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The pricing of European airbnb listings during the pandemic: A difference-in-differences approach employing COVID-19 response strategies as a continuous treatment

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ABSTRACT

The COVID-19 pandemic has been a major shock to the global tourism industry. Given its peculiarity, this paper analyzes one of the most intriguing questions in the Airbnb literature – the pricing of Airbnb listings – by taking advantage of a difference-in-differences methodology that largely draws on variations in country-level policy responses to the pandemic. Relying on a dataset containing weekly information from 130,999 continuously active listings across 27 European countries from 2019 to 2020, this study first investigates the exogenous impact of response policies (proxied by the COVID-19 Stringency Index) on demand. Secondly, accounting for the endogeneity of both demand and prices, this research analyzes pricing responses to demand variations. Results show that: i) increases in the COVID-19 Stringency Index cause significant declines in Airbnb demand; ii) increases in demand cause, on average, increases in Airbnb prices; and iii) pricing strategies between commercial and private hosts differ substantially.

1. Introduction

The COVID-19 pandemic had an unprecedented negative impact on the tourism and hospitality industry worldwide. According to UNWTO (2021), international tourist arrivals decreased by 74% between 2019 and 2020. Airbnb (www.airbnb.com), which has become a metonym for accommodation sharing, was no exception to this development: about 1800 employees had been laid off by November 2020 following a 72% drop in revenues since the outbreak of the pandemic (Abril, 2020). Nonetheless, Airbnb as a company has proven resilient during the pandemic with a successful initial public offering (IPO) on December 10, 2020 (Sonnemaker, 2020), and featured about 6 million active listing in more than 100,000 cities around the world as of December 31, 2021 (Airbnb, 2022).

According to Airbnb (2022), the average US host was able to generate annual earnings of approximately USD 9000 during 2021. However, not every US Airbnb host is an average US host, and even greater variation is evident beyond US borders. Across European countries, for instance, the COVID-19 pandemic has differed in terms of the timing and intensity of the various pandemic waves and also in the timing and intensity of (national, regional, and/or local) governmental countermeasures such as travel restrictions, lockdowns, or other precautionary actions (e.g., ECDC, 2022). Consequently, demand variations during the pandemic have affected individual European Airbnb hosts quite differently, depending on a variety of factors operating from the country level (i.e., aggregate perspective) to the neighborhood level (i. e., disaggregate perspective). This heterogeneity calls for a granular analysis at the listing level of the effects of these demand variations on pricing and revenue generation. Moreover, assuming that commercial hosts (i.e., hosts managing three or more properties in the baseline specification; Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019; Dogru, Mody, Suess, Line, & Bonn, 2020; Gunter & Önder, 2018) adopt a more sophisticated managerial approach than private hosts (Li, Moreno, & Zhang, 2016), this higher degree of professionalism may have rendered commercial hosts more resilient during the pandemic and may have added to the aforementioned heterogeneity.

To this end, this study employs weekly data at the listing level obtained from AirDNA (www.airdna.co) 130,999 active Airbnb listings from 27 European countries from January 2019 until December 2020, resulting in 13, 754, 895 property-week data points. The objectives of

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Table 1
Distribution of selected listings, reserved nights, and revenues (in USD) by country (2019 vs. 2020).

Country	# Properties	Res. Nights 2020 [thsd.]	Res. Nights 2019 [thsd.]	Δ 2020–2019 Res. Nights	Revenues 2020 [mln. USD]	Revenues 2019 [mln. USD]	Δ 2020–2019 Revenues
Italy	35,213	1655.9	3379.6	−51%	164.49	344.07	−52%
France	29,436	1725.7	2586.9	−33%	200.70	280.99	−29%
Spain	16,862	1014.1	2032.2	−50%	118.67	231.35	−49%
Germany	9562	753.6	1104.0	−32%	69.84	96.90	−28%
Portugal	6582	453.0	962.2	−53%	40.61	91.14	−55%
Greece	5795	208.1	462.0	−55%	21.57	47.93	−55%
Croatia	5139	122.5	317.2	−61%	12.51	31.89	−61%
Poland	2905	248.4	422.8	−41%	17.60	29.17	−40%
Netherlands	2592	292.0	424.3	−31%	35.06	52.82	−34%
Belgium	2084	192.9	299.9	−36%	24.50	34.29	−29%
Ireland	1776	124.0	193.3	−36%	16.19	22.87	−29%
England	1426	31.1	194.9	−84%	4.61	39.85	−88%
Denmark	1397	84.2	134.7	−37%	8.90	15.20	−41%
Austria	1260	95.5	202.3	−53%	10.41	21.16	−51%
Romania	1092	47.0	99.7	−53%	3.00	6.21	−52%
Sweden	1064	62.0	97.7	−37%	7.53	10.99	−31%
Hungary	980	64.0	187.7	−66%	4.17	14.37	−71%
Bulgaria	914	26.6	49.3	−46%	1.92	3.14	−39%
Finland	677	51.4	66.7	−23%	6.21	7.60	−18%
Malta	505	32.0	70.4	−55%	3.60	7.36	−51%
Slovenia	394	26.8	47.0	−43%	2.88	4.73	−39%
Lithuania	341	16.1	29.2	−45%	1.07	1.81	−41%
Slovakia	268	15.9	27.2	−42%	1.13	1.83	−38%
Estonia	232	15.9	29.2	−45%	1.35	2.66	−49%
Latvia	182	10.4	21.3	−51%	0.76	1.61	−53%
Luxembourg	39	4.3	6.6	−35%	0.39	0.58	−32%
Switzerland	2	0.0	0.1	−81%	0.00	0.01	−50%

Notes: a) Data Source: AirDNA. b) Data were arranged by means of Python (using *Pandas* library for data management). c) The number of properties contains those properties recorded in the final dataset, as explained in Section 3.1. Revenues and reserved nights refer to those properties. d) Countries are sorted in descending order according to the number of properties recorded.

this study are twofold: firstly, to investigate the exogenous impact of the COVID-19 pandemic on demand for European Airbnb listings by drawing on a granular and comprehensive panel dataset (composed of 2,205,347 observations resulting from the process of variable operationalization); and, secondly, to analyze pricing developments during the pandemic while respecting the endogeneity of Airbnb demand by taking advantage of a two-stage least squares estimation.

This research is embedded in neoclassical microeconomic (tourism) demand theory (Mas-Colell, Whinston, & Green, 1995; Song, Witt, & Li, 2009) with Airbnb hosts operating in an imperfectly competitive market environment called monopolistic competition (Chamberlin, 1933; Dixit & Stiglitz, 1977; Robinson, 1933). Monopolistic competition implies that demand for heterogeneous products or services is determined by differences in their prices and also by real or perceived differences in non-price characteristics. In fact, these non-price characteristics play a double role in influencing demand, as they also act as determinants of price within a hedonic pricing framework (Rosen, 1974). Effectively, demand and price are determined simultaneously in equilibrium, thus rendering both variables endogenous. Ignoring the endogeneity of Airbnb demand as a determinant of Airbnb price when finding coefficient estimates through standard ordinary least squares (OLS) estimation is likely to introduce systematic bias. Hence, Airbnb demand needs to be properly instrumented to avoid such bias (Wooldridge, 2010), yet this has not been regularly applied in Airbnb pricing and demand research to date: the recent contribution by Fleischer, Ert, and Bar-Nahum (2022) representing a notable exception.

Accordingly, a two-way fixed-effects (TWFE) difference-in-differences (DID) approach with clustered standard errors is used, whereby endogenous Airbnb demand is instrumented by a country-level continuous treatment: the COVID-19 Stringency Index (Hale et al., 2021). Not only is this the first time the COVID-19 Stringency Index has been used to instrument endogenous Airbnb demand in tourism economic research, but it is also the first use of a continuous group-level (i.e., country-level) treatment (Callaway, Goodman-Bacon, & Sant'Anna, 2021). Spatial, macroeconomic, and listing-level control variables – the latter representing host and listing characteristics – are included in the estimation as well (see Section 3 for more details).

In addition, an alternative specification of the above approach is carried out to investigate potential pricing differences while comparing different host types (i.e., commercial versus private hosts). Finally, three robustness checks complement the analysis, showing that the results are robust regardless the definitions of: i) the timing of the pandemic outbreak; ii) the moving average filter applied to the demand variable; and iii) the threshold distinguishing private and commercial hosts.

The remainder of the study is structured as follows: Section 2 reviews the related literature, Section 3 describes the dataset and the variables, Section 4 introduces the empirical methodology, Section 5 presents the estimation results, and Section 6 discusses the results and draws some overall conclusions including theoretical and practical implications.

2. Literature review

Over the past two years, the COVID-19 pandemic disrupted the global tourism and hospitality industry like no other crisis experienced in the past. Given that the sharing economy is often described as "a disruptive phenomenon" (Hossain, 2021), it comes as no surprise that many researchers are nowadays interested in exploring the impacts of the pandemic on the sharing economy as a whole and on Airbnb in particular, along with the recovery prospects. On that note, Dolnicar and Zare (2020) are likely the first to put forward the notion of two simultaneous disruptors (i.e., COVID-19 and Airbnb).

An important lesson learned so far is that COVID-19 exposed the vulnerability of the tourism and hospitality industry (Duro, Perez-Laborda, Turrion-Prats, & Fernández-Fernández, 2021), including the sharing economy. Chen, Cheng, Edwards, and Xu (2022) conclude about the vulnerability of the latter by assessing the income loss of Airbnb hosts at both spatial and temporal scales in Sydney with a comprehensive income accounting framework. Hossain (2021) concentrates on survivability and therefore examines the impact of the pandemic on various sharing economy activities. Similarly, the question

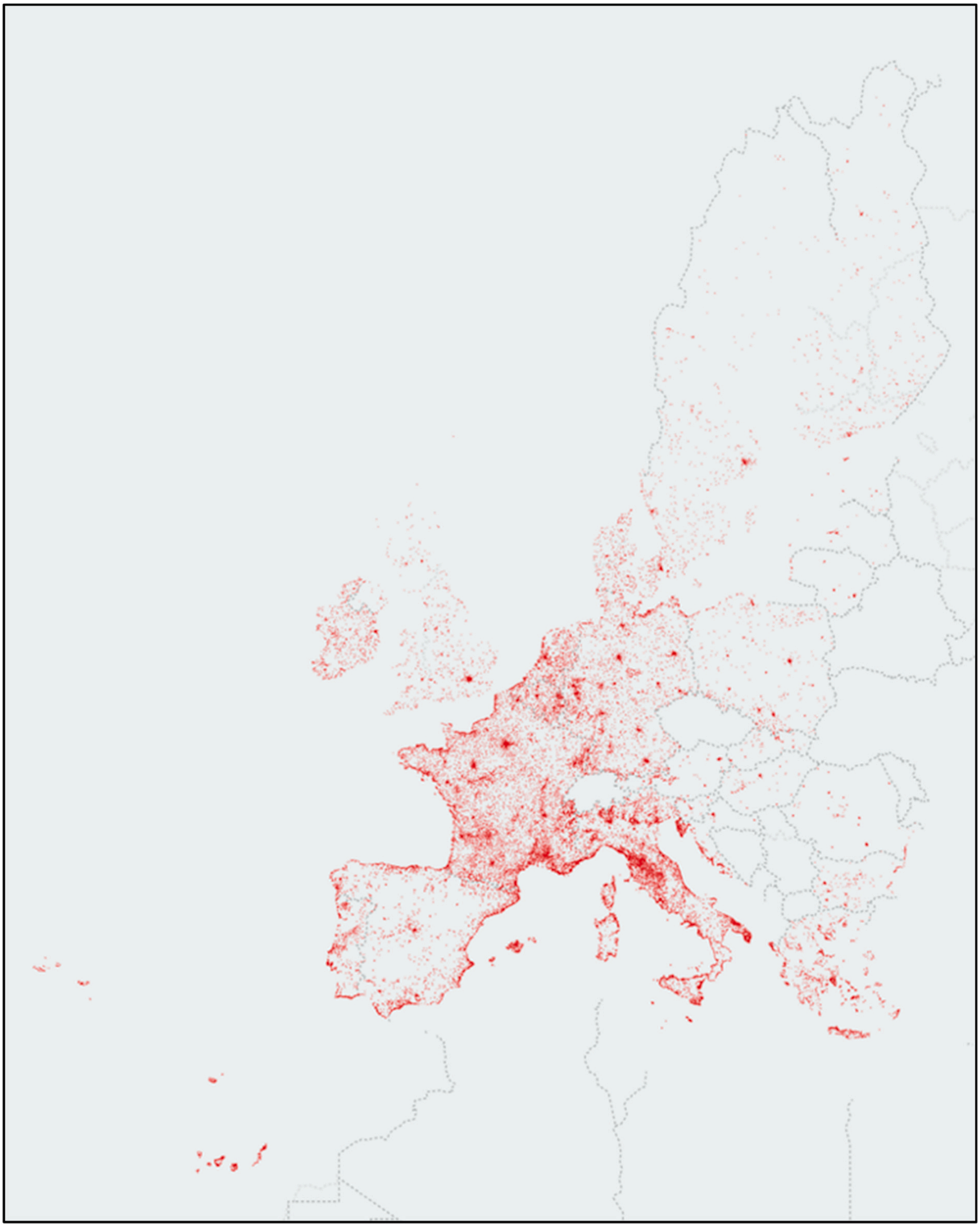

Fig. 1. Geographical distribution of Airbnb listings within the sample (continuously active listings in 2019 and 2020)
Notes: a) Data Source: AirDNA.
b) The properties shown in the maps are those included in the final dataset, as explained in Section 3.1.
c) The map was generated on Kepler.gl (https://kepler.gl).

