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Impact of Airbnb on the Hotel Sector

Evidence from Spanish Touristic Sites

MNM OF ADVANCED STUDIES IN ECONOMICS

Emmanuel Sukadi A Sukadi

R0777353

Thesis submitted to obtain
the degree of

Master of Advanced Studies in Economics

Promoter: Prof. Dr. Patrick Van Cayseele

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This paper aims at measuring the impact of the peer-to-peer rental platform Airbnb on the Spanish hotel industry. For that purpose, a difference-in-differences strategy has been implemented to evaluate the causal effects of Airbnb's entry in the touristic sites where the platform has been most fully adopted. The analyses cover a panel of 92 Spanish touristic sites over the period 2006Q1 to 2020Q1. The evidence suggests that Airbnb adoption has been detrimental to hotel frequentations and capacities. Moreover, the estimations have shown discrepancies in tourists' appeal for Airbnb based on their provenance. Tourists from foreign countries appear to be more likely than national tourists to choose Airbnb over hotels.

Keywords: Sharing economy, peer-to-peer platform, Airbnb, difference-in-differences

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Contents

1. Introduction

The emergence of the sharing economy has been fostered by the reduction of hurdles to market entry and by the higher supply flexibility made possible for peer-to-peer platforms through technological innovations. Uber, BlaBlaCar, Airbnb and various other online platforms have experienced steady growth since their launch and gradually became important actors in their respective markets.

Airbnb is an internet-based platform for peer-to-peer accommodation. Initially, as stressed by Zervas et al. (2017), professionals of the hospitality industry viewed Airbnb as a complementary offer rather than a direct threat for hotel chains. That idea was shared by Airbnb as the platform reported that most properties listed were located outside the main hotel districts. Moreover, Guttentag (2015) argued that Airbnb was less performant than hotels for many criteria considered by tourists in their accommodation choice (e.g. service quality, security and brand reputation). However, the platform has been expanding and gaining popularity amongst tourists, becoming a well-established competitor of the hotel industry (Strømmen-Bakhtiar & Vinogradov, 2019).

According to Guttentag (2015), the popularity of Airbnb is due to its relatively low costs compared to hotels, and to the benefits of staying in a residence that it provides to guests. Indeed, Airbnb hosts generally do not incur labor costs, and most of their fixed costs (e.g. rent, electricity, internet, etc.) are already covered. Moreover, Airbnb hosting is generally not the sole source of income for hosts. Therefore, they can charge very competitive prices for their spaces. In addition, tourists who choose Airbnb have the opportunity to live like locals, interact with hosts and benefit from practical residential facilities such as a kitchen or a washing machine.

The expansion of Airbnb has triggered the attention of hospitality professionals and of many local and tax authorities (Strømmen-Bakhtiar & Vinogradov, 2019). The rise of the platform has not only resulted in a higher number of listings but also in a greater professionalization of some hosts. In a growing number of cases, the activities of hosts have been going beyond the principals of the sharing economy. For instance, many properties formerly devoted to long-term rental have been entirely converted into permanent Airbnb offers. This goes against the idea of sharing underutilized assets which is intrinsic to the sharing economy. Moreover, it is less and less rare to encounter Airbnb hosts who provide services usually offered by hotels, such as restauration, laundry, or touristic activities planification (Gil & Sequera, 2020). Consequently, the hotel industry has been confronted to a greater competitive pressure from Airbnb. Moreover, several studies[1] report decreases in housing availability and livability for locals, and increases in rents in various regions due to the growth of Airbnb. In many cities, local authorities have undergone the tedious task of taming the expansion of the rental platform through regulation

[1] See for example Espinosa (2016), Oskam & Boswijk (2016), Füller & Michel (2014) and Niewland & Melik (2020)

measures ranging from taxation to partial ban of Airbnb activities (Wegman & Jiao, 2017 and Yeon et al., 2020).

Airbnb has been present in Spain since 2010. Figure 1 displays the number of Airbnb hosts whose listings received at least one review over the past years in nine Spanish cities. It appears that Airbnb's activity has experienced an exponential growth in many cities since the launch of the platform. The expansion phase has been particularly striking in cities such as Barcelona, Madrid, Girona, and Menorca which are important touristic areas. Note that the growth of Airbnb in Spain has been hampered in 2020, coinciding with the Covid-19 pandemic.

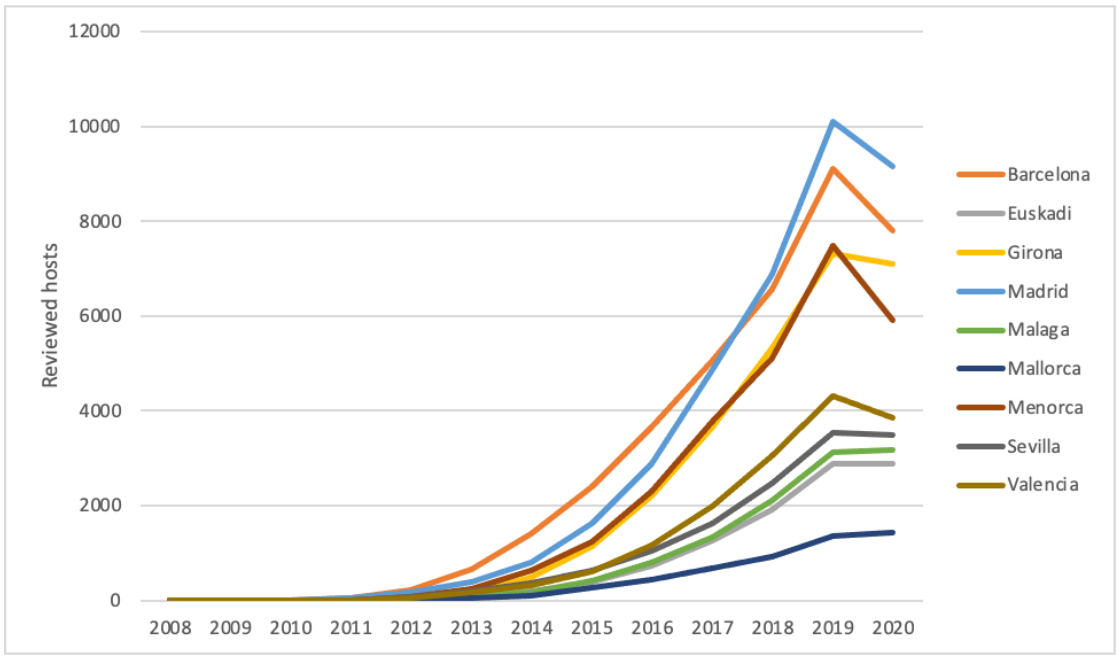

Fig. 1 Number of reviewed hosts from 2008 to 2020. Source: Inside AirBnB[2]

In 2020, there were about 245,000 Airbnb listings registered in Spain. This placed the country at the fourth rank of destinations with the highest number of listings behind the U.S. (660,000 listings), France (485,000 listings) and Italy (340,000 listings). In 2018, Spain was the third country in terms of Airbnb hosts incomes and estimated guests' expenditures with a total of $6.9 billion, after the U.S ($33.8 billion) and France ($10.9 billion)[3].

