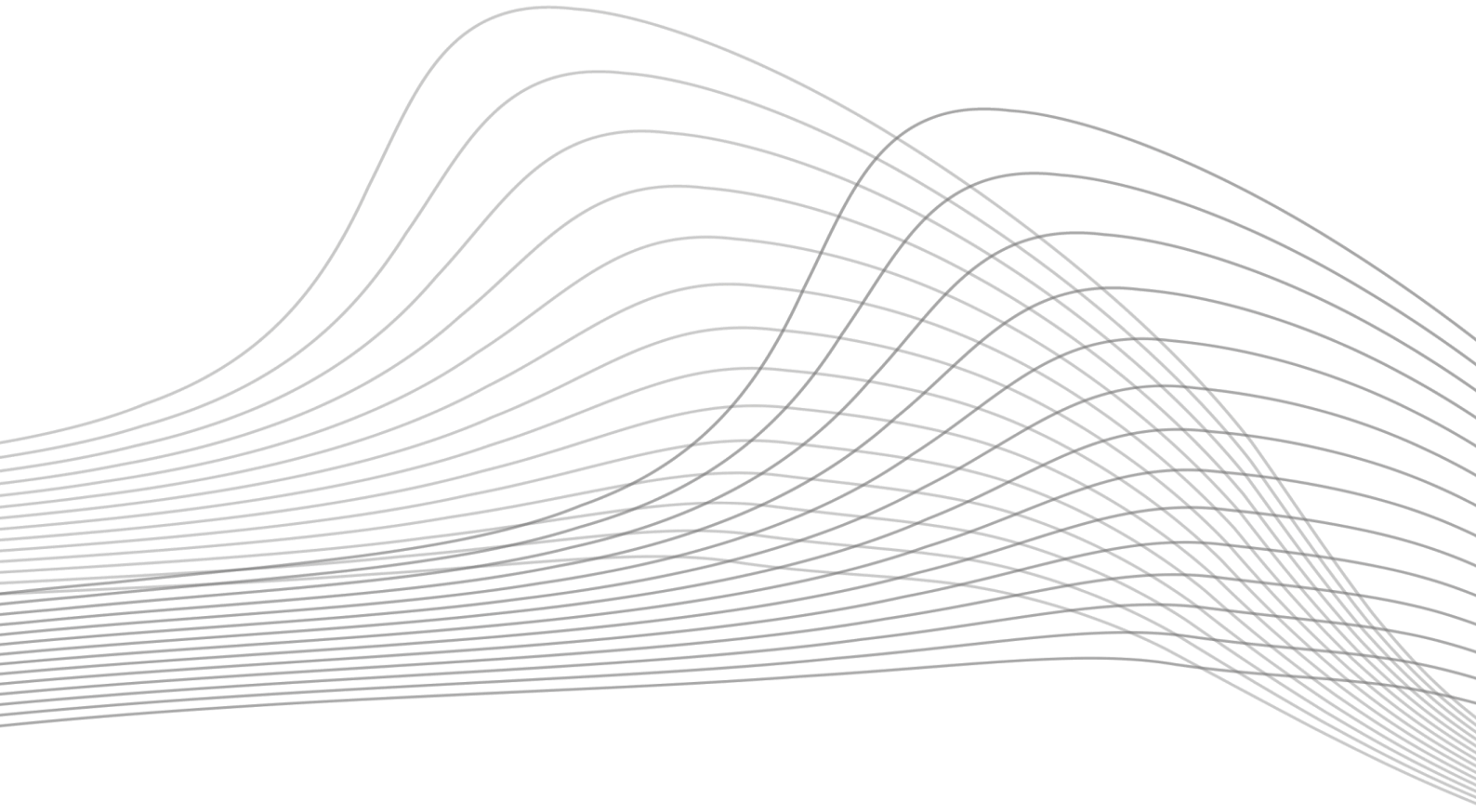
Working Paper DELab UW | No. 3(2017) | SEPTEMBER 2017

Kristóf Gyódi

# Airbnb and Booking.com: Sharing Economy Competing Against Traditional Firms?



*Abstract: Airbnb, an online platform for peer-to-peer short-term accommodation rental, is growing with a spectacular speed in most countries of the world. This creates a great regulatory challenge, as empirical evidence suggest that Airbnb may have a significant impact on the traditional hotel industry and on the housing market. The aim of this analysis is to compare the offers of Airbnb to traditional services and to examine the competition between the different business models. The empirical analysis is based on a unique dataset of scraped data on the listings of Airbnb and Booking.com in Warsaw, Poland. The offers are compared using descriptive statistics and KDE analysis. The paper supports that Airbnb is providing a cheaper alternative for hospitality services in all price segments. Controlling for common attributes (e.g. distance from the city centre), hedonic price regressions show significant price differences between the platforms.*

## 1. Introduction

Online platforms made way for new business models, which are often referred to as sharing economy or collaborative economy. Adopting a general approach, sharing economy can be defined as a "peer-to-peer-based activity of obtaining, giving, or sharing the access to goods and services, coordinated through community-based online services" (Hamari et al., 2015). This approach is appropriate to analyse the overall impact of the sharing economy, as it focuses on the technological change, instead of differentiating between the various types of collaborative services. Firms in the domain of sharing economy are intermediaries between peers, sellers and buyers of goods and services. Therefore, the major difference between traditional and sharing economy firms regards ownership of assets: sharing economy firms do not own the assets that is necessary to provide a service (Rauch and Schleicher, 2015).

