Does Airbnb Hurt Hotel Business: Evidence from the Nordic Countries

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Abstract: This paper wants to measure the impact of Airbnb on hotel revenue in Norway, Finland, and Sweden using a difference-in-differences strategy with many time periods and different level of treatment. We exploit the richness of our data to differentiate among Airbnb listings and to identify which type of hotel costumers Airbnb is more likely to attract.

1 Introduction

In this paper, we want to measure the impact of Airbnb in Norway, Finland, and Sweden on the hotel industry. More specifically, we look at the revenue per available hotel room, the price of hotel rooms, the room occupancy rate, and the composition of hotel guests such as country of residence and purpose of visit. The main reason why we chose these countries is that we can pool them together since they should be similarly affected by common shocks. Also, the data on the accommodation industry was freely available and comparable. Another reason is that many businesses (photographers, house cleaners, pricing tools, market analysts, etc.) gravitate around Airbnb in the U.S. and in many European countries, but not in the Nordic countries yet, at the best of our knowledge. This is important in our analysis as we only observe the price of a listing once, and the absence of pricing tools should make it more stable through time. These countries are also beyond the scope of most studies in this literature, maybe because they do not try to stop this platform from entering their country or city, unlike others. Finally, the three countries witnessed a significant entry of Airbnb. Figure 1 shows the relative size of all listings per region in May 2015 compared to the average number of room per hotel in the same region. To give a better idea, figure 2 displays the market share of Airbnb in each region, also as of May 2015.

Peer-to-peer platforms such as Airbnb and Uber are targets to controversy with regulators and incumbents trying to respond to these new entrants. World-wide, blogs and editorials attack or defend these business models with arguments mostly based on theory, without empirical backup. This is an important issue as many cities are doing everything in their power to block them. For instance, Uber is completely banned in the state of Nevada and also in India (although it keeps operating in some cities), and under partial banned in Brussels, Germany, and the Netherlands for their lower-cost services such as UberPOP and UberX which employs non-taxi drivers[1]. Similarly, Paris is performing raids in Airbnb listings that are suspected to be illegal (cannot be rented out for a short period of time if owners are not present during their stay). Furthermore, the city of Paris and San Fransisco have come up with some estimates that Airbnb is contributing to the housing shortage and price increases by removing apartments from the housing market[2][3].

In any case, truly objective databased research on the topic is still lacking in the literature as these platforms (mostly privately owned) keep their data for their in-house publications[4]. While they have the potential to achieve very high quality research thanks to the richness of the data they have access to, they are also likely to bias the results in their own interest.

The reader will find a very complete and recent literature review in Zervas et al. (2014) covering works on multi-sided platforms, substitution between online and offline markets, and external shocks on tourism and hospitality industry, which are all the fields we are contributing to. More recently, a paper by Müller (2014) wants to model the impact of the sharing systems on the social welfare, but his work is still in progress. Another research in progress from Gutt and Herrmann (2015) empirically measures Airbnb hosts' reaction to new reviews on their pricing behavior using a DD with matching in New-York city. They find that hosts increase their price by an average of 2.69 euros more than hosts with comparable listings that has not been rated yet, which is in line with Querbes (2014)'s simulated model on peer-to-peer platforms interaction.

This paper is closely related to Zervas et al. (2014) where they estimate the impact of Airbnb's entry on the hotel industry in Texas. They use a difference-in-differences (DD) approach with very detailed data on hotels and Airbnb listings at the individual level in Texas' biggest cities. They find that where Airbnb entered the most, the impact on the more vulnerable hotels' revenue is about 8-10% decrease in five years. They manage to differentiate the impact for different market segments, where cheaper independent hotels are competing more fiercely with this new platform, while hotels focusing more on business travelers and wealthier customers are reaching a different niche than Airbnb's typical

[1] http://www.businessinsider.com/heres-everywhere-uber-is-banned-around-the-world-2015-4

[2] http://roadwarriorvoices.com/2015/05/26/paris-officials-go-on-door-to-door-raid-of-illegal-airbnb-rentals/

[3] http://www.businessinsider.com/san-francisco-report-blames-airbnb-for-housing-shortage-airbnb-strikes-back-2015-5

[4] For instance, see: https://www.airbnb.com/economic-impact/

guests.

We contribute to their research by addressing one of the limitations mentioned in their paper, namely the specificity of Texas' accommodation industry. We closely replicate their methodology to see how their results may change when we look at countries like Sweden, Norway, and Finland. While we do not observe hotels individually, we exploit Airbnb's information details to analyze the impact of different types of listings. We go one step further by looking at how the demand for hotels has changed with Airbnb's market entry in different regions using data on hotels' guests. We will also point out some forces and weaknesses from their paper that are more easily seen by someone who has worked with this kind of data.

This paper is organized as follow: section 2 explains the data we used, then section 3 presents the model, the results are shown in section 4, section 5 presents our extensions, and section 6 concludes.

2 Data

2.1 Hotel

Data on accommodation was found on Statistics Finland[5], Statistics Sweden[6], and Statistics Norway[7].

We got monthly data on hotels from January 2004 until May 2015 for Norway and Finland, and from January 2008 until May 2015 for Sweden. We thus cover a large period before Airbnb first enters that market (which happened between August 2008 and April 2009 depending on the country). The lowest level of aggregation available for all countries was NUTS 3 which corresponds to 20 regions for Finland, 21 counties for Sweden, and 19 counties for Norway. Throughout this paper, the words "region", "county", and "NUTS 3" will be used as synonyms. Some data were available at the municipality level but would have been less accurate and also censored when too few hotels operate in the municipality. Aland and Svalbard are excluded from the dataset for many missing observations.

