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Differing Views of Lodging Reality: Airdna, STR, and Airbnb

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Abstract

Airbnb is an Internet-based firm that connects potential short-term renters with hosts who own or control rental properties. Its rapidly expanding activities are tracked by Airdna, an independent firm that generates seemingly conventional performance metrics describing Airbnb. These metrics include occupancy rates, average daily rates, and revenue per available room. However, Airdna does not adhere to long-established STR definitions for these variables. Using data from Virginia Beach, Virginia, we demonstrate that Airdna's performance metrics exhibit notable upward biases vis-á-vis STR's metrics. Potential rental hosts, hoteliers, tax collectors, and investors are at risk if they act on the assumption that Airdna's metrics are comparable with widely understood measures used by STR and tourism experts.

Keywords

Airbnb, Airdna, occupancy rate, average daily rate, revenue per available room, Smith Travel Research, hotel industry, rental properties

Introduction

The increasing success of Airbnb, an international, Internet-based firm that connects owners of rental properties with short-term renters, has attracted increasing attention since its inception in 2008. Airbnb is now active in more than 65,000 cities and 191 countries and has facilitated more than 160 million stays (Airbnb, 2017). By mid-2017, Airbnb claimed to have more than 3 million rental listings, raising concerns of disruption of the traditional lodging sector and, more locally, negative externalities such as loss of tax revenue, traffic congestion, noise, and disruptive behavior (Edelman & Geradin, 2016; Guttentag, 2015). Proponents, on the other hand, note the increased income accruing to property owners, improvements in economic efficiency, and the emergence of the "gig" economy for cities and municipalities (Koopman, Mitchell, & Thierer, 2015; Quattrone, Proserpio, Quercia, Capra, & Musolesi, 2016). Although Airbnb recently launched a public Application Programming Interface (API), this API is not sufficiently open for researchers and firms to access individual listing data across the Airbnb platform.[1] Hence, even though Airbnb's impact is of great interest to many different individuals, assessing that impact may require the use of data that present a skewed picture of Airbnb's activities.

Finding useful data on Airbnb and similar entities is increasingly important given the significant challenges these firms pose to the operations of the traditional lodging sector. Home-rental market revenue is only about one fifth the size of the traditional lodging sector but is growing at a faster pace than the hotel industry (Kirkham, 2017). Emerging evidence suggests that Airbnb and similar products not only expand the supply of available rooms but also reduce conventional hotel revenue on high demand dates by up to 40% (Jordan, 2015). The greater the market penetration of Airbnb, the lower the average price for conventional hotel rooms (Neeser, Peitz, & Stuhler, 2015). The economic impact of Airbnb is not uniform, however, with lower-priced hotels and those catering to nonbusiness travelers being most affected over time (Zervas, Proserpio, & Byers, 2017). Recent survey evidence of Airbnb users indicates that nearly two thirds used Airbnb as a hotel substitute (Guttentag & Smith, 2017).

Similar evidence suggests that Airbnb benefits the tourism industry by lowering tourism costs, leading to increased spending on nonlodging services and goods. Lower-end hotels, however, are displaced by Airbnb, suggesting a tradeoff between gains for the nonlodging sector and the lower end of the lodging sector (Fang, Ye, & Law, 2016). Finding useful data with regard to Airbnb rentals, however, is often an arduous task in that researchers must either manually sample the data (which is likely to introduce errors), scrape the data from Airbnb (which is often not replicable as the

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information on the site changes daily), or rely on others to produce information on Airbnb hosts and guests.

Airdna is a firm that generates data and analytics focusing on short-term rental entrepreneurs and investors. Airdna sells Airbnb performance data and is the dominant supplier of data concerning Airbnb's performance. Airdna's unique position is based in part on a proprietary algorithm that discerns whether specific Airbnb rental properties are available, reserved for occupancy, or blocked by the owner and unavailable for rental.[2] A large (and growing) number of public and private decision makers utilize Airdna's data to explore the impact of Airbnb on the traditional lodging sector, renter behavior, rental pricing, and investment profitability. Comparing Airdna data with seemingly comparable data from STR (formerly Smith Travel Research) concerning the performance of the traditional lodging sector is not only a "selling point" of Airdna but also of practical importance to prospective rental hosts, governments anxious to understand the Airbnb phenomenon, and investors.[3] An increasing number of articles and studies rely on Airdna's measures of average daily rate (ADR), occupancy, and revenue per available room (RevPAR).