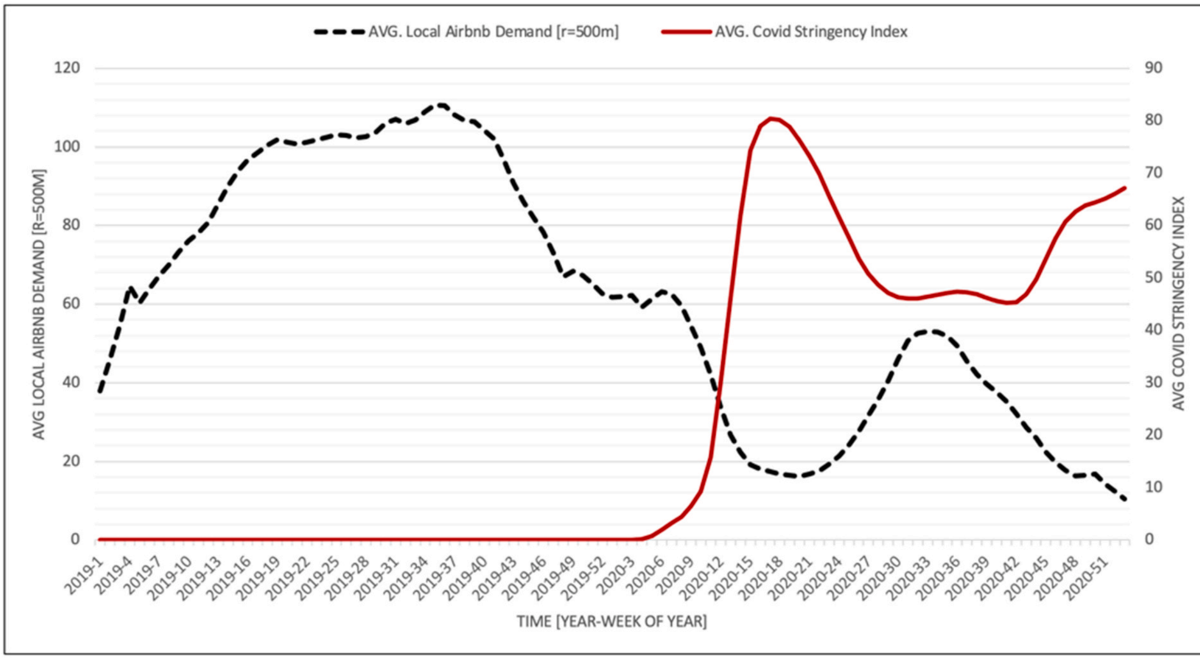

Fig. 2. Evolution of the average values of Local Airbnb Demand (with r = 500 m) and COVID-19 Stringency Index over time
Notes: a) Data Sources: AirDNA (for Local Airbnb Demand) and Our World in Data (for COVID-19 Stringency Index, see Hale et al., 2021).
b) Data were manipulated using Python (Pandas library) and the chart was generated with Microsoft Excel.
c) "AVG Local Airbnb Demand" is the European average value at time *t* of the variable Local Airbnb Demand using the radius of 500 m, "AVG COVID Stringency Index" is the European average value at time *t* of the variable COVID-19 Stringency Index.

of whether COVID-19 will terminate or rather accelerate the growth of peer-to-peer accommodation (P2PA) is raised in the study by Zhang, Geng, Huang, and Ren (2021), who investigate the responses of hosts to the pandemic in China. They ultimately find that COVID-19 is "an accelerator that preserves the "real" P2PA and eliminates hosts who only pursue profit opportunities" (Zhang et al., 2021, p. 8). P2PAs are also of interest to Farmaki et al. (2020), who identify existing variance in host perceptions and responses to the pandemic. Regarding organizational response strategies to the pandemic in the sharing economy, Mont, Curtis, and Palgan (2021) compare 30 platforms on shared mobility, space, and goods, and propose cross-platform learning to optimize both crisis response and preparedness.

Further insights on the impact of COVID-19 on vacation rentals in twelve mega cities across the world come from Liang, Leng, Yuan, and Yuan (2021), which can be used as a reference for other cities. One of the merits of this study is a methodological assessment framework for monitoring the hospitality sector. Exploring causal factors on performance, Gerwe (2021) outlines the underlying reasons for disruption (i.e., the weak points) of the accommodation sharing sector, along with the prospects for recovery as the pandemic may push the "reset button". Acknowledging the importance of destination-specific response strategies, Jang and Kim (2022) propose remedying Airbnb COVID-19 disruption through local resources: tourism clusters and community resilience.

There is also evidence that the changes in demand during COVID-19 differ by accommodation type. To this end, Bresciani et al. (2021) investigate the impact of the pandemic on different accommodation types and conclude that full flats are preferred over shared flats on Airbnb and over hotel rooms, in line with travelers' needs for physical distance. Perceived risks of using Airbnb were rated higher during the pandemic than previously (Lee & Deale, 2021). Moreover, based on the spatial and experimental analysis of P2PA consumption during COVID-19, it is found that (1) revenue losses differ across destinations (i.e., urban and rural areas) and destination attributes (i.e., tourism clusters, airport distance, and food safety violation) and (2) business tourists who perceive the pandemic as a low threat are more willing to use Airbnb listings than leisure tourists (Jang, Kim, Kim, & Kim, 2021).

As the latter finding holds irrespective of the destination type (i.e., rural or urban), the authors suggest a number of managerial implications for both rural and urban Airbnb hosts. Unsurprisingly, short-term rentals in low-density areas are described as a suitable option for travelers (Zoğal, Domènech, & Emekli, 2020), given the difficulty of social distancing in urban destinations (Jang et al., 2021). Such conclusions corroborate the pandemic-induced dynamic changes in overall travel demand and consumer preferences noted by Kim, Park, Kim, Lee, and Sigala (2021) and suggest revisiting the motivating factors and market segments for Airbnb that were proposed by Guttentag, Smith, Potwarka, and Havitz (2018). Moreover, social interaction was not found significant with regard to perceived enjoyment and repurchase intention of Airbnb experiences (So, Kim, & Oh, 2021), which is also likely to be reconfirmed in the aftermath of the pandemic.

Besides the impacts of COVID-19 on the sharing economy/Airbnb, another important aspect for the present research concerns the price determinants of Airbnb listings. Cai, Zhou, Ma, and Scott (2019) state that this topic is in "its infancy", however, three years later and with rapidly growing interest among researchers, this claim no longer holds. To support this, Hernández, Bulchand-Gidumal, and Suárez-Vega (2021) examine 18 studies published between 2016 and 2020 to summarize price determinant estimations for Airbnb listings. Five groups of price determinants are identified by these authors in the literature: structural attributes (e.g., property characteristics and services), host attributes (both personal and relational), management attributes (e.g., specific rental rules), reputation attributes (e.g., reviews and ratings), and location attributes (e.g., spatial and environmental factors). Such classifications are consistent across the literature (e.g., Arvanitidis, Economou, Grigoriou, & Kollias, 2020; Cai et al., 2019). Simply put, prices are driven by "the physical characteristics - the what; the factors which impact user perception - the why; and, the location - the where" (Perez-Sanchez, Serrano-Estrada, Marti, & Mora-Garcia, 2018, p. 26). Several important take-aways from past studies on Airbnb pricing are

Table 2
Descriptive statistics.

Variable Group	Variable	Mean	Std. Dev.	Min	Max
Dependent Variable	Average Weekly Price (AWP) (i,t)	100.52	80.03	20.14	754.43
Explanatory and Instrumented Variable	Local Airbnb Demand (LAD) (i,250 m,t)	65.78	118.99	1.00	1030.43
	Local Airbnb Demand (LAD) (i,500 m,t)	188.48	348.00	1.00	2386.57
	Local Airbnb Demand (LAD) (i,750 m,t)	344.83	634.73	1.00	3963.86
	Local Airbnb Demand (LAD) (i,1000 m,t)	510.67	924.65	1.00	5206.57
Instrumental Variable	COVID-19 Stringency Index (CSI) (t,g) *	55.56	12.93	2.97	96.30
Spatial Controls	Average Market Price (i,250 m,t)	78.83	68.96	0.00	748.86
	Average Market Price (i,500 m,t)	88.28	65.08	0.00	748.86
	Average Market Price (i,750 m,t)	92.50	62.31	0.00	748.86
	Average Market Price (i,1000 m,t)	95.35	60.62	0.00	735.29
	Number of Competitors (i,250 m)	15.77	27.46	0.00	180.00
	Number of Competitors (i,500 m)	48.16	81.76	0.00	476.00
	Number of Competitors (i,750 m)	89.40	150.01	0.00	787.00
	Number of Competitors (i,1000 m)	133.46	219.52	0.00	1033.00
Macroeconomic Controls	RGDP (i,g,t)	28,155.79	9071.53	6600.00	83,640.00
	CPI(i,g,t)	111.74	3.50	99.55	127.04
Property-Level Controls	Beds(i)	4.18	2.65	1.00	16.00
	Photos(i)	24.00	17.05	1.00	286.00
	Host's Properties(i)	3.23	9.19	1.00	619.00
	Multiplatform(i)	0.12	–	0	1
	Experience (i,t)	163.60	89.38	0.00	587.00
	Cancellation Policy(i)	0.86	–	0	1
	Instantbook(i)	0.69	–	0	1
	MidLong Rent(i)	0.001	–	0	1

Notes: a) Data Sources: AirDNA, Eurostat, ECB, Our World in Data. b) Subscripts: i = Property, t = Time (Year-Week), g = Country, 250 m/500 m/750 m/1000 m = Radius r defining the relevant market. c) The table was generated by means of Stata 17 (command *sum*). d) * = The descriptive statistics are provided from t=*63* onwards.

highlighted in the following, which explore various explanatory variables, pricing differences between private (also referred to as non-professional or casual) and commercial (i.e., professional) hosts, and price discrimination.

Cai et al. (2019) examine the impacts of five categories of explanatory variables in their investigation of price determinants of Airbnb listings in Hong Kong by employing hedonic price regression. Among other results, they find that the hosts' listings count has a negative effect and that the room type exerts an exceptionally high impact on the price. A comparison of different methodological approaches (OLS regression, random forest, and decision tree) is performed by Chattopadhyay and Mitra (2019) in their investigation of Airbnb price determinants in eleven US cities. Besides highlighting city-specific variable importance, the authors also estimate a composite score of variable importance. Furthermore, general product features, reviews of quantity and quality, as well as amenities and services are identified as important Airbnb price determinants in Toronto (Chattopadhyay & Mitra, 2020), whereas more reviews are linked with lower prices according to the hedonic pricing model applied to listings across five major urban destinations in Canada (Gibbs, Guttentag, Gretzel, Morton, & Goodwill, 2018). Another interesting finding is that the subjective and objective internal attributes in title descriptions play a differing role in determining the Airbnb prices in Swiss rural and urban locations (Falk, Larpin, & Scaglione, 2019).

Arvanitidis et al. (2020) contribute with an in-depth exploration of Airbnb listing prices between "casual" (i.e., with one or two listings) and professional (i.e., with more than two listings) hosts in Athens by applying hedonic price modeling and a Blinder-Oaxaca decomposition, thereby providing evidence of a statistically significant difference in pricing. Spatial price mimicking on Airbnb is the focus of the study by Boto-García, Mayor, and De la Vega (2021), who suggest that price mimicking is higher among non-professional (i.e., single-property) hosts in comparison to professional hosts in Madrid. The latter two studies demonstrate that there is no universal consensus in the Airbnb literature as to the listing count threshold defining an Airbnb host as 'professional' or not.

In terms of price discrimination, Aznar, Sayeras, Segarra, and Claveria (2018) conclude that Airbnb hosts in Barcelona discriminate prices according to seasonality, but generally not in terms of day of the week. Although host attributes are important price determinants (Wang & Nicolau, 2017) and act as trust indicators (Fleischer et al., 2022), the recent contribution by Barnes (2021) warns about the overvaluation of perceived facial trustworthiness in Airbnb host images, especially in combination with reputational measures.

Regarding locational factors, accessibility to certain amenities, walkability, noise, the ethnicity of residents, as well as spatial spillover effects are confirmed to have a statistically significant impact on Airbnb pricing in Málaga (Chica-Olmo, González-Morales, & Zafra-Gómez, 2020). Similarly, in their study on determinants of Airbnb prices in ten major EU cities, Gyódi and Nawaro (2021) identify attributes related to size, quality, and location as significant, and conclude that prices are spatially dependent. In addition, listing characteristics, the number of points of interests within an optimal radius (= 650 m for Tallinn, as estimated via a simulation study), and prices of other Airbnb listings and hotels within the same radius are found to positively impact prices of Tallinn's Airbnb listings (Önder, Weismayer, & Gunter, 2019).

