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FORECASTING TOURISM DEMAND WITH GOOGLE TRENDS FOR A MAJOR EUROPEAN CITY DESTINATION

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The purpose of this study is to investigate whether using Google Trends indices for web and image search improves tourism demand forecast accuracy relative to a purely autoregressive baseline model. To this end, Vienna—one of the top-10 European city destinations—is chosen as a case example for which the predictive power of Google Trends is evaluated at the total demand and at the source market levels. The effect of the search query language on predictability of arrivals is considered, and differences between seasonal and seasonally adjusted data are investigated. The results confirm that the forecast accuracy is improved when Google Trends data are included across source markets and forecast horizons for seasonal and seasonally adjusted data, leaning toward native language searches. This outperformance not only holds relative to purely autoregressive baseline specifications but also relative to time-series models such as Holt–Winters and naive benchmarks, in which the latter are significantly outperformed on a regular basis.

Key words: Tourism demand forecasting; City tourism; Monthly data; Google trends; Forecast accuracy

Introduction

The travel and tourism industry is tremendously important given that it contributed US$7 trillion to world gross domestic product and accounted for 266 million jobs worldwide in 2013 (World Travel and Tourism Council, 2013). The size of the industry and the number of travel-related players induce competition in terms of attracting visitors. The promotion of travel products and services provides customers with information and knowledge in a persuasive manner in the hope of producing sales of the services (Morrison, 2002).

Travel information provided to customers gives rise to functional, financial, psychological, and social risks (Lovelock & Wright, 1999). To reduce these risks, individuals invest time, effort, and financial resources to acquire the information they need to make decisions. There are many different travel information sources available, such as personal sources (e.g., friends and relatives via word of mouth) and marketer-dominated paid forms of

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communication (e.g., information from hotels, airlines, or destination management organizations [DMOs]) (Fodness & Murray, 1998). In the past two decades, the Internet has become one of the main channels for the communication of travel-related information. According to Fesenmaier, Xiang, Pan, and Law (2011), search engines are the starting point for interaction with DMOs. For potential and existing visitors, Google is recognized as the most fitting search engine for the online tourism domain (Xiang, Wöber, & Fesenmaier, 2008).

Since the beginning of the 1990s, consumers' use of the Internet has evolved from curiosity to reliance. Today, the Internet has become a ubiquitous commodity, such as electricity, which is integrated in individuals' daily lives. According to a Pew Research Center report, 46% of respondents indicated that the Internet is the most important technology that would be very hard or impossible to give up, followed by mobile phones with 44% (Fox & Rainie, 2014).

One of the main information sources on the Internet is search engines such as Google, Yahoo, and Bing. Among the leading search engines, Google dominates with approximately 5.9 billion searches per day, which accounts for 67% of all searches (Lee, 2013). In addition, Google provides the search data at an aggregated level on its Google Trends page (http://trends.google.com/trends/), where users can identify the trending topics in search results or investigate a search term to find out its popularity in different parts of the world. These data are open and free of charge to Google account holders and can be downloaded in common spreadsheet formats to be used for analytical purposes, including forecasting.

Meanwhile, tourism demand forecasting has become essential for the travel and tourism industry. It can be used in diverse ways, such as setting marketing goals for the following year; determining requirements for staffing, supplies, and capacity; and predicting the economic impact of visitors on a destination (Frechtling, 2001). For instance, tourism demand forecasting can improve the allocation of a marketing budget by estimating the future travel behavior of incoming markets to the destination.

The purpose of this study is to investigate whether Google Trends data have predictive power in terms of improving the accuracy of forecasting tourism demand. Assuming that individuals search for information about a destination on the Internet while they are planning their next vacation, and because Google Trends data show the popularity of search terms, this may provide an indication of interest in traveling to a given destination. On the basis of this assumption, Google Trends data regarding the search term "Vienna" under the travel category are used to predict tourism demand for Vienna. We further investigated whether this technique improves forecast accuracy relative to benchmarks that do not include Google Trends data as predictors in terms of common accuracy measures. In addition, the impact of the following characteristics on forecast accuracy are investigated relative to the accuracy of worldwide Google searches in the English language as a predictor of total (i.e., foreign and domestic) tourism demand for Vienna:

1. The origin of tourists and Google searches (domestic source market: Austria and Vienna's five most important foreign source markets: Germany, Italy, Russia, the UK, and the US),
2. The role of the native language in Google searches (available for searches in German and Russian only), and
3. The use of seasonally adjusted data versus seasonal data.

Using logged monthly data from 2008M1 to 2012M12 for worldwide Google searches and total tourist arrivals to Vienna, four types of reduced autoregressive distributed lag models (ADLMs) are derived by applying the general-to-specific modeling technique (Song, Witt, & Li, 2009) to test the hypothesis of Google Trends having predictive power and to investigate the impact of the above-mentioned characteristics: (a) a baseline model with lagged values of tourist arrivals to Vienna as the only explanatory variable (purely autoregressive specification), (b) a model additionally including the web search index (search term "Vienna" under the travel category), (c) a model additionally including the image search index (search term "Vienna" under the travel category), and (d) a model additionally including both indices. The same models are also derived and used for each of the main source markets for tourists to Vienna, which are the rest of Austria, Germany, Italy, Russia, the UK, and the US, and which together account for approximately 60% of arrivals to Vienna.

To highlight the impact of the search language, the same models (web search, image search, web and image search) are also derived and used for all source markets with native language Google Trends indices (for German and Russian), where data are available. Because monthly tourism data are used, seasonality in tourism demand and its proper treatment play a role. Therefore, the same procedure (deriving ADLMs) is conducted for all the source markets and respective languages using seasonally adjusted data to investigate whether there are differences between seasonal data and seasonally adjusted data, because seasonal data—even if seasonality was properly considered—may represent a component in the data potentially overlaying the information captured otherwise in the explanatory variables.

Concerning seasonal data, the ex-post forecasting accuracy of all ADLMs (for aggregate worldwide searches and for the six source markets individually as well as for the native language Google searches and the searches in English) and of three time-series models (additive seasonal Holt–Winters, naive-1, and seasonal naive—with the latter two serving as benchmarks) is assessed for forecast horizons $h = 1, 2, 3, 6$, and 12 months ahead in terms of the root-mean-square error and the mean absolute error on the basis of expanding estimation windows. The same procedure is conducted with regard to seasonally adjusted data, albeit with the time-series models adapted accordingly: nonseasonal Holt–Winters and naive-1 only. Significant outperformance of the naive benchmarks is tested by applying the Hansen test for superior predictive ability (Hansen, 2005).

One of the main contributions of this study is in combining textual search information originating from Google searches with quantitative tourist arrivals data to comprehensively assess the benefits of textual search information for the forecast accuracy of tourism demand for a major European city destination, Vienna, which is something that has not been performed previously.

Continuous research on city tourism, including city tourism forecasting, not only indicates its growing importance but also reflects its particularities, such as the difficulty of defining and isolating for-tourists-only facilities or the variety of motives and behaviors on the part of city tourists (Smeral, 2014). In addition, the models include image searches and a comparison between seasonal and seasonally adjusted data, which, to the best of our knowledge, are two novel aspects that have not previously been considered in forecasting studies using Google Trends. Furthermore, assessing searches in native languages and at the source market level has not so far attracted the attention of many researchers. The present study is also one of few to combine monthly data with econometric models for tourism demand forecasting.

