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Italy is in the Air(bnb).
The uneven diffusion of short-term rental markets between urban locations and selective tourism destinations

Italy is in the Air(bnb).
La diffusione ineguale del mercato degli affitti a breve termine tra spazi urbani e destinazioni turistiche selettive

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Abstract
Airbnb, the leading platform of short-term rentals acting as an intermediary for host and guest who wants to rent accommodation for a short period, is at the forefront of the reshaped hospitality industry since more than a decade. Questioning the urban features of the sharing economy, the article investigates the spatial pattern of Airbnb in Italy and scrutinizes the location of listing and revenues performances as related to the supply of hotel beds and population density. The study is conducted by using a dynamic panel model, with GMM-SYS estimation. Results show that, despite sharing economy is proposed as fair and equipotential, Airbnb turns out to be highly selective. The evidence indicates that 'access' alone, even if favoured by platforms, does not guarantee market power, and performances are much more concentrated than listings. Moreover, the urban appeal of Airbnb is confirmed; traditional hospitality turns out to be a significant predictor of Airbnb presence and performances; the economic condition of unemployment is positively associated with Airbnb supply.

Keywords: Airbnb, Italy, tourism hospitality, dynamic panel, GMM
JEL codes: O14, R11, R12,

1. Introduction

The sharing economy identifies market fields in which consumers temporarily exchange idle goods through the intermediation of a digital platform (Schor and Attwood-Charles, 2017), offering the possibility to speculate on personal assets (houses, cars, bikes, as well as time, performances, or skills). It gathers a "set of initiatives sharing underutilized assets (material resources or skills) to optimize their use" (Acquier et al., 2017: 4). This general definition hides a highly ambiguous and contested debate due to the flexible and wide-ranging field of application of sharing economy. One of the main points under discussion is related to the connection between the sharing economy and the technology-oriented revolution with its

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"feel-good rhetoric" (Frenken and Schor, 2017: 3). Indeed, as digital platforms are key elements for enabling sharing mechanisms, sharing economy is also critically defined as "platform economy" (Srnicek, 2017). The crucial role played by digital platforms is to concentrate exchanges in a virtual marketplace and to spread it in an infrastructural network. As an infrastructure, the innovative power of the platform lies in the indirect network effects generated by (digital) interactions between the different sides of the two-sided market, thus basically opposed to a more traditional linear supply chain (Hagiu, 2007). This mechanism enables the reproduction of a marketplace, ideally open to everyone, suggesting a new economic approach based on a more flexible, autonomous, and proto-entrepreneurial mode of work (Martin and Zysman, 2016). Notwithstanding a general and optimistic view, the prevalence of competition forces seems to lead to a monopolistic drift of platforms. Indeed, both the theoretical literature and the empirical evidence show the quick and homogenous concentration process in the platform industries (in the touristic sector, as well as in the real estate, delivery services, food providers, to name but a few; see Langley and Leyshon, 2016) and, at the same time, the continuous opening of entry opportunities, due to the strong dynamic competition and the continuous innovation affecting digital platforms (Evans, 2017).

The industries of individual mobility, housing, and hospitality services have been deeply involved in the process of innovation (more or less disruptive; Guttentag, 2015) related to the diffusion of digital platforms (Fields and Rogers, 2019). In this sense, Uber (in the market of vehicles for hire with a driver) and Airbnb (in the market of short-term rental) might be considered paradigmatic cases, attracting special attention in the empirical research (Barron et al., 2021; Cocola-Gant and Gago, 2019; Wachsmuth and Weisler, 2018). Both Uber and Airbnb entered the traditional markets of services offering a limited product differentiation with respect to the incumbents. However, they introduced new models for connecting demand and supply and for supporting new entrepreneurial ventures within the framework of the gig economy (Friedman, 2014; Burtch et al., 2018). They both provide an alternative offer to the already existing one, highlighting a demand not entirely satisfied by the traditional supply (Davidson and Infranca, 2016).

Focusing on Airbnb, the leading platform of short-term rentals acting as an intermediary for host and guest who wants to rent accommodation for a short period, this article investigates the spatial pattern of Airbnb in Italy and scrutinizes the location of listing and revenues performances as related to the supply of hotel beds and population density. Indeed, the rapid spread of Airbnb globally has given rise to numerous studies investigating the nature of the phenomenon from an economic, spatial, and political point of view, mostly focusing on single case studies (Balampanidis et al., 2019; Cocola-Gant and Gago, 2019; Fang et al., 2020; Freytag and Bauder, 2018; Semi and Tonetta, 2020; Yrigoy, 2019) while fewer showing the multiple geographies of Airbnb at national or macro-regional level (Adamiak, 2018, 2019; Crommelin et al., 2018; Jiao and Bai, 2019)[3]. Inserted in this debate, this article aims to fill the "scalar gap"

[3] This gap could be attributed to the difficulty in retrieving data. Airbnb does not share its performance data. They can be obtained either through commercial firms, such as AirDNA or Transparent or by

of the Airbnb research. It focuses on the geographic and economic features of Airbnb in Italy in order to critically discuss the underlying mismatch between the equipotential of the platform and the spatial selectivity of properties and revenues in both urban areas and tourist destinations. Methodologically, the research is based on a dataset that offers wide empirical evidence on the demand and supply of short-term hospitality through the Airbnb platform in Italy. The way demand and supply unfold in this specific market deserves special attention. Questioning the issue of the *accessibility* and *selectivity* of the platform economy, the article highlights three main points. The first one is the pattern drawn by the geographical distribution of Airbnb listings and performances at the national level, with a specific emphasis on the effect of platforms to reduce entry barriers; the second one is the role of competition in the market, and in particular, the evidence that 'access' alone, even if favoured by platforms, does not guarantee market power, so that performances are much more concentrated than listings; finally, the third one is the specific profile of competition between traditional and innovative forms of tourism hospitality.
The article is organized as follows. After the introduction, sec. 2 presents the key points of debate about the urban features of the sharing economy and especially of Airbnb; sec. 3.1 illustrates the data used for the analyses while sec. 3.2 discusses the geography of Airbnb in Italy and sec. 3.3 provides empirical estimates of a dynamic panel model predicting Airbnb supply and performances over local hospitality and spatial and economic variables. Sec. 4 discusses the main findings, illustrating the urban features of Airbnb and underlying the uneven distribution of the platform at the national level. Sec. 5 concludes the article and opens some insights for future research.

2. Sharing economy and the city

There is a flourishing literature on the sharing economy as an urban phenomenon, pertaining both to the advantages that the city offers to the location of its activities and the (possibly negative) external effects of platforms. Focusing on Airbnb, a first strand of the literature concentrates on the Airbnb led gentrification in several cities (see for instance: Wachsmuth and Weisler, 2018; Cocola-Gant and Gago, 2019) and the relationship between the increase in Airbnb and the increase in rental rates and house prices (see for instance: Horn and Merante, 2017; Garcia-López et al., 2019; Barron et al., 2020); a second strand of the literature highlights the role of population density, spatial proximity, and socio-economic specialization (Rauch and Scheicher, 2005; Davidson and Infranca, 2016) in attracting the location of Airbnb listings. With specific reference to the advantages of agglomeration, reinterpreted by Duranton and Puga (2004) as mechanisms of sharing, matching, and learning, Davidson and Infranca (2016) claim that the urban character of sharing economy refers both to the localization of practices and to the role of platforms as agents of urban transformation.

