The changing valuation of Airbnb amenities in Mexico during the COVID-19 Pandemic

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Abstract

We study how the COVID-19 pandemic changed the valuation of amenities in the prices of Airbnb listings in Mexico, a country with few tourism and mobility restrictions. Using the universe of Airbnb listings in Mexico from 2018 to 2022, we estimate hedonic price models and analyze how hedonic coefficients changed for amenities associated with lower COVID-19 infection risk and reduced face-to-face contact. Our results show that the valuation of remote-work amenities –such as workspaces–, open-space amenities –such as beach fronts–, and reduced-contact amenities –such as private spaces– significantly increased during the pandemic.

1 Introduction

Few sectors experienced such significant disruptions during the COVID-19 pandemic as the tourism sector. The closure of non-essential businesses and restrictions on national and international mobility sharply reduced the demand for tourism worldwide. UNWTO estimates

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that by the end of 2020, international tourism arrivals were down 74% compared to a year earlier.

Some tourism activity remained despite the significant restrictions. Nevertheless, the nature of tourism shifted dramatically. Suppliers started emphasizing cleanliness, open spaces, and flexible cancellation options to entice consumers (OECD). At the same time, consumers started demanding different tourism options and chose different tourism destinations.

We study how the valuation of amenities in short-term tourism rentals changed during the COVID-19 pandemic. Our analysis uses data from the universe of Airbnb listings –the largest short-term rental online platform– in Mexico. We show that the valuation of amenities related to remote work, open spaces, and reduced probability of contagion increased after 2020.

Mexico did not restrict national or international air travel during the pandemic, unlike other countries.[1] Land crossings through the Mexico-US border were restricted to essential activities from March 2020 to November 2021. Arguably because of these differences in regulation, Mexico became an attractive destination for tourists during the pandemic. In 2020, Mexico was the third most visited country in the world with 25 million tourists (Institute for Global Health Sciences 2021).

To estimate amenity valuations, we estimate hedonic price models with the average daily rate per listing as a dependent variable. We include a wide array of features related to the listings. These include listing amenities, geographical features, and listing owner's features. The rich dataset allows us to control for neighborhood and municipality-time fixed effects to address the effects of unobservable features at the neighborhood level and time-varying heterogeneity across municipalities. The coefficient estimates are the marginal valuations for the Airbnb amenities in the sample (Black 1999; Bayer et al. 2007). Our regressions explain approximately 80 % of the variance in the price of Airbnb listings. To address composition effects coming from changes in supply, we also calculate valuation estimates using a sample of properties that remained listed during the analysis period.

Our results show that the marginal valuation of several amenities changed substantially during the pandemic. The valuation of amenities such as access to a gym, a workspace, a pool, or a jacuzzi increased. These increases are consistent with an increased demand for open spaces and for amenities that were unavailable elsewhere because of business closures. We also find evidence of valuation change related to contagion avoidance behavior. Specifically, the valuation for having a private living room on the premises increased, while the valuation for elevators decreased.

1. The only requirement for air travel was an online health questionnaire. This requirement started in June 2020 (Gobierno de México 2020).

The changes in valuation we find are heterogeneous between touristic beach destinations and non-beach destinations. In touristic beach municipalities, the valuations of access to a gym and a waterfront show the most increases. In non-touristic places, the valuation for workspaces, pools, and jacuzzis had the most extensive positive changes. These results are consistent with people shifting their workplaces from offices to getaways, either by the beach o just away from city centers.

Our work contributes to the literature on the determinants of prices for touristic rentals such as hotel rooms and Airbnb properties. For hotel rooms, Chen and Rothschild (2010) study prices in Taipei, using a hedonic pricing model similar to the one in this paper. Cai et al. (2019) study the relationship between Airbnb prices and the location of the rental properties, along with host features such as reputation and listing flexibility. Lorde et al. (2019) use a hedonic pricing model to study nightly Airbnb rates in 12 Caribbean countries. Wang and Nicolau (2017) study the prices of Airbnb listings in 33 American and European cities. For Mexico, López Tamayo and Ramírez-Álvarez (2021) study the Airbnb market in Mexico City, emphasizing the differences in prices offered by professional vs. non-professional hosts.