As transaction costs are significantly reduced by online platforms, almost anyone can provide services outside the formal services sector. The emergence of online platforms lowered the entry barriers for certain types of services- most notably in the areas of urban passenger transportation and the provision of accommodation. The services provided on a collaborative basis gained significant market shares and seem to be substitutes (at least to a certain extent) to services supplied by traditional firms (Zervas et al., 2014; Guttentag and Smith, 2017). Furthermore, many sharing economy platforms proved to be disruptive innovators, changing the value proposition in several economic sectors.

Such disruptive innovator, being an example for sharing economy is Airbnb. Airbnb defines itself as a "trusted community marketplace" (Airbnb, 2017). Airbnb connects the owners of various types of accommodations with individuals looking for a place for overnight stay. Airbnb is a mere provider of the ICT infrastructure for the transaction, it does not own any of the listed properties. Airbnb charges a 6-12% service fee from the guest (depending on the value of the transaction- the higher the lower the share of the fee), and 3% from the host (Airbnb, 2016). Guests may be further charged with a cleaning fee or a security deposit by the host. As these examples show, the final price of the Airbnb listing is a sum of all these separate costs, which makes the booking process less transparent than in the case of regular hotel rooms (Henten and Windekilde, 2015).

The major innovation introduced by the business model of Airbnb is the facilitation of flat-sharing as an alternative for traditional hospitality services. Although there have been popular flat-sharing initiatives

before Airbnb, like Couchsurfing, Airbnb has been the first successful company that created a market for such transactions and gave the opportunity for flat owners to earn income. The Airbnb network has been subject to enormous growth since its founding in 2008: the current number of listings is above 3 million (more than tripled in the last two years) in 65000 cities and 191 countries (Airbnb, 2017).

The traditional sector has also adopted many innovations from the digital revolution. We can observe a growing platformisation in the hotel industry, with hotel aggregator platforms like Booking.com. Booking.com may be viewed as the counterpart of Airbnb offering traditional hotel services and private apartments. Unlike Airbnb, Booking.com groups not only private apartments, but also regular hotels (with all different stars). The website is offering similar transaction mechanisms, but without the necessity of social interaction between the two sides. The hotel or apartment owner is charged with a commission rate after every transaction, which is reportedly around 12%-15% (Schall, 2012). However, guests do not have to pay any additional commission for the platform, which is entirely financed by the provider side. Prices are also dependent on other factors, e.g. if the guest is paying upfront.

As other successful sharing economy ventures, the activity of Airbnb provoked many regulatory controversies. The question still remains to what extent the success of Airbnb can be attributed to the innovative business model and user preferences, or to unfair competitive advantages due to tax and regulation avoidance. Advocates of sharing economy solutions argue that sharing economy generates value by making use of underused assets (Wallsten, 2015). As an example, such underused asset is free space in one's home, which can be turned into a source of income on Airbnb. Local communities are benefiting from such platforms, as anyone can provide services and gain additional income. This means that tourism can spread to new, unexplored parts of cities, previously left out by traditional hotels. On the other hand, potential benefits are higher if the accommodation offered via Airbnb and similar platforms are not withdrawn properties from the long-term rental market. Airbnb is generating value from underused assets, if a host is offering free room in his permanent home, as without the platform the room would remain unoccupied. However, when entire homes are offered for short-term rental, Airbnb is simply providing a more profitable alternative for long-term home rental.

The aim of this article is to analyse Airbnb offers in Warsaw, and compare them to the accommodations provided via Booking.com. Such comparative analysis highlights the similarities and differences between traditional and collaborative services in the tourism sector. Furthermore, the potential of Airbnb to generate value from underused assets is analysed, along with its role in facilitating tourism in new, previously less visited districts of the city. Finally, the determinants of prices on Airbnb are going to be analysed.

The research hypotheses are the following:

*The Airbnb listings that generate revenue from underused assets constitute a minority. Accommodation provided via Airbnb is less expensive than comparable offers of the traditional sector. Airbnb provides an alternative to traditional hospitality services in most price segments.*

## 2. Literature Review

The empirical literature on the competition between sharing economy platforms and traditional firms mainly focuses on Uber and Airbnb. Zervas et al. (2014) analyse the impact of Airbnb on the hotel industry in Texas. The authors use a difference-in- difference approach and find that a 10% increase in the number of Airbnb offers results in a 0.37% decrease in hotel revenues. In comparison, a same increase in the supply of hotel rooms causes a 1.5% decrease in revenue, which suggests that Airbnb is a weak substitute for hotels in Texas. Analysing different types of hotels, the authors find that budget hotels are mostly affected by Airbnb, which confirms the intuition that Airbnb can be a substitute for certain types of costumers and traveling situations. The authors also highlight a special feature of sharing economy platforms: they are able to change supply at virtually no cost, while traditional hotels are only able to change prices. The authors conclude that Airbnb provides an imperfect alternative for the hotel industry. Neeser (2015) comes to a similar conclusion repeating the analysis for the Nordic countries. Fang et al. (2015) analyse the impact of Airbnb on tourism industry employment using scraped data from Airbnb website on listings in Idaho, USA between 2009-2013. The authors test a simple quadratic model explaining the employment rate in tourism industry by the number of Airbnb listings. The authors conclude that the entry of Airbnb has been beneficial for tourism industry, however, the marginal effect decreases with the increase of listing number. This finding is line with Zervas et al. (2014), as it suggests that lower-end hotels would be replaced by Airbnb. Coyle and Yeung (2016) examine the activity of Airbnb in 14 European cities using scraped data from Airbnb and data on hotel occupancy rate from a private source. The authors follow the same model as Zervas et al. (2014) to explain the hotel occupancy rate with the number of Airbnb listings. The authors find a negative effect on hotel occupancy rates, however, the effect on total hotel revenues and average hotel prices is positive. The authors conclude that the hoteling market may re-segment into high-end and low-end offers.