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scraping them with codes that activists have created online (for example, Tom Slee, 2017, or Murray Cox with its Inside Airbnb). In both cases, the availability of data is limited by the requirement for significant effort, both economic and of skill.

Moreover, the advantages that the city offers to the location of the Airbnb properties have been mostly related to the presence of touristic facilities (i.e., international airports) and the rise of a new global model of tourism mobility (Tussyadiah and Pesonen, 2016). Indeed, the contemporary touristic paradigm suggests a shorter, instant, ready-made kind of leisure travel, involving mostly urban destinations. According to Dunne et al. (2010), the so-called 'city break' presents some distinctive features: the duration (often a weekend length), the distance (short airplane distance), discretionary nature (city breaks are not intended as the main holiday of the year, but a short one) and date flexibility (city break reveal a lack of seasonal bias). International leisure travel has increased four times from 2007 to 2017 (Bouchon and Rauscher, 2019) and is significantly related to the explosion of the accommodation platforms, shaped to join such a market.

While the predominance of Airbnb listings in cities could be explained, at least in part, by these motivations, one point seems to be missed. Indeed, the internal feature of short-term rental platforms favors an overaccumulation on the supply-side: the platform accessibility is not hindered by severe entry barriers in terms of human capital, as it only needs the availability of a physical asset (the property). Entering the market is thus less selective. For this reason, the spatial concentration cannot be strictly related to the classical demand-offer dynamic. If low entry barriers and the solution of every geographic constraint for accessing a platform could lead to a spatial distribution of the supply correlated with the spatial profile of the demand, a significant mismatch between demand and supply is expected. In other words, it is no surprise that many of the Airbnb properties are fairly unprofitable: the incentive to make a property available on the platform is, in general, high, even if the expected demand is low.
However, despite the easiness to access the market, the concentration of performances highlights different dynamics; in particular, the economic performances are absorbed more than proportionally by professionals rather than individuals. Li et al. (2016) noticed that "a property managed by a professional host earns 16.9% higher average daily revenue, and has a 15.5% higher occupancy rate, despite being offered for the same number of days per week at similar average price" (ibidem, 2016: 3). Dogru et al. (2020), analyzing the economic weight of professional hosts in fifty U.S. states, confirm their dominant role in the platform, absorbing 69% of the overall revenues. Similarly, in New York, Deboosere et al. (2019) highlight that hosts with between 2 and 10 listings have almost the same price per night of the single-hosts but their monthly revenue is higher by 6.6% (i.e., a higher occupancy rate). While hosts with more than 10 listings have a lower price per night than single hosts (-9.2%) and a +8.9% in the monthly revenue; "these facts suggest that hosts who treat their listings as de facto hotels rather than opportunities for part-time 'home sharing' are considerably more successful in the Airbnb marketplace" (ibidem, 2019: 153).

In addition, the drastic reconfiguration of the hospitality industry due to the rise of the platforms opens various issues and, especially the profile of the competition between traditional and innovative hospitality. A large number of papers have been devoted to the analysis of competition between hotels and Airbnb properties in specific urban areas (see, for example, Gutiérrez et al., 2017 on Barcelona and Quattrone et al., 2016 on London). Such works highlight both negative (Zervas et al., 2021) and positive (Farronato and Fradkin, 2018) impacts of Airbnb on hotels. In particular, Farronato and Fradkin (2018) focus on the proximity between high-category hotels and Airbnb listings. According to the authors, the entry of Airbnb entrepreneurs has a significant influence on hotel prices in the sector (more than on the occupancy rate), especially when the demand is more elastic, and the hotel supply is capacity-constrained. As the demand for accommodation is usually more flexible the higher the hotel category is, the entrance of Airbnb seems to generate more consistent effects in the segment of higher category hotels. On the contrary, Dogru et al. (2019) show that in ten major cities in the United States an increase of Airbnb supply negatively impacts in a similar way across hotel class segments. The role of regulation asymmetries between traditional and innovative accommodation industries has also been investigated: Yeon et al. (2020a) and Yeon et al. (2020b) show that Airbnb regulation policies had a positive effect on the performance of (especially low-category) hotels performance in New York and Washington.

Airbnb as an urban phenomenon is at the same time a trivial evidence and an open issue, pertaining to a more nuanced interpretation of Airbnb related not only to the location of properties but also to their economic performances and the relationships, often contradictory, between the presence of Airbnb and the more traditional forms of tourism hospitality, considered in their various articulations. Following these hypotheses, the rest of the paper is devoted to the analysis of the spatial distribution of Airbnb in Italy and to identify the complex geography of its uneven location.
The empirical analysis provided in the following sections is then organized to provide evidence i) on the main drivers of Airbnb listings location in Italy, with a special emphasis on the "urban appeal" for Airbnb entrepreneurs, ii) on the emergence of a "demand-supply gap" and its determinants, and iii) on the complementarity or substitutability relationship between Airbnb and the traditional accommodation supply.

3. The geography of Airbnb in Italy

3.1 Data description

The analyses are supported by a dataset covering a complete set of information on Airbnb in Italy extracted from the datasets furnished by AirDNA, a provider of short-term vacation rental data. This data scraping commercial firm extracts information from Airbnb's official webpages and its datasets are widely used among scholars.

Tab. 1

Our dataset considers each property located in Italy that was listed for at least one day from January 2017 to December 2019. For each property, data include location[4], listing story (entry, reserved days, available days, and possibly exit), and daily price. Table 1 provides the general dimensions of the Airbnb phenomenon within the Italian territory. At a glance, data show the remarkable growth of Airbnb: active properties have increased by 30% from 2017 to 2019 and reserved nights by 74% throughout the same timespan as well as revenues. From the original information, we have obtained stock and flows of properties, revenues, occupancy rates, and average daily prices at a municipal level. Municipal measures were then aggregated at different higher scales, in particular at Local Labour Market Areas (LLMA) scale[5]. Without entering into the merits of the difficult, if not impossible, delimitation of the urban, LLMAs are divided into "rural", "town" and "city" in line with the Degurba classification proposed by Eurostat[6]. Consequently, in 2019, among the 611 Italian LLMAs, 31 are defined as "city" (e.g., Torino, Milano, Roma, Napoli, etc.), 342 are "town", and, finally, 238 are "rural". The low demographic threshold of Degurba fits with the Italian case due to the very moderate size of Italian urban centers (Dematteis, 1999).
In addition to the AirDNA datasets, we use extensively ISTAT (Italian National Institute of Statistics) data. In particular, our dataset includes, at a municipal level i) population and ii) measures concerning the traditional hospitality industry (number of hotels and beds, segmented by their rating). Additional morphological and economic information has been collected at the LLMA level such as i) unemployment rate and ii) surface, average altitude, and percentage of municipalities on the coastline.

