data from several sources between January 2019 and November 2020. We referred to hotels' daily occupancy change versus the same-day level in 2019 to measure tourism demand (Yang et al., 2014). These data were obtained from STR, LLC, the global leading hotel data vendor, and were collected from a large and representative sample of hotel properties (Haywood et al., 2017). Additional data were gathered to predict tourism demand. First, we obtained daily flight departure data from major international airports in each country from the International Civil Aviation Organization. Air traffic is largely inter-related with hotel demand (Yang et al., 2021), and in particular, due to the time lag between air flight arrival and hotel check-in, air traffic data can help predict hotel demand. Second, we obtained geotagged Twitter data to gauge the daily number of tweets from travelers in each country. Many studies confirmed the usefulness of geotagged UGC to proxy/monitor tourism demand along with the growing penetration of various social media platforms (Kim et al., 2022). In particular, during the COVID-19 pandemic, Twitter data can be powerful to demonstrate the human mobility dynamics (Huang et al., 2020), which can provide helpful information on predicting hotel demand. Third, we gathered data on the number of COVID-19 cases from the European Centre for Disease Prevention and Control (https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-COVID-19-cases-worldwide). Pandemic severity has been shown to influence tourism demand during the pandemic (Li et al., 2021). Fourth, we collected data on the stringency index of each country, which measures the degree of stringency in a country's policy responses to the pandemic (Hale et al., 2021); this information was gathered from Oxford's COVID-19 Government Response Tracker. More stringent policies limit people's mobility, ultimately lowering tourism demand (Plzáková & Smeral, 2021). As a result, it can be a vital predictor of demand during pandemics. Lastly, from Google Trends, we collected the daily Google search volume for four keywords: "[country name] hotel", "[country name] vacation", "[country name] travel", and "[country name] flight" (Rivera, 2016), which reflect different aspects of information that tourists are likely to search and collect before the trip.

Forecasting model

We employed a dynamic time series model, specifically an autoregressive exogenous model (ARX), to forecast tourism demand. The ARX model's final structure was as follows:

$$y_t = \alpha + \sum_{m=i}^{I} \rho_m\, y_{t-m} + \sum_{k=1}^{K} \sum_{m=j}^{J} \phi_{k,m}\, x_{k,t-m} + \sum_{w=1}^{6} \psi_w D_{t,w} + \sum_{v=1}^{11} \tau_v M_{t,v} + \varepsilon_t \tag{1}$$

where y_t is the variable to be forecasted, $x_{k,\,t}$ is the k-th explanatory variable, and $D_{t,\,w}$ represents the day-of-the-week dummy variable. $D_{t,\,1}$ is equal to 1, for example, when the t-th day is Sunday and is equal to 0 otherwise. Likewise, $M_{t,\,w}$ represents the monthly dummy variable to capture the seasonality of tourism demand. Here, ε_t denotes the model error, which is independent and identically distributed; I, J represents the maximum lag order of the variable; and $\boldsymbol{\theta} = (\alpha, \boldsymbol{\rho}, \boldsymbol{\phi}, \boldsymbol{\psi}, \boldsymbol{\tau})^\top$ are unknown parameters that need to be estimated. To estimate a model that enables ex-ante forecasts, we set $I \geq n$ and $J \geq n$ for n-step-ahead forecasts.

In this paper, the lasso method was used to select the optimal lag order for each variable. This approach has demonstrated advantages in dimensionality reduction and variable selection. In this research context, we have a large number of different predictors as well as their lags to choose for forecasting. In some cases, the number of these predictors can exceed the sample size, leaving traditional time-series models, such as ARIMAX and factor models, unable to select an appropriate set of predictors. We refer readers to Tibshirani (1996) for more details on the lasso method. Different from traditional ordinary least squares estimation, this approach uses an l_1-norm penalty to regularize parameter estimation; that is, the following score function is minimized to estimate unknown parameters $\boldsymbol{\theta}$:

$$\begin{cases} RSS = \sum_{t=1}^{n} \left(y_t - \alpha - \sum_{m=i}^{I} \rho_m\, y_{t-m} - \sum_{k=1}^{K} \sum_{m=j}^{J} \phi_{k,m} x_{k,t-m} - \sum_{w=1}^{6} \psi_w D_{t,w} - \sum_{v=1}^{11} \tau_v M_{t,v} \right)^2, \\ \hat{\boldsymbol{\theta}} = \arg\min \left\{ RSS + \lambda \left(\sum_{m=i}^{I} |\rho_m| + \sum_{k=1}^{K} \sum_{m=j}^{J} |\phi_{k,m}| \right) \right\} \end{cases} \tag{2}$$

where λ denotes the regularization parameter. In this study, we could control the weekday variable and monthly variable without being punished. Note that the choice of parameter λ is important: Uniejewski et al. (2019) explained that λ represents a trade-off between minimizing the residual sum of squares and variable selection. We employed two methods to select an appropriate λ value, namely cross-validation (CV) and the information criteria method. For the CV method, we chose the λ of the smallest mean squared prediction error (MSE) and the largest λ within one standard deviation of the minimum, respectively. Regarding the information criteria method, three criteria were used to select λ: the Akaike information criterion (AIC) (Akaike, 1973), the Bayesian information criterion (BIC) (Schwarz, 1978), and the bias-corrected AIC (AICc) (Sugiura, 1978).

