The Effect of Airbnb on Hotels

Evidence from Berlin*

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Abstract

This paper analyses the impact of Airbnb's market entry in June 2011 on the hotel industry in Berlin. By using fixed effects strategies we explore this relationship using district-level data for hotel occupancy and Airbnb listing data from 2010 until 2014. When controlling for economic conditions and increasing air travel to Berlin, we estimate that a one percent increase in Airbnb supply relates to a .01 percentage points decrease in hotel occupancy rates. Moreover, the impact is non-uniformly distributed, with lower-priced hotels and those hotels not catering to business travelers being the most affected. Our work provides empirical evidence that Airbnb may be successfully competing with incumbent firms. Future research should further explore the causal effect of Airbnb market entry in cities. Policy makers should focus on creating a level-playing field for both hotels and Airbnb hosts to create a fair legal framework for all market participants.

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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

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

neighbourhood 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 (2015), 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 final data set covers 720 monthly obversations across twelve districts in Berlin between 2010 and 2014. We also include a dummy variable 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: ?)

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

Analysis

Descriptive Analysis

Airbnb‘s popularity in Berlin has significantly increased 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 Figure 1, we can see the growth in Cumulative Airbnb Supply in each neighbourhood from 2010 to 2014. Each of the most popular neighbourhoods (Friedrichshain-Kreuzberg, Mitte, Pankow, & Neukoelln) is shown to have more than 1,500 listings by 2014. Growth is shown to accelerate in the city’s most popular disticts each year, and Friedichshain-Kreuzberg’s total number of listings is well above 2,500 by the end of 2014.

