

Sharing Means Renting?: An Entire-marketplace Analysis of Airbnb

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ABSTRACT

Airbnb, an online marketplace for accommodations, has experienced a staggering growth accompanied by intense debates and scattered regulations around the world. Current discourses, however, are largely focused on opinions rather than empirical evidences. Here, we aim to bridge this gap by presenting the first large-scale measurement study on Airbnb, using a crawled data set containing 2.3 million listings, 1.3 million hosts, and 19.3 million reviews. We measure several key characteristics at the heart of the ongoing debate and the sharing economy. Among others, we find that Airbnb has reached a global yet heterogeneous coverage. The majority of its listings across many countries are entire homes, suggesting that Airbnb is actually more like a rental marketplace rather than a spare-room sharing platform. Analysis on star-ratings reveals that there is a bias toward positive ratings, amplified by a bias toward using positive words in reviews. The extent of such bias is greater than Yelp reviews, which were already shown to exhibit a positive bias. We investigate a key issue—commercial hosts who own multiple listings on Airbnb—repeatedly discussed in the current debate. We find that their existence is prevalent, they are early-movers towards joining Airbnb, and their listings are disproportionately entire homes and located in the US. Our work advances the current understanding of how Airbnb is being used and may serve as an independent and empirical reference to inform the debate.

CCS CONCEPTS

• Information systems → Reputation systems; • Applied computing → Law, social and behavioral sciences;

KEYWORDS

Airbnb; measurement; sharing economy; online marketplace

1 INTRODUCTION

Recent years have seen a proliferation of online peer-to-peer marketplaces [10]. Examples abound and the services covered range from personal loans (Prosper, LendingClub, SocietyOne) and ride (Uber, Lyft) to household tasks (TaskRabbit) and accommodations

(Airbnb). Enabled by the Internet and information technology, these marketplaces aim to match sellers who are willing to share under-utilized goods or services with buyers who need them [3, 29]. Such marketplaces are thus often referred to as examples of the so-called “sharing economy” [6, 25, 33]. Airbnb, a primary example of this type of marketplaces, connects hosts who have spare rooms with guests who need accommodations. Founded in 2008, it now has more than two million listings located in more than 191 countries, and has accumulated more than 60 million guests.¹

Accompanied by its rapid growth, Airbnb has confronted intense debates, regulatory challenges, and battles. Advocates argue that the platform enables many householders to become small business owners and reduce their rental burden. It may also make travelers pay less than hotel prices and have a more local and authentic experience, exemplified by its slogan “live there.” Opponents argue that many hosts rent their entire homes for short-terms, which is illegal in many cities [17, 30, 31]. This usage also involves two other critical issues. First, entire homes that are used for short-term rentals on Airbnb may be taken down from local housing markets, which may drive the rents up. A recent study, however, suggested that this might not be the case [32]. Second, the coming-in of more travelers may be disruptive to residential neighborhoods. Another argument from opponents is that some hosts who own a large number of listings may be operating business on Airbnb but may fail to fulfill their tax obligations. This gives them advantages over hotels and makes them “free riders,” because accommodation taxes collected from hotels are often used for tourism promotions that benefit all accommodation suppliers [17].

Although much debated, to what extent the discussed arguments are empirically grounded remains to be seen. To this end, here we present the first large-scale data-driven study on Airbnb, focusing on the entire market. By measuring key characteristics directly related to these arguments, we paint a more complete yet complicated picture of Airbnb. First, regrading the issue of short-term rentals of entire homes, we document that across many countries, entire homes account for the majority of listings; 68.5% of all listings are entire homes and only 29.8% are private rooms. Although we do not further quantify the extent to which they are used for short-term rentals—a limitation of our work—simply due to the unavailability of proprietary data from Airbnb on listing bookings, we note that the statistics of room types have changed from 2012 when 57% are entire homes and 41% are private rooms [17]. This change suggests that Airbnb has been becoming more like a rental marketplace rather than a spare-room sharing platform. Moreover, listings owned by business operators may more likely be rented in short-terms, compared with other ordinary hosts.

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¹<https://www.airbnb.com/about/about-us>

Table 1: Statistics of our data set about Airbnb

Countries		193
Listings	Active	2,018,747
	Unavailable	284,039
	Total	2,302,786
Users	Hosts	1,313,626
	Guests	11,150,017
	Total	12,156,178*
Reviews		19,377,978

Note: * 307,465 users are both hosts and guests

Second, regarding the issue of business operators, we characterize in a great detail who they are and what their listings are. Our results suggest a heavier usage from business operators than previously thought. The number of listings owned by a host is distributed according to a power-law, spanning three orders of magnitude. One third of all listings are owned by 9.4% of hosts, each of whom has at least three listings, and one host even owns 1,800 listings. Furthermore, we show that business operators are early-movers towards joining Airbnb and behave more professionally than ordinary hosts and that their listings are disproportionately of the entire home type and located in the US. These results reinforce the rental marketplace notion of Airbnb.

Third, our analysis reveals predominantly positive star-ratings of listings, which is different from previously observed J-shaped distribution. This positivity bias is consistent with a bias toward using positive words in reviews, and the extent is greater than Yelp reviews. These results may suggest that many guests had overall positive experiences during their stays, corroborating advocates' argument on traveler experiences. It can also indicate the presence of selection bias in review behaviors [14]—only those who had great experiences chose to give reviews.