An alternative model is a factor model that incorporates a composite search index of Google search information into the time-series model (Li et al., 2017). We used factor analysis to get the factor scores of y_{t-m}'s and $x_{k,\ t-m}$'s and to replace $\sum_{m=i}^{I}\rho_m\, y_{t-m} + \sum_{k=1}^{K}\sum_{m=j}^{J}\phi_{k,\ m}\, x_{k,\ t-m}$ in Eq. 1. Only factors with an eigenvalue larger than one were kept.

Forecasting comparison

We conducted *ex-ante* forecasting in July 2020 (using data from January 1 to July 18, 2020 to predict the data in July 19 to 25, 2020 for one-step-ahead forecasting) and November 2020 (using data from January 1 to November 15, 2020 to predict the data in November 16 to 22, 2020 for one-step-ahead forecasting). While our data end in early November 2020, early July 2020 is close to the midpoint of our data sample, and it captures the beginning of summer travel in many countries in the northern hemisphere. Based on these two sets of data, we generated 1- to 7-steps-ahead forecasts (i.e., $n = 1, 2, \ldots, 7$). We assumed a maximum lag order of 24. We compared forecasting accuracy based on three metrics: the mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) (Peng et al., 2014). These measures can be calculated as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} |\hat{y}_t - y_t| \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (\hat{y}_t - y_t)^2} \tag{4}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{\hat{y}_t - y_t}{y_t}\right| * 100\% \tag{5}$$

where n denotes the number of forecasts; $\hat{y}_t$ represents the predicted value; and y_t is the actual value.

Data description

Table 1 lists descriptive statistics for dependent and independent variables in the model. In the sample, the average occupancy rate change is −51.378, indicating a substantial shock of the pandemic on hotel demand compared to the same day in 2019. The standard deviation is 26.200, unveiling considerable variation of occupancy rate change over time and across different countries. Likewise, the average flight departure change is −63.521, highlighting the dramatic hit on the aviation industry worldwide. Fig. 1 demonstrates the time series plot of these variables. For the demand variable, occupancy, it reached the bottom around early April 2020 and then bounced back. After June 2020, a significant weekly pattern was noticed in this variable. This pattern applies to air flight as well, while a lag between the two was also noticed. A similar pattern also characterized the trend of four different Google trends variables.

Table 1
Descriptive statistics of variables used for forecasting.

Variables	Definition	Sample size	Mean	Standard deviation
Occupancy	Change in daily occupancy rate compared to the same day in 2019	24,642	−51.378	26.200
Google_hotel	Daily Google Trends index based on search volume for the keyword "[country name] hotel"	24,642	40.516	10.977
Google_vacation	Daily Google Trends index based on search volume for the keyword "[country name] vacation"	24,642	20.131	12.446
Google_travel	Daily Google Trends index based on search volume for the keyword "[country name] travel"	24,642	34.216	16.389
Google_flight	Daily Google Trends index based on search volume for the keyword "[country name] flight"	24,642	37.205	17.185
Air_flight	Change in daily flight departures from international airports compared to the same day in 2019	24,642	−63.421	34.552
Policy	Daily degree of stringency in a country's policy responses to the pandemic	24,642	51.884	24.606
Twitter	Change in daily number of tweets of travelers compared to the same day in 2019	24,642	−6.013	8.173
Covid_cases	Daily number of confirmed COVID-19 cases	24,642	2257.581	2068.304

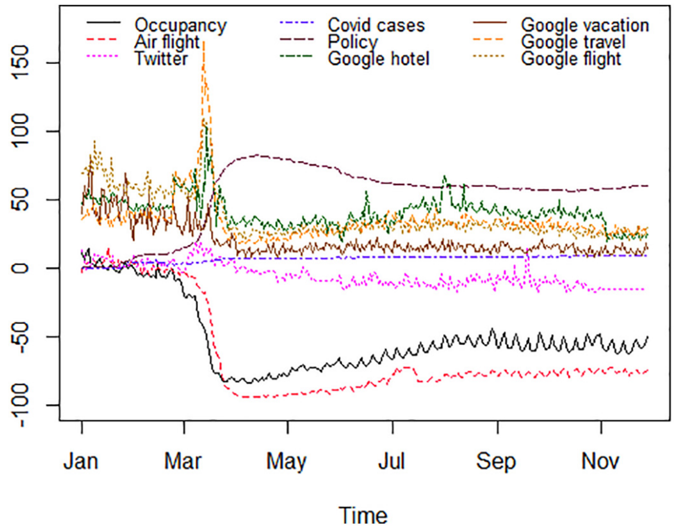

Fig. 1. Time series plot of major variables used in forecasting (Note: covid cases are plot in log).

Empirical results

Forecasting results

We first estimated the model using the lasso method for each of 74 countries in the dataset. We estimated a model for two periods: from January 1 to July 18, 2020 and from January 1 to November 15, 2020. To evaluate the effectiveness of Google Trends data, we estimated a model with and without Google Trends variables. In total, we estimated 74 (number of countries) × 2 (two forecasting periods: July and November 2020) × 2 (two models: one with and without Google Trends data) × 5 (five λ selection methods) × 7 (1- to 7-steps-ahead forecasting model) = 10,360 lasso models and 74 (number of countries) × 2 (two models: one with and without Google Trends data) × 7 (1- to 7-steps-ahead forecasting model) = 1036 factor models.

