The Effect of Airbnb on Hotels

Evidence from Berlin

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Abstract

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Introduction

Airbnb is a young company that has revolutionized the accomodation industry in much the same way that Uber has revolutionized transportation. It is an online platform that allows "hosts" to share their a room in their home or a rental home with travelers. For hosts, using Airbnb can be a valuable source of extra income. For guests, Airbnb provides accomodations that allows travelers to both save money and have a more authentic experience during their stay. Airbnb guests often remark that they interacted with their hosts and felt more like a local than a tourist. Indeed, Airbnb's recent "Don't Go There, Live There" advertising campaign is a reflection of their philosophy in reshaping the accomodation industry.

In Berlin more than 20,000 Airbnb hosts have been active over the past year, hosting more than half a million guests. According to Airbnb, their presence in Berlin brings more economic activity to the city, particularly to neighborhoods outside of the main hotel districts. Yet, Airbnb's entry in Berlin has been highly controversial. In 2014, the city passed a law that forbade renting out entire apartments to tourists on Airbnb. This came in response to an unprecedented 56 percent rise in rents in Berlin between 2009 and 2014, for which Airbnb and other online hosting platforms received some of the blame (France-Presse, 2016). The city's law was widely welcomed by Berliners hoping to slow the forces of gentrification, but it was also welcomed by another Airbnb victim in Berlin; the hotel industry.

While Berliners compete with tourists for apartments, the hotel industry has been quietly fighting a battle of their own against Airbnb. Airbnb represents an unprecedented challenge for the long-time incumbents, whose average price of 80 euros per night in Berlin cannot compete with the average Airbnb price of 55 euros per night (Skowronnek, Vogel, & Parnow, 2015). Moreover, Airbnb enjoys some real advantages over the hotel industry due to its new, still largely unregulated business model. For example, its informal business model has thus far allowed it to avoid the taxes and regulations that hotels and other traditional accomodation providers have to deal with (Guttentag, 2015). For their part, Airbnb claims that their service is complementary to hotels and that most of their listings are outside of cities' main hotel districts (Airbnb, 2015). Airbnb guests are also more likely to stay at the host's property long term than a hotel guest is, and it is not uncommon to find Airbnb listings that are rented out to the same guest for a month or longer. Yet despite these differences, many believe there must be some "Airbnb effect" on the hotel industry. A paper by Zervas, Proserpio, & Byers (2016) found that the rise of Airbnb had a negative effect on hotel revenue in the state of Texas. This shows that, while Airbnb may be complementary, they also compete with the incumbent hotel industry.

In this paper we will seek to illustrate the magnitude of the "Airbnb effect" on hotels in Berlin. To that end, this paper will proceed as follows. First, we will review the relevant literature in the field and outline our hypothesis going forward. Second, we will discuss the data sources and variables that we will use to explore this relationship. Third, we will outline the methology we use in this study and describe our model in detail. Fourth, we will analyze the data both descriptively and inferentially to evaluate our hypotheses. Finally, we will discuss our results, the policy implications of our findings, and opportunities for future research.

Literature Review

While the literature on the effect of Airbnb on hotels is quite limited, there is a diverse body of literature available on different aspects of Airbnb's business. In Berlin, much of the discussion has focused on the impact of Airbnb on rents in the city. Schäfer, Braun, Reed, & Johnston (2016), for example, found that 5,555 residential apartments are currently being misused for Airbnb in Berlin. However, as the *Zweckentfremdungsverbot* (Airbnb misuse law) came into effect this year, the main focus of this issue is likely to be enforcement going forward.

Like Uber, Airbnb has also been widely praised for providing a more personalized experience for consumers in an industry that may have lacked it before. In both Yannopoulou, Moufahim, & Bian (2013) and Guttentag (2015), the authors find that the desire for a personalized user experience played a role in the rise of Airbnb. This new expectation has changed the very nature of the accomodation and tourism industry. A working paper by Stors & Kagermeier (2015) shows that this trend extends to Berlin, and indicates that the motives for a tourist to use Airbnb rather than a hotel are both monetary and otherwise. In fact, Stors & Kagermeier found that guests' expectations of having a more authentic, personal experience during their stay were just as important as their monetary concerns. This suggests that the hotel industry in Berlin is not only being undercut in pricing, but also outclassed in the experience they provide.