Also applying a hedonic pricing model, Tong and Gunter (2020) determine that overall rating and characteristics indicative of the size of the listing have the strongest positive influence, whereas the number of reviews and distance from the city center exert the strongest negative influence on Airbnb prices in Barcelona, Madrid, and Seville. Recognizing the relevance of spatial factors in a study of listings in Los Angeles and New York, Hong and Yoo (2020) propose a multiscale geographically weighted regression (MGWR) approach for analyzing spatial variance of Airbnb pricing determinants. Despite this clear academic interest in Airbnb prices, the literature also notes differences between price and revenue determinants (Sainaghi, Abrate, & Mauri, 2021). The

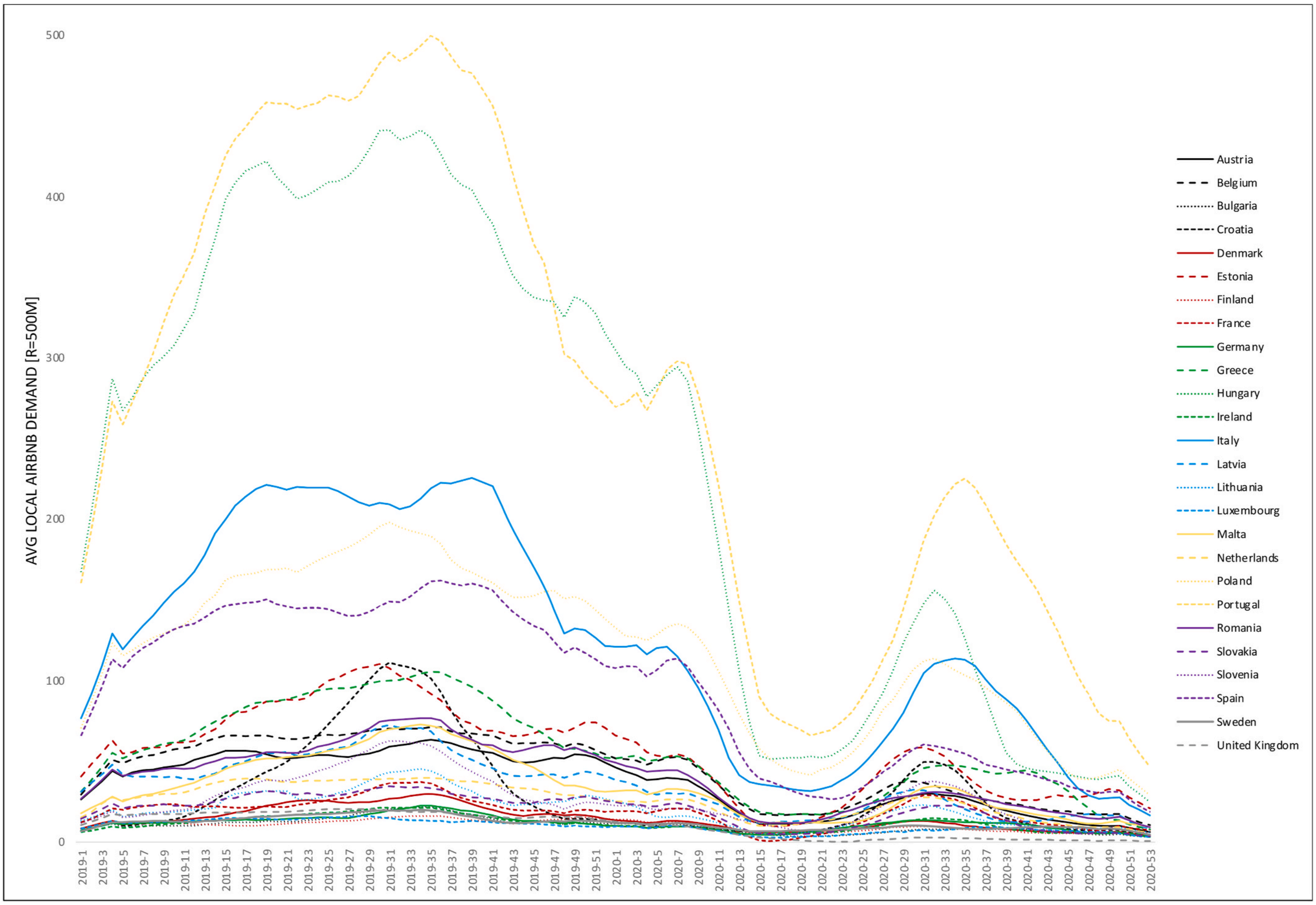

Fig. 3. Parallel trends assumption: Evolution of average Local Airbnb Demand by country (treatment group)
Notes: a) Data Source: AirDNA.
b) Data were manipulated using Python (Pandas library) and the chart was generated with Microsoft Excel.
c) AVG Local Airbnb Demand is the average value at time *t* of Local Airbnb Demand using the radius of 500 m.

determinants of demand, when measured through occupancy rates, for instance, reveal that "it is not all about price, indeed" (Leoni, Figini, & Nilsson, 2020, p. 1707). In addition, one of the most recent contributions on revenue of Airbnb listings in Milan and COVID-19 found that the pandemic reduced the city center advantage for the benefit of peripheral locations (Sainaghi & Chica-Olmo, 2022).

The final reflection concerns the Airbnb studies employing a two-stage least squares (2SLS) estimation in general, and a difference-in-differences (DID) approach in particular, since causal inference is at the core of our empirical analysis. For example, Benítez-Aurioles (2018) opts for a 2SLS regression in estimating the elasticity of Airbnb demand to price and distance in Barcelona and Madrid, finding similarities between the cities with respect to price elasticity of demand. In their exploration of the determinants of Airbnb location and its spatial distribution, Eugenio-Martin, Cazorla-Artiles, and González-Martel (2019) employ bivariate spatial correlation and spatial econometric techniques, thereby identifying price as the main determinant of Airbnb location. Among other analytical techniques, the 2SLS regression is used in the empirical investigation of the importance of tourism clusters in P2PA in the study by Lee, Jang, and Kim (2020).

Contributions employing the DID estimation technique within this thematical domain are also growing in numbers, especially over the past few years. Of interest to the present research is the study by Benítez-Aurioles (2019), who uses an extended DID formulation for assessing the impact of sociopolitical instability on Barcelona's P2P tourist accommodation market. Similarly, the DID technique is adopted to understand the impact of terrorist attacks on the P2PA market in Paris, which, predictably, has a significant negative effect on both market demand and rental performance (Chen, Chen, & He, 2021). Yeon, Kim, Song, and Kim (2020) apply both DID and a triple difference (DDD) approach in examining the impact of short-term rental regulation on P2PA performance, demonstrating a substantial difference between the pre- and post-regulation. Such types of modeling are also used in examining the impacts of: (1) Airbnb on hotel performance and employment (e.g., Mhlanga, 2019, 2020, 2021), (2) consumer animosity on demand for sharing-based accommodations (e.g., Li, Li, Wang, & Yang, 2021), and (3) the offshore wind farm on the vacation rental market (e.g., Carr-Harris & Lang, 2019).

Despite these diverse areas of application, to the best of authors' knowledge, no study to date has applied DID to Airbnb in the pandemic context. A further novelty of the present study is the application of DID with a continuous treatment, which has only very recently been added to the econometrician's toolbox (Callaway et al., 2021). Using a continuous treatment (i.e., the COVID-19 Stringency Index) permits a realistic modeling of the different and varying intensities of government response strategies to the pandemic at the country level (Hale et al., 2021). In addition, appropriately instrumenting endogenous Airbnb demand reduces the systematic upward bias of its impact on Airbnb price when using standard methods (see Section 5).

3. Data and variable description

In this section we present the data we use for our analysis, providing descriptions of the data sources and the operationalization of the variables, complemented by descriptive statistics for the variables employed in the econometric models.

3.1. Data sources

This paper takes advantage of the data provided by AirDNA, a leading provider of data on short-term rentals. Our panel dataset covers the period from January 1st, 2019, to December 31st, 2020, and contains information on prices, demand (i.e., the number of reserved nights), activity status, and other listing-level structural characteristics for continuously active[1] properties from 27 European countries, whose list is reported in Table 1. From the original dataset with a listing-daily scale, all variables were aggregated to a weekly basis in order to deal with the large dimensionality of a listing-level panel dataset covering properties from 27 European countries over two years. Given the nature of our analysis, we restricted the data to include only those listing-week observations that received at least one reservation during the observation period (Gunter & Önder, 2018). The final operationalization of the variables, which uses backward and forward time lags of demand variables (explained in the following sections), results in a final panel dataset containing 2,205,347 listing-week data points. Table 1 and Fig. 1 offer an overview of the distribution of listings and corresponding reservations and revenues by country, showing a clear dominance by the larger touristic markets such as France, Italy, or Spain, both in terms of property numbers and reservations/revenues.

The dataset from AirDNA is complemented by other data sources. From Eurostat[2] and from the European Central Bank[3], we retrieved macroeconomic variables such as the country-level real gross domestic product and consumer price index with the base year 2010, both expressed in USD. From Our World in Data,[4] we retrieved the COVID-19 Stringency Index, which measures the intensity of governmental restrictions in response to the COVID-19 pandemic at the country level (Hale et al., 2021) and is employed as an instrumental variable in the following econometric analyses.

3.2. Variable operationalization

3.2.1. Dependent variable: Average Weekly Price

The aim of this paper is to analyze whether variations in local demand can cause variations of listing-level prices. To this end, the dependent variable in our analysis is the *Average Weekly Price* (net of any additional fees, such as cleaning fees or extra people fees), measured in USD, that a property i proposes in week t (t varying from 0 to 104).[5] Departing from previous literature on pricing in the tourism sharing economy, which has mainly focused on the Average Daily Rate (ADR) as approximation of prices (Sainaghi et al., 2021), our analysis employs the real prices posted on the platform as the dependent variable. This approach yields several advantages for our research purpose, since we aim at measuring the causal impact of local demand variations on hosts' pricing decisions and the ADR represents the price that is effectively realized and not the price actually offered to customers (Canina & Enz, 2006); to assume that these two prices will be equivalent is to assume that supply and demand are always in equilibrium, which is considered unlikely during the pandemic. Thus, we believe that the usage of average weekly price fits better with our goal of understanding hosts' pricing decisions. In the econometric models, the variable has been log transformed.

3.2.2. Explanatory and instrumented variable: Local Airbnb Demand

The definition of *Local Airbnb Demand* in the present context is not obvious, as multiple determinants make the concept complex to measure; these include the dimension of the relevant market which the listing addresses (in our case the spatial boundaries determining the competitors of a property), and the timing of demand. To deal with this complexity, we propose the following definition in Eq. (1):

$$Local\ Airbnb\ Demand_{i,r,t,f} = \sum\nolimits_{t=\tau-f}^{t=\tau+f} Reserved\ Nights_{i,r,\tau} \Big/ (2f+1) \tag{1}$$

Local demand is thus defined as a moving average from f weeks in the past to f weeks ahead of t of the number of reserved nights of listing i plus the number of reserved nights of other listings in the neighboring vicinity, specified as those Airbnb listings located within radius r of listing i. On the basis of contributions investigating the size of the Airbnb listing-level relevant market (see, e.g., Önder et al., 2019, who find a radius of 650 m to be optimal for studying cross-price influences in the city of Tallin), we test our model specifications over four different r values ranging from 250 m to 1,000 m in 250-m increments.

We specify the length of the averaging period as three, thus conservatively assuming that demand over the coming three weeks is known in week t and that hosts decide on their prices in week t based on these future expectations as well as past experience. As often assumed in the Airbnb literature (see, e.g., Gunter, Önder, & Zekan, 2020), this implies a market structure of monopolistic competition characterized by heterogeneous Airbnb offerings allowing some leeway for hosts to set their own prices (Chamberlin, 1933; Dixit & Stiglitz, 1977; Robinson, 1933). Moreover, the application of a moving average allows our explanatory variable to smooth out potential seasonal patterns in the data. In line with our dependent variable, the explanatory variable has also been log transformed to enable the respective coefficient estimates in the econometric models to be interpreted as elasticities.

3.2.3. Instrumental variable: COVID-19 Stringency Index

To deal with the endogeneity of the variables employed in our models (i.e., using demand to explain prices), we identified the *COVID-19 Stringency Index* as a proper instrumental variable of *Local Airbnb Demand*. This metric, developed by Hale et al. (2021), is a composite daily measure based on nine policy response indicators (namely: school closures, workplace closures, cancellation of public events, restrictions

[1] A property i is defined active at time t if the sum of *Reserved Nights* plus *Available Nights* during t (where t is a week in this paper) is positive. Only this type of properties has been included in the analysis to ensure a more balanced panel and to mitigate any potential distortions stemming from the impact of irregular or one-time offerings on the Airbnb platform (Gunter et al., 2020; Gunter & Önder, 2018).

[2] Data can be accessed through the following link: https://ec.europa.eu/eurostat/data/database.

[3] Data can be accessed through the following link: https://www.ecb.europa.eu/stats/html/index.en.html.

[4] Data can be accessed through the following link: https://ourworldindata.org/covid-stringency-index.

[5] We decided to use this definition of price, first because our data provider allows us to directly observe this posted price, and second, because following the decision-making journey of a potential Airbnb customer, this variable represents the price shown to the customer when screening the list of available properties in each location.

Table 3A
First stage regression results: Full model with r = 500 m [Model 1].