After that, we conducted *ex-ante* forecasting to investigate the model's out-of-sample forecasting accuracy with and without Google Trends data (as predictors). Table 2 presents the three error measures for different models based on the average from all 74 countries. Interestingly, models selected by lasso method and determined by various information criteria, such as AIC, BIC, and AICc, consistently demonstrated significantly lower accuracy than their counterparts based on CV. The error measures from information criterion models are thus not presented for brevity but are available upon request. For forecasts across all horizons, we found that CV with one standard deviation of the minimum (CV_1SE) yielded less forecasting error than CV with the smallest MSE (CV_min). Therefore, we provided the specifications of CV_1SE lasso method in the online supplementary materials. We calculated error differences between the model with and without Google Trends data, labeled as "Difference (CV_min)" based on CV_min and "Difference (CV_1SE)" based on CV_1SE (Table 2). For all forecasts, Difference (CV_min) and Difference (CV_1SE) were positive across all three error measures, indicating higher average forecasting errors in the model with Google Trends data. However, in some cases, we found that models with Google Trends data lead to a lower average forecasting error, such as Difference (CV_min) for 6-steps-ahead forecasts. We further calculated two indicators reflecting the percentage of models with Google Trends data that yielded more accurate out-of-sample forecasts than their counterparts without such data (see Percentage [CV_min] and Percentage [CV_1SE]). These percentages were consistently lower than 50% for different error measures, providing no compelling evidence of the usefulness of Google Trends data in improving forecasting accuracy across all countries in our dataset. Lastly, when compared to the factor model, the model determined by lasso generates consistently lower forecasting errors as indicated by smaller MAE, MAPE, and RMSE values.

We mapped these percentage values across different countries in Fig. 2. Six maps were created based on two CV methods for the model determined by lasso and three error measures. In general, we found that Google Trends data could lower the forecasting error in some countries in Southern Asia and Oceania. More notably, these percentage values covered a large range, conveying substantial heterogeneity in the effectiveness of Google Trends data in boosting tourism demand forecasting accuracy during the pandemic.

Table 2 also outlines error measures across different forecasting horizons (i.e., from 1 to 7 steps ahead). Values in the first six columns indicate an increase in forecasting errors as the forecasting horizon expanded. We did not find any significant evidence on the usefulness of Google Trends data in reducing the error across different forecasting horizons. For instance, all values in Percentage (CV_min) and Percentage (CV_1SE) are below 50%, suggesting that less than half of models with Google Trends data outperform their counterparts without the Google Trends data. Fig. 3 demonstrates how the percentage of superior forecasting models with Google Trends data, Percentage (CV_1SE), changed across forecasting horizons. The potential usefulness of Google

Table 2
Forecasting performance of different models across different forecasting windows.

Error measure	CV_min (with Google)	CV_1SE (with Google)	Factor (with Google)	CV_min (without Google)	CV_1SE (without Google)	Factor (without Google)	Difference (CV_min)	Difference (CV_1SE)	Difference (Factor)	Percentage (CV_min)	Percentage (CV_1SE)	Percentage (Factor)
All												
MAE	8.199	7.126	10.577	7.949	6.572	10.729	0.250	0.554	−0.152	44.7%	43.1%	51.4%
MAPE	0.251	0.208	0.272	0.244	0.199	0.281	0.006	0.009	−0.009	44.2%	43.2%	52.1%
RMSE	9.571	8.119	11.652	9.382	7.578	11.755	0.189	0.541	−0.103	43.9%	43.0%	49.8%
1-step-ahead												
MAE	4.336	4.397	9.030	4.154	4.142	8.637	0.182	0.255	0.393	40.5%	38.5%	50.0%
MAPE	0.105	0.108	0.212	0.100	0.103	0.209	0.005	0.005	0.004	38.5%	37.2%	50.0%
RMSE	5.267	5.275	10.236	5.085	5.023	9.646	0.182	0.252	0.589	37.8%	39.9%	45.9%
2-steps-ahead												
MAE	6.480	6.063	9.470	6.094	5.740	9.425	0.386	0.323	0.045	44.6%	41.9%	47.3%
MAPE	0.157	0.151	0.220	0.147	0.145	0.227	0.011	0.007	−0.007	44.6%	41.9%	48.6%
RMSE	7.629	7.058	10.641	7.265	6.738	10.453	0.364	0.321	0.188	46.6%	41.2%	44.6%
3-steps-ahead												
MAE	7.658	6.895	9.946	7.128	6.379	9.951	0.530	0.516	−0.006	40.5%	42.6%	50.0%
MAPE	0.192	0.173	0.232	0.175	0.163	0.237	0.016	0.010	−0.005	40.5%	44.6%	50.0%
RMSE	8.832	7.864	11.041	8.338	7.372	11.018	0.494	0.492	0.023	43.2%	44.6%	47.3%
4-steps-ahead												
MAE	8.861	7.396	10.638	8.598	6.946	10.605	0.263	0.450	0.033	44.6%	46.6%	54.1%
MAPE	0.238	0.191	0.253	0.227	0.184	0.253	0.011	0.007	0.000	44.6%	45.9%	54.1%
RMSE	10.492	8.414	11.678	9.938	7.947	11.676	0.553	0.467	0.001	42.6%	43.9%	51.4%
5-steps-ahead												
MAE	9.341	7.913	11.029	8.884	7.462	11.379	0.458	0.451	−0.350	45.9%	43.9%	54.1%
MAPE	0.320	0.234	0.293	0.325	0.263	0.306	−0.005	−0.030	−0.013	44.6%	44.6%	54.1%
RMSE	10.862	8.908	11.979	10.472	8.494	12.348	0.390	0.415	−0.368	45.3%	46.6%	54.1%
6-steps-ahead												
MAE	9.972	8.287	11.764	10.881	7.501	12.169	−0.910	0.787	−0.405	47.3%	45.3%	54.1%
MAPE	0.345	0.269	0.329	0.361	0.252	0.341	−0.016	0.017	−0.013	47.3%	46.6%	54.1%
RMSE	11.569	9.327	12.778	13.093	8.566	13.176	−1.524	0.761	−0.397	43.2%	45.3%	52.7%
7-steps-ahead												
MAE	10.744	8.928	12.163	9.906	7.834	12.935	0.838	1.094	−0.772	49.3%	42.6%	50.0%
MAPE	0.397	0.327	0.368	0.375	0.280	0.396	0.022	0.047	−0.028	49.3%	41.9%	54.1%
RMSE	12.343	9.984	13.208	11.482	8.908	13.967	0.862	1.077	−0.759	48.6%	39.2%	52.7%