In Zervas, Proserpio, & Byers (2015), the authors explore user ratings on Airbnb and TripAdvisor. They find that the average user rating of Airbnb is significantly higher than that of the average hotel on TripAdvisor, 4.5 out of 5 stars compared to 3.8 out of 5 stars, respectively. They theorize that Airbnb hosts, being more entrepreneurial than their hotelier competitors, go above and beyond to ensure that they receive good reviews that bolster their individual "brand". Along similar lines, Gutt & Herrmann (2015) investigated how Airbnb hosts change their prices in response to their first review. They found that increased "rating visibility" causes hosts to raise their prices by an average of 2.69 euros.

In Guttentag (2015), the author argues that while many points discounting Airbnb's ability to compete with the traditional accomodation industry are valid, there is still no reason to completely discount the young disruptor's impact. Airbnb will probably never completely replace the hotel industry, but it is already large enough to have an impact nevertheless. Indeed, Guttentag estimates that Airbnb sold about 15 million room nights in 2012, which would have made its footprint on the industry that year similar to that of Fairfield Inn & Suites or InterContinental, two major hotel brands. Guttentag concludes his paper with some recommendations for future research on Airbnb, and highlights the need to investigate the impact of Airbnb on hotel occupancy rates and room prices.

Along those lines, there is one prominent paper that helped inspire our investigation. In their paper, Zervas et al. (2016) used a difference in differences method (DID) to measure the impact that Airbnb's presence had on Texas hotel revenue, and how this impact differed by region and over time. They found that a 10 percent size increase of the Airbnb market in Texas resulted in a .39 percent decrease in hotel revenue. This effect varied widely by region, however. Austin, for example showed a 8 to 10 percent impact on hotel revenue. Zervas et al. also went on to investigate the impact of Airbnb's presence on different types of hotels and how that presence may effect hotel pricing models. They found that hotels with lower prices are more affected than higher priced hotels, and that Airbnb has significantly hindered hotels' ability to raise prices during high demand periods.

In order to add to this body of research, and at the behest of Guttentag (2015), our investigation will focus on the effect of Airbnb listing on hotels in Berlin. Specifically, the following hypothesis will guide our thinking. Controlling for district and economic conditions, we assume that *the higher the Airbnb supply in Berlin, the lower the hotel occupancy rate will be.*

Data & Variables

To approach our research question we use data from four different sources, the Statistical Information System Berlin/Brandenburg (SBB) (StatIS-BBB, 2016), the Federal Statistical Office and the statistical offices of the Länder (FSO)[1] (Germany, 2015), *InsideAirbnb.com* (Cox, 2016), and Eurostat. In order to conduct our analysis we needed to clean, merge and manipulate these data sets.

The surveys from the Statistical Information System Berlin/Brandenburg are carried out at the beginning of each month and refer to the reporting period of the previous month. The results are organized regionally according to districts and municipalities, allowing us to use specific data for hotels in each of the twelve districts in Berlin. From this survey data, we collected monthly data on the number of overnight hotel stays, the number of hotel beds in each district, and the number of guests to arrive at their accommodations in the reporting period in Berlin (StatIS-BBB, 2016).

From the Federal Statistical Office and the statistical offices of the Länder (FSO), we gathered data for yearly household income groups and the number of employed and unemployed people per district. Based on the data, we calculated a yearly average household income and unemployment rate per district (Germany, 2015).

From *InsideAirbnb.com*, we scraped data on 15,368 listings, i.e. apartments or rooms, for Berlin from August, 2008 until October, 2015. This data was extracted from the Airbnb site between 18 July 2015 and 6 January 2016. This data set contained 92 variables for each listing covering topics ranging from room price to information on the host. For our purposes, the key variables were (1) the neighbourhood

[1] Both databases use JAVA-based website, which did not allow direct web scraping. The data was manually downloaded.

of each listing, (2) the date that an Airbnb host signed up, and (3) the date of the first review of each listing (Cox, 2016).