	Spec. 2
	r = 500m
ln COVID-19 Stringency Index (g,t)*$POST_{63}$	−0.149***
	(0.004)
ln Average Market Price (i,500 m,t)	0.628***
	(0.002)
ln Number of Competitors (i,500 m)*Season(t)	Yes
ln RGDP (g,t)	2.082***
	(0.018)
ln CPI(g,t)	−1.020***
	(0.070)
ln Beds(i)*Season(t)	Yes
ln Photos(i)*Season(t)	Yes
ln Host's Properties(i)*Season(t)	Yes
Multiplatform(i)*Season(t)	Yes
ln Experience (i,t)	Yes
Cancellation Policy(i)*Season(t)	Yes
Instantbook(i)*Season(t)	Yes
MidLong Rent(i)*Season(t)	Yes
Constant	−15.045***
	(0.294)
Time Fixed Effects	Yes
Individual Fixed Effects	Yes
Number of Observations	2,205,347
Robust Standard Errors	Yes
F	3419.176
R^2 Adjusted	0.983
R^2 Within	0.085
R^2 Within Adjusted	0.085
AIC	−340,204.744
BIC	−339,776.127

Notes: a) Subscripts: i = Property, t = Time (Year-Week), g = Country, 500 m = Radius r defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Local Airbnb Demand(i,r,t). c) Estimates were generated by the means of Stata 17 (command *reghdfe*). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1. e) The reference baseline of time-invariant variables interacted with Season(t) is autumn. f) Coefficients of the full model have been excluded due to space constraints, yet are available from the authors upon request.

on gathering sizes, public transport closures, stay-at-home policies, restrictions on within country movements, restrictions on international travel, and intensity of public information campaigns) adopted by countries to deal with the COVID-19 pandemic. The metric is computed per country and rescaled as an indicator varying between 0 (no restrictions at all) and 100 (the most restrictions). In line with the temporal dimension of the panel data, *COVID-19 Stringency Index* data were aggregated at a weekly level by taking the mean value. Furthermore, in order to correctly match the instrumental variable with the instrumented *Local Airbnb Demand*, the *COVID-19 Stringency Index* is included in the model as reported in Eq. (2):

$$COVID-19\ Stringency\ Index_{i,g,t} = \sum\nolimits_{t=\tau-f}^{t=\tau} Weekly\ COVID-19\ Stringency\ Index_{i,g,\tau} \Big/ (f+1) \quad (2)$$

where g is the country containing listing i and f is the window length of the moving average filter. In line with the definition of *Local Airbnb Demand*, f is set to three and thus reports the average restriction level over the preceding three weeks. Given the definition of the *COVID-19 Stringency Index* variable, we conservatively assume that the metric is highly correlated with the instrumented *Local Airbnb Demand*, yet is exogenous in our estimation as direct correlation with *Average Weekly Price* is highly unlikely. The instrument validity (i.e., significant correlation with the endogenous *Local Airbnb Demand*) is discussed in Section 5 by the means of proper statistical tests such as the Kleibergen-Paap weak instrument statistic (Kleibergen & Paap, 2006).

Fig. 2 reports the evolution of the average values of the *COVID-19 Stringency Index* and *Local Airbnb Demand* over time. At a glance, Fig. 2 shows a strongly negative correlation between the instrumented and the instrumental variable (the Pearson correlation coefficient between the two variables has been −0.85 since the outbreak of the pandemic). Indeed, as the *COVID-19 Stringency Index* rose following the pandemic outbreak, we note a strong decrease in *Local Airbnb Demand*. When restrictions declined in summer 2020, local demand grew, before reservations in the Airbnb market fell again with tightening restrictions from October to December 2020.

3.2.4. Control variables

Various control variables at different geographical levels are incorporated in our models to account for factors affecting both demand and prices.

Spatial Control Variables: Average Market Price, Number of Competitors. Firstly, given the spatial nature of the data and the likelihood of spatial autocorrelation (Tobler, 1970), we include in the set of control variables the average prices (*Average Market Price*) and the number of competing Airbnb listings (*Number of Competitors*) within the relevant market (i.e., the corresponding radius r as chosen for the definition of demand, tested across different model specifications).

We acknowledge that competition between Airbnb listings can come in different forms and not only because two listings are geographically close (see, e.g., Li, Natessine, & Koulayev, 2018, who study the price competition with hotels in New York City, or Voltes-Dorta & Inchausti-Sintes, 2020, who study the quality dimension of Airbnb markets within the city of Bristol). Additional dimensions of competition could be, for instance, quality or the relative size of a property. However, these time-invariant characteristics are largely controlled for by including individual (i.e., listing-level) fixed effects (see Section 4).

Macroeconomic Control Variables: RGDP, CPI. Secondly, we control for country-level macroeconomic factors, i.e., factors that jointly affect either pricing decisions or short-term rental demand for all Airbnb listings within country g in week t (Gunter et al., 2020). To this end, we include annual country-level real gross domestic product (*RGDP*) and the consumer price index *(CPI*), both in USD and referring to the same base year, 2010, as control variables.[6]

Airbnb Level Controls: Beds, Photos, Host's Properties, Multiplatform, Experience, Cancellation Policy, Instantbook, MidLong Rent. Finally, we control for time-invariant host and property characteristics, which supposedly impact both prices and demand. Specifically, we include among the control variables: i) the number of beds (*Beds*) since larger sized accommodations normally attract higher prices (Sainaghi et al., 2021); ii) the number of photos (*Photos*) proxying the way hosts market their property on the platform (Gunter & Önder, 2018); iii) the managerial competencies of the host, approximated by the number of properties they manage within the sample (*Host's Properties*; Dogru et al., 2020; Li et al., 2016; Xie, Heo, & Mao, 2021); iv) a dummy variable indicating whether the listing is active on multiple platforms such as

[6] These macroeconomic control variables were employed while retaining their original quarterly (*RGDP*) and monthly (*CPI*) frequencies.

Table 3B
First stage regression results: Reduced model with r = 250 m/500 m/750 m/1000 m [Model 2].

	Spec. 1	Spec. 2	Spec. 3	Spec. 4
	r = 250m	**r = 500m**	**r = 750m**	**r = 1000m**
ln COVID-19 Stringency Index (g,t)*$POST_{63}$	−0.133***	−0.146***	−0.154***	−0.155***
	(0.004)	(0.004)	(0.004)	(0.004)
ln Average Market Price (i,r,t)	0.434***	0.615***	0.714***	0.790***
	(0.002)	(0.002)	(0.002)	(0.003)
ln RGDP (g,t)	1.982***	2.085***	2.010***	1.969***
	(0.017)	(0.018)	(0.019)	(0.019)
ln CPI(g,t)	−0.784***	−0.851***	−0.752***	−0.747***
	(0.068)	(0.071)	(0.071)	(0.071)
ln Experience (i,t)	−0.012***	−0.015***	−0.016***	−0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−14.640***	−15.585***	−15.383***	−15.109***
	(0.286)	(0.294)	(0.293)	(0.292)
Time Fixed Effects	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	2,205,346	2,205,346	2,205,346	2,205,346
Robust Standard Errors	Yes	Yes	Yes	Yes
F	13,851.453	19,098.485	21,018.121	22,850.216
R^2 Adjusted	0.975	0.983	0.986	0.988
R^2 Within	0.055	0.076	0.087	0.097
R^2 Within Adjusted	0.055	0.076	0.087	0.097
AIC	−495,716.920	−317,481.635	−263,401.673	−240,072.580
BIC	−495,641.282	−317,405.997	−263,326.035	−239,996.941

Notes: a) Subscripts: i = Property, t = Time (Year-Week), g = Country, 250 m/500 m/750 m/1000 m = Radius r defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Local Airbnb Demand(i,r,t). c) Estimates were generated by the means of Stata 17 (command *reghdfe*). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1.

VRBO (*Multiplatform*; = 1, = 0 otherwise); v) the duration of host's subscription to the Airbnb platform in days (*Experience*; Zhang, Chen, Han, & Yang, 2017); vi) a dummy variable (*Cancellation Policy*) indicating the host's imposition of a strict or moderate cancellation policy (= 1) versus a flexible one (= 0; Tong & Gunter, 2020); vii) a dummy variable (*Instantbook*) for the possibility of instant booking (= 1, = 0 otherwise; Mayya, Ye, Viswanathan, & Agarwal, 2020); and, finally vii) a dummy variables (*MidLong Rent*) for properties only available for medium-to long-term rentals (i.e., more than 30 days = 1, = 0 otherwise; Deboosere et al., 2019).

In order to deal with the seasonal patterns within our data, these time-invariant controls are interacted with seasonal dummy variables in the following two-way fixed-effects models. Here, the seasons of the year correspond to the astronomical seasons of Europe. All continuous control variables are log transformed in the econometric models. Table 2 provides descriptive statistics of all variables employed in the econometric models.

3.2.5. *Additional specification*

Following the main estimations, we provide a post-hoc analysis disentangling differentials in our results according to the typology of the host. In this vein, the variable *Host Type* has been generated to distinguish categories of hosts according to the number of properties managed. The variable takes the value *Private Host* if the number of properties managed by the host is less than or equal to two and the value of *Commercial Host* if the number of properties managed is three or more. Although there is not a common threshold in the literature for distinguishing hosts as either private or commercial, a value of three falls within the range of values commonly used (Deboosere et al., 2019; Dogru et al., 2020; Gunter & Önder, 2018) and therefore reflects the typical Airbnb host typologies found in the literature. In total, 26% of listings within our dataset are managed by commercial hosts and 74% by private hosts. The topic of Airbnb host professionalization has become increasingly important over the past few years in both literature and practice (Chen, Wei, & Xie, 2022).

Other authors have opted for analyzing and contrasting other types of sub-samples, notably different property categories (e.g., Voltes-Dorta & Sánchez-Medina, 2020). In the present dataset, 69.34% of the Airbnb listings belong to the category "entire apartment", while 27.67% belong to the category "private room" and only 0.37% to the category "shared room" (2.62% are "other listing types").

4. Empirical methodology

Given the panel structure of our data, it is necessary to employ adequate panel-estimation techniques (see, e.g., Wooldridge, 2010, for an overview). As we are confronted with i) an endogenous explanatory variable of *Average Weekly Price* ($AWP_{i,t}$), namely *Local Airbnb Demand* ($LAD_{i,t,r}$), ii) the outbreak of the COVID-19 pandemic ($POST_t = 1$ if $t \geq 63$, i.e., the 11th week of 2020, $= 0$ otherwise), and iii) the *COVID-19 Stringency Index* ($CSI_{t,g}$) as a country-level continuous treatment (Callaway et al., 2021), a two-stage least squares (2SLS) approach — specifically, a two-way fixed-effects (TWFE) difference-in-differences (DID) design with continuous group-level (i.e., country-level) treatment — is applied (Callaway et al., 2021; Kandrac, 2020; Wooldridge, 2010). As opposed to the traditional DID design, in our empirical setting all individuals are treated at the same time (by the outbreak of the COVID-19 pandemic) yet with differing treatment intensities (according to the *COVID-19 Stringency Index*).

The econometric model for listing i in week t located in country g and dependent on radius r reads as follows (Kandrac, 2021):

$$\ln LAD_{i,t,r} = \beta \bullet \ln CSI_{t,g} \bullet POST_t + \boldsymbol{\delta} \bullet \boldsymbol{x}_{i,t,g,r} + \theta_t + \eta_i + u_{i,t} \tag{3}$$

$$\ln AWP_{i,t} = \alpha \bullet \ln \widehat{LAD}_{i,t,r} + \boldsymbol{\gamma} \bullet \boldsymbol{x}_{i,t,g,r} + \theta_t + \eta_i + u_{i,t} \tag{4}$$

Eq. (3) represents the first-stage regression of the 2SLS estimation, whereas Eq. (4) represents its second-stage regression and includes the fitted values of *Local Airbnb Demand* ($\widehat{LAD}_{i,t,r}$) obtained from the first-stage regression. $\boldsymbol{x}_{i,t,g,r}$ denotes a vector of spatial, macroeconomic, and listing-level control variables (see Section 3.2 for more details), including a constant term. θ_t represents the time fixed effects, η_i the individual fixed effects, and $u_{i,t}$ the idiosyncratic error terms.