Trends data (measured by the percent of models with Google Trends data as the superior model) peaked for 4- to 6-steps-ahead forecasts, no matter which error measure was used, and then declined.

We further compared forecasting results in July and November 2020, representing different pandemic situations across the world. Key results appear in Table 3. Based on all forecasting horizons, nearly all percentage values (i.e., Percentage [CV_min] and Percentage [CV_1SE]) were lower than 50% for July and November forecasts. Across forecasting horizons, the potential effectiveness of Google Trends data was slightly higher when forecasting 4- to 6-steps-ahead tourism demand as indicated by the large percentage values. However, only some values based on RMSE in November were found to be above 50%. Again, we did not find any convincing evidence on the general usefulness of Google Trends data in improving forecasting accuracy based on the average data.

Similar to Fig. 3, Fig. 4 reflects how the percentage of superior models with Google Trends data, Percentage (CV_1SE), varied across forecasting horizons for forecasts in July and November 2020. In general, some forecasting models with Google Trends data outperformed those without these predictors in November forecasts measured by RMSE. Echoing the results in Fig. 3, the percentage of superior forecasting models with the Google Trends data was higher in 4- to 6-steps-ahead forecasts based on the three forecasting error measures.

Factors influencing forecasting performance

As we observed mixed results on the usefulness of Google Trends data for improving daily tourism forecasting accuracy (as shown in Fig. 2 and Tables 2 and 3), we were particularly interested in determining which factors could explain the relative usefulness of this data. Therefore, a regression analysis was conducted to investigate which variables were statistically significant in explaining relative forecasting error as dependent variables. Two dependent variables were used: (1) *error_difference*, calculated as the forecasting error of a model with Google Trends data minus that of a model without these data; and (2) a dummy variable, *usefulness*, where $usefulness = 1$ if the $error\_difference < 0$, thus indicating the superiority of forecasts from a model including Google Trends data. Note that, as CV_1SE generated lower forecasting errors than CV_min in Tables 2 and 3, only model forecasts from CV_1SE were considered in regression analysis.

A set of independent variables was incorporated into regression analysis. As discussed in the previous section, the month of forecasting (either July or November 2020), the forecasting horizon (1 to 7 steps ahead), and error measures (MAE, MAPE, or