Literature Review

Tourism Demand Forecasting

According to Song and Li (2008), in major academic journals between 2000 and 2007, most tourism forecasting studies are conducted using quantitative methods. These studies can be divided into two categories: noncausal methods (i.e., time series analysis) and causal methods (i.e., econometric models), which include additional explanatory variables other than past realizations of the tourism demand variable itself. Time-series analysis is usually conducted using autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), and generalized autoregressive conditional heteroskedasticity (GARCH) models as well as naive-1, naive-2, seasonal naive, and exponential smoothing methods (Song & Li, 2008). The Error-Trend-Seasonal or ExponenTial Smoothing model class (Hyndman, Koehler, Ord, & Snyder, 2008; Hyndman, Koehler, Snyder, & Grose, 2002) has recently emerged as a complement to traditional exponential smoothing methods in tourism demand forecasting (Athanasopoulos, Hyndman, Song, & Wu, 2011).

With regard to econometric models, the most popular methods include the ADLM, the error correction model, the vector autoregressive (VAR) model, and the time-varying parameter model (Song & Li, 2008). To reduce the caveat of over-parameterization of classically estimated VARs, Bayesian shrinkage (Lütkepohl, 2005) has recently been applied to VARs to derive so-called Bayesian VAR models that have also been used for tourism demand forecasting (Song, Smeral, Li, & Chen, 2013). A recent study by Peng, Song, and Crouch

(2014), in which the authors conducted a metaregression analysis of the tourism forecasting articles that were published during the period 1961–2011, shows that forecast accuracy is significantly influenced by the origin of the visitors, destination, time period, data frequency, forecast model, demand variables, and sample size.

City tourism is particularly important to investigate because European city tourism has outperformed European Union (EU-27) national tourism in terms of bed-night growth rates over the past 5 years: +2.9% versus +1.3% (European Cities Marketing & MODUL University Vienna, 2013). Bauernfeind, Arsal, Aubke, and Wöber (2010) indicated that the main reasons for the absence of city level tourism demand studies are data availability and comparability. The dominant time series used in tourism forecasting studies is annual data; the quantity of previous research utilizing monthly time series for tourism forecasting is limited in comparison with research using annual time series. According to Song and Li (2008), only one study using monthly data was conducted at the city level between 2000 and 2007, performed by Vu and Turner (2006). Kim and Schwartz (2013) came to a similar conclusion in a recent survey article. Smeral (2014) and Gunter and Önder (2015) are two recent examples of city level studies using monthly data.

Besides tourism demand forecasting, tourism supply forecasting has started to draw more attention from tourism researchers, in particular supply forecasting for hotels at the city level. Whereas Smeral (2014) forecasted hotel bed supply for Vienna, Qu, Xu, and Tan (2002) focused on forecasting hotel room supply for Hong Kong, and Zheng, Bloom, Wang, and Schrier (2012) forecasted the weekly revenue per available room.

Pertaining to econometric models, the general-to-specific modeling technique to derive reduced versions from a general ADLM has been proposed in the tourism demand forecasting literature because it makes relatively few a priori assumptions on the model specification. This technique encompasses several econometric models that have been widely used in tourism demand forecasting, such as static regression, autoregression, or error correction model (Song et al., 2009). Examples in which reduced ADLMs have been used for tourism demand modeling and forecasting include Croes and Venegas (2005); Dritsakis and Athanasiadis (2000); Ismail, Iverson, and Cai (2000); Lim (2004); as well as Song, Wong, and Chon (2003)—to name but a few.

In the general-to-specific procedure, the ultimately used regression equation includes past observations of the dependent variable as well as current and past observations of explanatory variables, yet only retains those lags that are, at least, statistically significant at the 10% level. Using ADLMs therefore has two main advantages. First, the inclusion of past realizations of the dependent variable itself allows behavioral patterns such as habit persistence or tourism expectations to be taken into account (Song et al., 2003). Second, tourists are safely assumed to start searching for online information about a destination before they (decide to) travel. This makes ADLM a suitable model class for investigating the present research questions.

Travel Information Search

Information search is a central theme in the travel and tourism literature. The main reasons why consumers engage in information searches are to enhance the quality of a proposed trip and to decrease the level of uncertainty surrounding functional, financial, psychological, and social risks (Fodness & Murray, 1997) resulting from the intangibility of tourism products (Lovelock & Wright, 1999). Hence, the information search process is important for marketing management decisions (Wilkie & Dickson, 1985) as well as for consumers making travel-related decisions. The type of travel information needed depends on visitor and trip characteristics (Maumbe, Deng, & Selin, 2014) as well as the number of alternatives and prior knowledge regarding destination, length of stay, planning horizon, and types of travel groups (Park & Fesenmaier, 2014). Following the recognition of a need, information search is generally the second step in the decision-making process and includes consulting various sources before making a purchase decision (Moutinho, 1987).

Traditional travel information sources include personal sources (e.g., friends and relatives) and marketer-dominated paid forms of communication (e.g., hotel brochures; Fodness & Murray, 1998). The Internet as an information source is now an

integral part of the travelers' search hub, despite being initially perceived as a disruption by the supply side of the industry, which was especially concerned by travel meta search engines (Christodoulidou, Connolly, & Brewer, 2009). Some of the online travel information sources used include travel intermediaries, DMO websites, price comparison websites, blogs, and reviews of tourism products such as hotels and restaurants.

A frequent first step in online information searches is the use of a search engine, such as Google, to find the relevant travel-related websites. Jansen, Ciamacca, and Spink (2008) indicate that even in general purpose search engines, travel-related searches constitute a large proportion of all online searches. Moreover, geographical locations such as city, country, and region names are the most frequently used travel-related search terms, representing nearly 60% of travel search inquiries (Jansen et al., 2008).

Google Trends for Forecasting and Nowcasting

Google Inc. publishes aggregated data that show the volume of web searches on Google since 2004. For those who have a Google account, these data can be downloaded for free. Shimshoni, Efron, and Matias (2009) investigated the predictability of Google Trends data using a time-series model with Google Trends as both the dependent and explanatory variables, and they found that Google Trends data were predictable in 12-month-ahead forecasts, with approximately 12% mean absolute percentage error.

Previous research using Google Trends data includes identifying flu outbreaks from search terms (Doornik, 2009); predicting consumer behavior from web search volume (Goel, Hofman, Lahaie, Pennock, & Watts, 2010); comparing Google Trends data versus survey data to identify which indicator is better for forecasting private consumption (Vosen & Schmidt, 2011); forecasting UK movie admissions (Hand & Judge, 2012); predicting car sales, travel plans, unemployment claims, and consumer confidence (Choi & Varian, 2012); predicting inflation rates (Guzman, 2011); predicting the housing market (McLaren & Shanbhogue, 2011); and predicting stock market changes (Curme, Preis, Stanley, & Moat, 2014). Website traffic data have also been used to predict hotel demand (Yang, Pan, Evans, & Lv, 2015) and have been found useful in predicting tourism demand as well.

Gawlik, Kabaria, and Kaur (2011) used search engine data to predict visitor numbers and found that web search volume histories are useful for predicting tourism demand. Bangwayo-Skeete and Skeete (2015) also used Google Trends data for hotels and flights to predict tourism demand for Caribbean islands and found that the data are beneficial to tourism forecasters. In a recent study by Yang et al. (2015), search engine queries from Google and Baidu were used to predict visitor numbers to Hainan, China; the results show that forecasting models using queries from Baidu, which has a larger market share than Google in China, performs better than Google Trends models and the baseline models.

