Tourism Management 66 (2018) 411–421

Contents lists available at ScienceDirect

Tourism Management

journal homepage: www.elsevier.com/locate/tourman

Identifying the next non-stop flying market with a big data approach

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HIGHLIGHTS

- The paper introduces a conceptual model for identifying the next direct flight route for a destination.
- The model combines buying funnel theory and gravity model.
- The study examines three different visitor types: flight passengers, hotel guests, and mobile device users.
- The study compares the market's potential to travel to its interest in the destination to identify the most potential market.

ARTICLE INFO

Article history:
Received 19 May 2017
Received in revised form
29 October 2017
Accepted 5 December 2017

Keywords:
Gravity model
Buying funnel theory
Direct flight
Big data
Web traffic
Mobile data

ABSTRACT

Destination Marketing Organizations (DMOs) strive to increase visitor volume through targeting potential markets and eliminating barriers to travel, such as opening non-stop flight routes. This study develops a comprehensive model to identify the next direct flight route for a destination by deploying buying funnel theory and gravity model. In addition to the geographical and economic characteristics of each market of origination, web traffic at the destination's Convention and Visitors Bureau (CVB) website—a proxy for the market's interest in the destination—is used to determine the markets that would exhibit the most potential to generate visitors if a non-stop flight route was opened. The model estimates each market's potential, using multiple gravity models, and compares it to the market's interest in the destination based on buying funnel theory. The present study then empirically tests the model using the actual data of Charleston, South Carolina, where five potential cities were identified.

1. Introduction

Attracting more visitors is one of the primary responsibilities of a Destination Marketing Organization (DMO). A series of literature has tried to identify potential customers and pinpoint target markets through market segmentation (e.g., Andereck & Caldwell, 1994; Dolnicar, 2008; Jang, Morrison & O'Leary, 2002; Müller & Hamm, 2014; Smith, 1956; Tkaczynski, Rundle-Thiele, & Beaumont, 2009). Another method of increasing visitor volume is to identify and eliminate barriers to travel (Heung, Kucukusta, & Song, 2011), including opening direct flight routes (see Tables 1 and 2, Fig. 6).

The lack of a non-stop flight route can be a barrier for visitors from potential markets to reach a destination (Grosche, Rothlauf, & Heinzl, 2007). However, it has been difficult to locate any study that attempted to estimate the increase in visitor volumes as a result of offering a new direct flight route. This paper introduces a model for estimating potential markets by eliminating a possible barrier—the lack of a non-stop flight—for a tourist destination. It introduces a comprehensive model that is based on actual visitation and interest and tries to identify the markets that would produce the most significant increase in visitor volume if a non-stop flight route were to open for those points of origin.

The present study combines the buying funnel theory with a single-destination gravity model to estimate a market's potential to generate visitors in the case of a new direct flight route. Traditional gravity models explain tourism demand using the push and pull factors of tourism such as GDP per capita, population, income, transportation cost, and distance (Morley, Rosselló, & Santana-Gallego, 2014; Tinbergen, 1962). In marketing literature, buying funnel theory explains customers' decision process with four steps: awareness, research, decision, and purchase (Clow, 2013; Jerath, Ma, & Park, 2014). In the research and decision steps, prospective visitors may search online for destinations with desired features. People tend to pursue faster and more comfortable ways to travel. The availability of a direct flight would come into the decision-

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https://doi.org/10.1016/j.tourman.2017.12.008
0261-5177/

Table 1
Regression estimation steps.

Step 1	Step 2	Step 3	Step 4	Step 5
Regress different dependent variables	Compare fitted values to actuals	Estimate the potential numbers	Compare to web traffic volumes	Identify the candidate cities

Table 2
Three regression models.

Model	Dependent Variable	Independent Variables	Potential Market
1	Flight passengers	Income, population, distance, flight time[a], air	Potential market for airlines
2	Hotel guests	fare and availability of direct flight	Potential market for the hospitality industry
3	Mobile device users		Potential market for total visitor volume

[a] Flight time was excluded for hotel guests and mobile device users.

making process during the research process (Gronau, 1970). Thus, direct flights can potentially reduce transportation cost and thus be included in the gravity model as a cost factor. Creating a direct flight can function as a mechanism to increase the number of passengers for airlines and the number of visitors to the destination (Fujii, Im, & Mak, 1992; Tveteras & Roll, 2014). By estimating the parameters for the director flight variable and compare to the actual visitor volumes, we can estimate the potential visitor volumes if a direct flight were to open. Also, web traffic for the Convention and Visitors Bureaus (CVBs) of such destinations represents visitor interest and can be considered a proxy for potential interest as travelers search information online before visiting a city. An origin's potential can only be realized if there were enough interests to travel to the destination. This web traffic can corroborate the estimates from the modeling results.

With the estimation models and the actual data, the current study empirically tests the theoretical framework with a tourist destination, specifically, Charleston, South Carolina. The paper locates markets with high potential for travel to Charleston and a high interest in the destination, but without any direct flights available. This study identifies the top five potential markets for Charleston's next non-stop air route. The model could serve as a means for any destination to target its potential markets for generating inbound travel.

2. Literature review

This paper proposes a model for a single destination to identify potential markets using economic and geographical characteristics, availability of a non-stop flight route, and web traffic at the local DMO's website. In this section, the paper introduces previous studies that used gravity models to provide the basis for including economic and geographical factors. It also examines literature that incorporated the buying funnel theory to provide the rationale for interpreting a lack of direct flights as a barrier, as well as the level of web traffic as an indicator of destination interest.

2.1. Gravity model in social science and tourism research

Various disciplines of social science have adopted the gravity model. The gravity model originated from Newton's law of universal gravitation in physics (Newton, 1966). The law posits that distance and mass determine gravitational forces between two objects. Many researchers have used the model to explain visitor volumes between origins and destinations empirically (e.g., Balli, Balli, & Louis, 2016; Durbarry, 2008; Eryiğit, Kotil, & Eryiğit, 2010; Genç, 2013; Kaplan & Aktas, 2016; Keum, 2010; Khadaroo & Seetanah, 2008; Morley et al., 2014; Yang & Wong, 2012).

In tourism context, distance, as well as each market's attracting factors, are used to explain the gravitational pull that determines visitor volume. Greater distance between a destination and visitor origin is expected to decrease gravitational pull, whereas a higher number of people and a higher level of income is expected to increase it. Hence, the gravity model is presented as follows:

$$X_{ijt} = G\frac{\left(A_{it}^{\alpha}A_{jt}^{\beta}\right)}{Distance^{\gamma}}$$

X_{ijt} represents the number of visitors between location i and location j, at time t. A_{it} and A_{jt} represent attracting factors at location i and location j, respectively, at time t (e.g. population and income are widely used as attracting factors). G stands for the gravitational constant, and Latin superscripts indicate the degree of impact each factor has.