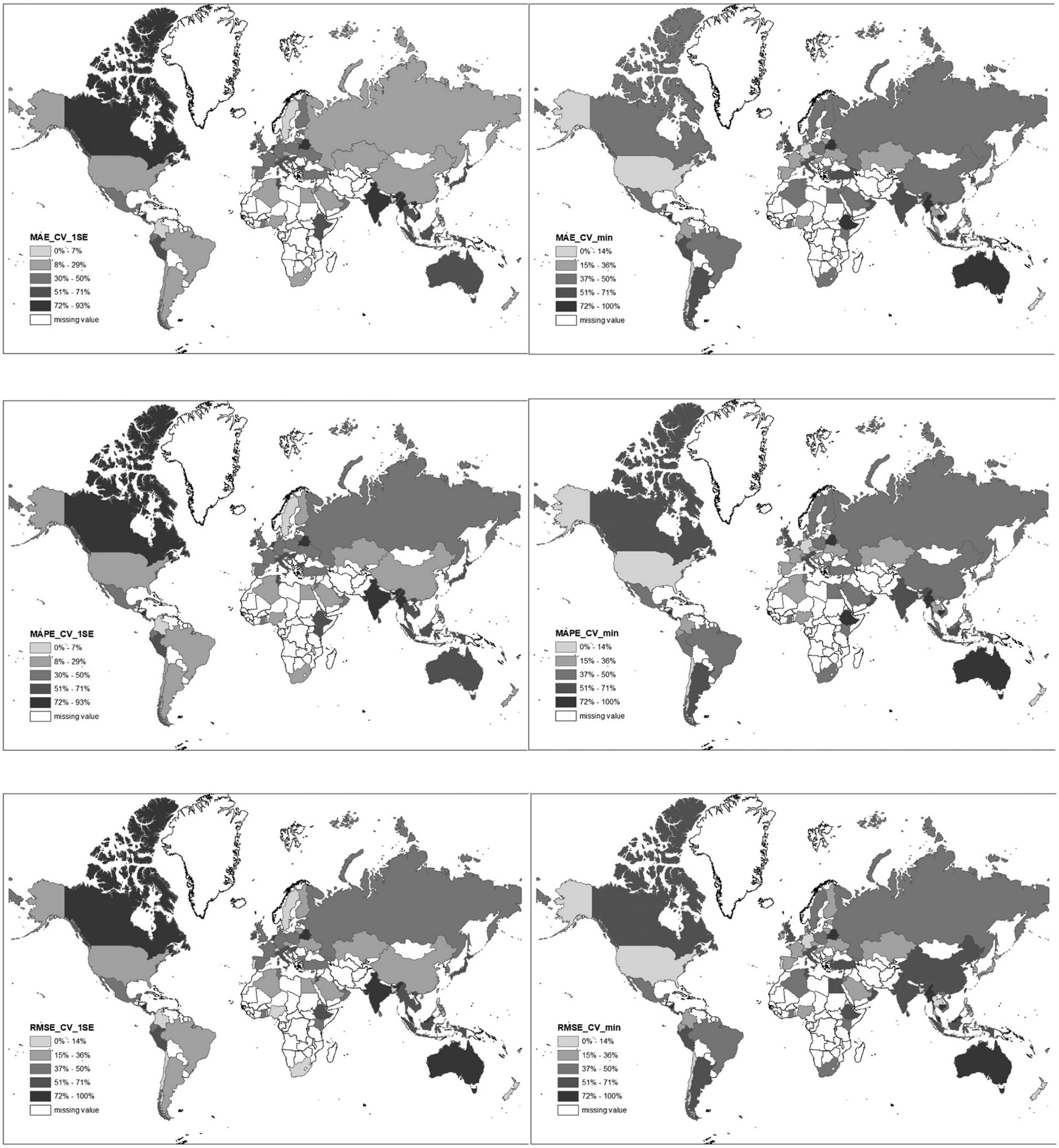

Fig. 2. Map of usefulness of Google Trends data in reducing forecasting errors.

RMSE) varied. We also proposed several other factors. First, *lnpandemic* measures the smoothed number of confirmed COVID-19 cases per million population (in log) on either July 18 or November 15, 2020. These data were collected from the European Centre for Disease Prevention and Control and used to measure a country's pandemic severity. Second, *lnforeign_percent* denotes visitor exports (foreign spending) over internal travel and tourism consumption in 2019 (in log); the data were collected from World Bank's TCdata360 database. This variable measures the relative importance of inbound tourism to domestic tourism. Third, *lnInternet* represents the log of individuals using the Internet (% of the population) in 2019, gathered from World Bank's World Development Indicator database. This variable was used as a proxy of a country's Internet infrastructure. Lastly, *island* represents a dummy variable indicating a country's geography: *island* $= 1$ for island countries and countries without land borders with other countries, and *island* $= 0$ otherwise.

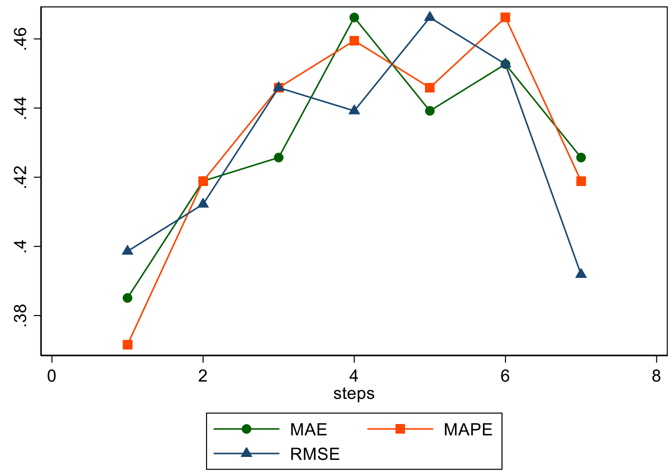

Fig. 3. Relative usefulness of Google Trends data across different forecasting windows (Note: The vertical axis represents the percentage of models with Google Trends data that outperform the corresponding model without Google Trends data.)

Table 4 presents the descriptive statistics of dependent and independent variables. Our sample consisted of 3108 observations from 74 countries. The mean value of *usefulness* was 0.431, indicating that only 43.1% of models with Google Trends data generated more accurate forecasts than their counterparts without these data. Also, 16.2% of observations were from island countries or countries without land borders. Due to data unavailability, *lnInternet* was only available for 2352 observations.

Table 3
Forecasting performance of different models across different forecasting windows in different forecasting periods.