Our work differs from previous studies because of the emphasis on how amenity valuations changed during the pandemic. Other papers have examined these changes in tourism and amenity valuation, but they are limited to more specific case studies and focus on listing features instead of amenities. Lin and Chen (2021) show that hotels with scenic views and belonging to international chains experienced fewer income losses than other hotels in Taiwan. Bode et al. (2021) show that the pandemic reduced the prices of entire homes on the Airbnb platform and that more experienced hosts did not reduce their prices as much as other hosts. Llaneza and Raya (2021) show how prices in Airbnb listings dropped substantially during the pandemic in Barcelona. Dolnicar and Zare (2020) and Zare and Dolnicar (2021) made forecasts of the Airbnb market during the pandemic, arguing that the pandemic's impact would vary across hosts and would negatively affect profit-oriented hosts to a greater extent.

We also contribute to the recent urban economics literature on the impact of the pandemic on the valuation of urban amenities and the changes in residential and work locations (Gupta et al. 2021; Rosenthal et al. 2022; Brueckner et al. 2021). Specifically, we show increases in the valuation of work-related amenities in Airbnb rental properties, which may be associated with the movement of workers from offices to working from Airbnb locations.

The rest of the paper proceeds as follows. Section 2 describes the Airbnb listings dataset we use and provides some facts about the Airbnb market in Mexico during the pandemic. Section 3 describes the empirical strategy. Section 4 shows our results on amenity valuation in Airbnb listings before and during the pandemic. Section 5 concludes.

2 Data and Descriptive Statistics

Airbnb data. We use monthly data on Airbnb listings in Mexico collected by AirDNA. The data contains listing-level information on the number of reservations, availability, prices, and characteristics of each Airbnb listing. We restrict our analysis from January 2018 to August 2021.[2] The data covers 17813 neighborhoods in 1031 municipalities in the country.

Our outcome of interest is the monthly average daily rate (ADR) for each Airbnb listing. The ADR is the total monthly income for a listing divided over the number of occupied nights for the listing.[3] We convert all prices to Mexican pesos of August 2018. We exclude listings in the bottom and top 1% of the distribution of prices in each state to remove outliers.

The explanatory variables are a large set of listing characteristics. We list these variables in table 1. Following Faye (2021) and Lorde et al. (2019), we classify these variables in four groups: intrinsic attributes, convenience attributes, reputation attributes and environmental variables. Intrinsic attributes correspond to listing features, including listing amenities. Among these amenities, there are dummy variables for the presence of a pool, a gym, or a workspace; kitchen amenities, shared spaces, and security features. We also include dummies for listing types (e.g., private room, entire residence) and the number of bedrooms and bathrooms in the property.

Convenience attributes are listing features that may make reservations easier for customers, such as low fees for extra guests, low security-deposit amounts, and flexible cancellation policies. Reputation attributes are characteristics of the listing and hosts that may be associated with more reliable listings. These include listing tenure and host ratings. The last set of attributes we include are those related to the listing's location, such as its distance to the center of the municipality, whether it is on a beach destination or not, and the degree of competition it faces.[4]

Tourism and the Airbnb market before and during the pandemic. Tourism is one of the main economic activities in Mexico. It accounted for 8.7% of GDP and for 8% of employment creation in 2019 (SECTUR 2022; INEGI 2022). The country is among the ten most-visited countries in the world (UNWTO 2021). Airbnb is a large player in the tourism market: since 2018, Airbnb has accounted for more than one-fifth of available rooms in the

2. We restrict the beginning of the analysis period to 2018 to omit changes in valuation that may be due to additional municipalities entering the dataset. From 2015 to 2018, the sample of municipalities is expanding because of Airbnb's rapid expansion in the country.

3. These ADR figures include cleaning fees, if applicable. Airbnb hosts sometimes adjust prices through cleaning fees instead of changing the listing price per night (Dogru et al. 2021).

4. The beach municipalities are: Acapulco, Campeche, Cancún, Cozumel, Huatulco, Isla Mujeres, Ixtapa Zihuatanejo, La Paz, Loreto, Los Cabos, Manzanillo, Mazatlán, Nuevo Vallarta, Playa del Carmen, Puerto Vallarta, Rosarito, Puerto Escondido, Tampico, Tulum, and Veracruz.