Although the properties offered on Airbnb in Spain are spread throughout the country, Adamiak et al. (2019) note a spatial pattern in their distribution. Most Airbnb properties are concentrated in major cities, coastal areas, and on the Balearic and Canary Islands. These areas are important touristic poles and also exhibit a greater hotel concentration than the other regions of the country. Figure 2 and Figure 3 display heatmaps of, respectively, the number of Airbnb listings and the number of hotel rooms in 92 Spanish touristic sites in 2018. These maps show a dense concentration of both Airbnb listings and hotel rooms in Barcelona, Madrid and Malaga, and a stronger concentration in coastal areas and islands than in central areas.

[2] insideairbnb.com/get-the-data.html
[3] www.ipropertymanagement.com

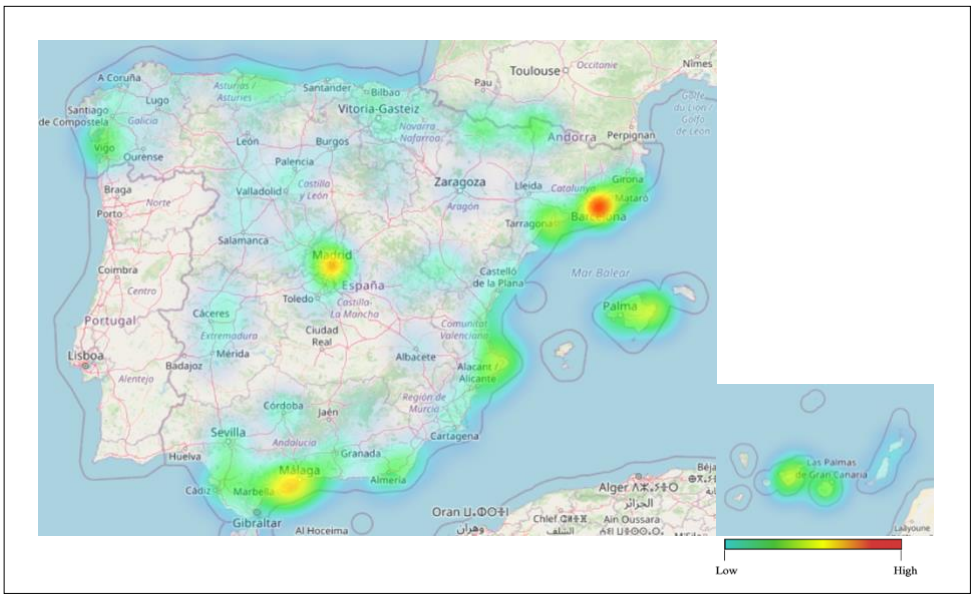

Figure 2. Concentration of AirBnb listings in 2018.

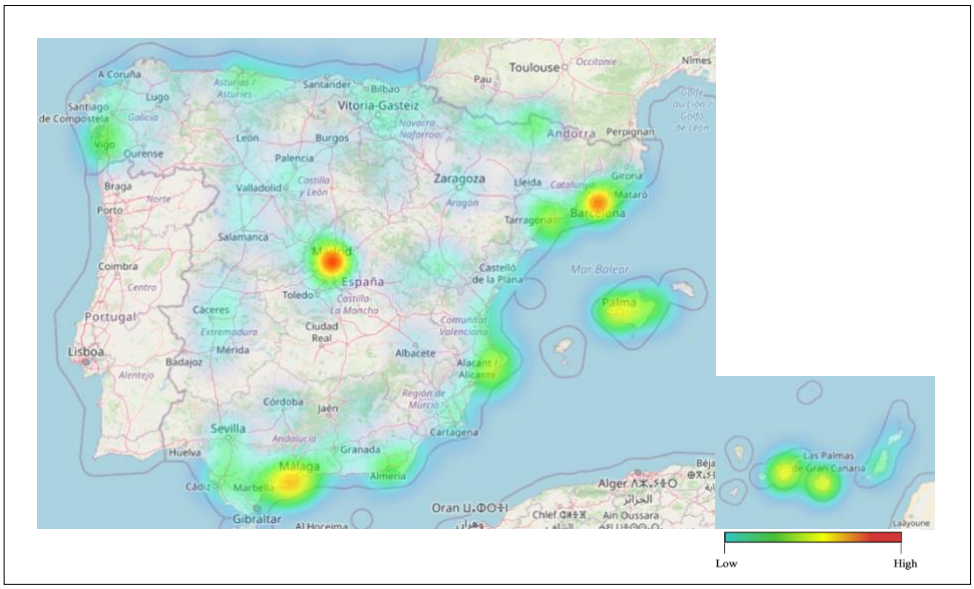

Figure 3. Concentration of hotel rooms in 2018.

In this paper, the focus is put on touristic areas given that such zones are important targets for hotels chains but also fertile lands for Airbnb. It is hypothesized that the cohabitation of Airbnb and hotels in touristic areas has been detrimental to the hotel industry in zones where Airbnb has been fully adopted. It is assumed that the tourists' appeal for the rental platform and the increasing professionalization of hosts have contributed to exacerbate the effects of Airbnb on hotels.

The following section of this paper glances at some previous works related to the current analysis. This paper adds to the rather scant number of studies devoted to assessing the impact of Airbnb on hotels in Spain. Moreover, while many of the previous works limited their analyses to a single city, this study encompasses several touristic areas spread throughout Spain. This allows for a more general view of the impact of Airbnb on the Spanish hotel industry. For the purpose of the study, the 92 Spanish touristic sites included in the analyses have been ranked

based on their level of adoption of Airbnb. A difference-in-differences strategy has then been developed to assess the impact of the rental platform on various hotel industry indicators (i.e. number of local and foreign guests, duration of stays and occupancy rate of bedrooms). These methodological aspects are discussed in section 3, and the results of the analyses are provided in section 4. Some robustness checks are performed in section 5 to support the causal nature of the estimates. The main takeaways and implications of the study are then discussed in the last section of the paper.

2. Literature review

The rise of the sharing economy and the increasing popularity of peer-to-peer online platforms have led to an emulation of studies devoted to assessing the impact of these newcomers on incumbent industries. Among all platforms, Uber and Airbnb are the ones that have caught the researcher's attention the most.

Influential studies on Uber include the works of Cramer & Krueger (2016) and Wallsten (2015) that examined the effects of the ride-sharing platform on the taxi industry. These studies provide some evidence that Uber has become a viable alternative to traditional taxis. Moreover, they reveal that the greater flexibility of the platform compared to taxi companies, and the efficient technology that it uses to match drivers with clients have made Uber activity more profitable than taxis in many cities. Other notable studies such as the works of Rogers (2015) and Angrist & Caldwell (2017) provide assessments of the social cost of Uber. These studies underline the voracious competition that the platform exercises on the taxi industry and the resulting decreases in drivers' wages and labor standards. In addition, concerns are raised about potential privacy violations imputable to Uber given the information on clients' movements stored by the platform.