Two different specifications of the econometric models, one including the time-invariant control variables (interacted with seasonal dummies to deal with the individual fixed effects) and one omitting

Table 4A
Second stage regression results: Full model with r = 500 m [Model 1].

	r = 500 m	
	Spec. 2 end	**Spec. 2 ex**
	OLS	**2SLS**
ln Local Airbnb Demand (i,g,500 m,t)	0.162***	0.123***
	(0.001)	(0.016)
ln Average Market Price (i,500 m,t)	0.681***	0.706***
	(0.002)	(0.010)
ln Number of Competitors (i,500 m)*Season (t)	Yes	Yes
ln RGDP (g,t)	0.119***	0.232***
	(0.011)	(0.035)
ln CPI(g,t)	0.198***	0.000
	(0.041)	(.)
ln Beds(i)*Season(t)	Yes	Yes
ln Photos(i)*Season(t)	Yes	Yes
ln Host's Properties(i)*Season(t)	Yes	Yes
Multiplatform(i)*Season(t)	Yes	Yes
ln Experience (i,t)	Yes	Yes
Cancellation Policy(i)*Season(t)	Yes	Yes
Instantbook(i)*Season(t)	Yes	Yes
MidLong Rent(i)*Season(t)	Yes	Yes
Constant	−0.966***	
	(0.172)	
Time Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes
Number of Observations	2,205,347	2,205,347
Robust Standard Errors	Yes	Yes
F	9578.177	6655.549
R^2 Adjusted	0.938	0.209
R^2 Within	0.242	
R^2 Within Adjusted	0.242	
R^2 Uncentered		0.239
AIC	−2,111,471.237	−2,103,789.793
BIC	−2,111,042.619	−2,103,386.388
Kleibergen-Paap Underid. Test (rk LM)		1272.740
Kleibergen-Paap Weak Id. Test (Wald F)		1235.318
Cragg-Donald Weak Id. Test (Wald F)		2924.894

Notes: a) Subscripts: i = Property, t = Time (Year-Week), g = Country, 500 m = Radius r defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Average Weekly Price(i,t). c) Estimates were generated by the means of Stata 17 (command *ivreghdfe* for 2SLS estimations and command *reghdfe* for OLS estimations). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1. e) end = Endogenous, ex = Exogenous (i.e., 2SLS approach). f) The reference baseline of time-invariant variables interacted with Season(t) is autumn. g) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects. h) Coefficients of the full model have been excluded due to space constraints, yet are available from the authors upon request.

these variables, are proposed as main estimation results. The majority of the models presented are estimated without including these controls because of the associated computational burden, and because we can conservatively assume that their effect is already included in the individual fixed effect and their seasonal variation does not significantly affect the elasticity of price to demand.

As reported in Section 3.2, all variables except for the dummy variables are transformed to natural logarithms to make effect sizes interpretable as scale-free elasticities.[7] As can be seen from Fig. 3, the necessary parallel trends assumption (Callaway et al., 2021) can be considered fulfilled: the outbreak of the COVID-19 pandemic represented a natural (quasi) experiment, an exogenous event that could not be anticipated and that had a common impact across European countries, which, however, has been treated at different and varying intensities. The employed standard errors are robust and clustered at the listing level. In addition to the 2SLS results, we also present cluster-robust OLS results to showcase the misjudgment of effect sizes if one fails to treat *Local Airbnb Demand* as endogenous (see Section 5.2 for the main estimation results). All estimations are performed in Stata Version 17, while employing the 'ivreghdfe' wrapper (Correia, 2018) for the 2SLS estimations and the 'reghdfe' wrapper (Correia, 2015) for the OLS estimations in order to deal with the large dimensionality of the fixed effects.

In the following, the econometric model given by Eqs. (3) and (4) is applied to various sub-samples of the panel dataset depending on the variable *Host Type*, which complement the analysis (see Section 5.3). To confirm the validity of the results regardless the operationalization of the main variables, three different robustness checks are tested (see Section 5.4). First, in the DID setting, multiple definitions of the timing of the pandemic outbreak are used (see the variable $POST_t$). Second, since no clear definitions exists in the extant literature for either the moving average period applied to demand or for the threshold distinguishing private and commercial hosts, further robustness checks vary the operationalization of these two variables.

5. Results

5.1. First stage results: the impact of rising restrictions on Local Airbnb Demand

Given the mounting interest in the impact of COVID-19 response policies, Table 3 shows the estimates of the first stage equation, estimating *Local Airbnb Demand* by means of the COVID-19 Stringency Index (i.e., the interaction term between the continuous treatment *COVID-19 Stringency Index* and the $POST_t$ dummy equals to one if $t \geq 63$). Two models are proposed: Model 1 (in Table 3A) includes all time-invariant control variables (interacted with the season-of-year categorical variable) and tests Eq. (3) over one specification (namely: Spec. 2: r = 500 m)[8]; Model 2 (in Table 3B) does not consider time-invariant characteristics (postulating that their effect is already accounted by the individual fixed effects and does not significantly vary over seasons), but tests Eq. (3) over four specifications (namely: Spec. 1: r = 250 m, Spec. 2: r = 500 m, Spec. 3: r = 750 m, Spec. 4: r = 1000 m). Given that both models provide comparable results as well as similar goodness-of-fit measures (i.e., the Adjusted R^2 is comparable), thereby confirming the assumption that time-invariant property-level characteristics are effectively captured by the individual fixed effects, the subsequent discussion focuses on Model 2, which analyzes the impact of restrictions on *Local Airbnb Demand* over different specifications of r.

Specifications 1 to 4 of Model 2 (Table 3B) show that, ceteris paribus, a one percent increase in the *COVID-19 Stringency Index* after the pandemic outbreak is associated with a decrease in *Local Airbnb Demand* varying from a −0.133 to −0.155 percent (all coefficients significant at 99.9% confidence level), with effects becoming larger as the radius defining *Local Airbnb Demand* increases. Interestingly, the performance of the models according either to the R^2 measures or the information criteria (Akaike's Information Criterion, AIC; and Bayesian Information Criterion, BIC; Lütkepohl, 2005) improve as the radius increases, confirming better model performance as the dimension of the relevant market gets closer to the group-treatment dimension. Most control variables included in the models show the ex-ante expected signs: increases in average prices of neighboring listings showing a positive impact in *Local Airbnb Demand* of listing i (a one percent increase in the variable *Average Market Price* is associated with a 0.43 to 0.79 percent increase in *Local Airbnb Demand*), positive variations in country-level *RGDP* are associated with positive variations in *Local Airbnb Demand* (1.97 to 2.09 elasticities), while increases in country-level *CPI* are

[7] To be precise, the transformation $\ln(1+x)$ was performed for all non-binary variables x.

[8] Table 3A shows only the relevant coefficients because of space constraints. The full regression output is available from the authors upon request.

Table 4B
Second stage regression results: Reduced model with r = 250 m/500 m/750 m/1000 m [Model 2].

	r = 250 m		r = 500 m		r = 750 m		r = 1000 m	
	Spec. 1 end	**Spec. 1 ex**	**Spec. 2 end**	**Spec. 2 ex**	**Spec. 3 end**	**Spec. 3 ex**	**Spec. 4 end**	**Spec. 4 ex**
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
ln Local Airbnb Demand (i, g,r,t)	0.165***	0.075***	0.164***	0.072***	0.163***	0.071***	0.162***	0.057***
	(0.001)	(0.018)	(0.001)	(0.016)	(0.001)	(0.015)	(0.001)	(0.015)
ln Average Market Price (i,500 m,t)	0.639***	0.678***	0.697***	0.753***	0.726***	0.792***	0.742***	0.825***
	(0.002)	(0.008)	(0.002)	(0.010)	(0.002)	(0.011)	(0.002)	(0.012)
ln RGDP (g,t)	0.211***	0.417***	0.152***	0.378***	0.129***	0.351***	0.128***	0.370***
	(0.011)	(0.037)	(0.011)	(0.036)	(0.011)	(0.033)	(0.011)	(0.032)
ln CPI(g,t)	0.161***	0.000	0.198***	0.000	0.209***	0.000	0.186***	0.000
	(0.042)	(.)	(0.041)	(.)	(0.041)	(.)	(0.041)	(.)
ln Experience (i,t)	0.003***	0.002*	0.004***	0.003***	0.005***	0.003***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−1.164***		−1.306***		−1.416***		−1.486***	
	(0.173)		(0.172)		(0.171)		(0.170)	
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	48,815.521	37,369.489	55,072.584	42,063.993	57,398.353	43,128.609	58,561.251	43,590.402
R^2	0.938	0.207	0.939	0.221	0.940	0.227	0.940	0.224
R^2 Adjusted	0.936	0.176	0.937	0.190	0.938	0.196	0.938	0.194
R^2 Within	0.220		0.235		0.242		0.244	
R^2 Within Adjusted	0.220		0.235		0.242		0.244	
R^2 Uncentered		0.207		0.221		0.227		0.224
AIC	−2048768.489	−2012682.668	−2092268.882	−2050714.823	−2110696.575	−2067716.937	−2117352.492	−2061060.688
BIC	−2048692.850	−2012632.243	−2092193.244	−2050664.397	−2110620.937	−2067666.511	−2117276.854	−2061010.262
Kleibergen-Paap Underid. Test (rk LM)		1175.762		1273.064		1450.041		1483.185
Kleibergen-Paap Weak Id. Test (Wald F)		1134.378		1232.496		1412.884		1448.173
Cragg-Donald Weak Id. Test (Wald F)		2584.863		2851.966		3179.501		3203.762

Notes: a) Subscripts: i = Property, t = Time (Year-Week), g = Country, 250m/500m/750m/1000 m = Radius r defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Average Weekly Price(i,t). c) Estimates were generated by the means of Stata 17 (command *ivreghdfe* for 2SLS estimations and command *reghdfe* for OLS estimations). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1. e) end = Endogenous, ex = Exogenous (i.e., 2SLS approach). f) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

associated with a negative impact on *Local Airbnb Demand* (−0.75 to −0.85 elasticities), as are increases in the duration of a host's subscription (*Experience*) to the platform (albeit with very low marginal impacts). All coefficients are significant at the 99.9% confidence level.

These results generally corroborate some core findings of earlier research on Airbnb accommodation in New York City prior to the pandemic (Gunter et al., 2020): neighboring Airbnb listings are substitutes for listing *i* (positive elasticities with respect to *Average Market Price*), and Airbnb accommodation is an ordinary good (negative elasticities with respect to *CPI*), as well as a normal and luxury good (positive elasticities > 1 with respect to *RGDP*; Mas-Colell et al., 1995). However, the negative impact of *Experience* on *Local Airbnb Demand* (−0.012 to −0.016 elasticities) needs some further elaboration. These estimates need to be interpreted jointly with the positive impact of *Experience* on *Average Weekly Price* (Table 4B): a comparably longer duration of subscription allows a host to charge higher prices, therefore needing less demand to reach the same revenue.

5.2. Second stage results: the pricing of Airbnb in response to local demand variations

Table 4 reports the second stage estimation results, estimating the causal impact of *Local Airbnb Demand* variations on *Average Weekly Price*. As with the first stage estimations, two models are proposed: a fixed effects model including time-invariant characteristics interacted with seasonal categorical variables (Model 1) and a fixed effects model assuming that time-invariant characteristics are effectively absorbed by the individual fixed effects with their impact not varying over time. For the sake of comparison, both the OLS (labelled *end* in Table 4) and the 2SLS estimation results (labelled *ex* in Table 4) are presented for each model, showing that OLS fails by systematically biasing coefficient estimates upward (e.g., in Spec. 1 *end*, the coefficient depicting the elasticity of the dependent variable to variations of *Local Airbnb Demand* is 0.165, while in Spec. 1 *ex*, which adopts the 2SLS approach, this coefficient is 0.075) and demonstrating the need for a method that properly deals with the endogeneity of the explanatory variable, *Local Airbnb Demand*.

For 2SLS estimation, various instrumental variable diagnostic statistics are provided, such as the Kleibergen-Paap Underidentification Test, the Kleibergen-Paap Weak Identification Test (Kleibergen & Paap, 2006), and the Cragg-Donald Weak Identification Test (Cragg & Donald, 1993). These statistical tests confirm the validity of our instrumental variable across all models, for instance by very high values on the Kleibergen-Paap Underidentification Test of 1272.7 in Model 1 and varying from 1175.7 to 1483.2 across the various specifications of Model 2.[9] As per the discussion of the first stage estimation results, the inclusion of time-invariant characteristics does not significantly increase goodness-of-fit measures, so only Model 2 (presented in Table 4B) results are discussed in the following.

Table 4 provides novel insights into the determinants of Airbnb prices by specifying the causal relationship between demand and pricing. Indeed, the estimates show a positive relationship between demand

[9] The Kleibergen-Paap Weak Identification Test and the Cragg-Donald Weak Identification Test also confirm the validity of our instrumental variable. Moreover, the comparison of the Kleibergen-Paap statistic with the Stock and Yogo (2005) critical values is successfully fulfilled.

