

Spatial and Socioeconomic Analysis of Host Participation in the Shared Accommodation Economy – Airbnb in New York City

Avijit Sarkar
University of Redlands
avijit_sarkar@redlands.edu

Mehrdad Koohikamali
University of Redlands
mehrdad_koohikamali@redlands.edu

James B. Pick
University of Redlands
james_pick@redlands.edu

Abstract

Limited academic research has examined factors that motivate hosts in short-term homesharing platforms to participate in the shared accommodation workforce. To fill this gap, this paper examines socioeconomic antecedents, motivations, and spatial patterns of Airbnb host participation in New York City's (NYC) shared accommodation marketplace. A conceptual model posits associations of demographic, socioeconomic, social capital, trust and greener consumption independent variables with host participation. The model is empirically validated for a large sample of NYC neighborhoods using OLS regressions. Regression findings indicate that host participation is associated with demographic variables – gender, age, and ethnic minorities; economic variables – median household income, households with a mortgage, and professional/scientific/technical services occupation; and attitude towards greener consumption. Descriptive mapping and cluster analysis reveal interesting spatial patterns of Airbnb property densities while the absence of associations of social capital and trust with host participation has interesting implications to understand motivations of the shared accommodation workforce.

1. Introduction

Modern collaborative consumption or the sharing economy is an economic innovation phenomenon [17]. Prior to the Industrial Revolution, a large percentage of economic activities were peer-to-peer, intertwined with social relations [29]. Today, activities such as borrowing someone's car and sharing a home or a product are not specifically new to many people. Sharing economy presents a new type of marketplace where peer-to-peer interactions occur with technology often mediating the exchange of information and money. Almost all types of sharing involve location information and reliance on Information Technology platforms.

Sharing economy is growing quickly. As of 2018, the number of sharing economy users in the US is 66.3 million and it is anticipated to reach to 86.5 million by

2021 [28]. This expansion in the contemporary sharing economy engenders a fundamental question – who are the sharing economy workers? What is their motivation to participate in the sharing economy? Those who share, swap, trade, or rent their personal assets in the sharing economy are mostly treated as “employer-less” contractors rather than employees, so they count the income resulting from sharing as a modest supplement to their main income [25]. In the case of short-term peer-to-peer shared accommodation platforms such as Airbnb, limited prior research [4] has indicated that the motivation of hosts for renting their homes on Airbnb is typically a blend of making extra money and meeting new people. As discussed more in the next section, previous research has mostly examined motivations of end-consumers to participate in sharing economy; however, the suppliers' point of view has been scarcely studied.

Given the paucity of theory-based examination of antecedents of host participation in the shared accommodation economy, this paper develops and empirically validates a theoretical conceptual model of host participation in the shared accommodation economy in New York City (NYC) along with locational patterns of host participation. NYC, the most populous city in the U.S. with more than 8.5 million people [9] is a popular hub of tourism, entertainment, and business. NYC is comprised of five boroughs – Manhattan, Brooklyn, Queens, Bronx, and Staten Island, that present a fascinating tapestry of demographic, ethnic, cultural, and socioeconomic diversity, enhancing its appeal as a hotspot for tourism. Demographic diversity and socioeconomic disparities often characterize populous, urban metropolitan geographies in the United States and beyond. Therefore, examining what motivates sharing economy workers – especially those on the supply side – can inform policy, regulation, urban planning, and economic development in such areas. At a time when popular sharing economy platforms such as Uber and Airbnb transform cities, their citizens, as well as local and national economies, understanding supply-wide motivations is critical. The knowledge and understanding of sharing economy

platforms about their “workers” also advances as a result. It can go a long way towards alleviating legitimate concerns that the sharing economy does not equally benefit everyone and only a small fraction of workers tend to benefit the most [1].

Situated in this context, the overall research question of this paper is — what are the spatial patterns and related socioeconomic influences and motivations of host participation in the shared accommodation economy (Airbnb) economy in NYC? To analyze spatial patterns of host participation, we employ geographical information systems to map Airbnb property densities (the study’s dependent variable) to gauge the extent of host participation in the shared accommodation market in NYC neighborhoods. Geostatistical methods (cluster and outlier analysis) are employed to identify neighborhood clusters of high versus low participation. The geographic locations and demographic and socioeconomic characteristics of those neighborhoods are subsequently analyzed. This provides the foundation to examine associations of demographic and socioeconomic variables along with social capital and attitudes towards trust and greener consumption with host participation in the shared accommodation economy. Finally, differences in such associations between two of NYC’s biggest boroughs – Manhattan and Queens are examined.

The development and empirical validation of a theoretical conceptual model that examines antecedents of host participation in the shared accommodation economy is one of the contributions of this paper. The work is novel since it focuses on those who provide goods or services for sharing in the peer-to-peer collaborative consumption marketplace, rather than on those who are consumers of such goods or services. Locational analysis of antecedent factors that motivate hosts to participate in the shared accommodation economy is another novel feature of this work. Where sharing economy workers live and whom they identify as neighbors can potentially influence their motivations to rent or share valued assets. Lastly, the emerging body of work examining motivations to participate in the sharing economy has focused more on ridesharing platforms. In contrast, the peer-to-peer shared accommodation marketplace is the subject of this study.

2. Literature Review

Academic interest in sharing economy research has grown steadily over the past few years including the field of MIS. Four models of sharing economy platforms were described in a recent study [7] based upon a combination of organizational and market mechanisms along two key dimensions – extent of control over participants, and degree of rivalry between participants.

Airbnb, as a peer-to-peer shared accommodation platform, was described in this study [7] as a chaperone that exerts loose control over platform participants and aims to orchestrate matchmaking between them, both on the supply- and demand-side. Airbnb hosts are referred to as competing micro-entrepreneurs who are informed of current levels of supply and demand by the platform, but are free to set their own prices guided by Airbnb’s recommendation algorithms, unlike a tightly controlled platform such as Uber. Airbnb hosts are also encouraged by the platform to innovate in terms of services that they can provide to guests, thereby gaining competitive advantage. Based upon guest reviews of hosts, Airbnb’s Hospitality Index continually strives to improve its matchmaking of prospective guests with hosts. The aforementioned study [7] provides valued insights about the chaperone model, yet it does not address what motivates Airbnb’s hosts to participate in homesharing.

A handful of studies has focused on the impacts of sharing economy on the society and individuals [7, 30]. A recent study [6] investigated the geographical distribution of sharing economy in NYC neighborhoods focusing on the ratio of short-term to long-term rental prices. That study demonstrated that Airbnb listings in NYC have geographically dispersed more over time (2011-16) to less central and more residential areas. Through an economic lens, findings suggest that short-term rentals are not as profitable as long-term rentals, and the former have become even less profitable over time [6].

