COMUNICACIÓN

Título: The effect of peer-to-peer (P2P) accommodations on the local economy: Evidence from Madrid

Autores y e-mails de todos: Alberto Hidalgo (alberto.hidalgo@imtlucca.it), Francisco Javier Velázquez (javel@ccee.ucm.es) and Massimo Riccaboni (massimo.riccaboni@imtlucca.it).

Departamento: Analysis of CompleX Economic Systems (AXES) and Department of Applied & Structural Economics and History.

Universidad: IMT School for Advanced Studies Lucca. Universidad Complutense de Madrid

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Resumen: *This paper investigates the effect of P2P accommodations on the local economy of the city of Madrid. We find that the arrival of Airbnb has fostered food and beverage services. We exploit the exogenous variation created by the timing and the unequal distribution of Airbnb listings across the urban geography to identify its effects on the number and employment of food and beverage services. Using an instrumental variable strategy, we find positive effects on both the number of restaurants and their employees: an increase in ten Airbnb rooms in a given census tract translates to one more restaurant, and the same increase in a given neighbourhood generates nine new tourist-related employees. The results are robust to sample composition, spatial spillovers and alternative measures of tourist-related activities. This paper contributes to the literature on the economic impacts of the platform economy on urban areas by providing evidence of positive economic externalities from P2P accommodations.*

Palabras Clave: *Sharing economy, Airbnb, Food and Beverage Services*

Clasificación JEL: R10, L8, Z30

1. INTRODUCTION

The economic landscape in urban areas may be changing as peer-to-peer accommodation platforms enter the cities (Ferreri and Sanyal, 2018). As the long-term residents (locals) are substituted by short-term residents (tourists), the Airbnb-induced tourism demand increases, potentially impacting tourist-oriented stores locally. To what extend local shops are positively affected by Airbnb? If, as Airbnb claims, guests prefer staying around and consuming near their listings, the arrival of these new temporal residents may represent a positive externality, leading to an increase in the number of businesses that cater to tourists or better performance of the existing ones.

To answer this question, we evaluate how Airbnb's arrival has fostered Madrid's food and beverage services. Four conditions allow us to identify the effect of short-term rentals on tourist-oriented shops. Firstly, Airbnb spread across the city instead of traditional accommodations that are fully concentrated in the city center. The possibility to bring visitors to non-tourist areas allows us to disentangle the effect of Airbnb from other accommodations. The second condition rests on the rapid adoption and diffusion of Airbnb. The flexibility and absence of regulation have provoked an impressive increase in those accommodations, which will be unthinkable for other regulated accommodation types. Moreover, our panel data set is long enough to observe changes in the business ecosystem that otherwise will be impossible to observe. Lastly, food and beverage services are characterized by reacting quickly to changes in the local demand due to their low startup cost.

To measure the impact of Airbnb on the food and beverage business, we use a Bartik-like instrumental variable approach, where we use the number of rented houses in 2011 (previous to Airbnb entry in Madrid) and the number of worldwide Airbnb Google searches as an instrument for the Airbnb activity. We exploit the sharp geographic and temporal variation in the availability of short-term rentals, using as the geographical unit of analysis the census tracts and the neighbourhoods.

Our main findings are that the entry of Airbnb has positively impacted both the employment and the number of tourist-related activities in the affected neighbourhoods and census tracts. We find no evidence of pre-trends and our results are robust to sample composition, spatial spillovers and alternative measures of tourist-related activities. This paper contributes to the literature of economic externalities generated by peer-to-peer (P2P) accommodations by providing, for the first time, evidence of the positive effect of Airbnb on the food and beverage sector in a European urban area. Moreover, this study provides a novel methodological approach by proposing a new way of exploiting the exogenous variation created by the unequal entry of Airbnb across the Madrid geography.

The rest of the paper is organized as follows. Section 2 provides a brief review of previous literature. Section 3 and Section 4 describe the data and methodology, respectively. Section 5 presents the results, and we draw our conclusions in Section 6.

2. LITERATURE REVIEW

Most of the literature about the externalities of P2P accommodation have been devoted to analyze the effect of short-term rentals (STR) on the real estate sector. In general, most studies have found evidence of the positive impact of Airbnb on housing prices and rents. Whereas the positive effect of STR on housing rental prices has been explained as a consequence of a negative shock in the housing rental stock due to reallocation of housing units away from the long-term rentals to short-term rentals, the positive impact on housing prices has been rationalised as an increase in the option value of owning a housing unit due to the possibility of short-renting and the capitalization of higher rental prices (Barron et al., 2021). Yet, as Garcia et al. (2020) found for Los Angeles county, the global effect found in previous studies may mask heterogeneous effects across the cities. Although the impact might be positive in most cities, some other areas may experience an adverse effect due to potential negative externalities created by P2P accommodations affecting local amenities.

The two closest papers to ours are Alyakoob and Rahman (2019) and Basuroy et al. (2020). Both contributions analyse whether Airbnb has positively affected the employment or revenue of the food and beverage services. Due to the lack of individual data, they use aggregated information at the ZIP code level for the state of Texas (Basuroy et al., 2020) and neighbourhood or ZIP code data for the New York City (Alyakoob and Rahman, 2019). Both papers rely on a DiD strategy that exploits the different timing and intensity in the entrance of Airbnb across their respective geographical areas. In this way, they can identify the effect of Airbnb, measured through the number of reviews or the number of reviews per household respectively, on restaurant performance by comparing high and low Airbnb intensity zones and before and after Airbnb entry. The main findings show that Airbnb positively affects restaurant outcomes. For instance, a 1% increase in the number of Airbnb reviews is associated with a 0.011% increase in the restaurant revenue for a ZIP code in the state of Texas, and a 1% increase in the number of reviews per household leads to a 1.7% increase in the restaurant employment for a ZIP code in New York.

