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An empirical analysis of Airbnb listings in forty American cities

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ABSTRACT

In the past ten years, Airbnb has rapidly grown from a small, online bed and breakfast product to a leading peer-to-peer hospitality magnate which operates in eighty thousand cities globally. It now offers rooms-for-rent, entire houses for rent, and even allows people to book 'experiences' through the platform. Consequently, cities, researchers, and the concerned public are focusing more on its impacts and exploring viable ways to regulate and facilitate the business while minimizing its potentially negative effects. To better understand Airbnb's operation in US cities, this paper explored how demographics, socioeconomics, and transportation might affect Airbnb listings in forty US cities. The results showed that Airbnb rentals were more likely to locate in neighborhoods with good transit service, short distances to the city center, and high median house value and household income. This study indicated the possible social inequality risk in the shared economy.

1. Introduction

This study explores where Airbnb rentals are located in forty major United States cities (detailed information in the Appendix). Airbnb is an online platform that "Operates an online community marketplace for people to list, discover, and book accommodations worldwide. The company allows people to rent out their extra space and showcase it to audiences. It also now allows people to book so-called experiences through the platform that are "activities designed and led by inspiring locals. They go beyond typical tours or classes by immersing guests in each host's unique world"" (Airbnb, 2018a). As the most popular online hospitality service provider globally, Airbnb has a presence in more than 34,000 cities in over 190 countries. It has an estimated valuation of 25.5 billion dollars as of 2015 (OECD, 2016). Unlike traditional hotel business, it doesn't own the property listed through the platform. Instead, it acts as a broker, receiving a commission from every booking (Kenny & Zysman, 2016). Usually, hosts can choose either to list their entire properties or to just rent out a spare bedroom or two in their homes to short-term renters to increase their household income (Airbnb, 2014). The advantage for tourists is that they can enjoy a flexible, hospitable, and "live-like-local" homestay (Benner, 2016). Additionally, while Airbnb may not be per se cheaper than a hotel, they do provide tourists and short-term renters with "better accommodations at more reasonable prices" (Farronato & Fradkin, 2018; Gerdeman, 2018).

As a peer-to-peer service provider, Airbnb is one of the more prominent members of the "shared economy", which has become a popular word on social media since 2010 (Cheng, 2016). However, the exact meaning of the term shared economy is ill-defined and there is "no 'shared' consensus on what activities comprise it" (Codagnone & Martens, 2016). To avoid confusion, in this paper we will use US Internal Revenue Service (IRS)'s definition of Shared Economy. According to the IRS "the [shared] economy allows individuals and groups to utilize technology advancements to arrange transactions to generate revenue from assets they possess - (such as cars and homes) - or services they provide - (such as household chores or technology services)" (IRS, 2018). Examples of goods that are shared are cars and homes (Frenken & Schor, 2017). Airbnb is a major member of the shared economy. Along with other high-tech companies such as Uber, Lyft, they have been treated as the pioneers of the shared economy who "unlock the commercial values in underused personal assets" (Kenny & Zysman, 2016). Other companies that have also been associated with the shared economy include delivery services like Postmates and labor-for-hire platforms like TaskRabbit, although it is somewhat less clear if these are truly part of the shared economy (Frenken & Schor, 2017). The shared economy has achieved great prominence and market penetration in a very short time. PricewaterhouseCoopers (PwC) sampled 1000 adult consumers in the U.S. in 2014 and asked their opinions on the shared economy. Results showed that 44% of the respondents were familiar with the term (shared economy) and over 80% of them agreed it made their life more affordable, convenient, and efficient (PwC, 2015). Industry professionals also projected the market value of the shared economy would potentially grow from 10 billion dollars in 2015 to 355 billion dollars in 2025 (PwC, 2015). Researcher also predicted that

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shared economy accommodation business such as Airbnb would eventually grow from niche market business to major online one-stop travel shop (Dolnicar, 2018).

Despite heady early days for shared economy services, they have come under scrutiny in recent years from both business and regulation perspective. Cities and consumers have come to understand that these services are not without consequences and are not completely win-wins for all those involved. For example, Uber, perhaps the shared economy's unofficial leader, has been subject to numerous scandals in its short existence (Kleinman, 2017). In 2012, zoning laws in San Francisco, California prohibited residents from charging guests for short-term stays (Shareable and Sustainable Economies Law Center, 2013). Likewise, D.C. had moved to ban Airbnb nearly entirely (McCartney, 2018). Australia researchers also pointed out that the potential impact of Airbnb on the local permanent rental market and related problems such as neighborhood nuisances, traffic, and parking (Khadem, 2016; Gurran & Phibbs, 2017). However, having been through a difficult time, the Airbnb business is now widely accepted in most US cities, albeit with some regulation (Jet, 2018). New York City even pioneered Airbnb regulation by working with the company rather than confronting it (Kaplan & Nadler, 2015). In the next section we outlined the existing Airbnb research from three perspectives: 1) Airbnb as a hospitality service, 2) its impact on cities, 3) policy and regulation discussions.

2. Previous Airbnb studies

According to some of the recently published studies, the majority of existing Airbnb studies were published in journals related to tourism and hospitality. Most of the Airbnb studies focused on North America or Europe used quantitative methods. Their data was collected through manual collection, web-scrapping, or from websites such as Inside Airbnb (www.insideairbnb.com), or AirDNA (www.airdna.co) (Prayag & Ozanne, 2018; Dolnicar, 2019; Guttentag, 2019; Dan, Teubner, & Weinhardt, 2019; Belarmino & Koh, 2020). In terms of content, Guttentag (2019) reviewed 132 peer-reviewed journal articles and found that Airbnb studies mainly focused on six categories such as Airbnb guests (e.g. why travelers choose Airbnb), hosts (e.g. motivations), supply and impacts on destinations, regulations, impacts of tourism sector, and the company itself.