Table 1: Variables Description

Category	Variable	Type	Description
Dependent variable	ADR	Continuous	Average daily rate. Includes cleaning fees
Intrinsic attributes	Entire home, private room, shared room	Dummies	Listing types
	Single family home, multifamily home, villa, B&B, hotel	Dummies	Property types
	Bedrooms	Continuous	Number of bedrooms
	Bathrooms	Continuous	Number of bathrooms
	Gym, cable, ac, hot water, workspace, pool or jacuzzi, tv, wifi, garden or backyard, patio or balcony, pets allowed, kitchen, free parking, elevator, waterfront, breakfast, coffee_machine, bbq area, doorman, crib, host checkin, room_shades, bathtub, toys, gas detector, washing_machine, dryer, oven, bed linens, cooking_basics, dishwasher, stove, bedroom door lock, microwave, refrigerator, dishes, fire extinguisher, family friendly, private living room, heating, high chair, hair dryer, hangers, iron, private entrance, smoke_detector, extra_pillows, first_aid_kit	Dummies	Amenities offered in the listing
Convenience attributes	Maximum_guests	Continuous	Maximum number of guests allowed
	Extra_people_fee	Continuous	Extra people fee chosen by the host
	Security_deposit	Continuous	Security deposit chosen by the host
	Minimum_stay	Continuous	Minimum nights of stay required
	Exact_location	Dummy	Exact coordinates of the property are shown on the platform
	Instant book	Dummy	The property can be booked without needing the host's approval
	Flexible-moderate, firm-strict, superstrict, lux policy	Dummies	Cancellation policy chosen by the host is Flexible or Moderate Firm or Strict Super Strict 30 or 60 Days Luxe stays
Reputation attributes	Seniority	Continuous	Number of months when the property has been listed on the platform
	Num of photos	Continuous	Number of photos displayed on the platform
	Num of reviews	Continuous	Number of listing reviews
	Response rate	Continuous	Percentage of inquiries and requests a host answers in a day
	Superhost	Dummy	The host has superhost status
	Professional	Dummy	The host has two or more listings on the platform
	Overall rating	Continuous	Average guest rating of the overall experience
Environmental variables	Beach destination	Dummy	The property is located in a top beach destination
	Competition	Continuous	Number of listings allowing the same number of maximum guests located in the same neighborhood
	Dist_centroid	Continuous	Distance (in km) between the property and the municipality's centroid calculated using the Harversine formula
Pandemic variables	Pre_covid, covid	Dummies	The reporting month is before or during Covid-19
	Exited, entered, prevailed	Dummies	The listing is observed only either before or after the pandemic; or else, in both periods

Source: AirDNA, author's classification.

country, including hotel rooms (Banco de México 2021).

Although both hotel rooms and Airbnb reservations declined substantially at the pandemic's beginning, recovery in the Airbnb market has been faster than in the hotel room market. Banco de México (2021) estimates that reservations in hotels and Airbnb in April 2020 were at 28% and 4% of their pre-pandemic levels. However, by March of 2021, the Airbnb market had recovered, while hotel room reservations were still half what they were in February 2020.

Figure 1 shows the evolution of Airbnb listings in Mexico during our study period. Our sample includes 1,692,091 listings in the pre-pandemic period before March of 2020 and 1,217,031 listings afterward. The impact of the pandemic is visible at its beginning, but recovery in the number of listings has been quick.

Figure 1: Evolution of Airbnb listings in Mexico

Source: AirDNA, author's calculation. The vertical line is on february of 2020, which we choose as the pandemic initial date.

Table 2 shows descriptive statistics about the listings and their features in the pre-pandemic and pandemic periods. The pandemic induced changes in listing features associated with a reduced probability of contagion. For example, the listings where the host personally helped the guest check-in decreased from 36% to 22.5%. At the same time, the percentage of listings with private entrances increased by 10.3 percentage points. Entire residence rentals gained about 6% of the market share in the pandemic, whereas private rooms in shared properties and shared rooms saw a market share decrease. We also see an increase in host flexibility, reflected in a fall in the share of listings with strict cancellation policies and a decrease in the average security deposit.