Many studies have added other factors to the simple gravity model to model visitor behavior more precisely. Some have used socio-institutional variables, such as tourism climate index, cultural index, incidents of earthquakes, a shared border, or one-off events such as the Iraq War and the September 11 terrorist attacks (Eryiğit et al., 2010; Zhang, Li, & Wu, 2017). Genç (2013) and Balli et al. (2016) both included immigration information in their gravity models, explaining tourism flow for New Zealand and bilateral traveler flows between 34 OECD countries, respectively. Khadaroo and Seetanah (2008) adjusted the gravity equation to account for the role of transportation infrastructure in inbound tourists. Yang and Wong (2012) and Massidda and Etzo (2012) included variables that represented tourist attractions. Yang and Wong used destination's number of national parks, World Heritage Sites and AAAA scenic spots to quantify tourist attraction; Massidda and Etzo employed destination's regional relative endowment of touristic places to the total national endowment as a proxy.

Some used economic variables in their gravity models. Durbarry (2008) included the real effective price of tourism products, along with common language and EU variables, to understand tourism inflows to the United Kingdom. Santana-Gallego, Ledesma-Rodríguez, and Pérez-Rodríguez (2010, 2016a,b) also examined the relationship between international tourism flows and exchange rate, participation in the European Union monetary system, and international trade. Similarly, Hanafiah and Harun (2010) include consumer price index as a consideration of price sensitivity, along with economic crisis as a possible factor that could affect Malaysia's tourism industry. In conclusion, socio-institutional and economics factors further explain tourism flow at an international scale.

The gravity model can explain how a market's economic, geographical, and social-institutional factors affect visitor flow to a destination. However, it is hard to explain the role of non-stop flights and web traffic in determining visitor volume. For that purpose, buying funnel theory provides insights by combining an individual-level decision process with an aggregated gravity model.

2.2. Buying funnel theory in tourism research

In tourism literature, buying funnel theory is often used to understand a visitor's process of choosing a destination (Clow, 2013; Jerath et al., 2014; Sirakaya & Woodside, 2005; Yoo & Chon, 2008). The theory dissects a consumer's decision-making process into four stages: awareness, research, decision, and purchase. At the awareness stage, a visitor is aware of the existence of the destination. The next stage is research, during which the visitor has a decision task, starts searching for information, and accumulates knowledge about some destinations that satisfy the visitor's goals and objectives. For example, the visitor may realize a need to choose a destination for an upcoming vacation. At the decision stage, the visitor forms a choice set of alternative destinations and compares the destinations to make a decision. The last stage is purchase when the visitor carries out the steps needed to book travel and reach the destination (Jansen & Schuster, 2011; Sirakaya & Woodside, 2005; Yoo & Chon, 2008).

Many studies have shown that internal and external factors affect the visitor's formation of choice set during the research and decision steps (Fodness & Murray, 1999; Jun, Vogt, & MacKay, 2010; Pan & Fesenmaier, 2006; Yoo & Chon, 2008). Internal factors are connected to personal experiences, such as attitudes, beliefs, and lifestyles. External factors account for the outside forces that affect visitors, such as word-of-mouth from the Internet, media, family, and friends. For example, recent studies assert that the Internet is the most critical external information source for a visitor's decision process (Jun et al., 2010; Murphy & Chen, 2016; Xiang, Wang, O'Leary, & Fesenmaier, 2015).

With data collected in 2001 by the Canadian Tourism Commission (CTC), Jun et al. (2010) were able to confirm that visitors—especially those who purchased accommodations online—were likely to search for information online and visit a destination's official websites while planning travel. Murphy and Chen (2016) observed and surveyed 19 participants to analyze visitors' online search behavior while planning visits. They were able to confirm that the participants visited online information sources ranging from search engines to destinations' official websites. With surveys conducted over six years, Xiang et al. (2015) found that approximately 40% of people looked at official websites of destinations to plan their travel. These results provide a rationale for interpreting web traffic on CVB websites as an indicator of interest in a destination.

While the review of previous studies provided a rationale to employ a gravity model and include web traffic in the analysis, our research was unable to locate any literature that used direct flights and web traffic information in a gravity model or in buying funnel theory. Both of these factors are critical in examining visitor behavior. Web traffic from a particular market may indicate a high level of interest in a destination, but a lack of non-stop flights can be a barrier for travelers visiting it. Without direct flights, travelers may eliminate a destination from their choice set during the research or decision stage.

In the next section, the study proposes a theoretical framework in merging buying funnel theory and gravity models. Incorporating direct flights and web traffic into the model is examined in detail.

3. Theoretical framework

This study adopts Charleston, South Carolina, USA as an example to illustrate the theoretical framework, (Figs. 1 and 2). In Fig. 1, the double circle in the middle represents the Charleston Metropolitan Statistical Area (MSA), and grey dots in the orbit are visitors' markets of origin as MSAs. The size of the grey dots is determined by the population and income of the originating market, and it represents the amount of possible travel volume. If an MSA has higher income and population, the MSA is considered to have a potential for high volumes of visitors traveling to Charleston. The black dashed circles indicate distance. The distance between Charleston and the originating MSAs, on the same dashed circle, is identical. The black solid-line orbits indicate the barriers that exist in reaching Charleston. Each barrier decreases the number of visitors from the MSAs, and some are entirely obstructed even though they have great potential to travel. The barriers can be explained using buying funnel theory (Fig. 2).

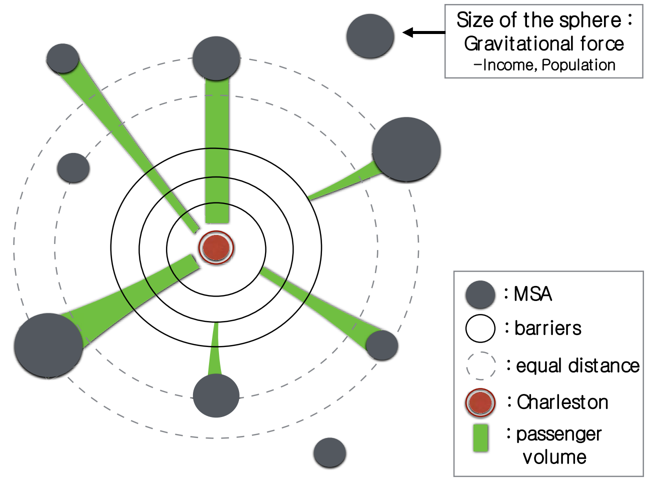

Fig. 1. Markets of origin and the destination city.