Ert et al. (2016) analyse the role of personal photos of hosts on Airbnb on prices and the probability of booking, using a dataset of scraped data on Airbnb listings in Stockholm. The price of Airbnb listings is also discussed by Wang and Nicolau (2017), who provide an analysis on the determinants of Airbnb prices in a wide sample of scraped data on Airbnb offers in 33 cities in Europe and in North-America. The authors analyse variables in 5 categories: host attributes, site and property attributes, amenities and services, rental rules and online review ratings. However, a major limitation of the study is that it is restricted to the attributes of Airbnb listings that are described on the website, without taking into account the role of other attributes, including location and city characteristics.

This research project is also inspired by the restrictions of the current literature on the spatial pattern of the Airbnb network. Quattrone et al. (2016) scraped the Airbnb website for the listings in London and show that Airbnb covers a larger area of the city than traditional hotels. The authors confirm that the number of Airbnb listings is decreasing from the various city centres of London. They are also able to observe the changes in the determinants in time. In the entry phase (2012) the most important determinant was the distance from the city centre, while over time the more bohemian, suburban districts gained importance. Furthermore, the share of hosts who are renting their homes (and do not own them) also increased with time. Gutierrez et al. (2017) provide a spatial analysis on the Airbnb network in Barcelona and conclude that Airbnb is strongly concentrated in the historic city centre, expanding on a wider area in the city centre than traditional hotels. Furthermore, the spatial distribution

of Airbnb is more regular, showing a centre-periphery pattern, while traditional hotels reveal more complex patterns. The authors also show that Airbnb is able to penetrate the city closer to tourist attractions than traditional hotels.

This work also builds on the literature analysing platforms for the traditional hotel industry. Byers et al. (2015) compare Airbnb review scores on properties with the reviews in the traditional sector. Using data on Airbnb listings worldwide, the authors find that 95% of the listings have at least 4.5 rating out of 5. However, in the case of hotels available on Tripadvisor (a popular hotel aggregating site), the average rating is only 3.8 stars, with much higher variance. The authors also examine cross-listed property ratings and find that their rating is also higher on Airbnb, and the correlation between the ratings is rather limited. Yacouel and Fleischer (2012) present an analysis on the role of guest reviews on hotel prices at Booking.com (aggregator platform for hotel offers). The authors prove in a theoretical model that if the review system reveals higher quality service, the hotel is able to charge higher prices. This finding is confirmed in an empirical analysis, using data on booking.com in three major EU cities. The regressions reveal that controlling for variables like number of stars, breakfast, hotel chain, the review score is statistically significant. Rodriguez-Diaz and Espino-Rodriguez (2017) also demonstrate that user reviews on Booking.com are suitable to measure perceived value, therefore they reflect the competitiveness of destinations.

Currently, the literature lacks comparative analyses on the services provided by sharing economy platforms and traditional firms. The major contribution of this analysis is the presentation of the entire population of Airbnb offers in a major city, and compare it to the traditional sector. Furthermore, this is also the first empirical analysis on the sharing economy in Poland.

## 3. Research Methodology and Data Set

The main goal of the analysis is to compare the services provided by a sharing economy platform (Airbnb) and the traditional industry (Booking.com). Therefore, the key issue of the analysis is the preparation of an adequate dataset. Data on Airbnb listings in Warsaw was collected using web-scraping technology in February 2017. Such methodology potentially enables to collect all Airbnb listings located in Warsaw. The dataset contains the following variables:

- Geographical location (longitude and latitude of the listing)
- Accommodation type (Single Room, Shared Room, Entire Home)
- Number of guests (maximum number)
- Price per night (shown by the website as the price of the listing for a night)
- Cleaning fee
- Number of pictures for the offer
- Host ID (an identification number of the host offering the listing)
- Superhost status of the host
- Review Count (number of reviews by guests)
- Satisfaction (overall user rating of the experience)
- Internet (dummy variable if the listing provides Internet)

- Kitchen (dummy variable)
- Real Bed (dummy variable for double bed)

Based on the geographical data, the distance from the city centre has been calculated for every listing in kilometres (using Vincenty's solution to the inverse geodetic problem). Furthermore, the distance to the closest metro station has also been determined using the same method. The number of listings provided by a host has been additionally calculated (based on the Host ID). The dataset on Booking.com has also been constructed using web-scraping methodology. The available offers were collected based on a request for accommodation for a working day.