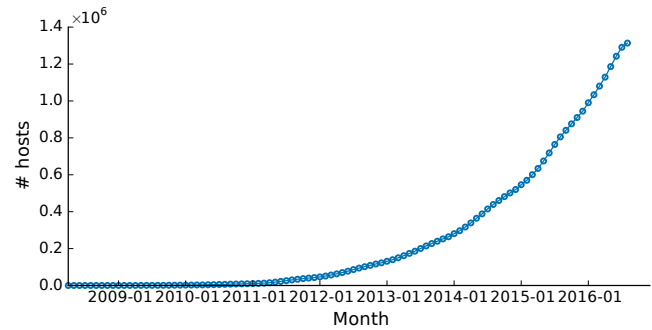
Taken together, we believe that our work significantly advances the current understanding of how Airbnb is being used. Our main contributions in this work are:

- We crawl Airbnb listing data on a global scale. (§ 2)
- We analyze geolocations, room types, star-ratings, and reviews of listings. (§ 3)
- We characterize hosts who own multiple listings on Airbnb and those listings owned by them. (§ 4)
- We investigate factors linked to listings' future rental performance. (§ 5)

2 DATA

2.1 Data Collection

On Airbnb, each listing has a web page showing its details such as room type, price, reviews from previous guests, host information, etc. For example, the listing called “Van Gogh’s Bedroom” can be visited at <https://www.airbnb.com/rooms/10981658>. The main goal of our data collection is to accumulate as many listings as possible, so that we can perform a systematic analysis. There are two steps in the data collection process: (1) accumulating listing IDs; and (2) downloading their HTML files and reviews. We describe them in

**Figure 1: Cumulative number of hosts.**

detail below, and before that, let us present in Table 1 some summary statistics about the collected data set. To our best knowledge, these are the first public and exact statistics about the Airbnb marketplace.

In the first step, we accumulated listing IDs by exploiting the hierarchical structure of the Airbnb site map, which has three levels: country, regions in the country, and search results of listings in the region. The top level at /sitemaps lists 152 countries, each of which has a hyperlink pointing to the web page that lists regions in the country. All the regions in Australia, for example, are listed at /sitemaps/AU. Each region, again, has a hyperlink pointing to the page of search results of listings in the region. Our script followed all these hyperlinks and obtained 83,174 regions in 152 countries. Then for each region, our script visited its search page and saved all the listing IDs there. We repeated this search process 7 times, with each new search resulting in a smaller number of new IDs. The only constraint stopping us from more searches is the availability of computing and storage resources. In total, we accumulated 2,302,786 unique listings.

In the second step, for each listing, our script visited its web page, saved the HTML file, and collected all the reviews. As we are also interested in rental performances of listings, we repeated this step 3 times—after the 1st, 2nd, and 7th search. The statistics in Table 1 and the analyses presented in § 3 and § 4 are based on the latest crawl. We found 284,039 (12.3%) listings were unavailable, by which we mean visiting them redirected to a search page with a message saying “the listing is no longer available.” As an example, see /rooms/11599049.

The entire data collection process was performed between May and September, 2016. Note that we followed the crawler-etiquette described in Airbnb’s robots.txt:² None of the three directories we visited—/sitemaps, /s/, and /rooms/{listing ID}—are specified as disallowed in the file.

2.2 Summary Statistics Analysis

We compare the statistics in Table 1 with official ones. The only official but approximate numbers we found were already mentioned in § 1: 191+ countries, 2M+ listings, and 60M+ total guests. Our obtained number of countries and listings seem to be comparable to official ones. We note, however, that the number of guests (11M) is much smaller than the official one (60M). One obvious reason is that here we have only counted those guests who have left at least

