Assessing the impact of “shared accommodation” for city tourism

(SESSION 6 ‘Measuring the sharing economy’)

1 Introduction

The influence of renting out beds, rooms and apartments through platforms of the sharing economy (“hosting platforms”) on local economy and community life is heavily discussed, specifically in cities. On the one hand, Airbnb, Wimdu, 9flats and others are an opportunity for residents to gain additional income and to meet interesting people from other parts of the country or world. On the other hand, these offers might lead to irritation for the neighbours, rising prices for living space (which is scarce in many cities anyway) and price pressure for hotels. The number of statements and contributions (mostly online) discussing these negative impacts is rising.

It can even be disputed if the term “shared accommodations” or “sharing economy” is justifiably used for this kind of offer: “Sharing” implies some private non-business, an assumption that can be doubted when looking at the number of professional or semi-professional offers rented out through these channels.

Knowledge about the offer on hosting platforms is an essential first step to gain understanding of the impacts. Most cities are aware of the number of listings and the basic parameters of the offer on hosting platforms. Few studies have been published and discussed.\(^1\) However, city-specific questions remain as to, among others,

- the distribution over the city and its districts
- the prices asked for apartments, rooms and beds
- the number and structure of the hosts
- the (spatial and economic) relation between these offers and traditional accommodation in hotels etc.

AirBnB is the biggest sharing platform and is said to cover about half of the listings worldwide. Because hosts have an incentive to publish listings on more than one platform (listing is free and fees are either paid by the guest or only in case of a booking), it can be safely assumed that Airbnb covers the vast majority of available listings.

Airbnb claim that “74% of Airbnb are properties outside the main hotel districts”.\(^2\) However, what a “main-hotel district” is and how it is defined for specific cities, is not very clear and open for discussion or individual specifications. In the same contribution, Airbnb claim that 81% of hosts share the home in which they live. However, the share of listings (or turnover, come to that) provided by the


other 19% of (more or less professional) hosts remains unclear. Therefore, it might be useful to look closer into this emerging type of accommodation and booking.

2 Data

In a project called “Balancing Tourism”, commissioned by Hamburg Tourismus (HHT), we analysed several of these aspects in more detail. For this purpose, we used listing data obtained from the AirBnB website.

These data are “scraped” from the website without knowledge of Airbnb. This methodology is in use for academic and commercial purposes, and many approaches are based on a Python script developed by Tom Slee, adapted to individual needs by Murray Cox and many others around the world. Currently, more than 90 data fields are available for analysis in these datasets. Slee and Cox have also, on their websites, published a number of methodological insights into the validity and reliability of the data.

Meanwhile, also data on the demand side and even spending are being published. These data are being estimated based on the calendar data available on the website. To distinguish between bookings and days blocked by the host, fuzzy logic is being used. A neutral assessment of validity and reliability of these data, however, is still missing.

Obviously, data has to be checked, cleaned and, through spatial joins, assigned to spatial or administrative units in the respective city.

3 Analyses

In a rather simple form, listings can be analysed by their number, types and spatial distribution and presented e.g. with a simple heat map (see Vienna example, Figure 1). It has to be noted, however, that location data is precise only within 150 m – Airbnb disguises the true location, probably in order to prevent competitors from addressing their hosts. By experience we can say, however, that the variation middles out with the large number of listings. Secondly, the number of listings has to be analysed carefully, because some hosts tend to offer the same bed in different listings (e.g. as a bed in a shared room, in a private room and again in a private apartment). Although there is no perfect way to clarify this, a careful analysis of descriptions and locations can reveal obvious candidates. Furthermore, data outside the city area needs to be excluded from the analysis, which can be done by simple geospatial matching (or areas can be left in the dataset intentionally, as for Fredriksberg and Dragør in the Copenhagen example, Figure 2).

In the Hamburg case, we were able to analyse in more detail the spatial distribution of Airbnb listings over the statistical units (districts) of the city. Thus, districts with high and low Airbnb density could be identified. It also became clear, that Airbnb beds are heavily concentrated (with a Hoover index of more than 50%), although not as heavily as hotel beds. In combining Airbnb listings with location of

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3 This fact can be of some importance, because there is some evidence, that data provided by a hosting platform can be manipulated, see the New York City case on Tom Slee's website: http://tomslee.net/how-airbnb-hid-the-facts-in-nyc
4 A known critic of the companies and businesses behind the “sharing” economy, see his most recent publication “What’s Yours Is Mine: Against the Sharing Economy”, February 2016.
5 See e.g. the methodology applied by the data provider airdna.co
6 The Hoover index, named after the American economist Edgar Malone Hoover, is a measure of inequality. It gives the percentage of units that would have to be redistributed to have distribution uniformity. E.g., the above stated Hoover index of 50% would mean that 50% of the beds would have to be redistributed so that all districts have an equal number of beds.
hotels, we were able to identify spatial clusters of districts (e.g. districts characterized by Airbnb beds vs. those characterized by (premium) hotel beds, see Hamburg example, Figure 3). Subsequently, we could combine these clusters with socio-economic statistics and found a completely different structure between the clusters (which then will help us to find arguments for questions like “Should new hotels be built in the city centre or not?”, “How high is the housing volatility in the Airbnb cluster?” etc.).