In previous studies using search engine data for forecasting, only one has taken into consideration the search language (Gawlik et al., 2011). Image search has been similarly neglected and has not been part of previous studies, despite the fact that it may also influence travel decisions and therefore have predictive power for tourism demand forecasting.

Methodology

Google Trends Data

Google has the majority share of the search engine market with 65.2% of Internet users worldwide, followed by Baidu (8.2%) and Yahoo (4.9%) (Sullivan, 2013). It has become synonymous with searching for information on the Internet, as revealed by the verb "to Google something," which shows how important Google is for information searches on the Internet.

Google Trends data are always relative given that Google Trends is an index of the volume of a search term (e.g., "Vienna") from a given geographical area (e.g., "worldwide") and, optionally, for a category of interest (e.g., "travel"). The index is based on the query share (i.e., the number of search queries for "Vienna" relative to all other search queries from the specified geographical area within the category of interest [if specified]) and the highest volume day within a given time range is normalized to be 100 (Choi & Varian, 2012).

Search queries generally include short descriptive terms that are related to individuals' needs, such as "Vienna hotels." An individual may use various search terms to retrieve information from search engines; however, Google Trends data capture all travel-related search terms under the travel category, including attractions, accommodation, transportation, and other travel-related interests (Google, 2014a). Thus, using Google Trends data captures all travel-related search terms entered into Google, in addition to the search term used in the study ("Vienna").

As mentioned earlier, Google Trends categorizes search terms under different sections such as travel, sports, shopping, arts, and entertainment. Because the present study considers Google Trends data about Vienna as a destination for the whole travel category, the information captured by the respective indices can be considered comprehensive.

Another important feature of Google Trends is the option of obtaining the popularity of a search term (i.e., "Vienna") according to the country in which the search was conducted. In the present case, the popularity of "Vienna" was investigated in searches originating from Austria, Germany, Italy, Russia, the UK, and the US, which are the main source markets of (foreign) tourists in Vienna. The issue of language was also considered by retrieving data from each source country in the respective local language—that is, because the German name of Vienna is "Wien," this is the search term that was applied in retrieving data from German and Austrian search locations. The same procedure was applied to Russia, in which "Вена" was used as the search term to reflect the local vernacular for Vienna. As the Italian name for Vienna is also "Vienna," separate data retrieval was not necessary for Italy.

In the case of Vienna, the Google Trends image search index is only available from January 2008 onward, and tourist arrivals data for all source markets are only available up to December 2012, which limits the data sample used in this study to the period from 2008M1 to 2012M12. The data from Google Trends are generally available only in weekly format, although data are restricted to monthly increments for searches with low search volumes (Google, 2014b), such as the case of searches from Russia in the present study. Because the tourism demand variable is only available at a monthly frequency, the Google Trends indices retrieved in weekly increments were aggregated to monthly data by taking the 4-week average.[1] To ensure a linear functional relationship between the variables, all Google Trends indices as well as tourist arrivals were transformed into natural logarithms.

Tourism Demand Data

Vienna is one of the top-10 city destinations in Europe, with more than 13 million bed nights in 2013, followed by Munich, Hamburg, and Amsterdam, and therefore is of particular importance for a study on city tourism forecasting (European Cities Marketing & MODUL University Vienna, 2014). In terms of arrivals to paid accommodation establishments, Vienna received approximately 6.3 million total foreign and domestic arrivals in 2013, of which nearly 5 million were foreign tourists. The main foreign source markets—which together account for 38.1% of all the foreign arrivals to Vienna and which are included in the study—are Germany, Italy, Japan, the UK, and the US.

Data on monthly tourist arrivals in Vienna (total and for the six source markets of interest) were retrieved from TourMIS (http://tourmis.info/), where (European city) DMOs upload their most recent tourism data. The tourist arrivals data regarding Vienna include arrivals in all paid forms of accommodation in the greater city area. Visual inspection of the variables reveals (slightly) trending behavior of all variables and individual seasonal patterns on the part of tourist arrivals, both at the source market and at the aggregate levels. The positive trend in total arrivals, for instance, underlines the continuously growing attractiveness of Vienna as a city destination, whereas the differences in seasonal patterns across source markets reflect the particularities of the single source markets. The development of the total market can be seen in Figure 1, in which it should be noted that a decrease in the Google Trends indices could either stem from a drop in the destination attractiveness of Vienna relative to competing destinations or merely from the ever growing number of search queries in the travel category.

For total tourist arrivals and worldwide web and image search indices, Augmented Dickey–Fuller tests including trend and intercept reject the null hypothesis of the presence of a unit root for all variables (at the 5% level in the case of tourist arrivals, at the 1% level in the case of web and image search indices). These results are confirmed by Kwiatkowski–Phillips–Schmidt–Shin tests, including trend and intercept for which the null hypothesis of stationarity cannot be rejected for any of the variables (detailed test results are available on request).[2] Therefore, it can be concluded that the variables are trend-stationary and that it is permitted to continue working with variables in levels. However, to accommodate the trending behavior of the data, a deterministic linear trend is included in the models.

With regard to the seasonal patterns, testing for stochastic seasonality—for example, by applying the monthly version of the Hylleberg–Engle–Granger–Yoo test (Beaulieu & Miron, 1993; Hylleberg, Engle, Granger, & Yoo, 1990)—would not be useful because seasonal unit roots at any frequency found in the data would entail seasonal differencing, thereby considerably shortening the sample. For this reason, two alternative options for treating seasonality are pursued. Option 1 is to treat seasonality as deterministic by including 11 seasonal dummies in all models. Option 2 is to seasonally adjust the data by applying a centered moving average filter.

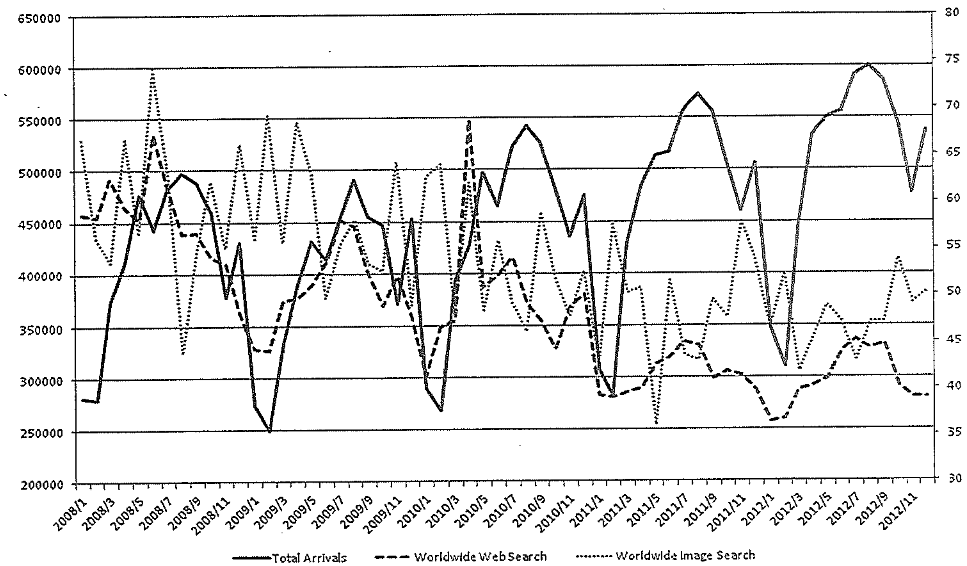

Figure 1. Evolution of total arrivals as well as worldwide Google Trends web and image search indices. Total arrivals (left axis) are given in total numbers. Worldwide Google Trends web and image search indices are given in percentages (right axis).