²<https://www.airbnb.com/robots.txt>

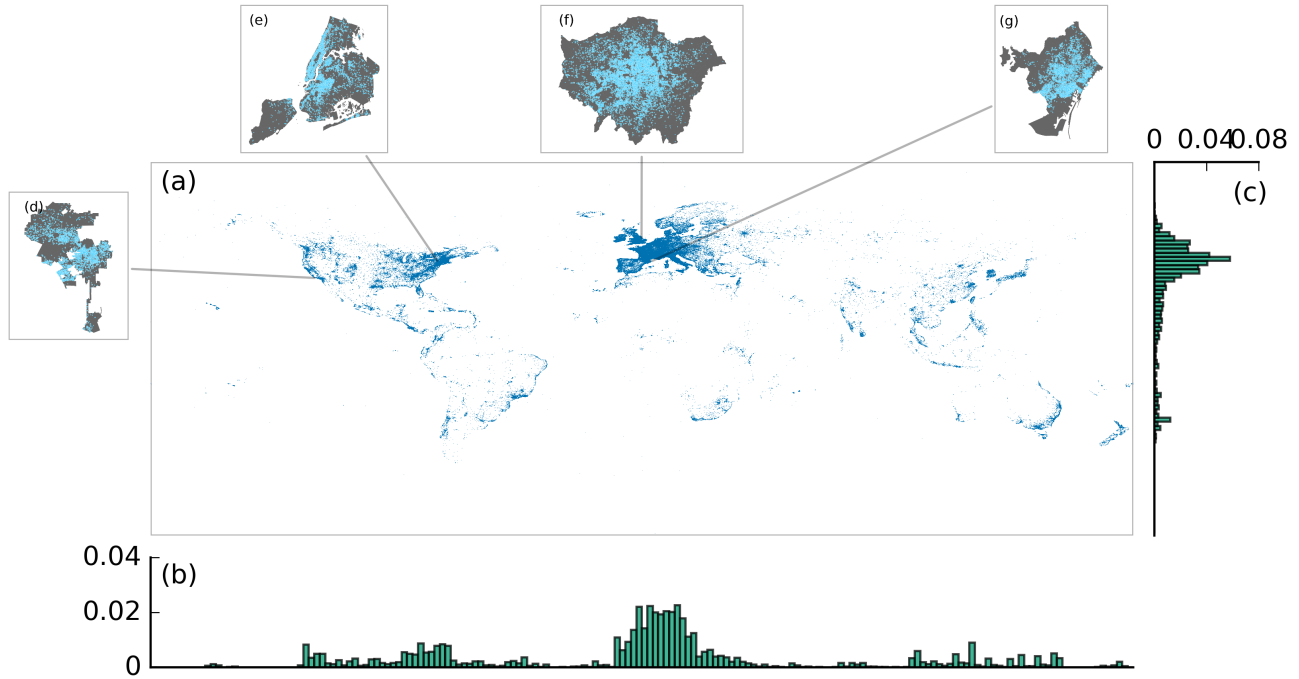


Figure 2: Geolocations of Airbnb listings. (a) Dot plot of all the 2,018,747 active listings; (b–c) Histogram of longitude and latitude; (d–g) Dot plot of listings in the city of Los Angeles, New York, London, and Barcelona. See Appendix A for the copyright of city maps.

one review captured in our data set but not every guest has given reviews.

Next, we provide estimations of some statistics that are still unknown or may be outdated. First, 307,465 users are both hosts and guests, accounting for 23.4% of all hosts, counted based on the observation that they own listings and give reviews to other listings. This gives one answer to the Quora question.³ Second, Fig. 1 presents the cumulative number of hosts in each month from March 2008 to August 2016, constructed using the month information that indicates when they joined Airbnb. We see that an exponential growth of number of hosts started from around 2012. Third, we make an estimate of an important statistic—the guest-to-host review rate—meaning the fraction of stays where guests have left reviews to their hosts after the conclusion of their stays. We approximate it as

$$\begin{aligned} \text{guest-to-host review rate} &= \frac{\# \text{ stays with reviews left}}{\# \text{ total stays}} \\ &\approx \frac{19,102,711}{102,718,148} = 18.6\%. \end{aligned} \quad (1)$$

Here the number of stays with reviews left is simply the number of reviews (excluding automatic reviews, cf. § 3.4), and the total number of stays is estimated by extrapolating the distribution of number of reviews per guest showed in Fig. 5(a) from the 11M guests to the entire population of 60M guests. Our estimate has already been significantly smaller than the reported 72% in 2012 by

³<https://www.quora.com/What-percentage-of-Airbnb-hosts-are-also-guests>

Airbnb’s CEO Brian Chesky.⁴ It remains to be seen how accurate our estimation is and how the one disclosed in early days is different from the one nowadays.

3 MEASURING AIRBNB LISTINGS

3.1 Geolocations

Let us start with where Airbnb listings are located—a question repeatedly asked by hoteliers, policy-makers, and other stakeholders (e.g., [30]). Using each listing’s approximate geolocation information in latitude/longitude values provided by Airbnb, we present in Fig. 2(a) a dot plot showing geolocations of all active listings across the world. We see that listings are globally distributed. To understand their geographic concentration, Figs. 2(b) and (c) respectively show the histograms of longitude and latitude values. We observe that, on the continental level, listings are heavily located in Western Europe, North America, East and South Asia, and Pacific Asia. Focusing on the country level, Airbnb has reached a world-wide yet heterogeneous coverage. US is the largest market for Airbnb, with 308,714 listings totaling for 15.29% of all listings, followed by France (11.82%), Italy (10.07%), Spain (6.16%), and United Kingdom (3.93%). Figure 3(b) lists the top 30 countries, which in total account for 83.55% of all listings. Meanwhile, many countries have only hundreds of listings, and there are no listings in a lot of African countries.