More than half of the existing Airbnb research were generated from tourism and hospitality fields (Guttentag, 2019; Dan et al., 2019). Business management professionals often used statistical models to investigate how Airbnb consumer behaviors were related to advertising and online information sharing (Ert, Fleischer, & Magen, 2016; Liang, Choi, & Joppe, 2018; Liu & Mattila, 2017). This line of research showed that advertising strategies, detailed online information, and user satisfaction were essential components to the success of Airbnb. Some related studies had focused on the price of Airbnb listings. Wang and Nicolau used a general Ordinary Least Square model (OLS) and a quantile separated OLS model to explain the effect of service attributes on listing price and found out that host information, room type, and amenities are significantly related to listing price (Wang & Nicolau, 2017). Research also showed that Airbnb had challenged hotel business by forcing hotels to reduce their room rates and redistribute tourist resources within the cities (Oskam & Boswijk, 2016). Some studies also suggested that Airbnb might serve a different market segment than regular hotels. Guttentag and Smith compared the room quality between Airbnb listings and regular hotel rooms. They found Airbnb listings were cleaner and more comfortable than low-cost hotels, similar to mid-range hotels, but worse than expensive hotels (Guttentag & Smith, 2017). Researchers in Barcelona used Geographic Information System (GIS) to map out the spatial distribution of both hotels and Airbnb listings in Barcelona and concluded that not only Airbnb had different spatial patterns from traditional hotels, but the explanatory factors to the location of Airbnb listings were also different from those for traditional hotels (Gutierrez, Garcia-Palomares, Romanillos, & Salas-Olmedo, 2017). A similar study of Airbnb in Barcelona found that Airbnb served a very distinct market segment of foreigners in Barcelona with German, Italian and Portuguese speakers overrepresented in the market (Sans & Quaglieri, 2016). It is fair to argue that Airbnb is serving a niche market in these cities.

The second group of Airbnb studies investigated how Airbnb is impacting cities' development. Wegmann and Jiao used web-scraped Airbnb data in five US cities to analyze the spatial distributions of listings and found that Airbnb listings were mainly concentrated in certain neighborhoods with good transportation, more storefronts, and more college-educated young people (Wegmann & Jiao, 2017; Jiao & Wegmann, 2017). This finding implied that the ability to viably and realistically use Airbnb i.e. to list your property on the site and generate worthwhile income from it may not be evenly distributed. Additionally, researchers also pointed out commercial-based Airbnb operations may significantly impact local residential markets (Gurran & Phibbs, 2017; Wegmann & Jiao, 2017). One study found that Airbnb, in Los Angeles, California, was likely to reduce the supply of affordable housing in LA by encouraging otherwise affordable rentals to be converted into short term rentals (Lee, 2016a, 2016b). Gant (2016), studied Airbnb rentals in the historic center of Barcelona and argued that Airbnb was actually a new tourism investment opportunity and a new battlefront for gentrification, which would displace long-term residents in desired neighborhoods. Wachsmuth and Weisler (2018) studied Airbnb activities in New York City in the last three years and found Airbnb had major negative impacts on local rental markets. They also argued that Airbnb rental is the newest gentrification form. However, not all studies found Airbnb had negative impacts of local rental markets. For example, Levendis and Dicle (2016) argued that Airbnb actually did not increase housing rental prices in New Orleans, Louisiana.

The third group of Airbnb studies explored different theoretical frameworks for regulating Airbnb and its impacts on cities. Some scholars argued that cities should enforce current zoning laws, occupancy taxes, etc. on Airbnb to protect residents and the character of their cities (Willis, 2017). Others believed that cities should make sure that Airbnbs are paying the same taxes that hotels or similarly situated bed and breakfasts would pay. Cities should make sure that Airbnbs respect zoning laws and avoid becoming impromptu night clubs or bars, as has happened in various cities (Melugin, 2018; Totten, 2018). Willis (2017) also argued for local regulation of Airbnb, claiming that state-level regulation of Airbnb is ineffectual because different cities have different goals and values with regards to Airbnb. Another study looking at Airbnb in four major European cities, also argued for local Airbnb regulations as cities might have different policy goals regarding Airbnb (Dredge, Birkbank, & Jensen, 2016). On the other hand, some scholars argued Airbnb and other similar businesses should not be regulated like their traditional counterparts because "third-party platforms that mediate exchange fundamentally alter what the market is capable of providing on its own" (Cohent & Sundararajantt, 2016, p. 117). They believed a more balanced regulation approach would benefit both cities and Airbnb operations. Oskam and Boswijk (2016) also believed that strict regulations might hurt tourism and hospitality innovations. They argued receptive policies would be ideal for markets with modest tourism growth. But for fast growing markets, such policies might lead to unexpected over commercialization (Edelman and Geradin, 2015). Oskam (2019) further argued that local governments should develop different policies based on their city development scenarios. Clearly there is no an all-agreed solution on how planners and policymakers could regulate Airbnb operations.

From urban planning's perspective, the study of shared economy like Airbnb provides a new reflection of a long-term discussion between urban economic growth and social justice (Morgan and Kuch, 2015). In the 21st century, many western cities are demographically multi-cultural and economically diverse, thus planning as a social practice is subject to providing an acuminous and customized response to the challenges of otherness (Sandercock, 2004). Campbell (1996) argued that the property conflict between urban economic development and social justice is one axis of, as he illustrated in his work, the planner's triangle, that fundamentally challenges the tension between the private interest and the public good. In his article, Campbell conceptualized the conflict of property as the contradictory definition of the claim or use of property (i.e. housing or land) as a private commodity, yet it is simultaneously influenced by government intervention and capital investment (Campbell, 1996). Scholars further argued that planners should play important roles in guaranteeing equitable outcomes of economic development (Campbell, 2016; Gunder, 2006; Oden, 2016).

The absence of the shared economy in the above discussion limits the comprehensiveness of the equity theory in planning scholarship because of the following reason. New economic forms like Airbnb and Uber are no longer initiated by the overall demand/supply in the capital market, but rather are spontaneous and self-invested activities (i.e. vacant rooms in privately owned houses or personal vehicles unused in non-work times). Everyone has the right and opportunity to participate. Therefore, the shared economy market seems to be more open to the physically and/or economically challenged group of people. However, does it mean that shared economy is a solution to the growth-equity conflict? In recent years, some scholars outside the urban planning domain, such as public affairs and business management, have provided insights on Airbnb's downside regarding social inequality (Dan et al., 2019; Dolnicar, 2019). Randle and Dolnicar (2019) discussed the challenges for people with impairments to use short-term rental platforms like Airbnb in traveling. They analyzed data from interviews and surveys and concluded that physically challenged groups were marginalized in the business due to the attitudinal barrier (i.e. ignorance of the issue) and information/communication barrier (i.e. insufficient qualified online information) than the physical barrier. Ganapati and Reddick (2018) mentioned a number of unequal instances that the public sector needs to recognize when making policies that fit the shared economy in the traditional urban economy, for example, the favorability towards homeowners over renters in peer-to-peer (P2P) accommodation business or transportation network companies like Uber and Lyft undercutting the workplace benefit of part-time chauffeurs. The answer to this question is yet to be officially confirmed by empirical evidence in planning scholarship. This is partially because of the limited data sharing between the public and private companies. As a result, most of the shared economy studies cannot be generalized due to very small sample sizes (Belarmino & Koh, 2020).

