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Antecedents and consequences of home-sharing stays: Evidence from a nationwide household tourism survey

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ABSTRACT

This study aims to understand the demand for home-sharing lodging and whether this accommodation choice influences guest experiences, in terms of overall trip satisfaction and perceived value. Using a dataset from a large-scale nationwide household tourism survey, we adopted a two-step empirical analysis to investigate the antecedents and consequences of home-sharing stays. In the first step, results from logit models highlight various factors explaining the drivers behind choosing home-sharing lodging versus hotel lodging, such as tourists' tripographics, prior travel experiences, tech savviness, sociodemographics, destination home-sharing supply, and crime rate. In the second step, we employed propensity score matching to compare trip satisfaction and perceived value between home-sharing users and hotel users who were matched based on a similar propensity to choose home-sharing. Results suggest that while home-sharing users perceive a higher value for the trip, no significant difference exists between the two groups' trip satisfaction. Lastly, practical implications are provided.

1. Introduction

The concept of sharing homes with guests is not new (Poon & Huang, 2017). Technological innovations have greatly facilitated commercial home rentals for lodging purposes (Guttentag, 2015; Olson & Kemp, 2015) between homeowners and tourists (i.e. peer-to-peer or P2P) with a fee paid via an online platform. Home-sharing in the digital business era has become a viable alternative to traditional business-to-consumer lodging and can satisfy needs that traditional lodging supply has not always been able to meet, such as household amenities and extra space (Quinby & Gasdia, 2014), experiential authenticity (Lamb, 2011; Nowak et al., 2015), host-guest interactions (Su & Wall, 2010), novelty (Guttentag & Smith, 2017), and giving back to the local economy (Guttentag & Smith, 2017). In fact, home-sharing lodging has gained such traction and popularity that it is now a commonly considered accommodation option for many consumers. For the purpose of this paper, we define home-sharing lodging as commercially-driven peer-to-peer (P2P) short-term home rentals.

The growth and prevalence of home-sharing via digital platforms, such as Airbnb and HomeAway, are most evident in the collective economic impact of these and similar websites. Home-sharing began to expand after the launch of Airbnb in 2008. By 2014, home-sharing lodging had witnessed such phenomenal growth that it was identified as one of the five key sharing sectors worldwide with the other four being finance, staffing, car sharing, and music/video streaming (PwC, 2014). Together, these five sectors accounted for a total global revenue of USD15 billion in 2014, a figure expected to increase to USD335 billion by 2025 (PwC, 2014). Other research has suggested that home-sharing lodging in the U.S. alone is expected to reach USD107 billion or 10% of total accommodation bookings by 2025 (Olson & Kemp, 2015). Much of the optimism underlying the projected growth of home-sharing lodging arguably lies in its hitherto untapped potential. Even with home-sharing lodging continuing to expand rapidly over the past decade, studies indicate that only approximately 11% of all U.S. adults have used a home-sharing platform (Smith, 2016). It is therefore essential to understand this demand segment to leverage it properly.

Research on Airbnb users has revealed that demand for home-sharing lodging is driven largely by economic considerations, namely cost savings relative to traditional hotels (Cho & Bokyeong, 2016; Lin, Wang, & Wu, 2017; Möhlmann, 2015; Tussyadiah & Pesonen, 2018). Similarly, consumers are attracted to Airbnb accommodations and similar lodging options given their experiential appeal; travelers staying in Airbnb accommodations versus hotels have opportunities to live more authentically, like a local, including the patronizing of a non-commercial neighborhood and/or interacting with their hosts (Guttentag, 2015; Tussyadiah & Pesonen, 2018). Others' lodging decisions are shaped more by the people with whom they travel (Smith, 2016) or what they need from their accommodations, such as

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household amenities or a larger space (Quinby & Gasdia, 2014). Previous scholarly efforts have also analyzed the appeal of home-sharing lodging from a sharing economy perspective by highlighting its fundamental ideology encompassing community, sustainability, and direct contributions to locals (Guttentag & Smith, 2017; Lamb, 2011; Tussyadiah & Pesonen, 2018). In addition, an emerging stream of research has examined satisfaction determinants of P2P lodging (Möhlmann, 2015; Tussyadiah, 2016). However, to the best of the authors' knowledge, no study has yet endeavored to connect the antecedents of home-sharing stays with the consequences of perceived value and trip satisfaction.

To bridge this research gap, the present study conducts a two-step empirical analysis to uncover the antecedents and consequences of home-sharing stays based on nationwide household tourism survey data from U.S. domestic tourists. By doing so, we attempt to make at least three major contributions to the understanding of P2P lodging demand. First and foremost, we draw from behavioral data rather than stated preferences. Therefore, our data are free from laboratory effects that can plague stated behavior data, contributing to potentially unreliable results stemming from sample selection bias and possible subjective manipulation (Yacouel & Fleischer, 2012). Moreover, behavioral data have been shown to be more reliable than stated preferences, as the former tends to be measured as a vague inspiration rather than in a probabilitistic manner (McKercher & Tse, 2012). Second, the nationwide household survey covers a large sample of tourists with heterogeneous traveling behavior and consists of a wide array of destinations that may explain home-sharing preferences associated with destination-specific factors. Third, we employ propensity score matching, a quasi-experimental contrast analysis, to draw more rigorous conclusions regarding the consequences of home-sharing stays by matching treatment (i.e. travelers who used home-sharing lodging) and control (i.e. travelers who used hotel lodging) groups. With this method, we can closely approximate randomized controlled trials after balancing a set of characteristics between the two groups and making matched observations that reveal similar propensities to stay in home-sharing lodging.

2. Literature review

2.1. Industry structure

Home-sharing lodging is one of the most heavily discussed sectors of the sharing economy (Olson & Kemp, 2015). Within this sector, Airbnb is the leading platform with an estimated valuation of USD31 billion as of March 2017 (Thomas, 2017), only USD6 billion less than that of Marriott International, the world's largest hotel chain (Forbes, 2017). The rise of Airbnb exemplifies the transformation of the lodging industry over the past decade. The idea of sharing existing house space captures the essence of collaborative consumption wherein participants engage in sharing activities through renting, lending, trading, and bartering for goods, services, transportation, space, or money (Botsman & Rogers, 2011). Underutilized home space—whether in the form of a couch, an empty room, or an entire residence—that were previously unavailable to average tourists can now be shared for a fee, thereby creating more lodging inventory.

This transformation of the lodging industry is underpinned by advances in information and communication technologies (Horton & Zeckhauser, 2016). Extensive research has been carried out to examine the power of technology in shaping the business model of the modern sharing economy. The development of information technology and the growth of web 2.0 is widely credited with the creation of online sharing platforms (Guttentag, 2015; Kaplan & Haenlein, 2010), including Airbnb. The premise of Airbnb as an online platform matches owners (i.e. hosts) with buyers (i.e. guests) while maintaining a reputation system that has been touted as the main driver behind its rise and growing popularity (Einav, Farronato, & Levin, 2016). Structurally, technology has introduced online functions that enable Airbnb to attract traffic to the website (Guttentag, 2015). Scholars have contended that Airbnb's platform provides hosts with firm-like resources allowing them to reach out to potential guests, showcase their accommodations, take reservations, and accept payments (Einav et al., 2016; Horton & Zeckhauser, 2016). The format of Airbnb as an online marketplace has also been examined through the lens of disruptive innovation (Guttentag, 2015; Guttentag & Smith, 2017). This line of research describes how Airbnb, as a new disruptive product, underperforms on key traditional lodging attributes but is cheaper than conventional accommodations (e.g. hotels) and offers novel benefits, such as localized experiences (Guttentag, 2015).

To date, much of the existing P2P lodging research has focused specifically on Airbnb; hence, our review reflects this focus as well. We consider these findings to be extendable to the broader home-sharing lodging industry given the dominance of Airbnb in the market.

2.2. Home-sharing lodging demand

With the industry-level changes brought by Airbnb and other P2P online lodging marketplaces, an intuitive next step is to understand the nature of home-sharing lodging demand, primarily its different types, preferences, and user motivations. Cost savings compared to traditional hotels represent a key motivator across most studies (Cho & Bokyeong, 2016; Guttentag & Smith, 2017; Lin et al., 2017; Möhlmann, 2015; Tussyadiah & Pesonen, 2018). This observation echoes a basic tenet of the sharing economy in that collaborative consumption offers greater value for less cost (Botsman & Rogers, 2011), and cost benefits are paramount (Guttentag & Smith, 2017; Möhlmann, 2015).

In addition to the aforementioned motivations, Tussyadiah and Pesonen (2018) identified several barriers to using Airbnb such as cost, trust, and efficacy. Cost serves as a barrier rather than a motivator when guests believe a price to provide insufficient savings to be considered valuable (Tussyadiah & Pesonen, 2018). Similarly, distrust towards hosts and the Airbnb platform in general has deterred some American and Finnish travelers from using P2P lodging (Tussyadiah & Pesonen, 2018). This finding aligns with work by Möhlmann (2015), who discovered that trust significantly influences satisfaction with and the likelihood of using Airbnb again. Efficacy refers to tourists having insufficient knowledge and ability about how the online platform works (Tussyadiah & Pesonen, 2018), which is unsurprising given that 53% of 4787 American adults surveyed had never heard of home-sharing lodging (Smith, 2016).