Buying funnel theory connects the aggregated gravity model with an individual visitor's decision making. At the research and decision stage, the web traffic at a CVB website can occur as the consumer searches for features and activities at specific destinations. Hence, web traffic at a CVB website can be considered as the potential visitors' level of interest. If a market of origin is not interested in the destination, targeting such a market would be to no avail. Though CVB web traffic cannot capture 100% of the potential visitors as they also search online resources, it is the second most important online resource for Charleston visitors after travel review sites (Patience, Watson, & Pan, 2016). The traffic for the latter is not available. Also, researchers have shown its predictive power in forecasting future hotel occupancy (Yang, Pan, & Song, 2014). Hence, the model also examines each market's interest in the destination, which is estimated by the market's web traffic at the destination's Convention and Visitors Bureau (CVB) website.

The consumer would also decide on the maximum distance to travel due to time and budget constraints at both stages. In doing so, the consumers would encounter transportation options, and they prefer to travel in a more risk-free, comfortable and less time-consuming way (Anderson & Kraus, 1981; De Vany, 1974; Gronau, 1970). Availability of a direct flight can function as one of the positive factors to keep the destination in one's choice set, given that a direct flight can decrease travel time, uncertainty, and discomfort (Nicolau & Màs, 2006). Having no direct flights can make the travel less comfortable and more time-consuming, and thus deter visitors. Accordingly, the study includes distance, length of the flight, availability of a direct flight, and transportation cost in the model. An individual traveler's decision process (Fig. 2) impacts the number of total visitors to a destination due to these barriers of travel (Fig. 1).

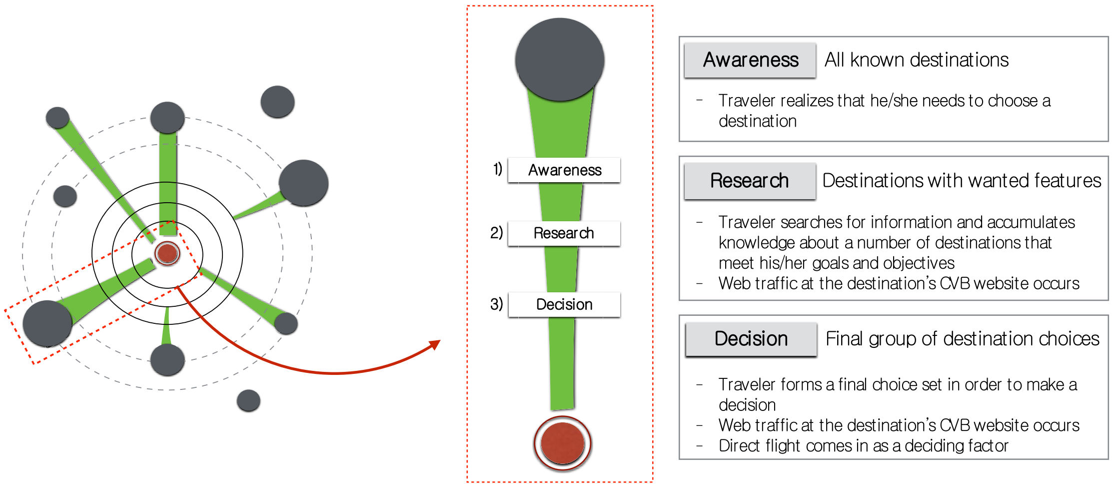

Fig. 2. Buying funnel and gravity model.

In conclusion, the gravity model explains the movement between the markets and the destination. Population, income, distance, and availability of a direct flight all work as factors affecting gravity between the market and destination. The gravity between them represents the pulling force from the destination to attract visitors from the market. Closer distance and availability of a direct flight are expected to increase gravity, while gravitational pull can be obstructed by barriers posed during the purchasing decision process. These barriers include time-related constraints, such as distance and a lack of direct flights, as well as financial and physical constraints.

4. Methods

Based on the proposed theoretical framework, this study fits three gravity models. Unlike the popular longitudinal form of gravity model with bilateral tourist flows between all pairs of countries over time, the gravity model employed here takes a single-destination and multiple-origin form, i.e., destination-centric model (Niedercorn & Bechdolt, 1969), and is cross-sectional in nature. A single destination model is more practical for DMOs as the model can useful to destination-focused data. It is difficult to expect DMOs of a specific destination to observe bilateral visitation between other destinations besides themselves.

The destination centric gravity model takes the following form:

$$V_{ic} = \alpha_0 Pop_i^{\alpha_1} Pop_C^{\alpha_2} GDP_i^{\alpha_3} GDP_C^{\alpha_4} DF_{iC}^{\alpha_5} Price_{iC}^{\alpha_6} D_{iC}^{\alpha_7} \varepsilon_i^{\alpha_8}$$

where $\varepsilon_i$is an error term with $E[\varepsilon_i | Pop_i,\ Pop_C,\ GDP_i,\ GDP_C,\ DF_{iC}, S_{iC}] = 0$ and $\alpha_{k,\ (k=0\ to\ 8)}$ is an unknown parameter. We assume that the number of visitors, V_{iC}, can be explained by the vector of independent variables: population, income, distance, direct flight, and cost of transportation. By exponentiating both sides, we get

$$lnV_{iC} = ln\alpha_0 + \alpha_1 lnPop_i + \alpha_2 lnPop_C + \alpha_3 lnGDP_i + \alpha_4 lnGDP_C + \alpha_5 DF_{iC} + \alpha_6 lnPrice_{iC} + \alpha_7 lnD_{iC} + \alpha_8 \varepsilon_i$$

a) V_{iC}represents the number of visitors from origin i to Charleston, which is either the number of flight passengers, F_{ic}, hotel guests H_{iC}, or mobile devise users, M_{iC};
b) Pop_irepresents the population of origin i, and Pop_C the population of Charleston;
c) $GDP_i$and GDP_C represent median family income of origin i and Charleston respectively;
d) D_{iC}represents the physical distance between origin i and Charleston;
e) DF_{iC}represents the dummy variable for the availability of a direct flight. DF_{iC} is 0 if there is no direct flight, and it is 1 if there is a direct flight available;
f) $Price_{iC}$represents the average air fare from origin i to Charleston.