The Models

A maximum of four different econometric models per source market, language, and type of treatment of seasonality (depending on data availability) are derived and estimated over the whole sample (2008M1–2012M12) to assess the in-sample fit of the two Google Trends indices: (a) a baseline model with lagged values of tourist arrivals to Vienna as the only explanatory variables (purely autoregressive specification), (b) a model additionally including the web search index (search term "Vienna" under the travel category), (c) a model additionally including the image search index (search term "Vienna" under the travel category), and (d) a model additionally including both indices.

The estimated model specifications are derived from a general ADLM (Song et al., 2009), which reads as follows:

$$\ln(arrivals)_t = \alpha + \sum_{i=1}^{12} \gamma_i \cdot \ln(arrivals)_{t-i} + \sum_{i=0}^{12}\sum_{k=1}^{2} \beta_{i,k} \cdot \ln(x)_{t-i,k} + \sum_{l=1}^{11} \delta_l \cdot dummy_l + \phi \cdot trend + \varepsilon_t \quad (1)$$

In Equation 1, the dependent variable ln(*arrivals*) is assumed to be a function of own past realizations, of present and past realizations of one or two of the explanatory variables $\ln(x)_k$ (web search and/or image search), of the 11 monthly *dummy* variables (for seasonal data only), and of a deterministic linear *trend*. In Equation 1, α denotes the intercept term; γ_i, $\beta_{i,k}$, δ_l, and ϕ denote the regression coefficients; and ε denotes the error term assumed to be independently and identically distributed, $\sim N(0, \sigma_\varepsilon^2)$. By using a general-to-specific approach starting at a maximum lag order of $p = 12$ for monthly data, insignificant lags of the lagged dependent variable are dropped until the purely autoregressive baseline specification is obtained with lags significant at least at the 10% level. When including one of the explanatory variables or both, the procedure is repeated analogously to obtain the lag structure of the models that are finally estimated by ordinary least squares.

The general-to-specific procedure is similarly carried out for the single source markets, for the native language versions of the search indices, and for the seasonally adjusted data. Table 1 provides an overview of the ADLMs able to be derived on the basis of data availability and the significance criterion (10%) for the lags. As can be concluded from this table, more of the theoretically derived models survived the significance criterion in the case of seasonally adjusted data—thereby corroborating the conjecture addressed in the first section that seasonal patterns may overlay information otherwise captured in the explanatory variables. The detailed lag structure of the ADLMs derived at the source market level and used for the forecast competition is available on request.

Estimation Results for Worldwide Searches (Seasonal Data)

As an example for the in-sample fit of the ADLMs with and without Google Trends as additional explanatory variables, estimation results for worldwide searches and total tourist arrivals in Vienna for seasonal data are shown in Table 2 (Models A–D). Not only do the estimated regressions feature highly significant F statistics and favorable adjusted coefficients of determination (Adjusted R^2) so that the goodness-of-fit for all models is satisfying but the specifications are also robust against several diagnostic residual checks (detailed test results are available on request).

As can be seen from Table 2, apart from Lags 1, 2, and 6 of tourist arrivals themselves (Model A), various current and past realizations of web and image searches also have a statistically significant impact on tourist arrivals (Models B–D), which can be interpreted as a preliminary sign for their predictive ability. In addition, both the seasonal pattern and the deterministic trend play a significant role in explaining the number of tourist arrivals in Vienna.

Table 1
Overview of Autoregressive Distributed Lag Models (ADLMs) Used in the Forecast Competition

Source Market	Total	Austria	Germany	Italy	Russia	UK	US
Seasonal data							
Baseline model	✓	✓	✓	✓	✓	✓	✓
Web search (English)	✓	✓	✓	✓	✓	✓	✓
Web search (native language)	same	✓	✓	same	✓	same	same
Image search (English)	✓	✓	NA	✓	NA	NA	–
Image search (native language)	same	✓	NA	same	NA	NA	same
Web and image search (English)	✓	–	NA	–	NA	NA	–
Web and image search (native language)	same	✓	NA	same	NA	NA	same
Seasonally adjusted data							
Baseline model	✓	✓	✓	✓	✓	✓	✓
Web search (English)	✓	✓	✓	✓	✓	✓	✓
Web search (native language)	same	✓	✓	same	✓	same	same
Image search (English)	✓	✓	NA	✓	NA	NA	✓
Image search (native language)	same	✓	NA	same	NA	NA	same
Web and image search (English)	✓	–	NA	✓	NA	NA	✓
Web and image search (native language)	same	✓	NA	same	NA	NA	same

Note. A check denotes that the respective ADLM was derivable according to data availability and fulfillment of the significance criterion for the lags (significant at least at the 10% level). A dash denotes that data were available, but the significance criterion was not met. "Same" means that English and native language versions coincide, and no differentiation was possible. "NA" means that Google Trends data were simply not available.

Table 2
In-Sample Fit of Reduced Autoregressive Distributed Lag Models (ADLMs) With and Without Google Trends Indices (Worldwide Searches and Total Tourist Arrivals for Seasonal Data)

Explanatory Variables	Baseline Model (A)	Model With Web Search (B)	Model With Image Search (C)	Model With Web and Image Search (D)
ln(arrivals) (−1)	0.2950**	0.1293	0.1323	−0.3932**
ln(arrivals) (−2)	0.5613***	0.4454***	0.5040***	0.4161***
ln(arrivals) (−6)	−0.1737*	−0.3105***	−0.3062***	−0.5051***
ln(web)	–	−0.1129**	–	–
ln(web) (−1)	–	0.1016*	–	–
ln(web) (−4)	–	–	–	0.2592***
ln(web) (−7)	–	0.1197**	–	0.1659***
ln(web) (−9)	–	−0.1230**	–	–
ln(web) (−11)	–	0.1450***	–	–
ln(image) (−4)	–	–	–	−0.0869**
ln(image) (−5)	–	–	–	−0.0720*
ln(image) (−7)	–	–	–	−0.0816**
ln(image) (−9)	–	–	−0.0826**	−0.1222***
ln(image) (−11)	–	–	−0.0673*	−0.0925***
ln(image) (−12)	–	–	–	−0.1048***
d_jan	−0.3700***	−0.3643***	−0.3228***	−0.2139***
d_feb	−0.4025***	−0.4508***	−0.4425***	−0.5395***
d_mar	0.2196***	0.1015	0.1562**	−0.0540
d_apr	0.2862***	0.2276***	0.2450***	0.2432***
d_may	0.1038***	0.0601*	0.0855**	0.1631***
d_jun	−0.0003	−0.0041	0.0235	0.1958***
d_jul	−0.0333	−0.0833	−0.0741	−0.0239
d_aug	−0.0168	−0.0593	−0.0530	−0.0013
d_sep	−0.0534	−0.0417	−0.0357	0.1410***
d_oct	−0.1097***	−0.1149***	−0.0819**	0.0523
d_nov	−0.1974***	−0.1881***	−0.1464***	−0.0472
Trend	0.0018***	0.0057***	0.0033***	0.0092***
Constant	4.1145***	8.9318***	9.2434***	19.5373***
Adjusted R^2	0.9844	0.9921	0.9897	0.9941
F	223.6869	303.7792	273.0637	344.6965
p	0.0000	0.0000	0.0000	0.0000

Note. Dependent variable = ln(*arrivals*). Estimation results are obtained by ordinary least squares and are based on the full sample (2008M1–2012M12).
*Statistical significance at the 10% level. **Statistical significance at the 5% level. ***Statistical significance at the 1% level.