3.2. Airbnb as an urban phenomenon

The urban location of Airbnb properties in Italy is shown in Table 2, which compares the regional distribution of Airbnb properties and hotels, subdivided between central municipalities of the LLMAs and other municipalities: the effect of the higher demand for accommodation in the central municipalities clearly emerges. However, adding the distinction between "city", "town" and "rural" LLMAs illustrates some specific features of Airbnb diffusion: the big cities (centre municipalities of "city" LLMAs) attract Airbnb much more than the traditional accommodation supply of hotels. Hotels instead are more

[4] Airbnb random obfuscates the geo coordinates of each single property. Listings are not exactly located on latitude and longitude provided by AirDNA, but in a random point within a 200m radius from the provided location (Doboosere et al., 2019). Obfuscation, however, does not affect our results since our analysis will be at a municipal or higher scale.

[5] The Local Labor Market Areas represent a geographical subdivision beyond the administrative borders, based on the commuting flows, i.e. they are economically integrated spatial units. The concept includes a harmonised methodology and standardised definition, which should be usable and replicable in the whole EU (ec.europa.eu/eurostat/cros/content/labour-market-areas_en). The definition of LLMA in Italy is updated in accord with every general Census by ISTAT (Istituto Nazionale di Statistica). The last Census is dated 2011.

[6] LLMAs are classified considering the population and the population density in the main municipality of each LLMA. "City" LLMAs are those with a centre municipality with more than 50.000 inhabitants and a population density greater than 1.500, "town" LLMAs are those with a centre municipality with more than 5.000 inhabitants and a population density greater than 300. The remaining are "rural" LLMAs. All thresholds adopted are those used by Degurba classification (ec.europa.eu/eurostat/web/degree-of-urbanisation/background).

concentrated in "town" LLMAs. Figure 1 supports this evidence providing the plot of the univariate associations between population density and active Airbnbs, showing a higher number of Airbnb listings in presence of higher values of population density. Moreover, Airbnb revenues are still more concentrated than Airbnb properties in metropolitan areas.

Tab.2
Fig. 1
Tab.3

Table 3 examines in detail the Airbnb phenomenon in 2019 in the 15 most populous Italian LLMAs (with at least 250 thousand inhabitants in 2019) and their respective centre municipalities. All the centres of the urban LLMAs, have a greater concentration of the supply through Airbnb compared to the other municipalities of the area. However, this concentration varies between a maximum of 90% in Venice and a minimum of 54% in Catania. The revenues are also concentrated in the centre, varying between a maximum of 97% in Venice and a minimum of 59% in Catania. The revenues vary greatly throughout the big cities: from 2.22 million USD in Messina to 560.29 million USD in Rome[7], and the variance is much larger than the dimensional heterogeneity.
The distribution of Airbnb properties throughout Italy also highlights a cluster of cities with a strong tourist attraction (Rome, Venice, and Florence) with high rates of occupancy (around 47%) and high average prices (from about 100 USD in Rome to 146 USD in Venice) in the central municipality. There is a further category of cities with occupancy rates of between 30 and 40% and very variable average prices (from up to about 100 USD in Milan and Verona to about 64 USD in Turin). Finally, a further cluster of cities in Southern Italy, except for Naples and Bari, shows low rates of occupancy (e.g., Messina with 15% in the centre municipality and 9% in the rest of the LLMA) and prices comparable to the lower band of the preceding cluster. This point is further confirmation of the heterogeneous gaps between demand and supply in Airbnb due to the small costs of entry.

3.3 The determinants of Airbnb diffusion

With the purpose of describing the spatial distribution of Airbnb's supply and performances, we estimate the following dynamic panel model,

$$Y_{i,t} = \alpha + \beta Y_{i,t-1} + \gamma X_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}$$

Eq. 1

with i = 1, …, 611 LLMAs and t = 2017, 2018 and 2019. Variables are as follows:

[7] The long-term profitability of an Airbnb property depends on the occupancy rate and average price. Actually, all the occupancy measures reported in this study refer to the rate of occupancy compared to the period of listing. The revenues could also therefore be lower because the property is available on Airbnb for periods shorter than a year: however, there is no evidence of significant disparities in this respect between the big cities.

a) $Y_{i,t}$ is the dependent variable: we have tested two separate equations using as dependent variable both the (log of the) number of active Airbnb listings[8], as a supply measure, and the occupation rate, expressed as the ratio of reserved days to the available days, as a performance measure. $Y_{i,t-1}$ is the lagged dependent variable as we study a dynamic panel model.
b) $X_{i,t}$ is the set of time-variant covariates containing: i) the log-transformed number of hotel beds[9], which proxies the supply of traditional hospitality services; ii) the unemployment rate; iii) the population density. The variables i) and ii) are one year lagged and in our empirical settings are treated as predetermined. Moreover, in a further econometric specification, we have interacted the log-transformed number of hotel beds with a set of dummy variables representing the respective LLMA's classification (see section 3.1.) to show differential in elasticities of Airbnb supply and performances with traditional hospitality presence.
c) μ_i is a set of time-invariant control variables relating to the physical features of the area (coastal position, average altitude) and the specialization of the industry. Physical features are highly correlated with population density: the model with geographic dummy variables (available on request) does not present significant additional explanatory power, thus they have not been included in the main models in Tables 4 and 5. The ratio of luxury (4-5 star) hotel beds to the total number of hotel and residence beds, is included in order to reveal the *specialization* of hospitality, thus representing the relative dimension of the luxury segment over the total traditional supply, that anticipates the presence of Airbnb in a particular area. This ratio is calculated according to the traditional hospitality census in 2011 with the purpose of i) avoiding endogeneity issue, since industry specialization in 2011 can be considered not affected by Airbnb entry (which was at the beginning of its diffusion process in that year) and ii) avoiding multicollinearity issue with the log-transformed number of hotel beds per LLMA.
d) δ_t is a set of year dummies.

Equation 1 has been first estimated through a random effects panel model; still, the use of a dynamic panel model introduces some methodological concerns. Indeed, according to Nickel (1981), the model may suffer from the dynamic panel bias, potentially leading to biased estimated coefficients. To prevent potential biases in our estimates, besides the random effect models, we use the GMM-SYS approach as suggested by Arellano & Bond (1991) and Blundell & Bond (1998). The choice of a GMM-SYS is particularly suitable for our case study since our panel is organized as small t (t assumes three values) and large n (n is up to 611), as suggested by Roodman (2009). In particular, we use the Stata routine *xtabond2* developed by Roodman (2009) considering the lagged dependent variable $Y_{i,t}$ as endogenous, while the vector $X_{i,t}$ exogenous. The estimation of the GMM-SYS panel adopts the two-step procedure as well as the Windmeijer (2005) finite sample correction of the covariance matrix. Over-identification problems, as a consequence of the higher number of instruments, have been arranged by collapsing the instrument set such as the ratio between instruments and observation is far below one (Grilli & Murtinu, 2014)[10].

[8] The number of active Airbnb listings is calculated considering those with at least one available day during year t. We have added one unit before transforming the number of listings in logs.
[9] Again, we have added one unit before transforming the number hotel beds in logs.
[10] Note that the minimum condition for adopting our methodology is met, since the panel dataset has T = 3. GMM-SYS adopts a system of moment conditions for both the difference and the level equations,

Finally, geographic-specific relationships within our observations (e.g., local regulations or clusters of high-performances or high level of supply), have been considered using robust standard errors clustered at NUTS2 level[11] both in the random effects and in the GMM-SYS models[12].