For all counties, we observe the number of establishments, the price of a room and the occupancy rate of the rooms from which we compute the widely used revenue per available room (RevPAR) which is simply the product of the last two. We convert all prices in US dollar to fit Airbnb data. We also observe the number of rooms for all types of accommodation, as well as the number of nights spent in hotels per country of residence. Since the countries of origin were not homogeneously reported across the three databases, and the strict majority of guests are from the hosting country, we categorize guests from Finland, Sweden, Norway, Denmark, Russia and the rest of the world.

[5]http://pxnet2.stat.fi/PXWeb/pxweb/en/StatFin/StatFin__lii__matk/?tablelist=true
[6]http://www.statistikdatabasen.scb.se/pxweb/en/ssd/
[7]https://www.ssb.no/en/transport-og-reiseliv/statistikker/overnatting

Norway's database also includes data on guest nights per purpose of accommodation, namely course or conference, occupation, and holiday or recreation. Sweden provides similar data where they report the number of occupied rooms per category of guests which are either conference, business, group, or leisure.

An obvious drawback is the fact that the treatment is assumed to affect all hotels within the same region independently of the distance they are from Airbnb listings. This is a strong assumption as some regions such as Lapland cover a large land area from north to south with few inhabitants[8]. This is why we also include the population density for each NUTS 3.

Data on population but especially unemployment was difficult to get at the county level for all countries. For population, we had to extrapolate between the quarters/years. For Sweden, we observe either monthly unemployment at the country level, or yearly unemployment at the NUTS 2 level. We decided to use the first one as it would have been far-fetched to extrapolate yearly unemployment in monthly observations.

Finally, we also include the variable GDP per capita that we observe at the country level, since most of hotel guests (between 70 to 90%) are national tourists. Table 1 reports summary statistics for the main variables.

2.2 Airbnb

Data on Airbnb was very difficult to get and took a lot of time to gather. Although a high level of detail is available for each listing, not all features are homogeneously reported. This is why we only kept the variables that could categorize every listings. We thus have the price of a night for each listing, the type of rental (entire home/apartment, private room, and shared room), the type of property (house, apartment, cottage, island, etc.), and type of cancellation policy, as we trust these characteristics influence the substitutability with an hotel room, and thus should have a different impact.

We now describe each characteristic in more details. Listings can be split in three categories called "room type" which describes more or less the level of intimacy of the place: Entire home/apartment, private room, and shared room. The first two are more likely to attract customers from hotels while the last one features more of a hostel dorm. A second distinction can be made in the research filter according to the "property type". While most listings are either a house, an apartment, or a bed & breakfast, you can also find boats, planes, castles, islands, and many more. Another important aspect of a listing to consider is the cancellation rule that the host chooses. The main three different options are "flexible", "moderate", and "strict"[9]. They differ in how long in advance you must cancel, and how much it will refund you. Important to mention here is that the additional percentage directly paid to Airbnb cannot be reimbursed. This is why we consider all these factors in this paper.

[8]Data at the hotel level is available at a cost from the STR census including most hotels in these countries.

[9]See https://www.airbnb.com/home/cancellation_policies for more details about cancellation policies

Additional information that we have for each listing is reviews from previous guests, reviews of other listings belonging to the same host if he has more than one, potential number of guests, and the creation date of the host's profile. Remaining information, although interesting, could not be included in this paper as they were much harder to scrape and not available for all listings. This includes different price schemes (weekly fee, monthly fee), extra fee per additional guest, different amenities, type of bed, number of bathrooms, minimal stay, cleaning fee, security deposit, etc.

The paper from Zervas et al. (2014) also obtained a cross-section of all accommodations listed on Airbnb at the time they scraped the website. They then proxy the date of entry with the date the user became member of Airbnb. They mention that one must assume that users with many listings have put them all online the month they went on Airbnb. More importantly, they do not observe listings that exited the market. Although this is usually an important issue as market exit is endogenous, it appears to be less important when market entry is exponential as they argue Airbnb is. When we scraped the data from Airbnb, it first took several days just to obtain the url of all available listings. By the time we used this list to get all information from each listings, many where no longer available already. This means that exit might be more important than expected, at least in the countries we are interested in where rural depopulation could explain part of this phenomenon[10].

3 The Model

Following Zervas et al. (2014), our analysis takes advantage of the fact that Airbnb entered these regions at different points in time, and also grew differently depending on the geographical area. In figure 4, one can see the different Airbnb entry patterns in the most populated regions of our sample. This high variability allows us to look at how hotel room revenue evolved differently where Airbnb was more present, and thus identify the impact of Airbnb on hotel revenue.

Our main specification for the DD identification strategy looks like this:

$$logRevPAR_{it} = \beta logAirbnb_{it} + \delta_i + \tau_t + X_{it}'\gamma + \epsilon_{it} \tag{1}$$

where log RevPAR is the log of the average revenue per available room for all hotel in region i at time t. Log Airbnb is the total number of Airbnb listings in log, δ is a region fixed effect, and τ is a month-year time dummy. In X we include all region-specific observables that change with time and could be correlated with both log RevPAR and log Airbnb such as unemployment rate, population, GDP per capita, and a region-specific time trend (linear or quadratic)[11]. This allows us to account for unobservables that evolves differently across counties but follow a structural trend.

[10]See Martti Lujanen (2004)

[11]Following Zervas et al. (2014), we use a quadratic region-specific time trend. They mention that the use of such a trend could be problematic without many pre-treatment periods.