Table 5
Second stage regression results: Comparing *Commercial Hosts* and *Private Hosts*.

	r = 250 m				r = 500 m				r = 750 m				r = 1000 m			
	S1 end	**S1 end**	**S1 ex**	**S1 ex**	**S2 end**	**S2 end**	**S2 ex**	**S2 ex**	**S3 end**	**S3 end**	**S3 ex**	**S3 ex**	**S4 end**	**S4 end**	**S4 ex**	**S4 ex**
	PR	**CH**	**PR**	**CH**	**PR**	**CH**	**PR**	**CH**	**PR**	**CH**	**PR**	**CH**	**PR**	**CH**	**PR**	**CH**
ln Local Airbnb Demand (i,r,t,f)	0.174***	0.125***	−0.011	0.264***	0.172***	0.128***	0.001	0.213***	0.170***	0.133***	0.015	0.192***	0.168***	0.136***	0.006	0.170***
	(0.001)	(0.001)	(0.021)	(0.039)	(0.001)	(0.001)	(0.019)	(0.035)	(0.001)	(0.001)	(0.017)	(0.038)	(0.001)	(0.001)	(0.016)	(0.039)
ln Average Market Price (i,r,t)	0.512***	0.893***	0.592***	0.830***	0.570***	0.984***	0.674***	0.929***	0.604***	1.016***	0.713***	0.972***	0.622***	1.031***	0.749***	1.004***
	(0.002)	(0.003)	(0.009)	(0.018)	(0.002)	(0.003)	(0.012)	(0.023)	(0.002)	(0.004)	(0.012)	(0.028)	(0.002)	(0.004)	(0.013)	(0.032)
ln RGDP (g,t)	0.146***	0.407***	0.519***	0.200*	0.096***	0.346***	0.465***	0.208**	0.081***	0.277***	0.413***	0.205**	0.081***	0.268***	0.419***	0.241**
	(0.012)	(0.026)	(0.041)	(0.079)	(0.012)	(0.027)	(0.040)	(0.076)	(0.012)	(0.028)	(0.035)	(0.078)	(0.012)	(0.028)	(0.034)	(0.078)
ln CPI(g,t)	0.062	0.275***	0.000	0.000	0.120*	0.175*	0.000	0.000	0.137**	0.209*	0.000	0.000	0.121**	0.171*	0.000	0.000
	(0.048)	(0.080)	(.)	(.)	(0.048)	(0.082)	(.)	(.)	(0.047)	(0.083)	(.)	(.)	(0.047)	(0.083)	(.)	(.)
ln Experience (i,t)	0.002*	0.005***	−0.000	0.007***	0.003***	0.006***	0.001	0.007***	0.004***	0.005***	0.002*	0.006***	0.005***	0.007***	0.002**	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Constant	0.548**	−5.257***			0.241	−4.809***			0.002	−4.529***			−0.112	−4.421***		
	(0.205)	(0.308)			(0.202)	(0.308)			(0.200)	(0.308)			(0.199)	(0.310)		
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161	1,629,176	576,161
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	28,412	22,448	17,323	23,024	33,257	26,259	20,388	27,866	35,542	25,311	21,998	26,590	36,946	24,316	22,810	25,416
R^2	0.940	0.934	0.114	0.312	0.942	0.934	0.142	0.319	0.943	0.933	0.162	0.317	0.943	0.932	0.162	0.313
R^2 Adjusted	0.938	0.932	0.078	0.285	0.940	0.931	0.108	0.292	0.941	0.930	0.128	0.290	0.941	0.930	0.129	0.286
R^2 Within	0.174	0.335			0.199	0.328			0.210	0.321			0.215	0.315		
R^2 Within Adjusted	0.174	0.335			0.199	0.328			0.210	0.321			0.215	0.315		
R^2 Uncentered			0.114	0.312			0.142	0.319			0.162	0.317			0.162	0.313
AIC	−1,606,163	−487,110	−1,491,962	−467,504	−1,656,418	−480,890	−1,544,725	−473,400	−1,679,231	−474,961.634	−1,582,322	−471,443	−1,690,579	−469,608	−1,583,708	−468,458
BIC	−1,606,089	−487,042	−1,491,913	−467,459	−1,656,344	−480,823	−1,544,676	−473,354	−1,679,158	−474,894.050	−1,582,272	−471,398	−1,690,505	−469,541	−1,583,659	−468,412
Kleibergen-Paap Underid. Test (rk LM)			938.847	289.285			942.928	373.219			1156.347	338.366			1209.086	327.977
Kleibergen-Paap Weak Id. Test (Wald F)			900.491	285.807			907.095	373.450			1120.382	339.877			1172.056	331.745
Cragg-Donald Weak Id. Test (Wald F)			1950.059	711.563			2053.014	891.359			2463.082	796.561			2532.367	763.370

Notes: a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250 m/500 m/750 m/1000 m = Radius *r* defining the relevant market. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Average Weekly Price(i,t). c) Estimates were generated by the means of Stata 17 (command *ivreghdfe* for 2SLS estimations and command *reghdfe* for OLS estimations). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1. e) end = Endogenous, ex = Exogenous (i.e., 2SLS approach). f) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

Table 6A
First stage results according to different specifications of $POST_t$

	RC1 - Spec 1	RC1 - Spec 1	RC1 - Spec 1	RC1 - Spec 2	RC1 - Spec 2	RC1 - Spec 2	RC1 - Spec 3	RC1 - Spec 3	RC1 - Spec 3	RC1 - Spec 4	RC1 - Spec 4	RC1 - Spec 4
	s = 64	**s = 65**	**s = 62**	**s = 64**	**s = 65**	**s = 62**	**s = 64**	**s = 65**	**s = 62**	**s = 64**	**s = 65**	**s = 62**
	r = 250m	**r = 250m**	**r = 250m**	**r = 500m**	**r = 500m**	**r = 500m**	**r = 750m**	**r = 750m**	**r = 750m**	**r = 1000m**	**r = 1000m**	**r = 1000m**
ln COVID-19 Stringency Index (g,t) *POST*s*	−0.146*** (0.004)	−0.139*** (0.004)	−0.105*** (0.003)	−0.156*** (0.005)	−0.144*** (0.005)	−0.116*** (0.003)	−0.163*** (0.005)	−0.150*** (0.005)	−0.124*** (0.003)	−0.163*** (0.005)	−0.149*** (0.005)	−0.125*** (0.003)
ln Average Market Price (i,r,t)	0.434*** (0.002)	0.434*** (0.002)	0.434*** (0.002)	0.615*** (0.002)	0.615*** (0.002)	0.614*** (0.002)	0.714*** (0.002)	0.714*** (0.002)	0.713*** (0.002)	0.790*** (0.003)	0.790*** (0.003)	0.790*** (0.003)
ln RGDP (g,t)	1.981*** (0.017)	1.989*** (0.017)	1.992*** (0.017)	2.086*** (0.018)	2.096*** (0.018)	2.096*** (0.018)	2.011*** (0.019)	2.023*** (0.019)	2.020*** (0.019)	1.972*** (0.019)	1.983*** (0.019)	1.980*** (0.019)
ln CPI(g,t)	−0.812*** (0.068)	−0.777*** (0.069)	−0.702*** (0.068)	−0.869*** (0.071)	−0.816*** (0.071)	−0.765*** (0.070)	−0.764*** (0.072)	−0.703*** (0.072)	−0.665*** (0.071)	−0.753*** (0.071)	−0.690*** (0.072)	−0.662*** (0.071)
ln Experience (i, t)	−0.012*** (0.001)	−0.012*** (0.001)	−0.012*** (0.001)	−0.015*** (0.001)	−0.015*** (0.001)	−0.015*** (0.001)	−0.016*** (0.001)	−0.016*** (0.001)	−0.016*** (0.001)	−0.016*** (0.001)	−0.016*** (0.001)	−0.016*** (0.001)
Constant	−14.491*** (0.288)	−14.746*** (0.288)	−15.154*** (0.283)	−15.499*** (0.296)	−15.867*** (0.297)	−16.122*** (0.291)	−15.337*** (0.296)	−15.753*** (0.296)	−15.927*** (0.290)	−15.099*** (0.295)	−15.528*** (0.295)	−15.638*** (0.288)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347	2,205,347
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	13,826.193	13,810.738	13,874.499	19,070.348	19,052.112	19,121.626	20,975.528	20,944.779	21,049.927	22,805.766	22,774.429	22,883.483
R^2	0.976	0.976	0.976	0.984	0.984	0.984	0.987	0.987	0.987	0.988	0.988	0.988
R^2 Adjusted	0.975	0.975	0.975	0.983	0.983	0.983	0.986	0.986	0.986	0.988	0.988	0.988
R^2 Within	0.054	0.054	0.054	0.076	0.076	0.076	0.087	0.087	0.087	0.097	0.096	0.097
R^2 Within Adjusted	0.054	0.054	0.054	0.076	0.076	0.076	0.087	0.087	0.087	0.097	0.096	0.097
AIC	−495,620.745	−495,138.061	−495,350.404	−317,254.354	−316,610.784	−317,121.671	−263,079.948	−262,351.065	−263,054.024	−239,690.378	−238,951.197	−239,759.774
BIC	−495,545.106	−495,062.423	−495,274.766	−317,178.716	−316,535.145	−317,046.033	−263,004.310	−262,275.426	−262,978.385	−239,614.739	−238,875.558	−239,684.135

Notes: a) Subscripts: i = Property, t = Time (Year-Week), g = Country, 250 m/500 m/750 m/1000 m = radius r defining the relevant market, s = definition of $POST_s$. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Local Airbnb Demand(i,r,t,f). c) Estimates were generated by the means of Stata 17 (command *reghdfe*). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1.

Table 6B
Second stage results (2SLS regressions) according to different specifications of $POST_t$

	RC1 - Spec 1.1	RC1 - Spec 1.2	RC1 - Spec 1.3	RC1 - Spec 2.1	RC1 - Spec 2.2	RC1 - Spec 2.3	RC1 - Spec 3.1	RC1 - Spec 3.2	RC1 - Spec 3.3	RC1 - Spec 4.1	RC1 - Spec 4.2	RC1 - Spec 4.3
	s = 64	**s = 65**	**s = 62**	**s = 64**	**s = 65**	**s = 62**	**s = 64**	**s = 65**	**s = 62**	**s = 64**	**s = 65**	**s = 62**
	r = 250m	**r = 250m**	**r = 250m**	**r = 500m**	**r = 500m**	**r = 500m**	**r = 750m**	**r = 750m**	**r = 750m**	**r = 1000m**	**r = 1000m**	**r = 1000m**
ln Local Airbnb Demand (i,r,t)	0.090*** (0.018)	0.128*** (0.019)	0.073*** (0.019)	0.089*** (0.017)	0.129*** (0.018)	0.065*** (0.017)	0.086*** (0.016)	0.123*** (0.017)	0.065*** (0.016)	0.071*** (0.016)	0.105*** (0.017)	0.054*** (0.015)
ln Average Market Price (i,r,t)	0.671*** (0.008)	0.655*** (0.008)	0.679*** (0.008)	0.743*** (0.010)	0.719*** (0.011)	0.758*** (0.010)	0.781*** (0.011)	0.755*** (0.012)	0.796*** (0.011)	0.814*** (0.013)	0.787*** (0.014)	0.827*** (0.012)
ln RGDP (g,t)	0.387*** (0.037)	0.310*** (0.039)	0.420*** (0.038)	0.342*** (0.036)	0.258*** (0.039)	0.394*** (0.036)	0.320*** (0.033)	0.245*** (0.036)	0.364*** (0.033)	0.343*** (0.033)	0.272*** (0.036)	0.377*** (0.032)
ln CPI(g,t)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
ln Experience (i, t)	0.002** (0.001)	0.003** (0.001)	0.002* (0.001)	0.003*** (0.001)	0.004*** (0.001)	0.003*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.003*** (0.001)	0.004*** (0.001)	0.005*** (0.001)	0.004*** (0.001)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346	2,205,346
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	37,688.752	38,430.442	37,328.027	42,582.125	43,722.652	41,819.907	43,685.359	44,951.161	42,905.109	44,130.524	45,472.621	43,434.542
R^2 Adjusted	0.180	0.187	0.175	0.195	0.203	0.187	0.201	0.208	0.194	0.198	0.208	0.192
R^2 Uncentered	0.211	0.218	0.207	0.225	0.233	0.218	0.231	0.239	0.225	0.229	0.238	0.223
AIC	−2,023,566.852	−2,042,626.884	−2,011,415.303	−2,064,382.256	−2,085,980.456	−2,043,612.082	−2,080,564.492	−2,102,198.174	−2,062,099.418	−2,074,260.615	−2,100,446.529	−2,057,075.443
BIC	−2,023,516.426	−2,042,576.458	−2,011,364.878	−2,064,331.830	−2,085,930.030	−2,043,561.656	−2,080,514.066	−2,102,147.749	−2,062,048.992	−2,074,210.190	−2,100,396.104	−2,057,025.018
Kleibergen-Paap Underid. Test (rk LM)	1082.248	933.598	1193.196	1113.966	900.740	1323.847	1229.208	971.401	1545.349	1229.900	961.274	1611.162
Kleibergen-Paap Weak Id. Test (Wald F)	1030.080	873.237	1138.332	1060.824	840.859	1259.987	1172.391	906.258	1480.411	1173.351	896.859	1543.961
Cragg-Donald Weak Id. Test (Wald F)	2476.075	2034.140	2279.317	2623.212	2036.993	2554.966	2864.371	2194.635	2887.851	2833.554	2154.186	2943.777

Notes: a) Subscripts: i = Property, t = Time (Year-Week), g = Country, 250 m/500 m/750 m/1000 m = radius r defining the relevant market, s = definition of $POST_s$. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Average Weekly Price(i,t). c) Estimates were generated by the means of Stata 17 (command *ivreghdfe*). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1. e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

and prices, meaning that Airbnb listings facing increasing demand are prone to raise their prices (i.e., all coefficients of the regressor *Local Airbnb Demand* are positive and statistically significant, ranging from 0.057 to 0.075 for 2SLS estimation and from 0.162 to 0.165 for standard OLS estimation). This result is in line with theoretical expectations. Further, in a market where the offer is constrained or decreasing and demand tends to increase, we expect increases in general price levels according to standard microeconomic theory. This theoretical expectation is also confirmed in the sample, whose time interval spans the pre-to post-pandemic period, when tourism supply not only failed to increase but even decreased. The coefficients in Table 4 show the elasticity of prices in response to demand variations, indicating that a one percent increase in *Local Airbnb Demand* might result in prices rising by 0.06 to 0.07 percent (all significant at the 99.9% confidence level). In line with expectations, the magnitude of the coefficient decreases as the radius defining the relevant market increases, being at its maximum if r is equal to 250 m and at its minimum if r is equal to 1000 m. This suggests a higher tendency to increase prices among hosts facing increases in demand for their specific neighborhood (i.e., maybe due to local events) than for hosts facing a general increase in demand over a broader area. Furthermore, in line with Table 3, the models' goodness-of-fit measures improve as the radius defining the relevant market gets closer to the treatment dimension (i.e., country level).

