PRELIMINARY

Understanding Airbnb in Fourteen European cities

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Abstract:

This paper gives an introductionary account of the activities of Airbnb in 14 European cities. Since Airbnb provides an online platform for short-term leases between local properties owners and foreign visitors, its impacts should be observed in both the hotel industry and the domestic rental market. We discuss the structure and the sementation of the accomodation market, and then present some basic statistics of Airbnb activities in the 14 cities. Finally, we estimate the impact of Airbnb on the hotel industry and the rental market, while taking care of non-stationarity of the variables. We find negative impact on hotel occupancy rate, and positive effect on ADR and total hotel revenue. Meanwhile, the impact on the rental market is ambiguous, hinting the importance of local regulations and management.

JEL codes: D22, L83, L88, R31

1. Introduction

Since the launch of Airbnb across Europe from 2010, the platform has grown rapidly, and clearly offers travellers and property owners a service they value. However, Airbnb is controversial because it potentially competes both with hotels and with the private rental market, yet without the same tax and regulatory constraints of either of these existing short-term or long-term accommodation markets. Hoteliers perceive the entry of Airbnb as an 'unfair' competitive threat. There are also concerns that property owners are switching from long-term residential tenancies to short term Airbnb lets in major cities where housing is expensive and hard to find. Thus several cities around Europe have introduced regulatory restrictions on Airbnb or are discussing doing so. This paper aims to provide some empirical evidence on the scale of the impact Airbnb entry has had on the hotel and private rental markets, in a number of European cities.. To date, there is relatively little empirical research and yet there is considerable pressure on local authorities to regulate Airbnb more restrictively, despite the value it offers to users on both sides of the platform.

The assessment of potential harm requires answers to empirical questions. How much has Airbnb grown in different locations, and have Airbnb lettings affected the quantity of other short-stay accommodation (hotels) and the prices they charge? Has Airbnb affected on the other hand the price and availability of longer-term accommodation (the private rental market)? These effects could be large or small depending on whether Airbnb expands the supply of available properties, expands the demand by offering a wider menu of choice to travellers, or both; and also on the extent to which

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it is eroding the traditional segmentation between short-term and long-term urban accommodation. Other empirical questions are: how much do the effects of Airbnb vary between different cities depending on the market context? Where are Airbnb properties located, compared to hotels and to neighbourhoods of privately rented longer-term accommodation?

For local authorities, the questions concern the effectiveness of their regulatory frameworks. Hoteliers complain that sellers on Airbnb do not pay the occupancy taxes imposed on hotels and can avoid other regulations such as safety rules. Tax authorities might be concerned that Airbnb hosts are not reporting all their income, as they might not be registered as self-employed or freelance workers. Local residents might have concerns about a larger number of short-term visitors in largely residential areas. Local authorities in cities where there is high demand for rental housing worry that the supply will be diminished by owners turning to Airbnb rentals.

The contribution of this paper is to provide some empirical evidence on these questions in European cities. While demand for short stay and longer term rented accommodation is highly segmented and likely to remain so, the entry of Airbnb could break down supply side segmentation between these markets, as well as potentially increasing the supply of short term accommodation as owners of properties take advantage of the platform to rent out (part of) their property for the first time.

We have a large volume of web scraped data on Airbnb in a number of European cities, provided by the information company Airdna. Daily information from September 2014 to April 2016 for 14 European cities is extracted from Airbnb's website, from which the average monthly and annual performance are computed.[2] This includes the occupancy rate and revenue (in US dollars in the original data set) from April 2015 to March 2016. Together with all visible online features of the hosts and the properties, we are able to look at the connections between performance in terms of occupancy and revenues and property characteristics. Among the characteristics, the start date of the listing, the listing type (private room, shared room or entire apartment/home), and the location of the listing are particularly interesting, and we briefly describe these. Secondly, we were provided with data on hotels – average daily rate (ADR) per room, total revenues, and average occupancy rate – by the hotel information company STR. We also gathered data on private rents, available from official sources for the capital cities, and for the wider regions in which other cities are located; and other data on city or region level explanatory variables.

This paper provides some initial descriptive information on the novel data, the Airbnb listings. We describe also the hotel characteristics for the same cities. We discuss the potential effects of Airbnb entry into a segmented accommodation market. We then present econometric results the cities for which we were able to collect the necessary data. We find that

a rise in the number of Airbnb listings in a city was associated over this period with a fall in the average occupancy rate, but an increase in the average daily rate received by hotels. The combined effect on total hotel revenues was ambiguous but in any case

2 The 14 cities are Nantes, Paris, Strasbourg, Toulouse, Berlin, Cologne, Frankfurt, Munich, Edinburgh, Glasgow, London, Manchester, Amsterdam, and Barcelona.

small. On the other hand, the number of Airbnb listings is positively correlated with the rental price index in the UK, but not in Germany.

2. Previous research

The economics of so-called 'sharing economy' peer-to-peer asset rental platforms in general are surveyed in a number of recent books and papers, including Coyle (2016), Edelman and Gerardin (2015), and Sundararajan (2016). Such markets have grown rapidly, thanks to a combination of the spread of smartphones enabling constant real-time online access and to innovations in algorithmic and marketplace design. A model of the consumer choice in a P2P market is discussed in Horton and Zeckhauser (2016). In their model, in which there is a single pool of owners and renters, there is a short-term equilibrium after the emergence of a P2P rental market, in which both owners and renters use the asset as if they were paying the market-clearing rental rate – the owners as there is now an opportunity cost to their own use of the asset. In the long run, the availability of the market can change the buy or rent decision: the (normalized) purchase price equals the market clearing rental rate. If the short run rental rate is below (normalized) purchase price, demand for asset ownership will decline. These results are tempered by the presence of 'bring to market' costs, which include costs such as labour to prepare the asset for renting out (cleaning, key exchange) and also the temporal indivisibility of some assets (is It easy or hard to lend them out in small chunks of time). The existence of such costs means that consumers placing enough value on the use of the asset will tilt toward ownership rather than renting. Income is also a constraint on ownership high-value assets such as urban properties. Like other analyses of P2P platforms, Horton and Zeckhauser find that the existence of the platform increases social welfare (eg Edelman and Giradin 2015, Benjafaar et al 2015, Einav et al 2015).

The empirical literature on Airbnb is small but growing. Zervas et al (2014) group hotels into budget hotels likely to be competing with Airbnb rentals, and high-end hotels catering to business travellers. Looking at data for Austin, Texas, they found an 8-10% drop in hotel revenue in locations where Airbnb supply is highest. They also found that the lower-priced hotels and those not catering to business travellers were the most affected. The effect was uneven since rooms in private apartments are highly heterogeneous in their features. Hotels still commanded a premium over Airbnb because some customers prefer the quality, the consistency of service, and other standard attributes provided by hotels. A study on the Netherlands found a negative but small effect of Airbnb entry on hotel prices. (Hooijer 2016). Neeser (2015) looked at three Scandinavian countries and found no significant effect on average hotel room prices, but a small negative effect in the places where there had been most growth in Airbnb listings. Quattrone et al (2016) explore Airbnb in London, finding that listings on the platform are linked to socio-economic characteristics of neighborhoods, with more listings in desirable areas with young populations and more residents who are employed, and born outside the UK. Listings are less likely to be found in more distant residential areas with more houses than flats. However, the listings have expanded over time from the desirable central areas to more distant areas. (Quattrone et al 2016).

Horton and Zeckhauser (2016) present a model looking at the individual decision to use oneself or rent out to somebody else an already owned asset such as a house or apartment, and additionally at the long term equilibrium decision to buy or rent a property. They conclude that in the short run equilibrium, owners will face an opportunity cost of own use that is equal to the market rental, and the rental rate will be positive in the owners' valuation of the asset (which reduces supply as it rises) and also in the valuation of the renters (which increases demand). In the long run equilibrium, the (normalized) purchase price will also equal the rental rate. The individual's 'rent or buy' decision will depend on their valuation, and also the 'bring-to-market' costs of renting out the property (cleaning, key handover etc).