The main advantage of our approach is that we do not have to worry about unobservables simultaneously affecting hotel revenues and Airbnb entry that does not change with time, or change equally across all regions. Indeed, the first difference uses the region fixed effects to account for time-invariant differences in average hotel revenues between treated and non-treated counties (i.e. counties with and counties without Airbnb respectively). In a second time, the year-month fixed effects account for revenue differences variations that are common in all regions. For instance, awareness to Airbnb should increase similarly across the three countries and is thus accounted for. In the same way, if one region is more attractive to tourists because of its access to the sea or the mountains, this is also implicitly included in our model as it remains constant for the observed period. The coefficient β is the one we are interested in as it estimates the percentage change in hotel room revenue in treated regions after treatment, against the control group. We will consider later the remaining possible endogeneity between hotel revenue and Airbnb supply coming from temporary local demand shocks.

We decided to weigh each region according to its population density for all specifications. The reason behind this is that some counties such as Oslo are one big city, while others like Lapland cover a huge but sparsely populated area. Therefore, if Airbnb enters in Oslo, it should impact a greater proportion of the hotels in the county than would the same happen in Lapland, as greater distance between hotels decreases competition[12]. This is why we want regions densely populated to weigh more in the regression. All standard errors are robust to heteroskedasticity and autocorrelation within regions.

4 The Results

Table 3 compares the results for the different controls. Column 1 is the naive model where we only include region and month-year fixed effects. We hence assume that everything affecting hotel revenue and Airbnb supply is either fixed in time, or varies equally in all regions. This is clearly a bold assumption since the coefficient of interest loses its significance when we introduce observables varying differently across regions or countries such as the log of population, the unemployment rate or the log of GDP per capita. We then want to control for unobservables that evolve following some trend that can differ from a region to another. This is often done in DD papers by including a linear or a quadratic region-specific time trend[13]. Column 3 and 4 reports the results with a linear and a quadratic region-specific time trend respectively. Whilst β has the expected negative sign in all our specifications, it is only significant when we abstract from any additional control. In Zervas et al. (2014), they only report estimates with the quadratic city-specific trend since their results were apparently not really affected by this choice. The impact they find is three times higher than the one we have in column 4, and is significant at the 1% level. In

[12]See Balaguer & Pernias (2013)
[13]See Zervas et al. (2014) p.4

what follows, we explore different specifications to see if our coefficient remains insignificant.

Because we observe Sweden for a shorter pre-treatment period, we have an unbalanced panel data. Column 2 in table 4 uses the same specification that the last column of table 3 (which we reproduced in column 1 of table 4 for easier comparison) but we excluded Sweden from the sample to obtain a balanced panel data. One can see that the β coefficient becomes more negative (although still not significant). This could indicate that Airbnb's impact is heterogeneous across the countries which casts doubt on the relevance of pooling them. It is true that Sweden differs from its neighbors with respect to its housing market[14]. In its most important agglomerations, regulation to keep prices for housing low is such that demand is not fully supplied and part of Airbnb listings might just be using this to rent their place for a much higher price, and should have no impact on hotels. If this is truly happening, the observed increase in magnitude of β when excluding Sweden should be more important when we weigh regions with respect to their population density than when we do not. To give the intuition behind this, remember that the shortage of housing in Sweden is only present in its most important cities, thus in its most densely populated counties. Hence, when we give more weight to these regions, including Sweden in the sample should logically push the coefficient more toward zero since Airbnb would compete relatively much less under this assumption. To test this hypothesis, we report in column 3 and 4 the equivalent of column 1 and 2 respectively when we give the same weight to every regions in the sample. To put it more clearly, under the null hypothesis that Sweden is comparable to Finland and Norway, $|(1) - (2)| \ngtr |(3) - (4)|$, where (x) designs table 4's column x. Since $0.007 < 0.01062$, we cannot reject the null hypothesis and must find another explanation for what we observe[15]

What we believe is that this effect comes from the short pre-treatment period available for Sweden. Figure 3 shows the evolution of log hotel revenue per available room for all counties (seasonally adjusted). As we can see, hotels have experienced an important drop in their revenue between 2008 and 2010, which coincides with the whole pre-treatment periods for Swedish counties where Airbnb entered the earliest. Even though we control for the GDP per capita, it is likely that we do not completely overcome this issue. Provided that this is the only thing that causes our estimates to differ, we can take the results from the subsample and extend them to Sweden. From this point we will always report the results with and without Sweden[16]

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[14]See Martti Lujanen 2004

[15]The conclusion of the test is robust to different controls, although not reported here.

[16]One thing to consider though is that we always cluster at the region level so that removing Sweden leaves us with only 38 regions. This could be considered as a few clusters problem with the possibility that we underestimate the standard errors. Since our standard errors do not get smaller, we do not address this potential issue. See Cameron and Miller (2015) for more on clusters.

Adressing endogeneity

As we mentioned earlier, our model does not account for temporal local demand shocks. In Zervas et al. (2014), they claim to control for that by including the log of hotel rooms supply in a city excluding hotel i. They explain that a demand shock anticipated by both hotels and Airbnb could cause them to change their capacity in the same direction, increasing the impact on hotel i's revenue. We cannot replicate this strategy in our work since we do not have observations at the hotel level. On the other hand, we also have our doubts on the effectiveness of their method for two reasons. First of all, this assumes that hotels use quantity rather than price to adjust for short-term demand fluctuations. Intuitively, unless they close during low seasons, hotels should be more likely to adjust their price or their staff instead of closing some rooms. Second, if Airbnb has an effect on hotel rooms supply, then the model will not assess the net impact of Airbnb on hotel revenue, but only the direct one.