2.3. Impact of home-sharing on hospitality and tourism

Along with the importance of understanding tourist demand for Airbnb, it is equally important to delineate the various effects of Airbnb on the hospitality and tourism industry given their interconnectedness. One of the most debatable impacts is how and to what extent Airbnb competes with traditional hotels. Guttentag and Smith (2017) found that nearly two-thirds of tourists surveyed had used Airbnb as a hotel substitute. In looking specifically at hotel performance figures, Ytreberg (2016) found that a 10% increase in Airbnb supply in Norway decreased hotel revenue by 0.3%. On the contrary, Coyle and Yeung (2016) and Hooijer (2016) both showed that hotel revenue increased in line with a growing Airbnb presence in fourteen European cities and the Netherlands, respectively. Airbnb has been found to compete most often with mid-to low-end hotels (Coyle & Yeung, 2016; Ytreberg, 2016; Zervas, Proserpio, & Byers, 2017). These effects may continue to expand as Airbnb seeks to target business travelers (Sickel, 2015) and with its acquisition of Luxury Retreats, a high-end vacation rentals platform (Zaleski & De Vynck, 2017).

In a series of impact studies commissioned by Airbnb (Airbnb 2013, 2017), various economic contributions (e.g. direct local spending and creation of jobs by Airbnb guests) were highlighted in nine cosmopolitan cities worldwide. For instance, Airbnb guests were found to have spent more time (6.4 nights vs. 3.9 nights) in New York than typical hotel guests along with spending more money (USD880 vs. USD 690) than typical tourists (Airbnb, 2013). The studies also revealed that Airbnb generated USD105 million in direct spending in the outer boroughs of New York, which typically do not benefit from the tourism dollar (Airbnb, 2013). Notably, these figures have not been independently verified (Oskam & Boswijk, 2016). In studying the spatial distribution of Airbnb customers in London, Quattrone, Proserpio, Quercia, Capra, and Musolesi (2016) observed that such patterns remained similarly concentrated in touristic areas from 2012 to 2015. Guttentag (2015) further argued that spending on P2P lodging, such as Airbnb, may suffer as a result of the cheaper positioning of such accommodation options. This assertion was corroborated by Fang, Ye, and Law (2016) in their analysis of the effects of Airbnb on tourism industry employment. They concluded that while the tourism industry benefits overall from new jobs generated by the growing number of tourists taking advantage of lower accommodation costs, the marginal effect decreases as the size of the sharing economy increases.

2.4. Other impacts of home-sharing

Research has also shown that the impacts of Airbnb extend beyond the hospitality and tourism industry, primarily to the local housing market. Proponents of Airbnb suggest that home-sharing lodging allows owners to earn additional income on underutilized assets (Moylan, 2016). At the same time, critics contend that Airbnb raises the cost of living for local renters, as landlords shift from supplying the market with long-term housing to catering to shorter-term stays. While empirical research in this area remains limited, studies on local housing markets in the U.S. point to a slight increase in posted rents, albeit to varying degrees, as Airbnb listings in neighborhoods increase (Barron, Kung, & Proserpio, 2017; Horn & Merante, 2017). More importantly, these studies conclude that this effect is larger in areas with a smaller share of owner-occupier units, suggesting that absentee landlords are putting their homes up for short-term Airbnb rentals in lieu of tapping the long-term rental market (Barron et al., 2017; Horn & Merante, 2017).

Other potential impacts of Airbnb may foster tension within local communities. Home-sharing lodging does not add amenities but promotes greater use of existing local facilities (Barron et al., 2017). For example, residents in Sydney have expressed general dissatisfaction over new renters occupying residential premises on a weekly basis while resident owners in an apartment building had more specific complaints, such as issues with garbage disposal and parking (Barron et al., 2017). Similarly, residents of La Barceloneta in Barcelona have also complained about unruly tourist behavior such as drunkenness, public urination, and loud parties that continue until the early hours of the morning (Croft, 2015). In Florida, the spatial relationship between Airbnb and crime levels was found to be significant and positive, moderated by crime type (i.e. property crime vs. violent crime) and room type (i.e. shared room vs. private room vs. an entire unit) (Xu, Kim, & Pennington-Gray, 2017).

3. Conceptual framework

Based on the above summary of Airbnb and its impacts, we have identified the antecedents and consequences of using home-sharing lodging via a conceptual framework (see Fig. 1). This framework is grounded in the theory of tourism consumption systems (TCS), which suggests that “thoughts, decisions, and behaviors regarding one activity influence the thoughts, decisions, and behaviors for a number of other activities” (Woodside & Dubelaar, 2002, p. 120). TCS can be classified into three phases: (1) prior to and during travel relationships, (2) during and after travel relationships, and (3) post-travel relationships. If a home-sharing stay is regarded as a Phase 2 travel behavior (“accommodation used” as specified in TCS), then most tourist-specific antecedents and consequences of this behavior should occur in Phases 1 and 3, respectively. More specifically, following various propositions of TCS (Woodside & Dubelaar, 2002; Li, Li, & Hudson, 2013), tripographics, past travel experience, and sociodemographics can help to explain individuals’ accommodation choices between home-sharing and hotel lodging. Trip satisfaction and trip value, as components of post-trip evaluation, are affected by accommodation choices.

TCS was developed nearly two decades ago, before the internet and social media era, and it considers information search mainly in term of “use of advertising information.” Given that the home-sharing revolution was spurred by technological advances, we deem it necessary to expand the theory boundary and incorporate tourists’ technology competence (“tech savviness”) as a key factor affecting their choice between conventional versus P2P lodging. Lastly, although TCS focuses exclusively on tourist-specific factors, we still consider several important destination characteristics as predictors of home-sharing lodging choices. The following paragraphs provide more detailed justification on each factor included in the framework.

3.1. Tripographics as antecedents

It has been documented that tourists' lodging option is affected by users' tripographics or travel trip characteristics (Hu & Morrison, 2002), thus we presume the same applies to their choices of P2P lodging. Tripographics have traditionally been studied for their influence on travel-related decisions. In the case of travelers’ choice of holiday format (i.e. independent travel vs. a basic tour package vs. an inclusive tour package), Sheldon and Mak (1987) empirically tested travel attributes such as length of stay, number of destinations visited on the trip, and whether the trip was domestic or international. Wang, Rompf, Severt, and Peerapatdit (2006) assessed the effects of sociodemographic, tripographic, and psychographic variables on travel expenditure. They found that among these three groups of variables, income and tripographics had the greatest influence on tourism expenditure.

With regard to Airbnb, the desire of American and Finnish platform users to have more meaningful social interactions with locals as well as unique experiences in authentic settings have resulted in increased travel frequency, longer stays, and participation in more activities (Tussyadiah & Pesonen, 2016). This preference for Airbnb on longer trips and when traveling with friends was also reflected in a study conducted in Hong Kong by Poon and Huang (2017). Similarly, home-sharing accommodations were most often cited by users as an option for families or individuals traveling as a group (Smith, 2016).

3.2. Past travel experience as an antecedent

Past travel experience is another antecedent of P2P lodging demand. Research has demonstrated that individuals who already used P2P accommodations are likely to continue using them in the future (Tussyadiah & Pesonen, 2018). With a higher level of experience with or use of P2P lodging, such travelers are postulated to experience satisfaction levels that should motivate continued use. In general, expectations about the quality of goods and services have an effect on customer satisfaction (Kim, 2017). Past experience is one way to develop accumulated knowledge of market conditions; favorable information about past quality has been found to positively affect customer satisfaction and vice versa (Anderson, Fornell, & Lehmann, 1994). This pattern extends to tourism and hospitality, where previous experience is identified as a primary source of knowledge acquisition and accumulation (Chen & Gursoy, 2000). Chow, Garretson, and Kurtz (1995) further found prior experience to be one of the most fundamental factors in determining subsequent hotel selections.

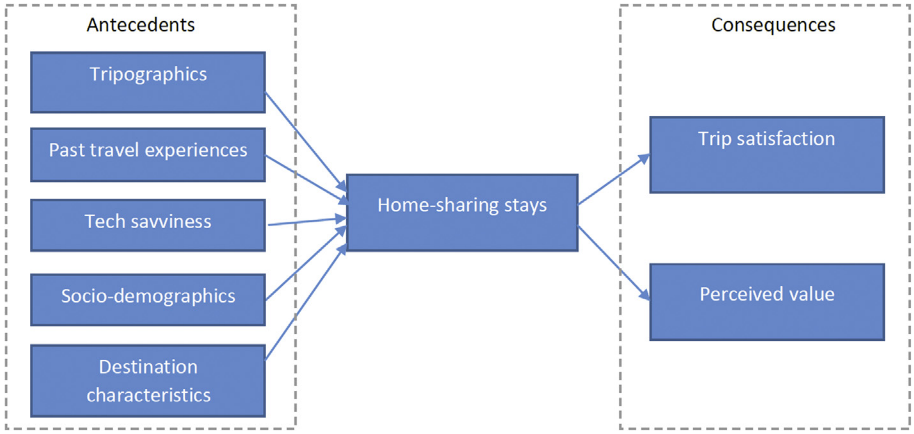

Fig. 1. Conceptual framework on the antecedents and consequences of home-sharing stays.

