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The effect of short-term rental platforms on rental prices: Evidence from Airbnb in Berlin

by Felix Mindl

This article investigates the effect of short-term rental platforms on the housing market, using the explosive growth of Airbnb experienced in Berlin as a case study. To identify a causal effect, I exploit the structure of Airbnb in Berlin and combine a hedonic housing model with a Triple Difference-in-Difference approach. The analysis of six hundred thousand apartments shows that rapid growth of professional Airbnb listings has led to a three percent increase in asking rents in city districts with high Airbnb concentration.

Key words: Sharing economy, peer-to-peer markets, housing markets, Airbnb

JEL Codes: R31, L86

1 Introduction

On April 14th 2018, more than 13,000 people came together in Berlin, Germany to rally for affordable housing.¹ This was the biggest demonstration on the housing situation and housing policy that Berlin has ever seen. Residents expressed their displeasure for strongly increasing asking rents and the following social consequences. Developments, that can easily be validated by the data: The vacancy rate in Berlin has fallen to a minimum of 1.2%,² while asking rents have increased between 2010 and 2018 by more than 60%³ and the average household income that is spent for housing increases to 29%.⁴ These trends are amplified by a growing demand due to a positive net immigration to Berlin and the fact that the city council lags behind on its plans for new housing.⁵ In short: Berlin is in the midst of an affordable housing crisis; this adds fuel to a contentious debate over the influence of the sharing economy on the housing market.⁶ The term “sharing economy” emerged in the early 2000s based on the development of information and communication technology as well as home computers. It describes peer-to-peer markets where individuals offer their private goods to one another for monetary reimbursement

¹ FAZ – “Berliner demonstrieren gegen hohe Mieten”. 14.04.2018

² Wohnmarktreport Berlin 2018, Berlin Hype & CBRE p. 9.

³ Average asking rents from Q3 2010 to Q3 2018. Data from empirica-institut.de.

⁴ Wohnmarktreport Berlin 2018, Berlin Hype & CBRE p. 54.

⁵ Berliner Morgenpost - “Berlin baut nur halb so viele neue Wohnungen wie geplant”. 22.12.2017

⁶ Zeit – “Auf Aenger eingerichtet”. 15.08.2018

(Einav et al., 2015). At the forefront of the sharing economy are, among others, short-term rental platforms. These platforms provide an online market that simplifies the matching process of people offering part of their home for short-term accommodation and travelers in search of such. Airbnb is the biggest player in this emerging home-sharing market. This new economical branch experienced rapid growth during the last decade and thus, has received increasing attention by researchers.

Zervas et al. (2017) have analyzed the effect of Airbnb on the hotel industry, Edelman et al. (2017) have investigated racial discrimination in the sharing economy and Wachsmuth and Weisler (2018) examined the effects on gentrification. Another salient topic is the question of how Airbnb interferes with the housing market.

Advocates of the sharing economy argue that such platforms foster community building, broaden the variety of tourism and help local residents to earn some extra money, enabling them to retain their residency.⁷ At the same time, arousing critics argue that Airbnb enables professional tourism while skirting existing regulations, which would lead to unfair competition with the hotel industry.⁸ Also, tenant initiatives and city councils are concerned about Airbnb's impact on neighborhoods. On the one hand, complaints arise that increasing numbers of tourists in regular housing units distort neighborhood communities.⁹ On the other hand, it is argued that the increasing number of Airbnb units are standing in competition with long-term tenants. It is claimed that Airbnb takes housing supply of the market and thereby, puts upward pressure on already tight housing markets in big urban centers.¹⁰ These circumstances call policy makers into action. In 2016 regulators have introduced a home-sharing ordinance (HSO) in Berlin to prevent use alienation of apartments.¹¹ Recently, Airbnb has encountered a vast variety of regulations, in different cities. However, there is limited research of the effect of the sharing economy on housing markets. Hence, politicians have to make regulation decisions based on inadequate information.

To fill this gap, Merante and Horn (2017) and Barron et al. (2018) have examined and quantified the effect of Airbnb on the housing market in the United States. So far, there is no comparable study for urban centers in Europe.

This research contributes to the young body of literature that investigates Airbnb's effect on the housing market by using a triple Difference-in-Difference strategy -a methodology new to this field. Precisely, I estimate the effect of Airbnb on asking rents in Berlin.

This research builds upon the segmentation of the Airbnb listings introduced by Barron et al.

⁷ www.airbnbaction.com.

⁸ Welt – "Das ist unfairer Wettbewerb". 18.04.2016

⁹ Islington Gazette – "All night Airbnb rave". 09.03.2017

¹⁰ Tom Slee - "What's yours is mine" pp.32.

¹¹ Zweckentfremdungsverbot-Gesetz - ZwVbG.

(2018) who separate listings into professional and casual listings. It finds that in Berlin by 2015 84% of all active Airbnb listings were managed professionally which take long-term housing supply of the market. When examining the geographical location of these listings, one can make out high-density areas in the city center, while there is almost no professional Airbnb listing in outside districts, like Spandau. A Further concentration level can be detected in the size of Airbnb offers; these mainly provide small flats with three rooms or less. The variation that is given by the explosive growth, varying concentration by district and apartment size is exploited in a triple Difference-in-Difference to estimate the effect of Airbnb on asking rents in Berlin. The empirical results show that in the city center of Berlin the entrance of Airbnb into the market has driven the asking rents of small flats (flats with three rooms or less) by 3% over a period of two years (2nd quarter 2013 to 2nd quarter of 2015) which accounts for 17.4% of the overall asking rent growth during this time. For the average asking rent of the sample, this leads to an increase of 20€ per month or 240€ annually.

This study proceeds with a literature review, which is followed by giving background information including a brief portray of Airbnb, describing the situation of the Berlin housing market and a reporting of how the Berlin city council has attempted to regulate the home sharing economy. Chapter 4 explains the assumed mechanisms of Airbnb. After this follows the presentation of the underlying data sets and a descriptive analysis of the structure of Airbnb in Berlin. The subsequent chapter (chapter 6) provides the methodology which is the basis for the empirical results presented in chapter 7. Chapter 8 concludes with a discussion of the findings.