Instead, we try to tackle the problem by reducing the frequency of observations to quarterly or biannual data. That way we should be able to ignore local demand shocks that are temporary enough and thus solve our main endogeneity concerns. The results are reported in table 5 where the first two columns report the previous estimations with monthly data from before for comparison, and even column numbers exclude Sweden from the sample. In column 3 and 4, we used quarterly data for the analysis, and biannual data for the last two columns. We still do not find any significant impact, so that if this successfully solves the endogeneity issue, we must conclude that Airbnb did not significantly affect hotel revenue per available room since it first arrived in these countries.

The revenue per available room is the product of the price of a room and the occupancy rate of the rooms. We thus repeat the same exercise with occupancy rate and the log of price as independent variable. Table 6 reports the estimates for the log of the price of a room. First thing to notice is that the impact becomes significant at the 5% level when we exclude Sweden. The impact also increases in column 3 and 4 as we use quarterly observations, pointing toward the possibility that this solves the endogeneity problem. The estimate even becomes slightly significant in the full sample when using biannual data (column 5), although column 6 shows a lower impact than column 4[17]. Estimates for occupancy rate are not reported since the coefficients never became significant (although always negative as anticipated).

These results let us believe that hotels tend to adjust to the market using the price rather than the quantity. Hotels might prefer to reduce their price to maintain a certain level of occupation in order to cover costs that are fixed in the short run. The estimate tells us that whenever Airbnb listings increase by 10%, hotel room monthly revenue decrease by 0.111%[18] (to be conservative) in Finland or Norway, which we could extrapolate to Sweden.

We also explore the possibility that the impact from Airbnb's entry may take

[17] One must be careful in interpreting the estimates from column 6 since the number of observations is much lower.

[18] $1 - (1.1^{-}0.0117) = 0.001114$

some time to be felt. Intuitively, most people traveling plan their trip in advance so that listings entering the market at the time of traveling do not impact their choice of accommodation. We compare both specifications in table 7. β is indeed of higher magnitude when we take one month lagged value of Airbnb listings, but only for the non significant coefficient, while it loses significance in column 6. The results are thus inconclusive.

As opposed to Zervas et al. (2014) we did not find that Airbnb had a significant impact on hotel revenue per available room when extending their methodology to the Nordic countries. We present here some possible reasons why our results differ from their analysis.

First of all, they individually observed all hotels while we only had the average values at the region level. This difference has three major implications. First, we measure the impact of Airbnb supply on a much greater area while they get a much more local effect which is likely to be of greater magnitude. Second, they can focus on big cities while we must also include rural areas in our sample in which hotels compete differently[19]. Finally, the impact we measure could still be underestimated because we do not observe hotels individually. For instance, if Airbnb has a strong impact on the lower cost hotels to the point that they put them out of business, the net impact on the average price or revenue would be upward biased.

Alternatively, Texas and our countries of interest are different in many ways which we cannot account for. For instance, maybe hosts join Airbnb in Texas because they need it to pay their rent, whilst in Norway or Finland they do it to accommodate tourists. In other words, it could be the case that people use Airbnb to absorb individual shocks when the government provides less insurance (people in Texas receive less benefits from the State when they become unemployed than people in the Nordic countries). We would thus be faced with more endogeneity in our sample, hence underestimating Airbnb's impact. A last hypothesis that we cannot test is whether most hotels in the Nordic countries are only a front to bleach money from illegal activities. If that would be the case, revenue per hotel room should not correlate with Airbnb supply as they do not compete against each others, which would explain our results.

5 Some Extensions

Differentiating Listings

Now that we have a good idea of the average impact of any additional listings on hotel revenue, we can dig deeper to see how listing's characteristics matter. As they advertise it themselves, Airbnb lists all sort of accommodations, from a house or an apartment to some more extravagant ones such as a tipi, a boat, a lighthouse, or even an island. As we mentioned earlier, all these characteristics should influence how closely they can replace a hotel room, and thus have a different impact on their revenue. To verify this, we regressed the log of Airbnb

[19] See Balaguer & Pernias (2013)

supply on revenue, occupancy rate, and hotel room price, excluding certain types of listings. For instance, we first took out listings categorized as "shared room". One can argue that people searching for a shared room are looking for a different experience than what hotels typically provide. As expected, the coefficient does increase from the original settings.

We then kept only listings that are not categorized as tent (including yurts and igloos) or as a mean of transportation like boats or RV. We also exclude "others" as it was hard to find out what it was without looking manually into each of them. Surprisingly, found a lesser impact than without that filter. Apparently, at least in these countries, these sort of "into the wild" accommodation do compete with hotels somehow.

The last feature we use to differentiate listings is the cancellation policy. This is important as uncertainty is always part of a trip, and most hotels on booking sites have relatively flexible cancellation rules. On Airbnb, flexible and moderate cancellation rules are comparable with standard hotels, while all rules beyond that should make the listing less substitutable. This is why we try and exclude these from the sample and find slightly higher β. To avoid too much redundancy, we do not report each of these specifications, but these results show that shared rooms and strict cancellation policies capture less costumers than other types of listings. To show it more explicitly, we have excluded both types from table 8, as well as Sweden otherwise no coefficient would be significant. Now a 10% increase in this type of listing reduces the price of a hotel room by 0.12% in Norway and Finland.