⁴<https://www.quora.com/What-percent-of-Airbnb-hosts-leave-reviews-for-their-guests/answer/Brian-Chesky?sr=1&u9cX>

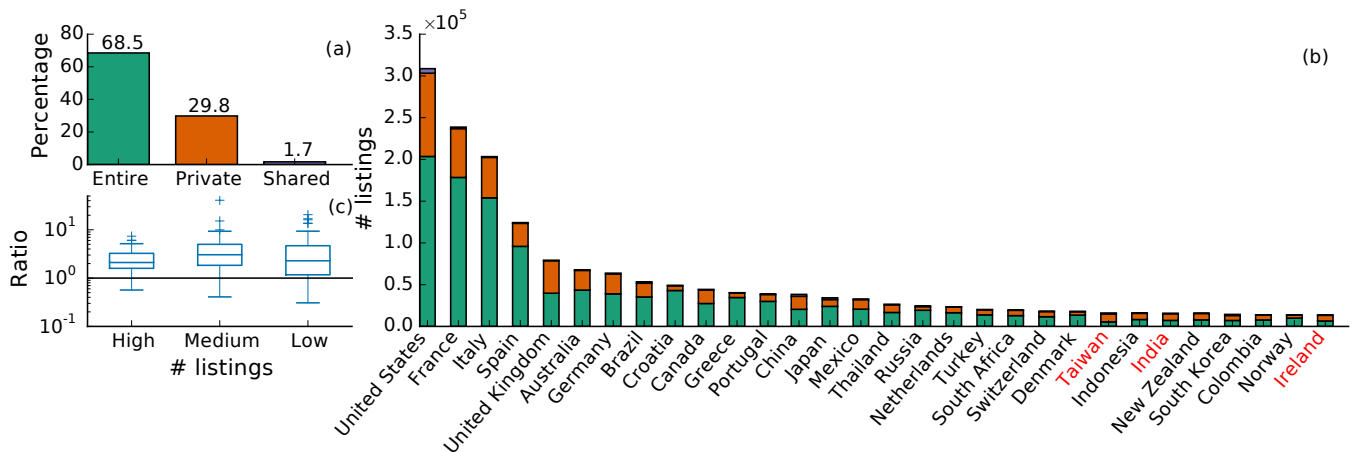


Figure 3: Room types of Airbnb listings. (a) Distribution of room types of all active listings; (b) Number of listings by room type in the top 30 countries with the highest number of listings. Countries with smaller number of entire homes than private rooms are marked red; (c) Distribution of the ratio between entire homes and private rooms in countries with high, medium, and low number of listings.

Focusing on cities, Figs. 2(d)–(g) respectively display locations of listings in the city of Los Angeles, New York, London, and Barcelona. As here we are interested in the global distribution, we leave the detailed study of how listings are located within cities as future work. Some studies have done so focusing on London [28] and Barcelona [16].

3.2 Room Types

Next, we study the distribution of the three types of rooms of Airbnb listings: *entire home/apartment*, *private room*, and *shared room*. As suggested by their names, entire home means that the host will not be present in the home during one’s stay; private room means that the guest will occupy a private bedroom and share other spaces with others; and shared room means the guest will share the bedroom with other guests. While the latter two types of listings may align with the symbolism of the sharing economy that hosts occasionally share their spare rooms, it is the type of entire home that (1) directly contrasts with such symbolism; and (2) becomes the necessary condition for hosts to convert residential houses into short-term rentals and for business operators to conduct business by renting out their numerous properties. Hosts who use entire homes in such ways have become one of the main targets of regulations in some cities. For instance, the New York State Legislature recently passed a bill that subjects hosts to fines when they rent their entire homes for less than thirty days,⁵ and the bill was recently signed by New York Governor Andrew M. Cuomo.⁶ The statistics about room types are therefore among the key characteristics mentioned in many reports by various interest groups (e.g., [30]), yet they are still unknown at the entire-marketplace level.

Figure 3(a) shows that on the entire market, 68.5% of listings are entire homes, while only 29.8% are private rooms; Airbnb has 1.3 times more entire homes than private rooms. These statistics

are in contrast with the ones back in 2012 when 57% were entire homes and 41% were private rooms [17]. Such change indicates that Airbnb, a primary example of the “sharing economy,” is more like a rental marketplace rather than a spare-room sharing platform.

We investigate variations of the room type distribution across countries. Figure 3(b) shows the number of the three types of listings in the top 30 countries with the largest number of listings. Among them, 27 countries have more entire homes than private rooms. In the US, which has the largest number of listings, 65.8% are entire rooms, and the ratio between number of entire homes and private rooms reaches 2. The only three countries or regions where there are more private rooms than entire homes are Taiwan (0.57), India (0.91), and Ireland (0.96), though the ratio is close to one for the latter two countries. We further calculate the ratio for each of the 150 countries with more than 100 listings (Countries with small number of listings have large fluctuations of the ratio.), and show in Fig. 3(c) the distributions of the ratio for the three equally-sized groups of countries, based on their total number of listings. We see that the ratio is greater than one across many countries and even larger for countries with smaller number of listings.

3.3 Star-ratings

We now focus on star-ratings and reviews, which are the reputation system of Airbnb and important sources of information for guests to pick listings [24]. At the conclusion of each stay, both the host and guest can give reviews to and rate each other at a scale from 1 to 5 stars with a unit of 0.5 star. Each listing will receive an average star-rating once it is rated by at least 3 guests.⁷ The star-rating of each individual review, however, is not publicly disclosed.