We are not aware of any empirical work looking specifically at the private rental market. Furthermore, given that the hotel and rental market contexts in terms of both demand and supply can differ greatly between cities, it is important for policy makers to have evidence specific to their own locations.

3. The structure of the accommodation market

There are a number of regulatory issues at stake when it comes to understanding the market impacts of Airbnb. In terms of the impact on the incumbent hotel business, tourism is an important sector of the economy. The EU28 countries received 457 million international tourists in 2014 compared to 331 million arrivals in 2000.[3] While there are many factors contributing to its growth, digital technology has revolutionised the travel and tourism business, enabling individuals to construct their own trips from a far wider array of choices. The first stage in the technology-driven evolution was the growth of online travel agencies (OTAs), which have largely replaced traditional high street agencies. They improved competition among hotels by providing smaller hotels with a platform. But competition authorities have been concerned about the business model and structure of the industry. Booking.com is the most popular online hotel booking platform, especially in the US but globally ranking at 112 among all websites. It is the dominant player in the market and despite interventions by competition authorities, its pricing tactics still make it hard for a new entrant to gain market share through price competition (Coyle 2016).

Hoteliers complain that Airbnb specifically presents unfair competition because hosts listing on the platform can avoid the taxes and regulation applied to the formal hotel sector, and see it as increasing the supply of short-stay accommodation competing with hotel rooms. Local authorities are most concerned about loss of tax revenues, safety issues, and in some cases also about the increased volume of visitors to already-crowded city centres.

City authorities may also be concerned about the other side of the coin, that the growth of Airbnb might reduce the supply of private rental accommodation available to residents, in tight housing markets. There have also been some issues about externalities such as additional noise in residential areas and anonymous visitors in residential areas. An additional issue is safety, since some non-tourist residential areas could potentially be more dangerous. A hotel seems safer since there are staff and also other travellers. Meanwhile, some sorting is going on. The maps show that properties are sparsely located, if not absent, in poorer or rougher areas of the cities. They are

3 The sharing economy and tourism: Tourist accommodation. European Parliament Briefing September 2015.

absent perhaps due to the fact that users are informed enough to avoid certain areas, while hosts in areas will accumulate fewer visits and reviews. Still, it is difficult to disentangle the demand-side factors from those of the supply-side.

A number of European cities have recently tightened regulations applied to Airbnb rentals. Berlin has banned unregistered short term rentals. In Brussels owners need permission from their building owners or commune. Amsterdam has limited the number of people who can jointly rent one property (to prevent noisy parties). Barcelona requires the host to be in residence during the rental period, or otherwise treats the property in the same way as a hotel. Many cities limit the amount of time during the year a property can be rented out through Airbnb-type platforms, a policy directed at preventing the crowding out of residents in the private rental market. Barcelona and Paris have fined Airbnb for various regulatory violations. Airbnb has agreed to collect tourism taxes in a number of places.

Other researchers have considered separate aspects of these issues. Although long-term renters' sensitivity to price will be affected by liquidity constraints, in equilibrium rental prices should be equal to (suitably normalised) property purchase prices. This rent-or-buy decision is the one analysed by Horton and Zeckhauser (2016). We do not consider the rent-or-buy decision further here as it is not one of the relevant regulatory concerns.

Einav et al (2015) present a stylised model of new flexible entry like Airbnb into a hotel market, where hotels have fixed upfront as well as variable costs, and the new entrants have variable costs only. Their results support the intuition that when demand is high, additional flexible supply is induced. This will reduce the equilibrium price and the profitability of owners of fixed supply (hotels). The higher fixed costs and the lower variable costs, the more flexible supply there will be. An additional element is the cost of visibility in the market, a fixed cost assumed to be equal for all suppliers. Lower visibility costs will increase total capacity and flexible capacity; but decrease fixed capacity, and also prices.

This is only part of the story, however. The context into which Airbnb is entering is one of inter-related but segmented property markets. The demand side in urban rental markets is normally segmented: demand for long-term rentals and short-term stays in cities have been largely (although not completely) distinct. The entry of Airbnb into the market is unlikely to affect long term rental demand, which will depend on factors such as employment and population growth; but it could increase demand for short stay accommodation if travellers either have sufficiently price elastic demand or are attracted by other characteristics (such as the greater ease of visiting with children). In any case, short and long stay demands will probably retain distinct characteristics, preserving demand-side segmentation.

Within short-stay demand there may additionally be other relevant market segments: less price sensitive business travellers and more price sensitive tourists. Despite the cost-advantage of Airbnb listings, hotels are obviously not always an inferior choice, so these segments may also be preserved. Business travellers are much more able or willing to pay for convenience and reliability. For example, Airbnb hosts can cancel reservations at short notice and the platform does not penalize the hosts who renege on their promises, or compensate the users who find themselves nowhere to stay at short notice. The informality of the sharing economy does not (yet) sustain service norms. On the other hand, we always expect hotels to observe their promises. By screening out budget travellers, hotels may be better able to identify customers with less price-elastic demand and thus possibly even raise prices and obtain higher revenue thanks to the greater scope for price discrimination. Thus the entry of flexible low cost supply could in effect push up the prices and revenues of some hoteliers, though low-cost hotels may suffer.

The literature on segmentation in housing (or labour) markets focuses largely on differences in preferences and search costs on the demand side.[4] However, the entry of Airbnb may be eroding supply side segmentation between hotels and rental apartments, as well as increasing the supply of flexible/informal short-term accommodation. Entry into the hotel market has always been expensive, requiring both significant financial investment and a number of one-off regulatory and other barriers (licensing, inspections, marketing etc) so supply is inelastic. Entry into property ownership (for own use or rental) is similarly costly and constrained by physical supply in large cities, but existing owners may be concluding that the Airbnb platform gives them the option of short-term rentals.[5]

There are therefore two margins of choice to consider post-Airbnb entry:

- for existing private owners who can now choose to supply spare capacity to short-term renters if they perceive demand to be sufficiently high and revenues to exceed the costs of joining the platform and providing the services such as key exchange and cleaning;
- for existing landlords who can choose to supply to short-term rather than long-term renters. Landlords will want to consider whether this is a more profitable option. They are also likely to face fewer regulatory constraints on both price and tenancy conditions if they switch. On the other hand, there may (in principle) be higher visitor taxes on short-term rentals.

Note, however, that the different regulatory concerns about the effects of Airbnb will not be simultaneously valid. If the entry of the platform is reducing the profitability of hotels, it is unlikely that it will be tempting private landlords to switch from long-term rentals into behaving more like hotels. In what follows we therefore look at the effects of Airbnb expansion on both hotel performance and private rental costs.

Hotel and Airbnb are generally believed to be competitors. Assume that hoteliers face downward sloping individual demand, i.e. each of them commands a certain degree of market power. Profit maximization requires marginal revenue equal marginal cost:

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4 See for example Islam et al 2009.

5 Demand will be a function of price p, and other characteristics k. These can include reliability, location, length of contractable stay and so on. (Demand can also be shifted by events exogenous to the market, of course.)

$D = D(p, k)$

Costs of providing accommodation include:

Upfront fixed costs $c(q)$ to provide q units (person-nights) of accommodation

Variable cost c_o per unit

Market visibility costs $b > 0$

A stylised picture of the market would assume hotels will have both fixed and variable costs, Airbnb hosts have variable costs only, and private landlords fixed costs only. All three kinds of suppliers will incur visibility costs.

where ε is the price elasticity of demand. The prominence of Airbnb very likely causes some visitors to shift their demand away from hotels. A fall in demand then causes the marginal cost to fall. But if the demand now becomes less price elastic, the term in the bracket decreases and the price may go up to restore the equilibrium. Therefore, a fall in demand for hotel rooms due to the booming of Airbnb may cause the room rate to increase, if the remaining customers are less price elastic. The overall effect on total revenue is ambiguous, which may also increase if the magnitude of the price rise overwhelms that of the fall of occupancy of hotel rooms.