Web searches about a destination are conducted during the planning stage in most cases; however, web searches can be also conducted immediately before departure and during the stay at the destination—for example, by using mobile devices on location (see the impact of current web searches on current tourist arrivals from the estimation results for Model B in Table 2)—thus, this is an influential component of travel decision making. Image searches, starting a minimum of 4 months before the actual travel date, coincide with web searches during the travel decision making process and represent another influential factor.

Forecasting Results

The ex-post out-of-sample forecasting performance for ln(*arrivals*) of all models is assessed in terms of root-mean-square error and mean absolute error as error measures for the seasonal and seasonally adjusted data. In addition, pure time-series models are used as competitors: The additive seasonal Holt–Winters model (all smoothing parameters are estimated) as well as the naive-1 and the seasonal naive models are used for the seasonal data, whereas the nonseasonal Holt–Winters model and the naive-1 model are used for the seasonally adjusted data.

To obtain dynamic forecasts for forecast horizons $h = 1, 2, 3, 6$, and 12 months ahead, the expanding windows technique is used for each forecast model and forecast horizon, with 2011M1 denoting the first forecast origin. This results in 23 one-step-ahead (2011M2–2012M12), . . . , 12 twelve-step-ahead (2012M1–2012M12) forecast values for each model. Forecast evaluation results including a ranking (whereby 1 indicates the best performing forecast model per source market and forecast horizon; best performing models are also indicated by boldface numbers) are given in Table 3 (seasonal data) and Table 4 (seasonally adjusted data).

In addition, the Hansen test on superior predictive accuracy (Hansen, 2005) is used to investigate whether at least one of the seven competing forecast models is able to statistically significantly outperform the naive-1 and seasonal naive benchmarks (in the case of seasonal data) or the naive-1 benchmark only (in the case of seasonally adjusted data). Boldface Hansen consistent p values in Tables 3 and 4 (calculated on the basis of a minimization of squared forecast losses) indicate a statistically significant outperformance of the naive-1 benchmark, at least at the 10% level. Because of the limited number of observations available, these tests have not been evaluated for the forecast horizon $h = 12$. The main results of the forecast evaluation exercise and their interpretation are as follows.

Seasonal data results (see Table 3) indicate that, except for the US, at forecast horizons 2, 3, and 6 months ahead and for the total market at forecast horizon 12 months ahead, the models with Google Trends indices as additional explanatory variables improve forecast accuracy relative to the purely autoregressive baseline model. Whereas the additive seasonal Holt–Winters benchmark performs quite well (it even ranks first in three cases, therefore corroborating its general usefulness for forecasting in the presence of seasonality), the naive-1 benchmark is significantly outperformed in all cases (although it ranks first for the Italian source market for $h = 12$ and also gains momentum at that forecast horizon for other source markets). The seasonal naive benchmark is similarly significantly outperformed on a regular basis; only for the Italian (where it ranks first) and US source markets can it not be outperformed in one-step-ahead forecasting. The general outperformance of the naive-1 model is due to the seasonal patterns that it is unable to capture, making it lag one period behind. The frequent outperformance of the seasonal naive model, however, means that the rival forecast models not only capture the individual seasonal patterns well but also provide predictive information on top of these patterns.

Both English and native language web searches were particularly useful predictors in Austria and Germany, but German language searches proved most valuable. For the Russian source market, web searches in English were better predictors than web searches in Russian—probably because of a greater availability of information about Vienna in English. In the UK, web searches were the best predictors for forecasting actual travel flows to Vienna. For visitors from the US, web searches were good predictors for 1 and 12 months ahead of arrivals in Vienna; for the other forecast horizons, however, past visit behavior was a better predictor than online searches. For visitors from Italy, web and image searches were both good indicators for all forecast horizons except 12 months ahead.

Worldwide image searches were better indicators for 2 and 3 months ahead forecasting for Vienna. Other than for three markets (total, Italy, and Germany), image searches were not good indicators for predicting tourist arrivals in Vienna.

Seasonally adjusted data (see Table 4) show that, in general, web, web in native language, or web and image search models outperform the baseline model for all markets. For searches from Austria and Germany, native language models are better than the English models most of the time. For Russia, web searches in English outperform web searches in Russian. For searches from Italy, web and image searches improve forecasting accuracy for all forecast horizons except 12 months ahead, where again naive-1 ranks first. For Russia and the UK, the web search model is the best performing for all forecast horizons. For the US, the web and web and image search models outperform others. At the worldwide level, the web model is characterized by better accuracy for short forecast horizons ($h = 1$, 2), the image model for longer horizons ($h = 6$, 12), and the web and image model for medium horizons ($h = 3$, 6). The nonseasonal Holt–Winters model performs quite well, but, unlike the results for seasonal data, it never ranks first. In contrast to seasonal data, the naive-1 model cannot always be significantly outperformed, although it is in the majority of cases.

Conclusion and Implications

The results of this study show that using Google Trends for tourism demand forecasting is a valuable option both for seasonal and seasonally adjusted data. The forecast accuracy of the models is improved when Google Trends data are included relative to a purely autoregressive baseline specification, especially for the web search model. Web search improves the accuracy of the forecasting models over nearly all forecast horizons and for all source markets, regardless of whether the search is conducted in English or in the native language. There is a tendency, however, toward native language searches (ranking first more often), except in the case of Russia.

For seasonal data, the web search models are more accurate than others for the source markets of Russia, the UK, and the US. Hansen test results suggest that the two naive benchmarks (naive-1 and seasonal naive) are generally significantly outperformed; this applies to seasonal data for nearly all source markets and forecast horizons, with the exception of Italy and the US for $h = 1$. The results are mixed for forecasting 12 months ahead because the accuracy of naive-1 improves for this horizon, even ranking first for the Italian source market.

For seasonally adjusted data, web or web and image search models outperform the others, except for Italy (where naive-1 again ranks first for $h = 12$). Compared with seasonal data, however, the naive-1 benchmark is not so frequently significantly outperformed on the basis of Hansen test statistics. The Holt–Winters benchmark performs quite well for both seasonal and seasonally adjusted data, but it only ranks first three times for seasonal data.

Generally speaking, seasonal adjustment of the variables by applying a centered moving average filter has a beneficial effect on the derivability of ADLMs in terms of meeting the significance criterion for the lags of the variables (significant at least at the 10% level). Furthermore, this procedure also has a beneficial effect on the predictive power of the models with Google Trends indices. Whereas the accuracy of the Holt–Winters benchmark loses momentum when using seasonal adjustment, the naive-1 benchmark can be less frequently significantly outperformed—thereby corroborating the notion that individual seasonal patterns overlay information otherwise measured by explanatory variables. Any impact of the original frequency of the Google Trends data (weekly or monthly), however, is not perceivable.

For forecasting up to 6 months ahead using either seasonal or seasonally adjusted data, web search indices in English or in the native language as well as web and image search indices from Google Trends are excellent predictors of actual tourist arrivals in Vienna. This is also the case when forecasting 12 months ahead and using seasonally adjusted data. However, for 12-months-ahead forecasting using worldwide searches and seasonal data, the baseline model outperforms the others; thus, using past tourist arrivals alone is better than including Google Trends data to predict total tourist arrivals in Vienna.