From the literature review above, we see Airbnb operation might affect cities from different perspectives. However, due to the data limitations, most previous studies mainly focused on one or, at most, a handful of cities. There was no large-scale country-wide study, which might provide a more complete picture of Airbnb's operation and its impact on cities. To bridge this research gap, this paper used web-scraped Airbnb data and investigates its characteristics in forty US cities. This study was a follow-up study from Wegmann and Jiao (2017) which investigated Airbnb operation in five major US cities (Austin, Boston, Chicago, Washington D.C., and San Francisco). The following paper was divided into four parts. First, we discussed data specification issues. The second section detailed the study methodology. It was followed by the Results section. In the last section, we discussed the implications of our findings.

3. Data specification

Researching Airbnb or other shared economy services is a challenge mainly because of the data limitation. Although data shared mandates have been formally discussed in the latest literature (Ferreri & Sanyal, 2018), they have not been widely adopted. To work around these issues, web-scraping has been widely used and is still the most cost-effective means to harness big data and understand digitalized housing markets (Boeing & Waddell, 2016; Wegmann & Jiao, 2017; Guttentag, 2019). Some practical mapping visualization work and data analyses on Airbnb listings undertaken by practitioners around the world have already proven the value of web-scraping data (Adamiak, 2018; Dodd, 2018; Jiao & Bai, 2019). In this paper, we have also used web-scraping technology to obtain Airbnb datasets for the analysis.

Airbnb listing data was web-scraped from Airbnb.com on November 6, 2017. The raw dataset included a total of 130,097 listings from forty major cities across the United States (Appendix Table 1a). We obtained various attributes of interest for each Airbnb listing, including price per night per person, number of beds, super-host status (i.e. an experienced host who provides excellent service for their guests (Airbnb, 2018c)), number of pictures posted online, number of reviews online, and star rating. Since Airbnb will not show rating for listings with less than 3 reviews, we decided to filter out all these listings (less than 3 reviews) from our analysis. This removed 46,028 (35%) listings from the dataset.

Then, we excluded outlier records based on the price per night using the following criterion:

$$valid\ price \in \{p \mid p_{0.25} - 1.5 * (p_{0.75} - p_{0.25}) < p < p_{0.75} + 1.5 * (p_{0.75} - p_{0.25})\} \quad (1)$$

where: $p_{0.25}$ denotes the 0.25 quantile price; $p_{0.75}$ denotes the 0.75 quantile price. This removed 4871 (4%) listings from the analysis. After cleaning the data, the total number of Airbnb listings in 40 cities was 79,198. Fig. 1 shows the number of Airbnb listings per 10,000 housing units by cities and the average price per person per night in US dollar. The data showed that Seattle had the highest Airbnb listing density with 142 listings per 10,000 housing units. It was followed by Nashville and Portland with 126 and 121 listings, respectively. San Francisco and Austin were numbers 4 and 5, with 109 and 95 listings per 10,000 housing units, respectively. On the other hand, Detroit and Fort Worth had the least Airbnb listing intensity in all these cities, with only 12 and 9 listings per 10,000 housing units, respectively.

In terms of average rental price per person per night, San Francisco had the highest average listing price at $62 per night per person, followed by New York City and Boston with $55 and $48, respectively. The high Airbnb listing prices confirmed the common understanding about the housing and living cost in these three cities. Kansas City (KS), Colorado Springs, Albuquerque, and Las Vegas had the lowest average listing price in these 40 cities. All were lower than $25 per person per night, making them the most affordable Airbnb rental cities in the US.

Demographic and Socio-economic data included population density, housing unit, median housing value, and median household income at census tract level from the American Community Survey (ACS) 5-year estimates. Since the most recent ACS data was from 2016 and our Airbnb data was collected in 2017, we had to extrapolate the ACS 2016 data into 2017 data by assuming the growth rate between 2016 and 2017 was the same as the growth rate in 2015 and 2016:

$$d_i^{2017} = d_i^{2016} * \left[1 + \frac{(d_i^{2016} - d_i^{2015})}{d_i^{2015}}\right] \quad (2)$$

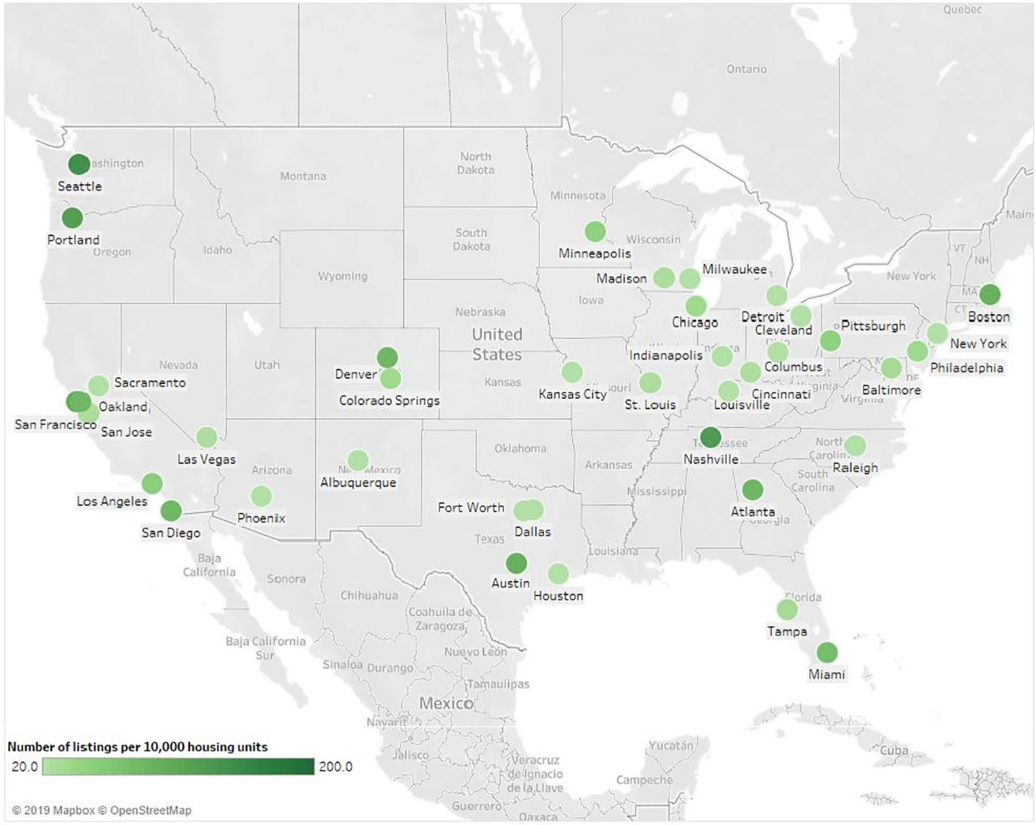
where: d_i denotes population density, housing unit, median housing value, and median household income at tract level, $i = 1, 2, 3, 4$.