Airbnb impacts on the traditional rental market in a different way. Owners may supply their properties to the Airbnb platform instead of the traditional long-term rental market. The prospect of earning a higher return from the Airbnb platform causes the supply of the long-term leases to fall and also the rent to rise to match the opportunity cost. Still, short-term lease and long-term lease are not completely substitutes. Owners may prefer the certainty associated with long-term leases, while some of them prefer the flexibility of Airbnb.

4. Description of the data

Airbnb

Number of listings, occupancy rates and average revenue of Airbnb hosts

According to the Airdna database, 227,093 listings were to be found in the 14 cities by April 2016.[6] Figure 1 displays the number of listings in the 5 biggest cities in the sample from January 2008 to April 2016. Paris ranks the top with 65,217 listings (for perspective, the population the metropolitan region is roughly 12 million).[7] A mild catch-up in the smaller cities is evident; the average growth rate of the small cities (those with fewer than 10,000 listings up to April 2016) has outpaced that of the 5 big cities.[8] Properties on Airbnb are highly heterogeneous. The most frequent type of property is ‘apartment’, accounting for 87.8% of all listings, but it is not unusual for Airbnb users to spend a night on a boat or in a castle. The most common type of listing is ‘entire home/apartment’, reaching 65% of the total number listings. However, the cities show a considerable variation in this respect, ranging from just 36% in Manchester to 87% in Paris.

Judged by the performance of the Airbnb listings in the sample from April 2015 to March 2016, at any given time most of the listed properties are not rented. The average occupancy rate was about 30% during the 12 months of the sample period and is significantly influenced by seasonal fluctuations of demand. Taking Paris as an example, the average occupancy rate of a listed Parisian property was 35%. Among those having at least one successful transaction, 23% of them had only one customer every ten days. Other cities exhibit a similar pattern (see Table 1).

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6 The listing is “active” if it has at least one transaction during last 12 months. We will stick with those active listings throughout the analysis.

7 The number of hotel rooms in Paris was roughly 76,600 in 2010.http://www.hvs.com/Content/3131.pdf

8 The big 5 are Paris, London, Berlin, Barcelona and Amsterdam.

Source: Airdna

Table 1	**Average Occupancy Rate**	**Proportion of Listings with an occupancy rate**		
City		less than 10%	less than 50%	more than 90%
Amsterdam	39.42%	16.48%	65.40%	2.49%
Berlin	36.44%	20.32%	69.48%	3.44%
Barcelona	35.18%	21.91%	70.83%	1.73%
Paris	35.07%	22.74%	71.10%	1.00%
Glasgow	33.88%	21.03%	74.49%	3.69%
London	33.30%	24.31%	73.47%	1.30%
Nantes	33.27%	23.91%	73.91%	1.08%
Manchester	31.25%	26.01%	76.73%	2.51%
Edinburgh	30.00%	27.29%	78.35%	2.19%
Strasbourg	29.80%	28.58%	77.84%	2.02%
Toulouse	28.69%	26.27%	81.05%	2.60%
Munich	26.26%	37.45%	81.50%	1.24%
Frankfurt	25.04%	33.18%	84.68%	4.41%
Cologne	23.86%	35.93%	86.24%	2.47%

Source: Airdna

Revenue is also unevenly distributed among hosts (See Table 2). For example, among those active listings in Paris, almost 27% have earned less than US$1,000, while just 3.4% earned more than US$30,000 during the past year. This suggests a wide range of behaviours on the part of owners.

Table 2	**Average Annual Revenue US$**	**Proportion of Listings with an annual revenue**		
City		Under US$1,000	Under US$10,000	Over US$30,000
London	7928.88	23.48%	72.86%	5.73%
Amsterdam	7792.49	15.26%	73.00%	4.34%
Edinburgh	6714.75	19.35%	76.67%	2.82%
Paris	6535.50	26.82%	79.47%	3.39%
Glasgow	6268.78	22.44%	78.41%	2.33%
Barcelona	6163.10	26.11%	78.66%	2.40%
Manchester	5594.82	29.64%	80.41%	2.42%
Berlin	3858.84	40.10%	88.44%	1.02%
Munich	3754.48	36.59%	89.71%	1.03%
Toulouse	3731.30	29.22%	90.92%	0.22%
Frankfurt	3207.95	34.57%	93.28%	0.33%

Cologne	3149.16	39.10%	93.34%	0.27%
Nantes	2798.53	38.75%	94.59%	0.00%
Strasbourg	2663.29	43.84%	94.89%	0.07%

Source: Airdna

Reputation

An effective evaluation system is fundamental to the success of any online platform. Airbnb, like other platforms, has an evaluation system for both hosts and visitors. It works as follows: A user books a property through Airbnb. The telephone number and the exact address are revealed to the user only after confirmation. If the host cancels a booking before the visit date, an automatic comment is posted on the wall of reviews of the host:

The host canceled this reservation X days before arrival. This is an automated posting.

The host manages the reception of the visitor (access to keys). After the stay, the host can decide whether to invite the visitor to comment. If yes, the visitor will receive an email with a link to an e-form through Airbnb. The visitor is asked to rate six aspects of the property: Accuracy, Communication, Cleanliness, Location, Check-in, and Value. A final score, from 0 to 5, is then computed accordingly. Besides the numerical score, the visitor is asked to comment, including the location, the facilities, the environment, and the host's friendliness. The host will then see the comment before deciding whether to reply and whether to review the visitor. If the host chooses not to reply, the comments left by the visitor will not be shown on the wall of the host. Therefore, no comment will be shown if the host thinks it is inappropriate. If the host chooses to comment, both reviews will be visible on the wall of both parties.

This evaluation system seems to protect the host from malicious reviews. But at the same time it might create a fake 'feel good' environment. Listings are not very differentiable in terms of ratings. This phenomenon is already well-recognized in the literature (Dellarocas and Wood, 2008; Bolton et al, 2013; and Fradkin et al. 2014). Zervas, Proserpio and Byers (2015) compare Airbnb and TripAdvisor, which does not use a bilateral evaluation system but allows unilateral comments by visitors, and they find that users tend to give higher ratings on Airbnb. Luca (2016) reviews the design choices available to reduce the bias in reviews but observes that there are inescapable trade-offs (such as the amount versus the quality of information provided by reviewers).

In practice, visitors seem to use the length of time a property has been listed, or the number of reviews posted, rather than the actual rating score to evaluate properties. Figure 2 shows the average annual revenue and the occupancy rate from April 2015 to March 2016 of all listed entire homes/apartments in Paris, sorted by the date of first being listed on Airbnb. A negative trend is clear.[9] Figure 3 plots the average number of reviews and the average rating of the listings of the same period. The sharp fall in

9 Fluctuations in 2008 and 2009 are mainly due to the small number of listings and thus not significant.

number of reviews is not surprising since a new entry takes time to accumulate visitors and reviews. But old and new listings are almost identical in terms of ratings. Thus longer-listed properties do not systematically receive higher ratings, but have accumulated larger numbers of reviews and are thus able to attract more customers and earn higher revenues. Users seem not rely on the rating for selection but instead on the number of reviews and/or longevity of the listing as a measure of trustworthiness. This is consistent with findings about the ineffectiveness to date of online ratings in some other contexts, due to either gaming of the system or a reluctance to post negative reviews.[10]

Location

The location of a listing will certainly influence its revenues. Figures 5 to 8 plot the listings with occupancy rate higher than 75% in Berlin, London, Paris and Toulouse respectively.[11] One of the advantages Airbnb claims to provide is that it directs some of the economic benefit of tourism to local communities outside city centres. Loosely speaking, these maps seem to confirm its claim. Take London as an example. One previous study of web scraped Airbnb data for London concluded that the listings on the site cover a far wider geographical area than hotels, which are concentrated in the centre and towards the west of London. It found that the renters of rooms and those of whole properties had different socio-demographic characteristics and were concentrated in different kinds of neighbourhoods: “Properties are more likely to be concentrated in tech-savvy and well-to-do areas with young renters. In practice, Airbnb listings are very different among them though. A clear distinction that the website makes is between entire homes/ apartments and private rooms. … We observe significant differences: Airbnb rooms tend to be offered in areas with highly-educated non-UK born renters, while homes tend to be offered in areas with owners of high-end homes in terms of house price.” (Quattrone et al 2015)