3.3. Tech savviness as an antecedent

Tech savviness also influences travelers' P2P lodging choices. P2P lodging has grown in popularity with the development of online platforms (Guttentag, 2015; Kaplan & Haenlein, 2010). For P2P lodging providers including Airbnb, an online platform is the sole place where potential guests make home-sharing lodging reservations. In other words, potential guests must be able to use the internet and its associated technologies to book accommodations. In line with research indicating that self-perceived tech savviness positively predicts purchase intentions online (Dinev & Hart, 2005; Novak & Hoffman, 1997), we suggest that tech savviness is an antecedent of home-sharing lodging usage.

3.4. Sociodemographics as antecedents

The choice of P2P accommodations over traditional hotels is presumably informed by personal sociodemographic characteristics, such as gender, age, ethnic background, and education level. Several different demand types and motivations have been identified to describe users of Airbnb lodging, including a desire for community, sustainability, authenticity, and direct contributions to locals (Guttentag & Smith, 2017; Lamb, 2011; Tussyadiah & Pesonen, 2018). Together, these drivers suggest that tourists place varying emphasis on different attributes, reflecting the underlying philosophy of the broader stream of research on tourist and lodging demand typologies. After all, the types of goods and services that individuals seek evolve as people age and proceed through various life stages (Cleveland, Papadopoulos, & Laroche, 2011).

For instance, security, personal services, and low prices at hotels are more important to female business travelers than their male counterparts (McCleary & Weaver, 1991). Likewise, gender and nationality are two sociodemographic factors found to influence hotel guest satisfaction in a more recent study by Ariffin and Maghzi (2012). Age has also been shown to affect tourism motivations, planning, and travel costs between tourists younger and older than 50 (Anderson & Langmeyer, 1982). Similarly, age influences the choice criteria of mature versus younger travelers (Ananth, DeMicco, Moreo, & Howey, 1992) as well as preferences for environmentally friendly hotel attributes (Millar & Baloglu, 2011).

3.5. Destination characteristics as antecedents

Destination characteristics could also shape tourists' home-sharing selections. These characteristics mainly include lodging costs, home-sharing supply, and security. Price has been identified as a top motivating factor in several Airbnb-related studies (Guttentag & Smith, 2017; Anderson et al., 1994; Lin et al., 2017; Cho & Bokyeong, 2016; Tussyadiah & Pesonen, 2018; Möhlmann, 2015). The same is true for traditional hotel accommodations, where price is identified as a key selection attribute (Dolnicar & Otter, 2003). The importance of price has partially inspired the proliferation of low-cost accommodations, such as motels and hostels, suggesting that price alone is insufficient to encourage Airbnb purchases. Rather, home-sharing facilitates the matching of tourist preferences with accommodation amenities at a suitable price point that best satisfies their needs (Zervas, Proserpio, & Byers, 2015). Home-sharing supply also reflects the availability of home-sharing alternatives: because home-sharing properties vary widely in terms of price, amenities, room size, and location, more home-sharing options reflect a greater likelihood that a tourist's specific lodging needs will be met through a home-sharing unit. Destination security also plays an important role: So, Oh, and Min (2018) found travelers' perceived destination insecurity to be a major constraint on their intentions to consider, use, and recommend Airbnb.

3.6. Trip satisfaction as a consequence

A major consequence of P2P lodging is variation in trip satisfaction. Marketing and consumer research has revealed that satisfaction with a service is associated with the use of said service (Möhlmann, 2015). Similarly, satisfaction with home-sharing lodging is a consequence of utility, trust, savings, and familiarity (Möhlmann, 2015). Studies have found that user-generated ratings on Airbnb are much more positive compared to those on other platforms despite a comparable precedent in vacation rental property ratings on TripAdvisor (Zervas et al., 2015). Just as accommodation facilities represent a key factor influencing tourists' overall trip satisfaction (Alegre & Garau, 2011; Lu & Stepchenkova, 2012), it is reasoned that accommodation ratings will affect overall trip satisfaction as well.

3.7. Trip value as a consequence

A second consequence of selecting P2P accommodations as a lodging choice relates to trip value. Consumer-perceived value refers to an individual's assessment of his/her perceived cost or sacrifice versus perceived benefits (Zeithaml, 1988). For users of sharing economy services, a higher perceived value gained at a lower cost motivates participation (Botsman & Rogers, 2011). Such value is not limited to lower prices in home-sharing lodging; value is also reflected in the benefits derived from needs that were previously un- or under-addressed in traditional hotel settings but are met by home-sharing lodging. Therefore, we suggest that the use of P2P lodging contributes to a higher trip value.

4. Research methods

4.1. Data collection

We obtained American domestic tourist travel data from Longwoods Travel USA® 2016 survey. Conducted quarterly since 1990, this survey is among the most extensive ongoing research on the nation's business and leisure travel, providing comprehensive tourist profiles including sociodemographics as well as destinations visited, travel group, purpose of visits, accommodations used, activities, trip duration, expenditure, and evaluation of trip experiences. Each quarter, a random cross-section of online panelists is invited to participate in the survey. The goal is to achieve a nationally representative sample of American adults 18+ years of age. To reduce potential recall bias, respondents are asked to report trips from the previous quarter only. In 2016, the data covered 218,648 trips from 122,958 respondents who had taken at least one overnight trip in the past 12 months.

In the survey, respondents were asked if they had booked any accommodations via home-sharing platforms such as Airbnb. As this question was asked regarding trips that may consist of multiple destinations, we focused on tourists traveling to a single U.S. domestic destination to obtain reliable information on where they stayed in a home-sharing property. We also identified tourists who stayed in hotels based on their responses to accommodation choice questions. Most destinations in the questionnaire were cities in metropolitan statistical areas (MSAs). We excluded trips to non-metropolitan areas, such as Yellowstone National Park and the Grand Canyon, due to unavailable data for destination-specific variables. Our total study sample consisted of 187 U.S. destination cities. The sample yielded 34,694 valid observations from tourists who stayed overnight in a home-sharing unit or hotel property while traveling domestically. Fig. 2 presents the proportion of domestic tourists staying in home-sharing units among travelers using paid accommodations in different locations.

4.2. The first step: logit modeling

We employed a two-step analysis to investigate the antecedents and consequences of home-sharing stays. In the first step, we estimated binary logit models to uncover factors explaining home-sharing accommodation choice as an antecedent of home-sharing stays. The probability of a U.S. domestic tourist choosing a home-sharing accommodation was specified as follows (Cameron & Trivedi, 2005):

$$\Pr(HS_i = 1|\mathbf{x}_i) = \exp(\mathbf{x}_i'\beta)/(1 + \exp(\mathbf{x}_i'\beta)) \tag{1}$$

where HS_i represents tourist i's accommodation choice in the destination. $HS_i = 1$ if the tourist chose to stay in home-sharing accommodations, whereas $HS_i = 0$ if the tourist stayed in hotels. Given that the conditional probability of home-sharing stays is a non-linear function of the independent variable $\mathbf{x}_i$, we introduced the concept of odds to interpret the estimated coefficient β as a marginal effect (Long & Freese, 2006). In this context, odds are defined as the probability ratio of observing home-sharing stays ($HS = 1$) over $HS = 0$:

$$\text{odds}_{HS=1|HS=0}(\mathbf{x}_i) = \Pr(HS_i = 1|\mathbf{x}_i)/\Pr(HS_i = 0|\mathbf{x}_i) = \exp(\mathbf{x}_i'\beta) \tag{2}$$

Therefore, $\exp(\beta_j) - 1$ can be interpreted as the factor by which odds increase with a one-unit increase in the associated independent variable x_j.

As suggested by the proposed conceptual framework (Fig. 1), we included a large set of independent variables in $\mathbf{x}_i$ as antecedents of home-sharing stays; Table 1 presents the variable definitions. A tourist's tripographic characteristics are captured by variables including *purpose*, *distance*, *nights*, *expenditure*, *plan_time*, *children*, *group_size*, *activities*, *cul_interest*, *car*, *month*, and *repeat*. Most variables were obtained directly from the household survey data. For *activities*, we calculated the number of tourists' selections across activity types listed in the data, drawn from 48 options in the original questionnaire. Apart from tripographic information, we also collected information on tourists' prior travel