To counteract the disparities between cities (e.g. a census tract with a density of 5000 people per square mile is considered a dense area in less populous cities but not in the cities with a massive population), the study standardized each parameter using the corresponding parameter at the city level:

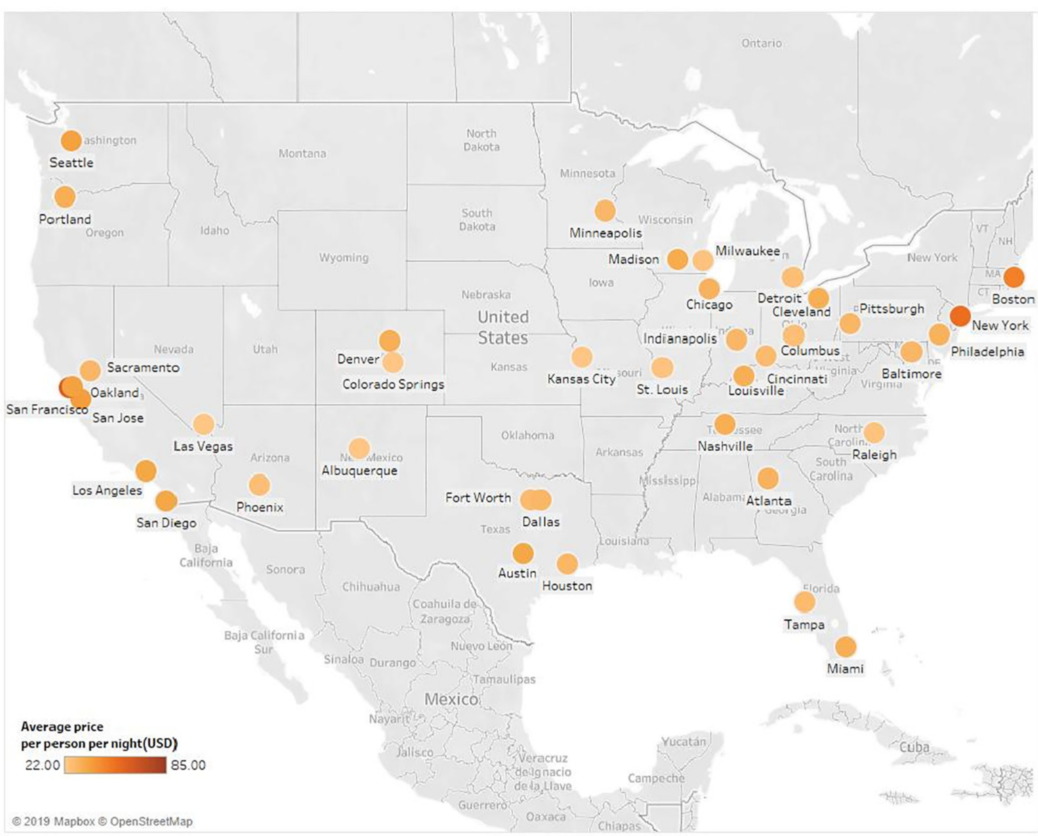
$$std.\ d_i^{2017} = \frac{d_i^{2017}}{city.\ d_i^{2017}} \quad (3)$$

where: $std.\ d_i^{2017}$ denotes standardized demographic and socio-economic parameters; $city.\ d_i^{2017}$ denotes the corresponding parameter at the city level.

Entertainment venues vary from city to city. To standardize the analysis, the paper used places where tourists could dine and have fun



a) Airbnb listing intensity (listings per 10,000 housing units) by cities



b) Average price per person per night (USD) by cities

Fig. 1. a. Airbnb listing intensity (listings per 10,000 housing units) by cities. b. Average price per person per night (USD) by cities.

as a substitution, namely restaurants, bars, pubs, etc. The paper downloaded these place locations from openstreetmap website (openstreetmap.org) and compiled them to a point shapefile in ArcGIS. Finally, the authors counted the number of points of interests within each tract and calculated the density as the indicator for Entertainment venue.

Location and transportation data included the distance from individual listings to the city centers, Entertainment venues (i.e. restaurants, bars, food courts, etc.) density, transit friendliness (transit frequency and accessibility). To calculate the city center distance, we built a model in ArcGIS to automatically calculate the Euclidean distances from each individual listing to its corresponding city center. We measured transit-friendliness using two indicators: accessibility to transit and transit frequency, both of which were published by the United States Environmental Protection Agency (Ramsey & Bell, 2014). An Airbnb listing was considered "accessible to transit" if the distance from each listing to the nearest transit stop was less than three-quarters of a mile (i.e. approximately a 15-minute walk). Transit frequency aggregated the service frequency per hour for each 0.25-mile buffer around each listing. Using these methods, the study calculated transit accessibility and frequency information for each listing.

4. Methodology

The following Table 1 described the data structure of the study. Since data were aggregated to the census tract level in forty U.S. cities, the unobserved clustering effect of listing observations in the same city violated the assumption of independent observations in an OLS regression model. Therefore, to explore the association between Airbnb listings and the explanatory parameters, the authors chose to use a multilevel mixed-effect model to establish the association equation. For these forty cities, Kansas City (KS) and Los Angles had the minimal and maximum number of Airbnb census tracts as 32 and 778, respectively. On average, each city had at least 169 census tracts with Airbnb listings.

Multilevel mixed-effects models are widely used in urban studies in which independent variables usually have hierarchical geographic units (Huang & Clark, 2002; Jones & Bullen, 1994; Paez & Scott, 2004). Another merit of the mixed-effect model is that given the possible multicollinearity between variables, the model could produce relatively unbiased estimates (Shieh & Fouladi, 2003). Specifically, the model in this paper assumed the effect of each predictor on two outcome variables (i.e. average listing price and listing intensity) were the same across cities (i.e. fixed coefficients). The random part was the hidden disparities among different cities that cannot be modeled explicitly (i.e. random intercepts). Another critical assumption is that political variation across cities is released in the location choice of Airbnb hosts. Granted that different cities might approach the shared economy like Airbnb distinctly (see Hong & Lee, 2018), we assume that Airbnb hosts list their properties online solely based on individual financial interest. The detailed information about these variables in each city can be found in Appendix Table 1a.