This article examines whether Airdna's performance metrics are comparable with the norms of the traditional lodging sector by examining the performance of Airbnb rentals in Virginia Beach, Virginia. We compare the Airdna metrics with those of STR and inquire whether Airdna overstates the performance of the short-term lodging sector. If, as we argue, Airdna's underlying definitions of occupancy and RevPAR are biased upward, then Airbnb's impact is overstated—a conclusion of significant interest to hoteliers, renters, investors, tax collectors, and policymakers alike.

The remainder of the article is structured as follows. In the following section, we briefly review the extant literature on the use of Airdna data to examine the performance of Airbnb. We then discuss the potential flaws in the Airdna methodology, with specific attention to the difference between listing nights and room nights. We illustrate the potential biases using Airdna data for the City of Virginia Beach, Virginia. We then discuss Airdna's response to our queries and findings. The concluding section places our findings in context and offers suggestions on how to correct for these biases.

The Use of Airdna Data by Researchers and Decision Makers

A growing number of popular press articles, consulting studies, and peer-reviewed manuscripts rely on Airdna data to estimate Airbnb activities. In some cases, Airdna data are used to examine host characteristics, for example, whether Airbnb hosts are comparable with those of free alternatives such as "couch surfing" (Jung et al., 2016). Airdna data are used to examine whether obtaining and maintaining reputable ratings is important for "superhosts" (Gunter, 2018). In these cases, Airdna data may prove useful and reasonably reliable as these studies rely more on characteristics of listings rather than the performance of listings.

HVS Consulting and Valuation (2015) employed Airdna data to estimate the impact of Airbnb on the New York City lodging market and found that Airbnb poses a significant threat to hoteliers' revenues. CBRE Hotels' Americas Research (CBRE) found that Airbnb is not only growing rapidly in major metropolitan areas but also that, in some localities, Airbnb ADR exceeds hotel ADR (Lane & Woodworth, 2016). CBRE also noted that in almost every major market, the share of hosts with multiple units markedly increased in 2016 and that revenue from hosts with multiple units is growing faster than single unit hosts (CBRE Hotel Americas Research, 2017). These, and other consulting studies, rely extensively on Airdna data.

Airdna data have been used to examine the development of Airbnb in the United States and other countries, to include Austria (Gunter & Önder, 2017), Canada (Sovani & Jayawardena, 2017), the Netherlands (Boswijk, 2017), and South Africa (Visser, Erasmus, & Miller, 2017). Gibbs, Guttentag, Gretzel, Yao, and Morton (2017), for example, use Airdna listing data and STR data to argue that while hotels employ dynamic pricing strategies to maximize revenues, many Airbnb hosts in Canada do not employ a similar strategy.

Not surprisingly, listings for entire homes and private rooms, listings with pictures, and host responsiveness command higher prices on Airbnb (Dogru & Pekin, 2017; Gunter & Önder, 2017). Airdna occupancy data have been used as the basis for an estimate that Asian and Hispanic hosts charge 8% to 10% lower prices in San Francisco (controlling for rental unit characteristics, as well as additional information on neighborhood property values and demographics; Kakar, Voelz, Wu, & Franco, 2017). For Boston, Airdna data suggest that Airbnb listings earn a significant price premium relative to the long-term rental market (Horn & Merante, 2017).

A number of new studies directly compare Airdna and STR performance data such as supply, ADR, and RevPAR for Airbnb and hotels in Boston (Mody, Suess, & Dogru, 2017). For Los Angeles, Airbnb hosts' ADR is higher than the traditional lodging sector; however, occupancy and RevPAR are lower than in the traditional sector (Dell, Doby, Tillipman, & Zhuplev, 2017). The same authors found that ADR and RevPAR are lower for Barcelona. These studies employ Airdna's performance metrics without any adjustment.

Thus, Airdna data are being widely used for a variety of purposes by many different parties. To the extent these data do not impart the information their users believe to be the case, the usefulness of studies and decisions based on these data can be called into question.

Are the Airdna Performance Measures Biased?

A central question relating to Airdna's data is whether its performance metrics are comparable with STR's data, which have constituted the industry standard for many years. To understand the difference between the two sets of data, we draw on the example of Virginia Beach. With almost 450,000 residents, Virginia Beach is the most populous city in Virginia. The city is a well-known resort location that annually attracts hundreds of thousands of visitors to its beaches and other attractions. These visitors anchor the city's large conventional hotel and tourism sector. The U.S. Travel Association estimated in 2016 that tourism was responsible for US$1.494 billion of economic activity in Virginia Beach (U.S. Travel Association, 2017). The performance of the traditional lodging sector is of understandable importance to hoteliers, tax collectors, and others associated with the tourist industry in Virginia Beach.