Tab. 4

Models 1 in Table 4 demonstrate how effectively the presence of hotels is a significant predictor of Airbnb's presence in the individual markets (positive and very significant coefficient of ln(*Hotel Beds*). Models 2 show that Airbnb supply is positively and significantly correlated with the unemployment rate, confirming how this economic condition is associated with lower opportunity costs for entrants and probably a lower demand in the business segment. Models 3 confirm the previous findings on the urban appeal of Airbnb: the number of properties increase as the population density increases[13]. Finally, analysing the specialization of traditional hospitality (i.e., the share of the luxury segment), Models 4 show that Airbnb presence is negatively correlated with a higher dimension of the luxury segment (only Model 4a is significant, while model 4b using GMM not). Models 5 shows that, despite positive, there is no significant differential elasticity of Airbnb vs. hotel supply with respect to LLMA classification.

All results in GMM-SYS estimates (Models 1b to 5b) are confirmed in random effects estimates. (Models 1a to 5a), both in terms of the sign of the coefficients and statistical significance. The only exception is for the coefficient of population density, which loses statistical significance.

Tab. 5

in contrast to the GMM difference approach that uses only the difference equations. In our case, the moment conditions are: i) $E[Y_{i,2017}(\Delta Y_{i,2019}-\beta\Delta Y_{i,2018})]=0$ for the in first difference equations (in other words, we use the t-2 lag to instrument the first different in t-1), and ii) $E[\Delta Y_{i,2018}(Y_{i,2019}-\beta Y_{i,2018})]=0$ in the level equation (in other words, we use the first difference of t-1 to instrument the level in t-1). According to Roodman (2009), under the assumptions required for the application of GMM-SYS, the provided estimates will be unbiased.

[11] Each LLMA has been assigned according to the NUTS2 of the central municipality. This procedure allows to deal with multi-province LLMA, thus permitting a unique assignment.

[12] Despite the LLMAs are sufficiently vast areas and spatial overlapping can be considered in most cases as negligible, we have also tested the model exploiting a spatial panel econometric technique (i.e., using a Spatial Autoregressive Model). The results, estimated through the *spxtregress* command in Stata are similar to those reported in Tables 4 and 5. Compared to the main estimates, the results confirm the presence of spatial autocorrelation of both *log(Airbnb)* and *Occupation Rate*: we interpret the presence of such autocorrelation as a prevalent consequence of geographical and morphological similarities of contiguous LLMAs.

[13] The model estimated with random effects has positive but not statistically significant coefficients. This happens only when clustering standard errors at NUTS2 level (as reported in our estimations), while with other specifications coefficients are still positive, but significant. These additional specifications are available upon request to the authors.

Table 5 shows the estimated regression coefficients for the occupation rate dependent variable, using the same covariates of the previous model of Airbnb diffusion[14]. Models 1, again, show that Airbnb performances are positively associated with a higher presence of traditional hospitality, while Models 2 show a significant negative relationship between the unemployment rate and Airbnb performances, in contrast with the positive effect shown in Table 5. This evidence demonstrates the gap between supply and demand (oversupply) in areas where entry is explained primarily by the low opportunity costs of entry, but the demand is weak. Finally, models 3 and 4 show that Airbnb performances are positively correlated with population density and the dimension of the high-quality segment of short-term accommodation demand. The positive coefficients of the interaction between *ln (Hotel Beds i, t-1)* and the dummies *City* and *Rural* (using *Town* as baseline) show, in models 5, that in urban and rural areas Airbnb performances grow faster as traditional hospitality supply increases. In other terms, Airbnb has relatively better performance when competing in urban or rural contexts.
As before, even in this case, Models 1a to 5a using random effects estimates confirm the sign and the statistical significance of GMM-SYS models.

4. The uneven and selective distribution of the short-term rental market

Our findings are consistent with the hypotheses of oversupply in not favourable economic environments, where unemployment is higher and the demand for high-quality accommodation is lower. The excess of supply is confirmed by the fact that Airbnb performances – differently from Airbnb diffusion – are inversely correlated with unemployment and directly correlated with the demand for higher quality hospitality. This is compatible both a) with greater substitutability of Airbnb with the supply of high-quality hotels (Airbnb enters these markets mainly because it competes with the demand for hotels of higher quality, possibly relaxing the constraints on the supply of the latter, as suggested by Farronato and Fradkin, 2018); but also b) with greater substitutability of Airbnb with the supply of low-quality hotels (Airbnb enters into the markets where the supply of lower quality hotels is unable to develop, offering a differentiated service which better meets the demand for lower quality accommodation).

The analysis of the determinants of the location and the performance of Airbnb properties in Italy indicates an uneven distribution of listings and likewise an uneven – but different – distribution of performance as captured by occupation rates. Indeed, the results of the regression indicate a positive correlation between the presence of listings and the rate of unemployment; however, when the occupation rate is taken into consideration, the rate of unemployment assumes a negative value (Table 4 compared to Table 5). In the most fragile areas of the country (whether they are the cities of Southern Italy or the internal areas not "touched" by tourist development), the magnitude of the Airbnb supply appears to relate

[14] Since Occupation Rate is a fractional outcome (i.e., variable varying with continuous values from zero to one), we have tested the model also with *fractional logistic regression* estimation technique (available upon request to the authors). In particular, we have used the Stata Command *fracglm*: (www3.nd.edu/~rwilliam/stats3/FractionalResponseModels.pdf).

mainly to the low costs of entry, since the only restriction to the entrance is the ownership of the dwelling (which in the case of Italy, and according to data from ISTAT, is 76% as at 2018). Many listings on the platform are largely unproductive, or, at the very least, only slightly productive. On a national level, the distribution of the listings and, above all, of the revenues and occupation rate, therefore, seems to track the geography of the "strong areas" of Italy, providing a sort of "mirror" of the socio-economic inequalities across the country.

The spatial selectivity of the diffusion of Airbnb in Italy also appears confirmed going down the scale and observing the lack of homogeneity in the distribution of the listings and revenues in the urban LLMAs. Overall, Airbnb is a form of hospitality that tends to favour bigger cities. However, this does not appear to be perfectly correlated with the presence of hotels. The diffusion of Airbnb is greater as compared to that of the hotels even in cities that are not considered attractive by the traditional hotel industry. Indeed, the presence of Airbnb in urban LLMAs identifies three different clusters. The first cluster, constituted above all by cities with very strong tourist demand, and therefore a strong supply of traditional hospitality, demonstrates high rates of occupancy and high average daily prices; the second cluster shows average to high rates of occupancy and variable average prices (from 80 Euro in Milan and Verona down to 50 Euro in Turin); finally, the third cluster, comprising mainly the cities of Southern Italy, has lower occupancy rates and average prices compared to the earlier ones. According to these findings, the saturation of the supply tends to increase the prices. The less active listings occur where the market is less dynamic but, at the same time, the risks between costs and opportunities are lower. In the urban LLMAs, the listings are concentrated in the central municipality whereas, in the neighbouring areas, they are far fewer in number; the revenues, and therefore the effective activity of the listing, display an even more accentuated concentration. The presence of listings and, above all, the greater concentration of income in the central cities of the urban LLMAs compared to the neighbouring areas, is further evidence of the spatial selectivity of the Airbnb market, which is concentrated in the central cities of the different LLMAs. Exceptions to this are some of the cities of art (e.g. Florence) and southern Italy (e.g. Catania), where there is a different trend linked, at least in part, to the tourist appeal of neighbouring areas such as the Chianti region, near Florence, or Taormina, close to Catania. Overall, Airbnb presents itself as a form of hospitality that attempts to meet the tourist demand in a more selective way than hotel accommodation. Unreported evidence shows that it tends to favor seaside tourism, above all in Southern Italy, and cultural urban tourism. Meanwhile, in the more "traditional" tourist spots, such as, for example, the Adriatic coast, it provides a somewhat limited offering, opening up the need also to investigate the supply side of the probable differentiation of the demand directed at the two different segments of the market.