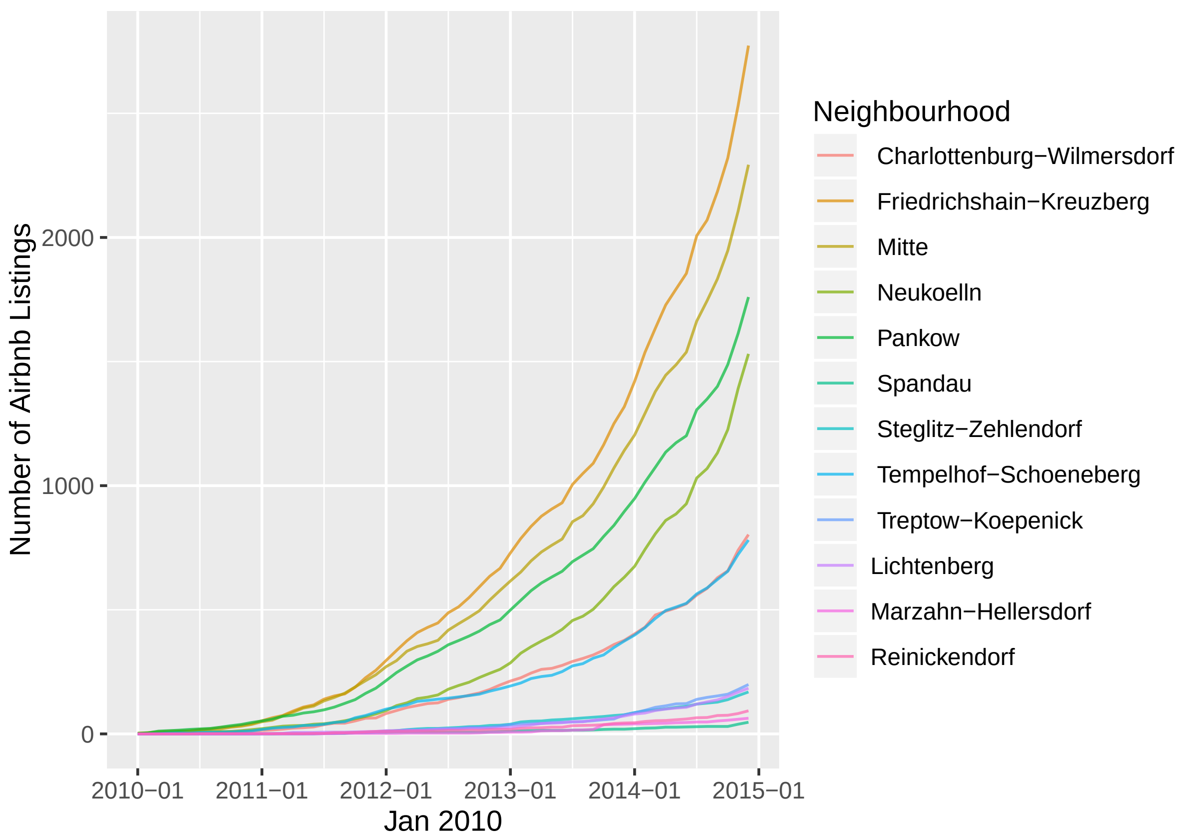

Figure 1: Cumulative Airbnb Supply per Neighbourhood (2010 - 2014)

However in Figure 2, we can see that our Dynamic Airbnb Supply tells a slightly different story. In mid-2014 we see Airbnb supply peak in each district before falling dramatically in the second half of the year. Indeed, Friedrichshain-Kreuzberg's supply even appears to drop below it's supply level at the start of the year. Upon closer examination, the supply peak appears to coincide with the passage of the *Zweckentfremdungsverbot* (Airbnb misuse law) in the summer of 2014. This highly publicized law prohibited listing full apartments on Airbnb in Berlin, but allowed the continued listing of individual rooms. However, the law did not come into effect until 2016, and *InsideAirbnb.com* data from 2015 shows that Airbnb supply came back stonger than ever immediately following our obervation period. These considerations led us to conclude that it was better to use our Cumulative Airbnb Supply variable for our inferential analysis. Despite the shortcomings of the cumulative variable, it more accurately represents the overall supply growth of Airbnb in Berlin, which both variables likely understate anyway due to the 33 percent of Airbnb guests who do not leave reviews (Fradkin et al., 2015).