Error measure	Difference (CV_min)	Difference (CV_1SE)	Percentage (CV_min)	Percentage (CV_1SE)	Difference (CV_min)	Difference (CV_1SE)	Difference (Factor)	Percentage (CV_min)	Percentage (CV_1SE)	Percentage (Factor)
	July	July	July	July	November	November	November	November	November	November
All										
MAE	0.649	0.853	42.47%	40.35%	−0.149	0.254	−0.152	46.91%	45.75%	51.35%
MAPE	0.018	0.018	40.93%	40.15%	−0.006	0.000	−0.009	47.49%	46.33%	52.12%
RMSE	0.509	0.869	41.70%	38.80%	−0.131	0.212	−0.103	46.14%	47.10%	49.81%
1-step-ahead										
MAE	0.297	0.352	40.54%	35.14%	0.066	0.157	0.393	40.54%	41.89%	50.00%
MAPE	0.008	0.008	37.84%	31.08%	0.003	0.003	0.004	39.19%	43.24%	50.00%
RMSE	0.367	0.372	35.14%	28.38%	−0.002	0.131	0.589	40.54%	51.35%	45.95%
2-steps-ahead										
MAE	0.428	0.501	44.59%	39.19%	0.345	0.145	0.045	44.59%	44.59%	47.30%
MAPE	0.015	0.011	40.54%	40.54%	0.007	0.002	−0.007	48.65%	43.24%	48.65%
RMSE	0.431	0.519	41.89%	39.19%	0.297	0.122	0.188	51.35%	43.24%	44.59%
3-steps-ahead										
MAE	0.655	0.698	41.89%	43.24%	0.406	0.335	−0.006	39.19%	41.89%	50.00%
MAPE	0.017	0.014	40.54%	44.59%	0.016	0.006	−0.005	40.54%	44.59%	50.00%
RMSE	0.580	0.667	45.95%	44.59%	0.409	0.317	0.023	40.54%	44.59%	47.30%
4-steps-ahead										
MAE	0.781	0.638	43.24%	44.59%	−0.255	0.263	0.033	45.95%	48.65%	54.05%
MAPE	0.021	0.013	41.89%	44.59%	0.000	0.000	0.000	47.30%	47.30%	54.05%
RMSE	1.337	0.712	43.24%	40.54%	−0.231	0.222	0.001	41.89%	47.30%	51.35%
5-steps-ahead										
MAE	1.433	0.874	41.89%	39.19%	−0.517	0.028	−0.350	50.00%	48.65%	54.05%
MAPE	0.031	0.018	39.19%	39.19%	−0.041	−0.077	−0.013	50.00%	50.00%	54.05%
RMSE	1.228	0.901	41.89%	41.89%	−0.449	−0.072	−0.368	48.65%	51.35%	54.05%
6-steps-ahead										
MAE	−1.156	1.366	43.24%	43.24%	−0.664	0.208	−0.405	51.35%	47.30%	54.05%
MAPE	−0.002	0.029	43.24%	44.59%	−0.030	0.006	−0.013	51.35%	48.65%	54.05%
RMSE	−2.447	1.363	40.54%	40.54%	−0.600	0.158	−0.397	45.95%	50.00%	52.70%
7-steps-ahead										
MAE	2.103	1.543	41.89%	37.84%	−0.426	0.645	−0.772	56.76%	47.30%	50.00%
MAPE	0.039	0.032	43.24%	36.49%	0.004	0.062	−0.028	55.41%	47.30%	54.05%
RMSE	2.065	1.548	43.24%	36.49%	−0.342	0.606	−0.759	54.05%	41.89%	52.70%

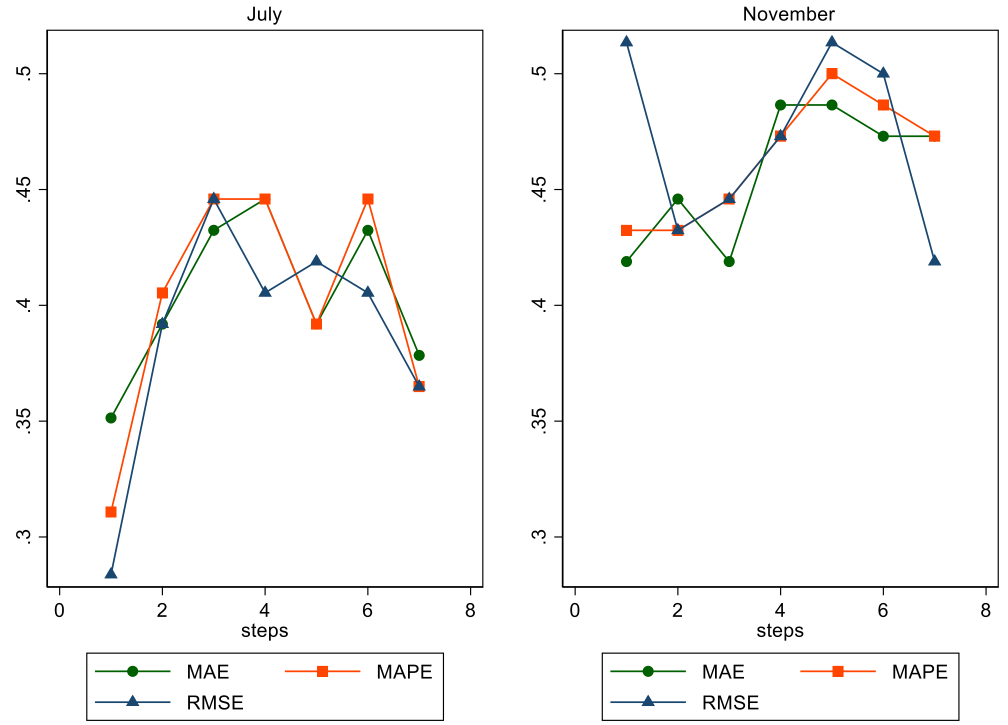

Fig. 4. Relative usefulness of Google Trends data across different forecasting windows over different periods (Note: The vertical axis represents the percentage of models with Google Trends data that outperform the corresponding model without Google Trends data.)