The following variables were included in the dataset:

- Name of the object
- Geographical location (longitude and latitude of the listing)
- Price per night (For two persons, the cheapest available option)
- Number of guest reviews
- Satisfaction (user rating of the experience)
- Number of stars in the case of hotels

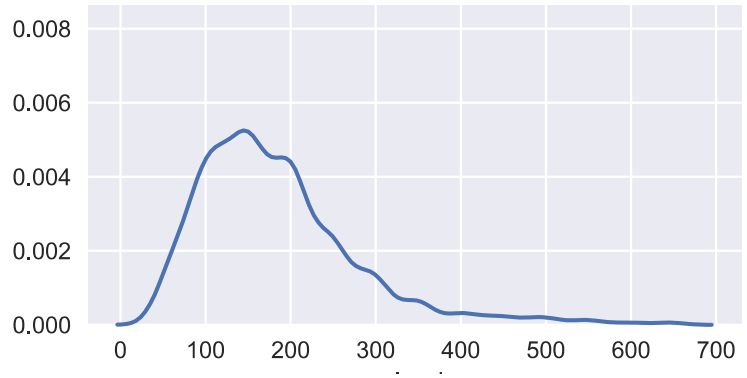
Distance from the city centre and distance from the metro has been calculated. Finally, the type of the accommodation (hotel, hostel, apartment) has been additionally determined. Furthermore, the average price of hotels and hostels were calculated for every district for the empirical analysis.

Based on the datasets, the offers of the competing platforms are analysed. Descriptive statistics and the density function of prices will be used to examine whether Airbnb and traditional hotels are competing in the same price segments. Furthermore, the determinants of prices on Airbnb will be analysed using OLS regression, and the significance of price differences will be tested controlling for several attributes. The data has been cleaned from outliers for the KDE (kernel density estimation) and OLS regressions: the first 2 percentiles and the last 2 percentiles of price distribution have been removed.

Altogether 3457 unique listings were collected for Airbnb: 2699 entire homes, 680 private rooms and 78 shared rooms. Therefore, the data shows that the overwhelming majority of Airbnb listings (78%) present entire homes. This may suggest that the Airbnb platform is used as an alternative for long-term flat renting. The situation when the host is potentially offering free space in the permanent place of living (single rooms and shared rooms) is at best only 22%. However, more advanced analysis methods (text-mining) would be necessary to determine if the host is living in the offered home, as many of the shared rooms stand for regular hostels (Business-to-Consumer offer).

Figure 1. presents the histogram and estimated density of the price distribution of the entire Airbnb population. The skewed price distribution with a long tail suggest that the population of Airbnb offers is a heterogeneous group.

Figure 1. Histogram and kernel density estimation of prices on Airbnb (without cleaning fee)




*Source*: Own calculation

As expected, the prices are increasing with the space of the rented property (cheapest are shared rooms, most expensive apartments).

Table 1. Airbnb Listings in Warsaw (Prices in PLN)

| | | Entire home/apt | Private room | Shared room |
|---|---|---|---|---|
| | Number of observations | 2699 | 680 | 78 |
| *Price without cleaning fee* | mean | 226.21 | 117.67 | 66.05 |
| | median | 186.00 | 89.00 | 52.00 |
| | standard dev. | 321.19 | 211.37 | 54.20 |
| *Price with cleaning fee* | mean | 260.93 | 130.94 | 71.04 |
| | median | 210.00 | 101.00 | 52.00 |
| | standard dev. | 355.01 | 212.37 | 58.16 |
| *Cleaning Fee* | mean | 34.72 | 13.27 | 4.99 |
| | median | 0.00 | 0.00 | 0.00 |
| | standard dev. | 64.21 | 27.83 | 18.63 |
| *Superhost* | mean | 0.16 | 0.13 | 0.04 |
| | median | 0.00 | 0.00 | 0.00 |
| *Host ID* | Number of hosts | 1549 | 526 | 52 |
| *Distance* | mean | 2.68 | 4.42 | 3.67 |
| | median | 1.91 | 3.87 | 2.17 |
| | standard dev. | 2.31 | 3.13 | 3.57 |
| *Review Count* | mean | 16.15 | 12.70 | 7.22 |
| | median | 4 | 2 | 1 |
| | standard dev. | 30.77 | 24.58 | 15.09 |
| *Satisfaction* | number of obs. | 2051 | 439.00 | 47.00 |
| | mean | 93.39 | 94.02 | 92.55 |
| | median | 96.00 | 96.00 | 96.00 |
| | standard dev. | 8.90 | 8.06 | 9.99 |

*Source*: Own calculation

When it comes to distance, half of all apartments is in the radius of 2 kms from the city centre. Private rooms are further from the centre, and also more varying in distance, based on the standard deviation.

Table 1. also presents some descriptive statistics on user reviews. The data suggests that many listings are new or inactive, as the median number of reviews is very low. On the other hand, the data confirms the extremely high user ratings, typical for Airbnb and other popular sharing economy platforms.