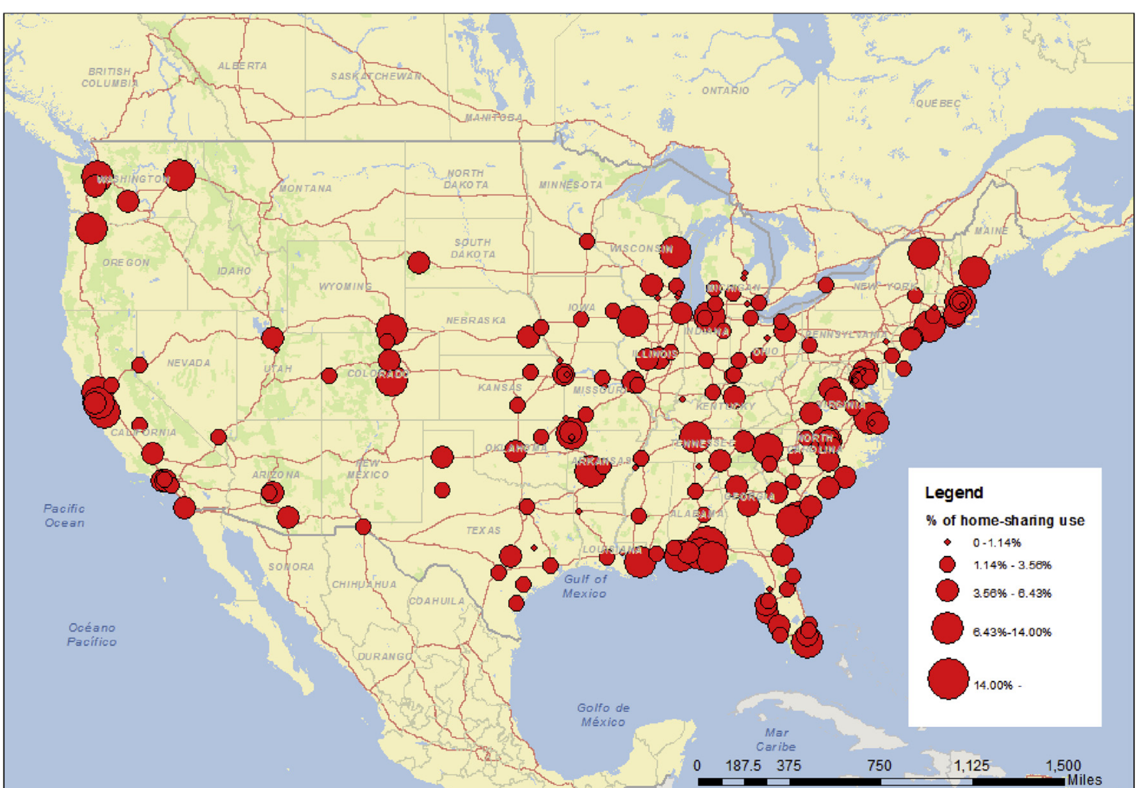

Fig. 2. Spatial distribution of home-sharing lodging use across U.S. destinations.

Table 1
Definition of variables in the first-step logit model.

Variable	Definition	Data source
HS	Indicator of home-sharing accommodation vs. hotels in the destination	Travel USA*
purpose	Purpose of travel: 1 = VFR, 2 = non-VFR leisure (reference group), 3 = business, 4 = business and leisure	Travel USA*
distance	Geographic distance (in 1000 miles) from home city to destination	Travel USA*
nights	Number of nights in destination	Travel USA*
expenditure	Total expenditure (in USD 1000) in destination	Travel USA*
plan_time	Time of travel planning: 1 = more than 1 year in advance (reference group), 2 = 6–12 months, 3 = 3–5 months, 4 = 2 months, 5 = 1 month or less, 6 = did not plan anything in advance	Travel USA*
children	Indicator of children (under age 18) traveling together: *children* = 1 if adults traveling together with at least one child; otherwise, *children* = 0	Travel USA*
group_size	Number of people (including adults and children) traveling together	Travel USA*
activities	Number of activity types participated in destination	Travel USA*
cul_interest	Indicator of cultural activities as special interest: *cul_interest* = 1 if cultural activities are listed as special interests in destination; otherwise, *cul_interest* = 0	Travel USA*
car	Indicator of use of personal auto vehicle in destination: *car* = 1 if personal auto vehicles are used; otherwise, *car* = 0	Travel USA*
month	Month of travel to destination	Travel USA*
repeat	Indicator of repeat travel to destination: *repeat* = 1 if the tourist traveled to the destination before; otherwise, *repeat* = 0	Travel USA*
past_HS	Indicator of past use of home sharing accommodation in the months of surveying quarter before the trip: *past_HS* = 1 if the tourist used home-sharing accommodations before; otherwise, *past_HS* = 0	Travel USA*
trips	Number of overnight trips taken last year	Travel USA*
social_media	Number of social media use types in daily life	Travel USA*
gender	Tourist gender: 1 = male, 2 = female	Travel USA*
age	Tourist age: 1 = 18–24, 2 = 25–34, 3 = 35–44 (reference group), 4 = 45–54, 5 = 55–64, 6 = 65+	Travel USA*
income	Tourist annual household income: 1 = under $30,000 (reference group), 2 = $30,000–$49,999, 3 = $50,000–$74,999, 4 = $75,000+	Travel USA*
education	Tourist educational achievement: 1 = high school or less (reference group), 2 = some college, 3 = college graduate, 4 = post-graduate	Travel USA*
race	Tourist race of tourist: 1 = white (reference group), 2 = African American, 3 = other	Travel USA*
airbnb_supply	Number of Airbnb properties per hotel room in destination in 2016	AirDNA, STR
price_dif	Price difference between Airbnb and hotel accommodation in destination in 2016, defined as (*hotel_ADR* – *Airbnb_ADR*)/*hotel_ADR*	AirDNA, STR
crime	Violent crime rate (per 100,000 inhabitants) in destination in 2016	FBI

experiences to construct the independent variables, *past_HS* and *trips*. For the former, due to data limitations, we could only track past home-sharing stays during the months of the quarter before the trip. Tourists' daily social media use was also surveyed in the questionnaire, and fourteen items address different uses of social media. We calculated the total number of uses, *social_media*, as a proxy for tourists' tech savviness. Lastly, the survey data provide extensive sociodemographic information on tourists, from which we constructed *gender*, *age*, *income*, *education*, and *race* variables accordingly.

We also incorporated three destination-specific variables: *airbnb_supply*, *price_dif*, and *crime*. Because Airbnb is the leading home-sharing platform in the U.S., we used Airbnb supply and demand data to represent all home-sharing businesses. The variable *airbnb_supply* reflects the supply of Airbnb units relative to hotel rooms in a destination, whereas *price_dif* represents the relative price of hotels compared to Airbnb properties. Airbnb and hotel market data at the MSA level were obtained from AirDNA and STR, respectively. AirDNA is the leading vendor of Airbnb data based on advanced crawling of public information from Airbnb websites (Abrate & Viglia, 2017; Gunter, 2018); STR collects and tracks supply and demand data for the global hotel industry (Kosová & Sertsios, 2016). The other destination-specific variable, *crime*, was used to measure the overall insecurity of a destination, with corresponding MSA-level data collected from the U.S. Federal Bureau of Investigation.

4.3. The second step: propensity score matching

In the second step, we investigated the effects of home-sharing stays on trip experiences. An intuitive approach would be to regress the experience measures on a dummy variable indicating *HS* after controlling for other variables; however, this method can lead to substantial endogeneity problems related to sample selection (Cameron & Trivedi, 2005). Although ideal, it would have been prohibitive in terms of cost and feasibility to use a randomized experiment to assign tourists to stay in either home-sharing units or hotels and then compare their experiential outcomes. Alternatively, propensity score matching allowed for quasi-experimental analysis by comparing outcomes of tourists who had similar probabilities of using home-sharing lodging with hotel users. This probability, modeled in the first-step analysis, predicted the propensity score; then, observations in the home-sharing user group were matched with observations in the hotel user group based on the closest propensity score. This matching algorithm is called nearest-neighbor matching. Ideally, matching should lead to balanced covariates (i.e. independent variables of first-step models). The validity and reliability of propensity score matching hinge on several assumptions, one of which is the common support assumption that requires a common support region of propensity scores shared by both groups (Guo & Fraser, 2014).

We followed a five-stage modeling approach for propensity score matching per the recommendation of Caliendo and Kopeinig (2008). First, we estimated the propensity score of home-sharing stay for each observation using the logit model estimated in the first step. We disregarded insignificant independent variables to avoid the over-parameterization problem. Bryson, Dorsett, and Purdon (2002) suggested that over-parametrized propensity models can increase the chance of violating the common support assumption and increase the variance of estimates, making the estimates inconsistent. Second, we chose nearest-neighbor matching as the matching algorithm. Third, we checked the common support assumption by inspecting the density distribution of the propensity score for both groups (Lechner, 2008). Fourth, we estimated the difference between groups after matching and verifying matching quality. Finally, we conducted a sensitivity analysis by specifying different numbers of matched nearest neighbors.

4.4. Data description

Table 2 presents the descriptive statistics of variables used in the first-step analysis. Our sample included 34,694 observations (trips) from 26,896 U.S. domestic tourists in 2016. The upper panel presents information on the continuous variables. Tourists' mean travel distance was 757 miles, with approximately three nights spent in a destination on average. Furthermore, the mean travel expenditure including transportation to the destination was USD1,143, and the average group size was nearly three. Tourists in the sample participated in an average

Table 2
Descriptive statistics of variables in the first-step logit model.

