The Effect of Airbnb on Hotels

Evidence from Berlin*

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Abstract

This paper analyses the impact of Airbnb supply 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 the increasing popularity of Berlin, we estimate that a ten percent increase in Airbnb supply relates to a .12 percentage point decrease in hotel occupancy rates. Our work provides empirical evidence that Airbnb may be competing with the incumbent hotel industry, but that this effect is so small in Berlin that it has likely gone unnoticed. Future research should further explore the causal effect of Airbnb market entry in different cities and regions. Policymakers should focus on creating a level playing field and a fair legal framework for both hotels and Airbnb hosts.

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I. Introduction

Airbnb is an online peer-to-peer platform that allows private persons ("hosts") to share their a room in their home or a rental home with travelers. Since its founding year in 2008, the company has revolutionized the accomodation industry profoundly. For hosts, using Airbnb can be a valuable source of extra income. For guests, Airbnb provides accomodations that allows guests to 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 neighbourhoods outside of the main hotel districts (Airbnb, 2015). 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 its 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 guests are also more likely to stay 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 (Airbnb, 2015). 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, it also competes 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. Section 2 will review the relevant literature in the field and outline our hypothesis going forward. In section 3, we will discuss the data sources and variables that we will use to explore this relationship. Section 4 will outline the methodology we use in this study and describe our model in detail. Using a Fixed Effects approach, we will analyze the data inferentially to evaluate our hypotheses. Finally, we will discuss our results, the policy implications of our findings, and opportunities for future research in the last section.

II. 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 about 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 other peer-to-peer marketplaces, 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 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 may be 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 competition, 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 the first review they receive. 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 arguments doubting Airbnb's ability to compete with the traditional accomodation industry are valid, there is 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 nonetheless 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. 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 ten percent size increase of Airbnb supply in Texas resulted in a .39 percent decrease in hotel revenue. This effect varied widely by region, however. Austin, for example showed a eight to ten 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, our investigation will focus on the effect of Airbnb listings 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.*

III. Data & Variables

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

From the SBB (2016), we collected monthly survey 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. The surveys 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 the FSO (2015), 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 .

From *InsideAirbnb.com* (2016), 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 on 18 July 2015 and on 6 January 2016. The data set containes 92 variables for each listing covering topics

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

ranging from room price to information on the host. For our purposes, the key variables were (1) the neighbourhood of each listing, (2) the date that an Airbnb host signed up, and (3) the date of the first review of each listing.

From Eurostat (2015), we gathered monthly data on the number of passengers to arrive at Berlin's two major airports, Tegel and Schoenefeld. We use this data to construct a variable that combines the passenger arrivals to both airports every month. In keeping with the Zervas et al. (2016) methodology, we use this variable as a control for the signifiant increase in the popularity of Berlin.

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. Our analysis includes two measures of district-specific Airbnb supply, a cumulative measure and a dynamic measure. For both our cumulative and dynamic Airbnb supply variables, we calculated the date six 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.[2] The cumulative measure simply adds new listings to the supply either as they recieve first reviews or as their owner registers on the site if the apartment lacked in review data. 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 month six months prior to the first review, 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 re-enters the dynamic supply.

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

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, an increase was about 22 percent between 2010 and 2014. To account for this, 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

[2]If a listing had neither, it was excluded from the analysis. Only five listings were excluded on this basis.

each district multiplied by the number of days in each month.

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

After merging and cleaning the data, our final data set covers 720 monthly obversations across twelve districts in Berlin between 2010 and 2014.

Descriptive Analysis

Airbnb‘s popularity in Berlin has significantly increased since its 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 (TheNextWeb, 2011). 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 distincts each year, and Friedichshain-Kreuzberg’s total number of listings is well above 2,500 by the end of 2014.