All in all, there is still a paucity of evidence on the effect of P2P accommodations on local employment. Our study contributes to fill this gap and extends previous contributions in the following ways. Firstly, we use a quarterly finer- grained data set for the universe of all economic activities in Madrid from 2014 to 2018. The richness of our data allows us to better identify areas where Airbnb enters by using the smaller geographical unit of analysis available: census tracts. Using a small geographic unit of analysis help to overcome the problems of heterogeneity within larger spatial units as ZIP codes and neighbourhoods. Secondly, we can evaluate the heterogeneous effects of P2P accommodations across food and beverage services typologies, identifying which type of food and beverage services cater to potential Airbnb users. Thirdly, we propose a new Bartk-like instrument to solve for the endogeneity in the Airbnb activity variable: the number of rented houses for each census tract in 2011. In this manner, we solve for potential violation of the exclusion restrictions in previous instruments due to those are related with the city center characteristics. Lastly, this is the first study that analyses the

Airbnb economic spillovers effect in a European city[1]. This is of special interest since the distinction between commercial and residential areas is more nuanced in European urban areas than in the US, despite the fact the difference is reducing over time (Gordon and Cox, 2012). As such, it is expected that the arrival of short-term rental to residential zones has a more significant impact on the business configuration, fostering the tourist-oriented store openings.

3. DATA

Our primary geographical unit of analysis is the census tract. Census tracts are the smaller statistical unit in Spain[2]. As they are built to represent a similar population (1000-2500 people) across the territory, and their size is reduced, they are suitable to analyze social phenomena that occur at the local level.

3.1. AIRBNB

We build the Airbnb activity variable by collecting quarterly consumer-facing data from Inside Airbnb. As stated on its website, Inside Airbnb is an "independent, non-commercial set of tools and data that allows you to explore how Airbnb is being used in cities around the world". It offers listing information at different points in time from different cities around the world. For our purposes, we are mainly interested in the information regarding the geographical coordinates of the listing, the size, and insights about the activity of the short-term rentals in the city of Madrid. As we want to build a measure for the Airbnb activity for each census tract, we must come up with a way to define when a listing is active or not. To do so, we use the date of the first review and

[1] Although not related to our research question, the only few papers that analyzes other Airbnb externalities in the European contexts are Garcia-Lopez et al. (2020) (rents), Almagro and Dominguez-Iino (2019), (neighbourhood amenities) and Fontana (2021) (discontent against tourists).

[2] The city of Madrid is organised from the largest to the smallest administrative or statistical unit as follows: districts (21), neighbourhoods (130) and census tracts (2432).

the date of the last review as a proxy for the time that the listing has been active in the platform. On top of that, we weight each listing by the number of beds to consider each accommodation unit's size. In this manner, we are correctly identifying the potential critical mass of food and beverage services users[3].

3.2. RESTAURANT LOCAL STORES

We obtained quarterly information from the Madrid census about local stores and activities from March 2014 to October 2018. The data set compresses the establishment-level data under a four-digit NACE-based classification, location, and status (opening, closing, or under some reform). In particular, we are interested in the business regarding the food and beverage services (NACE I.56) as it is the second activity in terms of budget tourist expenses for nationals' tourists and the third for foreign tourists (INE, 2020). So, our first dependent variable will be the total number of food and beverage services at the census tract-level.

We also have accessed yearly food and beverage services employment from the Madrid Statistic Department (Servicio de Estadística Municipal). However, because the employment data is confidential, we only have access at the neighbourhood level from 2012 until 2018. Therefore, as a second dependent variable we consider the number of employees of the food and beverage service sector at the neighbourhood level.

3.3. ADDITIONAL VARIABLES

We complement our data set with a set of variables to control for other factors related to either the number or employment in the food and beverage business as the population, the proportion of foreign people, the number, capacity in the traditional accommodation

[3] Previous contributions have trusted in different metrics of the Airbnb activity such as the simple number of listings (Xu and Xu, 2021), the number of reviews (Garcia-López et al., 2020; Barron et al., 2021) or the proportion of listing over the number of dwellings (Franco and Santos, 2021).

(hotels and hostels) in each census tract. Last, we get tenancy type information for the Spanish census in 2011, such as the number of rented or empty houses or the number of dwellings.

4. EMPIRICAL STRATEGY

4.1. SPECIFICATION

The aim of this paper is to study the relationships between the Airbnb entry in Madrid and changes in the local food and beverage business and employment. To answer our research question, our baseline specification takes the following form:

$$Y_{i,t} = \alpha + \delta Airbnb_{i,t} + \rho X_{i,t} + \epsilon_{i,t}$$

(1)

where Yi,t is the number of food and beverage services[4] in a census tract i and in quarter t, Airbnbi,t is the number of listings weighted by the number of beds in each census track and Xi,t are time-varying variables plus census and quarter specific fixed effects. Among the time-varying characteristics, we include the population, the proportion of foreign residents and the number of traditional accommodation rooms. With this set of variables, we aim at controlling for time-varying census-specific trends correlated with the number of food and beverage services and Airbnb listings as a local process of urban revival or tourism trends other than short-term rentals. We include census tract fixed effect to account for time-invariant characteristics like the size area and quarters fixed effects for local or seasonal changes. Last, as in Garcia-López et al. (2020), we include the interaction between a time trend and the distance to the center. In this manner, we are allowing that more central census tracts having a steeper time trend.

We are interested in δ of Eq. 1, which measures the average treatment effect of Airbnb on the number of food and beverage services. However, the number and type of Airbnb listings are likely to be correlated with the disturbance term due to time-varying

[4] Our baseline specification takes a level-level form due to a large number of census tracts with a low number of food and beverage services. Using log, instead of levels, we would be giving more importance to small absolute changes than warrants. Moreover, the number of food and beverage services is constrained by the space, which imposes an upper bound to its growth.

unobserved location characteristics (e.g., changing census tract amenities). Moreover, we may have a problem of reverse causality as the number of food and beverage services might attract (agglomeration effect) or deter (competition effect) new Airbnb listings. Finally, we may have to approximate the number of active Airbnb listings, and we do not know precisely whenever they are active or not. All in all, the empirical setting calls for an instrumental variable (IV) strategy to deal with the endogeneity in our variable of interest.