The other control variables behave as theoretically expected, since i) *Average Weekly Price* is spatially autocorrelated with the prices of neighboring listings (with elasticities varying from 0.68 to 0.83, all significant at the 99% confidence level), ii) *RGDP* positively impact prices (with elasticities varying from 0.37 to 0.42, all significant at the 99.9% confidence level), iii) *CPI* is positively correlated with prices (with elasticities varying from 0.16 to 0.21, all significant at the 99% confidence level),[10] and iv) duration of the subscription (*Experience*) is positively associated with higher prices (still with very low marginal effects).

5.3. Additional evidence: differences in pricing between commercial and private hosts

To determine differentials in price to demand elasticities according to the hosts' professionality status, Eq. (4) is estimated separately for two sub-samples — properties managed by *Private Hosts* (i.e., owning 1 to 2 properties) and properties managed by *Commercial Hosts* (i.e., owning 3 or more properties) — according to the various specifications of Model 2 (testing the elasticity across different radii while omitting the time-invariant characteristics interacted with seasonal dummies). As in Table 4, both the endogenous and the exogenous (2SLS) specifications are presented for each estimate in Table 5. The instrumental variables provided in Table 5 confirm that the instrument is valid, despite achieving lower Kleibergen-Paap Underidentification Test values than the main model (values vary between 938.8 and 1209.1 for the private host sub-sample and from 289.3 to 373.2 for the commercial host sub-sample). As in Section 5.2, the 2SLS model results are discussed in the following.

According to Table 5, commercial hosts vary prices substantially according to demand variations. Indeed, per one percent increase in *Local Airbnb Demand*, the model predicts a 0.170 to 0.264 percent increase in *Average Weekly Price* (all coefficients significant at the 99.9% confidence level). In contrast, the pricing response of private hosts are less pronounced, with the coefficients not being statistically significant. It is worth noting that the global model's (i.e., the model including private and commercial hosts together) predicted pricing response (i.e., the coefficient of *Local Airbnb Demand* in Table 4) lies in the interval of the private/commercial hosts' pricing response coefficients, confirming the validity of the proposed model.

This result contributes a novel finding to the flourishing research stream on Airbnb supply side professionalization (Dogru et al., 2020). Building on the widespread acknowledgement that professional hosts have significantly better performance (measured according to monthly revenues or RevPAR; see Deboosere et al., 2019, or Sainaghi et al., 2021, who provide an exhaustive literature review), the present analysis shows that such differences are based on differentials in pricing efficiency, thereby complementing the pioneering results of Li et al. (2016) or the more recent literature on "dynamic pricing" for Airbnb (Abrate, Sainaghi, & Mauri, 2022; Kwok & Xie, 2019). On the one hand, the model predicts a causal relationship between demand variations and prices for commercial hosts, suggesting that those hosts are able to recognize trends in demand and consequently adjust their prices. On the other hand, we show that the major pricing components of private hosts are captured by the fixed effects (individual or time fixed effects) or by macroeconomic conditions common to the whole industry.

We interpret these results as a consequence of differing managerial skill levels between the two types of hosts (Abrate et al., 2022). Private hosts, who are generally "regular people", may be unable to benefit from the use of advanced tools (Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018), or only benefit from the tools provided by the platform. Consequently, they tend not to change prices, or even to decrease them (when adopting price-cutting strategies), and fail to exploit the opportunities presented by increasing demand in a capacity-constrained market. Another plausible explanation is that private hosts base their pricing on hedonic-based models rather than adopting a market-based perspective, which would require economic knowledge and time to be effective.

5.4. Robustness checks

This section provides further analysis aimed at corroborating the results according to multiple alternative specifications of the main variables: i.e., the time of the pandemic outbreak, the length of the time-interval defining the moving average of *Local Airbnb Demand*, as well as the threshold distinguishing between private and commercial hosts. In short, all results reported in the previous sections are robust to different variable operationalization and all regression goodness-of-fit metrics, as well as instrumental variable diagnostics, fully confirm the validity of our 2SLS approach.

First, given that the pandemic erupted at different points in time in different European countries in terms of both rising COVID-19 cases and the imposition of restrictions, further robustness checks relax the assumption that global pandemic effects started in the 11th week of 2020 (i.e., the variable $POST_t = 1$ if $t \geq 63$, $= 0$ otherwise) by employing alternative definitions of the $POST_t$ variable. Both the first stage and second stage (2SLS) models are tested by defining $POST_s = 1$ if $t \geq s$, with $s = 62, 64, 65$ (respectively, the 10th, 12th, and 13th weeks of 2020). Results of first stage models are reported in Table 6A, while Table 6B shows second stage results. The results of both first and second stage models fully confirm the results reported in Sections 5.1. and 5.2. Concerning the first stage, the tendency to find higher average elasticities of demand compared to the *COVID-19 Stringency Index* as r increases is confirmed. Interestingly, and in line with theoretical expectations, the average impact of the *COVID-19 Stringency Index* on *Local Airbnb Demand* is higher when interacted with a postulated earlier start of the pandemic (e.g., $s = 62$, compared to $s = 65$).

Second, given that the literature provides no clear evidence defining the past and future planning horizons of hosts, multiple definitions of the parameter f in the definition of the variables *Local Airbnb Demand* and *COVID-19 Stringency Index* are tested. Table 7 shows the results for both first and second stage models, which strongly confirm the main estimates shown in Tables 3 and 4 On the one hand, the first stage model confirms the negative and strongly significant impact of rising governmental restrictions on *Local Airbnb Demand*. On the other hand, second

[10] The estimator *ivreghdfe* employed in the analyses has partialled out the variable *CPI* because it is collinear with the fixed effects included in the models; thus, the estimated coefficients refer to the OLS estimation.

Table 7A
First stage results according to different specifications of f in *Local Airbnb Demand* (i,r,t,f).

	RC2 - Spec 1.1	RC2 - Spec 1.2	RC2 - Spec 2.1	RC2 - Spec 2.2	RC2 - Spec 3.1	RC2 - Spec 3.2	RC2 - Spec 4.1	RC2 - Spec 4.2
	f = 2	**f = 4**	**s = 62**	**s = 64**	**s = 65**	**s = 62**	**s = 64**	**s = 64**
	r = 250m	**r = 250m**	**r = 500m**	**r = 500m**	**r = 750m**	**r = 750m**	**r = 1000m**	**r = 1000m**
ln COVID-19 Stringency Index (g, t,f)$POST_{63}$	−0.094***	−0.147***	−0.104***	−0.163***	−0.108***	−0.173***	−0.107***	−0.178***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln Average Market Price (i,r,t)	0.400***	0.473***	0.566***	0.672***	0.659***	0.783***	0.727***	0.868***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
ln RGDP (g,t)	2.035***	1.946***	2.146***	2.049***	2.070***	1.977***	2.025***	1.938***
	(0.018)	(0.017)	(0.019)	(0.018)	(0.020)	(0.018)	(0.020)	(0.018)
ln CPI(g,t)	−0.413***	−1.013***	−0.485***	−1.071***	−0.349***	−0.967***	−0.312***	−0.948***
	(0.070)	(0.066)	(0.073)	(0.068)	(0.074)	(0.068)	(0.074)	(0.068)
ln Experience (i,t)	−0.010***	−0.015***	−0.012***	−0.018***	−0.013***	−0.020***	−0.013***	−0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−16.820***	−13.355***	−17.743***	−14.428***	−17.671***	−14.358***	−17.208***	−14.209***
	(0.295)	(0.275)	(0.303)	(0.282)	(0.302)	(0.281)	(0.302)	(0.279)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,877,764	2,649,779	1,877,764	2,649,779	1,877,764	2,649,779	1,877,764	2,649,779
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	12,229.223	15,446.303	16,554.234	21,889.914	18,161.973	24,541.938	19,282.446	27,123.435
R^2	0.981	0.967	0.987	0.979	0.989	0.982	0.990	0.984
R^2 Adjusted	0.980	0.966	0.987	0.978	0.989	0.982	0.990	0.984
R^2 Within	0.058	0.049	0.079	0.072	0.090	0.084	0.096	0.094
R^2 Within Adjusted	0.058	0.049	0.079	0.072	0.089	0.084	0.096	0.094
AIC	−834,699.448	152,767.359	−664,442.995	328,615.322	−610,785.487	378,868.711	−549,815.145	398,162.182
BIC	−834,624.775	152,844.099	−664,368.322	328,692.062	−610,710.814	378,945.451	−549,740.471	398,238.921

Notes: a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250 m/500 m/750 m/1000 m = radius *r* defining the relevant market, *f* = definition of Demand Moving Average filter. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Local Airbnb Demand (i,r,t, f). c) Estimates were generated by the means of Stata 17 (command *reghdfe*). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1.

stage results confirm a positive relationship between rising demand and *Average Weekly Price* (although its statistical significance is lower).

Third, recognizing that multiple definitions of private and commercial hosts have been proposed and tested by scholars in the Airbnb literature, two additional models vary the distinguishing property count threshold. The new models are tested using a threshold of 2 (i.e., *Private Host* = manages one property, otherwise *Commercial Host*) and 4 (i.e., *Private Host* = manages up to three properties, otherwise *Commercial Host*). Table 8 shows the second stage regression results using the 2SLS approach, presenting private hosts in Table 8A and commercial hosts in Table 8B. Beyond confirming the results shown in Section 5.3., this robustness check provides interesting insights into the validity of our results. Table 8B shows that the average demand elasticity of price increases strongly as the threshold increases, thus amplifying the difference between private and commercial hosts.

6. Discussion and conclusions

This paper provides several results that are of interest from the perspective of multiple research streams, from which both theoretical and managerial implications can be derived. Its limitations are also addressed and areas for future research are highlighted in the following sections.

This paper supports the growing literature on the estimation of the impact of the COVID-19 pandemic on tourism-related services demand by providing an empirical analysis of the relationship between governmental response policies (efficiently tracked by the *COVID-19 Stringency Index*) and the *Local Airbnb Demand* faced by hosts on the platform, complementing a previous analysis by Hu and Lee (2020), who empirically determined the impact of rising COVID-19 cases on Airbnb reservations. The estimate, beyond shedding light on the impact of national closures on short-term rental demand, provides a methodological contribution to the economic literature on Airbnb (broadly: tourism demand analysis) by employing the novel approach of a difference-in-differences (DID) framework with a continuous treatment at the group level (Callaway et al., 2021).

The adoption of a two-stage least squares (2SLS) approach to estimate the relationship between demand and price introduces a novel instrumental variable for tourism demand, which could solve endogeneity problems when addressing various research questions. The analysis of the relationship describing demand and prices provides further knowledge on the pricing determinants of Airbnb listings, complementing the established literature on short-term rental pricing, which has mainly focused on hedonic-based models describing the impact of listing and/or host level features on prices, typically proxied by ADR (see Sainaghi et al., 2021, for an exhaustive literature review), or on dynamic pricing practices (Abrate et al., 2022; Kwok & Xie, 2019).

The results of this research show that an average host on the platform tends to increase its price when facing increasing demand, even when controlling for individual unobserved and time-invariant, seasonal, and time-varying characteristics, macroeconomic factors, and spatial autocorrelation of prices across a given area. This result corroborates theoretical expectations that in a capacity-constrained market – where we can reasonably assume that supply does not vary at the same rate as demand, particularly in this empirical setting that largely covers the COVID-19 period – when demand tends to increase, the general price level also rises. Furthermore, the results show that this pricing behavior differs between the two main host types distinguished in literature (i.e., private versus commercial; Dogru et al., 2020), with the prices of commercial listings being far more responsive to demand variations than properties managed by private host. We believe that these findings can enrich the growing literature that is thoroughly studying Airbnb supply-side professionalization, which has already shown the tendency of professional hosts to dynamically change their prices more frequently than private ones (Abrate et al., 2022; Kwok & Xie, 2019).

In line with common conceptions of these two host typologies (Dogru et al., 2020), we interpreted these results as explained by different degrees of involvement in the Airbnb environment. On the one hand, professional hosts typically invest more time into the platform, enabling them to leverage developed managerial skill sets and industry expertise

Table 7B
Second stage results (2SLS regressions) according to different specifications of f in *Local Airbnb Demand* (i,r,t,f).