Finally, the geographical location of Airbnb as compared to that of the hotels, subdivided by the quality of services, shows a distribution which seems, in many ways, to contradict the results presented in other research highlighting the competition between the Airbnb supply and the hotel supply (for the case of Barcelona, see Benítez-Aurioles, 2019), especially in the lower quality hotels. In Italy, the concentration of Airbnb reservations (and consequently higher values of occupation rates) is particularly high in the LLMAs where there is a strong presence of high-quality hotels (4-5 stars). Moreover, our econometric analyses show that

Airbnb performances' elasticity with respect to hotels' supply is higher in urban contexts, suggesting that the platform better competes in these markets. The entry of Airbnb into the tourist market does not therefore necessarily mean that it competes with the traditional market, but it does appear to open, at least in certain specific contexts – the tourist LLMAs with very high-quality traditional hospitality – new markets in hospitality. Where traditional cheap accommodations have failed to become established, Airbnb seems to have carried out an innovative role, providing an innovation, both in product and process, in the field of tourist hospitality able to capture a significant volume of tourists (more or less 100 thousand daily reservations). However, this aspect requires further in-depth study at the level of the single locations which have a strong presence of high-quality hotels, to investigate both the supply side of the demand (in particular if, and to what extent, the reasons people are turning to the Airbnb market in these tourist markets are dictated solely by lower prices) and that of the supply (for example, what are the qualitative features of the listings on Airbnb and their prices).

5. Conclusions

The geographical distribution of Airbnb throughout Italy enables some reflections concerning both the general features of the sharing economy and the economic/spatial behaviour of Airbnb at a national level.

The first aspect concerns the premises (and promises) of the sharing economy. "Will the sector evolve in line with its stated progressive, green, and utopian goals, or will it devolve into business as usual?" asks Schor (2016: 1). According to her, achieving the objectives of the sharing economy requires the democratization of the property and governance of the platforms. Both these topics have their own territoriality. "Where" the properties are located is everything but of no consequence with respect to the more or less "progressive" effects allowed by the exchange via the platform. In the same way, the "deterritorialization" of the platform would appear to make illusory (or at the very least, extremely controversial) each attempt by the public institutions to regulate its practices and effects on a territorial basis. "Space really matters", wrote Doreen Massey in 2005 and this is worth also in the "fluid" world of the platforms, in re-configuring the possibilities and limits of the sharing economy as an "alternative" form of economy to business as usual. The space matters, for example, in the assessment of the advantages linked to the processes of redistribution of resources brought about and facilitated, theoretically at least, by practices of the sharing economy, even if strongly influenced by the economic sector concerned.

The second aspect concerns the specific features of Airbnb. Schor (2016), in her classification of the different platform "forms", explicitly identifies Airbnb as an example of a "for-profit" platform. Although all the platforms in the sharing economy, as they facilitate exchanges, effectively create "markets in sharing", the imperative of a "for-profit" platform influences how the sharing itself takes place, just as it does the amount of assets earmarked for servicing the platform and the owners. These elements require further investigation aimed at studying, for example, the behaviour of the hosts, especially the hosts of multiple properties whose behaviour in the Airbnb market is, in many ways, “anomalous” in respect of the principles of sharing, the rhetoric of belonging and local community, and the illusion of possible disintermediation of the short-term rentals market. In addition, the relationship between Airbnb and the traditional hotel sector, mainly focusing on the extent to which the two segments of the market substitute or complement each other (Zervas et al., 2017; Mhlanga, 2019; Dogru et al, 2020), need to be questioned.

The Covid-19 pandemic has imposed an almost total “closure” in many parts of the world with an impact that limits both individual and collective mobility. It is not yet possible to establish what the effects of this closure will be on the tourist sector and, specifically, on the types of hospitality advertised via platforms. What would seem to be a reasonable certainty is a collapse of the flow of tourists, with a consequently drastic decline in the apparently incessant advance of the spread of Airbnb, in Italy and beyond. What will happen "after", when the pandemic will be hopefully more or less over? Airbnb will regain all its presence in the short-term accommodation market, or the platforms are definitively losing their role? The issues open by the seemingly limitless rise of Airbnb, and in particular, the often-contradictory relationships between Airbnb and the cities and between Airbnb and the hotels, will continue in the next future in the same line of the past?

References

Acquier, A., Daudigeos, T., and Pinkse, J. (2017), Promises and paradoxes of the sharing economy: An organizing framework. *Technological Forecasting and Social Change*, 125, 1-10.

Adamiak, C. (2018), Mapping Airbnb supply in European cities. *Annals of Tourism Research*, 71(C), 67-71.

Adamiak, C. (2019), Current state and development of Airbnb accommodation offer in 167 countries. *Current Issues in Tourism*. DOI:10.1080/13683500.2019.1696758.

Arellano, M., and Bond, S. (1991), Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, 58(2), 277–297.

Balampanidis, D., Maloutas, T., Papatzani, E., and Pettas, D. (2019), Informal urban regeneration as a way out of the crisis? Airbnb in Athens and its effects on space and society. *Urban Research & Practice*. DOI:10.1080/17535069.2019.1600009

Barron, K., Kung, E., and Proserpio, D. (2021), The effect of home-sharing on house prices and rents: Evidence from Airbnb. *Marketing Science* 40.1 (2021): 23-47

Benítez-Aurioles, B. (2019), Is Airbnb bad for hotels? *Current Issues in Tourism*. DOI: 10.1080/13683500.2019.1646226

Blundell, R., and Bond, S. (1998), Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115–143.

Bouchon, F. and Rauscher, M. (2019), Cities and tourism, a love and hate story; towards a conceptual framework for urban overtourism management. International Journal of Tourism Cities.

Burtch, G., Carnahan, S., and Greenwood, B. N. (2018), Can you gig it? An empirical examination of the gig economy and entrepreneurial activity. *Management Science,* 64(12), 5497-5520.

Cocola-Gant, A., and Gago, A. (2019), Airbnb, buy-to-let investment and tourism-driven displacement: A case study in Lisbon. *Environment and Planning A: Economy and Space*. DOI:10.1177/0308518X19869012.

Crommelin, L., Troy, L., Martin, C., and Pettit, C. (2018), Is Airbnb a sharing economy superstar? Evidence from five global cities. *Urban Policy and Research,* 36(4), 429-444.