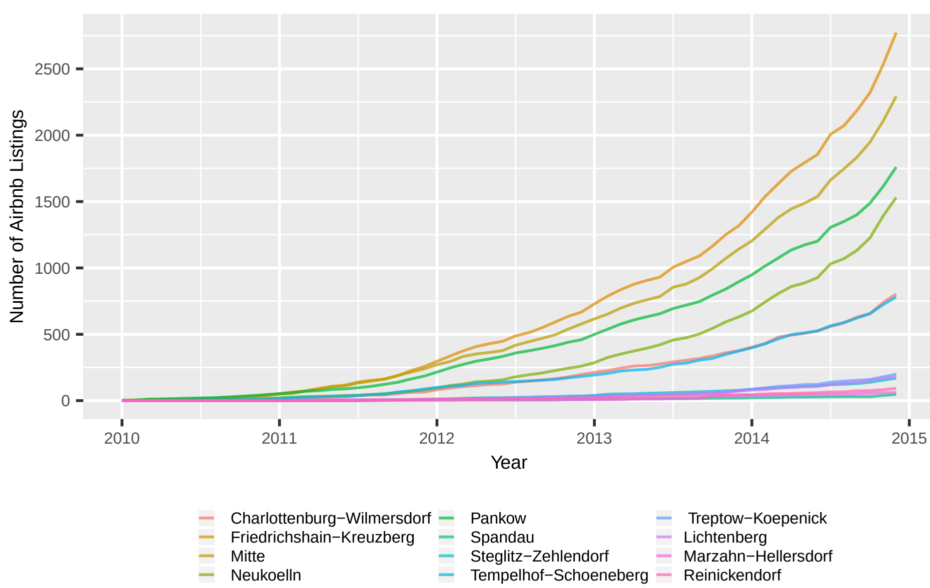

Figure 1: Cumulative Airbnb Supply per Neighbourhood (2010 - 2014)

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 its supply level at the start of the year. Upon closer examination, this supply peak appears to coincide with the passage of the 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 (Cox, 2016). 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).

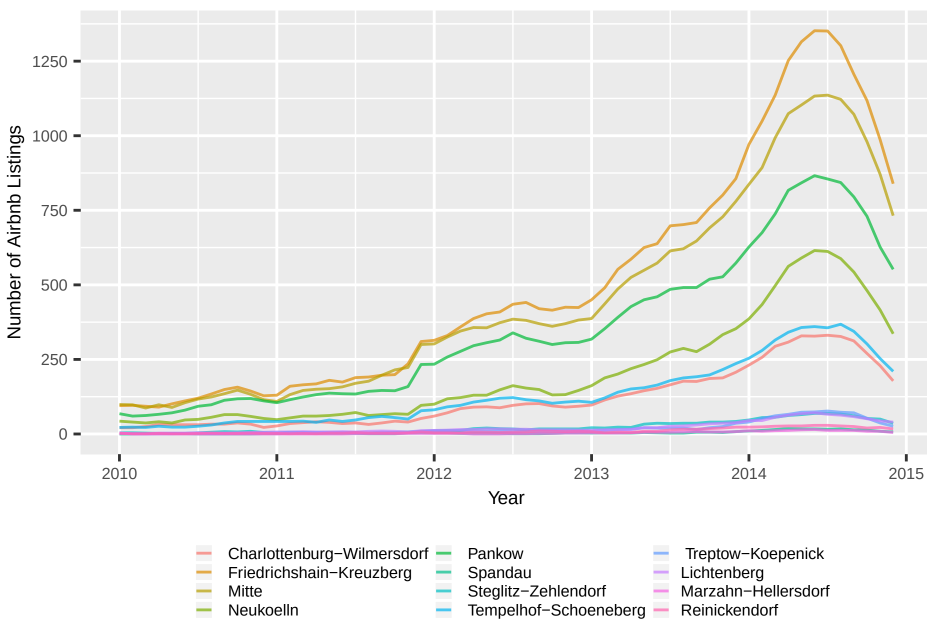

Figure 2: Dynamic Airbnb Supply per Neighbourhood (2010 - 2014)

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. In contrast to that, hotel occupancy rates appear to have a fairly normal distribution.

Upon plotting this relationship, we were surprised to see a clear positive relationship between cumulative Airbnb supply and hotel occupancy rates and a correlation coeffecient of 0.343 *(cf. Figure 3)*.[3] We believe this counterintuitive result is likely due to an omitted variable that is driving hotel

[3]Note that Figure 3 excludes all observation points in time in which Airbnb was not present with at least 10 apartments in a given district.

occupancy rates. Given the increase in Berlin's popularity, we identified increased accomodation demand in Berlin 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, which experienced an increase of roughly 25 percent from 2010 until 2014. 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.