Furthermore, we could analyse price differences between districts (see Amsterdam example, Figure 4) and also between the hotel and Airbnb market or even between cities (for example it can be shown that Airbnb prices in Berlin are somewhat lower than in Hamburg, but prices in Barcelona are about a quarter higher than in Hamburg). Here, some careful differentiation of the data is needed to avoid comparing apples and oranges – obviously, not every shared room can be compared to the hotel industries’ ADR and RevPAR metrics.

The data also allows for estimating the demand size in the Airbnb market (which then can be easily compared to the accommodation statistics available in all European cities). Obviously, these demand figures are not exact, but existing estimation approaches seem to be reasonably accurate. The estimate follows the “San Francisco Model” (first imposed by Alex Marqusee and the San Francisco Planning Department
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Lastly, an analysis of the host structure can be added (see the example of CPH, AMS and BCN, Figure 5). Because every listing is connected to a unique host ID, the number of listings per host and their distribution can be seen. Furthermore, it can be inferred where (in which districts) there is a high density of shared vs. professionally rented apartments.

4  Implications and outlook

Obviously, complex and challenging issues like dealing with visitor pressure or discussing use limitation of housing space for tourist apartments cannot be answered solely based upon these data. Certainly, however, these data deliver an indispensable factual basis for these discussions.

Undoubtedly, the data gain a lot more value when being compared to either cross-sectional data from other cities (as a starting point, we noted some key facts on selected cities in the annex) or longitudinal data over time. Therefore, it would be quite interesting to discuss and implement options to

(a) Analyse these data in more detail,

(b) Meaningfully compare different cities and

(b) Monitor over time the development of this facet of urban tourism.

Ultimately, we think that these data would provide an excellent basis to assess implications of hosting platforms on local economies, neighbourhoods and housing, leading to a more precise picture about the extent of use, overuse and gentrification in a city destination. Furthermore, it can provide a factual basis for the discussion of control mechanisms, be it in terms of administrative regulation, destination marketing or involving locals.

5 Sample Maps

**Figure 1**: Vienna: Airbnb listings in the Inner City (density heatmap)

**Figure 2**: Copenhagen: Airbnb listings by type in Copenhagen, Fredriksberg, Tårnby and Dragør
Figure 3: Hamburg: District clusters

Figure 4: Amsterdam: Average prices for entire apartments by buurtcombinatie (combined quarters)
Figure 5: Listings per host in CPH, AMS and BCN

Based upon data from Murray Cox, Tom Slee and others, various years, preliminary data
Analysis: NIT, 2016
### 6 Some key facts about selected cities

<table>
<thead>
<tr>
<th>City</th>
<th>Possible administrative units</th>
<th>Inhabitants (millions)</th>
<th>Area (km²)</th>
<th>Airbnb listings (estimate)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Copenhagen</td>
<td>Københavns Kommune with 10 districts</td>
<td>1.2</td>
<td>607</td>
<td>9,300 (incl. Fredriksberg)</td>
</tr>
<tr>
<td>Berlin</td>
<td>Ortsteil (96)</td>
<td>3.5</td>
<td>892</td>
<td>14,900</td>
</tr>
<tr>
<td>Amsterdam</td>
<td>Buurtcombinaties (99)</td>
<td>0.8</td>
<td>219</td>
<td>11,400</td>
</tr>
<tr>
<td>Barcelona</td>
<td>Barrios (73)</td>
<td>1.6</td>
<td>101</td>
<td>10,600</td>
</tr>
<tr>
<td>Munich</td>
<td>Stadtbezirksteile (108)</td>
<td>1.4</td>
<td>311</td>
<td>n/a</td>
</tr>
<tr>
<td>Lisbon</td>
<td>Freguesias (53)</td>
<td>0.5</td>
<td>85</td>
<td>5,700</td>
</tr>
<tr>
<td>Hamburg</td>
<td>Stadtteil (104)</td>
<td>1.8</td>
<td>755</td>
<td>4,100</td>
</tr>
<tr>
<td>Vienna</td>
<td>Zählbezirk (250)</td>
<td>1.8</td>
<td>415</td>
<td>5,400</td>
</tr>
</tbody>
</table>

Airbnb data are from different sources and from various points in time (reflecting differences between cities, but also seasonal variation and market growth) and are therefore not completely comparable. In a comparison (benchmarking) project, data would be needed to be drawn at the same time and rectified by identical procedures.

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