Davidson, N. M., and Infranca, J. (2016), The Sharing Economy as an Urban Phenomenon. *Yale Law & Policy Review*, 34(2), 216-279.

Duranton, G., and Puga, D. (2004), Micro-foundations of urban agglomeration economies. In J. V. Henderson and J.-F. Thisse (Eds.), *Cities and Geography,* volume 4 of Handbook of Regional and Urban Economics, 2063–2117. Elsevier.

Deboosere, R., Kerrigan, D. J., Wachsmuth, D., and El-Geneidy, A. (2019), Location, location, and professionalization: a multilevel hedonic analysis of Airbnb listing prices and revenue. *Regional Studies, Regional Science*, 6(1), 143-156.

Dematteis, G. (1999), Introduction. Cities as nodes of urban networks. In P. Bonavero, G. Dematteis, and F. Sforzi (Eds.), *The Italian Urban System. Towards European Integration*, (1-16). Ashgate.

Dogru, T., Mody, M., and Suess, C. (2019), Adding evidence to the debate: Quantifying Airbnb's disruptive impact on ten key hotel markets. *Tourism Management*, 72, 27-38.

Dogru, T., Mody, M., Suess, C., McGinley, S., and Line, N. D. (2020), The Airbnb paradox: positive employment effects in the hospitality industry. *Tourism Management*, 77: 104001.

Dunne, G., Flanagan, S., and Buckley, J. (2010), Towards an understanding of international city break travel. International Journal of Tourism Research, 12(5):409–417.

Evans, D. S. (2017), Why the dynamics of competition for online platforms leads to sleepless nights but not sleepy monopolies. SSRN:3009438.

Fang, B., Ye, Q., and Law, R. (2016), Effect of sharing economy on tourism industry employment. *Annals of Tourism Research*, 57, 264-267.

Farronato, C., and Fradkin, A. (2018), The welfare effects of peer entry in the accommodation market: The case of Airbnb. *National Bureau of Economic Research*, Working paper 24361.

Fields, D., and Rogers, D. (2019), Towards a critical housing studies research agenda on platform real estate. *Housing, Theory and Society*, DOI:10.1080/14036096.2019.1670724

Frenken, K., and Schor, J. (2017), Putting the sharing economy into perspective. *Environmental Innovation and Societal Transitions*, 23, 3–10.

Freytag, T., and Bauder, M. (2018), Bottom-up touristification and urban transformations in Paris. *Tourism Geographies*, 20(3), 443-460.

Garcia-López, M. À., Jofre-Monseny, J., Martínez Mazza, R., and Segú, M. (2019), Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona. *Barcelona Institute of Economics*, Working Paper 05.

Gillespie, T. (2010), The politics of 'platforms'. *New media & society,* 12(3), 347-364.

Grilli, L., Murtinu, S., (2014), Government, venture capital and the growth of European high-tech entrepreneurial firms. *Research Policy*, 43(9), 1523-1543.

Gutiérrez, J., García-Palomares, J. C., Romanillos, G., and Salas-Olmedo, M. H. (2017), The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tourism Management*, 62, 278-291.

Guttentag, D. (2015), Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism,* 18(12), 1192-1217.

Hagiu, A. (2007), Merchant or two-sided platform? *Review of Network Economics,* 6(2), 115-133.

Horn, K., and Merante, M. (2017), Is home-sharing driving up rents? Evidence from Airbnb in Boston. *Journal of Housing Economics*, 38, 14-24.

Hu, M. R., and Lee, A. D. (2020), Airbnb, COVID-19 risk and lockdowns: local and global evidence, *mimeo*.

Jiao, J., and Bai, S. (2019), Cities reshaped by Airbnb: A case study in New York City, Chicago, and Los Angeles. *Environment and Planning A: Economy and Space*, 52(1), 10-13.

Langley, P., and Leyshon, A. (2017), Platform capitalism: the intermediation and capitalisation of digital economic circulation. *Finance and Society*, 3(1), 11-31.

Li, J., Moreno, A., and Zhang, D. (2016), Pros vs joes: Agent pricing behavior in the sharing economy. Ross School of Business Paper, (1298).

Mhlanga, O. (2019), Peer-to-peer-travel: is Airbnb a friend or foe to hotels? *International Journal of Culture, Tourism and Hospitality Research*, 13(4), 443-457.

Nickell, S. (1981), Biases in Dynamic Models with Fixed Effects. *Econometrica*, 49(6), 1417–1426.

Rauch, D., and Schleicher, D. (2015), Like Uber, but for local governmental policy: the future of local regulation of the 'sharing economy'. *George Mason Law & Economics,* Research Paper 15-01.

Roodman, D. (2009), How to do xtabond2: an introduction to difference and system GMM in Stata. *The Stata Journal*, 9, 86-133.

Schor, J. (2016), Debating the sharing economy. *Journal of Self-Governance and Management Economics,* 4(3), 7-22.

Schor, J., and Attwood-Charles, W. (2017), The “sharing” economy: labor, inequality, and social connection on for-profit platforms. *Sociology Compass,* 11(8), e12493.

Semi, G., and Tonetta, M. (2020), Marginal hosts: Short-term rental suppliers in Turin, Italy. *Environment and Planning A: Economy and Space,* DOI:10.1177/0308518X20912435

Slee, T. (2017), *What's yours is mine: Against the sharing economy*. Or Books.

Srnicek, N. (2016), *Platform capitalism*. Polity Press.

Tussyadiah, I. P., and Pesonen, J. (2016), Impacts of peer-to-peer accommodation use on travel patterns. *Journal of Travel Research*, 55(8), 1022-1040.

Yeon, J., Kim, S. J., Song, K., and Kim, J. (2020a). Examining the impact of short-term rental regulation on peer-to-peer accommodation performance: a difference-in-differences approach. *Current Issues in Tourism*, 1-13.

Yeon, J., Song, H. J., and Lee, S. (2020b), Impact of short-term rental regulation on hotel industry: a difference-in-differences approach. *Annals of Tourism Research*, 83, 102939.

Yrigoy, I. (2019) Rent gap reloaded: Airbnb and the shift from residential to touristic rental housing in the Palma Old Quarter in Mallorca, Spain. *Urban Studies*, 56(13), 2709-2726.

Wachsmuth, D., and Weisler, A. (2018), Airbnb and the rent gap: Gentrification through the sharing economy. *Environment and Planning A: Economy and Space, 50*(6), 1147-1170.

Windmeijer F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics, 126(1), 25-51.* https://doi.org/10.1016/j.jeconom.2004.02.005

Zervas, G., Proserpio, D., and Byers, J. (2017), The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of Marketing Research,* 54(5), 687-705.

Zervas, G., Proserpio, D., and Byers, J. (2021), A first look at online reputation on Airbnb, where every stay is above average. *Marketing Letters*, 32.1, 1-16.

Tables

Table 1 – Airbnb in Italy

	2017	2018	2019	Δ2017-19
Listed Properties (000)	499.7	594.1	650.2	+30.1%
Listed Beds (000)	2,142.5	2,562.8	2,806.0	+31.0%
Revenues (millions USD)	2,772.8	3,857.4	4,827.5	+74.1%
Reserved Nights (millions)	23.4	31.8	40.8	+74.4%

Source: Authors' calculation on Airdna
'*Listed*' means that the property has at least one available night during the year.