Figure 4(a) shows a bimodal distribution of star-ratings over all listings. More than half of them (54.6%) have not received their ratings, and 40.6% have 4.5 or 5 stars. These three categories of listings account for over 95% of all listings, and the number of

⁵<http://www.forbes.com/sites/briansolomon/2016/06/17/new-york-wants-to-fine-airbnb-hosts-up-to-7500>

⁶<http://www.nytimes.com/2016/10/22/technology/new-york-passes-law-airbnb.html>

⁷<https://www.airbnb.com/help/article/1257/how-do-star-ratings-work>

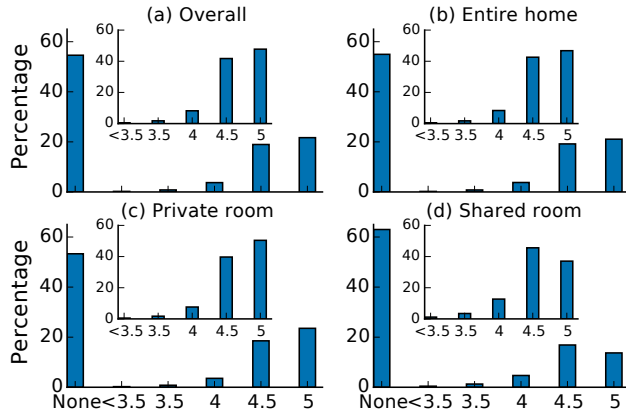


Figure 4: Distribution of star-ratings.

listings with 3.5 or lower stars is essentially negligible. Focusing on listings that have received star-ratings, Fig. 4(a) inset shows that star-ratings are overwhelmingly positive; 89.5% of them have 4.5 or 5 stars, and the mean (median) rating is 4.67 (4.5). These results are consistent with a previous small-scale study [35]. However, this heavily skewed distribution is slightly different from previously observed J-shaped distribution of product reviews [18]. In particular, such distribution suggests that the number of 1-star products is high, which is not the case for Airbnb listings.

We explore variations of this distribution by room type. Figures 4(b)–(d) respectively show the star-rating distributions of entire homes, private rooms, and shared rooms. Although, for shared rooms, 4.5-star listings are of a higher fraction than 5-star listings, there is very limited variation of the distribution: The majority of listings, irrespective of room type, have either no or very high ratings. This, on the one hand, suggests that many guests had great experiences during their stays, but makes star-ratings less informative and distinguishable for future guests to choose among potential listings, on the other.

3.4 Reviews

There are 19,377,978 reviews given by 11,150,017 guests. We are aware that Airbnb will post an automatic review if a host cancels a reservation, serving as one penalty for the cancellation.⁸ We find 275,267 automatic reviews, amounting to 1.4% of all reviews. This provides an upper bound of the cancellation rate by hosts, as not every stay yields a review. We removed all automatic reviews before further analysis.

3.4.1 Distribution of Review Counts. On the Airbnb review system, which is different from others like Yelp, only guests who concluded their stays can give reviews. This makes the number of reviews a listing has received a proxy of its business attention, although the review rate and number of stayed nights associated with each review may be different. Therefore, we analyze how reviews are distributed among listings, showing in Fig. 5(a) the survival distribution. We shift it by one to make the zero-review data point

⁸<https://www.airbnb.com/help/article/314/why-did-i-get-a-review-that-says-i-canceled>

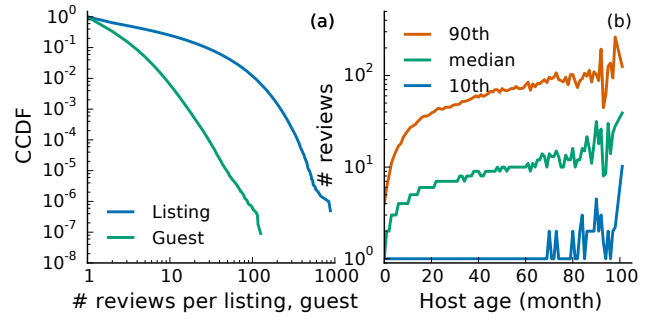


Figure 5: Review counts on Airbnb. (a) Distribution of number of reviews per listing and guest; (b) Number of reviews of listings with different host ages.

visible in the logarithmic scale. We see that although Airbnb is a relatively young marketplace, reviews have already been heterogeneously distributed among listings. About 35.7% listings do not have reviews, and respectively 12.2% and 7.4% listings have one and two reviews. The remaining 44.6% listings, each of which has at least three reviews, account for 93.6% reviews. In § 5, we demonstrate the presence of the rich-get-richer mechanism in explaining the growth of reviews.

We next analyze the relation between listing age and number of reviews. As we do not know when each listing was established, nor do we know when each and every review was given, we use the Airbnb age of its host—the number of months passed since they joined Airbnb—as a proxy of the listing age. Focusing on listings with at least one review, Fig. 5(b) shows the 10th, 50th, and 90th percentile of number of reviews of listings grouped by host age. We observe that (1) the number of reviews in general increases with host ages; (2) even for hosts who joined Airbnb for years, the median number of reviews still remains in the order of ten; and (3) the review count is heterogeneously distributed even for hosts who joined Airbnb in the same month.

Figure 5(a) also shows a heavy-tailed distribution of number of reviews per guest. Respectively 66.3% and 17.8% guests have given one and two reviews, while only 0.63% guests have left at least 10 reviews.