Our IV strategy is based on a Bartik-like instrument, where we use as the initial shares, the number of rented houses in each census tract in 2011 (before Airbnb arrival to Madrid), and as the shift, the worldwide Airbnb Google searches[5]. It can be easily seen that, whereas the shares explain either the extensive and the intensive margin of the treatment, the shift describes timing. More formally,

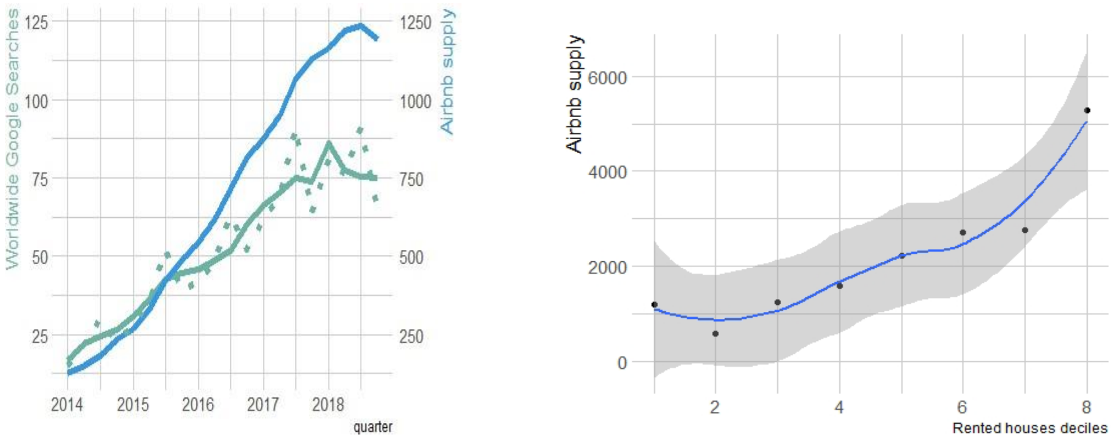
$$Shift\,share_{i,t} = \sum_{n=1}^{N} z_{i,2011} m_t$$

(2)

where zi are the number of rented houses in census tract i in 2011, and mt are the normalized worldwide Airbnb Google searches. The relevance of our instrument rests on the fact that as Horn and Merante (2017) have shown, the main mechanism through which Airbnb is affecting the real estate sector is by decreasing the stock of long-term rentals whereas increasing the supply of short-term rentals. In fact, we can see that there is a positive and significant relationship between the number of rented houses and the posterior Airbnb activity in Figure I. Moreover, we can also observe that the evolution for worldwide Airbnb Google Searches mimics the Airbnb growth.

Figure I: Shift-share instrument relevance. Plot (a) shows the evolution of worldwide Airbnb Google searches (solid lines refer to the seasonally adjusted time series and dashed line raw data) and the growth of Airbnb in Madrid. Plot (b) depict how Airbnb supply is positively correlated with the number of rented houses represented by deciles.

[5] This variable is measured at a quarterly level and is normalized to 100 for the month with the highest number of searches.



(a) Worldwide Airbnb Google searches and Airbnb supply (b) Airbnb Madrid supply and rented houses

Differently from Garcia-López et al. (2020) and Barron et al. (2021), we rely on a supply share rather than a demand share instrument for two reasons. First, the number of rented houses may predict the prospective Airbnb activity, not only in the city center but also in the rest of the urban area. The underlying mechanism is that between two census tracts located at the same distance to the city center, it is more likely that new Airbnb listings appear in the census tract with the higher number of rented houses as hosts may find easy to switch from long-term rentals to short-term rentals rather than investing in new flats. Second, the number of tourist features used previously in Garcia-López et al. (2020) and Barron et al. (2021) may violate the exclusion restriction as they are directly related to the distance to the city center as most of the tourist amenities are concentrated in that area. With respect to our shift instrument, the worldwide Airbnb Google searches parallels the timing and expansion of Airbnb in Madrid as Figure I show. The basic idea behind the use of this shift is that potential hosts in Madrid are more likely to rent their property in the short-term market in response to learning about Airbnb (Barron et al., 2021).

Concerning the exclusion restriction, it is highly unlikely that worldwide Airbnb Google searches are directly related to unobserved census tract-specific changes in Madrid's number of tourist-related activities. Airbnb is an international company with a presence in more than 100,000 cities in over 190 countries. Therefore, we can claim that the shift part of our Bart-like instrument is exogenous to local conditions in Madrid. On the other hand, to our share instrument to satisfy the exclusion restriction, zi,2011 must be only correlated with the changes in our dependent variable through the effect of Airbnb. In our setting, the main channel through which the number of rented houses should affect the number of food and beverage services is through the change from long-term (locals) to short-term (tourists) residents provoked by Airbnb. As tourists have different consumption patterns than residents, we should expect that Airbnb arrival fosters tourist-related activities in the treated neighbourhoods. Our instrument will be invalid if long-term residents' taste towards tourism-related activities changes over the study period. However, we think that this is quite unlikely as we are in a relatively short panel setting.

If the relevance and exclusion restriction hold, we still have an identification problem coming from the non-random location of the Airbnb listings as most short-term rentals are located in the city center. The main challenge that we are facing due to this non-random Airbnb listing location is to disentangle the impact of Airbnb on food and beverage services from other effects triggered by traditional accommodations or local visitors, i.e., the number of food and beverage services may be increasing due to the additional tourist flows coming from new or existing hotels. The first issue is partially solved by controlling for time-varying accommodation activities that directly affect tourist-related business. Still, we cannot rule out other phenomena like, for example, a taste change for locals towards eating out in the city center. Moreover, whenever the local tourist consumption does not hold, we will be overestimating the impact of Airbnb as short-term rental guests whose listings are outside downtown are more likely to commute to consume in the city center due to the larger number of touristic amenities. Therefore, we decide to remove all census tracts located in the five neighbourhoods that conform to the district "Centro" in Madrid[6]. Notice that our decision to prune our sample for observations in the city center is conservative because we expect that most Airbnb-induced demand affects those areas as they concentrate most of the overall Airbnb activity. Yet, we are still able to identify the effect of Airbnb on food and