Studies which analyze the impact of Airbnb on the hotel industry can be clustered into two segments. The first one regroups works aiming at understanding the factors that lead hosts to choose Airbnb over hotels. The relatively low cost of Airbnb compared to hotels is a major factor influencing tourists accommodation decision (Guttentag, 2015).[4] Beside cost considerations, tourists' appeal for Airbnb lies in the different experience that the platform offers. Guttentag et al. (2018) identify five important factors that motivate guests to opt for Airbnb, namely: (1) interaction with hosts and locals, (2) home benefits such as large amount of space, access to household amenities and homely feel, (3) novelty (new, exciting and unpredictable experience), (4) sharing economy ethos (e.g. the desire to see the money spent go directly to locals, the environmental friendliness of sharing accommodation, the appeal for Airbnb's philosophy, etc.), and (5) local authenticity (e.g. possibility to enjoy an authentic local experience and to stay in non-touristic neighborhoods). Mao & Lyu (2017) stress the importance of trust in the use of peer-to-peer platforms and underline the influence of positive reviews on the intention to use (and re-use) Airbnb.

[4] Wang & Nicolau (2017) and Magno et al. (2018) provide analyses of price determinants of peer-to-peer accommodation platforms.

The second segment of studies encompasses papers analyzing the impact of this new competition on hotel revenues and occupancy rates. Several studies cover the U.S market. Zervas et al. (2017) find that a 10% increase in Airbnb activity is associated with decreases in monthly hotel revenues (0.39%), occupancy rates (0.05%) and prices (0.19%) in Texas. Dogru et al. (2017) and Dogru et al. (2019) arrive to comparable conclusions for Boston and 10 major U.S. cities, respectively. Lane & Woodworth (2016) find a negative impact of Airbnb on hotel supply, while Li & Srinivasan (2019) find a negative impact on hotel demand in the U.S. Beyond the U.S. market, Dogru et al. (2020a) argue that increases in Airbnb listings lead to decreases in hotel revenues, prices and occupancy rates in some other major Airbnb markets (i.e. London, Paris, Sydney and Tokyo). Neeser et al. (2015) analyze Finland, Norway and Sweden and find negative impacts of Airbnb on hotel prices. Leslie & Waight (2018) and Roma et al. (2019) find negative impacts of the platform on lower-end hotels. The formers observe a decrease in revenues in economy and budget hotels in Belize, while the latter find a decrease in prices in lower scale hotels in 13 cities in Italy which can be attributed to Airbnb.

Although numerous studies tend to corroborate the idea that Airbnb phagocytizes the activities of the traditional hotel industry, some researchers find non-significant, or even positive, impacts of Airbnb penetration on hotels. Blal et al. (2018) analyze the market of San Francisco and consider various hotel measures (i.e. room supply, occupancy rate, revenue and price). The authors find no significant impact of Airbnb activity on these hotel indicators. Dogru et al. (2020b,c) cover the entire U.S. market and find no significant impact of Airbnb on hotel occupancy rates. Beyond the U.S., Choi et al. (2015) and Neeser et al. (2015) find no impact of Airbnb on hotel revenues in South Korea for the formers and in three northern European countries for the latter. More unexpectedly, Aznar et al. (2017) found a positive correlation between the presence of Airbnb lodging at proximity and hotels return on equity in Barcelona. Roma et al. (2019) argue that high-end hotels tend to increase their prices in areas where Airbnb has a higher penetration.

Despite various empirical attempts to assess the impact of Airbnb on the hotel industry, no clear consensus seems to emerge. Moreover, although Airbnb is becoming a worldwide phenomenon, most studies focus on the U.S. market. This paper aims at contributing to the literature by providing evidence from Spain, one of the countries with the most dynamic Airbnb activities in the world. The Spanish case is of particular interest as the country is a highly touristic destination and has an important hotel industry which is a non-neglectable source of income for the country and major job provider.

3. Data and methodology

A. Data

Data on the hotel industry were gathered from the Spanish National Statistics Institute (INE) database. The INE compiles results of hotel occupancy surveys and provides data aggregated by touristic sites. These sites correspond to municipalities where the concentration of tourist amenities is significant. For the current analysis, quarterly data running from 2006Q1 to

2020Q1 were collected for the 106 touristic sites available in the database. Therefore, the dataset covers four years before the launch of Airbnb in Spain and excludes the period of the Covid-19 pandemic which has been particularly harmful for the hotel industry.

Hotel measures observed for each touristic site include: the number of open establishments and rooms, the occupancy rate of bedrooms, the number of bed-places (and bed-places during weekends), the number of guests from Spain and from abroad, the number of overnight stays of Spanish and foreigner guests, and the number of workers employed in the hotel sector.[5] Data on population and regional unemployment were also collected from the INE database.

Note that this study does not include data on hotel revenues for touristic sites given that they were not readily available for the period covered. Indeed, the INE provides data for touristic sites on revenue per available room and average daily rate, which are commonly used in the literature, only starting from January 2021. For earlier periods, these measures are only available at higher levels of aggregation (i.e. by autonomous communities and provinces). These levels of aggregation are not suitable for the analyses performed in this paper.

After removing sites with numerous missing values, a total of 92 touristic sites remained in the dataset. Airbnb data for these touristic sites have been tedious to collect. There exist three main platforms providing data on Airbnb activity, namely: Inside Airbnb[6], DataHippo[7] and AirDNA[8]. The first platform has accurate data on Airbnb listings and reviews since the launch of the platform in Spain. However, as depicted on Figure 1, these data cover only 9 Spanish municipalities. DataHippo provides figures for all Airbnb listings in Spain, yet only for the year 2018. The most complete database appears to be that of AirDNA, however the platform does not provide these data for free.[9]

Given these hurdles in the collection of data on Airbnb activity, the choice has been made to use data of 2018 provided by DataHippo to build a dummy variable of Airbnb adoption for each touristic site. Two reasons provide support for that choice. Firstly, it appears from Figure 1 (i.e data for 9 municipalities collected from Inside Airbnb) that the year 2018 lies far away enough from the entry of Airbnb in the country to see a clear pattern in the adoption of the platform by Spanish cities. Indeed, it can be assumed that by that year, the level of awareness regarding the existence and benefits of the platform was similar across the country. Therefore, it seems plausible that the number of listings observed in 2018 reflect the true profile of each site regarding Airbnb adoption. Secondly, unlike the work of Zervas et al. (2017), this paper uses aggregated data for the hotel industry by touristic sites rather than data by hotel.[10] While Zervas

[5] Definitions of the hotel variables are provided in appendix A1.
[6] insideairbnb.com/get-the-data.html
[7] DataHippo
[8] AirDNA | Short-Term Rental Analytics | Vrbo & Airbnb Data
[9] A remaining option for data collection consisted in proceeding to data scrapping from the website of Airbnb. Beside potential legal concerns linked data scrapping, that option turned out to be utterly time-consuming and could not be completed on time to be considered for the current version of the paper.
[10] In that sense, our database resembles to that of Neeser et al. (2015) which used aggregated regional data for the hotel sector. However, unlike in that paper, the database employed here does not include Airbnb data for each site and at each period.

et al. (2017) were able to build a control group including hotels located in cities with no presence of Airbnb, the level of aggregation of data in the current study does not allow for such sampling procedure. Moreover, all the touristic sites considered in the current analysis counted at least one Airbnb listing in 2018.[11] Therefore, the idea of a control group consisting of sites in which Airbnb would be totally absent is discarded. Consequently, the distinction between treated and control groups for the difference-in-differences analyses will be based on the level of adoption of Airbnb rather than on the presence of listings.