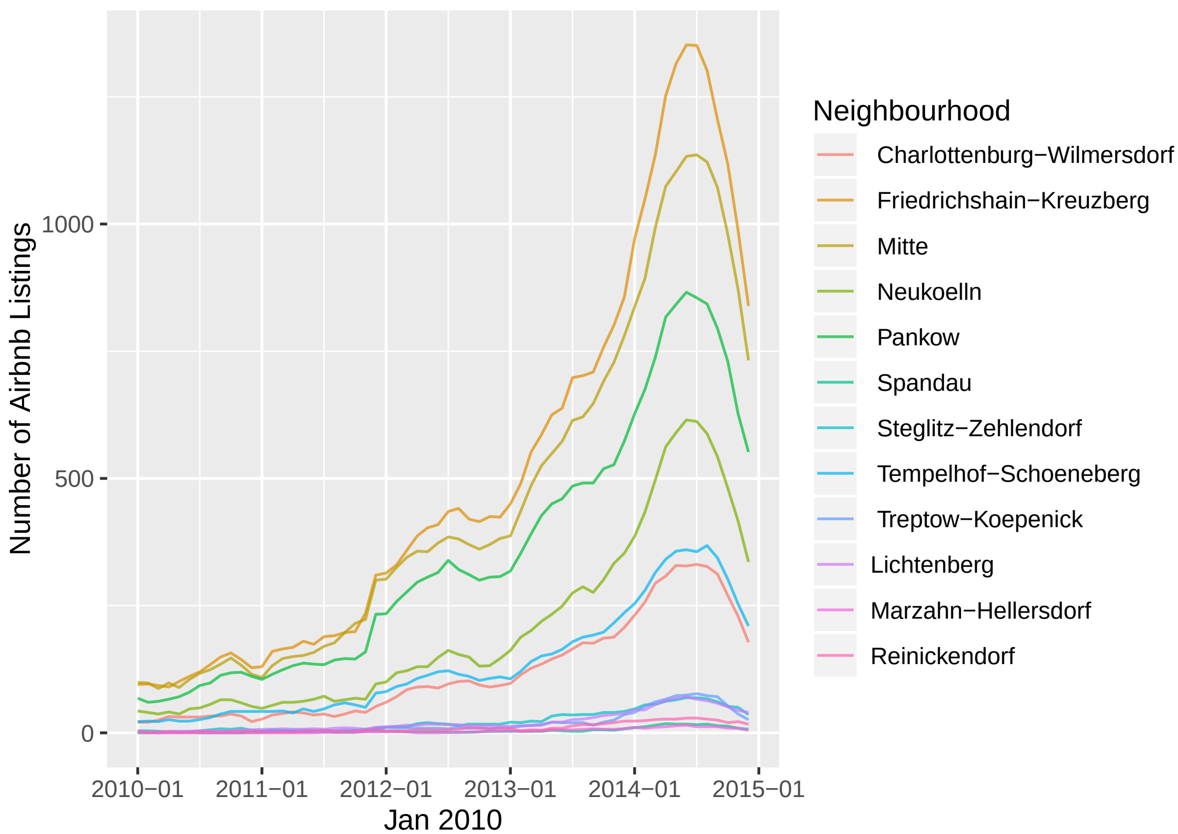

Figure 2: Dynamic Airbnb Supply per Neighbourhood (2010 - 2014)

In order to take a first look at the relationship between Airbnb supply and hotel occupancy rates, we plotted the log of 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. We refrained from taking the log of hotel occupancy rates since they are smaller than one, and appear to have a fairly normal distribution.

Upon plotting this relationship, we were surprised to see a clear positive correlation and a correlation coeffecient of 0.343 *(cf. Figure 3)*. We believe this counterintuitive result is likely due to an omitted variable that is driving hotel occupancy rates. Given the increase in Berlin's popularity, we identified increased accomodation demand in general as the most likely suspect. Zervas et al. (2016) controlled for this effect by using the number of 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, our inferential analysis 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 incorporating the proper controls into our model will eliminate the positive correlation we observe here.