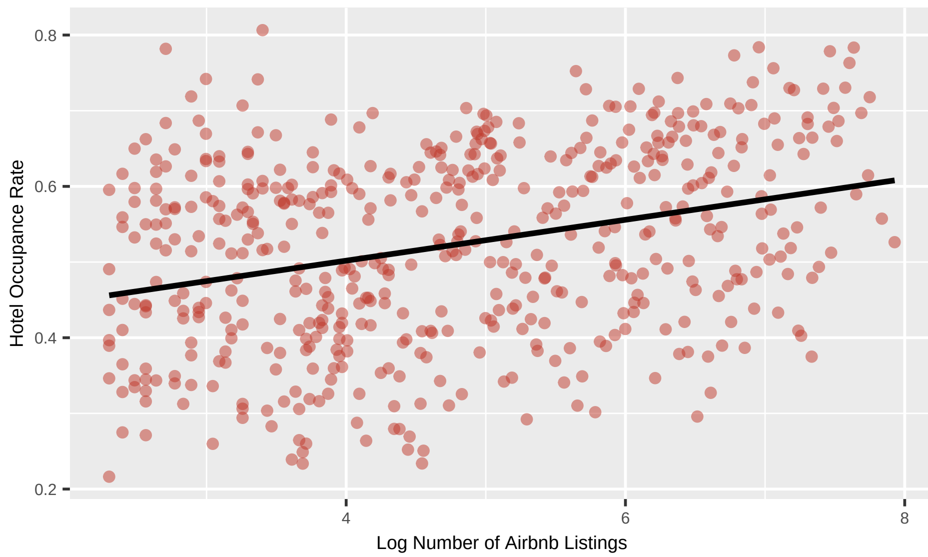

Figure 3: Effect of Increase in Airbnb Listings on Berlin Hotel Occupancy Rates (2010 - 2014)

IV. Inferential Analysis

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 either between different neighbourhoods or over time, because the models look at neighbourhood-specific within-variation (Wooldridge, 2015).

In order to decide whether to use a fixed or random effects model, we ran a Hausman test to see whether the unique errors are correlated with the regressors (Maddala & Lahiri, 1992). Upon execution, the test showed a p-value of 1. 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).

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. Further, 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.

Taking these considerations into account, the main specification for our analysis looks like this:

$$OccupancyRate_{it} = \beta_i * \log cumulativeAirbnbSupply_{it} + \tau_i + \beta_j * X' + \varepsilon_{it}$$

Here, *Occupancy Rate* is the occupancy rate for all hotels in district i at time t. *Cumulative Airbnb Supply* is the log of the approximated total number of Airbnb listings available in district i at time t. X' controls for yearly district-level specific economic conditions (unemployment rate and yearly log average household income) and air passenger arrivals in Berlin. Finally, by using a month-year time dummy τ, we account for unobserved heterogeneous variation across districts and time.

Results & Discussion

Table 1 compares the results for different models.

Table 1: Summary of Hierarchical Regression Analysis for Variables Predicting Hotel Occupancy Rate in Berlin (2010 - 2014)

	Dependent variable:					
	Hotel Occupancy Rate					
	LM (1)	FE (2)	FE (3)	FE (4)	FE (5)	FE(6)
Log Airbnb Listings	0.009^{***}	0.026^{***}	-0.010^{***}	-0.008^{***}	-0.009^{***}	-0.012^{***}
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Average HH Income (Log)	-0.139^{*}	-0.388^{*}	-0.280^{***}	-0.291^{***}	-0.522^{***}	-0.618^{***}
	(0.078)	(0.202)	(0.096)	(0.097)	(0.122)	(0.125)
Unemployment Rate	0.141	0.862^{**}	0.351^{*}	0.310	0.262	0.226
	(0.152)	(0.406)	(0.194)	(0.197)	(0.197)	(0.196)
Incoming Passengers			0.00000^{***}	0.00000^{***}	0.00000^{***}	0.00000^{***}
			(0.000)	(0.000)	(0.000)	(0.000)
Market Entry				-0.008	-0.004	-0.004
				(0.007)	(0.007)	(0.007)
Number of Listings					0.00003^{***}	0.0003^{***}
					(0.00001)	(0.0001)
Log Supply*Level						-0.00004^{***}
						(0.00001)
District/Time FE?	No	Yes	Yes	Yes	Yes	Yes
Observations	720	720	720	720	720	720
R^2	0.996	0.077	0.790	0.791	0.794	0.796
Adjusted R^2	0.995	0.075	0.773	0.772	0.774	0.775
Note:	*p<0.1; **p<0.05; ***p<0.01					
	LM (1) controls for time and neighbourhood-specific trends					