B. Difference-in-differences strategy

The approach followed in this paper consists in comparing pre- and post-Airbnb adoption periods to assess the impact of the platform on the hotel industry. In line with Neeser et al. (2015) and Zervas et al. (2017) a difference-in-differences (DD) identification strategy is implemented for that purpose.

Although Airbnb is present in all the touristic sites considered in this study, the concentration of Airbnb listings varies substantially among sites. It is argued that hotels located in touristic sites where Airbnb adoption has been the most important have been more affected by the rise of the platform than those located in areas where Airbnb penetration has been more tenuous. As shown in appendix A2, touristic sites have been ranked based on the number of Airbnb listings per km² in 2018. Sites located in the 4th quartile constitute the treatment group (i.e. sites where Airbnb has been fully adopted) while those located in the 1st quartile are used to build a control group (i.e. sites where Airbnb has not penetrated). Each group is composed of 23 touristic sites.

Appendix A2 shows that Airbnb concentration is at most 5 listings per km² in the control group while it is between 50 and 751 listings per km² in the treatment group. The lack of time series data of Airbnb listings for all sites renders impossible the observation of specific Airbnb entry dates for each site. This obliges to assume a common Airbnb entry date for all the touristic sites. Based on the data for 9 Spanish municipalities provided by the platform Inside Airbnb, it appears that the entry of Airbnb on the Spanish market occurred in 2010. Therefore, the period 2010Q1 is set as a common entry date of Airbnb for all sites even if, in reality, not all sites had active listings during that period.

The main DD model for this analysis is the following:

$$Y_{it} = \alpha + Site_i + Time_t + \beta(Site * Time)_{it} + \gamma X'_{it} + (Touristic\ site_i * Quarter_t) + Province_i + \epsilon_{it} \quad (1)$$

The dependent variable Y_{it} refers to a list of hotel measures on which we examine the impact of Airbnb. This list includes hotel occupancy measures (i.e. occupation rated of bedrooms, bed-places and bed-places during weekends), number of guests and overnight stays, number of open

[11] Given the highly touristic profile of these sites, it is likely that they have had at least one Airbnb listing since the first quarter following the entry of the platform in Spain.

hotels and number of employees in the hotel sector[12]. Note that all variables, except the ones expressed in rates, are taken into logarithms. $Site_i$ is a touristic site dummy variable which is equal to 1 for sites which belong to the treatment group and to 0 for the sites of the control group. $Time_t$ is a time dummy variable which switches on in 2010Q1 until the last period covered (i.e. 2020Q1). $(Site * Time)_{it}$ is an interaction term which spots observations of the treatment group for the periods in which Airbnb has been operating in Spain. In the current DD identification strategy, the first difference is taken using $Site_i$ which allows for time-invariant differences in hotel performances between Airbnb adopting and non-adopting touristic sites. The second difference is taken using $Time_t$ to account for time-varying differences in hotel performances which are common amongst sites.

The coefficient of interest is the β associated to the interaction term. It represents the causal effect of Airbnb adoption on hotel measures. It is interpreted as the percentage increase or decrease in the analyzed hotel measure attributable to the adoption of Airbnb. X_{it} is a vector which includes site- and time- varying covariates (i.e. size of provincial population and provincial unemployment rate, quadratic site-specific time trends and hotel supply). Angrist & Pischke (2008) argue that the inclusion of such covariates helps controlling for omitted site-specific confounders that may vary over time. Moreover, the incorporation of site-specific time trends[13] makes the DD estimation more robust by allowing the treatment and control group sites to follow different trends.

Zervas et al. (2017) highlight the fact that over time, hotel firms are likely to expand their offer in areas of anticipated high demand. The geographical patterns observed in the distribution of hotels and Airbnb listings suggest that high demand for accommodation may be correlated with both hotel supply and Airbnb adoption. This might introduce some bias in the DD estimation given that increases in hotel supply may result in lower hotel occupancy rates which would be wrongly attributed to Airbnb adoption. Incorporating hotel supply (i.e. number of open establishments per km^2) to the list of control variables helps correcting for this potential bias.

Touristic site-quarter fixed effects are included to the model to control for potential seasonal demand patterns that may vary across sites. For instance, the period July-August-September usually coincides with higher accommodation demand in the site of Valencia. This is due to the July fair and the traditional Bull Runnings taking place in the city during that period. Eventually, provincial fixed effects are incorporated to control for regional specificities (e.g. regional non-Spanish language, administrative institutions, legal jurisdiction, etc.) that sites located in the same province may have in common.

4. Results

All the regressions executed in this section include quadratic site-specific trends, touristic site-quarter fixed effects and provincial fixed effects of which coefficients are not reported. Variance inflation factor (VIF) and endogeneity tests were implemented, and no issues of multicollinearity nor endogeneity have been detected. It appears from Table 1 that the adoption

[12] Descriptive statistics of dependent and control variables are provided in appendix A3.
[13] Following Zervas et al. (2017) a quadratic form is specified for the site-specific time trends.

of Airbnb has led to decreases in the number of guests and overnight stays in hotels. These decreases are higher for tourists coming from abroad than for Spanish clients. Overnight stays of Spaniards decreased by 9.17 percent while those of foreigners decreased by 13.2 percent. Regarding the number of guests in hotels, the model detects decreases of, respectively, 10.3 and 16.9 percent for local guests and for foreigners. These results are consistent with expectations given that Airbnb is assumed to attract some clients of the hotel industry, especially foreigners.