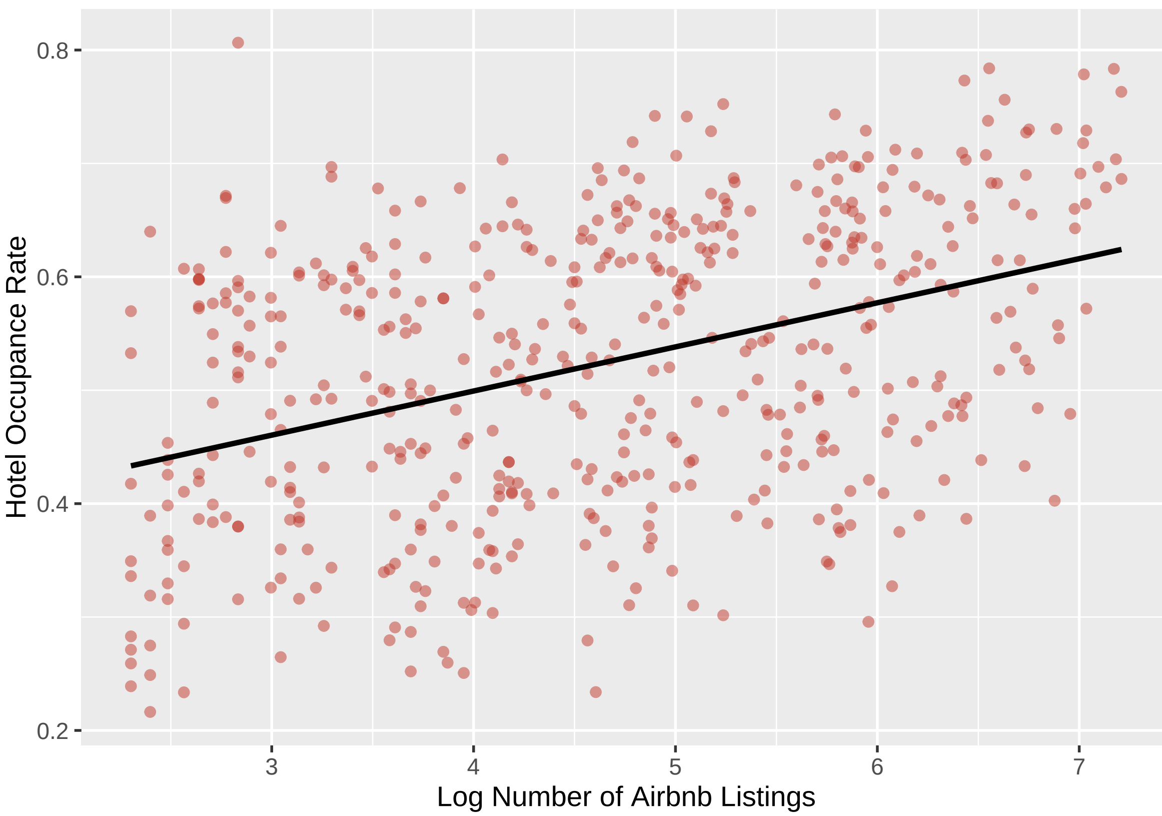

Figure 3: Effect of Increase in Airbnb Listings on Berlin Hotel Occupancy Rates (2010 - 2014)

Methodology

In order to explore the relationship between Airbnb supply and hotel occupancy rates further, we apply several different approaches of multivariate analysis. After beginning with an OLS approach, we use fixed effects models to account for unobserved time-varying and neighbourhood-specific factors. These are constant over time and correlated with the control variables, independent variables, and the hotel occupancy rate. In doing so, we do not systematically vary both between different cities and over time, because the models look at neighbourhood-specific within-variation (Wooldridge, 2015).

As discussed above, our analysis differs from that of Zervas et al. (2016) in that our unit of analysis is hotel occupancy rates rather than hotel revenue. However our methodology differs from Zervas as well, as our analysis cannot take advantage of a treatment and control regions accounting for different Airbnb market entry patterns. Instead, we use regional fixed effects to account for time-invariant differences in hotel occupancies in each region.

Considering these arguments, the main specification for our analysis looks like this:

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

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.

We ran a Hausman test in order to decide whether to use a fixed or random effects model, since a regular OLS regression does not consider heterogeneity across groups or time (SOURCE: Green, 2008). This test checks to see if the unique erros are or are not correlated with the regressors. Upon execution, the test showed 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.

Column 1 is a simple Ordinary Least Squares (OLS) model that only includes our economic control variables (neighbourhood specific unemployment rate and average household income) in addition to neighborhood and time specific trends. As stated earlier, we interpret the coefficient β of $\log \textit{Airbnbsupply}$ as indicative of the extent to which Airbnb listings act as a substitute for hotel rooms. In Column 1 we estimate the coefficient $\beta = 0.009$ as being highly significant ($p < 0.01$). This means that a 10 percent increase in Airbnb listings is associated with a statistically significant 0.009 percentage point increase in the monthly hotel occupancy rate. This positive effect seems counter-intuitive, leading us to beleive that the simple linear model does not adequately analyze the relationship.

Table 1: OLS and Fixed Effects regression models for hotel occupancy rate

	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		

In Column 2 we employ a fixed effects model to account for changes in time and variation across neighbourhoods. Here, we once again find a highly significant ($p < 0.01$) positive coefficient of 0.02, indicating that a 10 percent increase in Airbnb listings is associated with a statistically significant 0.2 percentage point increase in the monthly hotel occupancy rate. This result shows that we had underestimated the effect of changing from a linear model to fixed effects, and continued to surprise us by revealing a positive relationship between $\log Airbnbsupply$ and monthly hotel occupany rates. However, this model does not control for the dramatic increase in popularity that Berlin has experienced during this time period.