3.4.2 Review Content. We start investigating text content of reviews with what languages are used. Using the langdetect language detection library,⁹ we found 49 languages used. Table 2 reports the percentages of reviews written in the top 10 most used languages. English dominates this ranking, with 72.8% of reviews using it, followed by French, Spanish, German, and Italian. From now on, we focus on the 14,094,229 English reviews.

Positive/Negative words: Recall that a vast majority (89.5%) of listings have 4.5 or 5 stars (Fig. 4(a) inset). This raises the question of whether this strongly skew toward positive star-ratings is consistent with a usage bias toward positive vocabulary. To answer this, we use a recently released resource that contains norms of almost 14K English words [34], each of which has a valence score from 1 to 9, where valence greater than 5 means positive words

⁹<https://pypi.python.org/pypi/langdetect>

Table 2: Top 10 languages used in reviews

Language	%	Language	%
English	72.8	Chinese (Simplified)	1.6
French	10.3	Korean	1.3
Spanish	3.8	Portuguese	1.0
German	3.5	Dutch	0.9
Italian	2.3	Russian	0.9

and smaller than 5 negative words. We calculate the ratio of the frequency of positive and negative words in Airbnb reviews. To compare the skewness, we also calculate the ratio for 2.7M Yelp reviews.¹⁰ Table 3 shows that the ratio doubles for Airbnb reviews. This confirms a bias toward using positive words, and the extent is even greater than reviews on Yelp, which already exhibits a positive bias [20]. Given that Airbnb is a P2P platform where hosts can also choose which guests to accommodate, this finding may open up further investigations into user behaviors on different platforms.

4 MEASURING MULTI-LISTING HOSTS

In this section, we investigate a key issue repeatedly discussed in the current debate—the existence of hosts who own multiple listings on Airbnb. Hereafter, we call them “multi-listers.” Note that they may have different names in various reports, such as “commercial hosts,” “professional hosts,” and “business operators,” all attempting to capture the possibility that they may operate business on Airbnb, as an ordinary host is less likely to own numerous listings. Despite being a critical issue, there has been no systematic analysis about multi-listers and their listings.

4.1 Existence of Multi-listers

Recall that there are 2, 018, 747 active listings owned by 1, 313, 626 hosts (Table 1), thus on average every host owns 1.54 listings. Figure 6(a) shows the survival distribution of number of owned listings per host. We observe a somewhat surprising heavy-tailed distribution that spans more than three orders of magnitude, similar to what have been observed in many complex systems [1]. We fit the empirical distribution with a power-law function $p(x) = \frac{\alpha-1}{x_{\min}} \left(\frac{x}{x_{\min}}\right)^{-\alpha}$ using the methods developed in refs [2, 4], and obtain $\alpha = 2.65$ and $x_{\min} = 15$. These results not only demonstrate the existence of “super multi-listers”—hosts who can own up to 1, 800 listings, but also indicate that the existence of multi-listers is prevalent. Simply put, although the vast majority of hosts have a small number of listings, there is a consistent number of hosts who own a large number of listings. In particular, 1, 030, 134 (78.4%) and 159, 627 (12.2%) hosts respectively own one and two listings, and the remaining 9.43% hosts own 33.16% of all listings.

To further characterize multi-listers and their listings, we need to answer a key question—which threshold of number of owned listings per host allows us to separate hosts into two groups and then compare them. Previous literature have not reached a consensus about this. The New York State Attorney General, for example, defined “commercial hosts” as those who have three or more unique

Table 3: Ratio of frequency of positive and negative words used in Airbnb and Yelp reviews

	Airbnb reviews	Yelp reviews
Ratio	13.749	6.705

listings [30]. Li *et al.* defined “professional hosts” as those who have two or more listings [23]. Here, we argue that a typical threshold value may not be well-defined, as Fig. 6(a) clearly suggests that the number of owned listings is a multi-scale phenomenon. Moreover, as we shall show, focusing on a particular value loses the whole picture and can even be misleading.

Instead, we simply increase the threshold and study how various measures of interest change accordingly. Specifically, for a given threshold, we characterize (1) the subset of hosts whose number of owned listings *exceeds* the given threshold; and (2) the subset of listings owned by those hosts. If the threshold is zero, we simply focus on all hosts and all listings.

4.2 Listings Owned by Multi-listers

Figures 6(b)–(e) present the characterization results for listings owned by multi-listers. Figure 6(b) shows the percentages of listings in 5 countries, United States (US), Spain (ES), Croatia (HR), Italy (IT), and Australia (AU), selected because they have the largest number of listings when the threshold is 20. We observe that as we increase the threshold, listings owned by multi-listers are disproportionately located in the US. We also see that a decreasing portion of listings are from Italy, while Spain and Croatia have an increasing portion. Figure 6(b) (and Fig. 6(d)) also illustrates why focusing on a particular threshold can be misleading. For example, if one focused on a particular value (1 or 2), one would have concluded that the number of US listings owned by multi-listers is proportional to total listings in the US, which is not the case.

Figure 6(c) focuses on how the total number of listings and number of reviews received by them change as we increase the threshold. We observe a faster decrease of review counts, indicating that the average number of reviews per listing decreases. When the threshold is 0, on average a listing has 9.6 reviews, which decreases to 2.6 when the threshold reaches 20. Therefore, listings owned by multi-listers are less reviewed.