From Eurostat, we gathered monthly data on the number of passengers to arrive in Berlin's two major airports, Tegel and Schonefeld. We use this data to construct a variable that combines the arrivals to both airports every month. In keeping with the Zervas et al. (2016) methodology, we use this variable as our control for the dramatic increase in the popularity of Berlin.

Our analysis also includes a proxy for Airbnb's market entry. It is based on date of of acquisition of the German peer-to-peer market place Accoleo in June 2011, which is considered Airbnb's first move to expand their business model to the European market (TheNextWeb, 2011).

Our most significant methodological challenge was the absence of precise listing availability during our period of interest, as it is not directly available in the data. This would have been the ideal data with which to construct our Airbnb supply variable. However, Airbnb itself is also unable to produce this type of precise data, as hosts do not accurately update their listings' availability. In keeping with the Zervas et al. (2016) methodology, we countered this problem by using review data as a proxy for availability. For both our cumulative and dynamic Airbnb supply variables, we calculated the date 6 months prior to a listing's first review as its listing date. If there was no first review, we used the date that a host signed up on the site as the listing date. If a listing had neither, it was excluded from the analysis. Only five listings were excluded on this basis.

Our analysis includes two measures of district-specific Airbnb supply, a cumulative measure and a dynamic measure. The cumulative measure simply adds new listings to the supply either as they either recieve first reviews or as their owner registers on the site. The weakness of this measure is that it does not eliminate listings that may have ceased to be available. To account for this, we constructed a dynamic measure of Airbnb supply. Like the cumulative measure, the dynamic variable uses either the first review (minus 6 months) or the hosts sign-up date as the listing date. From there, the dynamic measure searches the six months prior to each month in our analysis to find a review. If it does not find one, the listing is assumed to have become unavailable, and drops out of the supply. However, when a listing receives a new review it reenters the dynamic supply.

Admittedly, our approach of using Airbnb reviews as a proxy for Airbnb supply produces something of a conservative Airbnb supply estimate. Fradkin, Grewal, Holtz, & Pearson (2015) found that only 67% of Airbnb guests leave a review following their stay. However, in the absence of exact listing availability data the review data must suffice.

Our dependent variable throughout our analysis will be the occupancy rate of hotels in a given district. We could also have used the number of overnight stays as our dependent variable, as it was directly available in the data. However we did not believe this would sufficiently account for the growing supply of hotel beds in Berlin each year. Therefore, we calculated district specific hotel occupancy rates for each month of our analysis by dividing the number of overnight stays in that month by the product of the supply of hotel beds in each district multiplied by the number of days in each month. (growth rate: ?)

$$OccupancyRate_{it} = \frac{OvernightStays_{it}}{HotelBeds_{it} * days_t}$$

The final data set covers 720 monthly obversations across twelve districts in Berlin and covers the time period between 2010 and 2014.

Methodology & Analysis

Descriptive Analysis

Airbnb‘s popularity in Berlin has exploded since it’s official debut in the city in June 2011. Flatsharing was already on the rise in the ciy, but Airbnb’s acquisition of Accoleo consolidated the Berlin flatsharing industry into one well-known name. As Berlin’s increase in popularity coincided with the rise of Airbnb, many Berliners used the site to list apartments and rooms. The growth in Airbnb listings has not been equal across all neighbourhoods in Berlin, but it has dramatically increased since 2010. In order to take a sneak peek at this relationship, we plotted the log of the dynamic Airbnb supply against hotel occupancy rates. We chose to work with the log of Airbnb supply here in order to normalize the distribution, which was otherwise quite skewed. Yet upon doing so, we were surprised to see a clear positive correlation and a correlation coeffecient of 0.343 *(cf. Figure 1)*. Upon reflection, we realized the importance of controlling for the increased popularity of Berlin in our time period. for the remainder of our analysis, this will be one of our key control variables.