Having more accurate short-term (i.e., within a year) tourist arrival forecasts for the total market

Table 3
Seasonal Data: Ex-Post Out-of-Sample Forecasting Performance of Rival Models

	h = 1				h = 2				h = 3				h = 6				h = 12			
Source Market/Forecast Model	RMSE	Rank	MAE	Rank	RMSE	Rank	MAE	Rank	RMSE	Rank	MAE	Rank	RMSE	Rank	MAE	Rank	RMSE	Rank	MAE	Rank
Total																				
Baseline	0.036	3	0.027	3	0.038	3	0.029	3	0.043	4	0.036	4	0.050	4	0.039	3	**0.033**	1	**0.029**	1
Web	0.039	4	0.030	4	0.042	5	0.034	5	0.040	3	0.031	3	0.049	3	0.040	4	0.044	3	0.036	2
Image	0.033	2	0.026	2	**0.032**	1	**0.025**	1	**0.033**	1	**0.025**	1	0.043	2	0.034	2	0.043	2	0.038	3
Web and image	**0.031**	1	**0.024**	1	0.033	2	0.028	2	0.034	2	0.027	2	**0.037**	1	**0.027**	1	0.058	4	0.050	4
Additive seasonal Holt–Winters	0.041	5	0.033	5	0.042	4	0.030	4	0.046	5	0.038	5	0.061	5	0.046	5	0.097	6	0.078	6
Naive 1	0.161	6	0.113	6	0.242	7	0.177	7	0.282	7	0.226	7	0.369	7	0.280	7	0.072	5	0.068	5
Seasonal naive	0.072	7	0.068	7	0.190	6	0.141	6	0.265	6	0.206	6	0.362	6	0.271	6	0.221	7	0.169	7
Hansen p value (naive-1)	**0.013**				**0.008**				**0.002**				**0.000**							
Hansen p value (seasonal naive)	**0.000**				**0.005**				**0.007**				**0.001**							
Austria																				
Baseline	0.049	5	0.040	6	0.060	5	0.049	5	0.063	3	0.051	2	0.064	3	0.060	3	0.052	3	0.043	3
Web	0.043	2	**0.032**	1	0.055	3	**0.046**	1	0.064	4	0.055	5	0.090	6	0.079	6	0.075	5	0.063	6
Web (N)	0.045	4	0.038	5	**0.055**	1	0.046	2	**0.057**	1	**0.050**	1	**0.056**	1	**0.051**	1	**0.044**	1	0.040	2
Image	0.051	6	0.037	4	0.077	7	0.060	7	0.098	7	0.077	7	0.154	8	0.141	8	0.228	9	0.179	9
Image (N)	0.044	3	0.035	3	0.057	4	0.047	3	0.066	6	0.058	6	0.081	4	0.075	5	0.053	4	0.043	4
Web and image (N)	**0.042**	1	0.034	2	0.055	2	0.050	6	0.063	2	0.051	3	0.081	5	0.074	4	0.116	7	0.088	7
Additive seasonal Holt–Winters	0.134	9	0.111	9	0.060	6	0.048	4	0.064	5	0.052	4	0.063	2	0.054	2	0.044	2	**0.037**	1
Naive 1	0.128	8	0.104	8	0.182	9	0.164	9	0.201	9	0.162	8	0.111	7	0.096	7	0.079	6	0.061	5
Seasonal naive	0.072	7	0.059	7	0.146	8	0.116	8	0.201	8	0.177	9	0.186	9	0.151	9	0.163	8	0.135	8
Hansen p value (naive-1)	**0.000**				**0.000**				**0.000**				**0.008**							
Hansen p value (seasonal naive)	**0.028**				**0.005**				**0.000**				**0.004**							
Germany																				
Baseline	0.059	3	0.050	4	0.057	3	0.049	4	0.054	3	0.048	4	0.056	2	0.048	2	0.066	3	0.055	3
Web	0.053	2	0.042	2	0.051	2	0.040	2	**0.048**	1	**0.039**	1	0.069	4	0.054	4	0.078	5	0.069	5
Web (N)	**0.048**	1	**0.040**	1	**0.047**	1	**0.039**	1	0.049	2	0.043	2	**0.052**	1	**0.046**	1	0.072	4	0.066	4
Additive seasonal Holt–Winters	0.063	4	0.050	3	0.058	4	0.045	3	0.057	4	0.044	3	0.060	3	0.049	3	**0.048**	1	**0.038**	1
Naive 1	0.176	6	0.120	6	0.289	6	0.223	6	0.354	6	0.262	6	0.422	5	0.357	5	0.060	2	0.052	2
Seasonal naive	0.074	5	0.063	5	0.182	5	0.135	5	0.280	5	0.219	5	0.372	6	0.302	6	0.221	6	0.159	6
Hansen p value (naive-1)	**0.011**				**0.004**				**0.001**				**0.000**							
Hansen p value (seasonal naive)	**0.074**				**0.003**				**0.004**				**0.001**							
Italy																				
Baseline	0.132	4	0.104	5	0.131	3	0.101	4	0.135	3	0.103	4	0.157	4	0.126	4	0.199	5	0.169	5
Web	0.127	3	0.098	3	**0.123**	1	0.095	3	**0.124**	1	0.094	2	**0.145**	1	0.116	2	0.190	4	0.159	3
Image	0.125	2	**0.094**	1	0.123	2	**0.091**	1	0.127	2	**0.093**	1	0.147	2	**0.115**	1	0.189	3	0.159	4
Additive seasonal Holt–Winters	0.141	5	0.100	4	0.132	4	0.095	2	0.135	4	0.096	3	0.152	3	0.119	3	0.164	2	0.135	2
Naive 1	0.596	6	0.503	6	0.711	6	0.577	6	0.581	5	0.500	5	0.767	6	0.603	6	**0.145**	1	**0.114**	1
Seasonal naive	**0.123**	1	0.098	2	0.624	5	0.521	5	0.728	6	0.584	6	0.596	5	0.534	5	0.564	6	0.458	6
Hansen p value (naive-1)	**0.000**				**0.000**				**0.000**				**0.000**							
Hansen p value (seasonal naive)	0.762				**0.000**				**0.000**				**0.000**							
Russia																				
Baseline	0.095	3	0.074	4	0.139	4	0.098	4	0.130	3	0.094	3	0.109	2	0.091	2	0.114	2	0.086	2
Web	0.083	2	0.063	2	**0.100**	1	**0.070**	1	**0.088**	1	**0.067**	1	**0.062**	1	**0.049**	1	**0.065**	1	**0.051**	1
Web (N)	**0.076**	1	**0.062**	1	0.103	2	0.078	2	0.108	2	0.090	2	0.131	3	0.114	3	0.148	3	0.136	3
Additive seasonal Holt–Winters	0.102	4	0.073	3	0.137	3	0.097	3	0.135	4	0.099	4	0.160	4	0.125	4	0.205	5	0.149	4
Naive 1	0.290	6	0.205	5	0.273	5	0.212	5	0.253	5	0.167	5	0.297	5	0.228	5	0.202	4	0.190	5
Seasonal naive	0.271	5	0.250	6	0.398	6	0.345	6	0.427	6	0.342	6	0.446	6	0.382	6	0.550	6	0.479	6
Hansen p value (naive-1)	**0.021**				**0.005**				**0.027**				**0.003**							
Hansen p value (seasonal naive)	**0.000**				**0.000**				**0.002**				**0.000**							
UK																				
Baseline	0.092	3	0.066	3	0.095	3	0.075	3	0.084	3	0.073	3	0.101	2	0.087	2	0.122	2	0.110	2
Web	**0.069**	1	**0.051**	1	**0.068**	1	**0.048**	1	**0.066**	1	**0.045**	1	**0.072**	1	**0.058**	1	**0.062**	1	**0.048**	1
Additive seasonal Holt–Winters	0.086	2	0.058	2	0.089	2	0.061	2	0.076	2	0.056	2	0.108	3	0.089	3	0.132	4	0.121	4
Naive 1	0.201	5	0.148	5	0.291	5	0.223	5	0.344	5	0.272	5	0.451	5	0.356	5	0.129	3	0.116	3
Seasonal naive	0.112	4	0.094	4	0.222	4	0.179	4	0.285	4	0.233	4	0.429	4	0.330	4	0.286	5	0.195	5
Hansen p value (naive-1)	**0.015**				**0.004**				**0.002**				**0.000**							
Hansen p value (seasonal naive)	**0.006**				**0.006**				**0.008**				**0.005**							
US																				
Baseline	0.113	3	0.084	2	**0.099**	1	**0.079**	1	**0.107**	1	**0.081**	1	0.097	2	**0.076**	1	0.086	2	0.071	2
Web	**0.108**	1	0.089	3	0.110	3	0.088	3	0.117	3	0.096	3	0.114	3	0.083	3	**0.070**	1	**0.059**	1
Additive seasonal Holt–Winters	0.108	2	**0.079**	1	0.103	2	0.081	2	0.111	2	0.086	2	**0.097**	1	0.076	2	0.102	4	0.089	4
Naive 1	0.339	5	0.287	5	0.519	5	0.436	5	0.644	5	0.536	5	0.833	5	0.747	5	0.094	3	0.086	3
Seasonal naive	0.118	4	0.097	4	0.392	4	0.343	4	0.542	4	0.447	4	0.838	4	0.729	4	0.409	5	0.319	5
Hansen p value (naive-1)	**0.000**				**0.000**				**0.000**				**0.000**							
Hansen p value (seasonal naive)	0.360				**0.000**				**0.000**				**0.000**							