Table 1. DD estimates of the impact of Airbnb adoption on overnight stays and guests.

	ln overnight stays of:		**ln number of guests from:**	
VARIABLES	**spaniards**	**foreigners**	**Spain**	**Abroad**
Time	0.102***	0.297***	0.114***	0.339***
	(0.0309)	(0.0527)	(0.0312)	(0.0505)
Site	0.187	1.248**	0.0468	0.725
	(0.394)	(0.561)	(0.353)	(0.457)
Site*Time	-0.0917**	-0.132*	-0.103**	-0.169***
	(0.0412)	(0.0728)	(0.0432)	(0.0640)
Hotel supply	0.402***	0.649***	0.299***	0.547***
	(0.106)	(0.128)	(0.0846)	(0.110)
ln Population	0.251	0.826**	0.201	0.834***
	(0.164)	(0.329)	(0.190)	(0.259)
Unemployment	-0.00938***	-0.0173***	-0.0103***	-0.0191***
	(0.00235)	(0.00273)	(0.00176)	(0.00248)
Constant	6.510***	-2.430	6.613***	-3.185
	(2.189)	(4.332)	(2.557)	(3.421)
Observations	2,554	2,554	2,554	2,554
R-squared	0.467	0.660	0.352	0.617
Number of touristic sites	46	46	46	46

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Counterintuitively, Table 2 shows that hotel bedroom occupancy rates increased by almost 3 percent owing to the adoption of Airbnb. The model detects no significant impact of Airbnb adoption on bed-place occupancy rates, including during the weekends.

The increase in bedroom occupancy may be attributable to the reaction of the hotel industry to the expansion of Airbnb. The lack of data on hotel prices does not allow to investigate to what extent price adjustments have been made by hotels to counter the increasing competitive pressure triggered by Airbnb. Nevertheless, as shown in Table 3 it appears that hotels reduced their capacity due to Airbnb entry. Indeed, the model detects a decrease in hotel bed-places of 8.65 percent resulting from Airbnb adoption. These reductions in hotel capacity, along with likely price adjustments, may explain the increase in hotel occupancy rates despite decreases in the number of guests and overnight stays.

Table 3 shows negative, though insignificant, effects of Airbnb adoption on the number of open establishments. Eventually, the model detects no significant impact of Airbnb adoption on the number of employees in the hotel sector in the touristic sites analyzed.

Table 2. DD estimates of the impact of Airbnb adoption on hotel occupancy rates.

	Occupancy rate of:		
VARIABLES	**bedrooms**	**bed-places**	**bed-places at weekend**
Time	4.254***	3.603***	5.211***
	(1.226)	(1.189)	(1.225)
Site	-3.866	-4.615	-3.572
	(5.329)	(5.670)	(4.715)
Site*Time	2.962*	2.276	1.297
	(1.674)	(1.609)	(1.541)
Hotel supply	8.282***	9.410***	7.004***
	(2.216)	(2.447)	(2.037)
ln Population	5.201**	3.953	2.810
	(2.302)	(2.657)	(2.220)
Unemployment	-0.745***	-0.577***	-0.654***
	(0.0738)	(0.0686)	(0.0695)
Constant	-11.26	-3.492	22.66
	(29.45)	(34.33)	(28.75)
Observations	2,554	2,554	2,554
R-squared	0.313	0.283	0.212
Number of touristic sites	46	46	46

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3. DD estimates of the impact of Airbnb adoption on bed-places, establishments, and hotel employment.

	ln number of:		
VARIABLES	**bed-places**	**open establishments**	**employees in the hotel sector**
Time	0.0645**	0.0726**	-0.0308
	(0.0269)	(0.0304)	(0.0304)
Site	0.508*	0.551***	0.0581
	(0.263)	(0.201)	(0.257)
Site*Time	-0.0865***	-0.0609	0.00264
	(0.0299)	(0.0388)	(0.0360)
Hotel supply	0.381***		0.416***
	(0.0651)		(0.0782)
ln Population	0.501***	0.217	0.849***
	(0.183)	(0.154)	(0.193)
Unemployment	0.000421	-0.00293**	-0.00691***
	(0.00128)	(0.00139)	(0.00178)
Constant	0.953	0.598	-5.494**
	(2.438)	(2.037)	(2.569)
Observations	2,554	2,554	2,554
R-squared	0.679	0.355	0.685
Number of touristic sites	46	46	46

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5. Robustness checks

In this section, some assessments of the main DD model are conducted to support the causal interpretation of the results. To do so, it is checked whether the estimates are robust to some alternative specifications of the model. Firstly, in line with Besley & Burgess (2004) and Zervas et al. (2017), various forms of site-specific trends are tested for the DD specification in equation (1). Table 4 displays the coefficients of $(Site * Time)_{it}$ for specifications including, respectively, no trend, linear trends, quadratic trends, and cubic trends. Note that the third column corresponds to the results presented in the previous section. It appears that most of the findings remain valid and broadly similar independently on the chosen form of site-specific trends. Note that in the specification with cubic site-specific trends, the model detects significant negative effects of Airbnb adoption on the number of hotels open with a decrease of 6.36 percent.

Table 4. DD estimates of the impact of Airbnb adoption using site-specific trends of increasing order.

DEPENDENT VARIABLES	(1)	(2)	(3)	(4)
Occ. rate of bedrooms	3.605**	2.882*	2.962*	3.256**
	(1.576)	(1.638)	(1.674)	(1.634)
Occ. rate of bed-places	2.763*	2.235	2.276	2.502
	(1.545)	(1.589)	(1.609)	(1.582)
Occ. rate of bed-places at weekend	1.874	1.228	1.297	1.558
	(1.444)	(1.525)	(1.541)	(1.495)
ln overnight stays of Spaniards	-0.0885**	-0.0921**	-0.0917**	-0.0897**
	(0.0386)	(0.0401)	(0.0412)	(0.0410)
ln overnight stays of foreigners	-0.0844	-0.127*	-0.132*	-0.118*
	(0.0655)	(0.0706)	(0.0728)	(0.0711)
ln number of guests from Spain	-0.0983**	-0.104**	-0.103**	-0.0999**
	(0.0405)	(0.0421)	(0.0432)	(0.0430)
ln number of guests from Abroad	-0.129**	-0.165***	-0.169***	-0.158**
	(0.0605)	(0.0624)	(0.0640)	(0.0631)
ln number of bed-places	-0.0811***	-0.0847***	-0.0865***	-0.0859***
	(0.0301)	(0.0299)	(0.0299)	(0.0298)
ln number of open establishments	-0.0585	-0.0565	-0.0609	-0.0636*
	(0.0409)	(0.0398)	(0.0388)	(0.0384)
ln number of employees in the hotel sector	-0.00650	1.13e-05	0.00264	0.00223
	(0.0372)	(0.0361)	(0.0360)	(0.0358)
	No trend	**Linear trends**	**Quadratic trends**	**Cubic trends**

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Secondly, an alternative model in which lagged dependent variables are included is attempted. This new specification controls for the potential impact of previous hotel sector performances on current outcomes. This alternative model takes the following form:

$$Y_{it} = \alpha + \lambda Y_{it-1} + Site_i + Time_t + \beta(Site * Time)_{it} + \gamma X'_{it} + (Touristic\ site_i * Quarter_t) + Province_i + \epsilon_{it} \quad . \qquad (2)$$

The estimated coefficients for equation (2) are displayed in Table 5[14]. The results suggest significant negative impacts of Airbnb adoption on the number of bed-places and on the number overnight stays and guests, with higher magnitudes for foreigners than for Spaniards. However, the sizes of these causal effects appear to be narrower under this alternative specification than in section 4. Note that unlike in the main analysis, this alternative model finds no impact of Airbnb adoption on hotel bedrooms occupancy rate and detects a significant decrease of 1.59 percent in the number of open establishments. In sum, with respect to the signs and significance of coefficients, most findings presented in the results section appear to be robust to this alternative specification.