Prices

Travellers using Airbnb can find accommodation at a lower cost than hotels and with different attributes. For example, in our dataset, the cost of a standard private room in Paris can be as low as US$30 (the median rate is US$54), whereas a single room in a budget hotel in Paris will cost at least US$60. An entire home sleeping 3-4 people may cost US$60 a night in Paris on Airbnb (the median rate is US$96), making a family stay in the city far more affordable than booking two rooms in a hotel. This could help explain why the occupancy rate for entire homes is in general higher that for private rooms. In these cases, Airbnb is likely bringing into the market some visitors who would not otherwise have been able to afford to make the trip. There are also some expensive rooms (>US$100 per night) and homes (>US$200 per night) listed. The people hiring these properties could easily afford hotels and so must choose Airbnb for other characteristics, such as personalization (hotels can be bland and rarely enable much interaction with local residents), or location (hotels are clustered in central business districts). The rates (and occupancy) for the 14 cities for the 18 month period in our data set show few signs of any trend but they do display

10 Surveyed in Dellarocas et al (2006)

11 All maps are drawn in the scale 1:120,000.

some clear seasonal variation – such as Oktoberfest in Munich and New Year (Hogmanay) in Edinburgh (see Figure 4 for the big cities). In most of the 14 cities the rate is stable but some cities (e.g. Nantes, Glasgow) shows a slight downward trend.

Multiple Listings

While the idea of home sharing is becoming popular all over the world, some critics argue that Airbnb is a platform for owners to circumvent existing regulations on leases. One insight into this argument comes from looking at the proportion of the hosts listing multiple properties on the website. Relatively few hosts have multiple listings. In Paris, for example, 91% of the hosts list just one property; the proportion is substantially lower in some of the other cities. Table 3 shows the extent of multiple listings in the 14 cities.

Table 3	**1 listing**	**2 Listings**	**3 Listings**	**4 Listings**	**5 or more Listings**
Paris	90.97%	6.73%	1.16%	0.36%	0.77%
Nantes	89.03%	8.61%	1.60%	0.35%	0.42%
Cologne	88.55%	8.33%	1.46%	0.66%	0.99%
Amsterdam	88.53%	7.92%	1.85%	0.69%	1.01%
Strasbourg	88.53%	9.01%	1.27%	0.47%	0.72%
Toulouse	87.55%	9.30%	1.53%	0.37%	1.25%
Munich	87.30%	9.47%	1.81%	0.79%	0.63%
Berlin	86.18%	9.83%	2.19%	0.72%	1.07%
Frankfurt	86.18%	10.34%	1.88%	0.86%	0.74%
Glasgow	83.50%	11.97%	2.45%	1.09%	1.00%
London	80.89%	12.03%	3.12%	1.27%	2.69%
Manchester	78.61%	13.18%	3.72%	1.62%	2.87%
Edinburgh	77.88%	14.03%	4.11%	1.66%	2.31%
Barcelona	69.37%	16.57%	6.11%	2.65%	5.30%