Country of origin

An interesting question that will be addressed here is what kind of hotel guests Airbnb is capturing. For the sake of data availability, we restrict our analysis on the country of residence and the category of the guests (business, conference, holiday). Table 1 shows that the majority of hotel guests (80% in average) come from the same country than the hotel is located in, which we will call national guests. These guests should be relatively less likely to use Airbnb since its main appeal, besides its relatively low price, is the "unique experience to live like a local" which should be more attractive to outsiders. We should therefore expect to see a positive impact of Airbnb supply on national guests' share of total hotel guests. Using the same model than equation 1 but substituting log of RevPAR by share of national guests, we find in table 9 what we were expecting. In column 1, we look at the impact on national guests' share. Column 2 takes the proportion of guests coming from Sweden, Finland, and Norway (Nordic guests), and column 3 adds Denmark and Russia in the share since they are neighbors (Nordic guests + neighbors). It is interesting to compare the three columns to find out that not only locals are relatively less interested in using Airbnb when traveling within their own country, but also within those three countries as the coefficient becomes slightly more positive for Nordic guests. Furthermore, including Danish and Russians reduces the impact, implying that they substitute hotels with Airbnb relatively more that Norwegians, Finnish, and Swedish. The absolute magnitude of the coefficient is of little interest since it tells nothing about the total number of guests.

GDP per capita is obviously positive and highly significant since a strong majority of hotel clients are national guests, and their ability to travel depends a lot on their income.

Category of guests

We repeat the same procedure but differentiating guests with respect to the purpose of accommodation. Table 10 regresses Airbnb supply on the fraction of guests sleeping in an hotel for leisure, for a conference or a course, and for work related purpose in column 1, 2, and 3 respectively. Although none of them is significant at the 5% level, the sign does coincide with Zervas et al. (2014)'s results where they find that Airbnb affected more hotels without a meeting space, meaning that people traveling for work are less likely to turn to Airbnb for their accommodation, at least at the time of this study. Indeed, Airbnb has lunched last year a campaign targeting business travelers[20] which should increase further their impact on hotels.

6 Conclusion

The purpose of this paper was to measure the impact of Airbnb on the hotel industry in Norway, Finland, and Sweden. The motivation for this was to empirically contribute to the actual heated debate taking place worldwide by looking at a different market than those more typically covered. We found that Airbnb did not significantly affect hotel's revenue per available room in average, but did contribute to a reduction in the average price of a room where Airbnb entered the most. We also found evidence that Airbnb's "cultural experience" makes it relatively more attractive for foreigners than locals.

The long term impact of peer-to-peer platforms is uncertain as companies such as Airbnb are receiving a lot of pressure from people who invested huge amounts of money in it and are expecting the same high returns they have achieved before due to their exponential growth worldwide. They have recently started to reposition themselves toward a more standardized experience in term of quality and have hired Chip Conley (founder of Joie de Vivre Hospitality) as the Head of Global Hospitality[21].

One aspect concerning Airbnb that we have briefly mentioned in our paper but have not given the appropriate attention is the impact that Airbnb has on housing markets. According to a report by the city of San Fransisco, Airbnb could be taking about 40% of potential rentals off the market[22]. Similar worries

[20] See http://techcrunch.com/2014/07/28/airbnb-concur/

[21] https://www.airbnb.com/press/news/airbnb-names-chip-conley-as-head-of-global-hospitality

[22] http://www.businessinsider.com/san-francisco-report-blames-airbnb-for-housing-shortage-airbnb-strikes-back-2015-5

have begun to emerge in other big cities around the world such as New-York, Vancouver, and Berlin. They fear that Airbnb reduces supply for long-term accommodation, which increases the price, or put people on the street where prices are regulated. Although some studies have tried to empirically verify these claims, they either lack of good data or objectivity. We believe that future research should focus on that aspect if we want to get a better idea about this type of peer-to-peer platform's impact on total welfare.

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7 Appendix

Table 1: Principal summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Log RevPAR	3.642	0.303	2.442	4.643	6959
Occupancy rate of room	0.47	0.112	0.158	0.891	6959
Log of room price	4.426	0.12	3.996	4.942	6959
National guests	0.803	0.122	0.204	0.982	6977
Nordic guests	0.836	0.115	0.23	0.985	6977
Nordic guests + neighbors	0.876	0.097	0.267	0.989	6977
Holiday travelers	0.41	0.173	0.101	0.944	4493

Table 2: Number of Airbnb listings depending on different search filters

Filter	Number	Percentage
No filter	16688	100.00
No shared room	16417	98.38
No camping & others	16487	98.80
No strict cancellation	15618	93.59
No shared room & no strict cancellation	15367	92.08

Figure 1: Comparison of number of rooms per hotel and total number of Airbnb listings as of May 2015, by county