In addition to above variables, the actual estimation included quadratic for of distance, $lnD_{iC}*lnD_{iC}$ since we believe distance may be non-linearly related to flight passengers.

Though the log-normal model is often used in gravity models, it tends to have severe disadvantages due to its strong assumptions of normality and homogeneous variances (Flowerdew & Aitkin, 1982; Silva & Tenreyro, 2006). First, the log-normal model transforms the data into the logarithm format, which can lead to under-estimation or biased estimation of the observed values (Silva & Tenreyro, 2006). The bias is more severe when there is heteroscedasticity since the log-normal model assumes homogeneous variance. Our dataset is vulnerable to such biased estimates as the dataset appears to have heteroskedasticity.[1]

Second, there is a high possibility that the logarithmic form of positive-valued integers would not follow a normal distribution (Flowerdew & Aitkin, 1982), violating one of the central assumptions. The third and most commonly known drawback is its innate inability to process zero values, and our dataset contains zero and positive values. These problems with log-normal models exist not only for panel data but also for cross-sectional data (Westerlund & Wilhelmsson, 2006). There are a few possible ways of processing zero values, such as adding a certain small number to zeros or treating them as missing variables. Both methods can still result in biased estimates. Many studies have suggested using Poisson pseudo-maximum-likelihood (PPML) method as an alternative solution (Flowerdew & Aitkin, 1982; Silva & Tenreyro, 2006; Westerlund & Wilhelmsson, 2006).

[1] From Stata's Breusch-Pagan/Cook-Weisberg test for heteroskedasticity (estat hettest), the constant variance null hypothesis is rejected with 0.0475 p-value.

Tourism researchers have incorporated the Poisson measure to analyze tourism demand and travel costs, often stating the method as the Count model (Creel & Loomis, 1990; Hellerstein, 1991; Hellström, 2006; Parsons, 2003). For example, Hellström (2006) employed a bivariate Poisson log-normal model to efficiently and accurately look at the household tourism demand. PPML does not require assumptions about the variance function—one of the restrictions of Poisson regression—and can provide consistent betas (Winkelmann, 2008). Therefore, the present study estimates the above estimation model using PPML method.

5. Data description

The dependent variables for gravity models in this study are three types of visitor volume: the number of flight passengers, the number of hotel guests, and the numbers of mobile devices used by visitors. The first dependent variable, flight passengers, account for the visitors that used an airplane as their mode to travel. Visitor volume can include visitors via various transportation types such as road, rail, air and water. As this paper aims to examine the impact of direct flight on visitor volume, visitors via flights are considered from transportation type.

The second dependent variable, hotel guests, is the number of hotel guests from each MSA based on the guest zip code data provided by 13 hotel management companies in Charleston, SC. The paper strives to find the next potential markets with economic benefits for the destination, we look at visitors who stayed at hotels among accommodation types as they are more likely to be overnight visitors with touristic purposes. Also, tourists planning hotel-based holidays are more likely to fly (Van Middelkoop, Borgers, & Timmermans, 2003), which indicates that creating a direct flight route can impact hotel guests. Flight passengers can overlap with hotel guests if they flew in and stayed in a hotel. However, hotel guests allow us to capture visitors that drove or took a train to reach Charleston and stayed overnight in a hotel.

The third visitor type, mobile device users, accounts for visitors that possess cell phones with two wireless carriers that account for 48.54% of total market share (Statistica, 2017a,b). The mobile device users can include visitors via any transportation and who stayed in any accommodation types. Moreover, they can include leisure tourists, business tourists, and family members visiting friends and relatives (VFRs). Hence, mobile device users incorporate the most general visitor types. They can capture the visitor types that flight passengers and hotel guests may be overlooking. The examination of above three different visitor types allows the study to provide a single model that can investigate different visitor types.

Analysis is run with each dependent variable. Then, the present study compares the fitted values from the estimation and the actual data to search for the markets with the highest potential but no direct flight. Those with fitted passenger numbers much higher than actual ones are considered as origin MSAs with the highest possibility to increase the number of flight passengers if there were a non-stop route. Flight passengers are most likely to be visitors from more distant MSAs because they are flying, rather than driving, to reach the destination. The difference between the fitted and actual number of mobile devices indicates the potential to increase total visitors via all transportation modes. Mobile device users would represent the most diverse group of visitors since 85% of U.S. vacationers bring their mobile devices while traveling (TripAdvisor, 2013). A significant gap between the fitted and actual number of hotel guests denotes the potential to increase overnight visitors. The present study compares the cities with the highest potential in three measures with to the volume of web traffic. Accordingly, MSAs with the highest potential to visit and with the highest interest level will emerge.

5.1. Data sources

More specifically, the airline traffic data is from Seabury APG (World Bank, 2009), a management consulting company specializing in aviation planning and management. The data is an annual average number of flight passengers between 2013 and 2015. The guests' zip code data from 13 hotel management companies in Charleston provide the hotel guest data. The number of hotel guests is a three-year average between 2013 and 2015.

The big data sources refer from digital traces left by visitors. Web traffic data is gleaned from the traffic log of the area's CVB website. A commercial company, AirSage, Inc provided the number of mobile devices (Tsai, Kelley, Cranor, & Sadeh, 2010). AirSage uses cell phone signals from two major mobile carriers, covering almost half of U.S. mobile device users (Statistica, 2017a,b). The company looks where a person's cell is most frequently used to determine that person's residential area. If the device stayed in the Charleston area for less than half of the period while it is tracked, the holder of the mobile device is considered a visitor. The paper used the data from four single-month periods in 2014 and 2015. The web traffic data represented the annual average number of web sessions on the CVB main website, from 2013 to 2015 and gleaned from Google Analytics (Clifton, 2012). Google Analytics is a service offered by Google that provides information regarding website visitors. The service allows the website to understand how many visits it gets and from what types of visitors. Google is not a single search engine available and hence may not account for all existing searches. However, Google is still dominant compared to all other search engines (StatCounter, 2017; Statistica, 2017a,b). On average, Google is believed to have almost 80% in market share of search engines in the U.S.

Regarding economic and population data, the paper used a 2015 estimate by the Census Bureau for the population of each MSA (US Census Bureau, 2015a,b). For income data, a 2015 median family income estimate by the Federal Financial Institutions Examination Council (FFIEC) was used (FFIEC, 2015). For MSAs that were missing income information, this study used a 2015 estimate by the Census (US Census Bureau, 2015a,b). Flight distance and driving distance were measured separately. Flight distance was calculated using the Mileage Calculator on WebFlyer.com (http://www.webflyer.com/travel/mileage_calculator). CDXzipstream provided driving distance. This program is a Microsoft Excel add-in that helps calculate the distance between zip codes.