Figure 8: Berlin

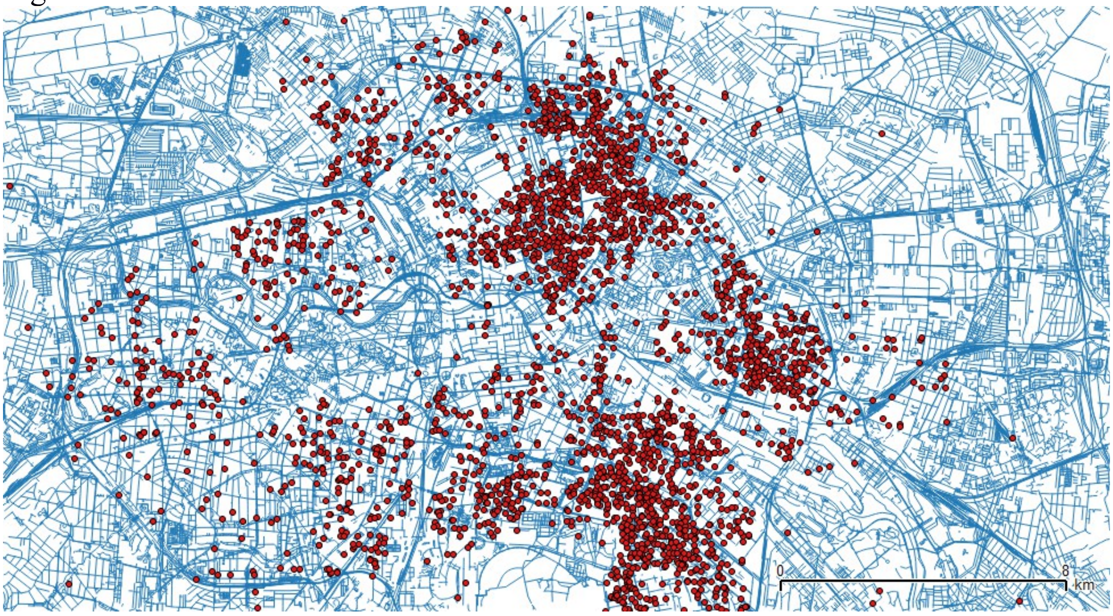


Figure 9: London

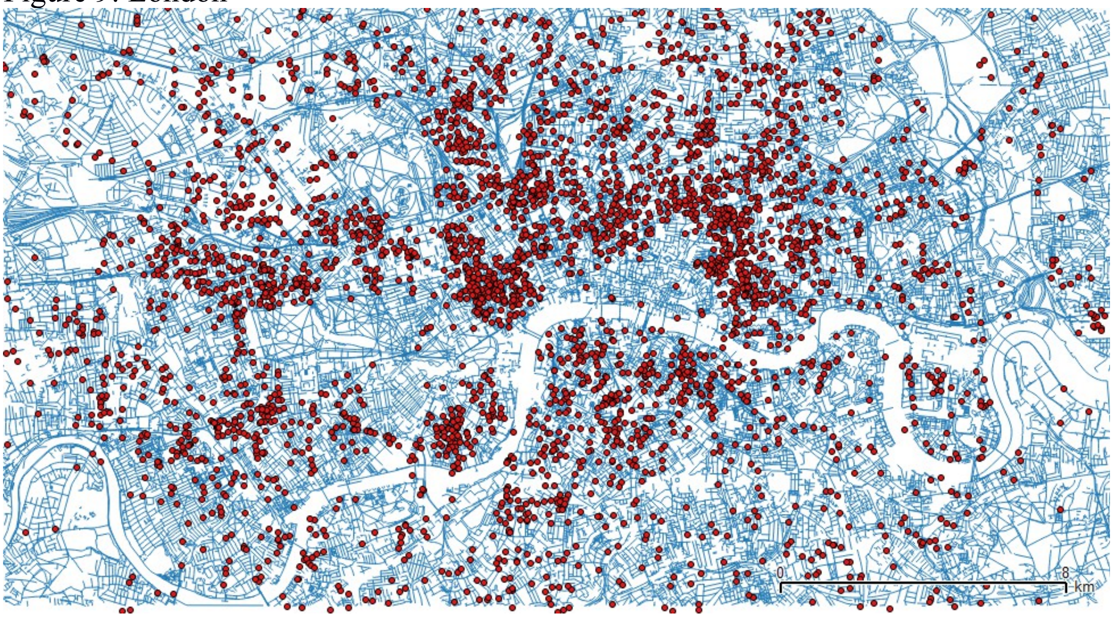


Figure 10: Paris

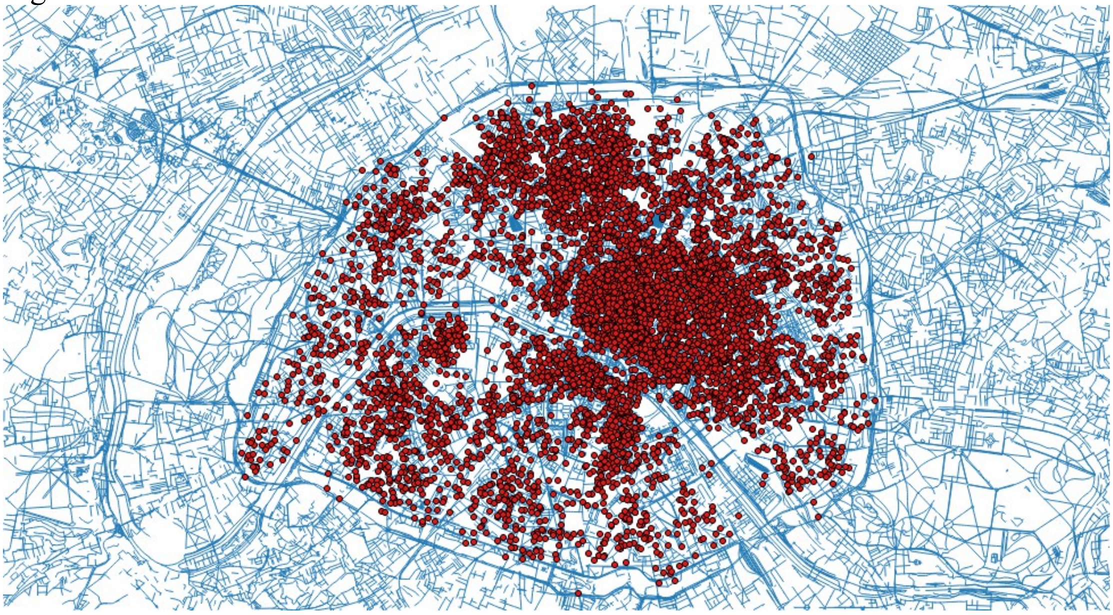


Figure 11: Toulouse

5. Estimation: hotels

In this section, we turn to econometric estimates of the impact of Airbnb activities on the performance of hotels in the 14 European cities.

To measure the actual extent of Airbnb activities, it would be ideal to have the data on all active listings during a given period. However, the data were not collected at the time the properties were doing business. Instead, the information we have only shows us they were created some time ago and still listed at the time of data collection. That means, we cannot retrieve the information of those unlisted properties. The best we can do is to measure Airbnb activities by the stock of listings in a specific month, given that they were listed at the time of data collection, following Zervas et al. (2016).

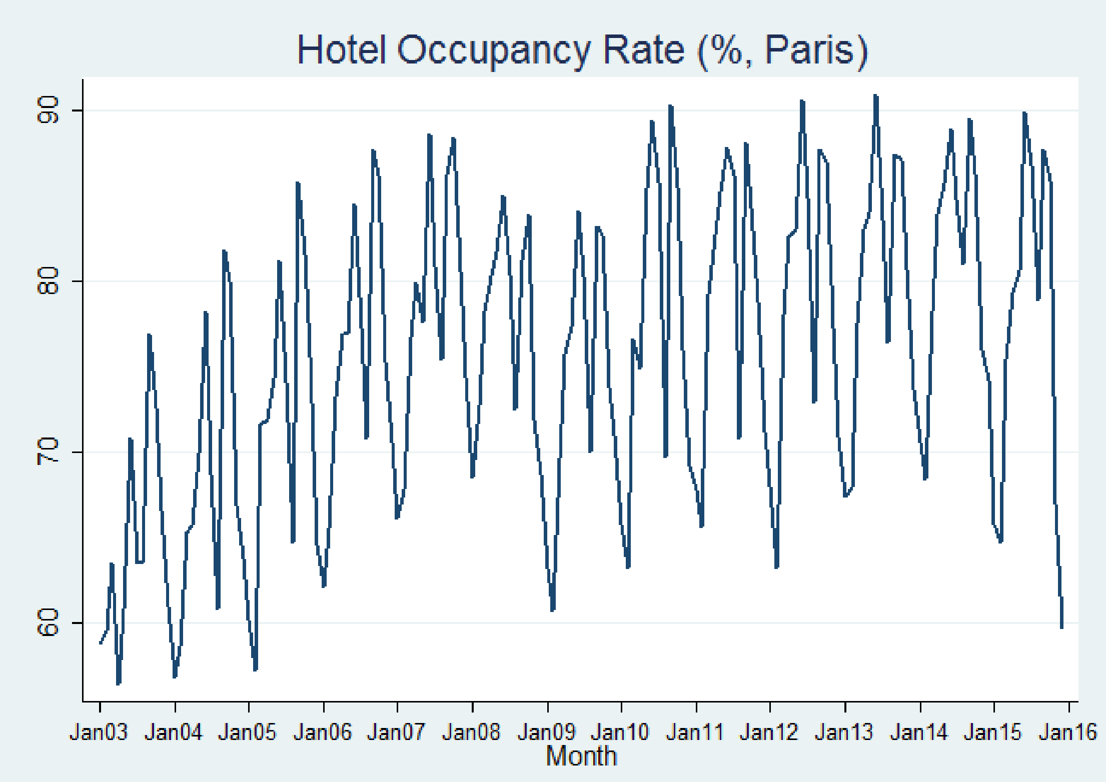
From the information scraped by Airdna, we can identify the first date each property is listed on the Airbnb platform. Some properties were never active, judged by the occupancy rate and the number of comments. Some of them had been active for a while but were inactive between April 2015 and March 2016 (over these 12 months Airdna computed the annual revenue and the occupancy rate). To screen out the inactive listings, we exclude those listings which do not have any reviews since listed AND are inactive during the 12 months. In other words, we make sure that those remain in the sample either have at least one review or are shown as active during the specified 12 months.

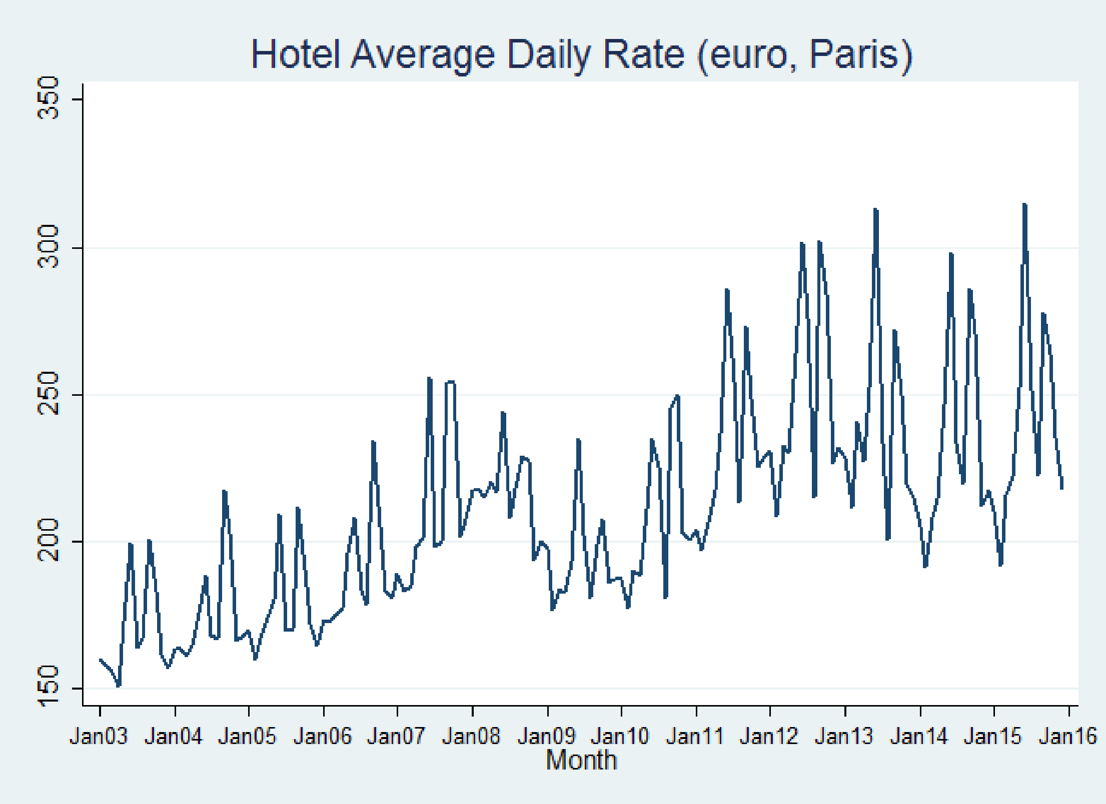
As an illustration, figure 12 displays the total number of Airbnb listings in Paris from January 2003 to April 2016. The number of listings took off in September 2008 and grew almost-exponentially; the series is clearly non-stationary.