Table 2. Airbnb listings by type and hosts

| *N. of properties listed by same host* | Type | Number of listings |
|---|---|---|
| *1* | Entire home/apt | 1211 |
| *1* | Private room | 374 |
| *1* | Shared room | 34 |
| *2* | Entire home/apt | 297 |
| *2* | Private room | 110 |
| *2* | Shared room | 3 |
| *3* | Entire home/apt | 127 |
| *3* | Private room | 70 |
| *3* | Shared room | 7 |
| *4* | Entire home/apt | 106 |
| *4* | Private room | 33 |
| *4* | Shared room | 5 |
| *5* | Entire home/apt | 94 |
| *5* | Private room | 27 |
| *5* | Shared room | 9 |
| *5+* | Entire home/apt | 832 |
| *5+* | Private room | 680 |
| *5+* | Shared room | 78 |

*Source*: Own calculation

The share of listings offered by hosts with 1 listing is only 47%. Therefore, 53% of the listings are multi-listings, which may mean a strong presence of various real-estate investors and professional agencies on Airbnb. As Table 2. reveals, more than a quarter of all accommodations offered via Airbnb belongs to hosts with more than 5 listings, which may suggest that various professional agencies are present on the platform, providing B2C services.

We continue the analysis with data collected from Booking.com. The dataset includes 528 apartments, 56 hotels and 52 hostels, which shows that traditional accommodation providers constitute a minority on the platform. The median prices reveal that hostels are the cheapest, followed by apartments and hotels. Interestingly, apartments and hostels are closer to the city centre, than hotels. When it comes to review counts, hotels and hostels are much more frequently rated than apartments, due to the larger number of offered rooms and guests.

Table 3. Booking.com offers in Warsaw (Prices in PLN)

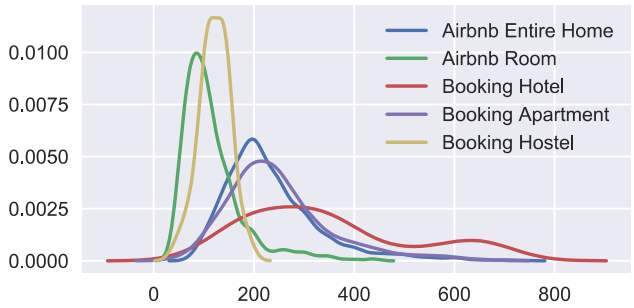
| | | Apartments | Hotels | Hostels |
|---|---|---|---|---|
| | Number of observations | 528 | 56 | 52 |
| *Price* | mean | 260.01 | 345.88 | 127.56 |
| | median | 240.00 | 314.50 | 124.50 |
| | standard dev. | 100.41 | 164.93 | 41.55 |
| *Distance* | mean | 2.64 | 5.12 | 4.60 |
| | median | 1.78 | 5.51 | 4.45 |
| | standard dev. | 2.54 | 3.90 | 3.57 |
| *Review Count* | mean | 161.49 | 1999.34 | 395.80 |
| | median | 57.00 | 1434.00 | 338.00 |
| | standard dev. | 280.14 | 1985.80 | 354.69 |
| *Satisfaction* | mean | 8.53 | 8.18 | 8.13 |
| | median | 8.70 | 8.20 | 8.30 |
| | standard dev. | 0.91 | 0.64 | 0.82 |

## 4. Airbnb and Booking.com in Warsaw: an empirical analysis

Let us briefly compare the available accommodation on Airbnb and Booking.com. As the listings in the shared room section are mixed (including single rooms and regular hostels as well), focus will be on the other accommodation types.

The median price of entire homes on Airbnb, including cleaning fee is 210 PLN, which is below the median price of apartments on Booking.com. However, the Airbnb price does not include the reservation fee, which may increase prices by 6-12%. Therefore, it seems that in the case of a reservation for 1 night the prices are comparable on the two platforms. This is also confirmed by Figure 2, which presents the kernel density estimate (KDE) on prices on the two platforms (the horizontal axis gives the prices, while the vertical one the density).

Figure 2. Kernel density estimation of prices on Airbnb and Booking.com (with Airbnb cleaning fee)



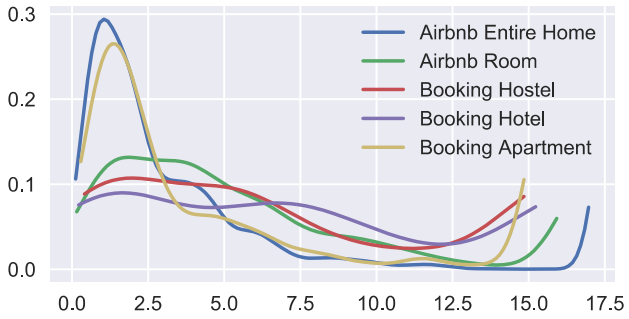

*Source*: Own elaboration

Airbnb single rooms seem to directly compete with traditional hostels. The median price of Airbnb single rooms is around 130 PLN, roughly at the median price of Booking.com hostels. As hostel rooms are usually rented for 4-6 person per night, Airbnb single rooms at similar price may be more attractive, as for similar price they provide more privacy and space. However, the KDE reveals that there is a wide array of Airbnb rooms in higher price range than regular hostels.

When it comes to traditional hotels, the sample covers a very wide variety of choice, including hotels from 2 to 5 stars. Based on the median prices and the KDE, it can be stated that in the long-tail, Airbnb apartments do compete with hotels. It is not uncommon to find Airbnb apartments positioned to a premium level, which may pose an alternative to traditional hotels.