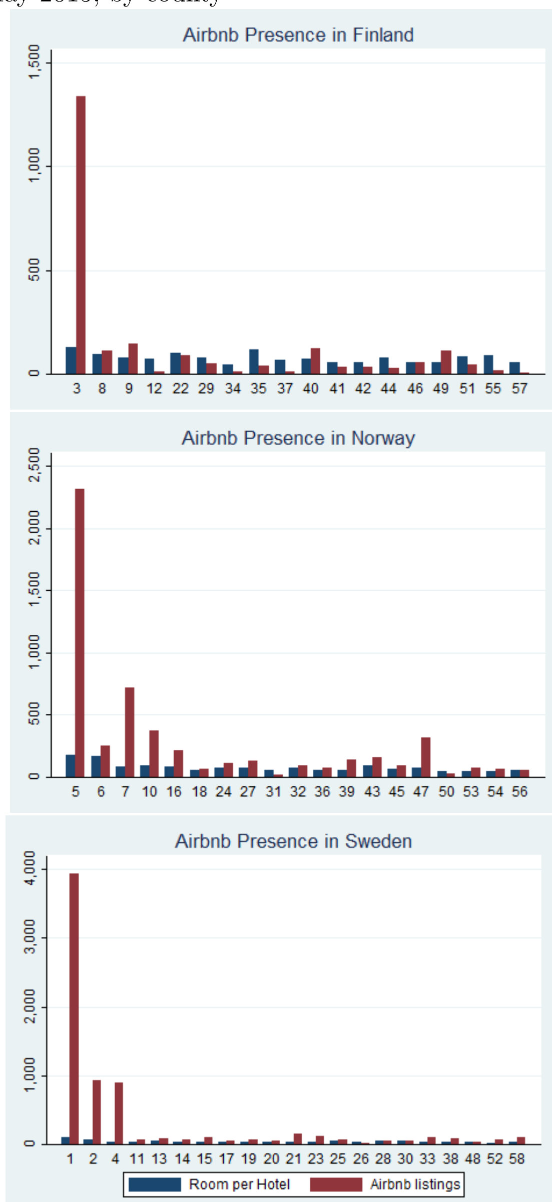

Figure 2: Market share of Airbnb measured by available rooms as of May 2015, by county

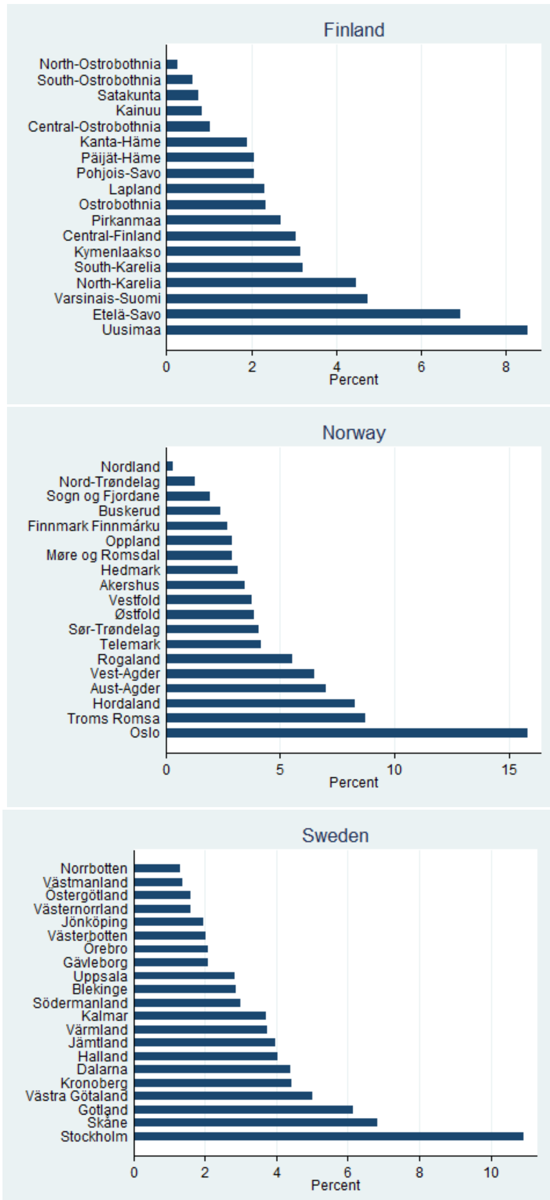

Figure 3: Evolution of log revenue per available hotel room (RevPAR), seasonally adjusted and biannual observations

Figure 4: Evolution of number of Airbnb listings relative to the number of hotel rooms before Airbnb entry for the 10 most populated regions

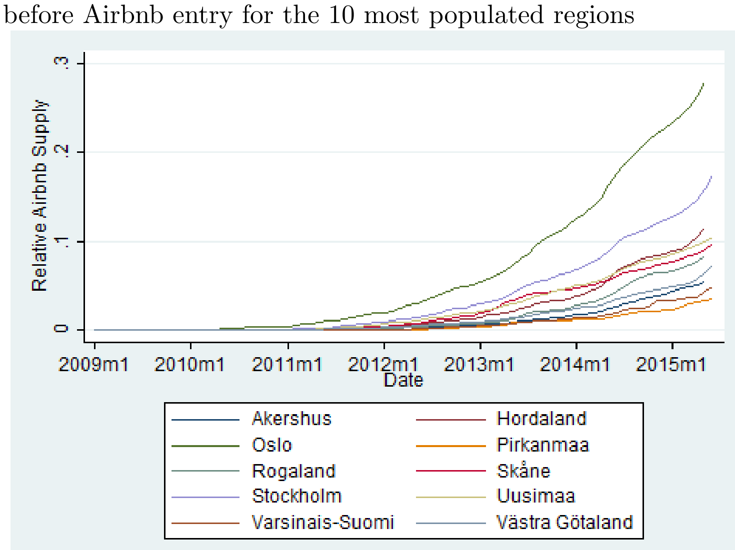

Table 3: DD estimates of the impact of Airbnb on hotel room revenue, with different controls.

	(1) Revenue	(2) Revenue	(3) Revenue	(4) Revenue
log Airbnb supply	-0.0138**	-0.00384	-0.00569	-0.0102
	(0.00579)	(0.00657)	(0.0101)	(0.0110)
log population		-0.581*	5.080**	2.680
		(0.293)	(2.013)	(3.074)
unemployment		-0.00861**	-0.00292	-0.00253
		(0.00339)	(0.00307)	(0.00249)
log GDP per capita		0.152	-0.0775	0.0105
		(0.285)	(0.281)	(0.326)
region-specific trend	No	No	linear	quadratic
Observations	6959	6959	6959	6959
Adjusted R^2	0.396	0.400	0.429	0.440

Cluster-robust standard errors in parentheses.