Regarding distance and transportation cost data, the paper used Google Maps (http://maps.google.com) to calculate the flight time between Charleston and the originating MSAs. Of all the flight options that appeared on Google Maps, the paper used the shortest time. There were 85 MSAs that were missing flight time information. Among them, the 30 MSAs that did not have average flight ticket prices were dismissed. For the remaining 45 MSAs, 11 had flight passenger data. Flight times for the 11 MSAs were estimated using the airports suggested by TripAdvisor, Orbitz and Cleverlayover. For the final regression, data from 230 MSAs were employed (228 MSAs for mobile users) (see Table 3).

6. Results

6.1. Regression model results

This paper sought to identify the potential MSAs expected to supply the most visitors to a destination by establishing new direct flight routes. Table 4 shows the descriptive statistics of the data used in the three estimations. From the table, we observe that the number of incoming flight passengers, mobile device users, and hotel guests varies significantly across MSAs. The variable of

Table 3
Variables and data sources.

Variable	Data Source
MSA Population	US Census Bureau, 2015a,b estimates
MSA Median Family Income	Federal Financial Institutions Examination Council (FFIEC) 2015 estimates
Nearest Airport	http://www.travelmath.com/nearest-airport/
Flight Distance	http://www.webflyer.com/travel/mileage_calculator/
Driving Distance	CDX zipstream
Flight Time	http://flights.google.com/
Number of Hotel Guests	Guests' zip code data from 13 hotel management companies, in Charleston, SC, 2013–2015
Web Traffic	Average unique web sessions from CVB websites, 2013–2015, gleaned from Google Analytics
Mobile Devices	Four months' mobile devices from two major mobile carriers, from AirSage Inc.

Table 4
Descriptive statistics.[a]

Variable	Min	Mean	Max	N
Air traffic (incoming, per year)	0	4224	195,485	357
Mobile device users (per 4 months)	2	1570	44,492	266
Hotel guests (per year)	19	3608	85,407	274
Family median income (1000 USD)	35.4	63.8	109.4	359
Population (10,000)	5.5	78.6	202	360
Direct flight (0 if no direct flight, 1 if yes)	0	0.03	1	361
Flight time (hh.mm)	0.55	4.68	12.25	286
Distance (miles)	61	962	4750	361
Flight ticket price (USD)	52	227	663	270
Web session (session per year)	139	15,833	393,457	357

[a] Slight differences per regression model due to missing values.

availability of direct flight has very low mean. This indicates that very few MSAs have a non-stop flight to Charleston as of the study.

Table 5 shows the estimation results of the three regressions. Except for direct flight, which is a dummy variable, all variables are in logarithm form. The first result column of Table 5 shows the coefficients of independent variables for flight passengers (see Table 6).

The variable of primary interest, availability of direct flight, has 0.19 as its coefficient. Since direct flight variable is a bivariate variable, this indicates that MSAs with a direct flight has 21% ($e^{0.19} - 1 = 0.21$) greater number of flight passengers compared to those that do not. The result is in accordance with Fujii et al. (1992) and Tveteras and Roll (2014). Hence, we can argue that having a direct flight route is expected to increase the number of flight passengers.[2]

Table 5
Regression result of gravity model of three regressions.[a]

Variable[b]	Flight passengers	Hotel guests	Mobile device users
Income	1.26	1.56	1.79
	(0.01)	(0.01)	(0.01)
Population	1.04	1.01	0.83
	(0.00)	(0.00)	(0.00)
Distance	0.24	−5.03	−5.18
	(0.00)	(0.02)	(0.03)
Distance^2	−0.01	0.30	0.28
	(0.00)	(0.00)	(0.00)
Direct Flight	0.19	0.20	0.19
	(0.00)	(0.00)	(0.01)
Flight Time	0.13		
	(0.01)		
Ticket price	−1.22	0.32	0.13
	(0.01)	(0.00)	(0.01)
Constant	−14.69	−5.17	−3.47
	(0.11)	(0.09)	(0.15)
N	230	269	261
Pseudo R^2	0.8816	0.9297	0.8928

Standard errors in parentheses.
[a] All coefficients are significant with p-values less than 0.01.
[b] All variables are in logarithm form except for direct flight which is a dummy variable with value either 0 or 1.

The population and income are positively correlated with the number of flight passengers. If family median income or population increases by 10%, the number of flight passengers is expected to increase by 12.6% and 10.4% on average respectively. Income shows a higher degree of impact than the population. This could be due to Charleston being a high-end destination where it is somewhat costly to stay and dine and thus, it attracted the residents from more affluent MSAs.

Contrary to popular belief, distance is positively correlated with the number of passengers. However, this is understandable since there will not be many flight passengers from a very close distance where people can drive to reach Charleston. Squared distance, Distance,^{2} has a negative coefficient, unlike the distance variable. This indicates that the positive impact of distance will decrease as the degree of distance increases. A similar explanation can be applied to flight time, as people are likely to fly if the distance is further, longer flight time is associated with higher number of flight passengers. Ticket price is negatively correlated with flight passengers, as expected.

Two other columns are the regression results with the dependent variable as the number of hotel guests and mobile device users, respectively. For hotel guests and mobile device users, we do not include flight time in the equation since the transportation mode is not solely airplane and distance would capture most of the impact due to travel time. Hotel guests, as previously mentioned, represent overnight visitors that include visitors who arrived at Charleston via both road and air. Availability of direct flight has lower but still positive impact on hotel guests. The number of hotel guests is expected increase 22% ($e^{0.20} - 1 = 0.22$) with direct flight on average.

Unlike flight passengers, hotel guests include visitors that drive to Charleston and hence distance has a very significant negative impact on their numbers. When an MSA is further away with 10% higher distance, hotel guests are expected to decrease by approximately 50%. However, the impact will gradually decrease as squared distance has positive coefficient and will counter the effect of distance. Ticket price shows a positive coefficient, which is unusual since higher ticket price would decrease the number of flight passengers. We could assume that higher demand can also increase the ticket price. That is, there could be a high number of visitors from MSAs with higher ticket price who drive. However, the degree of impact from ticket price is comparatively low—MSAs with a ticket price of 10% higher will have 3.4% greater number of hotel guest on average.

The number of mobile device users includes the most diverse

[2] To check causality, we ran a regression with availability of direct flight as dependent variable using PPML. The result showed that flight passengers—or any other independent variables—do not have any significant impact.