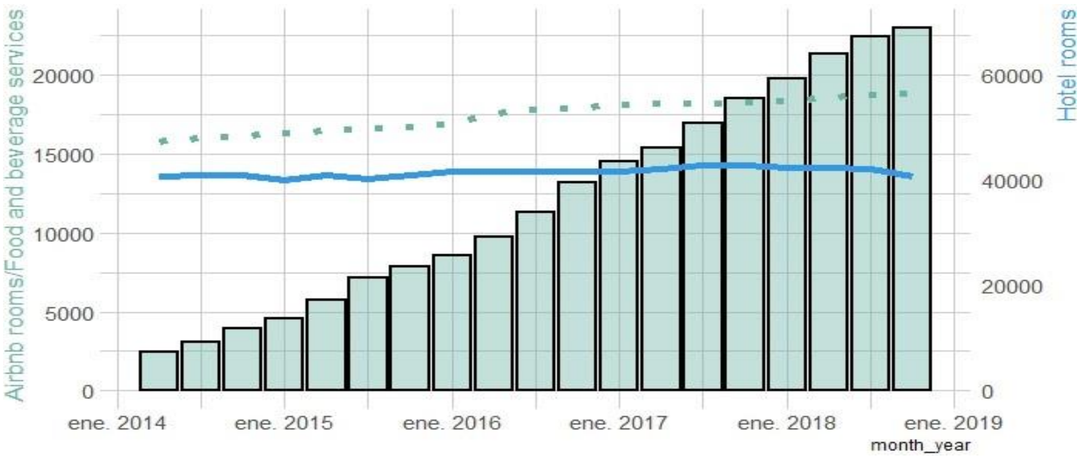
[6] The district "Centro" is composed by the following neighbourhoods: Sol, Palacio, Embajadores, Universidad, Cortes y Justicia

beverage services since we exploit the fact that Airbnb is spread across the city and may attract visitors to some areas that are outside of the touristic circuit where we do not have the problem of other confounded tourist effects.

4.2. DESCRIPTIVE STATISTICS

The Airbnb activity and the number of food and beverage services have strongly increased in Madrid over the analyzed period, whereas the total hotel room supply has barely changed (see Figure II).

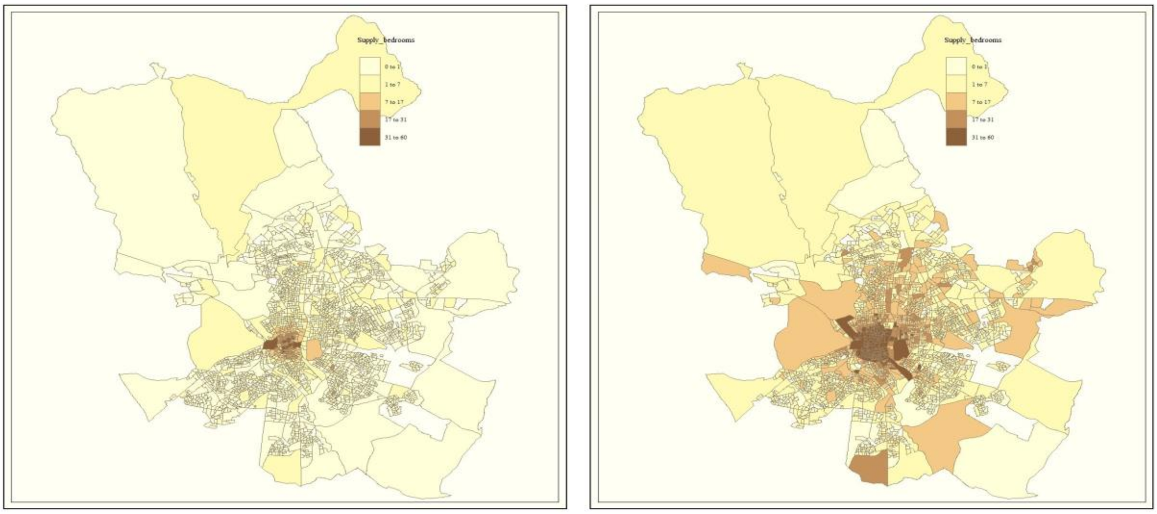
Figure II: Restaurants (dots), Airbnb rooms (bars) and hotel rooms (solid) evolution.



In Figure III, we can visualise the geographical distribution of Airbnb rooms in two different moments in time: April 2014 and April 2018. In 2014, most Airbnb supply was concentrated in the Madrid city center's census tracts, with almost no presence elsewhere. However, we can see a different picture four years later, where even though the bulk of Airbnb rooms are still located downtown, there are some areas near the city center where the Airbnb room supply has spread. Those areas are the ones that will help us to identify the effect of Airbnb on the change in the number of food and beverage activities.

year		2014			2018	
Variable	Sum	Mean	Sd	Sum	Mean	Sd

Figure III: Spatial distribution of Airbnb rooms in April 2014 (left) and April 2018 (right).



Consequently, we create two samples: the whole sample that includes all Airbnbs in the city of Madrid and the restricted sample that exclude all census tracts that are located within one of the five neighbourhoods that belong to the district "Centro" of Madrid. As can be seen Table 1 and in Table 2, our decision is grounded in the different characteristics of both samples as the Airbnb activity, but also the traditional accommodation activity is higher in the whole sample due to the presence of all those census tracts located in the city center. For example, we can observe that nearly one-third of the overall Airbnb activity and the traditional accommodation industry is located in the city center. As discussed above, our goal is to identify non-touristic areas where Airbnb has installed to analyze its impact on the local economy. The rapid and unequal diffusion of P2P accommodation across the urban geography, together with the modest increase of other types of accommodations, allow us to study how Airbnb may have influenced the food and beverage sector.