All specifications include region and time fixed effects.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: Evolution of log RevPAR for regions with low Airbnb presence compared to regions with high Airbnb presence, seasonally-adjusted biannual observations

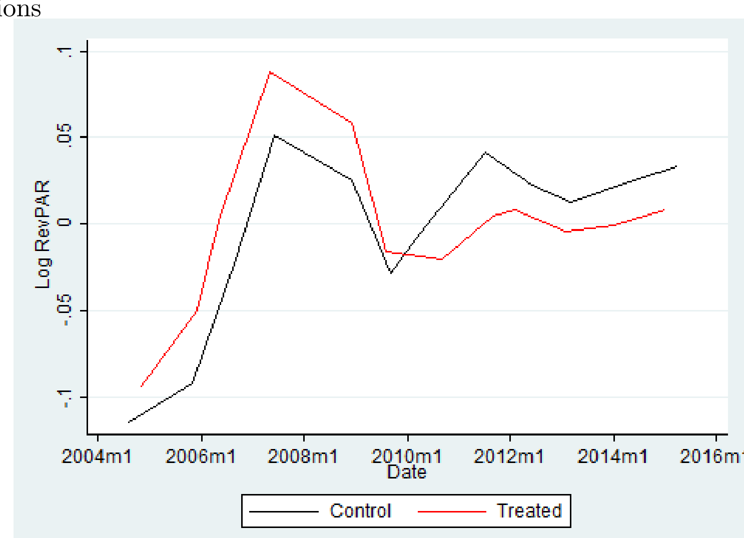

Table 4: DD estimates of the impact of Airbnb on hotel room revenue, weighed and unweighed regressions.

	weights		no weights	
	(1)	(2)	(3)	(4)
	Revenue	Revenue	Revenue	Revenue
log Airbnb supply	-0.0102	-0.0168	-0.00651	-0.0164
	(0.0110)	(0.0112)	(0.00995)	(0.0109)
log population	2.680	-2.393	4.729*	-0.500
	(3.074)	(3.068)	(2.692)	(2.768)
unemployment	-0.00253	-0.00298	-0.00357	-0.00469
	(0.00249)	(0.00283)	(0.00312)	(0.00353)
log GDP per capita	0.0105	-0.364	-0.301	-0.981
	(0.326)	(0.588)	(0.499)	(0.824)
Sweden	Yes	No	Yes	No
Observations	6959	5069	6959	5069
Adjusted R^2	0.440	0.476	0.357	0.397

Cluster-robust standard errors in parentheses.

All specifications include region and time fixed effects.

All specifications include a quadratic region-specific time trend.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: DD estimates of the impact of Airbnb on hotel room revenue at different frequency level.

	Monthly		Quarterly		Half yearly	
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue
log Airbnb supply	-0.0102	-0.0168	-0.0135	-0.0203	-0.0124	-0.0141
	(0.0110)	(0.0112)	(0.0116)	(0.0124)	(0.0106)	(0.0107)
log population	2.680	-2.393	2.911	-1.806	2.517	-2.293
	(3.074)	(3.068)	(3.131)	(3.142)	(2.926)	(3.089)
unemployment	-0.00253	-0.00298	-0.00312	-0.00384	-0.00103	-0.00124
	(0.00249)	(0.00283)	(0.00261)	(0.00290)	(0.00260)	(0.00280)
log GDP per capita	0.0105	-0.364	0.0396	-0.407	0.0419	-0.0541
	(0.326)	(0.588)	(0.278)	(0.545)	(0.231)	(0.370)
Sweden	Yes	No	Yes	No	Yes	No
Observations	6959	5069	2324	1694	1159	844
Adjusted R^2	0.440	0.476	0.420	0.479	0.553	0.611

Cluster-robust standard errors in parentheses.

All specifications include region and time fixed effects.

All specifications include a quadratic region-specific time trend.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: DD estimates of the impact of Airbnb on hotel room price at different frequency level.

	Monthly		Quarterly		Half yearly	
	(1)	(2)	(3)	(4)	(5)	(6)
	Room price	Room price	Room price	Room price	Room price	Room price
log Airbnb supply	-0.00608	-0.0117**	-0.00758	-0.0142**	-0.00816*	-0.0116**
	(0.00580)	(0.00567)	(0.00606)	(0.00597)	(0.00480)	(0.00502)
log population	0.952	0.356	1.018	0.669	0.962	0.608
	(1.289)	(1.599)	(1.307)	(1.614)	(1.255)	(1.618)
unemployment	-0.000460	-0.000661	-0.000758	-0.00102	0.000610	0.000502
	(0.00112)	(0.00121)	(0.00115)	(0.00120)	(0.00117)	(0.00121)
log GDP per capita	0.119	0.0417	0.125	0.00391	0.117	0.0486
	(0.108)	(0.204)	(0.0931)	(0.183)	(0.0812)	(0.146)
Sweden	Yes	No	Yes	No	Yes	No
Observations	6959	5069	2324	1694	1159	844
Adjusted R^2	0.283	0.300	0.366	0.429	0.576	0.619

Cluster-robust standard errors in parentheses.

All specifications include region and time fixed effects.