Table 6
Top five potential MSAs for direct flights.

MSA	Population	Income	Driving Time	Current Flight time[a]	Expected Flight time[b]	Web traffic	Market potential[c]
Portland-South Portland, ME	526,295	73,200	16h48	4h09	2h29	8282	241
Minneapolis-St. Paul-Bloomington, MN-WI	3,524,583	85,700	19h52	4h02	2h41	45,117	207
Jacksonville, FL	1,449,481	63,300	3h42	3h50	0h43	46,417	68
Allentown-Bethlehem-Easton, PA-NJ	821,173	71,200	10h45	3h40	1h36	12,230	64
Kansas City, MO-KS	2,087,471	74,700	15h59	4h05	2h18	28,905	44

[a] Shortest available time on June 1st, 2017 on Google Flights. Single stop-over. Does not include driving time to the nearest airport.
[b] Expected flight time when there is a direct flight, based on distance using AirplaneManager (https://airplanemanager.com/FlightCalculator.aspx).
[c] Market potential represents the expected increase in the number of incoming flight passengers per week.

population of visitors. It includes all visitors with a mobile device that reached the destination via all transportation modes. Moreover, it includes leisure tourists, business tourists, and family members visiting friends and relatives (VFRs)—in which case they stayed for any number of days. The result for mobile device users is similar to that of hotel guests. The MSAs with a direct flight to Charleston are again expected to have 21% more mobile device users.

From the results of three analyses, we can conclude that having a non-stop flight has significantly positive impact on the number of visitors. Therefore, creating a non-stop flight route to a potential market can help destinations to increase the number of incoming visitors. As opening a direct flight route is costly, it is vital to locate an MSA that will generate the most visitors. From this section's analyses, we can conclude that population, income, and proximity have a positive impact on the number of visitors.

At the same time, we observe many MSAs who have high population and income, and are relatively close to Charleston but do not visit as much compared to the MSAs that have similar traits. Hence, using the expected value of visitors from the regression results and an actual number of visitors from the data, we look for the MSAs that have a low number of visitors despite their favorable conditions. Even an MSA has favorable conditions, if people from it is not interested in the destination, creating a direct flight route would be to no avail. Accordingly, to locate potential markets, one must evaluate the interest of the MSAs. We consider web traffic at the destination's CVB website as the degree of interest.

In the next section, the paper locates potential markets by comparing the regression results with web traffic data.

6.2. Potential market identification

The fitted values from the regressions are compared to the actual values to identify potential markets. First, for the regression with the number of flight passengers as its dependent variable, the fitted value is the expected number of flight passengers given its income, population, distance, flight time, the relative cost of flying and availability of a non-stop flight route. Hence, the difference between the fitted value and the actual number is the market's potential to fly to Charleston:

Market's potential to fly = Fitted value − Actual flight passenger number

Those with higher negative values could be considered overachievers, whereas those with higher positive values could be seen as underachievers with a potential to visit by air.

Creating a non-stop flight would help realize such potential. However, if the market is not interested in the destination, there will be no increase in the number of visitors, even with high potential. The markets' potential to fly should be compared to their interest in the destination. The level of interest is the market's annual average web sessions at the destination's CVB website. The MSA with the highest potential increase in the number of flight passengers and with the highest interest in Charleston is Los Angeles-Long Beach-Anaheim, CA (Fig. 3). However, it was excluded from the final potential markets as we only looked at overlapping MSAs—marked with red circle—for all three types of visitors. Portland-South Portland, ME has the highest potential increase among those that overlap. Whereas Jacksonville, FL shows the highest interest. Other three common MSAs are Allentown-Bethlehem-Easton, PA-NJ, Kansas City, MO-KS and Minneapolis-St. Paul-Bloomington, MN-WI. These five MSAs are likely to show an increase in flight passengers, mobile device users, and hotel guests if there was a direct flight available.

In the case of hotel guests, that best represents overnight visitors, Jacksonville is dominant in both categories of interest and potential (Fig. 4) even though it did not have a high potential for the flight passengers. This is because mobile device users include visitors that drive to Charleston. People from Jacksonville can reach Charleston by four-hour driving. This does not indicate that it is not a viable non-stop flight route. Charlotte, NC has a direct flight to Charleston, and it is only three-hour drive away. Minneapolis-St. Paul-Bloomington and Portland-South Portland also demonstrate high potential to increase the overnight visitors(see Fig. 5).

Jacksonville is again the most outstanding market in mobile device users, which best represent general visitors. General visitors and overnight visitors have more common potential markets that do not appear as potential markets for flight passengers. They share similar characteristics due to visitors who arrive in Charleston via road. For instance, Deltona-Daytona Beach-Ormond Beach, FL appears both in mobile device users and hotel guests. However, the MSA has comparatively low income (USD 51,500) and population (623,297), and high ticket price (USD 203) compared to the five overlapping markets.

The volume of hotel guests and mobile device users are adjusted as they are partial data. The hotel guests are data from 13 hotels in Charleston. As of 2016, there are more than 150 hotels in the Charleston MSA (STR, 2016). The total number of hotel guests would be more than ten times the number used in the analysis. For mobile device users, the number should be multiplied by approximately six since it reflects four-month data from only two mobile carriers, which represent about 49% of the total mobile traffic (Statistica, 2017a). By comparing these three analyses, this study was able to locate the top five potential MSAs for the next non-stop flight route.

The analyses of flight passengers, mobile devices, and hotel guests identified five MSAs in common: Portland-South Portland, ME; Jacksonville, FL; Allentown-Bethlehem-Easton, PA-NJ; Kansas City, MO-KS; and Minneapolis-St. Paul-Bloomington, MN-WI. If the purpose is to increase overall visitor volume, targeting these MSAs would be beneficial. Minneapolis-St. Paul-Bloomington shows high interest and potential for all three types of visitors. Portland-South Portland, on the other hand, would be the most profitable for the