Variable	Obs				VIF
Continuous		**Mean**	**Std. Dev.**	**Min / Max**	
distance	34,694	0.757	0.859	0 / 5.090	1.34
nights	34,694	2.645	2.132	1 / 30	1.30
expenditure	34,694	1.143	1.588	0.001 / 33	1.31
group_size	34,694	2.866	2.094	1 / 24	1.35
activities	34,694	2.806	2.262	0 / 40	1.36
trips	34,694	3.074	2.793	1 / 30	1.06
social_media	34,694	2.412	2.240	0 / 13	1.19
airbnb_supply	34,694	0.090	0.068	0.004 / 0.305	1.55
price_dif	34,694	−0.116	0.252	−0.734 / 0.472	1.44
crime	34,120	459.726	161.68	77.6 / 1114.9	1.21
Categorical		**Frequency**	**Percentage**	**Cumulative Percentage**	
HS = 0	34,694	32,790	94.51	94.51	
HS = 1	34,694	1904	5.49	100.00	
purpose = 1	34,694	8080	23.29	23.29	1.15
purpose = 2	34,694	19,576	56.42	79.71	
purpose = 3	34,694	5783	16.67	96.38	1.28
purpose = 4	34,694	1255	3.62	100.00	1.05
plan_time = 1	34,694	1698	4.89	4.89	
plan_time = 2	34,694	5242	15.11	20.00	3.54
plan_time = 3	34,694	6970	20.09	40.09	4.20
plan_time = 4	34,694	6966	20.08	60.17	4.20
plan_time = 5	34,694	11,692	33.70	93.87	5.52
plan_time = 6	34,694	2126	6.13	100.00	2.21
children = 0	34,694	23,417	67.50	67.50	
children = 1	34,694	11,277	32.50	100.00	1.52
cul_interest = 0	34,694	22,411	64.60	64.60	
cul_interest = 1	34,694	12,283	35.40	100.00	1.21
car = 0	34,694	7373	21.25	21.25	
car = 1	34,694	27,321	78.75	100.00	1.14
month = Jan	34,694	2464	7.10	7.10	
month = Feb	34,694	2607	7.51	14.62	1.91
month = Mar	34,694	3189	9.19	23.81	2.10
month = Apr	34,694	2737	7.89	31.70	1.95
month = May	34,694	2835	8.17	39.87	1.98
month = Jun	34,694	3090	8.91	48.78	2.07
month = Jul	34,694	3308	9.53	58.31	2.14
month = Aug	34,694	3413	9.84	68.15	2.18
month = Sep	34,694	2710	7.81	75.96	1.95
month = Oct	34,694	3100	8.94	84.89	2.06
month = Nov	34,694	2810	8.10	92.99	1.97
month = Dec	34,694	2431	7.01	100.00	1.87
repeat = 0	34,694	5856	16.88	16.88	
repeat = 1	34,694	28,838	83.12	100.00	1.05
past_HS = 0	34,694	34,235	98.68	98.68	
past_HS = 1	34,694	459	1.32	100.00	1.02
gender = 1	34,694	15,088	43.49	43.49	
gender = 2	34,694	19,606	56.51	100.00	1.12
age = 1	34,694	3506	10.11	10.11	1.44
age = 2	34,694	11,098	31.99	42.09	1.65
age = 3	34,694	8116	23.39	65.49	
age = 4	34,694	4897	14.11	79.60	1.44
age = 5	34,694	4398	12.68	92.28	1.47
age = 6	34,694	2679	7.72	100.00	1.35
income = 1	34,694	2898	8.35	8.35	
income = 2	34,694	4865	14.02	22.38	2.36
income = 3	34,694	7155	20.62	43.00	2.95
income = 4	34,694	19,776	57.00	100.00	4.00
education = 1	34,694	2822	8.13	8.13	
education = 2	34,694	5665	16.33	24.46	2.54
education = 3	34,694	15,456	44.55	69.01	3.85
education = 4	34,694	10,751	30.99	100.00	3.79
race = 1	34,694	29,217	84.21	84.21	
race = 2	34,694	2338	6.74	90.95	1.05
race = 3	34,694	3139	9.05	100.00	1.03

of three types of survey-listed activities and used two of the survey-listed social media functions daily. Sampled tourists took an average of three overnight trips in previous year, 2015. Regarding destination-specific variables, the ratio of Airbnb properties to hotel rooms ranged from 0.004 to 0.305 ($M = 0.09$). Interestingly, the average hotel price premium over Airbnb was −0.116, indicating that the average daily rate (ADR) of Airbnb was higher than that of hotels in many destinations. One possible reason is that Airbnb and hotels cover different lodging classes, the ADRs of which vary substantially. For example, the ADR of renting an entire house via Airbnb can be higher than that of a low-end hotel room. In fact, in our sampled destinations, whole-house Airbnb properties dominated according to AirDNA statistics. Lastly, large differences in crime rates highlight the substantial cross-MSA variation of the U.S. urban security landscape. Due to unavailable crime data in some MSAs, the *crime* variable in this study consisted of 34,120 observations.

The lower panel of Table 2 lists the frequencies of categorical variables. For the dependent variable, *HS*, only 5.49% of tourists chose to stay in home-sharing lodging units, while another 94.51% stayed in hotels exclusively. For independent variables, more than half of tourists were non-visiting-friends-and-relatives (VFR) leisure tourists, followed by 23.29% VFR tourists and 16.67% business tourists. Many tourists (33.70%) planned the trip one month in advance or less; 6.13% did not plan the trip in advance at all. Furthermore, approximately one-third of tourists traveled with children younger than eighteen. One-third also visited a destination with particular cultural interests. Personal automobiles appeared a popular means of domestic travel around the U.S., with 78.75% of tourists reporting having traveled with their own or rented vehicles. Tourists traveled most frequently in August (9.84%) and least frequently in December (7.01%). Regarding past travel experiences, 83.12% of tourists were repeat visitors to their chosen destinations, and 1.32% of tourists had used home-sharing accommodations in the previous months of the surveyed quarter. In terms of sociodemographics, our sample was slightly over-represented by females (56.51% of total). Over half of tourists surveyed were between 25 and 44 years old, over half earned an annual household income above USD75,000, more than 75% of tourists held at least a college degree, and 84.21% were white. Table 2 also presents the variance inflation factor (VIF) measures for independent variables to check for multicollinearity; the average VIF was 1.97, and all variables (except for an indicator from a categorical variable) had a VIF smaller than 5. These results suggest an absence of severe multi-collinearity in the sample (Gujarati & Porter, 2010).

Table 3 presents the descriptive statistics of seven experience evaluation variables as consequences of home-sharing stays in a destination. These evaluation variables were measured using a 5-point scale (1 = *very dissatisfied*, 5 = *very satisfied*). For the home-sharing user and hotel user groups, the mean value of each experience evaluation was above 4, suggesting a high level of satisfaction among U.S. domestic tourists. We also used an independent samples *t*-test to assess whether these two groups' experience evaluations differed. As shown in the last column of Table 3, home-sharing users generally cited more satisfying experiences with sightseeing and attractions, music/nightlife/entertainment, and value for the money compared to hotel users.

5. Empirical findings

5.1. First-step logit modeling

Table 4 presents the estimation results of the first-step logit models. Model 1 estimated all observations without any destination-specific variables; results show that compared to non-VFR leisure (*purpose* = 2) tourists, business (*purpose* = 3) and business/leisure (*purpose* = 4) tourists are significantly less likely to choose home-sharing lodging while traveling. More specifically, compared with non-VFR leisure travelers, the odds of home-sharing stays was 57.68% lower (exp[-0.860]-1) for business travelers and 34.16% lower (exp[-0.418]-1) for non-VFR leisure travelers after controlling for other variables. Moreover, the positive and significant coefficients of *distance* and *nights* suggest that long-haul tourists and those staying longer at a destination are more likely to stay at home-sharing properties rather than hotels.

Table 3
Definition and descriptive statistics of variables in the second-step propensity score matching.

Consequence variable	Definition	*HS* = 0		*HS* = 1		t-stat
		Mean	Std. Dev.	Mean	Std. Dev.	
satisfaction1	Overall trip experience	4.681	0.629	4.695	0.620	0.902
satisfaction2	Quality of food	4.599	0.669	4.600	0.679	0.113
satisfaction3	Quality of accommodations	4.577	0.722	4.553	0.732	−1.377*
satisfaction4	Friendliness of people	4.476	0.788	4.474	0.811	−0.096
satisfaction5	Experience in sightseeing and attractions	4.403	0.833	4.514	0.765	5.665***
satisfaction6	Experience in music/nightlife/entertainment	4.238	0.912	4.355	0.848	5.471***
value	Value for money	4.268	0.933	4.364	0.882	4.417***
sample size		1904		32790		

Note: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level.

According to the magnitude of coefficients, a 100-mile increase in travel distance is associated with a 0.63% increase in the odds of home-sharing stays, whereas staying one night longer in a destination is associated with a 6.99% odds increase. The travel-related budget variable, *expenditure*, had a negative and significant coefficient, and results reveal that an additional USD100 in total trip expenditure leads to a 0.57% decrease in the odds of home-sharing stays. For different categories of planning time, results show that tourists planning a trip either 6–12 or 3–5 months in advance are more likely to choose home-sharing lodging compared to other tourists. Fig. 3 visualizes the effect of planning time on the probability of home-sharing stays; the likelihood generally declines as the planning time gets closer within one year of the trip.