2 Related Literature

Recently there is a growing body of literature examining online platforms and their concept of peer-to-peer markets (Einav et al., 2015). Nevertheless, the research on home sharing market is still limited. Zervas et al. (2017) look at the effect of Airbnb on the hotel industry. They use a Difference-in-Difference approach to take advantage of the Airbnb variation between cities in Texas. They compare the city of Austin, where the Airbnb supply is highest, to cities such as Houston, San Antonio and Dallas which have experienced very little Airbnb presence. The authors find evidence that Airbnb decreases hotel revenues by about 8-10%. Coles et al. (2017) have used data provided by Airbnb to explore the dispersion of Airbnb listings in New York. Their study claims that Airbnb listings have become more dispersed across the city and that Airbnbs are not as profitable as many assume. Though, the authors infer that the vast majority of Airbnb offers remain in the central districts (Coles et al., 2017).

As of now, I am only aware of two papers that empirically investigate on the effect of Airbnb on the housing market.

1) Barron et al. (2018) use a rental and house price data set, provided by Zillow.com,¹² in combination with a nationwide panel of Airbnb data obtained from web scrapes to study the effect of Airbnb on the housing market.¹³ In their main regression the authors use a shift and share Instrumental Variable approach. They find that an 1% increase in Airbnb listings leads to a 0.018% increase in rental rates and a 0.026% increase in house prices. In their sample the 100 regions with the largest Airbnb presence have a median annual Airbnb growth of 28% and which accordingly explains 0.5% of annual rent growth and 0.7% of annual house price growth.

2) Horn and Merante (2017) use individual rental listing data of a much shorter time period, lasting from September 2015 to January 2016. Equally, the Airbnb data is obtained by web scrapes. For the explanatory variable the authors create a spatial measurement of Airbnb density per census tract. Their regression results stem from a simple semi-log hedonic pricing model.¹⁴ They present results that estimate a 0.4% increase in asking rents for a one standard deviation increase in Airbnb listings. Both, their sample mean of Airbnb density and the standard deviation is 0.7%.

Methodically, this study builds upon recent literature that uses hedonic models in combination with quasi experimental methods to evaluate the effect of local amenities and dis-amenities on the housing market. For example Davis (2004) uses the sudden increase of pediatric leukemia cases to measure the implicit price of living in a cancer cluster area.

3 Background

The succeeding subsection introduces the sharing economy and describes the role of Airbnb. This is followed by a brief summary of how city authorities in Berlin try to regulate short-term rental platforms.

3.1 Airbnb and the sharing economy

The sharing economy describes markets that facilitate direct peer-to-peer exchange of goods and services. Airbnb, a tech company that started up in the Silicon Valley, is at the leading edge of this development. The sharing economy advertises to use excess supply of private goods that would otherwise go underutilized. The concept is appealing: Individuals rely more on each other than they do on companies. Someone receives a service or uses a good and in exchange someone else owning the good or providing the service, earns some extra money. Airbnb pro-

¹² Zillow.com is a real estate company in the US.

¹³ The data is collected by webscraping Airbnb.com. Webscraping describes the procedure of programming computers which automatically and repeatedly source information from the web. In this case, host information from the publicly provided listings on the Airbnb webpage and organize the data collected data in spreadsheets.

¹⁴ An introduction to hedonic pricing model follows in the *Methodology* section.

vides an online marketplace for individuals offering short-term accommodation (starting from one night) and for travelers in search of such. A private person that wants to share part of her home or to offer short-term accommodation when she is away, offers very similar services as the hotel industry. Thereby, she is directly competing with this industry. Traditionally, opportunities to offer accommodation were limited by high entry cost to the market. As a matter of search friction in the matching process of host and tourist, a host must invest a relatively large amount of money in visibility, which is rarely profitable. The advancement of the Internet enabled the creation of online marketplaces such as Airbnb, which facilitate the matching process and thereby, considerably reduce search costs. The Airbnb concept is exceptionally easy to use and very efficient in the matching process. Airbnb has grown at an exceptional pace during the last years. In 2017 Airbnb announced that since its founding in 2008 it had 200 million guest arrivals and lists 4 million accommodations in more than 191 countries.¹⁵ As a comparison, one of the by room number largest hotel groups in the world is the Inter Continental Group which has about 865.000 rooms.¹⁶ Up until 2017 Airbnb has raised \$4.4 billion of funding which values the company at \$31 billion,¹⁷ this compares to the market evaluation of the biggest companies of the hotel industry such as Marriot International (\$49 billion) and Hilton (\$25 billion).^{18,19} There are only a few noteworthy but significantly smaller competitors to Airbnb. The biggest of these competitors is HomeAway. HomeAway has acquired another (today) big competitor VBRO in 2006 and the HomeAway Group was bought by the ExpediaGroup in 2015. At the time before 2015 HomeAway has especially focused on the US market. In Berlin, Airbnb counted about 16,000 listings, whereas HomeAway listed just over 1,000 units in 2016.²⁰ Consequently, this research focuses on Airbnb.

3.2 Regulating short-term rental platforms

While affiliates of the short-term rental platforms praise the possibility to stay on vacation like a local, the community building through sharing and the opportunity to earn a little extra, housing advocates claim, that these platforms take long-term housing of the market, which increases housing shortage and puts upward pressure on rent prices. To limit additional pressure the Berlin city council initiated the first push against short-term rental platforms, in April 2014. The announcement to introduce a law to prevent use alienation (“Zweckentfremdungsgesetz”)

¹⁵ Airbnb - "4 -Million-listings announcement".

¹⁶ <https://www.ihgplc.com/about-us/our-global-presence>. 09.12.2019

¹⁷ business insider - "Airbnb made \$93 million in profit on \$2.6 billion in revenue". 06.02.2018

¹⁸ Marriot international: <https://www.forbes.com/companies/marriott-international/#59597a3c4fa0>. 09.01.2019

¹⁹ Hilton: <https://www.forbes.com/companies/hilton/#518afa98fc72>. 09.01.2019

²⁰ Beyond Pricing - <https://www.vrmintel.com/airbnb-vs-homeaway-winning-race-top-vacation-rental-industry/>. 09.01.2019

two years later, in April 2016, targeted to completely ban any short-term rental of residential space. However, reinforcement of the law appeared difficult and was not supported by court.²¹ Additionally, investigations on the legality of listings are a wearisome task. Hosts generally do not provide their real name on the user profile, neither the full address is advertised in the listing.²² Henceforth, Airbnb continued to grow in Berlin, in despite of most of the listings being illegal.²³

In a second attempt to get the situation under control, Berlin revised their legacy and introduced a novelty of the use alienation law in August 2018. Airbnb is now legal under certain conditions, which are²⁴:

1. Accommodation can only be subletted if the host does not sublet more than 50% of the apartment.
2. Second residencies cannot be subletted for more than 90 days per year and are only granted permission if the host does not possess another residency within Berlin.