Figure 3. presents the KDE estimation of distances from the city centre. Among the analysed accommodation, apartments can be found in the city centre with the highest probability. However, all accommodation types are focused in the vicinity of the city centre, with a decreasing density, until the 12$^{th}$ km from the centre. Further away their density increases again, possibly due to the numerous accommodations near the Chopin Airport.

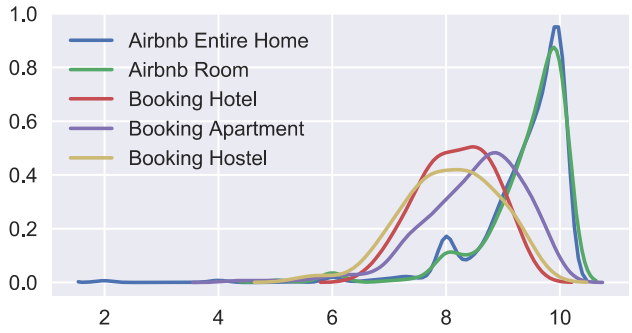
**Figure 3. Kernel density estimation of distance from city centre on Airbnb and Booking.com**




*Source*: Own elaboration

For the comparison of user ratings, Airbnb scores have been divided by ten, to get an identical scale (0-10), as on Booking.com. Our data confirm the finding from the literature that sharing economy platforms are characterised by higher ratings (e.g. Byers et al., 2015).

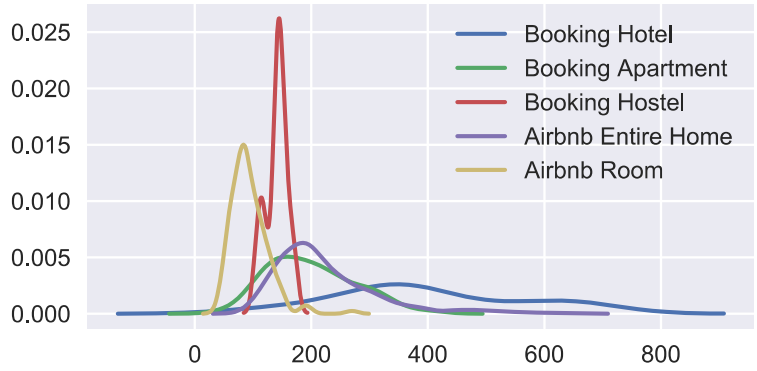
**Figure 4. Kernel density estimation of guest ratings on Airbnb and Booking.com**




*Source*: Own elaboration

Finally, the most popular listings are analysed. We assume that the most popular accommodations receive the most reviews, therefore we drop the observations below the third quartile of user review numbers. This enables us to make further observations on the differences between the two platforms. Figure 4. confirms our conclusions drawn from the entire sample. The accommodation types share a common price range under 200 PLN, however, they differ in distribution and maximum prices. Airbnb rooms are tend to be the cheapest, followed by hostels. Among the most popular apartments, homes on Airbnb seem to be more expensive, spreading into the premium segment. Hotels are again spreading across the entire price range, with a higher average price.

Figure 5. Kernel density estimation of prices on Airbnb and Booking.com (with Airbnb cleaning fee)-above the third quartile of review count




*Source*: Own elaboration

To sum up, Airbnb single rooms seem to be positioned for the prices of hostels. As hostels do not offer high quality hospitality services, Airbnb should be a strong competitor for them. Airbnb single homes are also characterised by lower median prices than traditional hotels, however, a considerable share of them is positioned for the premium segment. Furthermore, apartments on both platforms are more concentrated in the city centre than traditional service providers.

## 5. Determinants of prices on Airbnb

Next, the determinants of Airbnb prices will be analysed. For the analysis, Ordinary Least Squares estimation method is used. The form of the model is the following:

$$\log(y) = \alpha + B_i * X_i +$$

where $y$ is the price of the listing (without the cleaning fee), while $X_i$ is the vector of $i$ determinants. The correctness of the log-linear model specification has been tested with the Ramsey Reset Test, while the homoscedasticity of errors has been tested by the Breusch-Pagan Test. Additionally, the significance of the coefficient estimates have been checked with heteroskedasticity-consistent estimation of the covariance matrix.

The regression on single rooms shows that the following determinants have an impact on price: number of guest reviews, person capacity of the room, number of photos, whether it has a kitchen, cancellation policy, distance from the nearest metro station, average price of hotels and hostels in the

district. The option to accommodate an additional person increases price by almost 10% per person, while a stricter cancellation policy reduces prices by 4%. Interestingly, the distance from the nearest metro station better explains price differences than the distance from the city centre (one additional km from the metro decreases price by 2.73%). Furthermore, there is a difference between the impact of average prices by hotels and hostels: an increase in the average district price of hostels decreases Airbnb room prices (by 0.1% after every PLN) in the given district, while hotels have a weaker positive effect (0.04% increase after every PLN). This result also supports the hypothesis that Airbnb is directly competing with hostels, while hotel prices are less relevant for hosts in price setting. Finally, the analysis confirms that guest satisfaction ratings do not affect prices on sharing economy platforms (instead, the number of reviews is serving as a signal for quality).