We purchased data from Airdna for the Virginia Beach for the period of October 2014 through August 2017. The data contained individual listings aggregated by month as well as summary statistical information on various measures of performance by month. In January 2017, for example, the data contained information on 421 listings (the majority were residential homes) for Virginia Beach. The individual listings varied from single private rooms to significantly larger properties with as many as 10 bedrooms. The Airdna data contained a variety of market performance measures that, at first glance, correspond to published STR data.

Monthly Airdna data constitute a "list of listings." Airbnb classifies properties currently being offered for rent to guests as *available listings.*[4] Properties that are available and have at least one reserved night in a month are considered *booked listings.* Unlike STR data that aggregate the actual supply and bookings data of respondents, Airdna data are estimates generated by a proprietary algorithm.

In the case of Virginia Beach, we agreed with Airdna's count of total available listings and total booked listings when we examined listings of entire homes, private rooms, and shared rooms.[5] However, the first problem we noted was that all properties that were available were not included in the calculation of certain Airdna performance metrics. This is a centerpiece of our concern. Simply being offered for rent is not sufficient for a host's property to be considered "available" by Airdna when it calculates occupancy rates, ADRs, and RevPARs. Airdna includes only "booked listings" in the calculation of these variables. This is equivalent to a hotelier claiming that a room not rented during a month should be excluded from the calculation of occupancy rates and other measures.

In general, we found that the number of monthly available listings for one-bedroom homes exceeded the number of actual booked listings. Thus, in August 2016, Virginia Beach had 72 available listings for one-bedroom homes, and of those, 64 were booked listings. This is a not a large difference. During the offseason, however, the numbers were markedly different. In February 2017, Virginia Beach had 60 available listings for one-bedroom homes, but only 28 booked listings. On average, during the sample period in question, there were 52 available listings for one-bedroom homes compared to 37 booked listings each month. The exclusion of properties without reservations clearly understates the available supply of Airbnb listings.[6]

Depending on the characteristics of the market in question, the actual supply of Airbnb listings may be significantly higher. In Virginia Beach, for example, the actual supply of Airbnb listings was approximately 50% higher in some months when all listings were included in the measure of supply. This is not a trivial difference and constitutes significant bias.

A second problem emerged because of the way Airdna populates the denominators of its major activity measures. It employs *total available nights* as the denominator. However, its total available nights are not, in many cases, equal to the *total number of available room nights*, a subtle but very important distinction. For listings that consist of one bedroom (including shared rooms, private rooms, studios, and one-room entire houses), there is no distinction between total available nights and total available room rights. However, when the listing contains more than one bedroom, then they are not identical. One listing may contain multiple rooms.

With respect to Virginia Beach, we determined that the ratio of booked *room* nights to booked nights was 2.11 for the 35-month sample period. This average, however, concealed a rapid increase in the ratio of actual room nights to booked nights in late 2016 and into 2017, reaching a high of 2.88 rooms per listing in January 2017. The number of available listings of properties with four or more bedrooms increased significantly between 2015 and 2017.

We believe this reflects the increasing corporatization of Airbnb properties. Anecdotal evidence from Virginia Beach points to increasingly larger properties that are investor-owned with the specific intent of using these properties for short-term vacation rentals.[7] The evolution of the ratio strongly suggests that the trend in Virginia Beach is away from single-bedroom properties. Given that listings of multiroom properties are proliferating on Airbnb, this constitutes a bias that understates the number of available rooms and, thus, Airbnb supply. This phenomenon is not limited to Virginia Beach because investor-owned properties appear to be rising as share of Airbnb properties nationwide.

Airdna data for Virginia Beach reveal that approximately 87% of Airbnb-derived revenues during our sample period originated from apartments, condominiums, and full houses rather than from properties that sought to rent out a single room as part of a larger property. Of the revenues derived from "whole property" rentals, approximately 68% originated from properties with more than two bedrooms. We argue that this is evidence of the increasing proliferation of multiroom properties and underscores the need to use available room nights as opposed to Airdna's current practice of available listing nights.