Table 2: Descriptive statistics

Variable	Pre-pandemic	SE_1	Pandemic	SE_2	Difference	SMD^1	pvalue	Variable	Pre-pandemic	SE_1	Pandemic	SE_2	Difference	SMD^1	p-value
ADR	1618.791	1.644	1612.917	1.907	-5.873	-0.003	0.02	Iron	0.667	0.000	0.649	0.000	-0.018	-0.037	0.000
Bedrooms	1.813	0.001	1.839	0.001	0.025	0.018	0.00	Bedroom_door_lock	0.228	0.000	0.204	0.000	-0.023	-0.057	0.000
Bathrooms	1.722	0.001	1.733	0.001	0.012	0.010	0.00	Microwave	0.458	0.000	0.427	0.000	-0.030	-0.061	0.000
Gym	0.110	0.000	0.118	0.000	0.007	0.023	0.00	Oven	0.313	0.000	0.266	0.000	-0.046	-0.101	0.000
Workspace	0.675	0.000	0.628	0.000	-0.048	-0.100	0.00	Refrigerator	0.538	0.000	0.496	0.000	-0.042	-0.084	0.000
Pool_or_jacuzzi	0.381	0.000	0.400	0.000	0.019	0.039	0.00	Room_shades	0.110	0.000	0.117	0.000	0.007	0.023	0.000
Tv	0.758	0.000	0.796	0.000	0.038	0.090	0.00	Smoke_detector	0.236	0.000	0.241	0.000	0.005	0.013	0.000
Wifi	0.934	0.000	0.929	0.000	-0.006	-0.023	0.00	Stove	0.377	0.000	0.372	0.000	-0.005	-0.011	0.000
Free_parking	0.818	0.000	0.810	0.000	-0.009	-0.022	0.00	First_aid_kit	0.421	0.000	0.413	0.000	-0.008	-0.016	0.000
Elevator	0.172	0.000	0.145	0.000	-0.027	-0.073	0.00	Pets_allowed	0.228	0.000	0.252	0.000	0.025	0.058	0.000
Waterfront	0.084	0.000	0.083	0.000	-0.001	-0.004	0.00	Beach_destination	0.367	0.000	0.357	0.000	-0.010	-0.021	0.000
Breakfast	0.070	0.000	0.065	0.000	-0.006	-0.022	0.00	Entire_home	0.665	0.000	0.724	0.000	0.059	0.126	0.000
Washing_machine	0.459	0.000	0.432	0.000	-0.027	-0.054	0.00	Private_room	0.328	0.000	0.272	0.000	-0.056	-0.122	0.000
Patio_or_balcony	0.331	0.000	0.317	0.000	-0.015	-0.031	0.00	Shared_room	0.007	0.000	0.005	0.000	-0.002	-0.028	0.000
Garden_or_backyard	0.243	0.000	0.229	0.000	-0.014	-0.033	0.00	Seniority	16.913	0.012	23.639	0.017	6.726	0.379	0.000
Kitchen	0.863	0.000	0.852	0.000	-0.011	-0.032	0.00	Num_of_reviews	35.520	0.035	31.490	0.040	-4.030	-0.089	0.000
Private_living_room	0.031	0.000	0.036	0.000	0.005	0.029	0.00	Maximum_guests	4.602	0.002	4.768	0.003	0.166	0.052	0.000
Dryer	0.594	0.000	0.571	0.000	-0.024	-0.048	0.00	Response_rate	90.954	0.018	94.254	0.016	3.301	0.157	0.000
Coffee_machine	0.458	0.000	0.426	0.000	-0.033	-0.066	0.00	Superhost	0.360	0.000	0.315	0.000	-0.045	-0.094	0.000
Ac	0.673	0.000	0.690	0.000	0.017	0.036	0.00	Extra_people_fee	126.316	0.327	64.833	0.232	-61.484	-0.168	0.000
Cable	0.308	0.000	0.236	0.000	-0.071	-0.160	0.00	Professional	0.759	0.000	0.767	0.000	0.008	0.018	0.000
Hot_water	0.740	0.000	0.697	0.000	-0.043	-0.096	0.00	Security_Deposit	1553.023	4.485	829.676	3.254	-723.347	-0.144	0.000
Heating	0.154	0.000	0.158	0.000	0.004	0.011	0.00	Num_of_photos	21.868	0.012	22.922	0.014	1.055	0.068	0.000
Bbq_area	0.124	0.000	0.110	0.000	-0.014	-0.042	0.00	Minimum_Stay	2.481	0.008	2.123	0.007	-0.357	-0.038	0.000
Family_friendly	0.002	0.000	0.001	0.000	-0.001	-0.035	0.00	Overall_rating	93.789	0.007	94.279	0.008	0.490	0.057	0.000
Doorman	0.132	0.000	0.097	0.000	-0.034	-0.107	0.00	Exact_Location	0.206	0.000	0.183	0.000	-0.023	-0.058	0.000
Host_checkin	0.360	0.000	0.225	0.000	-0.135	-0.294	0.00	Competition	56.817	0.086	47.338	0.090	-9.478	-0.089	0.000
Private_entrance	0.403	0.000	0.506	0.000	0.103	0.208	0.00	Instantbook	0.583	0.000	0.177	0.000	-0.406	-0.826	0.000
Bed_linens	0.425	0.000	0.391	0.000	-0.034	-0.069	0.00	Dist_centroid	18.087	0.024	18.661	0.028	0.574	0.019	0.000
Bathtub	0.017	0.000	0.016	0.000	-0.001	-0.006	0.00	Single_family_home	0.342	0.000	0.324	0.000	-0.019	-0.040	0.000
Gas_detector	0.155	0.000	0.158	0.000	0.003	0.008	0.00	Multifamily_home	0.516	0.000	0.526	0.000	0.010	0.020	0.000
Toys	0.045	0.000	0.032	0.000	-0.013	-0.066	0.00	Villa	0.046	0.000	0.051	0.000	0.005	0.022	0.000
Cooking_basics	0.478	0.000	0.450	0.000	-0.028	-0.056	0.00	B&B	0.054	0.000	0.048	0.000	-0.007	-0.030	0.000
Crib	0.076	0.000	0.060	0.000	-0.016	-0.062	0.00	Hotel	0.041	0.000	0.052	0.000	0.011	0.052	0.000
Dishes	0.535	0.000	0.504	0.000	-0.032	-0.063	0.00	Flexible-moderate	0.616	0.000	0.694	0.000	0.079	0.164	0.000
Dishwasher	0.061	0.000	0.057	0.000	-0.004	-0.017	0.00	Firm-strict	0.376	0.000	0.301	0.000	-0.076	-0.159	0.000
Extra_pillows	0.312	0.000	0.282	0.000	-0.030	-0.066	0.00	Superstrict	0.008	0.000	0.005	0.000	-0.003	-0.035	0.000
Fire_extinguisher	0.314	0.000	0.319	0.000	0.005	0.012	0.00	Lux_policy	0.000	0.000	0.000	0.000	0.000	0.017	0.000
Hair_dryer	0.492	0.000	0.470	0.000	-0.021	-0.043	0.00	Entered	0.000	0.000	0.231	0.000	0.231	0.782	0.000
Hangers	0.825	0.000	0.806	0.000	-0.019	-0.048	0.00	Exited	0.231	0.000	0.000	0.000	-0.231	-0.677	0.000
High_chair	0.028	0.000	0.023	0.000	-0.005	-0.032	0.00	Prevailed	0.769	0.000	0.769	0.000	0.000	-0.001	0.545