Table 1: Whole sample (N= 40,033, Census tracts = 2,107)

year Variable	Sum	2014 Mean	Sd	Sum	2018 Mean	Sd
Food and beverage services	15532	7.372	8.518	16686	7.919	9.302
Airbnb listings	2830	1.343	4.34	15953	7.571	15.711
Airbnb rooms	3907	1.854	6.136	22733	10.789	23.341
Number of Hotels	386	0.183	0.787	407	0.193	0.823
Hotel rooms	40566	19.253	89.882	40463	19.204	92.904
Foreign population	331.7	0.157	0.102	377.3	0.179	0.118
Population	2775687	1317.364	454.645	2810313	1333.798	449.601

Table 2: Restricted sample (N= 38,437, Census tracts = 2,023)

year Variable	Sum	2014 Mean	Sd	Sum	2018 Mean	Sd
Food and beverage services	13384	6.616	6.453	14352	7.094	7.202
Airbnb listings	1461	0.722	2.321	10425	5.153	8.056
Airbnb rooms	2023	1	3.256	14557	7.196	11.336
Number of Hotels	270	0.133	0.548	276	0.136	0.551
Hotel rooms	31367	15.505	77.297	30440	15.047	78.891
Foreign population	307.9	0.152	0.098	352.2	0.174	0.115
Population	2674322	1321.958	459.171	2708795	1338.999	453.506

5. RESULTS

In this section we show the main results of our analysis. First, we provide the OLS and IV estimates of the effect of Airbnb on the food and beverage sector, in general, and in a subgroup of activities of this sector. Then, we perform a series of robustness checks to see whether our main tenets hold to the presence of potential confounders, alternative measures of our variable of interest, Airbnb activity, other sources of exogeneous variation and the existence of pre-trends, spatial spillovers and different geographical unit of analysis.

Table 3 presents the main results for our baseline specification, either the whole sample (columns 1-3) and the restricted sample (columns 4-6). Our baseline sample compresses 2,023 census tracts for the Whole sample and 2,107 for the Restricted sample for 19 quarters, from April 2014 until October 2018. Our dependent variable is the number of food and beverage services. In columns 1 and 4, we regress the number of food and beverage services on the number of Airbnb listings. Then, we augment this regression with time-varying additional controls, as seen in columns 2 and 5. Due to the potential existence of time-invariant census-specific characteristics related to the number of food and beverage services and the Airbnb activity or the existence of a common trend that affect equally all our geographical units, we add census tract and quarter fixed effects in

Table 3: Impact of Airbnb on the number of food and beverage services (OLS).

	Whole sample			Restricted sample		
Dependent Variable:	Food and beverage services					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
(Intercept)	5.851***	1.734***		5.699***	1.497***	
	(0.0410)	(0.1161)		(0.0373)	(0.1067)	
Airbnb rooms	0.3153***	0.2589***	0.0261***	0.3270***	0.2781***	0.0404***
	(0.0071)	(0.0065)	(0.0019)	(0.0081)	(0.0079)	(0.0035)
Population		0.0021***	0.0029***		0.0022***	0.0029***
		(7.46×10^{-5})	(0.0002)		(6.78×10^{-5})	(0.0002)
Foreign population		7.010***	-1.405***		7.287***	-1.261***
		(0.3464)	(0.3779)		(0.2976)	(0.3846)
Hotel rooms		0.0283***	0.0023**		0.0239***	0.0028***
		(0.0014)	(0.0010)		(0.0014)	(0.0011)
Fixed effects						
Quarters	No	No	Yes	No	No	Yes
Census tract	No	No	Yes	No	No	Yes
Fit statistics						
Observations	40,033	40,033	40,033	38,437	38,437	38,437
R^2	0.32123	0.42638	0.99078	0.15088	0.27024	0.98533

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Heteroskedasticity standard errors for columns 1-2 and 4-5 and cluster standard errors at the census tract level for columns 3 and 6.

columns 3 and 6.

At first glance, it is worth noticing that the results do not crucially depend on the selected model. We find a positive and significant effect of Airbnb activity on the change of the number of food and beverage services. The inclusion of several controls makes the coefficients for Airbnb activity somewhat reduced. However, they remain significant across all the specifications. It is important to notice that our measure of Airbnb activity approximately accounts for the number of tourists as we are weighting the number of listings by its respective number of rooms. Therefore, taking our preferred specification (column 6), we can observe that the effect of one additional tourist is fourteen times bigger than the inclusion of one resident, as we should expect, since short-term residents have different consumption patterns than long-term residents. We must be aware that this effect provides a lower bound of the overall impact since P2P accommodations are not fully booked during the whole year. In contrast, it is plausible to argue that residents remain at home most of the time. Likewise, the number of traditional accommodation rooms contributes positively to the change in food and beverage services, although it is lower in magnitude than the P2P accommodations. A priori, the greater positive externality of the P2P accommodations can be seen counterintuitive as most of those accommodations provide kitchen facilities. However, a potential explanation about the smaller effect for the traditional accommodation on the number of food and beverage services rests on the fact that those accommodations already provide those services inside the facilities; therefore, there is less scope to positive externalities in nearby areas. Moreover, as described in the previous Section, the number of traditional accommodation rooms barely changed in Madrid in the time window we consider. The last issue to notice is that the effect of Airbnb on the number of food and beverage services is lower in our restricted sample than in the Whole sample. In this regard, Airbnb has a greater impact on least tourist areas as this P2P platform may be seen as a substitute for hotels in some sense. Therefore, the Airbnb-induced tourism effect is attenuated whenever there are other accommodations around.

Although we control for an extensive range of factors, we cannot rule out unobserved time-varying characteristics related to Airbnb activity and the changes in the number of food and beverage services. Therefore, to overcome the potential problem of endogeneity in the Airbnb activity variable, we perform an instrumental variable strategy. Table 4 show the first and second-stage results for our most preferred specification (time-varying control variables plus quarter and census tract fixed effects). We can observe that our instrument, the interaction between the number of rented houses in 2011 and the worldwide Airbnb Google searches, predicts the Airbnb activity. In the second stage, we can see that the sign of the Airbnb effect remains positive, and the magnitude has increased.

In economic terms, our estimates for the restricted sample imply that for each increase in 10 Airbnb rooms, the number of food and beverage services increases on average in the unity in each census tract. Moreover, the IV coefficient (column 4 of table Table 4) is twice larger than the OLS (column 6 of table Table 3). The downward bias in the OLS estimates may be explained by omitted factors positively correlated with the presence of Airbnb in a census tract but negatively with the change in the number of food and beverage services. Also, measurement errors might play a role since we know neither the exact location nor the timing since the listing is on the platform, but only an approximation.

Table 4: Impact of Airbnb on the number of food and beverage services (IV).