Another body of research has investigated the motivating and deterrent factors to participate in sharing economy [14, 16]. In a prior study conducted by the authors, motivations of Airbnb hosts to participate in sharing economy were categorized as economic, education, employment, trust, social capital, and sustainability [26]. Economic factors such as supplemental income significantly determine why people share their belongings [24]. Modern sharing economy requires technology skills that encourage a particular group of educated people who are employed in certain industries to join the sharing economy [26, 29]. Social capital is a necessary factor for participation in sharing economy platforms [29]. Trust is the currency of sharing economy [4, 19]. Trust itself can be characterized as trust in the platform and trust in the sharing partnership. Greater trust in the platform increases the intention to engage in sharing [19]. Trust between peers can be established through reputation mechanisms such as star ratings or review sharing [17]. From the sustainability perspective, another motivation to participate in sharing economy is to benefit the planet by reducing the use of scarce natural resources [4, 29].

The literature on supplier and consumer participation in the shared economy is relatively

nascent. Deductive reasoning based theoretical models that analyze and examine antecedents of participation – especially in MIS, are yet to be developed. Borrowing from the organizational behavior literature, Social Exchange Theory (SET) has been used to explain and model how trust in the sharing platform and perceived relative advantage of sharing services contribute to consumers' intention to participate in commercial sharing [16]. In the model, trust in the sharing platform and perceived relative advantage of sharing services contribute to consumers' intention to participate in commercial sharing rather than traditional services. Self Determination Theory has been employed to propose a research framework comprised of intrinsic and extrinsic motivations for individuals to participate in the sharing economy [14]. Intrinsic motivations stem from the intrinsic value such as enjoyment that sharing and its concomitant environmental, social, and economic consequences bring to individuals, while extrinsic motivation is derived from external pressures, such as reputation and monetary gain. Somewhat similarly, a framework of determinants of likelihood by consumers to use a sharing option posits associations of utility, trust, cost savings, familiarity, environmental impact, and community belonging with satisfaction with a sharing option and likelihood to use it [20]. Both studies [14, 20] empirically validated research hypotheses for consumers, rather than suppliers/hosts who are the focus of this study. Only one study that has investigated the relative importance of economic, social, and environmental motivations to participate in peer-to-peer sharing, for both users and providers. Using a survey of respondents from Amsterdam, Netherlands, this study [2] found users to be more economically motivated than providers. Overall, a majority of these prior studies have examined motivations of consumers to participate in the sharing economy. However, understanding factors that influence suppliers or hosts to share their valued assets with others has not been examined in prior literature. In fact, there is a paucity of theoretical research models that examine antecedents of participation in the sharing economy among providers, or in this case, hosts of short-term accommodations. This paper fills this critical gap in the literature. It sheds light on the key question – who are sharing economy workers and what factors motivate Airbnb's host micro-entrepreneurs to participate in the shared accommodation economy. This is the main contribution of this paper.

3. Conceptual Research Model of Host Participation

Our conceptual model of host participation in the shared accommodation economy posits associations of

14 independent variables with 16 dependent variables. The dependent variables are densities of three types of Airbnb properties – entire home/apartment, private room, and shared room, as well as all property types combined in 2015, 2016, and 2017. The conceptual model is based on the Spatially Aware Technology Utilization Model (SATUM), which induces and examines associations of socioeconomic, innovation, societal openness, and social capital factors with the adoption and use of information and communications technologies (ICTs). An additional feature of SATUM [22] is its ability to diagnose and account for spatial bias in ICT adoption and diffusion. Similarly, based upon limited prior work in the literature [14, 16, 20, 29] as well as inductive reasoning, we posit associations of socio-economic, demographic attributes and indicators of trust, social capital, and attitude towards sustainability with aforementioned indicators of host participation in the shared accommodation economy. Next, independent variables that are part of the conceptual research model are grouped thematically and their associations as posited with the dependent variables, are discussed.

Demographic Influences: Recent reports [13, 26] have indicated that compared to the U.S. workforce, on-demand workers tend to be more male, younger, and more educated. The same report indicates that millennials are more likely to participate in the sharing economy compared to other generations. Part of the millennial motivation is economic. Despite higher educational levels, millennials' median income is close to that of previous generations when they were of the same age. Interestingly however, Americans aged 35 – 44 are nearly twice as likely to use home-sharing services than those aged 18 – 24 [26]. Therefore, we posit dependency ratio ($(\text{population } 0-19 + \text{population } 65+) / \text{population } 20 - 64$) as well as educational attainment (per capita high school and college-educated population) to be inversely associated with host participation. Since the American sharing economy worker is three times more likely to be male than female, we posit sex ratio (male age 21+ / female age 21+) to be positively associated with density of host participation. From a race/ethnicity standpoint, the sharing economy workforce is overwhelmingly white. Therefore, we posit minority race/ethnic groups (Black, Asian, Hispanic) to be inversely associated with host participation.

Economic Influences: Usage and awareness about home-sharing platforms are especially high among college graduates and the relatively affluent – groups that are more likely to afford travel than their less-affluent peers [26]. Recent Bloomberg reports also indicate that a primary motivation for on-demand workers to participate in the sharing economy is to find “enough” work that enables them to supplement their

traditional income [25]. Airbnb's economic impact reports have indicated that three-quarters of NYC hosts used the money they earned sharing their space to stay in their home. Since higher income is likely to dissuade hosts from renting their space on Airbnb, we posit median household income to be negatively associated with host participation. Arguing that households with a mortgage is a sign of relative financial stability and economic well-being, we similarly posit owner occupied households with a mortgage to be negatively associated with host participation. Among other economic variables introduced into the conceptual model are workforce variables. As documented recently, on-demand startups have been ushering white-collar workers into the sharing economy workforce [2]. Such workers are more comfortable with everyday technologies; while they would usually command higher salaries and extra perks compared to their blue-collar compatriots, some white-collar employees are increasingly craving the flexibility and mobility afforded by the sharing economy. We therefore posit professional, scientific, technical services (PSTS) employment to be positively associated with participation in the shared accommodation economy. According to the U.S. Department of Labor, activities of the PSTS workforce include legal advice and representation, accounting, bookkeeping, and payroll services, architectural, engineering, and specialized design services, computer services, consulting services, research services, advertising services, among others. We also reason that those employed in hotel/lodging or possessing meaningful work experience in this industry are more likely to be comfortable hosting guests or interacting with short-term "tenants". Accordingly, lodging employment is also posited to be positively associated with the dependent variables.