It could be, however, that some hotels have suites with multiple rooms, and this would skew STR data in a similar fashion. Our discussions with hoteliers revealed that hotel suites generally are considered as one room, per industry standard. We do not have information on the national distribution of two-or-more bedroom suites to one-bedroom suites or standard rooms, but we surveyed hotel owners in the Hampton Roads region (officially the Virginia Beach–Norfolk–Newport News Metropolitan Statistical Area) to determine their numbers of multiroom suites. Our survey included 69 hotels representing 7,782 rooms, or approximately 21% of all hotel rooms in the region. We found that two-bedroom suites accounted for only 4.2% of all hotel rooms among these surveyed hotels. There were zero two-plus bedroom suites among the surveyed hotels.[8]

In sum, we conclude that Airdna's performance measures are biased upward for two reasons. First, Airdna's metrics utilize *booked listings*. If a property is available for rent during a given month, yet does not have any actual reservations, it is excluded from Airdna's measures of performance. This methodology biases occupancy and RevPAR upward. Second, even if the property in question is available and rented for one (or more days), it is only one listing by Airdna, regardless of the number of available bedrooms in the property in question. Our conclusion is straightforward: Airdna's estimates of ADR, occupancy, and RevPAR for Airbnb are exaggerated. The actual numbers (i.e., the numbers based on standard STR definitions) are lower.

Hence, Airbnb and Airbnb properties appear to be more effective than they are in practice. The equivalent practice for the traditional lodging sector would be to exclude rooms that did not rent during a month from the calculation of occupancy rates and RevPARs. This would have a significant (and misleading) impact on these performance metrics, especially in tourist-centric areas that typically operate much slower during off seasons. These methodological flaws mean that it is difficult to make meaningful comparisons between Airdna and STR data. The two firms are not measuring the same things—it is a classic "apples and oranges" circumstance.

This makes it much more difficult to assess the relative importance and performance of Airbnb properties versus those of hotels and motels. Comparable metrics are required to do so. The publicly available Airdna market performance data are not comparable with STR data. For those interested in precision and accuracy, their only current recourse is to use Airdna individual listing data to calculate performance metrics that are comparable with the industry standard. Otherwise, they may rely on performance data that are biased upward and draw spurious conclusions as to the health of the Airbnb marketplace.

Discussions With Airdna

There is nothing dishonest about the way Airdna chooses to compute occupancy rates, ADRs, and RevPARs. Nevertheless, Airdna has chosen not to employ commonly accepted definitions of these performance metrics, and thus, its data will be misleading when unknowing individuals attempt to compare the Airdna performance information with that of STR.

Given our concerns regarding the methodological foundations of the Airdna performance metrics, we initiated a conversation with Airdna regarding the calculation of the performance metrics. The first response from Airdna was,

> Can you elaborate on your concerns for these metrics? We have been covering data on these locations for a significant period of time (30 months and counting in the US) and provided data to almost 20,000 customers from individual hosts/investors through to multinational organizations and over fifty globally recognized research institutions such as Harvard, Oxford, Princeton and National University of Singapore so our data has been thoroughly carved up and crunched. To date, we have not had any wide-ranging concerns on our methodology from any of these sources so we would be keen to hear your feedback in greater detail.[9]

On receipt of this communication, we asked two specific questions. Our first question highlighted the first potential source of bias, that is, the difference between total booked nights and total booked room nights. We wrote,

> . . . when Airdna reports ADR for the entire place, you are using as denominator your measure of total booked nights (regardless of the size of the property). The denominator is not the total number of booked room nights. This is a meaningless distinction where one bedroom homes are concerned because nights equal rooms, but makes a significant difference for the entire place when one recognizes that many Airbnb hosts rent homes with multiple bedrooms.

We received the following email response:

> We considered different ways to report ADR and we found using "Entire Place" to be the most helpful not looking at the ADR per room within an "entire home listing." If you wish to calculate this ADR you have the possibility doing so by using the property file.

Our second question was,

> In calculating available nights or available room nights, Airdna excludes from consideration any property that might have been available for rent, but had no reservations in the month in

> question. This exclusion means Airdna is underestimating available nights or available room nights resulting in overestimation of occupancy rates and RevPAR.