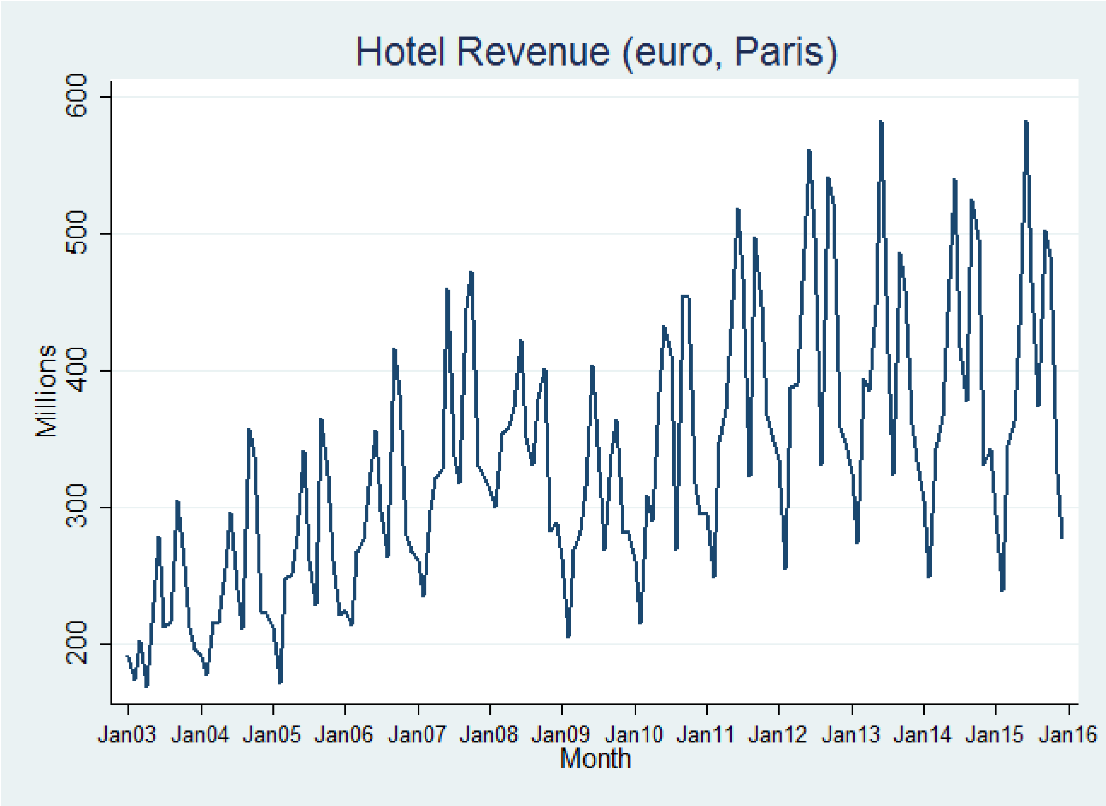
Figure 12

Our data on hotels were provided by the information company STR. We have monthly data from January 2003 to April 2016 for all 14 cities apart from Nantes. While not all hotels responded to STR surveys, the number of responses suggests the survey is representative, and these data are widely used by researchers. We therefore have data for the average daily rate (ADR) received, total hotel revenue, and the average occupancy rate. Figure 13a to 13c display these series for Paris as an illustration..

Figure 13a-13c


Hotel Occupancy Rate (%, Paris)
90
80
70
60
Jan03
Jan04
Jan05
Jan06
Jan07
Jan08
Jan09
Jan10
Jan11
Jan12
Jan13
Jan14
Jan15
Jan16
Month


Hotel Average Daily Rate (euro, Paris)
350
300
250
200
150
Jan03
Jan04
Jan05
Jan06
Jan07
Jan08
Jan09
Jan10
Jan11
Jan12
Jan13
Jan14
Jan15
Jan16
Month



There are strong seasonal fluctuations: local peaks are usually found every June and September. The average daily rate seems to follow an upward trend, while the total revenue follows a similar pattern but suffer a dip towards 2016, perhaps the impact of terrorist attacks. The average occupancy rate varies roughly between 60% to 90%, and again a dip towards 2016 is apparent. We report below on the formal tests for stationarity of these series.

Other Variables

Following Zervas et al. (2016), we expect that unemployment rate and the population of the city will affect hotel performance. However, data for these two variables is not readilyavailable at the city level. We search for the regional level data from their corresponding national statistics department.[12] However, not all of them cover the whole period from January 2003 to April 2016. To supplement the national sources, we rely on Eurostat that provides yearly unemployment rates at the region level (NUTS2) until 2015.[13] Based on the quarterly or yearly figures, monthly figures are

12 Quarterly unemployment rate at department level of France since 2003: http://www.bdm.insee.fr/bdm2/choixCriteres?codeGroupe=713
Monthly unemployment rate at state level of Germany since 2005: https://www-genesis.destatis.de/genesis/online
Monthly unemployment rate at region level of the UK since April 2011: http://www.ons.gov.uk/ons/rel/lms/labour-market-statistics/index.html
Quarterly unemployment rate at region level of Spain since 2003: http://www.ine.es/jaxiT3/Tabla.htm?t=4247&L=1
Monthly unemployment of the Netherlands since 2003: https://www.cbs.nl/en-gb/figures

13 See the definition of NUTS2 in http://ec.europa.eu/eurostat/documents/3859598/5916917/KS-RA-11-011-EN.PDF

computed by linear interpolations.[14] By assuming that the rate for the major cities of the region dominates the regional rate, the unemployment rate at the region level is taken as a proxy for the rate at the city level.[15]

Population size is trickier still. Cities have varied definitions of their boundary. Depending on the boundary they employ, figures from different sources are often inconsistent. Eurostat has collected the information from member states concerning the demographic variables at the city-level (NUTS3). However, the dataset is plagued with missing observations and does not stretch back to 2003. Instead, we rely on the data of yearly population of Metropolitan Regions, also gathered by Eurostat.[16] This covers all the cities from 2003 to 2015. We estimate the population in 2016 by a simple linear regression with a time trend. Since metropolitan regions are NUTS level 3 approximations of the Functional Urban Areas (city and commuting zones), it is arguably the most accurate data on city-level population.[17]

Estimation

As in Zervas et al (2016), we estimate the following model:

where Hotel Performance refers to either the average occupancy rate (expressed in percentage points), the log of average daily rate, or the log of total hotel revenue.[18] To avoid any undefined value, we add one to the number of Airbnb listings before taking the natural logarithm. Apart from the city fixed effects, we include the log of population and the unemployment rate as control variables. We used two ways to capture the time fixed effects. First, we included time dummies for each month in the estimation. In total 159 binary variables were thus added into the regression. As this greatly reduces the degree of freedom, secondly, we included a linear time trend and 11 calendar month dummies. This specification reduces the number of variables on the right-hand side and allows for seasonal regularities.

The first method is used for the odd numbered columns of Table 4, while the even ones display the results of the second method. Surprisingly, given the popular assumption, Airbnb activities have a positive impact on hotel performance. For example, focusing on the second method of time detrending, a 10 percentage point increase in Airbnb listings causes on average a 5.7 percentage point increase in hotel occupancy rate, a 0.15 percentage point increase in ADR, and a 0.27 percentage point increase in total revenue. The unemployment rate enters negatively into the regressions, as expected. Population does not show a significant impact on ADR and total revenue, but a negative correlation with occupancy rate is apparent.