Price per night per person and listing intensity were two outcome variables entering the analysis. These two variables were designed to capture the price and distribution information at the census tract level. The average price was calculated by dividing the summation of average prices of all listings in the tract by the number of listings in the tract. Listing intensity was defined as the number of listings per 10,000 housing units per census tract. Demographic parameters were acquired at the tract level. Then, the authors aggregated the listing data to tracts by taking the average of every continuous variable (i.e. number of beds, number of pictures, number of reviews, and star rating) and taking the percentage of the factor variable (i.e. super-host) within each tract. Similarly, the paper calculated the distance from each listing to the corresponding city center individually and took the average for each tract. Table 2 below presented descriptive statistics for both the dependent and independent variables.

In total, the multilevel mixed-effect linear regression fitted two models on the outcome variables separately with 13 explanatory variables in 3 categories. After aggregating all data and dropping observations with missing values, the final models included 6114 Airbnb Census tracts in the analysis.

5. Results

5.1. Descriptive analysis

Demographically, all four standardized parameters had a mean greater than 1, meaning most tracts had higher population density, number of housing units, median housing value, and median household income than their cities' averages. Secondly, the sample had a dispersed distribution of entertainment venues. Its density ranged from 0 to 1291 with an average value of approximately 10. Location-wise, the farthest Airbnb listing was about 26 miles away from the city center and the average distance from Airbnb listings to the city center was 5.70 miles. In terms of transit-friendliness, 87% of the Census Tracts in the sample

Table 1
Multilevel mixed-effect model description.

	Code	Data level	Description
Dependent variable			
Price	LOGP	Census tract	Average price per night per person in natural logarithmic form
Listing intensity	LOGL	Census tract	Number of listings per 10,000 housing units in natural logarithmic form
Independent variable			
Demographic and socioeconomics			
Population density	STDPOPDEN	Census tract	Standardized population density
Housing unit	STDHU	Census tract	The number of dwelling units
Housing value	STDHV	Census tract	Standardized housing value
Household income	STDINC	Census tract	Standardized household income
Entertainment venue	SUSDEN	Census tract	Restaurant, bar and pub density
Location and transportation			
Distance to city center	D2C	Census tract	Average distance from listings at tracts to the corresponding city center in miles
Transit accessibility	TRNSTACC	Census tract	Whether the tract is within walkable distance (3/4 mile) from transit stops
Transit frequency	TRNSTF	Census tract	Aggregated transit frequency per hour per square mile in hundreds
Room characteristics			
Beds	BED	Census tract	Average number of beds in each listing
Pictures online	PIC	Census tract	Average number of pictures of listings posted online
Reviews online	REV	Census tract	Average number of reviews of listings posted online
Super-host listings	PCTSUP	Census tract	Percentage of super-hosts among all hosts in percent
Star rating	STAR	Census tract	Average star rating (0–5)

Table 2

Descriptive statistics for model variables.

Variables	Obs.	Mean	Std. Dev.	Min	Max
Dependent variable					
log(Price per person per night)	6114	3.33	0.43	0.65	4.67
log(Number of listings per 10,000 housing units)	6114	3.53	1.19	0.50	11.04
Dependent variable					
Demographic and socio-economics					
Number of people per square mile*	6114	3.30	6.25	0.00	176.07
Number of housing unit*	6114	1.40	0.68	0.00	8.99
Median housing value*	6114	1.21	1.01	0.00	46.23
Median household income*	6114	1.16	0.62	0.00	5.78
Restaurants, bars, and pubs density	6114	10.21	37.17	0.00	1290.75
Location and transportation					
Distance to city center in miles	6114	5.70	4.41	0.13	26.19
Transit accessibility	6114	0.87	0.34	0.00	1.00
Transit frequency in hundreds	6114	20.94	45.71	0.00	817.64
Room characteristics					
Number of beds (mean)	6114	1.98	1.00	0.00	15.00
Number of pictures online (mean)	6114	16.62	7.60	1.00	115.00
Number of reviews online (mean)	6114	35.87	25.82	4.00	286.00
Percent of super-hosts	6114	38.76	31.00	0.00	100.00
Star rating (mean)	6114	4.82	0.21	2.50	5.00

Note: * variables were standardized to relative values using Eq. (3) above accordingly.

had Airbnb listings that were within walking distance from nearby transit stops and the average transit frequency was 2094 trips per hour per square mile.

In terms of room characteristics, on average these Airbnb listings provided 2 beds and 17 online pictures. This indicated that smaller Airbnb units might be more difficult to rent out and Airbnb users might desire a somewhat larger space because they tended to stay longer than traditional hotel guests (Airbnb, 2015). On average, at the census tract level, each Airbnb listing received 36 reviews and a 4.82 out of 5 stars rating from their customers. The result confirmed previous findings that majority of Airbnb listings received an average of 4.5 out of 5 stars from the customers (Zervas, Proserpio, & Byers, 2015). Lastly, among all hosts in the sample, around 25% of them were super-hosts, meaning they were above the average Airbnb standards, like receiving higher customer ratings, higher response rate, and lower number of cancellations, etc. (Airbnb, 2018b).

5.2. Multilevel mixed-effect linear regression model results

The paper used analytic tools in STATA 14.0 to fit multilevel mixed-effect models upon average price per night per person and listing intensity. Both variables were transformed into logarithmic forms to avoid data skewness. Table 3 summarizes the final model results.

For the purpose of explaining the association between Airbnb listings and their surrounding built environments, focal factors of interest were demographics, socioeconomics, location, and transportation. Room characteristics were control variables of which the interpretation was omitted due to the limited paper length. In the price model, twelve out of thirteen independent variables were statistically significant, including five demographics and socio-economics variables, all three location and transportation variables, and four room variables. In the listing intensity model, the number and the composition of significant variables was the same as the price model. The only difference between two models indicated different critical room characters that correlated with two outcome variables, namely average star rating in price model versus online reviews in intensity model. As we can see from the Table 3, population density was negatively associated with two outcome variables, but the coefficients were very small. Median household income was the most dominant variable with the largest coefficients (One unit increase for median household income was associated with 0.176 and 0.221 unit increase in price and intensity models). Entertainment venue density was positively associated with both outcome variables despite the weak impacts (i.e. one unit increase for entertainment venue density was associated with 0.001 and 0.002 unit increase in the price and intensity models).