Attitudes towards Trust and Greener Consumption: The analysis of trust in relation to participation in the sharing economy is well-researched [3, 19, 29], given the relative nascence of this general area. In inducing trust as an independent variable, the three-stage notion of the "trust stack" [3] – trust the idea of sharing or consuming collaboratively (stage 1), followed by trust in the platform, for example, Uber or Airbnb (stage 2), and finally trusting the other user (stage 3) – is important. Prior research has found that trust and perceived risk of the platform are significant factors that influence the users' intention to create an Uber account [18]. A prior study [20] found trust, along with utility, cost savings, and familiarity to be essential for car-sharing (Zipcar) and home-sharing (Airbnb) consumers likelihood to engage in collaborative consumption. Trust was found to impact the users' perceived self-benefit. A recent literature review of antecedents of trust in the sharing economy contended that most of the

reviewed studies focused on trusting beliefs towards the seller, thereby not doing justice to the peer-to-peer nature of the sharing economy [15]. In agreement with [15], the concept of perceived risk and trust are just as important to the seller/provider who shares valued assets. Given this study's attention on the Airbnb host, we focus on stage 3 of the trust stack [3] and operationalize the hosts' emphasis on trust based on whether hosts required verification of the renter's driver's license, Airbnb profile, and phone. This operationalization is consistent with the principles of digitization of trust, often enabled by validation – digital or otherwise – provided by external institutions such as governments [29]. We posit that a composite index measuring emphasis on trust (average proportion of hosts requiring the three aforementioned verifications) is positively associated with host participation. This posited association is consistent with the finding that 'trust in renters' significantly influences the providers' intention to 'offer an accommodation' and to 'accept a booking request' on Airbnb.com [18].

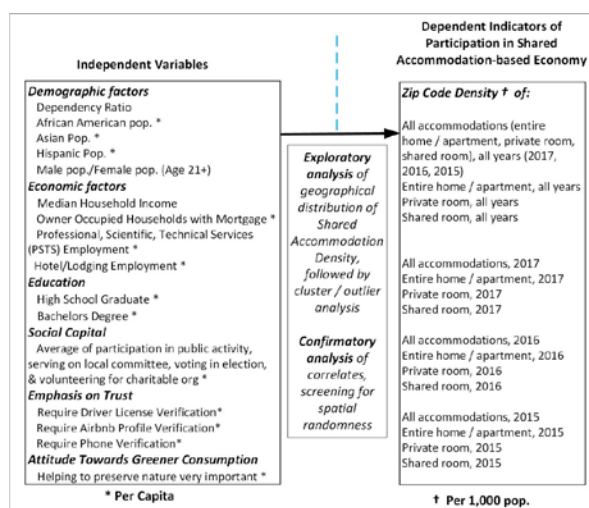


Figure 1. Conceptual Model of Host Participation in Shared Accommodation Economy

Prior studies have conceptualized ecologically sustainable consumption to be a key determinant of the intent to share and have argued that sharing solutions generally have a positive environmental impact, leading to increased intensity of usage of goods, thereby reducing waste [4, 20, 30]. While one study [20] posited environmental impact to have a positive effect on the satisfaction with a sharing option and the likelihood of using such an option by a consumer, we posit hosts' attitude towards greener consumption [14] to be positively associated with participation in the sharing accommodation economy.

Social Capital's Influence: Social capital is based on the central premise that social networks – physical and digital – have value. Social capital encompasses a wide variety of specific benefits that flow from the trust, reciprocity, information, and cooperation associated with social networks. Making real-world social capital digitally available provides a powerful cue of authenticity, trust, intent, and reliability of collaborative consumers [29]. While social capital has often been associated with trust and reputation of sharing economy participants, communal aspirations of the millennial generation has been argued to foster the practice of sharing and collaborative consumption [20]. In this study, we include a social capital construct comprised of four components described in a seminal study [23], and posit social capital to be positively associated with host participation in the sharing economy.

In conclusion, the conceptual research model of this paper (Figure 1) induces relationships between the dependent indicators of Airbnb property densities (proxies of host participation) with independent correlates – based predominantly on prior literature. It is based on an analogous model (SATUM, [22]) used to explain and analyze spatial patterns and socioeconomic influences on adoption, diffusion, and use of information and communications technologies (ICTs), and resulting digital divides. Prior literature has posited the sharing economy as a technological phenomenon and viewed it primarily through an information technology lens [14], specially that of technology participation and adoption. Many aspects of contemporary peer-to-peer sharing activities are enabled by advances in information systems and technology intermediation. Allied with demographic and socioeconomic underpinnings of ICT adoption and diffusion, positioning of the sharing economy as a technological phenomenon justifies the paper's conceptual model of host participation to be based upon prior theoretical models developed in the ICT adoption and digital divide contexts. The development of this induction-based research model of host participation in the shared accommodation economy is the central theoretical contribution of this paper.

4. Methodology and Data

Our research methodology is comprised of the following steps: (1) Data on three different types of Airbnb property listings – entire home/apartment, private room, and shared room, for New York City, New York is obtained from InsideAirbnb.com. For the sake of longitudinal consistency, the property listings used for this study were those that were compiled by InsideAirbnb at the same time (early October) each year for three years – 2015, 2016, and 2017. Data on

independent variables is obtained from a variety of U.S. Census Bureau datasets and compiled as part of Esri Demographics [12] as well as Esri/GfK MRI DoubleBase Survey [11]. Data on some independent correlates such as emphasis on trust is estimated using attributes from the same Inside Airbnb datasets on property listings used to obtain data on the study's dependent variables. (2) After ensuring property data completeness, individual listings were geocoded in a Geographic Information System (GIS); subsequently, listings were aggregated at the zip code level by property type and year, and aggregated counts were normalized by the population of a zip code to obtain densities by property type.

Subsequently, property densities – the dependent variables for this study and proxies of host participation, were calculated for each property type, and each year. For example, density of entire home/apartment in zip code 10001 in 2017 = (Total number of properties identified as entire home/apartment in zip code 10001 in 2017/Population of zip code 10001) × 1,000 population. (3) Property densities were then mapped and visualized using GIS. The descriptive maps provide important visual cues about the spatial as well as longitudinal patterns of participation in the shared accommodation market among Airbnb hosts in New York City. Additionally, such maps indicate if neighborhoods with high or low participation rates tend to cluster together – alluding to the possibility of spatial bias [21] among the dependent variables. We outline the diagnosis of spatial bias as ongoing work in this study. (4) K-means cluster analysis is then employed to determine clusters of zip codes that are most similar in terms of host participation in the Airbnb marketplace, as measured by property densities (descriptive statistics in Table 1).