The estimates of equation (2) must be taken with a pinch of salt as they appear to be inconsistent. Indeed, endogeneity tests revealed correlation between the lagged dependent variables and the error term in all regressions based of that alternative model. Thus, although the inclusion of lagged dependent variables provides a model to which the main analysis can be compared to, the coefficients of this alternative specification are not eloquent when taken alone.

[14] Note that quadratic site-specific trends are included in the set of control variables as in the main specification.

Table 5. DD estimates of the impact of Airbnb adoption on hotel measures (including lagged dependent variables).

VARIABLES	Occ. Bedrooms	Occ. Bed-places	Occ. Bed-places at W-E	ln Bed-places	ln Open establishments	ln Employees in hotels	ln Stays of Spaniards	ln Stays of Foreigners	ln Guests from Spain	ln Guests from Abroad
Time	-0.268	-0.980	-0.100	0.00332	0.0116	-0.0237	-0.0170	-0.0874*	-0.0361	-0.0718
	(1.150)	(1.249)	(1.238)	(0.0134)	(0.0199)	(0.0175)	(0.0363)	(0.0514)	(0.0284)	(0.0540)
Site	2.658	3.054	1.839	0.00535	0.0303	0.0108	-0.0624	0.0578	-0.0822*	0.0305
	(2.349)	(2.494)	(2.167)	(0.0301)	(0.0247)	(0.0360)	(0.0748)	(0.0841)	(0.0494)	(0.0792)
Site*Time	1.233	0.729	0.225	-0.0192**	-0.0159*	-0.0157	-0.0334*	-0.0628*	-0.0291*	-0.0641*
	(0.973)	(1.009)	(0.982)	(0.00916)	(0.00919)	(0.00977)	(0.0186)	(0.0355)	(0.0155)	(0.0346)
Occ. Berdrooms (t-1)	0.488***									
	(0.0665)									
Occ. Bed-places (t-1)		0.463***								
		(0.0644)								
Occ. Bed-places at W-E (t-1)			0.457***							
			(0.0590)							
ln Bed-places (t-1)				0.924***						
				(0.0207)						
ln Open establishments (t-1)					0.907***					
					(0.0375)					
ln Employees in hotels (t-1)						0.895***				
						(0.0291)				
ln Stays of Spaniards (t-1)							0.811***			
							(0.0349)			
ln Stays of Foreigners (t-1)								0.908***		
								(0.0178)		
ln Guests from Spain (t-1)									0.890***	
									(0.0236)	
ln Guests from Abroad (t-1)										0.895***
										(0.0193)
Hotel supply	1.631***	2.032***	1.744***	0.0462**		0.0587***	0.0986***	0.0820***	0.0588***	0.0749***
	(0.627)	(0.755)	(0.574)	(0.0185)		(0.0217)	(0.0310)	(0.0269)	(0.0226)	(0.0263)
ln Population	2.299***	1.679*	1.072	0.0389***	0.0408*	0.0558***	0.0969**	0.0871**	0.0525**	0.0993**
	(0.745)	(0.884)	(0.782)	(0.0143)	(0.0218)	(0.0197)	(0.0425)	(0.0361)	(0.0255)	(0.0399)
Unemployment	-0.242***	-0.160*	-0.179**	-0.000554	-0.00219	-0.000539	-0.00203	0.000313	-0.000683	-0.00102
	(0.0875)	(0.0884)	(0.0836)	(0.00121)	(0.00158)	(0.00154)	(0.00260)	(0.00292)	(0.00197)	(0.00308)
Constant	-2.142	2.904	16.57	0.0500	-0.200	-0.146	0.567	-0.411	0.304	-0.514
	(9.035)	(11.08)	(10.62)	(0.158)	(0.217)	(0.188)	(0.458)	(0.417)	(0.299)	(0.446)
Observations	2,462	2,462	2,462	2,462	2,462	2,462	2,462	2,462	2,462	2,462
R-squared	0.533	0.495	0.412	0.965	0.899	0.953	0.842	0.941	0.888	0.926
Number of touristic sites	46	46	46	46	46	46	46	46	46	46

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

6. Discussion and conclusions

This work aimed at analyzing the impact of Airbnb adoption on the hotel sector in Spain. Unlike many previous studies, this paper analyses a wide panel of locations and targets sites with significant touristic amenities. This allows to have a broader picture of the impact of Airbnb on the hotel industry in zones of particular interest for hotel firms. The evidence suggests that Airbnb adoption has been a cause of decrease in the number of guests and overnight stays in hotels. These effects appear to be stronger for tourists coming from abroad than it is for Spanish residents. This tends to corroborate the idea that Airbnb could be particularly appealing to foreigners as the platform would offer, more than hotels, the possibility to live local experiences.

Unexpectedly, the investigation revealed a positive impact of Airbnb on hotel occupancy rates. In parallel, the results show a shrink in hotel capacities due to Airbnb adoption through decreases in the number of bed-places. In some alternative specifications, decreases in the number of open establishments are also observed. These latter findings tend to counterbalance the observed increase in occupancy rates as this unexpected outcome could result from the tightening of hotel capacities. Overall, the findings of this analysis tend to confirm the fact that Airbnb exercises a competitive pressure on the hotel industry and constitutes a substitute to hotel offers. The lack of data on hotel prices and revenues does not allow to precisely analyze the reaction of hotels to the penetration of the platform. Nevertheless, it appears from the detected reduction in the number of hotel bed-places that part of the adjustment to the competition from Airbnb has been carried out by capacity shifts. The results of the main DD model appear to be robust to alternative site-specific trends and to the inclusion of lagged dependent variables. This tends to support the causality link between Airbnb adoption and fluctuations in hotel performance indicators.

This study has implications for hotel firms and policy makers. Firstly, hotel firms have been facing a strong competition from Airbnb in touristic areas. That competition exhibits some features which make it different from the rivalry within the hotel industry. The low costs endured by Airbnb hosts and the ease with which they can add or remove their properties from the platform are important factors. Indeed, they make the supply of accommodation on the platform way more flexible than it is for hotel firms. These latter must support important entry costs, and they need time to build additional capacity even in the absence of Airbnb. Another important takeaway of this study for hotel firms is that the impact of Airbnb on hotels can be differentiated based on the provenance of clients. This may influence the choice of marketing strategies in their attempts to compete with Airbnb. Indeed, foreign guests may be more sensitive to differentiation strategies (e.g. providing better-quality and more customized services, enhancing local-life experience, etc.) while local tourists may react more to cost reductions.