Before moving forward with our inferential analysis, we took a closer look at our two measures of Airbnb supply. We wanted to understand the different results of our supply measurements, and to understand how these might affect our inferential analysis. Upon plotting the neighbourhood specific Airbnb supply in

ggplot(meltdf,aes(x=Year,y=value,colour=variable,group=variable)) + geom_line()

Zervas et al. (2016) accomplished this by controlling for passengers listing the local airport as their final destination. We replicated this approach by using Eurostat data on the number of passengers arriving at Berlin’s two major airports. Upon cleaning this data, we see an increase of ____________________ in the number of passengers arriving in Berlin. Additionally, we will incorporate a time specific trend to account for unobserved heterogeneity. Given confirmation from Zervas et al. that Airbnb does indeed compete with hotels, we believe that the increase in Berlin’s popularity is largely responsible for the positive correlation we observe here.

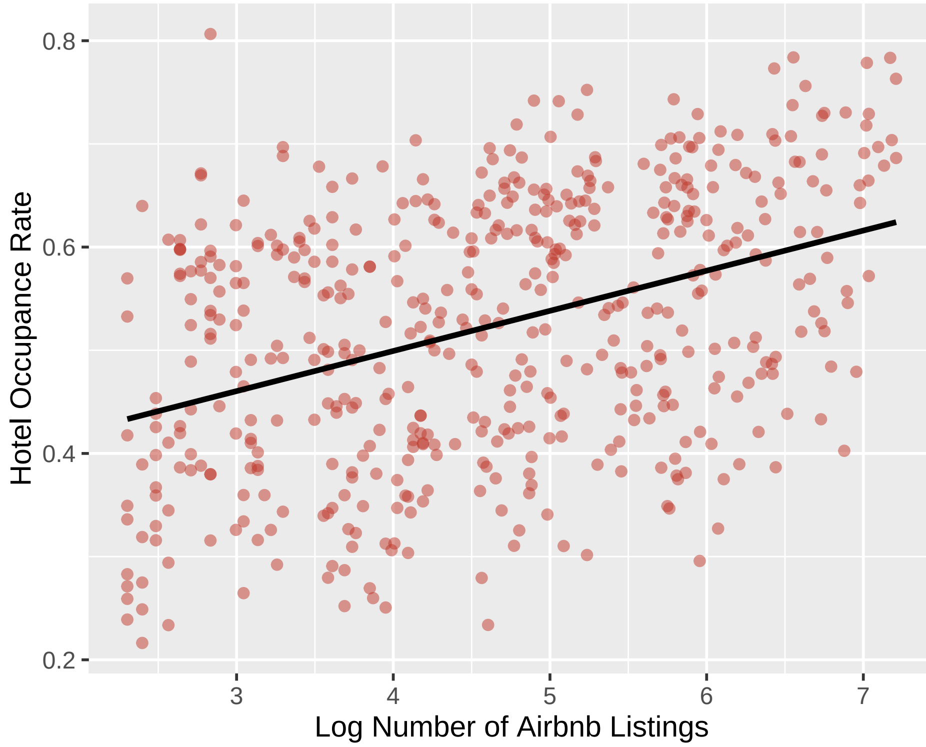

Figure 1: Effect of Increase in Airbnb Listings on Berlin Hotel Occupancy Rates (2010 - 2014)