	Whole sample		Restricted sample	
Dependent Variables:	First stage	Second stage	First stage	Second stage
Variables				
Airbnb rooms		0.0613^{***}		0.0974^{***}
		(0.0132)		(0.0253)
Shift share	0.010^{***}		0.005^{***}	
	(0.0001)		(5.99×10^{-5})	
Population	-0.0005	0.0029^{***}	0.0004	0.0028^{***}
	(0.0008)	(0.0005)	(0.0004)	(0.0005)
Foreign population	-16.89^{***}	-0.6885	-10.01^{***}	-0.6245
	(6.327)	(1.001)	(3.693)	(1.042)
Hotel rooms	0.0385^{**}	0.0009	0.0106^{*}	0.0022
	(0.0164)	(0.0022)	(0.0062)	(0.0024)
Fixed effects				
Quarters	Yes	Yes	Yes	Yes
Census tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	40,033	40,033	38,437	38,437
R^2	0.87262	0.99022	0.86644	0.98465
F-test (First stage)	75.067		65.112	

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Shift share represents the interaction between the number of rented houses in2011 and the worldwide Airbnb Google searches.

Along with the analysis, we were focusing on the impact of Airbnb on the number of food and beverage services. However, the employment in that activity may have grown too. Unfortunately, we do not have access to restaurant employment at the census tract level, but only at neighbourhood level on a yearly basis. So, to test whether employment in the restaurant industry has been affected by the entry of Airbnb in Madrid, we replicate our favourite specification using the neighbourhoods as our geographical unit of analysis and years as our time frame. Table 5 shows the main findings. We also reproduce the results for the number of food and beverage services tocompare.

Table 5: Impact of Airbnb on the food and beverage services employment and food and beverage services at the neighbourhood level (IV)

	Food and beverage services			Employment
Dependent Variables:	Whole sample	Restricted sample	Whole sample	Restricted sample
Variables				
Airbnb rooms	0.0435***	0.0683***	0.4588**	0.9090***
	(0.0077)	(0.0207)	(0.1835)	(0.3391)
Population	0.0002***	0.0002***	0.0005	0.0003
	(4.69×10^{-5})	(4.63×10^{-5})	(0.0009)	(0.0008)
Foreign population	4.831	1.448	695.4	388.2
	(32.10)	(32.13)	(987.8)	(963.5)
Hotel rooms	-0.0123	-0.0053	-0.2754	-0.2078
	(0.0091)	(0.0072)	(0.2278)	(0.1758)
Fixed effects				
Neighbourhood	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	625	600	625	600
R^2	0.99854	0.99795	0.98198	0.98098

***p < 0.001; **p < 0.01; *p < 0.05. Cluster standard errors at the census tract level.

As before, we can observe that the effect of Airbnb on tourism-related activities is more prominent in the least touristic areas. Interestingly, we can see the effect of Airbnb activity on employment is greater than in the number of food and beverage services, as the employment variable is jointly picking the effect of the extensive margin (positive variation in the number of restaurants) and in the intensive margin (positive variation in the employment of the existing restaurants). Due to the inaccessibility to individual employment data, we cannot disentangle one effect over the other. On top of that, the greater effect is also since the opening of a new food and beverage establishment does not map one-to-one with a new employee as it is unlikely that those business are notonly compressed by one person.

5.1. ROBUSTNESS CHECKS

5.1.1. FALSIFICATION TEST: THE IMPACT OF AIRBNB ON OTHER LOCAL ECONOMIC ACTIVITIES

A concern about our analysis is that there may be still census-tract specific time-varying unobservables correlated with both Airbnb and the number of food and beverage services. We decided to carry on the analysis on those activities as they may be related with confounding phenomenon like urban revival (Behrens et al., 2018). The existence of this confounder correlated with the presence of Airbnb and the number of food and beverage services may invalidate our identification strategy as we will erroneously claiming that Airbnb is behind the explosion in the number of food and beverage services. Conversely, if there is not any unobserved time-varying trend, we should find any effect of Airbnb on those economic activities as Airbnb mainly foster tourist-related activities. We perform a falsification test where we analyze the effect of Airbnb on non-touristic activities as the professional, scientific and technical and financial and insurance activities.

Table 6 present the results for professional, scientific and technical and finance and insurance activities for the restricted sample. Due to the fact that census tracts with finance and insurance or professional, scientific and technical may be different than those with food and beverage services, we decide to perform the falsification analysis on a subset of our initial census tracts sample, that is, those census tracts where there are food and beverage services and at least one of those non-tourists related activities. As can be seen, we do not observe any effect of the Airbnb on the change of non-tourist related activities.

Table 6: Impact of Airbnb on the number of professional, scientific and technical and finance and insurance activities (IV)

Dependent Variables:	Professional, scientific and technical		Finance and insurance	
	Whole sample	Restricted sample	Whole sample	Restricted sample
Variables				
Airbnb rooms	0.0047	0.0056	-0.0088	-0.0187
	(0.0045)	(0.0093)	(0.0091)	(0.0192)
Population	0.0005***	0.0005***	0.0008***	0.0008***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Foreign population	0.1740	0.1650	0.2866	0.3740
	(0.4232)	(0.4506)	(0.7207)	(0.7749)
Hotel rooms	9.65×10^{-6}	4.91×10^{-5}	0.0024	0.0027
	(0.0006)	(0.0006)	(0.0016)	(0.0020)
Fixed effects				
Quarters	Yes	Yes	Yes	Yes
Census tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	40,033	38,437	40,033	38,437
R^2	0.97122	0.97165	0.96804	0.96528

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Cluster standard errors at the census tract level.

5.1.2. ALTERNATIVE MEASURES OF AIRBNB ACTIVITY

The consumer-facing information retrieved from the Airbnb platform through Inside Airbnb compress a great variety of size-related variables like the maximum number of guests, the number of beds, or the number of rooms for each listing. As each variable conveys different information from the listing size, we decide to check whether our measure of Airbnb activity is robust under different specifications, Table 7 provides evidence from the most aggregated measure (listings) to the less aggregated (number of guests) that no matter the dimension used, the positive and significant effect remain across different specifications.