Let us now briefly summarise the results of the regression on entire home data. The differences to the previous regression is that distance from the city centre (1.1% increase after every additional km), real bed (13.6% increase of price relative to other beds), Superhost status (decrease of price by 4.2%), cleaning fee (decrease by 0.5% after increase of 1 PLN), and the number of listings owned by the host (0.05% after every additional listing) are significant. The significance of cleaning fee may suggest that hosts need to lower the basic price (shown to the user), if decides to charge a cleaning fee. Regarding hotel and hostel prices, the observed relationship is the same as in the case of rooms: hosts need to undercut the prices of hostels.

Table 4. OLS regression on the determinants of Airbnb prices

| | *Dependent variable:* | |
|---|---|---|
| | Log(Price without cleaning) | Log(Price without cleaning) |
| | Single Rooms | Entire Homes |
| Review Count | -0.001*** | -0.002*** |
| | (0.001) | (0.0002) |
| Person Capacity | 0.099*** | 0.091*** |
| | (0.020) | (0.005) |
| Number of photos | 0.004** | 0.002*** |
| | (0.002) | (0.001) |
| Distance from the centre | -0.013 | -0.011** |
| | (0.009) | (0.005) |
| Internet | 0.061 | 0.013 |
| | (0.072) | (0.035) |
| Kitchen | -0.196*** | -0.041 |
| | (0.076) | (0.053) |

| | *Dependent variable:* | |
|---|---|---|
| | Log(Price without cleaning) | Log(Price without cleaning) |
| | Single Rooms | Entire Homes |
| Real Bed | 0.051 | 0.136*** |
| | (0.040) | (0.026) |
| Superhost status | -0.056 | -0.042** |
| | (0.046) | (0.020) |
| Cleaning fee | -0.00004 | -0.0004** |
| | (0.001) | (0.0002) |
| Satisfaction | -0.003 | 0.001 |
| | (0.002) | (0.001) |
| N. of listings owned by host | 0.004 | 0.005*** |
| | (0.007) | (0.0003) |
| Cancellation policy | -0.043* | -0.010 |
| | (0.024) | (0.010) |
| Distance from the nearest metro station | -0.027** | -0.029*** |
| | (0.012) | (0.009) |
| Price of hotels on Booking | 0.0004*** | 0.0003*** |
| | (0.0001) | (0.0001) |
| Price of hostels on Booking | -0.001** | -0.001*** |
| | (0.0005) | (0.0003) |
| Constant | 4.825*** | 4.719*** |
| | (0.256) | (0.107) |
| Observations | 426 | 1,987 |
| $R^2$ | 0.203 | 0.351 |
| Adjusted $R^2$ | 0.174 | 0.346 |
| Residual Std. Error | 0.343 (df = 410) | 0.322 (df = 1971) |
| F Statistic | 6.966*** (df = 15; 410) | 70.960*** (df = 15; 1971) |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

*Source*: Own elaboration

In the next section, the determinants of Booking.com prices are tested. The form of the model is:

$$\log(y) = \alpha + B_i * \log(X_i) + D_i + \varepsilon$$

where $y$ is the price of the Booking.com accommodation, while $X_i$ is the vector of $i$ determinants, $D_i$ is a set of dummy variables to differentiate between the various types. Both the dependent and independent variables are log-transformed (due to the indication of the Ramsey RESET test that the previous log-linear form of the model was incorrect in this subsample).

The set of explanatory variables is narrower than in the case of Airbnb, due to the limited dataset. However, important variables are captured, like distance, number of reviews and overall guest satisfaction. Distance is not a significant determinant in the case of traditional accommodation providers. An increase in the number of user reviews decreases price (2.5% decrease following a 1% increase in the number). The results also suggest that user reviews better serve their quality signalling purpose, as they are significant with a powerful positive impact. The regression confirms our preliminary findings from the KDE analysis: controlling for other variables, hotels are the most expensive, while apartments are 42% cheaper, and hostels are the cheapest.

Finally, we perform a regression on the whole sample. The form of the model is log-linear, as in the case of regressions on the Airbnb sample. Distance from the city centre is significant, while there is weak evidence on the impact of satisfaction (stemming from the differences between the platforms). The analysis confirms that controlling for the common variables, Airbnb rooms are the cheapest, followed by hostels (18.6% more expensive), Airbnb apartments (76% more expensive), Booking.com apartments (87.5% more expensive) and hotels (121% more expensive).

Table 5. OLS regression on the determinants of Booking.com and the entire sample

| | *Dependent variable:* | |
|---|---|---|
| | Log(Price) Booking | Log(Price with cleaning) Entire sample |
| Distance from the city centre | -0.030 | |
| | (0.024) | |
| Distance from the nearest metro station | -0.031 | |
| | (0.022) | |
| Review Count | -0.025** | |
| | (0.011) | |
| Guest Satisfaction | 0.687*** | |
| | (0.133) | |
| Booking Apartment | -0.417*** | |
| | (0.057) | |
| Hostel | -1.035*** | |
| | (0.068) | |

| | : | *Dependent variable* |
|---|---|---|
| | Log(Price) | Log(Price with cleaning) |
| | Booking | Entire sample |
| | | -0.021*** |
| | | (0.004) |
| Hostel | | 0.186*** |
| | | (0.058) |
| Booking Apartment | | 0.875*** |
| | | (0.026) |
| Hotel | | 1.213*** |
| | | (0.072) |
| Airbnb Apartment | | 0.762*** |
| | | (0.020) |
| Airbnb Room | | |
| Review Count | | -0.00001 |
| | | (0.00002) |
| Guest Satisfaction | | -0.013*** |
| | | (0.004) |
| Distance from the nearest metro station | | -0.008 |
| | | (0.007) |
| Constant | 4.545*** | 4.806*** |
| | (0.304) | (0.045) |
| Observations | 538 | 3,034 |
| $R^2$ | 0.364 | 0.415 |
| Adjusted $R^2$ | 0.357 | 0.414 |
| Residual Std. Error | 0.324 (df = 531) | 0.371 (df = 3025) |
| F Statistic | 50.635*** (df = 6; 531) | 268.498*** (df = 8; 3025) |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