If hosts fulfill these requirements, they are eligible to apply for a short-term rental permit at the local district's council and only when permitted, then they are allowed to offer accommodation on a short-term rental platform. Whether this novelty successfully regulates the Airbnb usage, must be observed in the near future.

The described situation implies that politicians are not yet clear about the effects of short-term rental platforms and the design of well performing legacy. So long, the contentious debate over short-term rental platforms and their effect on the housing market continues.

4 Mechanisms of Airbnb

Listings offered on Airbnb can be segmented into professionally managed listings and listings that are only occasionally available for rent. The mechanisms described here stem from the professional usage of the short-term rental platform. These professional users offer accommodation year-round with housing units drawn from the long-term market.²⁵

On the one hand, professionals that hire housing units to offer them on Airbnb increase the demand and on the other hand, the conversion of long-term housing to short-term rentals decreases the supply of long-term housing.

²¹ Berlin filed an official request towards Airbnb to hand out names and addresses of illegal Airbnb hosts. This request was denied by Airbnb and a Berlin court affirmed Airbnb Berlin in their decision.

²² Even though, Airbnb captures all this information and it would be easy for the company to identify illicit listings and their hosts, they do not disclose the information.

²³ Data from insideairbnb.com shows that after April 2016, there were more than 12,000 active Airbnb listings.

²⁴ Zweckentfremdungsverbot-Gesetz - ZvVbG.

²⁵ The precise guidelines for segmentation into the two different groups and each segment's share are given in the subsequent data section.

Driven by profit incentives, some property owners decide to offer their housing unit as a short-term rental year-round. This leads to the conversion of units from long-term towards short-term rentals. Additionally, there are agents, which I call here entrepreneurs, that rent or even buy long-term housing units, to then sublet the same unit on Airbnb with the perspective to gain profits, that exceed the long-term rental or loan costs. Due to their profit expectations, it can be assumed that entrepreneurs have a greater willingness to pay than usual tenants. Both, conversion by property owners and entrepreneurs can be considered professional Airbnb usage and hence, reduce the housing supply of the long-term market. Further, the perspective of regularly renting out a room on Airbnb, causes individuals to rent larger apartments than they would usually afford. Ultimately, any housing which has previously been inhabited by a local resident and is now listed year-round on the Airbnb platform, is subject to conversion and thereby, decreases the overall supply for long-term housing. At the same time, anyone who takes up more long-term housing space than she would in the absence of Airbnb, increases the demand for long-term housing. In addition, the media reports that in some cases landlords have implemented conversion by canceling existing long-term contracts.²⁶ Consequently, this behavior reinforces market tightness, as the former tenants return to the long-term housing market and further boost the demand.

Nevertheless, opposing mechanisms need to be considered. Firstly, there are reports of nightly changing Airbnb guests that are noisy and ruthless to neighbors.²⁷ This is a dis-amenity in the neighborhood and should decrease the willingness to pay for long-term rent. Secondly, it might be the case that Berlin employees, that only spend several days a month for work in Berlin, but live outside, hold a second residency in the city. Now, the availability of Airbnb is –at least partly- a cheaper alternative to hotel accommodation. This opportunity might prompt these professionals to give up their permanent secondary residency and deviate to staying at an Airbnb unit. This in return will increase long-term housing supply, if the same number of professionals can be accommodated by fewer Airbnb apartments.

In Berlin, Airbnb grew rapidly and evolved from a niche provider to a big player within only a few years. Whether the magnitude of professional Airbnb usage and hence, the reduction of supply and increase in demand outweighs the effect of dis-amenities and efficiency increases, is an empirical question, that this research aims to answer.

²⁶ PlusMinus – "Wohnungsmarkt: Geschäft mit Urlaubern". 31.07.2018

²⁷ Islington Gazette – "All night Airbnb rave" *see Introduction*.

5 Data and Summary Statistics

To investigate on the empirical question at hand, three data sources are applied. Firstly, a panel data set of the Airbnb landscape, obtained from insideairbnb.com, is used to quantify the Airbnb presence in Berlin. Secondly, a pooled cross-section data set of individual long-term rental advertisements, from F+B GmbH, provides the basis for the main regression on asking rent prices. Thirdly, various data sets from the Berlin Statistics Department add spatial information.

5.1 Neighborhood definition

The geographical unit of observation is the *Lebensweltlich orientierter Raum* (LOR). The LOR structure is constructed by the Berlin Statistics department. There exist 447 LORs with an average 8,076 inhabitants. LORs appear as an appropriate neighborhood unit as they are designed to have a homogeneous population in terms of socioeconomic characteristics. I include spatial data for unemployment rates, inhabitant count, age structure, constructions and tourist statistics to control for regional differences. The unemployment rate per LOR is only available for the years 2010, 2011, 2013, 2015, also, the inhabitant count per LOR is only available for 2008, 2012 and 2015. Both are extrapolated by a linear trend for the missing years. Nightly tourist counts are only available on the district level. The number of newly constructed apartment units is documented on the LOR level at a yearly frequency.

5.2 Airbnb

Data to analyze the role of Airbnb in Berlin is taken from insideairbnb.com. [Insideairbnb.com](https://insideairbnb.com) publicly provides data of Airbnb obtained by "scraping" the Airbnb webpage.²⁸

The data set covers every Airbnb listing in Berlin, its specific characteristics, review record as well as the host's profile. This includes the entry date of the host to the platform, host name, number and date of reviews of the listing, type of accommodation, number of bedrooms, location coordinates (randomized within an area of roughly 150m close to the actual location), nightly prices and many more. The accuracy of the data collected by insideairbnb.com was approved in several instances.²⁹

²⁸ *Webscraping* describes the procedure of programming computers which automatically and repeatedly source information from the web. In this case, host information from the publicly provided listings on the Airbnb webpage and organize the data collected data in spreadsheets.

²⁹ The data collected by insideairbnb.com has been used for policy research in the city of San Francisco. Further, The New York data of insideairbnb.com was compared to data which Airbnb was forced to provide. Barron et al. (2018) have collected their own Airbnb data; the comparison to data from insideairbnb.com had a high degree of match.