Table 7: Impact of Airbnb on the number of food and beverage services using alternative Airbnb measures

	Restricted sample (IV)			
Alternative Airbnb measures:	Listings	rooms	Accommodates	Beds
Variables				
Airbnb listings	0.1314***			
	(0.0339)			
Airbnb rooms		0.0974***		
		(0.0253)		
Airbnb beds			0.0688***	
			(0.0180)	
Airbnb guests				0.0405***
				(0.0106)
Population	0.0028***	0.0028***	0.0028***	0.0028***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Foreign population	-0.6622	-0.6245	-0.7062	-0.7959
	(1.036)	(1.042)	(1.036)	(1.027)
Hotel rooms	0.0023	0.0022	0.0023	0.0022
	(0.0023)	(0.0024)	(0.0024)	(0.0024)
Fixed effects				
Quarters	Yes	Yes	Yes	Yes
Census tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	38,437	38,437	38,437	38,437
R^2	0.98473	0.98465	0.98447	0.98457

$***p < 0.001$; $**p < 0.01$; $*p < 0.05$. Cluster standard errors at the census tract level.

5.2. IV VALIDITY

5.2.1. IV VALIDITY CHECK

One potential problem in our research design strategy is the existence of previous trends in the changes of the number of food and beverage services for census tracts where the number of housing rentals was high in 2011, and therefore, the number of Airbnb listing is high currently. Our main identification strategy rests on the assumption of parallel trends in the change of the number of restaurant industry units across census tracts with more rented houses and those with less before Airbnb arrival. An increasing (decreasing) change in the number of food and beverage services previous to Airbnb arrival in Madrid will invalidate our analysis by violating the exclusion restriction assumption. Unfortunately, we do not have information of the number of food and beverage services at the census tract level previous 2014. However, we can use the employment level data for food and beverage services at the neighbourhood level from 2012 onward to check for the existence of parallel trends,

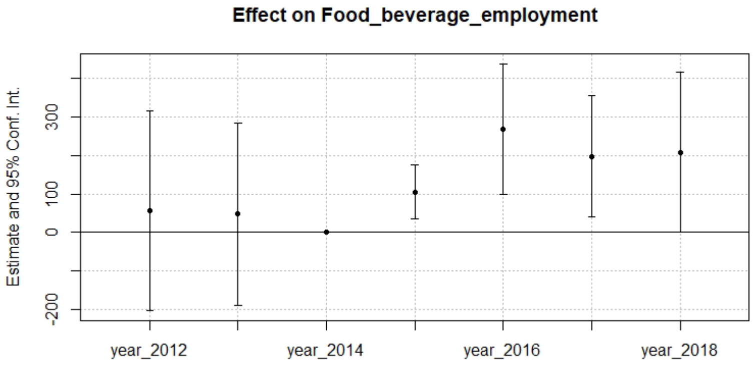
Therefore, following Goldsmith-Pinkham et al. (2020), we run the following event study

$$Y_{i,t} = \alpha + \sum_{t \neq 2014} \lambda_t \times \delta Airbnb\ high\ activity + \rho X_{i,t} + \epsilon_{i,t}$$

where we interact Airbnb high activity, a dummy variable for identifying those neighbourhoods with Airbnb activity is high[7], with year dummy variables λt, using 2014 year as the base year. We choose 2014 as our base year as from this year, the Airbnb activity in Madrid become more significant. As our main results are driven by mainly by those areas where the Airbnb activity is high, the main idea of this test is to check whether those areas were also experiencing a different trend in the evolution for the outcome variable. As can be seen in Figure IV, the coefficients before the Airbnb entry were not different from zero, which reassures that it was Airbnb the main culprit behind the increase in the employment of the food and beverage sector. Therefore, we can conclude that there is no violation in parallel trends and Airbnb did not entry in neighbourhoods after observing an expansion in food and beverage consumption amenities.

[7] The top decile neighbourhoods in terms of Airbnb activity are Sol, Palacio, Embajadores, Universidad, Cortes, Justicia, Palos de Moguer, Trafalgar, Goya, Arguelles, Guindalera, Puerta del Ángel y Arapiles.

Figure IV: Event study plots for the top decile Airbnb Neighbourhoods.



5.2.2 ALTERNATIVE INSTRUMENTS

The number of rented houses in 2011 interacted with the worldwide Airbnb Google searches has been used as our main Bartik-like instrument over the analysis. So far, we have shown that 1) our instrument does not predict the changes in the number of food and beverage services in those areas ever had any Airbnb activity and 2) those areas who has a higher presence of Airbnb activity have not any positive or negative pre-trend in the evolution of the employment for food and beverage services. To show that our main results hold no matter the source of exogenous variation exploited as our identification strategy, we select a series of share instruments that may be related with the number of food and beverage services only through their effect on the posterior evolution of Airbnb.

Table 8: Impact of Airbnb on the number food and beverage services using several instruments (IV)

	Food and beverage services			
Alternative Share Instruments:	Total dwellings	Empty houses	Share of rented houses	Share of rented + empty houses
Variables				
Airbnb rooms	0.0646***	0.0575*	0.1257**	0.1115**
	(0.0224)	(0.0337)	(0.0514)	(0.0463)
Population	0.0029***	0.0029***	0.0029***	0.0029***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Foreign population	-0.6213	-0.7649	0.6207	0.3326
	(1.162)	(1.309)	(1.276)	(1.187)
Hotel rooms	0.0007	0.0010	-0.0018	-0.0012
	(0.0022)	(0.0022)	(0.0034)	(0.0032)
Fixed effects				
Quarters	Yes	Yes	Yes	Yes
Census tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	40,033	40,033	40,033	40,033
R^2	0.99011	0.99033	0.98629	0.98747
F-test (First stage)	16.38	20.943	8.175	11.974

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Cluster standard errors at the census tract level.

We can see that our main tenets hold with either an absolute measure as the total number of houses or a relative measure such as the proportion of rented houses or the proportion of rented and empty houses, whereas the number of empty houses does not predict the posterior Airbnb distribution. However, our share instrument lost relevance as it can be seen by the lower values of the F-test.