While exploratory in nature, K-means cluster analysis yields meaningful agglomerations of zip codes that are similar in terms of their participation in the sharing economy. K-means clusters (zip codes belonging to each cluster) are characterized in terms of the demographic and socio-economic attributes, residents' attitudes towards trust and greener consumption, and social capital – all important antecedents of participation in the sharing economy, as discussed in the previous section. (5) Finally, OLS regression analysis is employed to examine posited associations of 14 independent demographic, socio-economic variables, emphasis on trust, social capital, and attitude towards greener consumption with 16 dependent variables – densities of various types of Airbnb properties across 2015-17 spanning 182 zip codes in NYC. Stepwise entry of independent variables is employed with significance levels equal or less than 0.05. As an additional test of multicollinearity, the variance inflation factor (VIF) is computed, and a cutoff

value of 5.0 is used to screen for independent variables that might cause multicollinearity. All independent variables in the regressions meet the VIF threshold.

Table 1. Definitions and Descriptive Statistics

Dependent Variables (*) -- Density of Airbnb Listings per 1,000 pop.							
	Source	Year of Data	Minimum	Maximum	Mean	Std. Dev.	
All accommodations, all years	Inside/Airbnb.com	2015-17	0.02	129.57	15.22	22.88	
Entire home/apartment, all years		2015-17	0.00	83.73	8.48	14.32	
Private Room, all years		2015-17	0.00	46.17	6.28	8.95	
Shared Room, all years		2015-17	0.00	5.56	0.45	0.70	
All accommodations, 2017		2017	0.00	50.88	5.82	8.50	
Entire home/apartment, 2017		2017	0.00	32.86	3.13	5.16	
Private Room, 2017		2017	0.00	16.73	2.53	3.53	
Shared Room, 2017		2017	0.00	2.38	0.16	0.27	
All accommodations, 2016		2016	0.00	42.76	5.22	7.76	
Entire home/apartment, 2016		2016	0.00	29.69	2.88	4.85	
Private Room, 2016		2016	0.00	14.15	2.17	3.07	
Shared Room, 2016		2016	0.00	1.85	0.17	0.26	
All accommodations, 2015		2015	0.00	41.57	4.18	6.73	
Entire home/apartment, 2015		2015	0.00	27.32	2.47	4.39	
Private Room, 2015		2015	0.00	15.84	1.58	2.44	
Shared Room, 2015		2015	0.00	1.85	0.13	0.23	
Independent Variables *							
	Source	Year of Data	Minimum	Maximum	Mean	Std. Dev.	
Demographic							
Dependency Ratio (Pop. 0-19 yr + Pop. 65+ yr) / Pop. 20-64 yr)	Esri Demographics	2015	0.09	0.98	0.59	0.15	
Black (%)		2015	0.01	0.93	0.23	0.26	
Asian (%)		2015	0.01	0.73	0.15	0.14	
Hispanic (%)		2015	0.06	0.77	0.26	0.20	
Male Age 21+/Female Age 21+		2015	0.55	1.67	0.88	0.13	
High School Graduate (%)		2015	0.01	0.41	0.19	0.08	
Bachelors Degree (%)		2015	0.07	0.52	0.23	0.10	
Economic							
Median HH Income		Esri Demographics	2015	20039.00	200001.00	63020.41	29796.39
ACS Owner Households with a Mortgage/Total Households (%)			2015	0.02	0.59	0.22	0.16
Prof. Scientific, Technical Serv. Emp. (%)	2015		0.01	0.27	0.09	0.07	
Hotel/Lodging Emp. (%)	2015		0.00	0.42	0.01	0.03	
Social Capital: Participation in public activity, serving on local committee, voting in election, and volunteering for charitable org (%)	Esri/CRK MRI DoubleBase Survey	2016	0.21	0.46	0.34	0.06	
Attitude for Greener Consumption: Helping to preserve nature very important (%)		2016	0.50	0.75	0.70	0.02	
Emphasis on Trust: Proportion of listings for which hosts required verification of driver's license, Airbnb profile, and phone	Inside Airbnb .com	2015-17	0.00	0.44	0.03	0.05	

* n = 182

5. Spatial Patterns of Host Participation

The density patterns of Airbnb properties in time and space reveal distinctive spatial distributions and longitudinal changes that inform the paper's cluster and regression analyses. The overall pattern of all Airbnb properties, with densities totaled for the three years shows the strongest New York City prevalence in lower Manhattan, Governor's Island, the northwest section of Brooklyn, and western part of Queens (Figure 2). The lower-mid Manhattan concentration reflects the prevalence in those areas of tourist sites, financial and other corporate headquarters and buildings, and tourist amenities such as restaurants, shopping, and entertainment. The high demand for accommodations in Manhattan is intuitive. Although real estate prices are high in this area, the area has on average an older population, i.e. people who might have extra space and be conducive to renting it, and it has a higher than average percent of workers in professional and technical occupations, who are likely to be more comfortable as shared accommodation hosts.

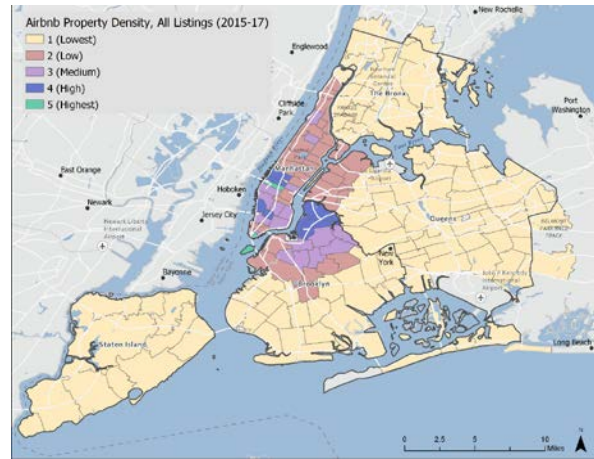


Figure 2. K-means clusters, Airbnb property densities, NY City (Oct 2015, 2016, 2017)

The northwest section of Brooklyn likewise has high densities of Airbnb, mostly in zip codes that have quite elevated real estate pricing. This section of Brooklyn also has many important New York tourist sites including Grand Army Plaza, Brooklyn Art Museum and Children's Museum, and Brooklyn Botanic Garden, as well as tourist amenities. This section of Brooklyn is connected by two bridges to Manhattan and the high demand for Airbnb properties is posited as similar to Manhattan. Western Queens has somewhat elevated Airbnb densities, which can be regarded as gentrification associated with two bridge connections with Manhattan, adjacency to northwest Brooklyn, and major tourist sites such as Shea Stadium and American Museum of the Moving Image, as well as close proximity to La Guardia Airport. Longitudinally from 2015 to 2017, the above described spatial distribution of high property densities has remained stable, a situation that might be ascribed to a steady demand overall.