Table 2 – Airbnb and hotels diffusion in 2019 in the municipalities of the LLMA (center vs. other municipalities) distinguishing "city", "town" and "rural" classification of LLMA

	Population (millions)		Airbnb Properties		Airbnb Beds (000)		Revenues (millions USD)		Hotels		Hotel Beds (000)	
"City" LLMA	**23.5**	**39%**	**212,970**	**33%**	**789.61**	**28%**	**1,758.41**	**36%**	**5,619**	**19%**	**475.0**	**23%**
Centre Municipality	11.1	18%	160,906	25%	571.30	20%	1,442.34	30%	3,386	11%	310.8	15%
Other Municipalities	12.4	21%	52,064	8%	218.31	8%	316.07	7%	2,233	7%	164.1	8%

"Town" LLMA	**24.4**	**41%**	**228,359**	**35%**	**1,020.34**	**36%**	**1,621.87**	**34%**	**12,989**	**44%**	**840.4**	**41%**
Centre Municipality	10.2	17%	102,556	16%	425.83	15%	801.24	17%	6,227	21%	446.7	22%
Other Municipalities	14.2	24%	125,803	19%	594.51	21%	820.64	17%	6,762	23%	393.7	19%
"Rural" LLMA	**12.1**	**20%**	**208,874**	**32%**	**996.09**	**35%**	**1,447.24**	**30%**	**11,196**	**38%**	**737.6**	**36%**
Centre Municipality	5.4	9%	91,306	14%	423.18	15%	648.12	13%	4,715	16%	377.4	18%
Other Municipalities	6.6	11%	117,568	18%	572.91	20%	799.11	17%	6,481	22%	360.2	18%
ITALIA	**59,9**	**100%**	**650,203**	**100%**	**2,806.04**	**100%**	**4,827.52**	**100%**	**29,804**	**100%**	**2,053.0**	**100%**
Centre Municipality	26,7	45%	354,768	55%	1,420.31	51%	2,891.70	60%	14,328	48%	1,134.9	55%
Other Municipalities	33.2	55%	295,435	45%	1,385.73	49%	1,935.82	40%	15,476	52%	918.0	45%

Note: LLMAs are classified according to the algorithm illustrated in footnote 5.
Source: Authors' calculation on Airdna and ISTAT, *Capacità degli esercizi ricettivi*

Table 3 – Airbnb diffusion in 2019 in the LLMAs of the first 15 Italian cities – Central (CM) and other (OM) municipalities

	LLMA Population (000)	**CM Population**		**LLMA Airbnb beds**	**CM Airbnb beds**		**LLMA Hotel beds**	**CM Hotel beds**		**LLMA Revenues (millions USD)**	**CM Revenues (millions USD)**		**CM Occupation Rate**	**OM Occupation Rate**	**CM ADR (USD)**	**OM ADR (USD)**
MILANO	3.920,7	1.396,0	36%	108.405	93.516	86%	75.119	52.322	70%	260,86	241,82	93%	40%	29%	106,38	68,97
ROMA	3.730,5	2.820,2	76%	196.922	167.416	85%	129.885	120.955	93%	590,81	560,29	95%	46%	20%	115,61	85,92
NAPOLI	2.514,9	954,3	38%	58.158	50.879	87%	20.424	12.849	63%	94,65	88,27	93%	36%	21%	75,66	66,99
TORINO	1.730,8	860,8	50%	29.121	23.843	82%	19.602	13.310	68%	38,99	34,78	89%	38%	21%	64,43	61,60
PALERMO	878,9	652,7	74%	44.536	35.619	80%	13.748	8.674	63%	48,88	42,01	86%	27%	14%	69,52	104,69
BOLOGNA	871,9	393,2	45%	25.901	21.325	82%	19.167	12.268	64%	63,39	58,21	92%	48%	24%	87,62	73,90
BARI	732,6	316,5	43%	12.205	7.481	61%	7.367	5.890	80%	19,60	15,26	78%	43%	17%	70,49	78,52
FIRENZE	708,1	369,9	52%	87.640	66.671	76%	39.513	32.987	83%	275,33	219,26	80%	49%	30%	117,54	181,33
CATANIA	687,0	297,8	43%	33.611	18.111	54%	9.167	4.466	49%	35,97	21,26	59%	30%	17%	59,03	105,46
PADOVA	681,2	210,0	31%	8.471	4.868	57%	25.282	5.228	21%	13,77	9,21	67%	43%	25%	68,06	94,25
GENOVA	660,3	569,2	86%	14.544	12.156	84%	8.833	7.408	84%	23,33	20,34	87%	38%	24%	74,36	101,00
VENEZIA	609,4	260,0	43%	55.551	49.971	90%	40.449	32.523	80%	234,04	226,18	97%	48%	29%	146,33	80,05
VERONA	471,0	258,6	55%	19.984	16.084	80%	10.987	6.237	57%	50,53	44,82	89%	41%	23%	108,22	104,27
PARMA	354,9	198,6	56%	4.132	2.954	71%	5.706	3.777	66%	6,71	5,71	85%	41%	19%	69,11	78,59
MESSINA	251,6	229,3	91%	3.856	3.344	87%	1.211	1.374	113%	2,43	2,22	91%	15%	9%	75,78	79,16

Note: Percentages are the shares of the central municipality as compared to the whole LLMA.
Occupation Rate = Reserved Nights / Available Nights. ADR (Average Daily Rate) = Revenues / Reserved Nights.
Source: Authors' calculation on Airdna and ISTAT, *Capacità degli esercizi ricettivi*

Table 4 – Regression Results. Dependent variable is ln(*Airbnb*)

	Random Effects					GMM-SYS				
	Model 1a	**Model 2a**	**Model 3a**	**Model 4a**	**Model 5a**	**Model 1b**	**Model 2b**	**Model 3b**	**Model 4b**	**Model 5b**
Time f.e.	x	x	x	x	x	x	x	x	x	x
ln(Airbnb i,t-1)	0.9603***	0.9587***	0.9573***	0.9575***	0.9575***	0.8476***	0.8797***	0.8735***	0.8961***	0.8952***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.046)	(0.038)	(0.039)	(0.029)	(0.029)
ln(Hotel Beds i,t-1)	0.0154***	0.0197***	0.0193***	0.0224***	0.0215***	0.0903***	0.0746***	0.0733***	0.0621***	0.0611***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.034)	(0.028)	(0.027)	(0.020)	(0.021)
Unemployement i,t-1		0.3700***	0.3539***	0.3746***	0.3680***		0.6106***	0.5331**	0.4723**	0.4656**
		(0.063)	(0.061)	(0.062)	(0.058)		(0.207)	(0.239)	(0.193)	(0.191)
ln(Population Density i,t)			0.0066	0.0073	0.0100			0.0277*	0.0238**	0.0242**
			(0.006)	(0.005)	(0.007)			(0.016)	(0.010)	(0.010)
Perc. Luxury Beds i				-0.0308***	-0.0315***				-0.0226	-0.0234
				(0.010)	(0.010)				(0.025)	(0.025)
*ln(Hotel Beds i,t-1) * "City" LLMA*					0.0004					0.0038
					(0.001)					(0.003)
*ln(Hotel Beds i,t-1) * "Rural" LLMA*					0.0013					0.0011
					(0.001)					(0.0016)
Constant	0.3457***	0.2781***	0.2588***	0.2371***	0.2259***	0.4437***	0.3011***	0.2204***	0.2042***	0.2090***
	(0.030)	(0.029)	(0.034)	(0.033)	(0.006)	(0.058)	(0.056)	(0.058)	(0.047)	(0.009)
N	1.219	1.215	1.215	1.199	1.199	1.219	1.215	1.215	1.199	1.199
Overall R2	0.9950	0.9953	0.9953	0.9955	0.9955					
Number of Instruments						4	6	7	8	10