Finally, the harmful effects of Airbnb on the hotel industry may reduce the contribution of that sector to regional and national fiscal incomes. Moreover, the expanding number of Airbnb

listings might tighten the availability of long-term rental accommodation for locals. Nevertheless, Airbnb activities constitute a source of additional income for thousands of households throughout the Spanish territory. All these elements should be considered by policy makers when legislating on potential regulation measures of Airbnb activities. In addition, the variability in the concentration of Airbnb listings across sites suggest that policies tailored to local idiosyncrasies must be preferred to global solutions.

This work has some shortcomings that could be tackled in further research. The main limitations of this analysis reside in the unavailability of time series data for Airbnb activity. One of the consequences of that issue is that a common entry date of Airbnb has been assumed for all sites while the reality may be different. Moreover, the use of a dummy variable for Airbnb masks some potential differences in Airbnb adoption patterns across touristic sites. Thus, the investigations performed in this paper do not take advantage of the variability in Airbnb entry dates and growth among touristic sites to assess causal effects more precisely. Note also that the absence of data on hotel prices and revenues undermines the strength of this paper as some important mechanisms of adjustment of the hotel industry to Airbnb adoption remain unexplored. Nevertheless, some mechanisms have been spotted by looking at hotel capacities.

Appendices

A1. Hotel measures definitions. Source: INE[15]

Variables	Descriptions
Hotel establishments	Establishments that offer collective accommodation services for payment, with or without other complementary services (hotel, hotel-apartment or apart-hotel, motel, inn, pension, etc.).
Estimated number of bedrooms	The number of bedrooms estimated by the survey in the establishments open for the season. A bedroom is the unit formed by one room or groups of rooms which are rented by tourists as a whole (and constituting an indivisible rental). Rooms may be single, double or multiple, depending on whether they are equipped permanently to accommodate one, two or several people.
Estimated number of bed-places	The number of bed-places estimated by the survey in establishments open for the season. The number of bed-places is equal to the number of fixed beds in the establishment. Extra beds therefore are not included and double beds equal two bed-places.
Occupancy rate of bedrooms	The ratio, as a percentage, between the average daily number of rooms occupied in the month and the total number of bedrooms available.
Occupancy rate by bed-places	Percentage-based ratio between the number of overnight stays and the number of vacancies by the days the overnight stays refer to plus the number of supplementary beds used. Supplementary beds are those that do not have a fixed nature and are not included in the vacancies declared officially by the establishment but do appear in the directory.
Weekend occupancy rate by bed-places	The relationship, as a percentage, between the overnight stays from Friday and Saturday during the reference week, and the product of the bed-places, including extra beds for those two days, and the days to which the overnight stays refer, in this case, two.
Overnight stay	An overnight stay is understood to be every night that a guest stays in the establishment. As occurs with the checking in of guests, occupied bed-places are broken down according to place of residence.
Guests	All persons who stay one or more consecutive nights in the same accommodation. Guests are classified by their country of residence, and people residing in Spain are classified by the Autonomous Community they usually live in.
Employed personnel	The number of people who work in a hotel establishment and people who, although work outside of the hotel establishment, are part of it and receive salary from it (e.g. sales representatives, courier staff and repair and maintenance teams working on behalf of the hotel).

[15] https://www.ine.es/dynt3/metadatos/en/RespuestaDatos.htm?oe=30235

A2. Airbnb listings by touristic site in 2018 (ranked by listings per km²). ***(continued)***

	Touristic site	Province	Autonomous community/Region	AirBnb listings (2018)	Listings/Km² (2018)	Listings/Hotel room (2018)
1st quartile	**Cáceres**	Cáceres	Estrémadure	393	0.02	0.32
	Murcie	Murcie	Région de Murcie	791	0.90	0.32
	Albacete	Albacete	Castille-La Manche	1242	1.10	1.08
	Trujillo	Cáceres	Estrémadure	851	1.30	1.78
	Mérida	Badajoz	Estrémadure	1191	1.38	1.23
	Cazorla	Jaén	Andalousie	440	1.45	1.20
	Jerez de la Frontera	Cadix	Andalousie	1800	1.51	1.01
	Carthagène	Murcie	Région de Murcie	879	1.58	0.34
	Saragosse	Saragosse	Aragon	1539	1.58	0.29
	Cuenca	Cuenca	Castille-La Manche	1448	1.59	1.38
	Gijón	Asturies	Asturies	320	1.76	0.13
	Lugo	Province de Lugo	Galice	606	1.83	0.65
	Soria	Soria	Castille-et-León	523	1.92	0.85
	Níjar	Almería	Andalousie	1206	2.01	1.81
	Albarracín	Teruel	Aragon	928	2.05	3.33
	Plasence	Cáceres	Estrémadure	498	2.28	1.01
	Zamora	Zamora	Castille-et-León	359	2.40	0.59
	Almería	Almería	Andalousie	726	2.45	0.41
	Teruel	Teruel	Aragon	1109	2.52	1.28
	Ronda	Malaga	Andalousie	1338	2.78	1.28
	Jaca	Huesca	Aragon	1403	3.45	1.45
	Benavente	Zamora	Castille-et-León	157	3.48	0.44
	Vitoria-Gasteiz	Alava	Pays basque	1004	3.63	0.65
	San Bartolomé de Tirajana	Las Palmas de Grande Canarie	Îles Canaries	1303	3.91	0.07
	Lérida	Lérida	Catalogne	850	4.00	0.80
	Llanes	Asturies	Asturies	1128	4.28	1.10
	Benasque	Huesca	Aragon	1011	4.34	1.60
	Tarifa	Cadix	Andalousie	1827	4.35	1.88
	Arcos de la Frontera	Cadix	Andalousie	2516	4.77	5.85
	Valladolid	Valladolid	Castille-et-León	962	4.87	0.46
	Cordoue	Cordoue	Andalousie	6290	5.02	1.81
	Pájara	Las Palmas de Grande Canarie	Îles Canaries	1993	5.20	0.16
	Saint-Jacques-de-Compostelle	La Corogne	Galice	1295	5.89	0.33
	El Puerto de Santa María	Cadix	Andalousie	964	6.05	0.75
	Ribadeo	Province de Lugo	Galice	682	6.43	1.49
	Orense	Province d'Ourense	Galice	571	6.76	0.79
	Palencia	Palencia	Castille-et-León	691	7.30	1.48
	Vielha e Mijaran	Lérida	Catalogne	1609	7.60	1.44
	Ávila	Province d'Ávila	Castille-et-León	1784	7.69	1.29
	Mogán	Las Palmas de Grande Canarie	Îles Canaries	1368	7.93	0.21
	Tolède	Tolède	Castille-La Manche	1862	8.02	0.84
	Naut Aran	Lérida	Catalogne	2147	8.39	2.07
	Oviedo	Asturies	Asturies	1679	9.00	0.58
	Logroño	La Rioja	La Rioja	717	9.01	0.53
	Vigo	Province de Pontevedra	Galice	1150	10.54	0.46
	Ségovie	Ségovie	Castille-et-León	1764	10.78	1.44
	León	Léon	Castille-et-León	461	11.81	0.25
	Malaga	Malaga	Andalousie	6106	15.34	1.12
	Estepona	Malaga	Andalousie	2142	15.64	0.80
	Calvià	Îles Baléares	Îles Baléares	2531	17.45	0.14
	Burgos	Burgos	Castille-et-León	1878	17.54	0.92