In addition to studying overall patterns, the research also examined spatial patterns for the categories of entire housing unit, private room, and shared room. Relative to overall pattern, housing units were quite stable and similar to the overall patterns. Private room revealed relatively higher densities in northwest Brooklyn and somewhat lower densities in Manhattan, with growth in Brooklyn over time. This might reflect younger renters who find a single room more affordable and prefer Brooklyn because of its popularity with millennials and GenXers. The spatial patterns for shared rooms reveals strong concentrations throughout Manhattan and in Brooklyn. Longitudinally over three years, the main change is wider geographic spread of host participation in Brooklyn and Queens. This spread merits further research.

K-means cluster analysis, which was performed for New York City for K=5 clusters, based on all the

dependent variables, reinforces the previous findings on higher property densities in lower Manhattan and in northwest Brooklyn and western Queens, in areas just to the southwest of the Queen's Midtown Tunnel and east of the Williamsburg Bridge (Figure 2). These areas are in the Medium (Cluster 3) to High (Cluster 4) categories on the map. The presence of the bridge and tunnel add transportation connections for these two clusters and unites these clusters on opposite sides of the East River. The highest Airbnb densities are in Cluster 5, which consists of two zip codes, for Governor's Island and on the West Side near 40th Street. The latter zip code is positioned in a transition zone just to the south and within easy walking distance of Midtown with its many tourist attractions.

The characterization of the five clusters by 14 independent variables reveals more specifics on the particular spatial relationships and contrasts for Airbnb properties. Geographical comparison of clusters 4 and 5 (high and highest density with 9 zip codes) with cluster 1 (lowest density with 118 zip codes) reveals high density central zones in clusters 4 and 5 that face each other on opposite sides of the East River. In contrast, low density areas of Cluster 1 form the wide periphery of the city including the Bronx, most of Queens, southern Brooklyn, and Staten Island. Relative to each other, the central high zones, compared to the periphery, have much lower dependency ratio, lower percentages for ethnic minorities, much higher household income, much lower percent of households with mortgages, much higher professional/scientific employment percent, 157 percent higher percent of hotel employees, and about 26 percent higher social capital.

We further examined the borough differences between Manhattan, with Airbnb properties in 44 zip codes, and Queens, with Airbnb properties in 61 zip codes. Comparing those two boroughs and considering Manhattan as high density and Queens as low density, a similar contrast for the independent variables was found to be present, with the exception of overall trust which is about 39 percent higher in Manhattan and hotel employment per capita which is much closer in value, with Manhattan exceeding Queens by only 18 percent.

In summary, there are significant socioeconomic differences that correspond to the geographical dispersion of higher Airbnb density in central clusters with low Airbnb densities in the broad periphery. These clusters can be considered for applications in geographic and economic planning for the sharing economy and for the commercial rental and hotel sectors in NYC.

6. Socioeconomic Determinants of Host Participation

OLS regression analysis results for $n = 182$ zip codes (in Table 2) reveal broad and strong support for most of the posited relationships between host participation dependent variables, measured by densities of Airbnb property listings, and their independent correlates. The model's independent variables exhibit no multicollinearity with VIF values consistently less than 4.0. Additionally, the independent variables explain between 36 – 72% variability in host participation in the shared accommodation economy at the neighborhood (zip code) level; in fact, when property types are not differentiated, the model explains 68 – 72% of the variation in host participation across all years. For two property types – entire home/apartment and private rooms, the conceptual model explains almost 70% and 62% of the variation, respectively, in host participation, indicating the model's high predictive power. For shared rooms, the model explains 36 – 45% of the variation in host participation across years. This decline in predictive power of the model for shared rooms is discussed later in this section. Among posited relationships, the most prominent correlates of neighborhood host participation are dependency ratio and sex ratio among demographic variables, Asian and Hispanic (both negative) among race/ethnic variables, and median household income and employment in professional, scientific, and technical services (PSTS) among economic variables. Attitude towards greener consumption is also a significant correlate of host participation for properties aggregated by type and year as well as for private rooms, but not for entire home/apartment and shared rooms. Standardized coefficients indicate comparatively weaker association of attitude towards greener consumption with the dependent variables compared to demographic and economic variables.

The negative association of dependency ratio ($[\text{pop. age } 0-19 + \text{pop. age } 65+] / \text{pop. age } 20 - 64$) and the positive association of sex ratio (male age 21+ / female age 21+) are both intuitive and supported by findings of prior industry reports [25]. As dependency ratio increases, i.e., holding the proportion of working adults constant, as children and older adults increase in the population, it is less likely for households in a neighborhood to host short-term tenants as Airbnb guests. Simply stated, young and old neighborhoods are less likely to participate in the shared accommodation economy in New York City. Also, the positive association of sex ratio indicates that the likelihood of participation in the shared accommodation economy as Airbnb hosts in NYC increases with an increase in the proportion of males, age 21 and older. Both findings are consistent with prior reports which found sharing economy workers to be more male and younger [13] compared to the traditional U.S. workforce.

From a race/ethnic standpoint, the inverse associations of both Asian and Hispanic with neighborhood density of Airbnb properties (except shared rooms for which there is only instance of negative association) indicates that host participation in the shared accommodation economy in NYC declines with higher proportion of ethnic minorities. Again, prior reports [25] indicate that much like the U.S. workforce, sharing economy workers are much more likely to be White than Black, Asian, or Hispanic. Independent reports also provide empirical evidence that in all 72 predominantly Black NYC neighborhoods, Airbnb hosts are 5 times more likely to be white [8]. While Airbnb itself has disputed this summary conclusion that Airbnb has been racially gentrifying NYC neighborhoods, our findings confirm that higher ethnic minorities per capita decreases host participation.