Figure 6(d) shows that an increasing portion of listings are entire homes as the threshold increases. When the threshold is 20, more than 92% of listings are entire homes, compared to 68.5% on the entire market. This confirms the previous conjecture that commercial hosts seek to rent out their entire home properties.

Figure 6(e) answers the question of how far away the listings owned by a single host. Using listings’ latitude/longitude values, we calculate, for each host, the maximum distance among all pairwise distances between two of their listings, capturing the geographical diameter of their “managerial” activities. Figure 6(e) shows that the median of the distribution of maximum distance over all hosts whose number of listings exceeds a given threshold, though keeps increasing, is in the order of 10km. This suggests that listings owned by multi-listers may locate within a city and that they may operate business locally.

¹⁰https://www.yelp.com/dataset_challenge/

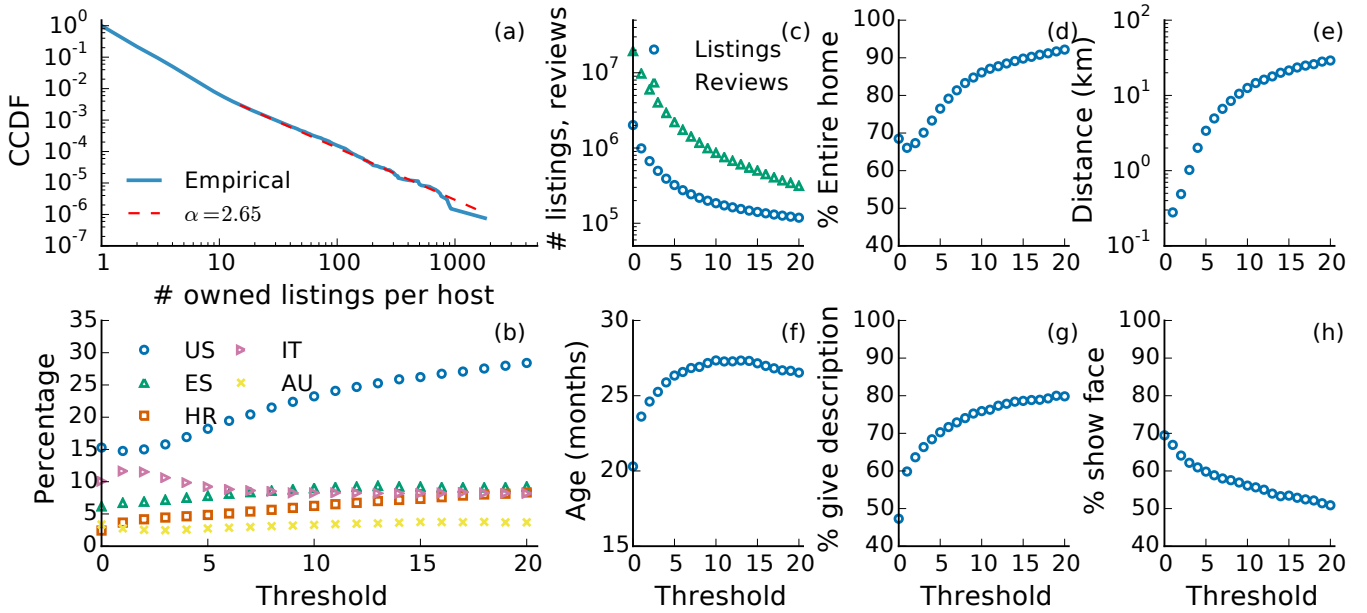


Figure 6: Characterizing multi-listers and their listings. (a) Survival distribution of number of owned listings per host. From (b) to (h), we focus on (1) the subset of hosts whose number of owned listings *exceeds* a threshold; and (2) the subset of listings owned by those hosts, and show how various measures change as we increase the threshold. (b) Percentage of listings located in 5 countries; (c) Number of listings and their total reviews; (d) Percentage of entire homes; (e) The median of the distribution of the maximum distance between pairs of listings owned by a host; (f) Mean Airbnb age of hosts; (g) Percentage of hosts who give descriptions; (h) Percentage of hosts whose profile photos have facial features.

4.3 Multi-listers

Figures 6(f)–(h) show the characterization results for multi-listers. First, Fig. 6(f) demonstrates that multi-listers are early-movers towards joining Airbnb, as their mean Airbnb age is larger than other hosts.

Figure 6(g) focuses on the percentages of hosts who give descriptions in the space-limited “Your Host” section on listings’ web pages. Presenting self-description is one important way to establish trust between guests and hosts. Surprisingly, only 47.3% of all hosts have given descriptions (threshold 0), and multi-listers are more likely to do so. Using the method described in ref. [26] and setting the threshold to 10, we find the top 10 overrepresented words used in multi-listers’ descriptions are “https,” “vacation,” “wilschö-nau,” “properties,” “rentals,” “team,” “villas,” “rental,” “apartments,” and “services,” indicating that they use the description section to advertise their listings.

Figure 6(h) examines another way to establish trust—showing faces in profile photos. Using a service provided by Face++ to detect whether there are facial features presented in a given photo,¹¹ we find that for 69.5% of all hosts, there are faces detected in their profile photos. Multi-listers are less likely to show faces in their photos, and a manual inspection reveals that many of them use company’s logos as profile photos.