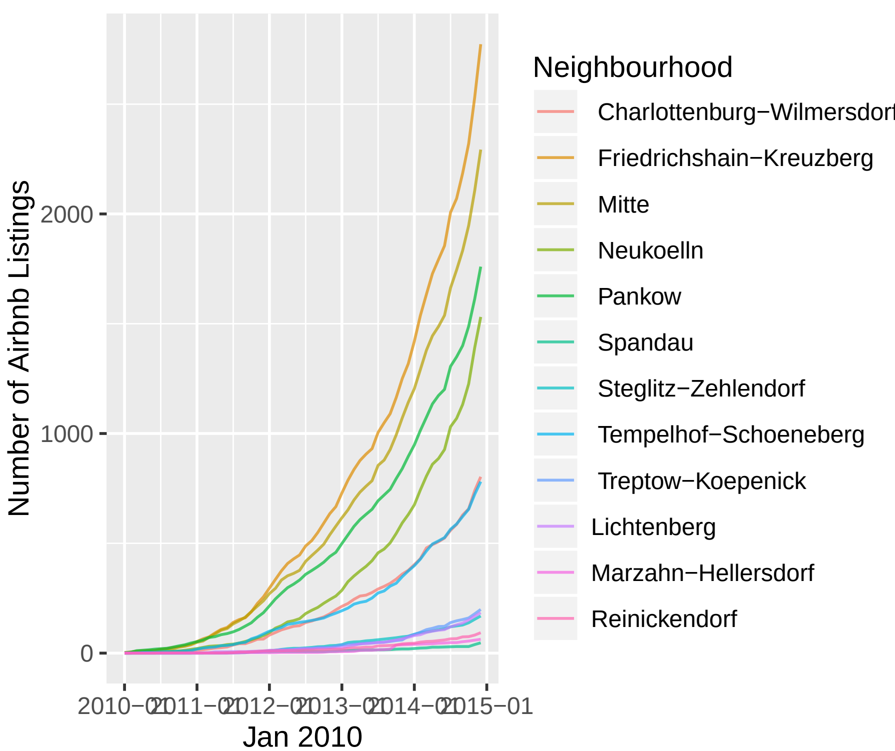

Figure 2: Cumulative Airbnb Supply per Neighbourhood (2010 - 2014)

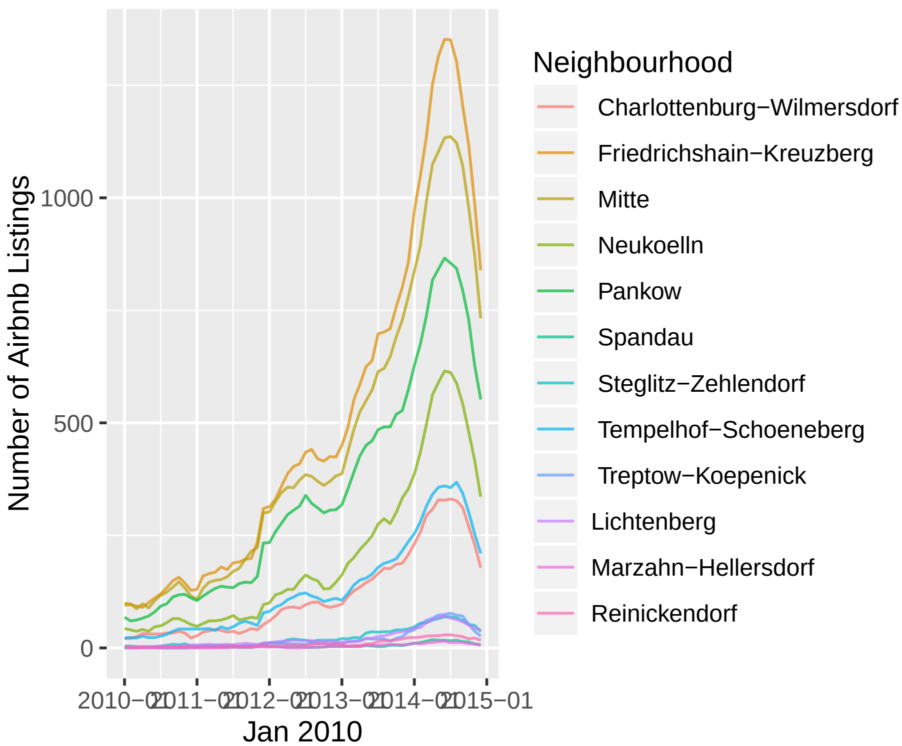

Figure 3: Dynamic Airbnb Supply per Neighbourhood (2010 - 2014)

Inferential Analysis

> The key identification assumption we have to make to support a causal interpretation of this DD estimate is that there are no unobserved, time-varying, city-specific factors that are correlated with both Airbnb entry and hotel room revenue. Stated differently, we assume that unobserved factors that could potentially jointly affect both Airbnb adoption and hotel room revenue do not systematically vary both between different cities and over time.

Unlike Zervas et al. (2016), we cannot use hotel revenue as our main unit of analysis due to data limitations. Instead, our analysis focuses on hotel occupancy rates. We calculated these Also unlike the model used by Zervas et al. (2016), our analysis cannot take advantage of a treatment and control region accounting for the different Airbnb market entry patterns.