Table 5 displays the estimation results of regression analysis. In Model 1, we estimated the model parameters based on ordinary least squares with all 3108 observations, excluding the variable *lnInternet*. The coefficient of *lnpandemic* was estimated to be negative and statistically significant; specifically, a 100% increase in daily COVID-19 cases led to a 0.0309 decrease in relative forecasting error between the model with and without Google Trends data. Moreover, *lnforeign_percent* was estimated to be negative and significant, showing that the relative forecasting error with Google Trends data was lower in countries whose tourism industry was more reliant on inbound/foreign tourism. The dummy variable, *island*, was also found to have a negative and significant coefficient, and the relative forecasting error was lower for island countries and countries without land borders

Table 4
Descriptive statistics of variables in regression analysis.

Variable	Description	Obs	Mean	Std. Dev.
error_difference	Forecasting error of the model with Google Trends data minus that of the model without Google Trends data.	3108	0.368	2.340
usefulness	*usefulness* = 1 if *error_difference* < 0.	3108	0.431	0.495
lnpandemic	Smoothed number of COVID-19 confirmed cases per million population (in log)	3108	3.016	2.501
lnforeign_percent	Visitor exports (foreign spending) over internal travel and tourism consumption in 2019 (in log)	3108	−0.974	0.766
lnInternet	Individuals using the Internet (% of population) (in log)	2352	4.276	0.393
island = 1	Island countries and countries without land borders with any other countries	3108	0.162	0.369
island = 0		3108	0.838	0.369
month = July	Forecasts generated in July 2020	3108	0.500	0.500
month = November	Forecasts generated in November 2020	3108	0.500	0.500
steps = 1	1-step-ahead forecast	3108	0.143	0.350
steps = 2	2-steps-ahead forecast	3108	0.143	0.350
steps = 3	3-steps-ahead forecast	3108	0.143	0.350
steps = 4	4-steps-ahead forecast	3108	0.143	0.350
steps = 5	5-steps-ahead forecast	3108	0.143	0.350
steps = 6	6-steps-ahead forecast	3108	0.143	0.350
steps = 7	7-steps-ahead forecast	3108	0.143	0.350
error = MAE	Forecasting error measure based on MAE	3108	0.333	0.471
error = MAPE	Forecasting error measure based on MAPE	3108	0.333	0.471
error = RMSE	Forecasting error measure based on RMSE	3108	0.333	0.471

Table 5
Estimation results of regression analysis.

	Model 1	Model 2	Model 3	Model 4
	error_difference (OLS)	*error_difference (OLS)*	*usefulness (Logit)*	*usefulness (Logit)*
lnpandemic	−0.0309**	−0.0669***	−0.0156	0.0154
	(0.015)	(0.020)	(0.015)	(0.020)
lnforeign_percent	−0.247***	−0.270***	0.318***	0.316***
	(0.061)	(0.063)	(0.048)	(0.062)
island	−0.159*	−0.185*	0.102	0.170
	(0.094)	(0.101)	(0.099)	(0.117)
lnInternet		−0.0618		−0.238
		(0.153)		(0.224)
month = November	−0.377***	−0.596***	0.300***	0.478***
	(0.083)	(0.102)	(0.077)	(0.092)
steps = 2	0.0460	0.0992	0.134	0.291*
	(0.078)	(0.093)	(0.138)	(0.160)
steps = 3	0.169*	0.295***	0.227*	0.291*
	(0.100)	(0.113)	(0.138)	(0.160)
steps = 4	0.137	0.317**	0.292**	0.279*
	(0.120)	(0.136)	(0.138)	(0.161)
steps = 5	0.108	0.362**	0.274**	0.242
	(0.141)	(0.152)	(0.137)	(0.158)
steps = 6	0.351**	0.427**	0.302**	0.365**
	(0.155)	(0.169)	(0.137)	(0.159)
steps = 7	0.568***	0.854***	0.115	0.0260
	(0.155)	(0.176)	(0.138)	(0.160)
error = MAPE	−0.545***	−0.692***	0.00804	0.0108
	(0.088)	(0.100)	(0.090)	(0.104)
error = RMSE	−0.0132	−0.0339	−0.00402	0.0108
	(0.123)	(0.138)	(0.090)	(0.104)
constant	0.424***	0.921	−0.289**	0.477
	(0.138)	(0.659)	(0.132)	(0.563)
N	3108	2352	3108	2352
R2 / McFadden's R2	0.034	0.068	0.016	0.023
adj. R2 / McFadden's adj R2	0.031	0.063	0.008	0.012
AIC	14,022.2	10,514.2	4208.8	3162.6
BIC	14,100.8	10,594.9	4287.3	3243.3

Notes: (1) *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. (2) Robust standard errors are presented in parentheses.

than for others. In Model 2, when *lnInternet* was included, our sample was small: 2352 observations. The coefficient of *lnInternet* was negative but statistically insignificant. In Model 2, the estimated coefficients of other independent variables were mostly similar to their counterparts in Model 1, confirming the robustness of our regression model. Models 3 and 4 estimated two logit models based on the binary dependent variable, *usefulness*. The coefficient of *lnpandemic* became insignificant while that of *lnforeign_percent* remained significant in these two models. These positive coefficients underscored the usefulness of Google Trends data in boosting daily tourism forecasting accuracy in countries more dependent on inbound/foreign tourism (vs. domestic tourism). The estimated coefficients of *island* and *lnInternet* were not statistically significant in Models 3 and 4.