*Source*: Own calculation

## 6. Conclusions

The results of the empirical analysis support the hypotheses. Airbnb may be facilitating the usage of free assets: the unused space in one's home. However, the data in Warsaw suggests that this may be the case at maximum 22% of the listings. In the vast majority of offers, Airbnb is functioning either as an alternative for long-term house rental, or a platform for professional agencies (Business-to-Consumer services).

The analysis of price and other attributes suggests that Airbnb is providing a cheaper alternative for hospitality services in all price segments. Single rooms are offering more space cheaper or at the price of hostels, similarly to apartments, which are competing with hotels. These assumptions are additionally tested in hedonic price analysis: controlling for certain attributes, price differences are robust and significant.

The analysis does not support the common belief that Airbnb is bringing tourism to places where traditional hotels and hostels are not present. The Airbnb is more concentrated in the city centre than traditional service providers.

The major contribution of this analysis is the comparison of sharing economy services with traditional services in the tourism sector. Furthermore, the empirical analysis is based on a unique dataset of scraped data.

The analysis also identifies additional research gaps. The determinants of the consumer choice between traditional and sharing economy services are unexplored in the literature. We may assume that the guests of Airbnb are attracted by enhanced social experience, however, there are other possibilities as well. The demand for Airbnb accommodation should be examined in order to formulate adequate, data-driven policy proposals.

## 7. References


1. Byers, J., Zervas, G., Georgios, Davide Proserpio, and. "A first look at online reputation on Airbnb, where every stay is above average." (2015).
2. Capra, L. "Who Benefits from the Sharing Economy of Airbnb?." *Proceedings of the 25th International Conference on World Wide Web*. International World Wide Web Conferences Steering Committee, 2016.
3. Coyle, D., Yeung, T. Understanding Airbnb in fourteen European cities, *The Jean-Jacques Laffont Digital Chair Working Papers,* 2016
4. Ert, Eyal, Aliza Fleischer, and Nathan Magen. "Trust and reputation in the sharing economy: The role of personal photos in Airbnb." *Tourism Management*55 (2016): 62-73.
5. Fang, B., Ye, Q., & Law, R. (2016). Effect of sharing economy on tourism industry employment. *Annals of Tourism Research*, *57*, 264-267.
6. Guttentag, Daniel. "Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector." *Current issues in Tourism* 18.12 (2015): 1192-1217.

7. Guttentag, D. A., & Smith, S. L. Assessing Airbnb as a disruptive innovation relative to hotels: Substitution and comparative performance expectations. *International Journal of Hospitality Management*, *64* (2017): 1-10.
8. Gutiérrez, J., García-Palomares, J. C., Romanillos, G., & Salas-Olmedo, M. H. The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tourism Management*, *62*, (2017): 278-291.
9. Hall, J. V. & Krueger, A. B. An analysis of the labor market for uber's driver-partners in the united states. Tech. Rep., National Bureau of Economic Research (2016).
10. Hamari, J., Sjöklint, M. & Ukkonen, A. The sharing economy: Why people participate in collaborative consumption. *Journal of the Association for Information Science and Technology* (2015).
11. Henten, A. H. & Windekilde, I. M. Transaction costs and the sharing economy. *info* 18, 1–15 (2016).
12. Neeser, Dâvid, Martin Peitz, and Jan Stuhler. "Does Airbnb hurt hotel business: Evidence from the Nordic countries." *Universidad Carlos III de Madrid* (2015): 1-26.
13. Quattrone, G., Proserpio, D., Quercia, D., Capra, L., & Musolesi, M. Who Benefits from the Sharing Economy of Airbnb?. In *Proceedings of the 25th International Conference on World Wide Web* (pp. 1385-1394), (2016)
14. Rauch, D. E. & Schleicher, D. Like uber, but for local government law: The future of local regulation of the sharing economy. *Ohio St. LJ* 76, 901 (2015).
15. Schaal, D. How Booking.com turned the other OTAs into converts (2012). Available online at: https://skift.com/2012/06/25/how-booking-com-conquered-world/.
16. Wallsten, S. The competitive effects of the sharing economy: how is uber changing taxis. *Technology Policy Institute* 22 (2015).
17. Wang, Dan, and Juan L. Nicolau. "Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb. com." *International Journal of Hospitality Management* 62 (2017): 120-131.
18. Yacouel, Nira, and Aliza Fleischer. "The role of cybermediaries in reputation building and price premiums in the online hotel market." *Journal of Travel Research* 51.2 (2012): 219-226.
19. Zervas, G., Proserpio, D. & Byers, J. The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. boston u. school of management research paper no. 2013-16. *Available at SSRN 2366898* (2014).