Taking the arguments above into account, we use a region fixed effects to account for time-invariant differences in hotel occupancies main specification for our proposal would look like this:

$$(1)\ \ OccupRate_{it} = \beta_i * \log Abb_{it} + \tau_i + \beta_j * X' + \varepsilon_{it}$$

Here, *OccupRate* is the occupancy rate for all hotels in district i at time t. Log *Abb* is the log of the approximated total number of Airbnb listings available in district i at time t. Further, we control for economic conditions (unemployment rate and GDP per capita at federal level) and a district-specific linear time trend to account for unobserved heterogeneous variation across districts by using a month-year time dummy τ.

To decide whether to use a fixed or random effects model, we ran a Hausman test, since a regular OLS regression does not consider heterogeneity across groups or time (SOURCE: Green, 2008). It tests if the unique erros are or are not correlated with the regressors. Performing the test we get a p-value of 1 (check whether this is really true). Thus, we reject the null hypothesis that they are not. The Breusch-Pagan Lagrange multiplier test confirms our results, as there is a panel effect, i.e. a significant difference across neighbourhoods (p-value = 0.01).

Results & Discussion

Table 1 compares the results for the different models.

Table 1:

	Dependent variable:			
	Occupancy Rate			
	LM (1)	FE (2)	FE (3)	FE (4)
Log Airbnb Listings	0.009^{***}	0.026^{***}	-0.010^{***}	-0.008^{***}
	(0.003)	(0.004)	(0.002)	(0.003)
Average HH Income (Log)	-0.139^{*}	-0.388^{*}	-0.280^{***}	-0.291^{***}
	(0.078)	(0.202)	(0.096)	(0.097)
Unemployment Rate	0.141	0.862^{**}	0.351^{*}	0.310
	(0.152)	(0.406)	(0.194)	(0.197)
Incoming Passengers			0.00000^{***}	0.00000^{***}
			(0.000)	(0.000)
Market Entry				-0.008
				(0.007)
Neighbourhood-specific trend	Yes	No	No	No
Time trend	Yes	No	No	No
District/Time FE?	No	Yes	Yes	Yes
Observations	720	720	720	720
R^2	0.996	0.077	0.790	0.791
Adjusted R^2	0.995	0.075	0.773	0.772
Note:				*p<0.1; **p<0.05; ***p<0.01

Column 1 is a simple model where we only include region and month-year fixed effects to account for changes in time in variation across regions. As stated earlier, we interpret the coefficient β of

Table 2: Effect of Airbnb Supply on Hotels in Berlin (2010 - 2014)

	Dependent variable:			
	Overnight		Occupancy Rate	
	(1)	(2)	(3)	(4)
log Airbnb listings	0.03***	0.05***	0.02***	0.02***
	(0.01)	(0.01)	(0.005)	(0.01)
Airbnb listings	0.0001***	0.0002***	0.0003	0.0003
	(0.0000)	(0.0000)	(0.0002)	(0.0002)
Log*Level			−0.0000	−0.0000
			(0.0000)	(0.0000)
Average HH income (log)	−0.20	−1.67***	−1.04***	−1.05***
	(0.24)	(0.59)	(0.26)	(0.26)
Unemployment rate	−1.76***	0.21	0.66	0.77*
	(0.39)	(0.95)	(0.41)	(0.41)
marketentry	0.15**	0.05		0.03
	(0.06)	(0.04)		(0.02)
Constant	14.76***			
	(1.83)			
Neighbourhood-specific trend	Yes	No	No	No
Time trend	Yes	No	No	No
District FE?	No	No	No	No
Observations	720	720	720	720
R^2	0.99	0.18	0.10	0.10
Adjusted R^2	0.99	0.18	0.09	0.10
Note:		*p<0.1; **p<0.05; ***p<0.01		

log *Airbnbsupply* as indicative of Airbnb listings being a substitute for hotel rooms, especially in neighbourhoods with a high Airbnb market penetration. We estimate the coefficient $\beta = 0.02$, or equivalently, a 10 per cent increase in Airbnb listings is associated with a statistically significant 2 per cent ($p < 0.01$) increase in monthly hotel overnight stays. As before, the positive effect of an increasing number of Airbnb listings seems counter-intuitive. Hence, Column 2 includes economic control varibales to mitigate the above effect. It introduces observations for the yearly unemployment rate and the yearly log of average household income varying differently across neighbourhoods. We then want to control for unobservables that evolve following some trend that can differ from one neighbourhood to another. This is done by including a neighbourhood-specific time trend. The results are presented in Column 3.