Source: Authors' calculation on Airdna
Stata command: *xtreg, re* for left-hand side regressions; *xtabond2* for right-hand side regressions. Standard errors are clustered according to LLMA.
In GMM-SYS estimates, the number of instruments varies from 4 to 8 in Models 1b to 5b. Consequently, the ratio Observations to Instruments is remarkably low (from 0.003 to 0.007) avoiding potential overidentification issues. The GMM-SYS estimator adopts the twostep procedure and the Windmeijer (2005) finite sample correction of the covariance matrix.

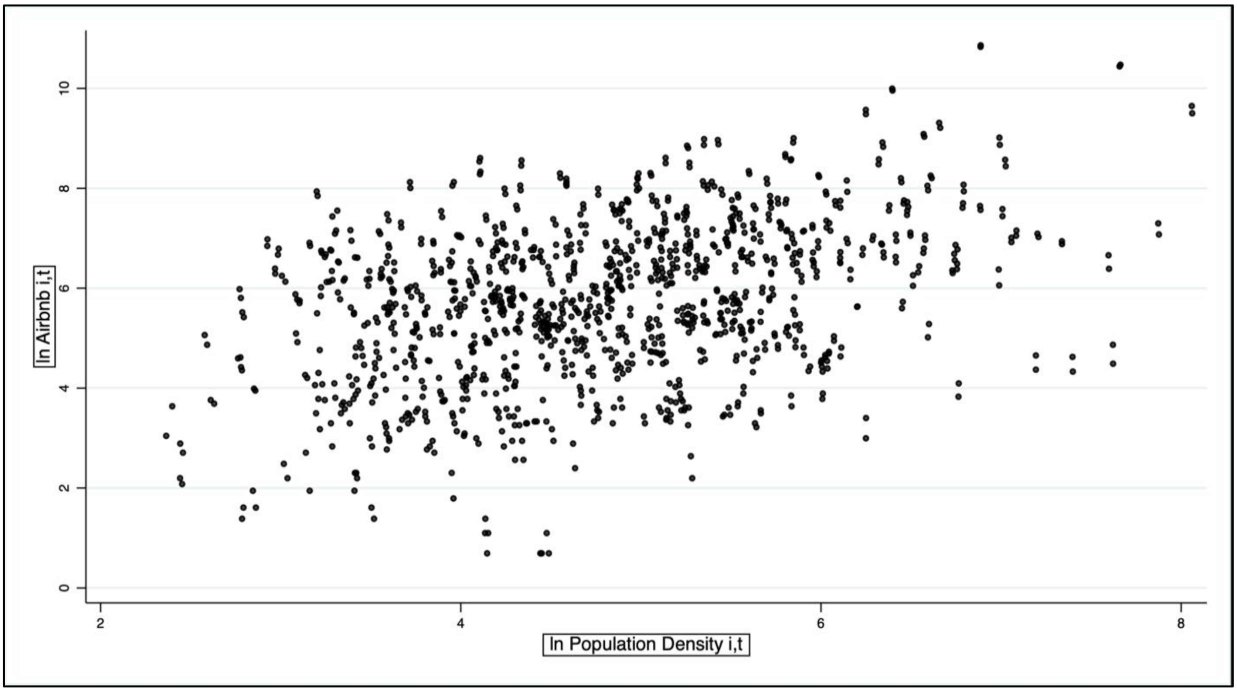
Table 5 – Regression Results. Dependent variable is *Occupation Rate*.

	Random Effects					**GMM-SYS**				
	Model 1a	**Model 2a**	**Model 3a**	**Model 4a**	**Model 5a**	**Model 1b**	**Model 2b**	**Model 3b**	**Model 4b**	**Model 5b**
Time f.e.	x	x	x	x	x	x	x	x	x	x
Occ Rate i,t-1	0.9875***	0.9295***	0.9106***	0.9118***	0.9000***	0.9703***	0.8711***	0.8544***	0.8620***	0.8469***
	(0.027)	(0.029)	(0.031)	(0.032)	(0.002)	(0.041)	(0.036)	(0.030)	(0.044)	(0.043)
ln(Hotel Beds i,t-1)	0.0029***	0.0029***	0.0024***	0.0025***	0.0020***	0.0033***	0.0038***	0.0033***	0.0035***	0.0029**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployement i,t-1		-0.1391***	-0.1591***	-0.1686***	-0.1779***		-0.1616***	-0.1847***	-0.1914***	-0.2048***
		(0.024)	(0.022)	(0.026)	(0.024)		(0.030)	(0.024)	(0.041)	(0.039)
ln(Population Density i,t)			0.0038***	0.0031**	0.0030**			0.0043***	0.0035***	0.0038***
			(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)
Perc. Luxury Beds i				0.0108**	0.0105**				0.0098**	0.0096**
				(0.005)	(0.004)				(0.005)	(0.005)
*ln(Hotel Beds i,t-1) * "City" LLMA*					0.0018***					0.0022***
					(0.000)					(0.001)
*ln(Hotel Beds i,t-1) * "Rural" LLMA*					0.0004**					0.0006***
					(0.000)					(0.000)
Constant	0.0104***	0.0352***	0.0249***	0.0256***	0.0297***	0.0079**	0.0384***	0.0265***	0.0255***	0.0288***
	(0.004)	(0.006)	(0.007)	(0.007)	(0.008)	(0.003)	(0.007)	(0.008)	(0.009)	(0.010)
N	1.219	1.215	1.215	1.199	1.199	1.219	1.215	1.215	1.199	1.199
Overall R2	0.9007	0.9066	0.9077	0.9095	0.9107					
Number of Instruments						5	6	7	8	10

Source: Authors' calculation on Airdna
Stata command: *xtreg, re* for left-hand side regressions; *xtabond2* for right-hand side regressions. Standard errors are clustered according to LLMA.
In GMM-SYS estimates, the number of instruments varies from 4 to 8 in Models 1b to 5b. Consequently, the ratio Observations to Instruments is remarkably low (from 0.003 to 0.007) avoiding potential overidentification issues. The GMM-SYS estimator adopts the twostep procedure and the Windmeijer (2005) finite sample correction of the covariance matrix.

Figures

Figure 1 – Univariate association Population Density – Airbnbs



Source: Authors' calculation on AirDNA data
The plot has been created on Stata 16. Command: scatter.
Both measures are in logs.