In the basket of economic variables, the consistent inverse association of median household income with property densities (except shared rooms) reinforces the now well-known finding that participants are often motivated by the supplemental income potential of the sharing economy [25]. This relationship has been validated in a prior study of host participation in the Airbnb platform for Los Angeles neighborhoods [26]. For shared rooms, the inverse association of proportion of owner occupied households with a mortgage with host participation is interesting. We reason that owner-occupied households with mortgages are likely younger (Pearson Correlation of 0.30 with dependency ratio, significant at .01 level) and therefore rooms occupied by children or younger adults are less likely to be available for short-term rentals. The absence of association of this independent variable for other property types – entire home/apartment and private room is curious and merits further investigation. Viewed holistically, these findings at the neighborhood are in agreement with prior works [14, 16] which have theorized and empirically validated that individuals view cost and time savings stemming from sharing [14, 20] to extrinsically motivate sharing economy participation.

From an occupational standpoint, the strong positive association (high standardized betas and significance at the .001 level for all properties except shared rooms) of PSTS with property densities reiterates that sharing in the modern peer-to-peer context requires intermediation by technology [29]. Thus, neighborhoods with a higher proportion of employees who are more likely to possess internet capabilities [20] and digital skills required to be comfortable with technology and its use and socially and digitally connected with PSTS peers (high positive correlation social capital) are more likely to participate in the shared accommodation marketplace as hosts. Neighborhood-level attitude toward greener consumption, measured by proportion of population

which believes that helping to preserve nature is very important, is positively associated with a selection of dependent variables – private rooms in all years, as well as all property types combined, for all years. While the standardized betas are noticeably lower compared to other independent correlates, the results nonetheless confirm prior arguments in the literature that crowd-based peer-to-peer renting and sharing of resources among a wider group of people represents a move away from traditional forms of ownership, thereby potentially delaying the onset of future environmental crisis [29]. Our finding demonstrates that this intrinsic motivation to engage in sustainable practices influences attitudes towards collaborative consumption and behavioral intentions to participate in the sharing economy, not just at the level of the individual host or participant [14], but also at the neighborhood level. This is among the novel findings of this study.

It is pertinent to note that attitude towards trust – estimated in the study by an emphasis of hosts on guests providing verifications of their driver's licenses, Airbnb profile, and phone numbers – is surprisingly not associated with any of the 16 dependent variables. This absence of association of the emphasis on trust with host participation in the shared accommodation economy contrasts with prior literature which has argued that the concept of perceived risk and trust, in the peer-to-peer economy, are just as important to the seller/provider [15]. Here we reiterate that our operationalization of trust focuses solely on emphasis on trust of the individual host (by verifying the renter's identity, Airbnb profile, and phone number), not on trust in the sharing economy platform or the idea of sharing – all of which are arguably considered to be principal determinants of choosing collaborative consumption options [4]. Unlike prior work [20], this study however posits emphasis on trust to be associated with actual participation in the shared accommodation economy, not with the satisfaction of a sharing option. This may explain the lack of association. Another possible explanation for trust's diminished importance lies in a pitfall associated with any georeferenced data, known as the Modifiable Areal Unit Problem (MAUP), which is closely related to a more general statistical problem: the ecological fallacy [21]. This fallacy arises when a statistical relationship observed at one level of aggregation is assumed to hold because the same relationship holds at a more detailed level. While 'trust in renters' was found to significantly influence the individual provider's/host's intention to 'offer an accommodation' and to 'accept a booking request' on Airbnb [18], the same phenomenon may not necessarily be true at an aggregated neighborhood (zip code) level, the unit of analysis in this study. Nonetheless, this

finding merits further investigation and is outlined as a future research direction.

Lastly, the absence of associations of educational attainment and social capital are important findings. While social capital has been posited to build social interconnectedness and influence trust in the digital environment, the absence of any direct association with any dependent variable is a novel finding. We reason that at the neighborhood level in a large U.S. city with high cost of living, economic motivations outweigh the need for social connectedness. This result – the limitation of social capital and community to influence sharing economy participation has been observed in limited prior studies on time banking [10] and peer-to-peer carsharing in which users (not providers) described their interactions as “anonymous” and “sterile”. This is the first study to find empirical evidence of the limitation of neighborhood-level social capital to influence host participation in the shared accommodation marketplace.

The absence of association of educational attainment is in contrast to a prior Pew study [27] which found homesharing services are especially popular with college-educated Americans with higher incomes. We observe that median household income in this study has a strong positive association with the dependent variables. Its strong positive correlation with neighborhood population with bachelors education (Pearson Correlation of 0.773 significant at .01 level) may explain the lack of association of the latter (educational attainment) with host participation thereby avoiding multicollinearity issues.

A separate set of regressions for Queens (n = 61 zip codes in study sample; therefore, limited to 6 independent variables to be entered into regressions) and Manhattan (n = 44 zip codes in study sample; therefore, limited to 4 independent variables to be entered into regressions) reveal interesting variations in antecedents of host participation. Queens and Manhattan are two of the three most populous boroughs in NYC, following Brooklyn. Dependency ratio among demographic variables and median household income, owner occupied households with a mortgage, and PSTS employment among economic variables continue to remain as key explanatory variables for both boroughs. In other words, in both boroughs, economic motivations for participation in the shared accommodation economy are clear. However, for Queens, a significant difference is the consistent inverse association of Asian population per capita with host participation, in comparison with Manhattan in which percent Asian has no association with any of the dependent variables. Given the significantly larger Asian population (23 per 100 population in Queens compared to 14 in Manhattan, in 2015), this inverse association for Queens, but not for

Manhattan is reasonable. Another important difference is the positive association of social capital – operationalized in this study as a composite index (comprised of per capita participation in public activities, serving on local committees, voting in elections, and volunteering for charitable organizations), with host participation in Queens, but not for Manhattan, and the overall study sample. This an important finding of this study. We reason that much higher ethnic diversity (almost two-thirds of the population split almost equally between Blacks, Asians, and Hispanics, in 2015) in Queens compared to Manhattan, fosters and builds bridging and bonding social capital [5] alleviating anxieties and potential misconceptions about this new paradigm of sharing one’s home with short-term renters. This manifests itself in positive association of social capital with host participation in Queens compared to Manhattan. Another interesting difference is the lack of association of attitude for greener consumption with host participation both Queens and Manhattan. While this merits further research, we reason that economic motivations outweigh sustainability considerations in Queens and Manhattan, but not in the overall study sample (182 zip codes).

Overall, the conceptual model of host participation in the shared accommodation economy is largely validated. Some results warrant further research to confirm generalizability. Interesting differences in regression associations for two of the most populous NYC boroughs confirm that regional variations in host participation in the shared accommodation economy exist, and merit further attention from researchers.