	RC2 - Spec 1.1	RC2 - Spec 1.2	RC2 - Spec 2.1	RC2 - Spec 2.2	RC2 - Spec 3.1	RC2 - Spec 3.2	RC2 - Spec 4.1	RC2 - Spec 4.2
	f = 2	**f = 4**	**f = 2**	**f = 4**	**f = 2**	**f = 4**	**f = 2**	**f = 4**
	r = 250m	**r = 250m**	**r = 500m**	**r = 500m**	**r = 750m**	**r = 750m**	**r = 1000m**	**r = 1000m**
ln Local Airbnb Demand (i,r,t,f)	0.027* (0.013)	0.062* (0.026)	0.027* (0.012)	0.063** (0.023)	0.030** (0.011)	0.062** (0.022)	0.023* (0.011)	0.043+ (0.022)
ln Average Market Price (i,r,t)	0.684*** (0.007)	0.696*** (0.010)	0.758*** (0.008)	0.779*** (0.013)	0.795*** (0.009)	0.822*** (0.015)	0.825*** (0.010)	0.860*** (0.016)
ln RGDP (g,t)	0.440*** (0.027)	0.506*** (0.054)	0.405*** (0.026)	0.454*** (0.051)	0.373*** (0.024)	0.425*** (0.048)	0.375*** (0.023)	0.453*** (0.048)
ln CPI(g,t)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
ln Experience (i,t)	0.001 (0.001)	0.001 (0.001)	0.002** (0.001)	0.002** (0.001)	0.003*** (0.001)	0.003** (0.001)	0.003*** (0.001)	0.003*** (0.001)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2,649,779	1,877,764	2,649,779	1,877,764	2,649,779	1,877,764	2,649,779	1,877,764
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	42,699.919	31,286.331	47,843.176	35,577.604	49,190.863	36,594.511	50,065.905	36,816.781
R^2 Adjusted	0.185	0.207	0.197	0.222	0.205	0.228	0.204	0.223
R^2 Uncentered	0.185	0.207	0.197	0.222	0.205	0.228	0.204	0.223
AIC	−2,246,477.121	−1,772,142.787	−2,286,494.820	−1,807,912.947	−2,310,336.991	−1,821,719.064	−2,306,917.582	−1,811,055.374
BIC	−2,246,425.961	−1,772,093.004	−2,286,443.660	−1,807,863.164	−2,310,285.831	−1,821,669.281	−2,306,866.422	−1,811,005.592
Kleibergen-Paap Underid. Test (rk LM)	1739.146	658.856	1989.568	728.352	2276.719	825.248	2445.904	805.491
Kleibergen-Paap Weak Id. Test (Wald F)	1701.859	635.848	1956.491	705.460	2262.170	804.105	2440.587	783.313
Cragg-Donald Weak Id. Test (Wald F)	3589.873	1610.170	4184.810	1781.372	4687.678	1924.656	4957.665	1828.674

Notes: a) Subscripts: *i* = Property, *t* = Time (Year-Week), *g* = Country, 250 m/500 m/750 m/1000 m = radius *r* defining the relevant market, *f* = definition of Demand Moving Average filter. Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Average Weekly Price(i,t). c) Estimates were generated by the means of Stata 17 (command *ivreghdfe*). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1. e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects.

to track demand variations and efficiently adapt their prices. On the other hand, private hosts typically use Airbnb as an additional source of income, investing less time and effort into the platform, and are not expected to dynamically adapt their prices. As such, the major price variation is captured by seasonal and property-level components. All these results are confirmed by several robustness checks, testing the validity of the results according to the main assumptions of the models (i.e., the effective date of the pandemic outbreak, the time-interval of the moving average applied to *Local Airbnb Demand*, and the threshold distinguishing private and commercial hosts).

6.1. Theoretical and managerial implications

The results of this research pave the way for future research into this touristic domain, as well as yielding implications for managers and policymakers. In applying the novel DID with continuous treatment to explain cross-property (-country) demand variations, while considering the country-level governmental pandemic response as exogenous, this paper shows that a new instrumental variable taking into account the endogeneity of demand is available to researchers, as long as data from different countries before and after the pandemic outbreak are available. Future studies adopting the demand for touristic services as a main explanatory variable (whether Airbnb or hotel level demand, or aggregated demand measures at the city, region, or country level) can take advantage of this methodology to efficiently tackle potential endogeneity issues.

Furthermore, relevant insights for policymakers can be derived from the analysis. Firstly, the development of effective tourism rebound measures necessitate empirical quantification of the losses caused not only by the diffusion of COVID-19 but also by the enacted policy responses. This analysis provides an effective methodology to evaluate such impacts, as well as an empirical application to the short-term rental context. Secondly, the additional analysis discriminating between host types again confirms a relevant issue in the sharing economy: the decline of "sharing" and the emergence of "capitalistic hosts" (as named by Dolnicar & Zare, 2020). In this vein, policymakers and sharing-economy platform managers must be informed of the asymmetries on platforms such as Airbnb, where capitalistic actors are outperforming other players (Sainaghi et al., 2021) thanks to superior managerial skills, which may explain pricing efficiency differentials in the present case. In addition, the aforementioned stakeholders learn about resilience asymmetries that are evident between host types. These could be considered in the development of any future crisis management plans that impact Airbnb.

Finally, the study has further theoretical implications for future research seeking to understand how prices evolve in a sharing economy market. The finding that higher prices are significantly associated with increasing local demand shows that pricing variation is not only based on seasonal or hedonic factors, and that a market-based perspective must also be taken into account.

Table 8A
Second stage results (2SLS regressions) according to different specifications of *Private Hosts* and *Commercial Hosts*: *Private Hosts*.

	RC3 - Spec 1.1	RC3 - Spec 1.2	RC3 - Spec 2.1	RC3 - Spec 2.2	RC3 - Spec 3.1	RC3 - Spec 3.2	RC3 - Spec 4.1	RC3 - Spec 4.2
	Thresh = 2	**Thresh = 4**	**Thresh = 2**	**Thresh = 4**	**Thresh = 2**	**Thresh = 4**	**Thresh = 2**	**Thresh = 4**
	r = 250m	**r = 250m**	**r = 500m**	**r = 500m**	**r = 750m**	**r = 750m**	**r = 1000m**	**r = 1000m**
ln Local Airbnb Demand (i,r,t)	−0.031 (0.024)	0.007 (0.019)	−0.004 (0.022)	0.014 (0.017)	0.001 (0.019)	0.025 (0.015)	−0.006 (0.019)	0.016 (0.015)
ln Average Market Price (i,r,t)	0.538*** (0.011)	0.623*** (0.008)	0.625*** (0.014)	0.703*** (0.011)	0.673*** (0.014)	0.741*** (0.011)	0.711*** (0.015)	0.775*** (0.012)
ln RGDP (g,t)	0.573*** (0.048)	0.519*** (0.038)	0.498*** (0.046)	0.467*** (0.036)	0.470*** (0.039)	0.418*** (0.032)	0.472*** (0.038)	0.426*** (0.032)
ln CPI(g,t)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
ln Experience (i, t)	−0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002* (0.001)	0.001 (0.001)	0.003** (0.001)	0.002* (0.001)	0.003*** (0.001)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1,261,031	1,808,542	1,261,031	1,808,542	1,261,031	1,808,542	1,261,031	1,808,542
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	10,034.925	22,578.192	12,802.559	25,820.622	14,727.340	27,209.265	15,655.602	27,923.251
R^2 Adjusted	0.031	0.108	0.076	0.131	0.095	0.147	0.097	0.147
R^2 Uncentered	0.069	0.142	0.113	0.164	0.130	0.180	0.133	0.180
AIC	−1,142,853.959	−1,670,830.920	−1,203,735.425	−1,717,292.795	−1,228,720.507	−1,751,825.760	−1,232,502.815	−1,751,749.739
BIC	−1,142,805.770	−1,670,781.288	−1,203,687.236	−1,717,243.163	−1,228,672.317	−1,751,776.128	−1,232,454.626	−1,751,700.107
Kleibergen-Paap Underid. Test (rk LM)	686.197	1097.861	681.761	1159.755	862.927	1371.912	913.461	1413.494
Kleibergen-Paap Weak Id. Test (Wald F)	656.764	1052.660	655.983	1116.655	835.400	1330.608	885.159	1372.799
Cragg-Donald Weak Id. Test (Wald F)	1413.171	2274.133	1479.929	2496.147	1834.507	2890.220	1904.464	2933.571

Notes: a) Subscripts: i = Property, t = Time (Year-Week), g = Country, 250 m/500 m/750 m/1000 m = radius r defining the relevant market Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Average Weekly Price(i,t). c) Estimates were generated by the means of Stata 17 (command *ivreghdfe*). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1. e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects. f) The sample of private hosts is displayed (with *Private Hosts* defined according to the threshold Thresh ≤ 2/4 properties owned).

6.2. *Limitations and future research*

Despite having shown that the methodology introduced in this paper can be of interest to future research on tourism-demand related topics, this research is not exempt from limitations, which themselves can suggest further avenues for research. Firstly, this analysis is confined to the short-term rental market; further analyses on the behavior of traditional hospitality suppliers would allow for an in-depth comparison between the competitive practices of short-term rentals and those of hotels. Secondly, despite robustness analyses strongly confirming the validity of the results, future endeavors could benefit from some methodological refinement of the definition of "local" demand, which does not have a clear definition among researchers, and of the definition of the moving average filter. Finally, further distinctions of property subsamples (e.g., distinguishing rural versus urban areas, shared versus entire apartments, or weekdays versus weekends) could be of interest to researchers, managers, and policymakers in the tourism domain.

Credit author statement

Francesco Luigi Milone: Data curation; Formal analysis; Investigation; Resources; Software; Visualization; Writing - original draft; Writing - review & editing. Ulrich Gunter: Conceptualization; Methodology; Supervision; Writing - original draft; Writing - review & editing. Bozana Zekan: Project administration; Validation; Writing - original draft; Writing - review & editing.

Impact statement

This paper provides relevant insights for both researchers and practitioners within the tourism industry, particularly within the Airbnb domain. First, to the extent that countries' response strategies to COVID-19 can be considered exogenous, we provide new tools to researchers by testing the impact of the *COVID-19 Stringency Index* on Airbnb demand with a novel methodology, namely difference-in-differences estimation with a continuous treatment (where all individuals are treated with different treatment intensities). Second, we quantify the impact of governmental restrictions on short-term rentals' demand, thereby providing relevant suggestions to local policymakers who are in charge of developing tourism rebound strategies. Third, we enrich the debate on Airbnb supply professionalization by putting emphasis on pricing differentials between commercial and private Airbnb hosts. Finally, further theoretical contributions can be derived from this study as we include a market-based perspective of pricing determinants within the P2P accommodation services domain.

Table 8B
Second stage results (2SLS regressions) according to different specifications of *Private Hosts* and *Commercial Hosts*: *Commercial Hosts*.

	RC3 - Spec 1.1	RC3 - Spec 1.2	RC3 - Spec 2.1	RC3 - Spec 2.2	RC3 - Spec 3.1	RC3 - Spec 3.2	RC3 - Spec 4.1	RC3 - Spec 4.2
	Thresh = 2	**Thresh = 4**	**Thresh = 2**	**Thresh = 4**	**Thresh = 2**	**Thresh = 4**	**Thresh = 2**	**Thresh = 4**
	r = 250m	**r = 250m**	**r = 500m**	**r = 500m**	**r = 750m**	**r = 750m**	**r = 1000m**	**r = 1000m**
ln Local Airbnb Demand (i,r,t)	0.145***	0.349***	0.099***	0.315***	0.113***	0.280***	0.096***	0.249***
	(0.029)	(0.051)	(0.026)	(0.049)	(0.027)	(0.053)	(0.028)	(0.053)
ln Average Market Price (i,r,t)	0.812***	0.817***	0.912***	0.896***	0.938***	0.937***	0.971***	0.966***
	(0.013)	(0.022)	(0.017)	(0.031)	(0.020)	(0.038)	(0.022)	(0.042)
ln RGDP (g,t)	0.293***	0.002	0.313***	−0.022	0.230***	0.002	0.257***	0.061
	(0.059)	(0.103)	(0.057)	(0.111)	(0.058)	(0.117)	(0.057)	(0.114)
ln CPI(g,t)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
ln Experience (i,t)	0.003*	0.009***	0.004**	0.010***	0.004***	0.008***	0.005***	0.009***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	944,309	396,797	944,309	396,797	944,309	396,797	944,309	396,797
Robust Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	30,014.178	16,382.880	32,520.186	20,305.928	29,439.205	20,030.789	28,479.344	19,215.309
R^2 Adjusted	0.281	0.253	0.275	0.265	0.272	0.273	0.265	0.275
R^2 Uncentered	0.308	0.282	0.302	0.293	0.299	0.301	0.293	0.303
AIC	−840,358.624	−281,400.557	−832,446.024	−287,747.858	−828,429.072	−292,052.485	−820,200.003	−293,237.300
BIC	−840,311.591	−281,356.992	−832,398.991	−287,704.294	−828,382.040	−292,008.920	−820,152.971	−293,193.735
Kleibergen-Paap Underid. Test (rk LM)	471.481	209.441	569.236	227.332	559.714	200.610	549.437	199.732
Kleibergen-Paap Weak Id. Test (Wald F)	461.228	211.465	559.112	230.561	554.069	203.463	546.037	203.862
Cragg-Donald Weak Id. Test (Wald F)	1098.872	559.117	1318.773	596.540	1272.156	522.170	1236.142	511.888

Notes: a) Subscripts: i = Property, t = Time (Year-Week), g = Country, 250 m/500 m/750 m/1000 m = radius r defining the relevant market Individual Fixed Effects stands for property-level (i) fixed effects included in the model. b) Dependent variable = ln Average Weekly Price(i,t). c) Estimates were generated by the means of Stata 17 (command *ivreghdfe*). d) ***p < 0.001, **p < 0.01, *p < 0.5, + p < 0.1. e) The coefficient of ln CPI(g,t) is partialled out by the *ivreghdfe* estimation command because of collinearity with the fixed effects. f) The sample of commercial hosts is displayed (with *Commercial Hosts* defined according to the threshold Thresh > 2/4 properties owned).

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