Note. Minimum root-mean-square error (RMSE) and mean absolute error (MAE) values per forecast horizon and source market are given in boldface. Boldface Hansen consistent p values denote rejection of the null hypothesis of no outperformance of the naive-1 and seasonal naive benchmarks by at least one competing forecast model at the 10% level or higher. Squared forecast losses are assumed to be minimized when calculating the Hansen statistics. "N" denotes models with Google searches in the native language.

Table 4

Seasonally Adjusted Data: Ex-Post Out-of-Sample Forecasting Performance of Rival Models

Source Market/Forecast Model	$h=1$				$h=2$				$h=3$				$h=6$				$h=12$			
	RMSE	Rank	MAE	Rank	RMSE	Rank	MAE	Rank	RMSE	Rank	MAE	Rank	RMSE	Rank	MAE	Rank	RMSE	Rank	MAE	Rank
Total																				
Baseline	0.025	4	0.019	4	0.026	4	0.021	4	0.029	4	0.025	5	0.037	4	0.031	5	0.030	2	**0.026**	**1**
Web	**0.022**	**1**	**0.018**	**1**	**0.023**	**1**	**0.018**	**1**	0.028	2	0.023	3	0.035	3	0.030	3	0.042	4	0.037	5
Image	0.024	3	0.018	3	0.025	3	0.020	3	0.028	3	0.023	2	0.034	2	**0.027**	**1**	**0.029**	**1**	0.027	2
Web and image	0.023	2	0.018	2	0.023	2	0.019	2	**0.027**	**1**	**0.022**	**1**	**0.032**	**1**	0.027	2	0.035	3	0.031	3
Nonseasonal Holt–Winters	0.027	5	0.020	5	0.028	5	0.021	5	0.030	5	0.026	6	0.039	5	0.031	4	0.051	5	0.036	4
Naive 1	0.032	6	0.026	6	0.030	6	0.025	6	0.031	6	0.024	4	0.048	6	0.037	6	0.072	6	0.068	6
Hansen p value (naive-1)	**0.029**				0.064				0.176				**0.027**							
Austria																				
Baseline	0.039	8	0.031	8	0.057	7	0.048	8	0.068	7	0.061	7	0.096	7	0.085	7	0.109	7	0.104	7
Web	0.038	7	0.031	7	0.055	6	0.046	6	0.065	6	0.057	6	0.087	6	0.076	6	0.092	6	0.083	6
Web (N)	0.034	3	0.029	5	0.042	2	0.036	2	**0.044**	**1**	**0.036**	**1**	**0.045**	**1**	**0.036**	**1**	**0.051**	**1**	**0.038**	**1**
Image	0.037	6	0.030	6	0.060	8	0.048	7	0.073	8	0.062	8	0.110	8	0.094	8	0.141	8	0.118	8
Image (N)	**0.032**	**1**	**0.025**	**1**	**0.041**	**1**	**0.035**	**1**	0.048	3	0.043	4	0.067	4	0.061	5	0.056	2	0.043	2
Web and image (N)	0.034	2	0.026	2	0.042	3	0.038	3	0.043	2	0.037	2	0.052	2	0.048	2	0.088	5	0.068	5
Nonseasonal Holt–Winters	0.036	4	0.026	3	0.046	5	0.039	4	0.053	5	0.046	5	0.069	5	0.053	4	0.062	3	0.052	3
Naive 1	0.037	5	0.027	4	0.045	4	0.039	5	0.049	4	0.042	3	0.067	3	0.052	3	0.078	4	0.061	4
Hansen p value (naive-1)	0.245				0.533				**0.355**				0.029							
Germany																				
Baseline	0.043	3	0.034	3	0.044	4	0.036	4	0.042	3	0.035	4	0.0473	3	0.040	3	0.059	4	0.048	4
Web	0.036	2	0.029	2	**0.036**	**1**	**0.029**	**1**	**0.033**	**1**	**0.029**	**1**	**0.037**	**1**	**0.031**	**1**	**0.036**	**1**	**0.025**	**1**
Web (N)	**0.036**	**1**	**0.028**	**1**	0.037	2	0.030	2	0.037	2	0.031	2	0.041	2	0.034	2	0.050	3	0.039	3
Nonseasonal Holt–Winters	0.047	4	0.037	4	0.043	3	0.035	3	0.042	4	0.034	3	0.053	4	0.041	4	0.048	2	0.039	2
Naive 1	0.063	5	0.052	5	0.057	5	0.049	5	0.046	5	0.034	5	0.063	5	0.051	5	0.060	5	0.052	5
Hansen p value (naive-1)	**0.010**				**0.012**				**0.054**				**0.004**							
Italy																				
Web	0.116	2	0.086	3	0.115	2	0.087	3	0.116	4	0.090	2	0.131	2	0.105	2	0.176	4	0.145	4
Image	0.118	3	0.087	4	0.117	3	0.087	2	0.123	2	0.093	4	0.145	3	0.113	3	0.19	5	0.165	5
Web and image	**0.107**	**1**	**0.081**	**1**	**0.107**	**1**	**0.083**	**1**	**0.106**	**1**	**0.082**	**1**	**0.118**	**1**	**0.097**	**1**	0.152	2	0.126	3
Nonseasonal Holt–Winters	0.128	5	0.085	2	0.124	5	0.088	4	0.129	3	0.093	3	0.151	4	0.116	4	0.156	3	0.125	2
Naive 1	0.182	6	0.118	6	0.134	6	0.096	6	0.145	6	0.100	6	0.178	6	0.120	5	**0.144**	**1**	**0.113**	**1**
Hansen p value (naive-1)	0.115				0.130				0.124				0.167							
Russia																				
Baseline	0.065	3	0.051	4	0.097	4	0.070	3	0.099	4	0.068	3	0.092	2	0.073	2	0.124	2	0.094	2
Web	**0.057**	**1**	**0.042**	**1**	**0.073**	**1**	**0.052**	**1**	**0.070**	**1**	**0.051**	**1**	**0.061**	**1**	**0.046**	**1**	**0.058**	**1**	**0.039**	**1**
Web (N)	0.059	2	0.049	2	0.079	2	0.064	2	0.085	2	0.075	4	0.108	4	0.096	4	0.137	3	0.126	3
Nonseasonal Holt–Winters	0.068	5	0.049	3	0.093	3	0.071	5	0.094	3	0.068	2	0.095	3	0.077	3	0.141	4	0.104	4
Naive 1	0.065	4	0.054	5	0.101	5	0.080	4	0.106	5	0.080	5	0.122	5	0.102	5	0.202	5	0.190	5
Hansen p value (naive-1)	0.214				**0.060**				**0.060**				**0.008**							
UK																				
Baseline	0.058	2	0.044	2	0.059	2	0.045	2	0.054	2	0.043	2	0.062	2	0.051	2	0.070	2	0.060	2
Web	**0.053**	**1**	**0.041**	**1**	**0.053**	**1**	**0.042**	**1**	**0.043**	**1**	**0.035**	**1**	**0.042**	**1**	**0.034**	**1**	**0.044**	**1**	**0.038**	**1**
Nonseasonal Holt–Winters	0.066	3	0.050	3	0.065	3	0.050	3	0.062	3	0.048	3	0.097	3	0.074	3	0.139	4	0.123	4
Naive 1	0.080	4	0.064	4	0.075	4	0.057	4	0.077	4	0.065	4	0.100	4	0.077	4	0.129	3	0.116	3
Hansen p value (naive-1)	**0.001**				**0.010**				**0.000**				**0.003**							
US																				
Baseline	0.079	4	0.058	3	0.077	4	0.063	3	0.082	2	0.068	2	0.081	2	0.068	3	0.088	5	0.078	5
Web	0.077	2	0.068	6	0.077	3	0.067	5	0.087	4	0.074	4	0.085	4	0.069	4	0.074	3	0.065	3
Image	0.078	3	**0.055**	**1**	0.075	2	**0.053**	**1**	**0.080**	**1**	**0.058**	**1**	0.083	3	**0.061**	**1**	0.083	4	0.068	4
Web and image	**0.076**	**1**	0.066	4	**0.075**	**1**	0.064	4	0.085	3	0.070	3	**0.075**	**1**	0.063	2	**0.048**	**1**	**0.043**	**1**
Nonseasonal Holt–Winters	0.082	5	0.055	2	0.087	5	0.060	2	0.098	5	0.075	5	0.109	6	0.089	6	0.064	2	0.046	2
Naive 1	0.096	6	0.072	6	0.089	6	0.067	6	0.105	6	0.085	6	0.101	5	0.076	5	0.094	6	0.086	6
Hansen p value (naive-1)	**0.023**				0.207				**0.008**				0.127							