Others tripographic variables were estimated to be statistically significant in Model 1. The positive coefficients of *group_size*, *activities*, *cul_interest*, and *car* suggest a higher probability of using home-sharing lodging for tourists traveling with a larger group, participating in diverse activities, pursuing special cultural interests, and using a personal vehicle during the trip. The coefficients of *children* and *repeat* were negative, indicating a lower probability of staying in home-sharing lodging for tourists traveling with children as well as repeat visitors to a destination. Regarding tech savviness as measured by daily social media use, the positive and significant coefficient of *social_media* confirms that individuals who are tech savvier are more likely to choose home-sharing lodging. Furthermore, *past_HS* was estimated to be positive and significant, indicating that tourists with past home-sharing experiences are likely to choose home-sharing accommodations again. However, the coefficient of *trips* was not significant, suggesting that travel frequency is not associated with home-sharing lodging choice.

Among different sociodemographic variables, *gender*, *income*, and *race* were estimated to be statistically insignificant. Therefore, our results suggest that these variables cannot explain tourists' home-sharing lodging choices. The variable *age* was found statistically significant together and separately for different categories. The youngest age group (18–24) demonstrated the highest probability of home-sharing stays. Fig. 4 demonstrates the effect of age on the probability of home-sharing lodging use by predicting the probability at different age levels; the probability decreases as age increases up to 64. The oldest group (65 or above) shows a slightly higher probability than the second-oldest group (55–64). In terms of educational achievement, the results show that tourists with college degrees are more likely to choose home-sharing lodging than those who graduated from high school or lower (reference group). Interestingly, the most educated group, those with post-graduate education, does not exhibit a significantly higher probability of choosing home-sharing lodging compared to those with college degrees.

In Model 2, we incorporated two additional destination-specific variables, *airbnb_supply* and *price_diff*, and in Model 3, we added the *crime* variable into Model 1. As some observations were missing *crime* values, the sample size of Model 3 is slightly smaller than Models 1 and 2. All three destination-specific variables were included in Model 4. In general, we found consistent and robust estimates for the three variables. A positive and significant coefficient was estimated for *airbnb_supply*, suggesting that tourists are more likely to stay in home-sharing lodging in destinations with greater home-sharing supply relative to hotel room supply. Another variable, *price_diff*, was estimated to be statistically insignificant and negative. This result shows that after controlling for other variables, the relative price premium of hotels to home-sharing is not a significant determinant in choosing home-sharing lodging. Lastly, the estimated coefficient of *crime* was negative and significant; thus, tourists are less likely to choose home-sharing lodging in destinations with a higher rate of violent crime.

We also investigated the different antecedents of home-sharing stays for tourists traveling for different purposes. Model 5 in Table 4 presents the estimation results for VFR travelers, and Model 6 presents the results for non-VFR leisure travelers. Because only 3.62% of tourists were business-leisure travelers, we combined this proportion with business travelers; estimation results are presented in Model 7. The estimated coefficients were quite similar for several variables across models. For example, in all three models, the coefficients of *nights*, *activities*, *social_media*, *past_HS*, and *crime* were significant, while those of *distance*, *income*, *race*, and *price_diff* were insignificant. However, some different antecedents of home-sharing stays were found; for example, planning time (*plan_time*) and educational background (*education*) were significant for VFR travelers only, and budget concern (*expenditure*), cultural interests (*cultural_interest*), and home-sharing supply (*airbnb_supply*) were estimated to be statistically significant for non-VFR leisure travelers only. Model 7 also presents some different results for business and business-leisure travelers compared to leisure travelers. For example, accompanying children (*children*), group size (*group_size*), past travel (*repeat*), and crime (*crime*) were not significant variables behind the choice of home-sharing lodging, but personal auto use (*car*) and gender (*gender*) were.

5.2. Second-step propensity score matching

We examined the effects of home-sharing stays on trip experiences using second-step propensity score matching. To test the robustness of our results, we used the nearest-neighbor number from 1 to 4. The propensity score was estimated from first-step logit modeling using Model 4 (see Table 4) excluding insignificant independent variables (Bryson et al., 2002): *distance*, *trips*, *gender*, *income*, *race*, and *price_dif*. Before matching the data, we checked the common region assumption by comparing the estimated density of predicted propensity for home-sharing users and hotel users. The graph presented in the appendix

Table 4
Estimation results of first-step logit models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	All	All	All	All	VFR	Non-VFR leisure	Business, Business-Leisure
***purpose* = 1**	0.175*	0.180**	0.148*	0.166**			
	(0.102)	(0.089)	(0.087)	(0.082)			
***purpose* = 3**	−0.860***	−0.842***	−0.913***	−0.880***			
	(0.161)	(0.148)	(0.147)	(0.143)			
***purpose* = 4**	−0.418**	−0.409**	−0.481***	−0.458**			
	(0.181)	(0.176)	(0.186)	(0.184)			
distance	0.0629**	0.0214	0.0725**	0.0454	0.0817	0.0144	0.128
	(0.031)	(0.039)	(0.030)	(0.033)	(0.051)	(0.044)	(0.097)
nights	0.0676***	0.0651***	0.0682***	0.0656***	0.0909***	0.0567**	0.0650**
	(0.014)	(0.013)	(0.014)	(0.013)	(0.021)	(0.022)	(0.031)
expenditure	−0.0574**	−0.0634***	−0.0558**	−0.0620***	−0.0266	−0.0658***	−0.173*
	(0.023)	(0.022)	(0.022)	(0.022)	(0.034)	(0.024)	(0.094)
***plan_time* = 2**	0.541***	0.531***	0.504***	0.497***	0.790***	0.292	1.253
	(0.155)	(0.153)	(0.154)	(0.152)	(0.292)	(0.201)	(1.103)
***plan_time* = 3**	0.563***	0.564***	0.533***	0.539***	0.738**	0.370**	1.239
	(0.149)	(0.146)	(0.149)	(0.147)	(0.297)	(0.186)	(1.079)
***plan_time* = 4**	0.411***	0.411***	0.381***	0.387***	0.676**	0.123	1.513
	(0.144)	(0.140)	(0.143)	(0.141)	(0.298)	(0.205)	(1.044)
***plan_time* = 5**	0.315**	0.318**	0.273**	0.284**	0.374	0.0632	1.533
	(0.137)	(0.135)	(0.137)	(0.136)	(0.326)	(0.174)	(1.042)
***plan_time* = 6**	0.0923	0.0816	0.0188	0.0227	0.407	−0.276	1.043
	(0.175)	(0.175)	(0.181)	(0.180)	(0.345)	(0.216)	(0.955)
children	−0.256**	−0.278***	−0.274***	−0.285***	−0.512***	−0.236*	0.441
	(0.121)	(0.106)	(0.099)	(0.096)	(0.125)	(0.121)	(0.284)
group_size	0.0856***	0.0869***	0.0885***	0.0889***	0.132***	0.0937***	−0.0258
	(0.016)	(0.015)	(0.015)	(0.015)	(0.026)	(0.015)	(0.039)
activities	0.112***	0.112***	0.112***	0.112***	0.0830***	0.121***	0.173***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.022)	(0.012)	(0.045)
cul_interest	0.217***	0.203***	0.200***	0.204***	0.144	0.218**	0.254
	(0.070)	(0.063)	(0.071)	(0.064)	(0.099)	(0.093)	(0.177)
car	0.230**	0.245**	0.223**	0.231**	0.0222	0.199*	0.570**
	(0.107)	(0.106)	(0.097)	(0.100)	(0.123)	(0.118)	(0.237)
repeat	−0.327***	−0.342***	−0.304***	−0.314***	−0.245**	−0.400***	0.0179
	(0.077)	(0.076)	(0.071)	(0.072)	(0.119)	(0.080)	(0.212)
past_HS	2.329***	2.342***	2.341***	2.353***	2.099***	2.480***	2.326***
	(0.104)	(0.102)	(0.106)	(0.105)	(0.216)	(0.148)	(0.253)
trips	0.0137	0.0138	0.0113	0.0117	−0.00591	0.0236**	−0.0308
	(0.010)	(0.010)	(0.010)	(0.010)	(0.017)	(0.011)	(0.033)
social_media	0.111***	0.111***	0.116***	0.115***	0.156***	0.0854***	0.195***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.019)	(0.013)	(0.030)
***gender* = 2**	−0.0424	−0.0381	−0.0465	−0.0438	0.133	−0.0800	−0.436***
	(0.059)	(0.058)	(0.065)	(0.063)	(0.111)	(0.078)	(0.150)
***age* = 1**	0.330***	0.308***	0.323***	0.313***	0.388**	0.326***	0.243
	(0.074)	(0.075)	(0.076)	(0.076)	(0.163)	(0.107)	(0.308)
***age* = 2**	0.251***	0.245***	0.238***	0.236***	0.0825	0.325***	0.0885
	(0.065)	(0.066)	(0.065)	(0.066)	(0.134)	(0.074)	(0.193)
***age* = 4**	−0.291***	−0.284***	−0.285***	−0.283***	−0.0847	−0.327***	−0.595**
	(0.088)	(0.087)	(0.090)	(0.090)	(0.175)	(0.123)	(0.271)
***age* = 5**	−0.408***	−0.398***	−0.413***	−0.405***	−0.656***	−0.323**	−0.447
	(0.107)	(0.107)	(0.109)	(0.108)	(0.201)	(0.141)	(0.347)
***age* = 6**	−0.319***	−0.311**	−0.324***	−0.320***	−0.0652	−0.470***	−0.551
	(0.123)	(0.121)	(0.123)	(0.123)	(0.215)	(0.170)	(0.492)
***income* = 2**	−0.0926	−0.0960	−0.0778	−0.0819	−0.408*	0.0468	−0.000535
	(0.128)	(0.128)	(0.131)	(0.130)	(0.225)	(0.161)	(0.365)
***income* = 3**	−0.0243	−0.0346	−0.00208	−0.0117	−0.216	0.156	−0.596
	(0.104)	(0.104)	(0.105)	(0.104)	(0.178)	(0.128)	(0.446)
***income* = 4**	−0.00425	−0.0260	0.00738	−0.00725	−0.144	0.120	−0.526
	(0.125)	(0.126)	(0.128)	(0.127)	(0.164)	(0.142)	(0.422)
***education* = 2**	0.00139	−0.00603	−0.00707	−0.0115	0.450*	−0.120	−0.524
	(0.127)	(0.129)	(0.130)	(0.131)	(0.235)	(0.175)	(0.419)
***education* = 3**	0.272***	0.257**	0.248**	0.243**	0.621***	0.203	−0.384
	(0.105)	(0.108)	(0.109)	(0.110)	(0.237)	(0.157)	(0.311)
***education* = 4**	0.126	0.103	0.0830	0.0771	0.499**	−0.0261	−0.281
	(0.121)	(0.126)	(0.124)	(0.128)	(0.213)	(0.183)	(0.332)
***race* = 2**	−0.0380	−0.0144	−0.0270	−0.0153	0.0927	−0.0730	−0.458
	(0.138)	(0.132)	(0.141)	(0.137)	(0.214)	(0.162)	(0.389)
***race* = 3**	0.127	0.123	0.150	0.144	0.266	0.0956	0.0867
	(0.118)	(0.111)	(0.100)	(0.100)	(0.194)	(0.122)	(0.275)
airbnb_supply		3.166***		2.399***	0.772	3.071***	2.454
		(0.972)		(0.763)	(0.886)	(0.888)	(1.535)
price_dif		−0.226		−0.305	−0.332	−0.360	0.360
		(0.301)		(0.293)	(0.258)	(0.340)	(0.536)