Model 1 is a simple Ordinary Least Squares (OLS) model that only includes our economic control variables (neighbourhood specific unemployment rate and log average household income) in addition to neighbourhood and time specific trends. As stated earlier, we interpret the coefficient of log *AirbnbSupply* as indicative of the extent to which Airbnb listings may 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 0.09 percentage point increase in the monthly hotel occupancy rate. This positive effect seems counter-intuitive, leading us to believe that the simple linear model does not adequately analyze the relationship.

In Model 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, Model 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 0.1 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 affected hotel occupancy rates.

Also notable in Model 3 is a dramatic increase in the adjusted R-squared, which rises from 0.075 to 0.773. This would indicate that our model explains 79 percent of the quadratic variance in hotel occupancy rates. We believe this sudden and pronounced increase is due to a high correlation between our Incoming Passengers control variable and our dependent variable, hotel occupancy rates. Indeed, we found that many researchers seeking to control for the increased popularity of a city actually use hotel occupancy rates as a control variable. This is unfortunate, but ultimately unavoidable in our study. Any variable measuring the increased popularity of Berlin will be inevitable highly correlated with hotel occupancy rates. The rest of the models in our study all exhibit an unusually high R-squared for this reason.

Model 4 adds another control to our analysis, a dummy variable for Airbnb's Berlin market entry. It is based on Airbnb's date of acquisition of the German peer-to-peer marketplace Accoleo in June 2011, which is considered Airbnb's first move to expand their business model to the European market (TheNextWeb, 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).

Finally, Model 5 and 6 seek to explore our intuition that the impact of Airbnb is likely dependent on reaching a critical threshold or level of market penetration. To determine whether this is the case, we first included the absolute level of listings. The result was not in line with our expectations, in that while it was highly signicant at the $p < 0.01$ level, the coefficient of the absolute level variable was close to zero. To explore this relationship further, we included an interaction term of the log of cumulative Airbnb supply and the absolute level of Airbnb supply to account for their potential (joint) non-linear relationship with regard to hotel occupancy rates. Again, the result here was highly significant, but the coefficient of the interaction term was close to zero. However, this final model does produce a slightly higher coefficient on log *AirbnbSupply* than Model 3, indicating that our previous models underestimated the impact of Airbnb supply growth. This effect is highly significant at the $p < 0.01$ level with a coefficient of -0.012. Our strongest finding, therefore, is that a 10 percent increase in Airbnb listings is associated with a 0.12 percentage point decrease in the monthly hotel occupancy rate.

While this finding is highly significant at the $p < 0.01$ level, the magnitude of the effect on hotel occupancy rates is still very weak. To put Model 6's findings in perspective, it means that adding about 1,530 Airbnb listings to the Airbnb supply merely causes a 0.12 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 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 Airbnb 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.

V. Conclusion & Future Research

The purpose of this paper was to measure the impact of Airbnb on the hotel industry in Berlin by mimicking recent work by Zervas et al. (2016), which found that Airbnb has a negative impact on the hotel industry in Texas. In our work, we sought to contribute to this emerging body of literature by exploring the relationship in the Berlin context. 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 0.12 percentage point decrease in the monthly hotel occupancy rate.

This negative, highly significant result supports our hypothesis that growth in Airbnb supply in Berlin relates to a decrease in 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 controlling for incoming passengers. The city is in such high demand that any impact that Airbnb has had on the hotel industry has been more than compensated for.

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. Yet the extent to which such business models impact incumbent industries will have implications for both regulators and policymakers seeking to respond to changes in the economy. With an eye towards attaining a complete understanding of disruptive business models such as Airbnb, policymakers should focus on creating a level playing field for both hotels and Airbnb hosts. Specifically, they should ensure that all market participants operate under a fair legal framework.

Future research in this area would do well to explore the impact of Airbnb on hotels in other cities around the world. 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.

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