7. Implications of Findings

OLS regressions confirm that the major influences on host participation overall are dependency ratio, Asian and Hispanic ethnic densities, gender ratio, household income, and PSTS workforce, with slight effects from attitudes towards sustainable consumption and mortgage prevalence. Overall, these findings on host participation in the shared accommodation economy are consistent with consumer-side motivations. Viewed from an economic development standpoint, the potential of homesharing to provide supplemental income implies that both cities and homesharing platforms can focus on citizenry and hosts respectively, who are more likely underemployed and/or desire the flexibility that steady employment is unlikely to provide. Allied with increasing neighborhood income is the potential for gentrification. Therefore, from the perspective of cities, identification of neighborhoods that are most susceptible to gentrification is a key implication. The race/ethnic findings (inverse associations of Asian and

Hispanic) allude to disinclination of such households to indulge in homesharing. Demographic shifts in populous U.S. metros have resulted in ethnic enclaves within cities such as Los Angeles and NYC that draw tourists and visitors interested in local cultures, businesses, cuisines, and entertainment. Hence, the availability of attractive, yet affordable accommodations at the heart of such neighborhoods or at least in close proximity can financially benefit residents of such neighborhoods and by extension, the city. The disinclination of ethnic minorities to indulge in homesharing poses a hindrance though and as such implies the need for additional targeted marketing of benefits of homesharing to such communities as well as understanding reasons for their disinclination to engage as hosts. Unexpected findings were the absence of effects of social capital and of hosts' emphasis on trust. Marketing and communication about Airbnb listings take place to a large extent through online means; hence the older concept of physical social interactions may play a much reduced role than in some digital divide studies [5]. The absence of this dimension of trust might reflect possibly the newness of widespread Airbnb markets, so owners are driven more by start-up and marketing success rather than trust, which is developed and often has impacts, such as return renters, over a longer term.

The associations of the independent factors with property densities show great stability, with very limited longitudinal changes. Perhaps a minor exception is for shared room, which has independent associations, in order of magnitude, in 2015 of dependency ratio (inverse), mortgage percentage (inverse) and PSTS workforce (positive), in contrast to 2017 of dependency ratio (inverse), mortgage percentage (inverse), and Hispanic (inverse). Although slight, there is a shift in the third factor. This stability of associations over time was also noted for greater LA for 2015-2017 [26].

8. Conclusions and Limitations

This paper develops and refines a theoretical conceptual model of host participation in the shared accommodation economy and examines socioeconomic antecedents of the same. Studies that examine the provider's perspective of sharing economy participants are scarce; therefore, this study is novel in its contributions. From the provider's perspective, there are different whys and wherefores to participate in sharing economy. Spatial patterns of Airbnb listings in New York City over a three-year span from 2015 to 2017 were analyzed in this study. Higher Airbnb property densities in lower Manhattan and in northwest Brooklyn and western Queens were identified. Regression findings suggest a consistent significant relationship

between dependency ratio (negative), Asian and Hispanic ethnicity (negative), sex ratio (positive), median household income (negative), employment in PSTS (positive), and attitude toward green consumption, and densities of Airbnb listings. We could not find statistical support for the relationship between hotel employment, social capital, and emphasis of trust. After conducting post-hoc analysis between two of NYC's most populous boroughs (Manhattan and Queens), interesting differences stemming from the impacts of social capital and Asian population were observed. In Queens, Asian population density negatively impacts host participation. In addition, social capital shows a significant positive relationship with host participation density in Queens. Micro-scale geographical differences in host participation motives suggest the importance of different local strategies for policy planning and regulation.

The study is limited by, first of all, not having more depth of behavioral knowledge about host motivations to participate in the shared accommodation economy. Surveys of Airbnb hosts would provide valuable cues on behavioral patterns and importance of trust expressed by such hosts. A second limitation relates to the independent variables, which are drawn from US Census and market surveys at the zip code level. The zip code unit of analysis, which often has heterogeneity within it, limits the findings of the present study. Also, the trust variable was created as an index from underlying factors. It does not actually reflect the trust of an individual host, but rather a zip code-level average estimate of host trust. This issue could be addressed by surveying a large sample of Airbnb hosts, with accurate spatial locations of their respective Airbnb properties. In addition, as more of the associations and mechanisms of decision-making by Airbnb hosts become known, and robust datasets corresponding to this paper's theoretical model become available, structural equation and other multi-pathway analytical models may be developed.

9. References

- [1] Bellafante, G. What the Sharing Economy Really Delivers: Entitlement. *New York Times*, 2018. <https://www.nytimes.com/2018/01/26/nyregion/what-the-sharing-economy-really-delivers-entitlement.html>.
- [2] Böcker, L. and Meelen, T. Sharing for people, planet or profit? Analysing motivations for intended sharing economy participation. *Environmental Innovation and Societal Transitions* 23, (2017), 28–39.
- [3] Botsman, R. *Who can you trust? : how technology brought us together : and why it could drive us apart*. New York, NY: Hachette Book Group., 2017.
- [4] Botsman, R. and Rogres, R. What's mine is yours: how collaborative consumption is changing the way we live. *Majeure Alternative Management*, HEC (2012), 1–9.