5.3 Rent prices

In Germany, in the past decade the tenant market was strongly affected by the digitalization. Traditionally, flat search was conducted via newspapers and real estate agency offices, nowadays the majority of search-and-match is done online on platforms such as Immoscout24.de and immonet.de. Equally, the company F+B GmbH collects data of the tenant market using webscrapes. Their databank captures the great majority of offered apartments in Berlin and is the foundation for this research. Alike the Airbnb data, this data set observes rent prices and many apartment characteristics.

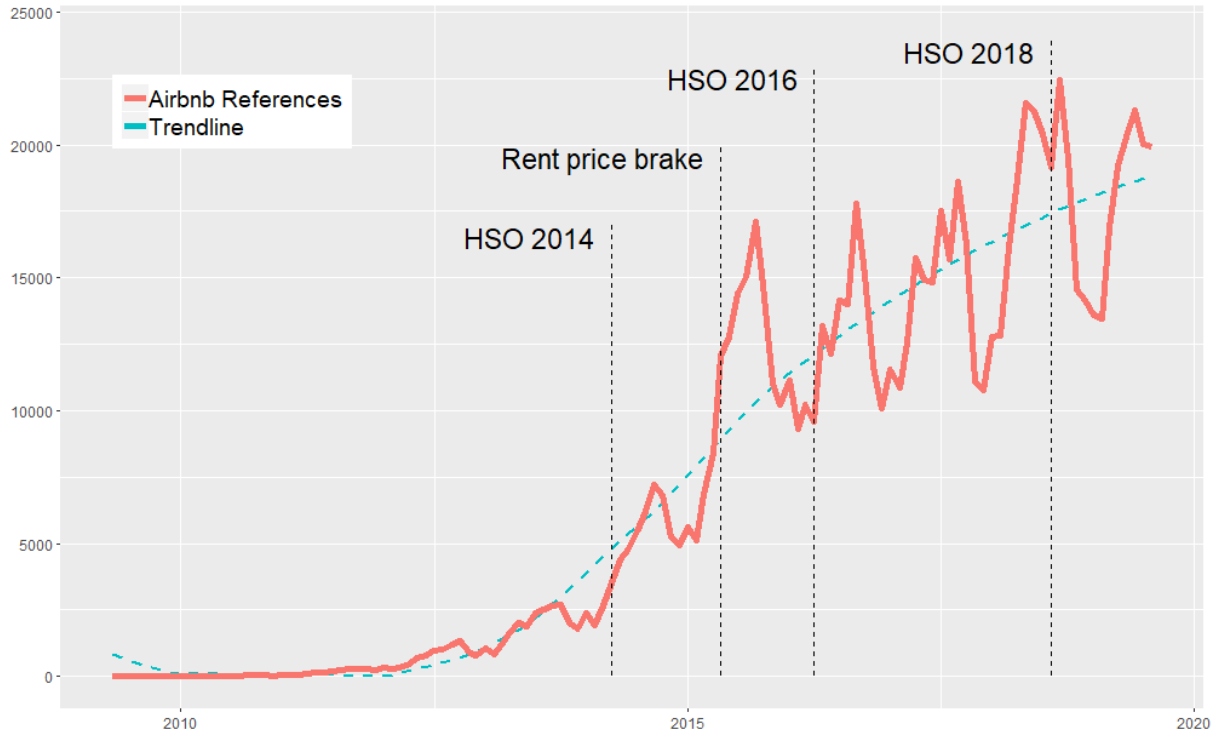
5.4 A story about sharing

Figure 1 shows the rapid growth of the number of references left by Airbnb guests per month in Berlin. After 2012 the reference count gradually increased and then grew exponentially between 2013 and 2015. One can observe the strong seasonality common to the tourist industry. Further, the figure supports the reported difficulties enforcing the home-sharing ordinance. The introduction of the HSOs before 2018 do not seem to significantly effect Airbnb growth. Whether the fairly young novelty of the HSO from 2018 shows more effect has to be evaluated in future research when additional data is available. However, the graph also shows the introduction of a rent control law in Berlin. I restrict my analysis to observations before June 2015 to avoid inference with the introduction of the law. It is assumed that only professional offers stand in competition with long-term tenancy. To asses the level of professionalism of a listing this study uses the cut-off proposed by Berlin city authorities. Accordingly, it considers listings that are booked for more than 90 days per year as professional.³⁰ If a listing received guests in the past half year, it is considered active. Table 1 shows that these considerations constitute a total of 6,841 active listings of which 2,160 are professional users. 71% of the professional listings are entire homes, 28% are private rooms and only 1% are shared rooms. Shared rooms are assumed to not take away space that would have been occupied by long-term tenants in the absence of Airbnb and are excluded from the sample. Studies on Airbnb usually only consider listed entire homes as competition to long-term tenants or the hotel industry like Barron et al. (2018) and Zervas et al. (2017). Though, any offer that is listed year-round on Airbnb, takes long-term housing off the market, including private rooms. Subsequently, this research also incorporates private rooms into the professional segment.

³⁰ Unfortunately, the collected data does not provide the number of nights that an Airbnb unit is booked. Though, reviews are displayed publicly with the according month in which the guest has stayed at the Airbnb unit. To approximate booking figures, I extrapolate the review count of a listing with the review rate and the average length of stay. The approximation takes a conservative review rate of 50% and combines it with the average stay length of tourists in Berlin, which is 3 days. A detailed discussion about the selection of parameters and the calculation of the number of nights that an Airbnb unit is booked, follows in the appendix 10.1.

Figure 1: Development of Airbnb in Berlin

Observed number of Airbnb References in Berlin per Month
From May 2009 to Sept 2019



HSO 2014 marks the announcement of the home-sharing ordinance,
HSO 2016 marks the implementation,
HSO 2018 marks the latest novelty.
Source: Own illustration with data from insideairbnb.com.