All specifications include a quadratic region-specific time trend.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Try with different lags

	(1) Revenue	(2) Occupancy rate	(3) Price room	(4) Revenue	(5) Occupancy rate	(6) Price room
log Airbnb supply	-0.0102	-0.00210	-0.00608	-0.0168	-0.00251	-0.0117**
	(0.0110)	(0.00404)	(0.00580)	(0.0112)	(0.00437)	(0.00567)
log population	2.680	0.293	0.952	-2.393	-2.229	0.356
	(3.074)	(1.358)	(1.289)	(3.068)	(1.393)	(1.599)
unemployment	-0.00253	-0.00128	-0.000460	-0.00298	-0.00147	-0.000661
	(0.00249)	(0.000861)	(0.00112)	(0.00283)	(0.000937)	(0.00121)
log GDP per capita	0.0105	-0.0690	0.119	-0.364	-0.271	0.0417
	(0.326)	(0.114)	(0.108)	(0.588)	(0.196)	(0.204)
Observations	6959	6959	6959	5069	5069	5069
Adjusted R^2	0.440	0.592	0.283	0.476	0.615	0.300

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) Revenue	(2) Occupancy rate	(3) Price room	(4) Revenue	(5) Occupancy rate	(6) Price roo
log Airbnb supply$_{t-1}$	-0.0126	-0.00353	-0.00624	-0.0184	-0.00339	-0.0116*
	(0.0108)	(0.00394)	(0.00598)	(0.0109)	(0.00418)	(0.00595)
log population	2.688	0.304	0.944	-2.369	-2.202	0.330
	(3.032)	(1.328)	(1.290)	(3.040)	(1.378)	(1.594)
unemployment	-0.00251	-0.00126	-0.000458	-0.00297	-0.00146	-0.000659
	(0.00249)	(0.000858)	(0.00112)	(0.00283)	(0.000936)	(0.00122)
log GDP per capita	0.00900	-0.0699	0.119	-0.364	-0.271	0.0430
	(0.327)	(0.115)	(0.108)	(0.589)	(0.196)	(0.204)
Observations	6959	6959	6959	5069	5069	5069
Adjusted R^2	0.440	0.592	0.284	0.476	0.615	0.300

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: DD estimates of the impact of Airbnb's closest hotel substitutes on hotel room revenue, occupancy rates, and prices.

	(1) Revenue	(2) Occupancy rate	(3) Price room	(4) Revenue	(5) Occupancy rate	(6) Price room
log Airbnb supply	-0.0181	-0.00225	-0.0126**	-0.0168	-0.00251	-0.0117**
	(0.0120)	(0.00454)	(0.00577)	(0.0112)	(0.00437)	(0.00567)
log population	-2.584	-2.268	0.224	-2.393	-2.229	0.356
	(3.132)	(1.410)	(1.662)	(3.068)	(1.393)	(1.599)
unemployment	-0.00292	-0.00146	-0.000619	-0.00298	-0.00147	-0.000661
	(0.00282)	(0.000935)	(0.00121)	(0.00283)	(0.000937)	(0.00121)
log GDP per capita	-0.367	-0.271	0.0394	-0.364	-0.271	0.0417
	(0.588)	(0.196)	(0.204)	(0.588)	(0.196)	(0.204)
All listings	No	No	No	Yes	Yes	Yes
Observations	5069	5069	5069	5069	5069	5069
Adjusted R^2	0.476	0.615	0.300	0.476	0.615	0.300

Cluster-robust standard errors in parentheses.

All specifications include region and time fixed effects.

All specifications include a quadratic region-specific time trend.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: DD estimates of the impact of Airbnb on hotel's guests composition by country of origin.

	(1) National guests	(2) Nordic guests	(3) Nordic guests + neighbors
log Airbnb supply	0.00466**	0.00486**	0.00342***
	(0.00202)	(0.00190)	(0.00110)
log population	-0.876	-0.855	-0.166
	(0.585)	(0.596)	(0.390)
unemployment	0.00129	0.00102	0.000305
	(0.000917)	(0.000864)	(0.000641)
log GDP per capita	0.391***	0.411***	0.411***
	(0.119)	(0.116)	(0.0936)
Observations	6977	6977	6977
Adjusted R^2	0.293	0.291	0.356

Cluster-robust standard errors in parentheses.
All specifications include region and time fixed effects.
All specifications include a quadratic region-specific time trend.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: DD estimates of the impact of Airbnb on hotel's guests composition by purpose of stay.

	(1) Holiday, recreation	(2) Course, conference	(3) Occupation
log Airbnb supply	-0.00442	0.00410*	0.000335
	(0.00352)	(0.00222)	(0.00310)
log population	-0.751	0.0175	0.740
	(0.822)	(0.682)	(0.759)
unemployment	0.00512*	0.000200	-0.00529**
	(0.00265)	(0.00102)	(0.00215)
log GDP per capita	-0.0764	0.0305	0.0464
	(0.0898)	(0.0437)	(0.0753)
Observations	4493	4493	4493
Adjusted R^2	0.767	0.630	0.636

Cluster-robust standard errors in parentheses.

All specifications include region and time fixed effects.

All specifications include a quadratic region-specific time trend.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Experimental 2SLS model instrumenting Airbnb supply with region-specific time trend.

	(1) Revenue	(2) Revenue	(3) Revenue	(4) Revenue
log Airbnb supply	-0.0334***	-0.0681***	-0.0169**	0.0126
	(0.0107)	(0.0138)	(0.00835)	(0.0105)
log population	4.632**	4.508**	6.615***	6.291***
	(1.944)	(1.952)	(1.064)	(1.066)
unemployment	-0.00358	-0.00359	-0.00497**	-0.00472**
	(0.00257)	(0.00258)	(0.00230)	(0.00230)
log GDP per capita	-0.324***	-0.353***	-0.334***	-0.333***
	(0.115)	(0.116)	(0.102)	(0.102)
region-specific trend	quadratic	quadratic	linear	linear
Observations	6959	6959	6959	6959
Instrument	degree 4	degree 3	degree 3	degree 2

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$