To control for the effect of Berlins rising popularity, Column 3 follows the methodology of Zervas et al. (2016) by using data on passengers arriving in Berlin as a proxy for the increasing popularity of the city. Upon adding this control to the fixed effects model, we observe an inverse relationship between $\log Airbnbsupply$ and monthly hotel occupany rates. This effect is highly significant ($p < 0.01$) with a coefficient of -0.01, meaning that a 10 percent increase in Airbnb listings is associated with a statistically significant 0.01 percentage point decrease in the monthly hotel occupancy rate. This was the relationship we had been expecting to find in our hypothesis, and demonstrates that to a very small degree, Airbnb acts as a substitute for hotels in Berlin. The effect of incoming passengers is weaker still, but positive and highly significant at the $p < 0.01$ level. This supports our thinking that the increasing popularity of the city has effected hotel occupancy rates. Column 3 also shows an increase in the significance of average household income, which is now significant at the $p < 0.01$ level.

Column 4 adds a final control to our analysis, a dummy variable for Airbnb's Berlin market entry. While our observation period is from 2010 to 2014, Airbnb did not officially enter the Berlin market until June 2011. However it seems that the official market entry of the site did not have any significant effect on hotel occupancy rates. The effect of log *Airbnbsupply* remains negative and significant at the $p < 0.01$ level here, albeit with a slightly weakened coefficient (-0.008).

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.

****Add More on non-liner model here*****

While our strongest finding, a coefficient of -0.01, is highly significant at the $p < 0.01$ level, the magnitude of the effect on hotel occupancy rates is very weak. Column 3 indicates that a 10% increase in Airbnb listings is only associated with a 0.1 percentage point decrease in hotel occupancy rates. To put that in perspective, it means that adding about 1,530 Airbnb listings to the Airbnb supply merely causes a 0.01 percentage point decrease in hotel occupancy rates. This suggests what while Airbnb may be affecting the hotel industry in Berlin, it's effect is so small that the hotel industry is unlikely to notice. That is especially true in light of Berlin's increasing popularity, which seems to be more than making up for any "Airbnb effect" on hotels in Berlin.

However, our model does have several limitations that we believe are important to keep in mind. First, significant data limitations impeded our analysis in a few different ways. As discussed above, we were unable to find precise data on Airbnb listing availability, and Airbnb is not even able to produce that data itself. In the absence of such data, it is difficult to be sure of how precise our Airbnb supply variable is. Another data limitation we faced was the lack of Berlin hotel data for 2015. This data will presumably be made available soon, but not having it to work with forced us to exclude 2015 from our analysis. This is a significant loss, as 2015 was an important year of growth for Airbnb in Berlin. According to *InsideAirbnb.com* data, the number of Airbnb listings in Friedricshain-Kreuzberg (Berlin's most popular neighbourhood on Airbnb) increased by 342 in March of 2015, compared to 97 in March of 2014.

This lack of 2015 data also means that the last six months of our observation period coincide with the with the passage of the *Zweckentfremdungsverbot* (Airbnb misuse law). This may have affected our results, as our dynamic Airbnb supply variable showed a significant drop in supply after the law's introduction. Despite having discarded our dynamic supply variable for this reason, the law's passage may also have affected our Cumulative supply if it discouraged a certain amount of new listings being made on the site.

Finally, the scope of our analysis is limited to Berlin. Our findings here, though statistically significant, are not strong enough in effect to assume that they can be extrapolated to other cities without investigation.

Conclusion & Future Research

The purpose of this paper was to measure the impact of Airbnb on the hotel industry in Berlin. Our analysis follows a recent paper by Zervas et al. (2016), which found that Airbnb has a negative impact on the hotel industry in Texas. More broadly, a paper by Guttentag (2015) concluded that while Airbnb is unlikely to replace hotels, it is large enough to have an impact on the hotel industry. In our work, we sought to contribute to this emerging body of literature on by exploring the relationship in the Berlin context. To that end, we used data from the Statistical Information System Berlin/Brandenburg (SBB) (StatIS-BBB, 2016), the Federal Statistical Office & Statistical Offices of the Länder (FSO) (Germany, 2015), *InsideAirbnb.com* (Cox, 2016), and Eurostat to investigate the impact of Airbnb supply on hotel occupancy rates. Ultimately, we found that Airbnb had a highly statistically significant ($p < 0.01$), but objectively weak negative impact on hotel occupancy rates in Berlin. Using a fixed effects model that controlled for economic conditions as well as the increased popularity of Berlin (as measured by arrivals at Berlin's airports), we found that a 10 percent increase in Airbnb listings is associated with a 0.01 percentage point decrease in the monthly hotel occupancy rate.