5.3. SPATIAL ANALYSIS

5.3.1 SPILLOVER EFFECTS

So far, we were assuming that the Airbnb-induced tourism demand effect is constrained to the census tract where the Airbnb listing is located. However, this is a strong assumption due to the small size of our geographical unit of analysis. Although using census tracts allow us to better capture the effect of Airbnb on the number of food and beverage services, its reduced dimension make them more salient to spillover problems from other P2P accommodations in the surroundings census tracts than bigger administrative units like neighbourhoods or ZIP codes. Not taking into account the presence of spillovers make lead us to overestimate, but also maybe infraestimate the effect of Airbnb on the number of food and beverage services. On the one hand, the critical mass of potential costumers increases not only with the Airbnb tourists of each census tract, but also with the Airbnb guests of the census tracts neighbourhoods. Conversely, Airbnb may be shifting demand away from census tracts due to the creation of food and beverage clusters which would lead to an increase in the number of food and beverage services on the census tracts with strong Airbnb presence and a decrease in the rest.

To take into account the potential spillover effects in the census tracks due to the Airbnb, we use a spatial cross-regressive model (SLX) where we include the spatial lag of our variable of interest, the weighted number of Airbnb listings in census tracts neighbours. The main reason of using a SLX model over other spatial econometric methods rests on the expected local effects; Airbnb guests are more willing to consume only in nearby census tracts. Therefore, we expect that Airbnb-induced tourism demand only affects nearby areas. One of the advantages of SLX model is that it can be easily used with other standard econometric techniques (Halleck Vega and Elhorst, 2015). Therefore, we instrument the spatial lag of Airbnb rooms with the interaction between the worldwide Airbnb Google searches and the spatial lag of the number of rented houses in 2011.

Table 9 shows the results of our baseline specification where we have augmented it including the Airbnb activity’s spatial lag and as its instrument, the spatial lag of our shift share variable. As can be seen, regardless the spatial weight matrix use we do not find evidence of the present of spatial spillovers.

Table 9: Impact of Airbnb on the number of food and beverage services controlling for spillover effects. (IV, Censustracts, quarters)

Dependent Variables:	Food and beverage services			
Spatial matrix:	Cut-off distance	Inverse distance	Rook	Queen
Variables				
Airbnb rooms	0.0687***	0.0749***	0.0694***	0.0674***
	(0.0178)	(0.0192)	(0.0181)	(0.0169)
Supply lag	-0.0159	-0.0293	-0.0174	-0.0155
	(0.0145)	(0.0170)	(0.0157)	(0.0140)
population	0.0029***	0.0029***	0.0029***	0.0029***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Foreign population	-0.8164	-0.9244	-0.8291	-0.8623
	(0.9975)	(0.9995)	(0.9882)	(0.9819)
Hotel rooms	0.0009	0.0009	0.0009	0.0009
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Fixed effects				
Quarters	Yes	Yes	Yes	Yes
Census tract	Yes	Yes	Yes	Yes
Fit statistics				
Observations	40,033	40,033	40,033	40,033
R^2	0.99007	0.98988	0.99005	0.99008
Within R^2	0.02976	0.01060	0.02783	0.03066

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Cluster standard errors at the census tract level. Cut-off distance500m.

5.3.2 MODIFIABLE AREAL UNIT PROBLEM (MAUP)

We further test whether our main tenets hold whenever we use the same regression specification, but we change our geographical unit of analysis. This is ubiquitous statistical problem in spatial analysis framed as the Modifiable Areal Unit Problem (MAUP). Table 10 show that even though we find a positive and significant effect of Airbnb activity on the number of food and beverage services, this effect is higher in magnitude whenever we use our smaller geographical unit of analysis, the census tracts. The reduced size of that administrative unit of analysis allows us better to identify the tourism-induced effect of Airbnb as they are less heterogeneous than within neighbourhoods, which may explain the smaller magnitude coefficient.

Table 10: Impact of Airbnb on the number of food and beverage services. (IV, Neighbourhoods and census tract)

Unit of Analysis:	Neighbourhood		Census tract	
Spatial matrix:	Whole sample	Restricted sample	Whole sample	Restricted sample
Variables				
Airbnb rooms	0.0380***	0.0530***	0.0613***	0.0974***
	(0.0064)	(0.0112)	(0.0132)	(0.0253)
Population	0.0038***	0.0038***	0.0029***	0.0028***
	(0.0007)	(0.0007)	(0.0005)	(0.0005)
Foreign population	-1.451	-1.968	-0.6885	-0.6245
	(1.412)	(1.492)	(1.001)	(1.042)
Hotel rooms	-0.0063	-0.0012	0.0009	0.0022
	(0.0057)	(0.0044)	(0.0022)	(0.0024)
Fixed effects				
Quarters	Yes	Yes	Yes	Yes
Neighbourhood	Yes	Yes		
Census tract			Yes	Yes
Fit statistics				
Observations	2,394	2,299	40,033	38,437
R^2	0.99865	0.99805	0.99022	0.98465
Within R^2	0.42161	0.33324	0.04417	0.04971

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Cluster standard errors at the census tract level.

6. CONCLUSIONS

This paper examines the impact of the most popular P2P accommodation platform, Airbnb, on the food and beverage industry. Using a fine-grained census of local store data set and exploiting the exogenous variation created by the rapid and unequal entry of the short-term rentals across Madrid geography, we find positive and significant effects in the number but also in the employment of that industry. We show that there are heterogeneous effects across the different activities included in the food and beverage services. Our results are very stable across different specifications. We show that they are not driven by either the way of measure the P2P accommodations, the presence of unobserved time-varying trends related to gentrification or the existence of pre-trends. Lastly, we do not find evidence of the existence of spillovers, and our main tenets hold regardless of the geographical unit of analysis.

With this paper, we contribute to the debate about the effects of the platform economy on urban areas. Even though most of the previous studies have focused on the negative consequences that P2P accommodations bring to the cities in terms of higher rental and housing prices, we show that it could also contribute positively to the local economy by bringing new economic activity to non-touristic areas. Besides, although it has been shown that the entry of P2P accommodations may have deleterious effects for low-ranked accommodations, the effect of the overall tourism sector seems positive. Nevertheless, further research is needed. Airbnb-induced tourism may be contributing to touristification, a phenomenon that may be expelling residents and, therefore, transforming the neighbourhoods into tourist attractions. Besides, the effect can be extended to those businesses that cater to locals and not tourists who would be forced to close in favour of tourist-related establishments due to the losses of their customers. In this regard, a more holistic approach about how P2P accommodations reshape cities is needed.

All things considered, the greater and undetermined externalities of P2P accommodations deserve more con- sideration to understand its potential impact on urban areas.

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