Table 1: Structure of Airbnb listings by professionalism and room type in June 2015

	# of listings	ratio in %	price in €	avg nights booked	avg revenue in €
Active listings	6,841				
Professional listings	2,160	0.32			
Entire home/apt	1,540	0.71	86.67	167	14,040
Private room	604	0.28	39.70	176	6,778
Shared room	16	0.01	51.22	164	8,148

Source: data from insideairbnb.com

Airbnb Inc. and Coles et al. (2017) state that Airbnb listings are usually spread all over the city. This way Airbnb particularly benefits outlying districts, it brings tourism to regions that traditionally do not receive tourists and do not have a hotel infrastructure. Contrary to this statement, I observe that the by far highest concentration of Airbnb accommodations can be found in central LORs, mainly in the districts Mitte and Friedrichshain-Kreuzberg while there

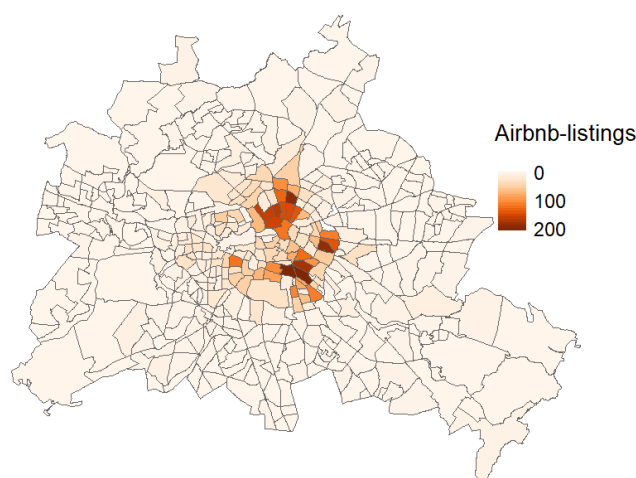
Table 2: Hosts with multiple Listings in June 2015

# of listings	# of hosts	total # of active listings
1	4688	4688
2	389	778
3	124	372
4 or more	135	1003

Source: data from insideairbnb.com

are no professional Airbnb listings in outer districts such as Spandau (figure 2). Due to data limitations the analysis concentrates on those three districts.³¹

Figure 2: Professional Airbnb listings per LOR in Berlin in June 2015



The high-density areas in the figure are located in the districts Mitte and Friedrichshain-Kreuzberg.

Source: Own illustration with data from insideairbnb.com.

A closer look at the characteristics of the Airbnb flats reveals further concentrations on the level of flat sizes. 93% of Airbnb listings have three rooms or less. Based on these findings table ?? puts the professional listings in perspective to the tenant market. I construct an Airbnb density measure. This measure relates the number of commercial Airbnb accommodations to the number of housing advertisements which have three rooms or less. Table 3 shows the 10% quantiles of this index for the LORs of Mitte and Friedrichshain-Kreuzberg in the second quarter of 2015.

50% of the LORs considered have an Airbnb density of at least 14%. Hence, in these LORs there are at least 1.4 commercial Airbnb accommodations for every ten long-term apartment advertisements. If you zoom in on the LORs around the Kottbusser Tor, the major junction of the north of Kreuzberg, you get an even more concentrated picture of the Airbnb density (Table

³¹ Nevertheless, these regions cover the LORs with the highest Airbnb concentration and give a good comparison group with LORs in Spandau. Data for entire Berlin has just been received and will be taken into account in future drafts.

Table 3: Quantiles of Airbnb density in %

	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Airbnb Density	0	5	7	9	11	14	19	24	35	56	500

Source: data from insideairbnb.com

4). There are on average 1.5 times as many professional Airbnb offers on any given day as housing advertisements during second quarter of 2015.

Table 4: Airbnb density at the Kottbusser Tor

	LOR Code	LOR Name	Professional listings	Ads	Airbnb Density in %
1	02030301	Oranienplatz	30	6	500
2	02010104	Wassertorplatz	9	5	180
3	02030302	Lausitzer Platz	38	44	86
4	02020206	Graefekiez	60	85	71
5	02030401	Reichenberger Strasse	56	94	60
6	02010103	Moritzplatz	12	61	20
7	Average				153

Source: data from insideairbnb.com

The descriptive study of the structure and distribution of Airbnb in Berlin shows that many of the active Airbnb providers rent their accommodation on a manner that can be considered commercial usage according to the guidelines introduced above. These commercial offers mainly provide the entire apartment. In addition, the corresponding offers are concentrated in the city center of Berlin with potential earnings that exceed those of long-term rentals. This gives incentives to take an entrepreneurial approach as a host on the Airbnb platform and to manage several accommodations at the same time. In relation to the total stock of housing Airbnb's share appears considerable low, however, in relation to the number of apartments available for new renters during one quarter the Airbnb density seems significant. If Airbnb listings significantly reduce the supply on the housing market, it is likely that they put upward pressure on rental prices. Whether this is the case will be subject to the following investigation.

6 Methodology

Typically, hedonic models are standard concepts to analyze the housing market. In hedonic modeling the price of a good is represented as the sum of the implicit prices of its various features (Jones, 1988). However, Cropper et al. (1988) have already emphasized the sensitivity to omitted variable bias. Parmeter and Pope (2013) pledge for the use of quasi-experimental

hedonic modeling in order to circumvent the problem of omitted variable bias.

As previously identified, Airbnb has very rapidly created a strong presence in the districts Mitte and Friedrichshain-Kreuzberg (MFK hereafter), while there is almost no professional Airbnb listing in Spandau. In the baseline analysis this study makes use of the sudden increase of Airbnb as well as the geographic variation to conduct a quasi-experimental approach to determine the effect of Airbnb on rental prices. Here, a hedonic housing model is embedded in a simple Diff-in-Diff set up including fixed effects, which is estimated with OLS:

$$\log(sqmprice_{ilt}) = \alpha + \beta_1 LOR_l + \beta_2 Post_t + \underbrace{\beta_3 LOR_l \times Post_t}_{Airbnb_{lt}} + \rho X_{ilt} + \lambda_t + \gamma_l + \varepsilon_{ilt} \quad (1)$$