(*continued on next page*)

Table 4 (*continued*)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	All	All	All	All	VFR	Non-VFR leisure	Business, Business-Leisure
crime			−0.00139***	−0.00114***	−0.000593*	−0.00144***	0.0000689
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
constant	−4.666***	−4.925***	−3.984***	−4.334***	−4.757***	−3.930***	−6.303***
	(0.305)	(0.298)	(0.349)	(0.348)	(0.609)	(0.442)	(1.490)
month	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	34694	34694	34120	34120	7914	19344	6862
Destinations	185	185	175	175	171	175	167
AIC	13166.3	13109.2	12896.4	12870.3	3444.5	7949.7	1454.3
BIC	13555.2	13515.0	13292.9	13283.8	3765.4	8311.7	1768.7
r2_p	0.114	0.118	0.119	0.121	0.114	0.123	0.153
ll	−6537.2	−6506.6	−6401.2	−6386.2	−1676.2	−3928.9	−681.2

Note: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level. Robust standard errors are presented in parentheses.

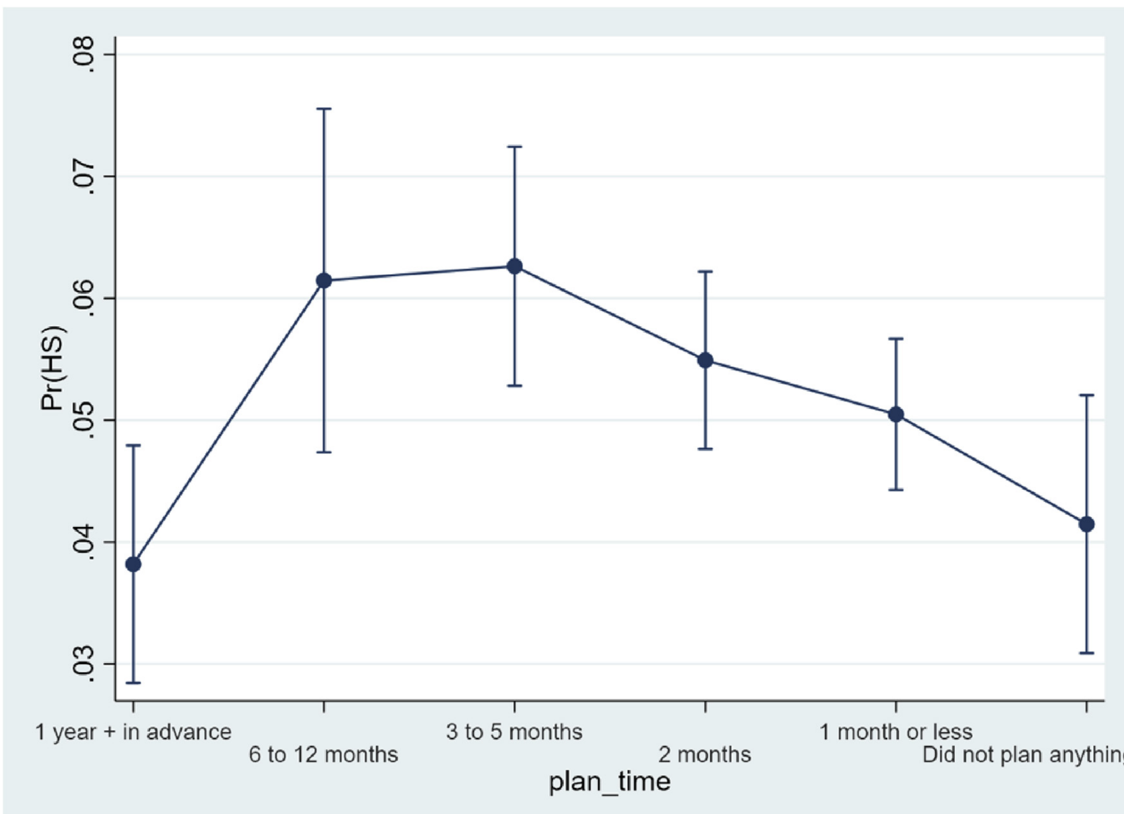

Fig. 3. Effect of planning time on the probability of home-sharing stays.

indicates that the two estimated densities overlap in terms of respective regional masses, suggesting that the assumption was not violated (Lechner, 2008).

Table 5 presents the estimation results from propensity score matching. Estimates represent the outcome differences between home-sharing users and hotel users after matching propensity scores. Among all satisfaction variables, only *satisfaction3* (accommodation satisfaction) was negative and significant at the 0.10 level in two specifications. Thus, using home-sharing lodging does not necessarily increase accommodation satisfaction. The other trip experience variable, *value*, was estimated to be significantly higher for home-sharing users compared to hotel users after matching. This result highlights the high value perceived by home-sharing users compared to hotel users. Upon comparing Table 5 with Table 3, we can see that experience comparison results between home-sharing users and hotel users vary substantially, indicating the importance of correcting for endogeneity when implementing causal relationship analysis on the effect of home-sharing stays.

We also conducted a series of post-estimation analyses to check the quality of the propensity score-matching results; these results are presented in the supplementary materials. We compared the density of propensity scores after matching. The densities of propensity scores were nearly identical between the home-sharing stay and hotel stay groups, suggesting that all matching specifications successfully balanced independent variables between the two groups. We checked the balance of every independent variable between the two groups after