5 MODELING REVIEW GROWTH

In the last section, we have found notable differences between multi-listers and other hosts. This raises the question of whether the differences are linked to listings’ future rental performances. To answer this, we approximate performances with number of new reviews, as we do not know listings’ actual booked nights. For each listing, we calculate the number of new reviews it has received in one month, which is our response variable. The first two columns in Table 4 list predictors and their definitions. Instant Book is a listing feature, meaning that a potential guest can book the listing without the host’s approval.¹² The superhost badge is awarded to a host if they satisfies a series of requirements set by Airbnb.¹³ Response time of a host is transformed into numerical values, so that a faster response corresponds to a larger value.

We fit a linear regression model by ordinary least squares (OLS) to understand factors linked to the growth of reviews. The last column in Table 4 presents the regression results. Other predictors being the same, listings with more existing reviews will have more new reviews, demonstrating the presence of the rich-get-richer mechanism that has been found to explain the growth of numerous systems [27]. Listings whose ratings have one more star will have 0.169 more review. A private room will gain 0.112 more review than an entire home, while a shared room will have 0.091 less review than an entire home. A listing that can be instantly booked will have 0.272 more review than those without the Instant Book feature.

¹¹http://www.faceplusplus.com/detection_detect/

¹²<https://www.airbnb.com/help/article/187/what-is-instant-book>

¹³<https://www.airbnb.com/superhost>

Table 4: Regression results for monthly new reviews

<i>reviews</i>	Number of reviews	0.037*** (0.0001)
<i>rating</i>	Star-rating	0.169*** (0.001)
<i>room_type</i>	Room type	
	private	0.112*** (0.003)
	shared	-0.091*** (0.011)
<i>amenities</i>	# available amenities	0.017*** (0.0003)
<i>instant_book</i>	Instant book is allowed	
	1	0.272*** (0.003)
<i>photos</i>	Number of photos	-0.002*** (0.0001)
<i>host_age</i>	Host age	-0.018*** (0.0001)
<i>host_super</i>	Host is a superhost	
	1	0.259*** (0.005)
<i>host_desp</i>	Host gives descriptions	
	1	0.040*** (0.003)
<i>host_resp_rate</i>	Host response rate	0.229*** (0.013)
<i>host_resp_time</i>	Host response time	0.220*** (0.002)
<i>host_nlisting</i>	# owned listings	-0.001*** (0.00002)
Constant		-0.446*** (0.011)
Observations		1,140,488
Adjusted R ²		0.388
Note: *p<0.1; **p<0.05; ***p<0.01		

Being a superhost, giving descriptions, maintaining high response rate, responding in short time, and owning a smaller number of listings all have positive effects on review growth, though the effect is small for the number of owned listings.

6 RELATED WORK

There is a growing interest in Airbnb and other sharing economy platforms from diverse disciplines, ranging from computer science to economics to law. Empirical studies have focused on, for example, star-ratings of listings [35] and geolocations of listings within cities [16, 28]. Our focus here is the entire Airbnb platform. There are studies that have reported the presence of discrimination on Airbnb [8, 9]. Some work have investigated factors associated with listings' price, such as the receipt of star-ratings [15] and race [21] and personal photos [11] of their hosts. The impact of Airbnb on hotel industry revenue [36, 37] and on tourism industry employment [12] has been investigated. Discussions about regulations of

Airbnb have also generated much attention [5, 7]. Li *et al.* investigated differences in performances and behaviors between professional hosts—those who own two or more listings—and non-professional hosts on Airbnb [23]. Our analysis, however, reveals the lack of threshold that allows us to separate professional and non-professional hosts. Studies focusing on the motivations behind joining Airbnb to provide hospitality have pointed out that monetary compensation and sociability are two important aspects [19, 22]. Fradkin *et al.* experimentally investigated the determinants and bias in the Airbnb review system [14]. Fradkin proposed ranking algorithms for the Airbnb search engine [13].

7 CONCLUSION AND FUTURE WORK

In this work, we have presented the first large-scale data-driven study on Airbnb. After crawling the largest ever number of Airbnb listings, we have measured their geolocations, room types, star-ratings, and reviews. We have also characterized in a great detail hosts who own multiple listings as well as their listings. We have built a linear regression model to understand factors linked to the growth of reviews. As these aspects are among the key points discussed in the ongoing debate and among important features in the sharing economy, we believe that our work provides valuable insights for various stakeholders and may serve as a public and empirical reference to inform the debate.

One major limitation of our work is that we do not measure listing occupancy. Therefore we do not know to what extent a listing is rented in short-terms or what revenue differences are between multi-listers and ordinary hosts. We notice that it is feasible to crawl listing calendar data. However, one issue of using such data is that, given a listing is unavailable on some dates, we cannot tell if it is rented out or simply blocked by the host for not renting. Another technical challenge is to large-scale monitor the calendar data on a daily basis. Future work may do so on a small scale. Other future work include studying geolocation at a finer level, measuring hosts' behavioral changes, and understanding the effect of review content on listings' future rentals.

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