Table 3

Results from the multilevel mixed-effect models on listing price and intensity.

	log(Price)		log(Intensity)	
	Coef.	z-Score	Coef.	z-Score
(Intercept)	2.215*	17.82	3.074*	9.02
Demographic and Socioeconomics				
Number of people per square mile	−0.007*	−8.01	−0.007*	−3.17
Number of housing units	0.061*	8.4	−0.235*	−11.76
Median housing value	0.027*	4.95	0.054*	3.6
Median household income	0.176*	19.22	0.221*	8.81
Restaurants etc. density	0.001*	3.67	0.002*	5.95
Location and transportation				
Distance to city center in miles	−0.014*	−11.33	−0.089*	−26.9
Transit accessibility	−0.040*	−2.5	0.280*	6.34
Transit frequency in hundreds	0.002*	21.04	0.003*	9.39
Room characteristics (control)				
Number of beds (mean)	−0.080*	−15.51	−0.033*	−2.32
Number of pictures online (mean)	0.006*	8.3	0.015*	8.03
Number of reviews online (mean)	−0.0003	−1.72	0.005*	9.61
Percent of super-hosts	−0.001*	−3.69	0.001*	2.73
Star rating (mean)	0.202*	7.81	0.051	0.71

Note: * denotes the coefficient is significant under the 0.05 significance level.

The price model showed that a one-mile increase between Airbnb listing and the city center would decrease the average listing price by 0.014 (roughly 4 cents per person per night). This is easy to understand as tourists are more likely to stay near city centers for the amenities. Thus, the average prices of Airbnb listing near cities would be higher. The higher demand for Airbnb listing near city centers was also confirmed in the intensity model, where a one-mile increase in distance from the center led to an 0.089 unit decrease in listing intensity, which equals to 0.25 Airbnb listing reduction per 10,000 housing units or 1 Airbnb listing reduction per 40,000 housing units. Transit accessibility was significant in both models, neighborhoods with good transit access on average were 0.28 unit denser but 0.04 unit cheaper in term of Airbnb listing intensity and price, which corresponds to 0.88 more Airbnb listing per 10,000 housing units or 11 cents cheaper per person per night. Noticeably, the smaller coefficients in the price model indicated that the average listing price was more likely to remain stable when location and transit status changed.

5.3. Importance analysis

To better understand the impact of different factors on average listing price and intensity, the authors run an importance analysis for the demographic, location and transportation variables in both models. Derived from importance-performance analysis (IPA) in transit service satisfaction research, the importance index was calculated using Eq. (4) (Figler, Sriraj, Welch, & Yavuz, 2011):

$$importance\ index = \frac{correlation\ to\ price/intensity}{median\ correlation\ to\ price/intensity} \tag{4}$$

As a modification, this paper took the absolute values of correlation coefficients of focal independent variables to eliminate the effect of signs. Table 4 showed the importance analysis results for these two models. Here, an importance index less than 1 indicated the variable was less important compared to other independent variables in explaining the association with the outcome variable.

Table 4
Importance rankings in price and intensity model.

Ranking	Price model			Intensity model		
	Variable	Corr. coef	Importance index	Variable	Corr. coef	Importance index
1	Transit frequency	0.30	1.88	Distance to center	−0.40	3.21
2	Median Household Income	0.28	1.71	Transit frequency	0.21	1.71
3	Housing value	0.21	1.27	Transit accessibility	0.20	1.56
4	Distance to center	−0.16	1.01	Restaurants etc. density	0.13	1.05
5	Housing unit	0.16	0.99	Population density	−0.12	0.95
6	Restaurants etc. density	0.14	0.87	Housing unit	−0.11	0.91
7	Population density	−0.11	0.66	Housing value	0.11	0.91
8	Transit accessibility	0.07	0.44	Median Household Income	0.06	0.48

To better present the results, the authors created two scatter plots to show the position of different variables in price and intensity models separately (Fig. 2.a and b). Results showed that in the price plot, transit frequency, household income, housing value, and distance to city center had a stronger positive impact on the average Airbnb listing price than other indicators. Housing unit had less impact on the price although it also had a positive impact. Both population density and transit accessibility were negatively associated with the price, but their ranks were lower than other predictors.

In the listing intensity plot, the average distance to the city center was the most important indicator and it was negatively related to the listing intensity. Transit frequency, accessibility, and restaurants etc. density were all important positive indicators for listing intensity. The influence of population density on listing intensity was trivial which also was shown in the plot. Median housing value was less important in the intensity model than in the price model. Median household income and the number of housing units in the neighborhood were also not very important in the intensity model.

6. Conclusion and discussion

Using the web-scraping method, this paper collected 130,097 listings from forty major cities across the United States. Among them, 79,198 records were included in the analysis. The authors explored the associations between the average Airbnb listing price and the listing intensity at the census track level and the surrounding demographics, socioeconomics, and built environments. In addition, the paper used the Importance-Performance Analysis (IPA) to analyze the impacts of different variables. Results showed that household income and housing value were positively related to the average listing price per person per night and the number of listings per 10,000 housing units at the census tract level. Housing unit was positively correlated with the price but negatively correlated with the intensity. Population density was significantly correlated to two outcome variables albeit the relationship was weak in both cases. Additionally, the study also found that being farther from the city center was associated with a lower listing price and fewer Airbnb listings. Finally, better transit service and more restaurants and bars within the neighborhood seemed to relate to higher listing price and more hosts in the area. It is possible that transit service measure actually served as an indicator for the neighborhood infrastructure quality.

The above results were similar to the findings from previous hotel location choice study (Li, Fang, Huang, & Goh, 2015; Shoval, McKercher, Ng, & Birenboim, 2011; Yang, Wong, & Wang, 2012), which showed hotels were more likely to be located in better neighborhoods with different amenities and good public transits. Many shared economy advocates (and the companies themselves) claimed that the shared economy provided an opportunity for many families to earn extra income (Martin, 2016; Ikkala & Lampinen, 2015; Dreyer, Ludeke-Freund, et al., 2017). However, it is probably not the case.