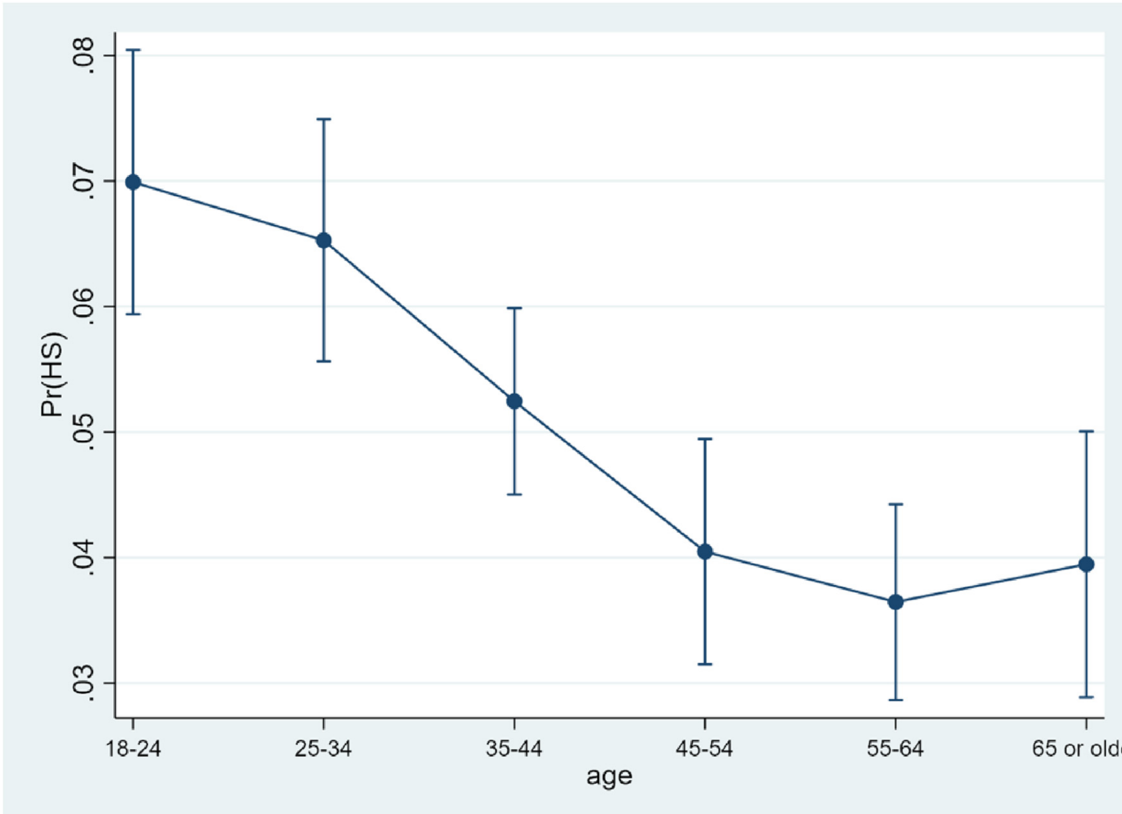

Fig. 4. Effect of age on the probability of home-sharing stays.

Table 5
Estimation results of second-step propensity score matching.

Consequence variable	NN(1)	NN(2)	NN(3)	NN(4)
satisfaction1	−0.0229	−0.0131	−0.0169	−0.0100
	(0.031)	(0.028)	(0.026)	(0.025)
satisfaction2	−0.0325	−0.0474	−0.0512	−0.0458
	(0.034)	(0.034)	(0.032)	(0.031)
satisfaction3	−0.0342	−0.0614*	−0.0584*	−0.0503
	(0.036)	(0.034)	(0.032)	(0.031)
satisfaction4	−0.0239	−0.0468	−0.0381	−0.0401
	(0.039)	(0.036)	(0.035)	(0.034)
satisfaction5	0.0149	−0.00541	−0.00697	−0.00934
	(0.037)	(0.035)	(0.034)	(0.034)
satisfaction6	0.0458	0.0212	0.0271	0.0258
	(0.040)	(0.036)	(0.034)	(0.034)
value	0.0818**	0.0762**	0.0711**	0.0709**
	(0.039)	(0.035)	(0.034)	(0.033)
Observations	34120	34120	34120	34120

Note: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level. NN(#) indicates nearest-neighbor matching based on number of nearest neighbors.

matching according to diagnostic statistics. The standardized differences in the sample after matching are all close to 0, and their variance ratios are all close to 1, confirming the quality of our results in terms of covariate balance (Austin, 2009).

6. Conclusions and implications

Based on the key premise of TCS, this study proposed a conceptual framework and applied a two-step analysis to understand the antecedents and consequences of home-sharing stays. In the first-step probit analysis, the estimation results underscored several factors explaining the use of home-sharing accommodations over conventional hotel stays. These factors can be classified into five broad categories: tripographics (i.e. trip purpose, nights of stay, trip expenditure, planning time, children companions, group size, activities, cultural interests, personal auto use, and repeated travel), past travel experiences (i.e. past home-sharing use), tech savviness (i.e. social media use), sociodemographics (i.e. age and education), and destination characteristics (i.e. home-sharing supply and crime rate). In the second-step analysis, we conducted propensity score matching to compare trip satisfaction and perceived value between home-sharing users and hotel users. To correct for endogeneity issues, we matched each home-sharing user with hotel users who showed similar propensities to choose home-sharing accommodations. The results demonstrated that while trip satisfaction did not differ between the two groups, the perceived value of the trip was significantly higher in the home-sharing group.

This study represents a pioneering research effort to explore the antecedents and consequences of home-sharing stays based on revealed behavior data. Our empirical results challenge the stereotype that home-sharing accommodations are cost effective – we did not find any significant effects of household income and hotel-Airbnb price differences on tourists' home-sharing accommodation choices. Therefore, economic incentives associated with cost factors do not sufficiently explain travelers' home-sharing stays. Instead, our empirical results support the argument that home-sharing accommodations are selected by travelers with particular needs. Second, we confirmed the effect of destination crime rate on home-sharing demand: when presented with crime-related security concerns in a destination, travelers are less likely to stay in home-sharing properties. Lastly, we did not find any difference between home-sharing and hotel users regarding trip satisfaction after propensity score matching. Past results reflecting a higher level of satisfaction for home-sharing users based on simple comparison could be attributed to an issue with endogeneity, which can be adequately alleviated using counter-factual analysis tools such as propensity score matching. Perceived value was found to be higher for home-sharing users compared to hotel users in this study; therefore, home-sharing accommodations were found to substantially improve the perceived value of a trip overall.

From a conceptual perspective, this study shows the utility of TCS in explaining tourists' accommodation choice (in terms of home-sharing stays versus traditional hotels) and its consequences. Efforts were also made to update or introduce new factors to the model, to maintain its relevance. For instance, selected destination characteristics, such as crime, were also added, and the empirical analysis verified their value in explaining the phenomenon. Tech savviness was brought to the model reflecting today's media environment, which is quite different from two decades ago when TCS was originally developed. This echoes Whetten (1989)'s “Why now” question when making value-added contributions.

Our study offers empirical evidence that the relative price premium of hotels does not necessarily motivate guests to choose P2P lodging over hotels. Hotels are therefore unlikely to need to adopt lower room rates or engage in price wars with P2P lodging providers to remain competitive. Conversely, for P2P accommodations, their relatively lower room rates may not be an advantage after all. Instead, hotels and P2P lodgings are more likely to compete in other aspects that deliver greater value to guests, such as household amenities, extra space, experience authenticity, and host-guest interactions (So et al., 2018). The emphasis on greater value for the consumer is further supported by our study results revealing that Airbnb users reported a significantly higher trip value compared to tourists staying in hotels.

Further attention should be paid to antecedents that significantly detract from the possibility of choosing P2P lodging, particularly crime. In destinations characterized by higher violent crime rates, P2P platforms and hosts should consider ways to assuage tourists' fears of crime, such as through a thorough introduction to home safety features, methods of crime prevention, or even by offering insurance coverage. It is equally important for home-sharing platforms and hosts to emphasize features shown to highly motivate guests to choose P2P lodging. For example, as larger groups are more likely to choose home-sharing accommodations, space-related advantages could be highlighted in advertising materials or on online platforms. Parking amenities and/or availability could be similarly emphasized given the reliance of P2P lodging guests on personal vehicles. Also, from an activities perspective, P2P lodging guests not only participate in more diverse activities but are also more likely to pursue special cultural interests. To cater to their needs, home-sharing lodging platforms and hosts might consider pricing specials or bundled offers with local cultural attractions such as museums, art galleries, and theatres.

For hotels and destination marketing organizations, this study also revealed some interesting findings. For instance, antecedents of home-sharing stays identified in this study could be equally useful for conventional hotels, as these antecedents may provide basis for effective market segmentation and positioning strategies. This study found tourists staying in P2P lodgings perceive their trip to have higher value. For popular, urban destinations traditionally plagued by high prices, this finding suggests P2P lodgings could provide a viable option to improve the destination's overall value perception, which may help destinations to identify and satisfy latent demand.

Some limitations may hinder the generalizability of our results. First, this study was cross-sectional by nature and therefore cannot provide longitudinal information about trends in home-sharing demand over time. In particular, due to data unavailability, we could not track tourists' history of home-sharing accommodation use and accompanying satisfaction over an extended period. Second, because the household tourism survey is not specifically tailored to home-sharing use, we could not obtain information on which types of home-sharing accommodations (i.e. entire house, entire room, or shared room) travelers selected. Demand for different home-sharing types is heterogeneous, and a separate analysis based on home-sharing types would be especially intriguing. Therefore, we call for future research efforts to collect longitudinal data on home-sharing demand to examine factors shaping lodging demand for different types of home-sharing properties.

Declarations of interest

None.

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Appendix

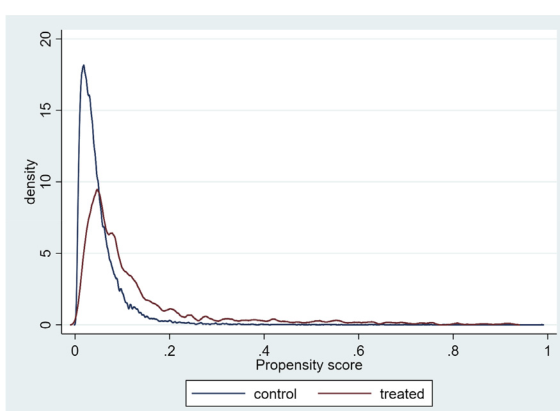

Fig. A1. Propensity density of two groups before matching.
Note: “control” represents hotel users (HS = 0); “treated” represents home-sharing users (HS = 1).

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.tourman.2018.06.004.

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