, where the subscript i denotes apartments and l denotes LOR. The time index t refers to the quarter of observation. The regression includes LOR fixed effects γ_l as well as quarter fixed effects λ_t . X_{ilt} includes individual and spatial characteristics of each apartment and neighborhood. The outcome variable $\log(sqmprice_{ilt})$ is the log of the sqmprice (monthly net rent/apartment size in square meter) of each available apartment. LOR_l is a dummy variable that is equal to one if a LOR lies in MFK and zero otherwise. $Post_t$ equals one if a listing appears after the second quarter of 2013 and zero otherwise.³² Accordingly, the interaction term $LOR_l \times Post_t$ aims to identify the Airbnb treatment and thus, to measure the effect of heavy Airbnb presence on rental prices of newly posted apartments. Though, the previous section has shown that 93% of the observed Airbnb listings have less than or equal to 3 rooms (“small flats” in the following). This means that the group of large flats in MFK is defined as treated in the Diff-in-Diff set up, when in fact they are not. Hence, in a second step the data is restricted to observations of small flats. Accordingly, identification is given if small flats in MFK developed just like small flats in Spandau. Unfortunately, these districts have likely followed different trends in recent years. While MFK represent the very heart of Berlin, Spandau is a little further outside. In order to deal with this problem, the analysis exploits the cross-apartment size variation of Airbnb presence, instead of simply eliminating it. Namely, this research takes a triple Difference-in-Difference (TD) approach as described in Lee (2016) and Wooldridge (2010). Thus, the benchmark analysis estimates the following semi-log regression:

$$\begin{aligned} \log(sqmprice_{ilt}) = & \alpha + \beta_1 LOR_l + \beta_2 Post_t + \beta_3 Small_i + \\ & \beta_4 LOR_l \times Post_t + \beta_5 LOR_l \times Small_i + \beta_6 Post_t \times Small_i + \\ & \underbrace{\beta_7 LOR_l \times Post_t \times Small_i}_{Airbnb_{lt}} + \rho X_{ilt} + \lambda_t + \gamma_l + \varepsilon_{ilt} \quad (2) \end{aligned}$$

³² The timing of treatment is set to the 1st Quarter of 2013. A more detailed discussion follows in section 7.2.

, where subscripts and λ_t , γ_l and X_{ilt} are as before. Also, the outcome variable, log of the *sqmprice* of each available apartment and the *LOR* and *Post* dummy remain unchanged. *Small_i* represents a dummy that equals one if an observed apartment has three rooms or less and zero otherwise. Now the interaction term of the three dummies indicates the treatment effect. Whether an observation is in the treatment group or control group is identified in three dimensions: the geographic location, the number of rooms and the timing for when the listing becomes available for rent. Thus, the treatment dummy measures the causal effect of whether small apartments in Berlin have experienced an increase in asking rents that can be associated with the strong Airbnb presence since 2013. This effect will be unbiased if the following identification holds, as Lee (2016) shows:

$$\begin{aligned}
& E(Y_2^0|X_2 = x, S = 1, D = 1) - E(Y_1^0|X_1 = x, S = 1, D = 1) \\
& \quad - E(Y_2^0|X_2 = x, S = 1, D = 0) - E(Y_1^0|X_1 = x, S = 1, D = 0) \\
& = E(Y_2^0|X_2 = x, S = 0, D = 1) - E(Y_1^0|X_1 = x, S = 0, D = 1) \\
& \quad - E(Y_2^0|X_2 = x, S = 0, D = 0) - E(Y_1^0|X_1 = x, S = 0, D = 0)
\end{aligned} \tag{3}$$

, Y represents the outcome, in this case *sqmprice*, where the subscript indicates either 1 for the pretreatment period or 2 for the posttreatment period. The superscript 0 denotes the (hypothetical) situation of *no-treatment*. X_t are individual and spatial characteristics. Defining $S=1$ for small flats and $S=0$ otherwise and $D=1$ if in MFK and $D=0$ otherwise, one can separate the four summands and construct the following four sub-groups (from left to right): the development of small flats in MFK (a), the development of small flats in Spandau (b), the development of large flats in MFK (c) and the development of large flats in Spandau (d) in the absence of treatment. Hence, equation (3) can be rewritten simpler:

$$\begin{aligned}
& (a - b) = (c - d) \\
& \Leftrightarrow (a - c) = (b - d)
\end{aligned} \tag{4}$$

Accordingly, two identification assumptions have to hold:

- i. The difference in asking rents of small flats in MFK to small flats in Spandau developed just like the difference of large flats in MFK to large flats in Spandau in the absence of Airbnb.
- ii. The difference in asking rents of small flats to large flats in MFK has developed just like the difference of small to large flats in Spandau in the absence of Airbnb.

This identification gives the advantage to also observe different trends between the districts.

Airbnb heavily penetrated the housing market in MFK for small flats in very little time, while there were almost no professional Airbnb offers in Spandau. Consequently, comparing small flats in MFK to small flats in Spandau will give information about the impact of Airbnb. Further, because Airbnb did not affect large flats in either of the regions MFK or Spandau, changes in outcomes of large flats do not represent the direct effect of Airbnb, but instead reveal trends that are specific to MFK.

7 Empirical Results

This subsection presents the main findings of the effect of Airbnb on asking rent prices. First, the estimation results from the Diff-in-Diff set up of equation 1 are presented and briefly discussed. Followed by the findings from the benchmark regression of the triple Diff-in-Diff strategy from equation 2. This is followed by a variety of robustness checks.

7.1 Airbnb and asking rent prices

Table 5 reports the estimation results for the Diff-in-Diff set up of equation (1), which mark the baseline scenario. Column (1) excludes any controls but uses LOR and quarter fixed effects. It is possible that composition of the features of apartments differ between MFK and Spandau. The rich data set of available apartments allows for a wide range of individual controls that serve to control for these differences. Column (2) includes a variety of individual characteristics³³ Including the individual controls, decreases the effect of Airbnb to 0.046 which confirms the suspicion that some of the coefficient of column (1) was capturing effects that can be accounted to the composition of flats. Assigning the listings to geographical areas, in this case LOR units, provides the opportunity to further control for spatial differences on a refined geographical level. Column (3) draws advantage of this fact and includes spatial controls on the LOR level.³⁴ Adding spatial controls only slightly decreases the coefficient of Airbnb to 0.041. All specifications show highly significant effects.

For both, the individual and spatial characteristics the unobserved characteristics upward biased the estimate of the effect of Airbnb. This delivers evidence that the identification of the Airbnb effect solely by district-variation, does not completely isolate the true effect of Airbnb on rents. If one successfully controls for all other effects that vary between the districts, the Airbnb effect

³³ These controls include Apartment size in square meter, Apartment size squared, room number, dummies for balcony, garage, built-in kitchen, luxury, renovated, garden, winter garden, basement, central heating, newly constructed, historical building and furnished.

³⁴ Spatial controls include on the LOR level: the log of the inhabitant count in 1,000s per quarter, log of inhabitants aged between 21 and 45 in 1,000s per LOR per quarter, unemployment rate per year and the number of newly constructed apartment units per year. On the district level: log of the nightly guest count per 10,000 per year.