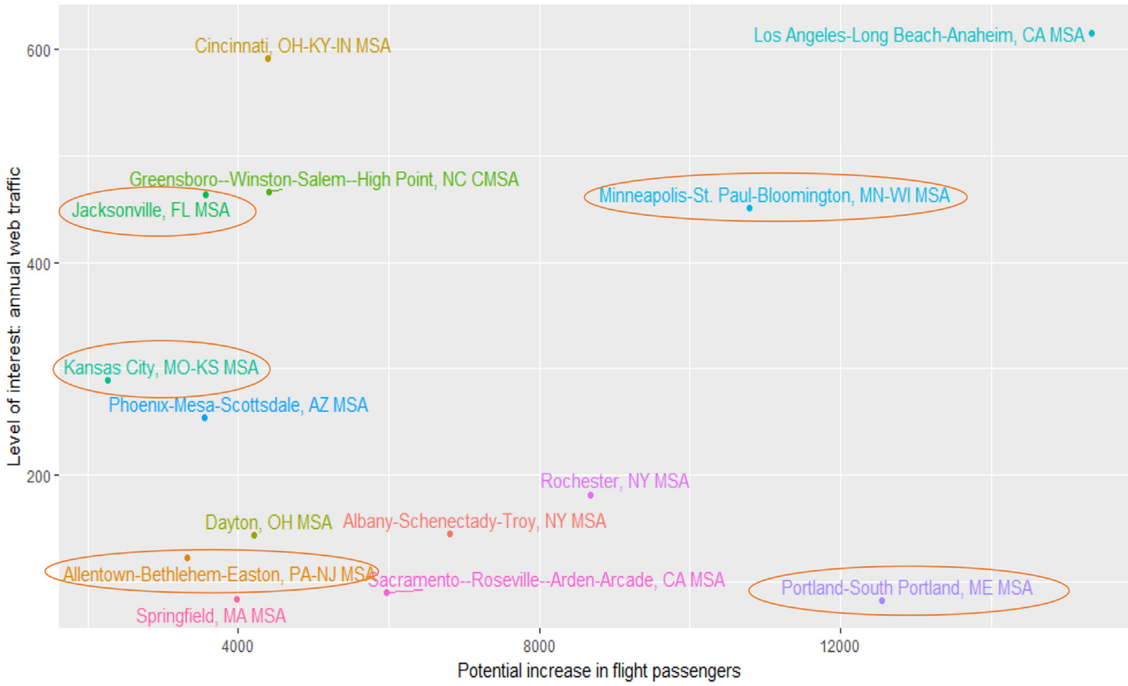

Fig. 3. Market potential to increase flight passengers versus web traffic.

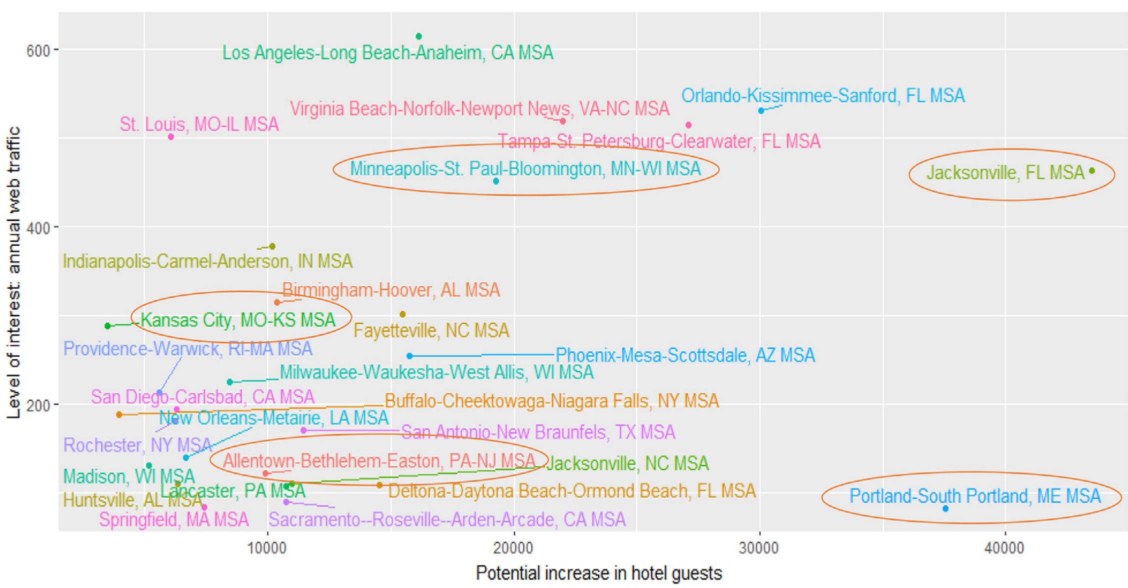

Fig. 4. Market potential to increase hotel guests versus web traffic.

airlines and hotel industry as it has high potential to increase the number of flight passengers and hotel guests. Jacksonville, which is relatively close to Charleston, is identified as a potential market for general visitors (mobile device users) and hotel guests. However, since it is only four hour-drive away, its potential for attracting flight passengers is low.

With the assumption that Charleston cannot open direct flight routes to all five MSAs, two top choices are recommended: Portland-South Portland and Minneapolis-St. Paul-Bloomington. Portland-South Portland is about two hours away from the closest airport that has non-stop connection to Charleston, Boston Logan International Airport. Non-stop flight is expected to bring approximately 241 passengers weekly, or 12,566 yearly. Minneapolis-St. Paul-Bloomington is more isolated as it takes about six hours to reach the closest airport with a direct flight to Charleston, Chicago's O'Hare International Airport. If a direct flight route were to open, Charleston is expected to increase 207 passengers weekly, or 10,794 yearly. If Charleston were to open a single non-stop route, this paper would recommend Minneapolis-St. Paul-Bloomington as it is further away from existing non-stop flight routes and shows greater potential in general and overnight visitors.