This negative, highly significant result supports our hypothesis that higher Airbnb supply in Berlin leads to the lower the hotel occupancy rates. However, the magnitude of the effect is so small that in practice it has likely gone unnoticed. We believe that in the Berlin context this is partially due to the rapidly increasing popularity of the city, as evident by the our "incoming passengers" control variable. The city is in such high demand that any impact that Airbnb has had on the hotel industry has been more than compensated for.

Future research in this area would do well to explore the impact of Airbnb on hotels in other cities around the world. The popularity of Berlin and the city's efforts to combat Airbnb's overuse make it difficult to confidently assert that Airbnb is indeed a substitute for hotels. Further investigations in cities where accomodation demand has been steady, and where Airbnb has been allowed to grow unimpeded could provide a clearer picture of this relationship. Moreover, future researchers with more data available to them should experiment with different measures of Airbnb supply as an independent variable and change dependent variables as they see fit. Where possible, a more detailed investigation into the impact of Airbnb on individual hotels would also shed light on which types of hotels should consider Airbnb to be a competitor.

Whatever their specific focus, future researchers in this area should undertake their work with an eye towards attaining a better understanding of disruptive business models such as Airbnb. The extent to which such business models impact incumbent industries will have implications both for regulators and for policymakers seeking to respond to changes in the economy.

Bibliography

Airbnb. (2015). Airbnb Economic Impact. Retrieved from http://blog.airbnb.com/economic-impact-airbnb/

Cox, M. (2016). Inside Airbnb. Retrieved from http://insideairbnb.com/get-the-data.html

Fradkin, A., Grewal, E., Holtz, D., & Pearson, M. (2015). Bias and reciprocity in online reviews: Evidence from field experiments on airbnb. In *Proceedings of the Sixteenth ACM Conference on Economics and Computation* (pp. 641–641). ACM.

France-Presse, A. (2016). Berlin's government legislates against Airbnb. *The Guardian.* electronically.

Germany, R. D. (2015). Retrieved from https://www.regionalstatistik.de

Gutt, D., & Herrmann, P. (2015). *Sharing Means Caring? Hosts' Price Reaction to Rating Visibility.* Working Paper.

Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, *18*(12), 1192–1217.

Schäfer, P., Braun, N., Reed, R., & Johnston, N. (2016). Misuse through short-term rentals on the Berlin housing market. *International Journal of Housing Markets and Analysis*, *9*(2).

Skowronnek, A., Vogel, L., & Parnow, J. (2015). Airbnb vs Berlin. Retrieved from http://airbnbvsberlin.com/#introduction

StatIS-BBB. (2016). Retrieved from https://www.statistik-berlin-brandenburg.de/webapi/jsf/dataCatalogueExplorer.xhtml

Stors, N., & Kagermeier, A. (2015). Motives for using Airbnb in metropolitan tourism – why do people sleep in the bed of a stranger? *Regions Magazine*, *299*(1), 17–9.

TheNextWeb. (2011). Airbnb takes on Europe. Will it revolutionize the industry, again? Retrieved from http://thenextweb.com/insider/2011/07/06/airbnb-takes-on-europe-will-it-revolutionize-the-industry-again/

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach.* Nelson Education.

Yannopoulou, N., Moufahim, M., & Bian, X. (2013). User-generated brands and social media: Couchsurfing and AirBnb. *Contemporary Management Research*, *9*(1), 85.

Yearbook, E. R. (2015). Eurostat. *European Commission.*

Zervas, G., Proserpio, D., & Byers, J. (2015). A first look at online reputation on Airbnb, where every stay is above average. *Where Every Stay Is Above Average (January 28, 2015).*

Zervas, G., Proserpio, D., & Byers, J. (2016). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Boston U. School of Management Research Paper*, (2013-16).