Table 5: Regression Results Diff-in-Diff

	log (square meter price) Double Differences		
	(1)	(2)	(3)
$LOR \times Post$	0.061*** (0.010)	0.046*** (0.009)	0.041*** (0.010)
Individual Controls	-	X	X
Spatial Controls	-	-	X
LOR fixed Effects	X	X	X
Quarter fixed Effects	X	X	X
#-LOR	108	108	108
N	76,697	76,697	76,697
R^2	0.660	0.709	0.711

Notes: Standard Errors clustered on the LOR-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

can still be estimated consistently. Unfortunately, the housing market is complex and despite of the rich set of controls, there is a remaining concern on whether the inter-district variation is fully captured.³⁵

Driven by these concerns, this study presents the results of a further variation of equation 1 and the estimation of equation 2. To exploit the fact that small flats comprise 93% of the Airbnb listings, Column (1) of table 6 presents the results of equation 1 with a restricted sample that includes only small flats. This specification yields a significant coefficient of 0.048. The effect is larger than the coefficient of equation 1 applying the full sample (Column 3 of table 5), which confirms the observation that Airbnbs are concentrated in the sub-group of small flats.

Finally, column (2 – 4) of table 6 present the results of the benchmark regression from equation 2 using the triple Diff-in-Diff approach. Column (2) includes only LOR and quarter fixed effects; the coefficient is at 0.025 (2.5%) and significant at the 5% level. Including individual controls (column 3) raises the coefficient only slightly to 0.03. Additionally, including spatial controls to the regression does not change the coefficient at all as presented in column (5).³⁶ This suggests that the unobserved characteristics downward bias the estimate of the triple Diff-in-Diff method of column (2) which gives confidence that the effect of Airbnb is not overestimated.³⁷ Consequently, the coefficient of the benchmark specification associates the presence of Airbnb

³⁵ As mentioned in the *Methodology* section, it is likely that the different district groups have experienced different gains in popularity and that this trend cannot fully be controlled by the nightly guest count per district.

³⁶ The F-statistic (=110.15) is in favor of including spatial controls.

³⁷ The coefficients for the individual and spatial controls in the specification of column (4) are presented in the Appendix 10.2.

Table 6: Main Results

	log (square meter price)			
	Double Differences	Triple Differences		
	$Small_i = 1$			
	(1)	(2)	(3)	(4)
$LOR \times Post \times Small$		0.025* (0.013)	0.030** (0.012)	0.030** (0.012)
$LOR \times Post$	0.048*** (0.010)	0.039** (0.017)	0.020 (0.016)	0.015 (0.015)
Spatial Controls	X	-	-	X
Individual Controls	X	-	X	X
LOR fixed Effects	X	X	X	X
Quarter fixed Effects	X	X	X	X
#-LOR	108	108	108	108
N	67,255	76,697	76,697	76,697
R^2	0.715	0.660	0.710	0.712

Notes: Standard Errors clustered on the LOR-level. *** $p < 0.01$,

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

with an increase of 3% in asking rents.

7.2 Robustness to selection of treatment timing

In equation 2 the timing of treatment is not straightforwardly selected. In the data section of this research, it is described how Airbnb experienced sudden growth starting from the 2nd quarter of 2013. To control whether the arbitrary selection of timing is consistent for a larger range of periods, Table 7 performs regressions according to equation 2, but using varying treatment timings. In column (1) the start of treatment is set to the first quarter of 2013, column (2) reproduces the results from table 6 (column (4)) for comparison and column (3) shows the result of Airbnb treatment, when the starting period is appointed to the third quarter of 2013.

Coefficients remain significant for all specifications, for either, the lag and lead quarter they are slightly smaller with estimates at 2.5% and 2.6%, but remain in the 95% confidence interval of the main finding of column (4) in table 6 (reproduced here in column 2) [0.0141, 0.0445]. This reassures the consistency of the effect and the selection of timing.

In an additional specification to verify treatment timing, every LOR's selection into treatment depends on a time varying Airbnb density measure. The density measure puts the professional Airbnb listings of every quarter and LOR in perspective to its total small housing units (with 3

Table 7: Robustness of timing, lag and lead of the starting period of treatment

	log (square meter price) Triple Differences		
	(1)	(2)	(3)
$LOR \times Post \times Small$	0.025** (0.009)	0.030** (0.012)	0.026** (0.009)
Individual Controls	X	X	X
Spatial Controls	X	X	X
LOR fixed Effects	X	X	X
Quarter fixed Effects	X	X	X
#-LOR	108	108	108
N	79,015	79,015	79,015
R^2	0.7138	0.7136	0.7135

Notes: Standard Errors clustered on the LOR-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

rooms or less).³⁸ The mean Airbnb density in MFK between the second quarter of 2013 and the second quarter of 2015 equals 0.93%. The median density lies at 0.55% and the highest concentration is in the LOR *Wilhelmstrasse* in Mitte with 11.66%. Proportionately, the selected threshold for treatment orientates between the mean and the median and is defined to 0.8. Thus, every observation that lies in a LOR at the time where the Airbnb density within this LOR passed the threshold of 0.8% and has 3 or less rooms appears as treated. Table 8 shows the associated Airbnb effect of 2.8% which is only 0.2 percentage points smaller than the main result and remains significant. In this set up, untreated LORs and treated LORs can be direct geographical neighbors. A separation on a such refined geographical-level, is likely to be affected by spill-over effects. Untreated LORs within MFK, that do not reach the density threshold, are very likely to be affected by the Airbnb presence of surrounding LORs. This possibly explains why the measured difference between treated and untreated appears slightly smaller than the findings of Table 6. Nevertheless, this specification allows for varying treatment timing and still produces positive and significant results very close to the magnitude of the main result. This gives additional confidence that the estimated effects on asking rents are induced by the appearance of Airbnb.

³⁸ The professional count incorporates entire apartments as well as private rooms. Of course, these cannot be rated one to one. As a consequence, the number of private rooms is weighted by the average number of rooms per apartment of the long-term tenancy sample, which corresponds to 2.4 rooms.