14 When the two sources do not match closely at the discontinuity, a uniform incremental amount is added onto or subtracted from the series of Eurostat to eliminate the discrepancy..

15 We suppose that the figures are the annual average of the year and attach them to the mid (June) of the corresponding year. We compute monthly unemployment rates and monthly population from the yearly figures by a linear interpolation.

16 See http://ec.europa.eu/eurostat/web/population-demography-migration-projections/population-data/main-tables

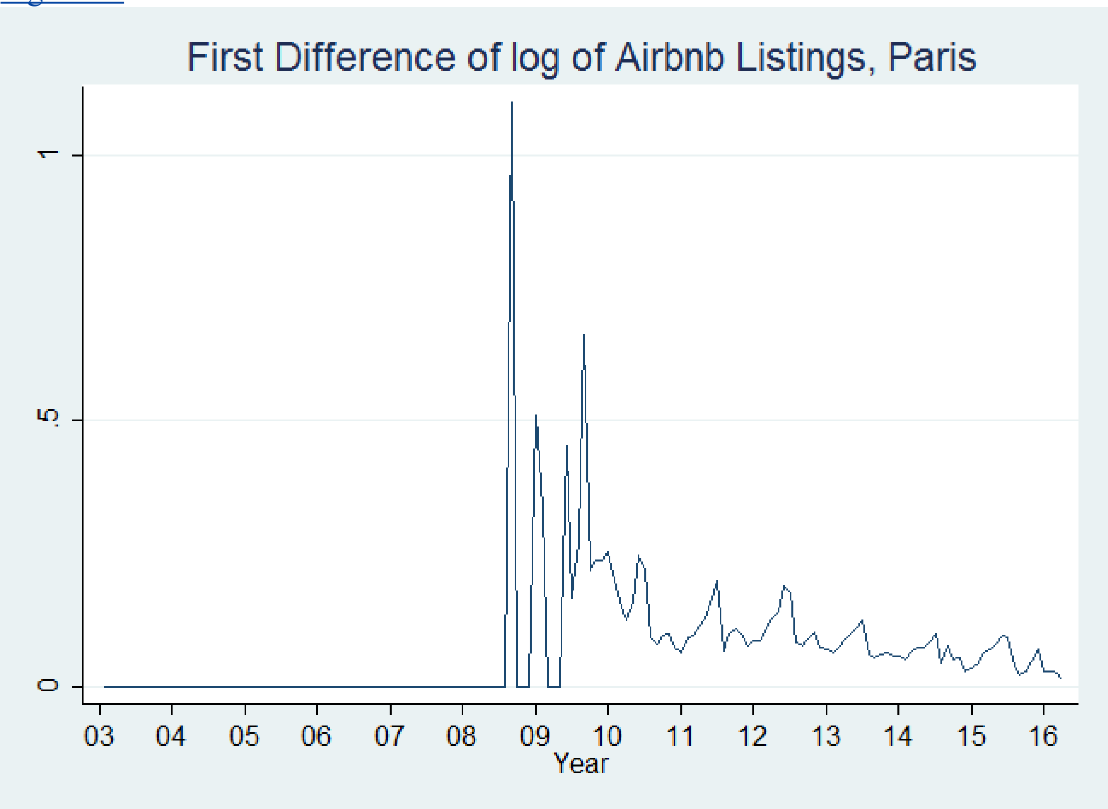
17 Note that all figures are in thousands.

18 Note that Zervas et al. (2016) were working with hotel-level dependent variables.

However, since the number of Airbnb activities soared rapidly during the period covered, it is almost certain that the series is non-stationary (to be confirmed by formal tests). The three measurements of hotel performance may also be non-stationary. Results in the existing literature have not considered the consequences of non-stationarity, which may be a drawback in the previous estimates. To illustrate the consequences, we report the first difference estimation in the Table 5, which shares the same structure with Table 4. In this case we do not find a significant correlation between Airbnb activities and the hotel occupancy rate, although the sign is negative as would be expected if they are substitutes. New Airbnb listings (as the series is first differenced) seem not to influence hotel average daily rate and total revenue. A change in the unemployment rate shows the expected sign: a higher unemployment rate indicates a worsening health of the general economy, which also affects hotel performance.

However, although the first differencing deals with the issue of non-stationarity, the economic meaning of the results is more obscure. First, the series of Airbnb activities began at zero and grew rapidly after September 2008. The log-difference transformation approximates percentage change of the variable. As a result, we find very big values around the time when Airbnb was launched but then relatively small values towards 2016, as displayed in the case of Paris in Figure 14. However, one would expect the impact of Airbnb activities to be more pronounced when the pool of Airbnb listings has become sufficiently big relative to the size of the accommodation market. The first difference model takes away the effect of the stock of Airbnb listings. New additions to the stock may not significantly influence the hotel market because they might not be active right in the month they were listed.

Figure 14



Next, we explore the possibility that there is cointegration relationship between Airbnb listings and hotel performance.

Since we have a long panel dataset of moderate size, we selected the Levin-Lin-Chu (LLC) test for the stationarity of the series (Levin et al., 2002; Baltagi, 2008). However, since the test requires a balanced panel dataset, we dropped Nantes from the sample. This reduced the total number of observations to 2,080. We allowed at most 12 lags in the augmented Dickey-Fuller (ADF) regressions because we suspect that the seasonal effect is strongly affecting the series. The choice of lags was then made by minimizing the Akaike Information Criterion (AIC). In all the tests we also included panel-specific means with or without time trends.

Table 6 shows the test results. We cannot reject the null hypothese that panels contain unit roots. In other words, all of the series must be supposed to be non-stationary. The usual fixed effect OLS may deliver spurious results.

We therefore applied the cointegration test developed by (Pedroni 1999, 2001, 2004), which is designed for nonstationary heterogeneous long panels. Nantes was still excluded to keep the panel dataset balanced. Since we have a reasonably long panel (T=160), we believe that all tests are roughly equally powerful, and thus only report the rho-statistics and the t-statistics, both panel and group, out of the seven statistics, which are normalized to N(0,1) under the null of no cointegration. Since these four statistics diverge to negative infinity under the alternative hypothesis, the left tail of the normal distribution is used to reject the null. Results are shown in Table 7. All statistics lead us to reject the null hypotheses, which means cointegration relationships exist between Airbnb activities and hotel performance.

To estimate the cointegration relationship, we use the panel dynamic OLS (hereafter PDOLS) (Pedroni, 2001) and the augmented mean group estimator (hereafter AMG) (Eberhardt, 2012). The former is an extension of the individual time-series dynamic OLS (DOLS). The idea is to conduct a DOLS regression in which leads and lags are included to capture the dynamic process in each city, and then the beta coefficients and the associated t-statistics are averaged over the entire panel by the Pedroni's group-mean method (Neal, 2014). However, this estimator is biased in the presence of cross-sectional dependence in the data, known as common shocks. The latter allows the unobservable common shocks to be accounted for. The main principle of the estimator is to first estimate the coefficients of the time dummies, and then the estimated process is subtracted from the dependent variable. Finally, the coefficients are obtained by averaging the results of the group-specific regressions across the panel. Interested readers are encouraged to read Eberhardt and Teal (2010) for a detailed discussion of the estimator.

The results are shown in Table 8. They show a negative, though not statistically significant, impact of Airbnb activities on the hotel occupancy rate, as shown by column 2 where the AMG is employed. A 10 percentage points increase in Airbnb listings causes on average a 6.9 percentage point fall in the average occupancy rate, which is economically considerable. The sign of unemployment rate is as expected but not statistically significant either. The significant coefficients on the common shocks in the AMG estimation justify the use of the estimator and imply that all panels follow a common dynamic process.

Both estimators show a positive impact of Airbnb activities on the ADR. A 10 percentage points increase in Airbnb listings causes on average 0.35 percentage point rise in the ADR, as shown by the AMG in column 2. If a room costs 100 euro per night, the impact is expected to be 0.35 euro, which seems quite small but the overall effect on total revenue could be very large. Both population and unemployment enter the regressions negatively. In column 4, while the common shock is highly significant, the group-specific time trends also help explain the variation in the ADR.