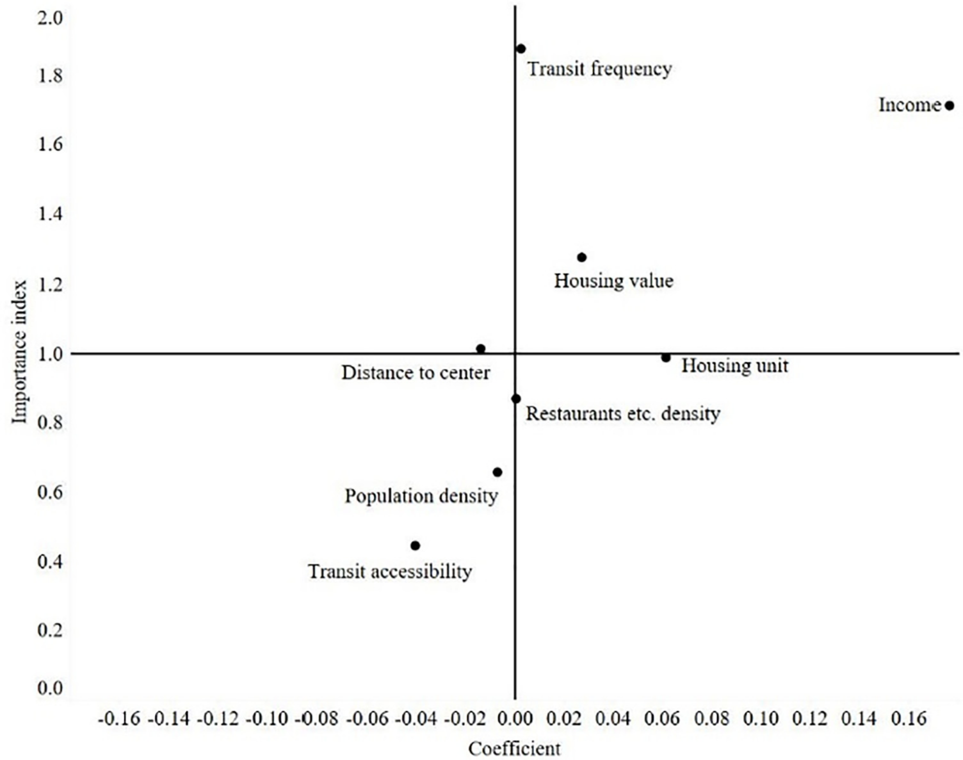
Economically challenged families may want to use Airbnb to list their extra rooms or houses for additional income, but their properties are not well situated to do so due to location or environment reasons. Results from this paper showed that tracts with higher housing value and household income tended to have more Airbnb listings and the listing prices were likely to be higher. A similar finding was reported in London, where the authors found a positive relationship between Airbnb offering and housing price, but a negative relationship between Airbnb offering and income (Quattrone, Proserpio, et al., 2016). It seems that those best positioned to rent out their houses are those who already relatively well off and live in better neighborhoods. This study made contributions to the equity planning theory by pointing out the possible social inequity in shared economy like Airbnb.

Low-income families usually live in either geographically or environmentally less pleasant neighborhoods with fewer amenities. Cities could work with them to improve their neighborhood environments and get them involved in the shared economy. Additionally, cities should avoid overburdening those ‘mom and pop’ rentals or smaller scale Airbnbs that are not fully “hotelized” (Dredge et al., 2016; Lee, 2016a, 2016b; Wegmann & Jiao, 2017). Shared economy like Airbnb seems to be more inclusive and easier to get involve than other formal economies, however, it could also bring similar social inequity problems due to physical or digital exclusiveness.

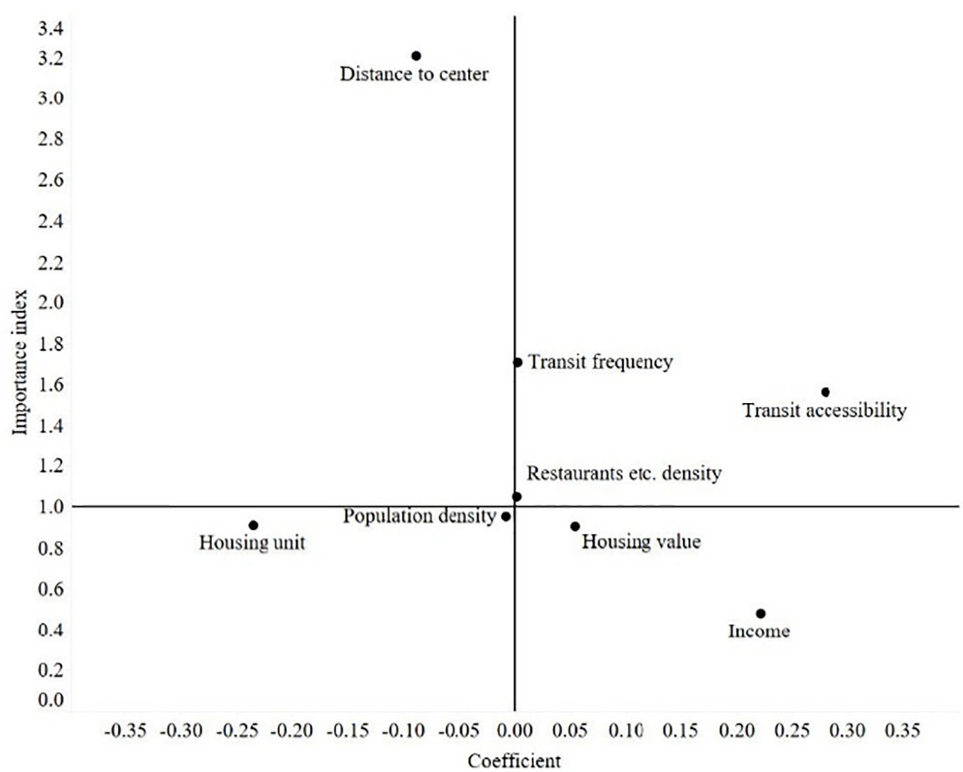
Another important policy implication is related to data sharing. Due to data limitation, many Airbnb researchers had to use web scraping technology to collect research data, which is a very time-consuming process. The lack of data makes it very difficult for urban planners or policymakers to truly understand the spatial distribution and the impacts of Airbnb in their cities.