Table 8: Robustness of timing - variable threshold dummy per LOR

	log square meter price Triple Differences
$LOR \times Post \times Small$	0.028*** (0.007)
Individual Controls	X
Spatial Controls	X
LOR fixed Effects	X
Quarter fixed Effects	X
#-LOR	108
N	79,015
R^2	0.7133

Notes: Standard Errors clustered on the LOR-level. *** $p < 0.01$,
** $p < 0.05$, * $p < 0.1$

7.3 Placebo Regressions

Table 9 shows the results of placebo regressions that check whether the *Airbnb* dummy signals an effect in the preperiod. Therefore, the sample is restricted to observations before 2012 and a placebo timing is initiated. Column (1), (2) and (3) represent different starting points (first quarter/ second quarter / third quarter of 2011) of treatment to test for a placebo effect of the dummy. None of the coefficients achieve significance and their magnitudes are close to zero. This assures that there is no trend that increases the asking rent of small flats in MFK in the preperiod and strengthens the assumption that the triple Diff-in-Diff strategy only measures asking rent increases through the rapid proliferation of Airbnb.

8 Discussion

In recent years, Airbnb has been confronted with media and political headwinds worldwide and is increasingly exposed to regulation. The basis for the new regulations is the debate about Airbnb's influence on the housing market. Airbnb insists on being far too small and therefore irrelevant for the general rental market. Though, empirical evidence is scarce. If Airbnb's distribution in Berlin is taken into account, it quickly becomes clear that there is a considerable concentration of Airbnb at the local level. To study whether this results in a local shortage of living space and increases local rents this study examines a micro data of asking rent prices and combines this with Airbnb data. Across different specifications, the entry of Airbnb into the Berlin housing market had a significant effect on the asking rents. The results of the benchmark

Table 9: Placebo Regressions

	log (square meter price) Triple Differences		
	(1)	(2)	(3)
Airbnb placebo	0.004 (0.012)	0.000 (0.013)	−0.009 (0.015)
Individual Controls	X	X	X
Spatial Controls	X	X	X
LOR fixed Effects	X	X	X
Quarter fixed Effects	X	X	X
#-LOR	108	108	108
<i>N</i>	31,379	31,379	31,379
<i>R</i> ²	0.6258	0.6260	0.6260

Notes: Standard Errors clustered on the LOR-level. *** $p < 0.01$,
 ** $p < 0.05$, * $p < 0.1$

regression imply a 3% increase in asking rents accounted to Airbnb in those areas with a strong Airbnb presence. The average sqmprice in asking rents of small flats in MFK increased by 17.2% from the second quarter of 2013 to second quarter of 2015. Subsequently, the estimated asking rent increase of 3% associated with Airbnb, accounts for 17.4% of the overall asking rent growth during this period. Small flats in MFK in 2013 had a mean asking rent of 656€ monthly, thus, the Airbnb induced rent increase leads to an asking rent of 676€, which equals an additional 20€ monthly or 240€ annually.

As seen in figure 1 even after the latest regulation in 2018 the usage of Airbnb remains at a very high level in Berlin. This gives reason to suspect that implemented regulations have not yet shown strong effects. Consequently, the regulation of short-term rental platforms remain on the agenda of policy makers. As long as short-term rentals prove to be more profitable than renting out to long term tenants and no credible enforcement can be achieved, platforms such as Airbnb will worsen the housing affordability. The findings of this study can contribute to the political debate about the effect of Airbnb on the housing market and can help to find a desirable design for future regulations.

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10 Appendix

10.1 Calculating the booking figures

Guests are asked to leave a review within 14 days of their stay. The Co-Founder Brian Chesky states the guests review rate to be 72%, whereas in the analysis of the impact of short-term rentals on housing from the *Budget and Legislative Analyst's office* of San Francisco the authors calculate a 30.5% review rate. The authors compare the New York Attorney General's report, which is based on data provided by Airbnb, to publicly available data from insideairbnb.com.³⁹ Data analysts of insideairbnb advocate the adoption of a review rate of 50% as it is just in between the investigated 30.5% and the alleged 72% from the Co-Founder.⁴⁰ A review rate of 50% is likely to yield conservative findings compared to the proven 30.5%. To calculate the average monthly-booked nights, the average monthly reviews of a listing are multiplied by the inverse of the review rate. This is multiplied by the average length stay. Airbnb reports that their guests stay on average 6.3 nights in Berlin, however, a length of 3 night seems more realistic (for usual tourists the average is 2.3 nights).⁴¹ From this follows:

$$avg\ monthly\ booked\ nights_i = avg\ monthly\ reviews_i * \frac{1}{50\%} * 3 \quad (5)$$

For the year estimator monthly booked nights are multiplied by 12 and capped at 310 days which corresponds to a 85% occupancy rate.

³⁹ City and County of San Francisco Board of supervisors Budget and Legislative Analyst p. 49.

⁴⁰ Insideairbnb.com data disclaimer.

⁴¹ Airbnb publication: Economic impact airbnb - <https://blog.airbnb.com/economic-impact-airbnb/>. 09.01.2019

10.2 Full regression output

Table 10.1: The Effect of Airbnb presence on the rental price in Berlin, Full Output

	log (square meter price) Triple Differences
$LOR \times Post \times Small$	0.0301*** (0.0121)
Apt. size	−0.0044*** (0.0001)
(Apt. size) ²	0.00002*** (0.000001)
Balcony	0.0075*** (0.0013)
Garage	0.0253*** (0.0017)
built-in kitchen	0.0643*** (0.0014)
Luxury	0.0809*** (0.0021)
Garden	0.0233*** (0.0021)
Renovated	0.0364*** (0.0015)

Notes: Standard Errors clustered on the LOR-level. *** $p < 0.01$,
** $p < 0.05$, * $p < 0.1$

Table 10.2: The Effect of Airbnb presence on the rental price in Berlin, Full Output

	log (square meter price) Triple Differences
Winter garden	−0.0209*** (0.0043)
Basement	−0.0151*** (0.0013)
Central heating	−0.0120*** (0.0013)
Newly constructed	0.0810*** (0.0020)
Historical	0.0339*** (0.0015)
Furnished	0.0955*** (0.0073)
log(Inhabitant)	−0.8250*** (0.0497)
log(Inhabitant 21-45)	0.5719*** (0.0345)
Unemployment	0.0006 (0.0013)
log(Tourism)	0.1024*** (0.0117)
log(Newly Constructed Apts)	−0.0054** (0.0024)
Constant	2.4510*** (0.0912)
Individual Controls	X
Spatial Controls	X
LOR fixed Effects	X
Quarter fixed Effects	X
#-LOR	108
N	79,015
R^2	0.7136

Notes: Standard Errors clustered on the LOR-level. *** $p < 0.01$,
** $p < 0.05$, * $p < 0.1$