Conclusion and discussion

In this study, we forecasted daily tourism demand across 74 countries in 2020. A lasso method was used to estimate the forecasting model based on a set of predictors, including Google search queries, air traffic, governmental policies related to the pandemic, and human mobility patterns. In particular, we assessed the effectiveness of online search queries in tourism forecasting by comparing forecasting errors between models with and without Google Trends data across different forecasting horizons. The results indicated that, while we found no dominant evidence to support the usefulness of Google Trends data. Regression analysis further implied that online search query data such as Google Trends data were more useful in certain situations: when a higher number of COVID-19 cases per capita was reported; in countries more dependent on inbound/foreign tourism instead of domestic tourism; and in island countries and countries without land borders.

Tourism scholars have consistently pointed out the usefulness of online search query data for improving forecasting accuracy (Pan et al., 2012; Pan & Yang, 2017a). Yet our results from a global sample imply that insufficient evidence is available to support the usefulness of these data across countries; this usefulness was observed in only less than half of our sample. Results highlight potential publication bias, referring to "the selective publication of studies with a particular outcome" (Ferguson & Brannick, 2012, p. 120). Authors may be motivated to present more favorable results, such as the effectiveness of online search queries in this case, to reviewers through the double-blind review process. Consequently, findings suggesting the ineffectiveness of these data have a slight chance of being published. Different from studies focusing on a single region/unit or a small number thereof, we estimated 11,396 models for 74 countries worldwide. After that, we generated forecasts across different forecasting horizons to provide representative insight on when and where digital footprints, such as Google Trends data, serve as helpful predictors to improve forecasting accuracy.

This study stresses that no one-size-fits-all model is currently available to forecast tourism demand based on online search queries. More importantly, our findings unveiled a set of factors explaining the relative effectiveness of Google search query data in tourism forecasting. First, when a country's pandemic situation is more severe, Google search queries can be more effective in enhancing tourism demand forecasting performance. A possible reason is that a challenging pandemic leads to high destination uncertainty. In this case, tourists are more likely to gather information from different sources, such as online search engines, to prepare themselves for travel (Xiang & Fesenmaier, 2020). This trip planning leaves richer and more informational digital footprints that can be leveraged for forecasting purposes. Second, Google Trends data are more useful in countries more reliant on inbound/foreign tourism. International travel involves greater risk than domestic trips due to tourists' relative unfamiliarity with a destination's socio-cultural environment and limited access to resources in an emergency (Seabra et al., 2013). Inbound/foreign tourists are therefore more likely to search online for information, making digital footprints more useful as demand predictors.

Our results also offer several important implications for industry practitioners. First and foremost, a single model's forecasting performance can vary substantially at different points in the pandemic (depending on local circumstances and other relevant indicators). As such, we advocate for referring to forecasting results from multiple models to gain a clearer sense of predictions. Second, as shown in our forecasting comparison, Google search query data can potentially improve daily tourism demand forecasting accuracy amid a pandemic surge. Third, various tourism demand forecasting systems/platforms should be used to gather information—especially digital footprint data such as from Google Trends—and incorporate predictors into tourism forecasting models. Last but not least, when designing time-varying combination weights to combine tourism forecasts during the pandemic (Shen et al., 2011), pandemic severity is critical to consider.

Several limitations may temper the generalizability of our results. First, we only investigated forecasting performance in the early stages of the pandemic; a more thorough analysis across different pandemic phases would paint a more vivid picture of digital footprints' effectiveness in tourism forecasting. Second, we only leveraged one forecasting model, the lasso method. Other models can be compared to identify best practices when incorporating digital footprint data into forecasting models. In particular, many studies have outlined the merits of hybrid forecasting (Shen et al., 2011), which was not evaluated in this study. Third, we considered short-term forecasting up to 7 days ahead. As Yang et al. (2014) indicated, most visitors browse online for roughly 4 weeks before traveling; therefore, a wider forecasting horizon can be assessed in future research efforts. Fourth, due to data unavailability, we were unable to incorporate seasonality factors in our forecasting model. As seasonality characterizes tourism demand and becomes a major focus in tourism forecasting, future studies need longer data to capture the seasonality pattern in the model. Lastly, daily tourism demand data were collected at the national level, yet daily forecasting for some large countries can mask substantial within-country heterogeneity in tourism. We hence call for forecasting studies at a more local level to verify and expand the findings of this research.

CRediT authorship contribution statement

Yang Yang: Conceptualization; Formal analysis; Project management.
Yawen Fan: Data curation; Formal analysis; Writing - original draft.
Lan Jiang: Writing - original draft.
Xiaohui Liu: Conceptualization; Visualization; Writing- revision.

Declaration of competing interest

None.

Appendix A. Supplementary data

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