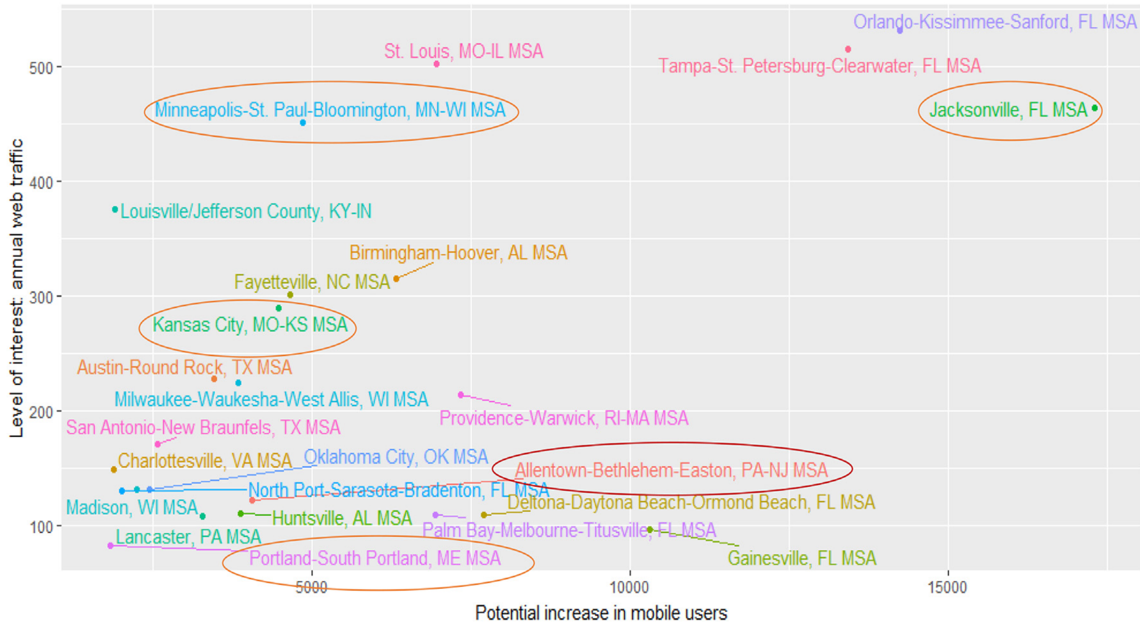

Fig. 5. Market potential to increase mobile device users versus web traffic.

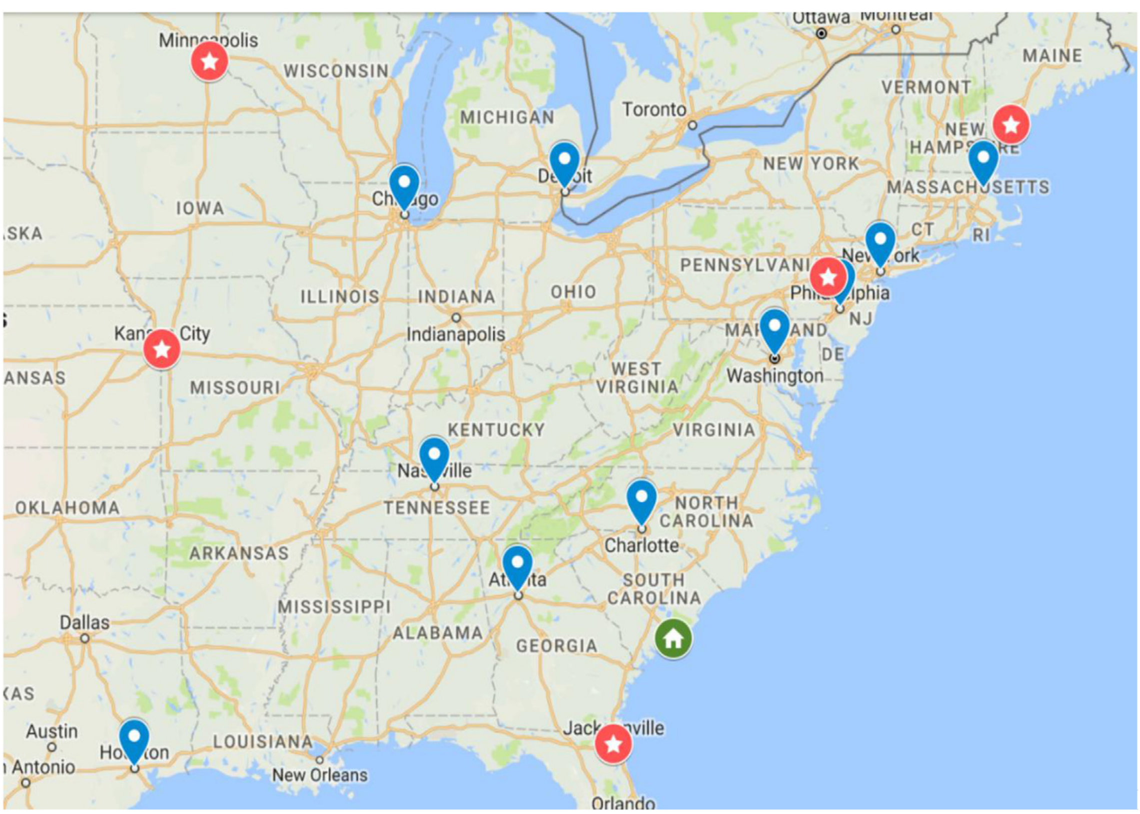

Fig. 6. Potential markets for direct flight (star) and existing direct flight routes (pin) of Charleston (house).

7. Conclusion and discussion

The present study has developed a theoretical framework that incorporates buying funnel theory with gravity models, which helped identify the most promising markets for a new direct flight route. The paper empirically showed the impact of direct flight route and validated that the availability of a non-stop route has a significant positive relationship with the number of visitors. From the regression results, this study also found the potential markets from which the number of visitors would increase if there were a direct flight available.

The paper looked at three types of visitors: flight passengers, those using mobile devices, and hotel guests. Flight passengers represent visitors via air; the number of mobile devices represents general visitors, and hotel guests represent overnight visitors. The three types of visitors provide three different types of visitor flow for more accurate examination of the visitor pattern. At the same time, the paper observes an additional flow: the flow of information, represented by the traffic at a destination's CVB website. The paper interprets the information flow as interest from potential visitors who can be dissuaded by the lack of direct flights. By comparing visitors' interests with the actual visitation volumes, one can further validate the potential market.

This study identified five potential markets for direct flights and two most significant ones. The airlines, however, may not agree with the potential markets because this study selected them in the interest of a destination. Critical factors for the airlines, such as current flight load, competition, and network effect were not considered when forming the model. For the airlines, the number of passengers on a flight is the sole focus. Therefore, they might create a new route for which there is already a large number of passengers. However, this does not mean that the number of visitors will increase. The number of passengers for an airline can increase while the number of total visitors remains the same. The airlines would also take into account how many competing airlines exist. Moreover, the airlines consider network effect when creating new flight routes, since forming networks can result in higher competitiveness and more customers (Pustay, 1980). Further research could be done incorporating the interests of the airlines for forecasting the best potential markets for the airlines.

Another major limitation of this study is omitting tourist attraction information. Though our model has a single destination, there are multiple origins, and tourist attraction in the origins can function as push factors when there are few attractions for sightseeing. We did not include the tourist attractions of each origin MSA as there is no universal standard to quantify. At the same time, tourist attractions of the origin markets are critical but less, we argue, compared to those of the destination. As the paper has a single destination and hence the tourist attraction is identical to all origin markets, we omit the tourist attraction variable. Standardization for quantifying the tourist attraction is very much needed for future research.

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