	Cangas de Onís	Asturies	Asturies	3735	17.56	3.67
	Roquetas de Mar	Almería	Andalousie	1485	24.75	0.29
	Benalmádena	Malaga	Andalousie	702	25.81	0.14
	Santa Cruz de Tenerife	Santa Cruz de Tenerife	Îles Canaries	4059	26.96	2.76
	Saint-Sébastien	Guipuscoa	Pays basque	1650	27.10	0.56
	Mojácar	Almería	Andalousie	1958	27.19	0.88
	Alicante	Alicante	Communauté valencienne	5867	29.15	1.46
	Palma de Majorque	Îles Baléares	Îles Baléares	6158	29.52	0.37
	Adeje	Santa Cruz de Tenerife	Îles Canaries	3204	30.24	0.21
	Salamanque	Salamanque	Castille-et-León	1195	30.96	0.41
	Peníscola	Castelló de la Plana	Communauté valencienne	2623	33.20	0.79
	Sallent de Gállego	Huesca	Aragon	5757	35.51	8.10
	Sanxenxo	Province de Pontevedra	Galice	1593	36.20	0.56
	Marbella	Malaga	Andalousie	4230	37.01	0.70
	Tías	Las Palmas de Grande Canarie	Îles Canaries	2443	37.81	0.54
	Cambrils	Tarragone	Catalogne	1401	39.80	0.54
	Castelló de la Plana	Castelló de la Plana	Communauté valencienne	4386	40.32	3.56
	Madrid	Madrid	Communauté de Madrid	26520	43.88	0.61
4th quartile	La Corogne	La Corogne	Galice	1889	49.93	0.69
	O Grove	Province de Pontevedra	Galice	1111	50.50	0.95
	Nerja	Malaga	Andalousie	4316	50.78	2.47
	Arona	Santa Cruz de Tenerife	Îles Canaries	4368	53.41	0.50
	Valence	Valence	Communauté valencienne	7467	55.45	0.83
	Pampelune	Communauté forale de Navarre	Communauté forale de Navarre	1398	55.61	0.78
	Séville	Séville	Andalousie	8034	57.39	0.73
	Gandie	Valence	Communauté valencienne	3519	57.88	1.34
	Las Palmas de Gran Canaria	Las Palmas de Grande Canarie	Îles Canaries	6456	64.21	2.31
	Grenade	Grenade	Andalousie	6606	75.05	0.89
	Benidorm	Alicante	Communauté valencienne	3126	81.17	0.16
	Santander	Cantabrie	Cantabrie	3152	90.06	1.49
	Bilbao	Biscaye	Pays basque	3996	96.29	0.97
	Torremolinos	Malaga	Andalousie	2405	120.25	0.29
	Sant Llorenç des Cardassar	Îles Baléares	Îles Baléares	12072	147.08	1.29
	Tarragone	Tarragone	Catalogne	8937	154.35	8.38
	Dénia	Alicante	Communauté valencienne	11016	166.40	9.55
	Capdepera	Îles Baléares	Îles Baléares	9264	168.68	1.24
	Salou	Tarragone	Catalogne	4277	283.25	0.32
	Lloret de Mar	Gérone	Catalogne	15202	312.16	1.69
	Barcelone	Barcelone	Catalogne	31947	315.06	0.79
	Fuengirola	Malaga	Andalousie	4964	486.67	1.10
	Puerto de la Cruz	Santa Cruz de Tenerife	Îles Canaries	6554	750.74	0.86

A3. Descriptive statistics of hotel performance and control variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A. Entire sample					
Overnight stays of Spaniards	5 123	58908,5	85972,47	1364	710978,7
Overnight stays of foreigners	5 123	114657,3	234569	47,33333	1869123
Guests from Spain	5 123	24608,37	40337,58	596	410916,7
Guests from abroad	5 123	27210,09	63937,14	38	673649
Occ. rate of bedrooms	5 123	55,65915	17,41677	8,165	95,63
Occ. rate of bed-places	5 123	49,76162	16,8516	9,77	94,19333
Occ. rate of bed-places at weekends	5 123	58,08393	15,77005	10,05667	93,85667
Bed-places	5 123	8921,455	13296,65	385	89096
Open establishments	5 123	63,12792	104,2829	7	902
Open establishments per km²	5 123	0,7026825	1,075292	0,0012919	6,903353
Hotel sector employees	5 123	1314,48	2182,594	32,5	15473,33
Population	5 244	990914,2	908757,4	89415	6747425
Unemployment rate	5 244	18,73862	8,343568	2,48	43,23
Panel B. Control group					
Overnight stays of Spaniards	1 287	26325	24033,79	1827,5	164039,7
Overnight stays of foreigners	1 287	7201,61	9340,364	47,33333	64831,67
Guests from Spain	1 287	13840,4	11877,4	1010,333	82557
Guests from abroad	1 287	3679,384	4895,614	38	38976,67
Occ. rate of bedrooms	1 287	46,68413	12,95751	8,67	84,48
Occ. rate of bed-places	1 287	41,19392	11,92785	10,6	77,45667
Occ. rate of bed-places at weekends	1 287	52,26135	13,26663	10,05667	83,04
Bed-places	1 287	2461,089	2033,673	385	10533
Open establishments	1 287	31,49534	17,17558	10	103
Open establishments per km²	1 287	0,0851113	0,0841781	0,0012919	0,3964758
Hotel sector employees	1 287	308,1013	233,0718	33,66667	1485,333
Population	1 311	604356,5	458226,1	89415	1683271
Unemployment rate	1 311	18,7353	8,516477	2,88	43,23
Panel C. Treatment group					
Overnight stays of Spaniards	1 267	94639,94	101145,5	1364	679682
Overnight stays of foreigners	1 267	206241,5	279377,1	519	1869123
Guests from Spain	1 267	34894,17	33359,12	929	154520,7
Guests from abroad	1 267	51686,4	91348,66	265	673649
Occ. rate of bedrooms	1 267	64,45312	15,13585	21,33333	95,63
Occ. rate of bed-places	1 267	58,40698	15,84425	18,22667	93,57333
Occ. rate of bed-places at weekends	1 267	64,50547	14,3188	24,75	93,85667
Bed-places	1 267	14547,52	14942,66	970	83471
Open establishments	1 267	87,17837	112,4432	7	700
Open establishments per km²	1 267	1,816161	1,531596	0,1096491	6,903353
Hotel sector employees	1 267	2071,861	2476,649	107	15473,33
Population	1 311	1470532	1006813	561042	5635043
Unemployment rate	1 311	18,98938	7,788802	4,28	38,25

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