The absence of data sharing also allows companies make different claims and further influence local policies (Dredge et al., 2016). We understand that more open data sharing approaches have been implemented in New York, San Francisco and other US cities (Lumb, 2018). Therefore, we argue that properly data sharing policy between the public and the shared economy companies could allow city administrators to better monitor the Airbnb operations and respond quickly before the negative effects amplify. Cities and Airbnb should work together to truly spread the benefit of shared economy and curb its negative impact. Airbnb could work with the residents in distressed neighborhoods and help them list their properties, attract more tourists, and control the nuisance (Gurran & Phibbs, 2017). Cities could partner with local transit agencies and provide more transit services between popular neighborhoods and major attractions. Furthermore, during holiday seasons, cities could increase the transit frequency to these neighborhoods and offset the high demand brought by tourists. Last but not least, Airbnb might need to pay operating tax like other hospitality businesses, which could help maintain and improve city infrastructure.

As a conclusion, in US cities, Airbnb rentals tend to be listed in neighborhoods with good transit service, short distances to the city center, and high median house value and household income. As the shared economy continues to grow and change forms, policy makers need to be aware of the impacts that Airbnb might bring. Through collaborative action between the public and the private, hopefully, we could address these challenges.



a) IPA plot of Airbnb price indicators



b) IPA plot of Airbnb intensity indicators

Fig. 2. a. IPA plot of Airbnb price indicators. b. IPA plot of Airbnb intensity indicators.

Author statement

We confirm that this paper has not been published in part or in whole elsewhere. There is no conflict of interest to be declared. Dr. Junfeng Jiao is the corresponding author and has the full access to all aspects of the research and writing process and takes final responsibility for the paper.

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Appendix A

Table 1a
Airbnb listings in forty US cities.

City name	Population	Area (sq. mi)	Pop. density Airbnb tracts	Census tract	Airbnb tract	PCT Airbnb tract	Total Airbnb listing	Avg. listing per Airbnb tract	Avg. price per night per person	House Unit per census tract	Housing value per census tract	Household income	Restaurant etc. density
Albuquerque	557,627	189	4622	152	120	79%	921	7.68	24.78	1959	200,025	54,054	3.71
Atlanta	463,980	134	5195	169	121	72%	3177	26.26	32.19	1957	242,833	56,468	6.82
Austin	928,981	327	4914	230	174	76%	7037	40.44	41.96	2219	318,439	69,779	5.59
Baltimore	619,549	92	12,125	245	153	62%	1456	9.52	29.08	1567	183,219	53,971	5.95
Boston	666,375	90	26,981	235	158	67%	4021	25.45	48.89	1707	485,709	67,914	22.13
Chicago	2,710,505	234	20,926	877	548	62%	5905	10.78	31.09	1629	291,322	59,757	13.66
Cincinnati	298,626	80	5732	158	88	56%	621	7.06	29.47	1547	154,204	39,778	9.70
Cleveland	387,751	82	6614	239	93	39%	965	10.38	103.73	1315	88,910	32,021	6.80
Colorado Springs	455,580	195	3994	113	101	89%	954	9.45	23.22	2093	236,535	63,312	1.64
Columbus	849,599	224	5741	271	121	45%	802	6.63	27.16	1909	146,534	48,528	4.46
Dallas	1,296,428	385	7082	392	195	50%	1842	9.45	30.16	2015	247,230	63,271	1.99
Denver	677,239	155	7953	212	138	65%	3410	24.71	31.89	2168	347,440	64,740	15.87
Detroit	676,876	143	6057	372	99	27%	653	6.60	28.48	1298	94,605	31,150	1.50
Fort Worth	835,714	353	3693	219	97	44%	444	4.58	27.15	2425	169,776	61,999	0.76
Houston	2,263,694	666	6139	765	380	50%	5786	15.23	80.18	2183	209,128	59,180	1.64
Indianapolis	851,931	368	3622	249	162	65%	1310	8.09	39.46	1936	134,679	49,783	1.05
Kansas City (-KS)	150,660	128	3369	94	32	34%	152	4.75	28.01	1252	120,371	45,381	1.98
Kansas City (-MO)	475,574	319	3634	212	104	49%	697	6.70	23.54	1702	147,182	55,276	3.61
Las Vegas	621,604	135	6813	201	139	69%	980	7.05	24.85	1748	210,844	57,182	1.26
Los Angeles	3,937,034	503	16,047	1185	778	66%	12,024	15.46	37.18	1539	594,507	61,596	3.40
Louisville	614,427	66	5357	113	65	58%	1423	21.89	82.06	1751	167,106	47,709	1.84
Madison	248,981	94	4930	78	55	71%	444	8.07	35.61	2101	244,872	65,783	7.63
Miami	440,762	56	18,524	126	83	66%	2475	29.82	33.21	2145	291,033	43,791	5.14
Milwaukee	597,847	97	9889	264	112	42%	485	4.33	23.95	1313	139,946	45,457	7.48
Minneapolis	409,446	57	9754	151	115	76%	1647	14.32	55.23	1571	225,483	58,548	10.17
Nashville	653,165	498	3031	196	152	78%	4777	31.43	33.59	1911	226,653	57,639	1.41
New York	8,497,326	468	77,609	2168	363	16%	9431	25.98	56.19	2681	775,523	80,333	58.92
Oakland	416,046	78	14,714	146	110	75%	2247	20.43	37.76	1512	533,951	69,865	16.47
Philadelphia	1,564,819	143	20,106	442	310	70%	6166	19.89	67.34	1818	200,770	46,683	14.67
Phoenix	1,597,556	519	5615	412	260	63%	2089	8.03	28.27	1882	221,015	59,024	2.34
Pittsburgh	304,683	58	8166	190	103	54%	980	9.51	28.67	1329	157,841	48,636	8.52
Portland	629,087	145	7494	173	146	84%	4161	28.50	31.54	1985	374,705	68,853	9.43
Raleigh	448,483	146	3312	108	75	69%	531	7.08	25.10	2494	266,998	67,951	3.27
Sacramento	488,527	100	6042	147	80	54%	507	6.34	29.85	1926	312,226	59,939	3.38
San Diego	1,389,999	372	9646	352	267	76%	6844	25.63	37.13	1991	537,516	77,777	7.86
San Francisco	859,909	232	29,536	345	177	51%	6473	36.57	64.48	2034	989,384	101,577	55.49
San Jose	1,017,938	181	9763	206	192	93%	1906	9.93	53.80	1730	707,110	101,458	4.79
Seattle	685,065	142	11,934	243	132	54%	6403	48.51	38.12	2509	523,995	83,833	41.30
St. Louis	314,220	66	7228	151	74	49%	664	8.97	25.16	1849	156,855	42,577	5.29
Tampa	367,448	175	4966	140	86	61%	760	8.84	27.58	1844	211,904	54,976	4.93

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