Concerning total hotel revenue, Airbnb activities exert aweak positive impact.A 10 percentage point increase in Airbnb listings causes on average 0.16-0.233 percentage point rise in the total revenue. The impact of the other variables is similar to their impact on ADR.

Discussion

It is widely presumed that Airbnb has had an adverse effect on hotels since the two forms of short-term accommodation seem to be substitutes. However, our results, taking due account of the time series properties of the data, suggest that Airbnb activities may not be as harmful as presumed to the hotel industry.

One possible explanation is that Airbnb reduces the demand of budget tourists for hotels, which can then charge a higher price for the less price-elastic demand from other travellers. Hotels would then enjoy a higher average daily rate but might or might not enjoy higher revenue, depending on the relative change in price and quantity. We would expect the occupancy rate to fall and the ADR to rise, , exactly as in our results, but the effect on the total revenue to be ambiguous, which is positive in our estimation.

As shown by previous study by Zervas et al. (2016), low-cost budget hotels in Texas were more affected by Airbnb than high-end hotels. We expect the same in Europe but unfortunately we do not have hotel level data to discern the effect. Economic reasoning tells us that the negative impact on hotels would be more pronounced among low-end hotels, and the positive impact on price and total revenue concentrated among the high-end. The investigation into the hotel level is now left for future research.

6. Estimation: Rental Market

Airbnb activities may also impact on the rental market. As we discussed above, property owners could easily get access to a pool of potential short-term tenants through the platform of Airbnb. They may then withdraw from the long-term rental market and channel their properties to the short-term market. Consequently, the supply of the properties in the traditional long-term market shrinks and the rent goes up.

Unfortunately we could not find comparable data on rental prices of all 14 cities. The limitation of data leads us to focus on Germany and the UK. The Office for National Statistics provides an index of private housing rental prices backdated to 2011, while the Federal Statisital Office of Germany computes a similar index since 2005. We combine the two sources by normalizing the index to 100 at January 2011. Note that the indices do not consider between-city variations—all cities score 100 at January 2005. Between-city analysis will only be meaningful if we study the impact of Airbnb activities on the change of the rental prices.

Since a regression on the rental index at level is flawed, we are left with First-difference model. Similar to the previous section, we include population, unemployment rate, and time fixed-effect in addition to the Airbnb activities on the right-hand side of the regression. Table 9 (to be inserted) reports the results where the standard errors are adjusted for clustering in city.

Column 1 reports the estimation of the sub-sample of Germany, and column 2 that of the UK, while column 3 shows the result of the whole sample. We do not find significant correlation in the sub-sample of Germany, but a positive and significant correlation between Airbnb activities and the rental prices in the UK. A 1 percentage point increase in the number of Airbnb activities is on average associated with a rise in the rental index of 0.22. But the correlation is again insignificant in the whole sample.

Since the series of rental index in the UK begins in January 2011, the first-difference model makes better economic sense because the initial period of the launch of Airbnb had been passed (there were 144 properties listed in London by January 2011). Still, we call for caution when interpreting the results. The impact varies considerately across countries. In column 4, we restrict the Germany sub-sample to cover only the information since 2011. Comparing with the result of column 2, we find the coefficients of Airbnb activities differ substantially. It may reflect the differences in regulations concerning the rental market and Airbnb activities. A more detailed and local investigation into the regulations is necessary before we can judge whether Airbnb encroaches the traditional rental market and does harms to local people.

7. Conclusion

In this paper we aim to understand the patterns of Airbnb activities in European cities. By merging the data on different sources, we present evidence of the influence of Airbnb activities on the hotel industry and also the domestic rental market. We find that a rise in Airbnb activities is in general associated with a fall of hotel occupancy rate, but a rise of average daily rate and total hotel revenue. On the other hand, Airbnb activities have differential impacts on the rental market in different cities, hinting the importance of local regulations and land management.

Table 4: Baseline Estimation

	1	2	3	4	5	6
	Occuapancy		ADR		Revenue	
Airbnb	.820	.570*	.030**	.015**	.042**	.027***
	(1.62)	(2.10)	(2.30)	(2.75)	(2.28)	(3.78)
Unemployment	-.349***	-.405***	-.020***	-.023***	-.025***	-.029***

	(-3.14)	(-4.23)	(-3.17)	(-3.48)	(-3.63)	(-4.25)
Population	-87.6*	-85.1*	-.566	-.414	-1.86	-1.69
	(-1.83)	(-1.89)	(-.53)	(-.39)	(-.90)	(-.84)
Time FE	Y	N	Y	N	Y	N
Month FE	N	Y	N	Y	N	Y
Linear Trend	N	Y	N	Y	N	Y
No. of Obs.	2122	2122	2122	2122	2122	2122
Within R-sq	.619	.569	.411	.332	.606	.551
Between R-sq	.193	.193	.467	.446	.796	.798
Overall R-sq	.019	.020	.246	.224	.704	.705
Robust SE are computed and t-statistics are shown in parentheses.						
* p<10% ** p<5% *** p<1%						

Table 5: First-Difference

	1	2	3	4	5	6
	Occuapancy		ADR		Revenue	
D.Airbnb	-.650	-.636	.020	.015	.009	.006
	(-.41)	(-.45)	(.67)	(.59)	(.19)	(.14)
D.Unemploy	-1.00	-1.09	-.015	-.002	-.003	-.018
	(-1.44)	(-1.63)	(.77)	(-.10)	(-.15)	(-.81)
D.Population	28.1	80.1	1.65	3.15	1.62	3.72
	(.08)	(.24)	(.26)	(.50)	(.16)	(.38)
Time FE	Y	N	Y	N	Y	N
Month FE	N	Y	N	Y	N	Y
No. of Obs.	2108	2108	2108	2108	2108	2108
R-sq	.470	.416	.341	.301	.407	.361
Robust SE are computed and t-statistics are shown in parentheses.						
* p<10% ** p<5% *** p<1%						

Table 6: LLC Stationary Test

	1	2	3	4	5	6
	Occuapancy		ADR		Revenue	
Average Lags of ADF	11.77	11.77	11.85	11.85	11.85	11.85
Linear Trend	N	Y	N	Y	N	Y
Adj. t-stat	23.6	46.8	8.12	13.3	2.60	26.1
Number of lags of the ADF regression is chosen by AIC.						

Table 7: Pedroni's Test of Cointegration

	1	2	3	4	5	6
	Occuapancy		ADR		Revenue	
Unemployment	N	Y	N	Y	N	Y
Population	N	Y	N	Y	N	Y
Panel rho-test	-53.4	-36.9	-39.6	-34.5	-51.5	-36.0
Group rho-test	-45.3	-36.0	-39.4	-33.6	-44.6	-35.1
Panel t-stat	-29.2	-27.6	-23.8	-26.9	-28.4	-28.0
Group t-stat	-30.2	-29.6	-26.8	-28.8	-29.9	-30.3
Number of lags of the ADF regression is chosen by AIC.						

Table 8: PDOLS and AMG Estimation

	1	2	3	4	5	6
	Occupancy		ADR		Revenue	
	PDOLS	AMG	PDOLS	AMG	PDOLS	AMG
Airbnb	.565	.634***	.016***	.035***	.016*	.023**
	(.76)	(-2.46)	(3.01)	(3.14)	(1.87)	(2.35)
Unemployment	-.406***	-.534**	-.041***	-.079	-.045***	-.016**
	(-3.16)	(-2.21)	(-9.14)	(-1.40)	(-7.41)	(-2.01)
Population	-55	45.8	-4.30***	-7.72**	-4.60	-8.67***

	(.004)	(.71)	(4.99)	(-2.12)	(-1.18)	(-3.29)
Common Shock		.999***		.936***		.974***
		(10.9)		(9.30)		(12.4)
Group-specific Trend		.011		.005**		.006***
		(.80)		(2.13)		(2.84)
No. of Obs.	2015	2080	2015	2080	2015	2080
t-statistics are shown in parentheses.						
* p<10% ** p<5% *** p<1%						

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PRELIMINARY

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