Note. Minimum root-mean-square error (RMSE) and mean absolute error (MAE) values per forecast horizon and source market are given in boldface. Boldface Hansen consistent p values denote rejection of the null hypothesis of no outperformance of the naive-1 benchmark by at least one competing forecast model at the 10% level or higher. Squared forecast losses are assumed to be minimized when calculating the Hansen statistics. "N" denotes models with Google searches in the native language.

and for single source markets in particular has important benefits for practitioners. The Vienna Tourist Board and other stakeholders of the Viennese tourism industry may use forecasts from models incorporating Google Trends data to improve their operational management—that is, to allocate their resources more efficiently and thus reduce costs. Being able to react adequately and quickly to predicted short-term peaks in tourist arrivals from certain source markets ensures, for example, that there will be enough tourist brochures available in English, a sufficient number of city tours offered in Italian, enough Russian-speaking guides present at Schönbrunn Palace, or additional busses from the airport to the city center. Besides the free and timely availability of Google Trends data, as opposed to many traditional tourism demand predictors, the structure of the reduced ADLMs is sufficiently simple and thus ready for use by practitioners.

This study uses Vienna and its most important source markets as a case example, thereby recognizing Vienna's importance as a top-10 European city destination; however, we acknowledge that results could be different for other cities and other source markets. ADLMs were not always derivable, which could be different for other cities and source markets as well. The availability and usability of certain Google Trends indices may also differ across cities and source markets; therefore, the Google Trends YouTube search index and/or the Google Trends news search index, which were only available for some of the Viennese source markets but did not have any explanatory power, may also be suitable. The results indicate that image search on its own is not such a good predictor of tourist arrivals in comparison with web searches. However, in some cases, using image searches as a complement to web searches has a positive impact on predictive accuracy.

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Notes

[1]The Google Trends indices originally retrieved at a weekly frequencey were as follows: web search index worldwide in English, web search index Austria in English, web search index Austria in German, web search index Germany in English, web search index Germany in German, web search index Italy in English/Italian, web search index UK in English, web search index US in English, image search index worldwide in English, and image search index Austria in German.

[2]Thus, all three variables are integrated of order $I(0)$, which makes testing for potential cointegration relationships between the variables infeasible. For variables to be cointegrated, a common degree of integration at least of order $I(1)$ would have been necessary.

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DETERMINANTS OF DESTINATION LOYALTY AND THE MEDIATING ROLE OF TOURIST SATISFACTION

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Within the tourism literature, many researchers recognize destination loyalty to be critical for the sustainable development of tourist destinations during the mature stage of life cycle. This study features a structural model designed to identify the most important determinants of tourist loyalty, with a specific focus on the complex role of tourist satisfaction. Empirical results based on a representative sample of 483 international tourists in Thailand reveal that the satisfaction of tourists fully mediates the effects of push and pull motivations and perceived value for money on destination loyalty, and that it partially mediates the relationship between perceived service quality and destination loyalty. These findings suggest that the success of efforts by destination management organizations to attract return travelers pivots on building tourist satisfaction. Destination managers should also continuously improve and measure tourists' perceptions of service quality at tourism destinations.

Key words: Destination loyalty; Tourist satisfaction; Push and pull motivations; Perceived value for money; Perceived service quality; Structural equation modeling

Introduction

For countries in the maturity stage of the travel destination life cycle, the tourism industry relies heavily on loyal visitors (T. H. Lee, 2009). The literature on tourism identifies four reasons why travel destinations can benefit from cultivating loyalty among tourists. First, marketing costs associated with attracting repeat tourists are lower than those associated with attracting newcomers (Kozak, 2001; Lau & McKercher, 2004). Second, repeat tourists produce more revenue than new tourists (Ajzen, 1991; Lehto, O'Leary, & Morrison, 2004). Third, repeat tourists are more likely to revisit a destination than newcomers (Alegre & Cladera, 2006; Kozak, 2001). Finally, repeat tourists tend to recommend destinations to other potential visitors (Hui, Wan, & Alvin, 2007; Mechinda, Serirat, & Gulid, 2009).

Destination loyalty is a complex concept influenced by a number of factors: satisfaction, push and pull motivations, perceived value for money, and

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