Airdna's response was,

> About our occupancy rate calculation, when we designed our reports we had a lengthy internal discussion about this. Our CEO had many Airbnb properties and knows that if someone is actively managing their property they should be able to have a reservation every month. We decided on the annual occupancy rate calculation not to take into consideration months with no booking as throwing lots of un-managed, zero occupancy, properties into the calculation doesn't give a good picture of occupancy.[10]

In effect, Airdna's collective responses were, "Lots of people are using our data. They aren't complaining. What's the problem?" Nevertheless, we suspect that firms, governments, and researchers would view Airdna data differently if they were aware of the measurement differences we have highlighted here. We appreciate Airdna providing us with insight into its methodological decisions underlying its performance metrics because the firm did not have to do so. Even so, its practices have made its performance metrics incompatible with industry standards. Airdna metrics are biased upward and provide a rosier picture of the health (and potential profitability) of Airbnb properties than would otherwise be provided if Airdna chose to adapt their methodology to widely accepted practices.

Final Observations

The Bureau of Economic Analysis (BEA) of the U.S. Department of Commerce defines and computes Gross Domestic Product (GDP). Using the same broad definition—the total value of the goods and services produced in each jurisdiction during a given period, usually a year—the BEA also computes GDP at the state and metropolitan area level. Suppose now that another organization began to produce estimates of GDP for specific cities, but in doing so decided to alter the BEA definition by adding the value of leisure time. Would we consider these new numbers to be comparable with the widely accepted BEA estimates? We are confident the answer is no.

The same reasoning applies to Airdna's performance measures. Life would be easier for the hotel and motel industry, cities and counties, elected officials, Airbnb hosts, and researchers if Airdna adhered to standard, widely accepted definitions. We recommend that Airdna change its methodology in two specific ways. When determining market supply, Airdna should employ available listings rather than booked listings. If a property is available for rent, then it should not be excluded from analysis merely because it failed to secure a rental during a given month. Given that Airbnb supply was underestimated by approximately 50% in Virginia Beach in some months, this is an important adjustment to make to ensure that consumers of Airdna data have an accurate measure of Airbnb supply.

Second, Airdna should use available room nights rather than available nights when calculating ADR and RevPAR. As the number of multiroom properties increases, the bias of calculating based on listings will undoubtedly increase. While this adjustment lowers the estimated performance of Airbnb rentals as we found that there was an average of two rooms per listing in Virginia Beach, it is necessary if one desires to compare and contrast the performance of the short-term rental sector with the traditional lodging sector.

In the meantime, we recommend that individuals interested in using the Airbnb data use the individual listing data to make the adjustments that we have discussed in this article. In the end, we should neither formulate public policies nor make private investment decisions on the basis of apples and oranges comparisons.

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Notes

1. Airbnb launched an official Application Programming Interface (API) in October 2017. The API is not open as interested parties must apply for access, and it appears to be focused on property owners.
2. Note that Airdna currently captures and sells data for Airbnb but does not offer similar data for other vacation rental websites such as Flipkey, Homeaway, or Vacation Rentals By Owner (VRBO) .
3. According to Airdna, the market summary reports "provide a high level overview of Airbnb rentals in major markets around the world. With revenue per available room (RevPAR), average daily rate (ADR), Occupancy, and monthly supply & demand trends." Airdna claims these reports "bring hotel-style performance metrics to the vacation rental industry" (Airdna, 2017).
4. Each individual observation contains a listing status identifier that categorizes the listing status as either "true" or "false." A listing property's status is false if all the days in a month are blocked days (i.e., unavailable to guests) or if the Airbnb calendar for the property in question was not visible on Airbnb for that month. A listing's property status is true if there is at least one day a month that is not blocked, or if the Airbnb calendar for the property is visible and the owner is accepting reservations. A status of true implies that a listing is currently being

offered for a guest to rent or that it has been rented by a guest in each month.

5. Subsequently, we chose to exclude shared rooms because the total number of such listings was very small; the number never exceeded nine, and the single room share of total available listings never exceeded 2.44%.
6. Smith Travel Research, "A Guide to Our Terminology," www.strglobal.com/resources/glossary/en-gb. For example, Smith Travel defined occupancy (OCC) as the "percentage of available rooms sold during a specified time period. Occupancy is calculated by dividing the number of rooms sold by rooms available."
7. In our discussions with representatives of the Virginia Beach Commissioner of Revenue and that city's Convention and Visitors Bureau, it became apparent that several new developments of apartments and condominiums were investor-owned and targeted for short-term rentals.
8. Survey questions and aggregated responses are available on request.
9. Email received from Adam Alexander of Airdna on May 10, 2017
10. Email received from My Larson of Airdna on June 16, 2017.

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