By using the number of overnights per month and district as dependent variable we imply a constant number of beds over the course of the explored time period. This is certainly not the case, as capacity in Berlin hotels grew on average by around 15% across all districts from 2010 to 2014. To account for the increased capacity we compute the theoretical hotel occupancy rate. From the Regional Database of Germany, we collected data on the supply of hotel beds in each district in a given year. Unfortunately this data is only recorded annually. Hence, our analysis must assume that the number of beds in each hotel stay constant throughout the year. For our main dependent variable, we used data on the number of beds generally available in each district per day in a given year and the monthly data on the number of overnight stays from guests to compute a variable as a proxy for hotel occupancy (as a percentage). The results are presented in table 2.

Our new main specification takes further into account that the effect of Airbnb is likely best observed, once it has reached a critical threshold or market penetration. However, even when introducing an interaction between log Airbnb supply and the absolute level of Airbnb listings we find that Airbnb supply has a highly significant positive effect on hotel occupancy, with a p-value on the .01 % level.

Whilst the effect of Airbnb listings seems to be significant in all our specifications, the expected negative effect is in fact positive, even when controlling for economic heterogeneity.

So far, this paper was not able to identify a negative impact of Airbnb on the Hotel industry in Berlin.

Here, we would try to account for the fact that Airbnb supply is more complicated than we have so far defined it. In light of Zervas, we introduce review data, and redefine airbnb supply to include our best inference as to whether Airbnb was available at a given time based off of those reviews. To do that, we would define supply as the number of airbnb's available in a given apartment in a given month. This would be calculated by looking at the date of the first review of the apartment on Airbnb and the date of the individual reviews. Upon the sign up date, the listing would be assigned a "life period" of 6 months, which would then be renewed every month upon each subsequent review. If a listing exceeds its life period without a review, then we assume that it is no longer available. However, once it recieves another review it would then be considered available again for another 6 months.

Further methods of data exploration

> 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. 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.

how listing's characteristics matter?

Airbnb lists all sort of accommodations, from a house or an apartment to shared rooms. This has an influence on how closely they can replace a hotel room, and thus have a different impact on hotel occupancy. We thus excluded all listings categorized as "shared room".

In contrast to Zervas et al. (2014) we did not find that Airbnb had a significant negative impact on hotel revenue per available room when looking at Berlin. Several reasons migh

First of all, they had used individual data for all hotels while we only had a computed value on hotel occupancy at the district level. Thus, we measure the impact of Airbnb supply on a much smaller scale and might have some sort of omitted variable bias.

Policy Implications & Conclusion

The purpose of this paper was to measure the impact of Airbnb on the hotel industry in Berlin. Whilst a paper by Zervas et al. (2016) found that Airbnb has a negative impact on the hotel industry in Texas, we could not find a similar effect in Berlin. Much to our surprise, we found a positive highly significant effect of Airbnb supply on both, overnight stays and hotel occupancy rates accross all districts between 2010 and 2014.

From our point of view, this might have different reasons. First, our observation period is not ideal. Aside from its obvious time limitation of only four years, our analysis does not include the year 2015. This is a significant loss for the Airbnb supply variable, as it appears that 2015 was the year that Airbnb supply in Berlin truly skyrocketed. We can see in the raw data from *InsideAirbnb.com*, for example, that the number of listings in Friedricshain-Kreuzberg increased by 342 in March of 2015, compared to 97 in March of 2014. Unfortunately, data limitations in the rest of our variables for the year 2015 prevented us from fully utilizing this Airbnb supply data.

Second, Airbnb accomodations and hotel rooms may be better considered as complements and not substitutes.

Perhaps the most likely explanation, however, is that Zervas et al. was simply blessed with much richer data than we were. Specifically with respect to Airbnb supply, we believe that both our investigation and Zervas's would benefit from detailed listing availability data.

richness using data on hotel level (less aggregated)

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