- [5] Chen, W. The Implications of Social Capital for the Digital Divides in America. *The Information Society* 29, 1 (2013), 13–25.
- [6] Coles, P., Egesdal, M., Gould Ellen, I., Li, X., and Sundararajan, A. Airbnb Usage Across New York City Neighborhoods: Geographic Patterns and Regulatory Implications. *Cambridge Handbook of the Law of the Sharing Economy Forthcomin*, (2017), 85–103.
- [7] Constantiou, I., Marton, A., and Tuunainen, V.K. Four Models of Sharing Economy Platforms. *MIS Quarterly Executive* 16, 4 (2017), 231–251.
- [8] Cox, M. Inside Airbnb: The Face of Airbnb, New York City. *Inside Airbnb*, 2017, 1–22.
<http://insideairbnb.com/reports/the-face-of-airbnb-nyc.pdf>.
- [9] DCP. New York City Population. *NYC Department of City Planning*, 2015.
<https://www1.nyc.gov/site/planning/data-maps/nyc-population/population-facts.page>.
- [10] Dubios, E., Schor, J., and Carfagna, L. New cultures of connection in a Boston time bank. Sustainable lifestyles and the quest for plenitude: Case studies of the new economy. *Sustainable Lifestyles and the Quest for Plenitude: Case Studies of the New Economy*, (2014), 95–124.
- [11] Esri. *Methodology Statement: Esri US Market Potential Database*. 2015.
- [12] Esri. *Esri Demographics*. 2018.
- [13] Fretz, D. Demographics drive sharing economy as millennials seek more for less. In *The Sharing Economy. Bloomberg Briefs, Bloomberg*, 2015, 13.
http://newsletters.briefs.bloomberg.com/repo/uploads/pdf/false_false/bloombergbriefs/4vz1acbgrfxz8uwan9_0_1019.pdf.
- [14] Hamari, J., Sjöklint, M., and Ukkonen, A. The sharing economy: Why people participate in collaborative consumption. *Journal of the Association for Information Science and Technology* 67, 9 (2016), 2047–2059.
- [15] Huurne, M., Ronteltap, A., Corten, R., and Buskens, V. Antecedents of trust in the sharing economy: A systematic review. *Journal of Consumer Behaviour* 16, 6 (2017), 485–498.
- [16] Kim, J., Yoon, Y., and Zo, H. Why People Participate in the Sharing Economy: A Social Exchange Perspective. *PACIS 2015 Proceedings*, (2015), 1–6.
- [17] Martin, C.J. The sharing economy: A pathway to sustainability or a nightmarish form of neoliberal capitalism? *Ecological Economics* 121, (2016), 149–159.
- [18] Mittendorf, C. What Trust means in the Sharing Economy: A provider perspective on Airbnb.com. *Americas Conference on Information Systems*, (2016), 1–10.
- [19] Mittendorf, C. Trust and Distrust in Two-sided Markets: An Example in the Sharing Economy. *51th Hawaii International Conference on System Sciences* 9, (2018), 5402–5411.
- [20] Möhlmann, M. Collaborative consumption: Determinants of satisfaction and the likelihood of using a sharing economy option again. *Journal of Consumer Behaviour* 14, 3 (2015), 193–207.
- [21] O’Sullivan, D. and Unwin, D.J. *Geographic Information Analysis*. John Wiley & Sons, 2014.
- [22] Pick, J. and Sarkar, A. *The global digital divides: Explaining change*. Springer, 2015.
- [23] Putnam, R. *Bowling Alone: The Collapse and Revival of American Community*. Touchstone Books by Simon & Schuster, 2001.
- [24] Ramirez, E., Ohlhausen, M.K., and McSweeney, T.P. *The Sharing Economy: Issues Facing Platforms, Participants, and Regulators*. 2016.
- [25] Rossa, J., Crombie, J., Riley, A., and Fretz, D. The Sharing Economy. *Bloomberg Brief*, 2015.
<https://newsletters.briefs.bloomberg.com/document/4vz1acbgrfxz8uwan9/front>.
- [26] Sarkar, A., Koohikamali, M., and Pick, J.B. Spatiotemporal Patterns and Socioeconomic Dimensions of Shared Accommodations: the Case of Airbnb in Los Angeles, California. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences IV-4/W2*, (2017), 107–114.
- [27] Smith, A. *Shared, collaborative, and on demand: The new digital age economy*. 2016.
- [28] Statista. Number of sharing economy users in the United States from 2016 to 2021 (in millions). *Travel, Tourism & Hospitality*, 2018.
- [29] Sundararajan, A. *The Sharing Economy: The End of Employment and the Rise of Crowd-Based Capitalism*. The MIT Press, Cambridge, MA, US, 2016.
- [30] Zervas, G., Proserpio, D., and Byers, J.W. The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *Journal of Marketing Research* 54, 5 (2017), 687–705.

10. Acknowledgement

This authors acknowledge and sincerely thank Ms. Lisa Benvenuti, Spatial Resources Manager, Center for Spatial Studies, University of Redlands for providing valuable mapping and spatial analysis support for this paper and overall project.

Table 2. OLS Regression Results, Host Participation in Shared Accommodation Economy

Independent Variable		All yr, All Listings	All yr, Entire home/apt	All yr, Private Room	All yr, shared room	2017 All Listings	2017, Entire Home/Apt	2017, Private Room	2017, Shared Room	2016 All Listings	2016 Entire home/apt	2016, Private Room	2016, Shared Room	2015 All Listings	2015, Entire Home/Apt	2015, Private Room	2015, Shared Room
Demographic	Dependency Ratio	-0.350***	-0.356***	-0.328***	-0.468***	-0.372***	-0.370***	-0.344***	-0.509***	-0.345***	-0.338***	-0.307***	-0.455***	-0.322***	-0.298***	-0.321***	-0.394***
	Black																
	Asian	-0.243***	-0.123**	-0.276***		-0.255***	-0.126**	-0.284***		-0.247***	-0.184***	-0.282***		-0.184***	-0.172***	-0.247***	
	Hispanic	-0.227***		-0.244***		-0.246***		-0.254***	-0.131*	-0.230***	-0.184**	-0.250***		-0.164**	-0.159**	-0.215**	
	Male Age 21+ / Female Age 21+	0.208***		0.271***		0.204***		0.253***		0.211***	0.112*	0.287***		0.155**	0.124*	0.268***	
	High School Grad. Bachelors Degree				-0.147*												
Economic	Med Household Income	-0.635***	-0.357***	-0.816***		-0.667***	-0.370***	-0.834***		-0.659***	-0.483***	-0.839***		-0.530***	-0.416***	-0.735***	
	Owner Households with a Mortgage/Total Households (%)				-0.221***				-0.291***				-0.289***				-0.179**
	Prof. Scient, Tech Serv Employment	0.780***	0.774***	0.743***		0.759***	0.760***	0.713***		0.799***	0.769***	0.775***		0.777***	0.767***	0.721***	0.190*
	Hotel / Lodging Employment																
Social Capital	Index of Social Capital																
Attitude for Greener Consumption	Helping to preserve nature very important	0.103*		0.146**		0.109*		0.144**		0.108*		0.153**				0.136*	
	Average Proportion of Hosts requiring License, Profile, Phone Verification																
Emphasis on Trust																	
Sample Size		182	182	182	182	182	182	182	182	182	182	182	182	182	182	182	182
VIF		3.956	3.682	3.956	1.764	3.956	3.682	3.956	1.400	3.956	3.954	3.956	1.091	3.954	3.954	3.956	1.961
Adjusted R-squared		0.709***	0.689***	0.620***	0.450***	0.702***	0.681***	0.602***	0.427***	0.719***	0.706***	0.636***	0.359***	0.682***	0.688***	0.590***	0.372***
		= * p < .05, ** p < .01, *** p < .001															