Source: AirDNA, author's calculations. Columns pre-pandemic and pandemic report the means in every period. SE_1 and SE_2 report the standard errors of the means. The difference and SMD columns report the difference and the standardized difference in means between the pre-pandemic and pandemic periods. The p-value columns correspond to a test of equality of means across periods.

3 Empirical strategy

This section describes the hedonic price modeling strategy we use to estimate the valuation of amenities in Airbnb listings before and during the pandemic. We estimate log-linear regressions where we explain the average daily rate (ADR) with a rich set of Airbnb amenities. Our detailed dataset allows us to use neighborhood and municipality-time fixed effects to address possible omitted variable bias from neighborhood- and municipality-level unobservables.

Our regression specification is the following:

$$\ln P_{ijnt} = X'_{ijnt}\beta + \gamma Competition_{jnt} + \delta_{jn} + \tau_{nt} + \theta_t + \epsilon_{ijnt}. \tag{1}$$

Here, $\ln P_{ijnt}$ is the log of the ADR for listing i, located in neighborhood j of municipality n at time t. We observe these prices at a monthly frequency. The matrix X includes listing characteristics. We estimate the model separately for the pre-pandemic and pandemic periods to see how the coefficients β change during the pandemic. $Competition_{jnt}$ is the competition faced by properties in neighborhood j of municipality n at time t, measured as the number of Airbnb listings that have the same maximum number of guests allowed.

We include three groups of fixed effects to account for possible bias arising from omitted variables and unobservables. The parameters θ_t are time fixed effects that account for country-wide changes in Airbnb nightly prices. Another set of parameters, τ_{nt}, measures time-varying unobservables at the municipality level. They also capture seasonal patterns in tourism demand (Juaneda et al. 2011; Llaneza and Raya 2021). For example, beach municipalities will have higher demand and prices during the summer months.[5] The parameters δ_{jn} are neighborhood fixed effects. The error term is the variable ϵ_{ijnt}. We allow to be correlated across listings in the same neighborhood over time, so we cluster our standard errors at the neighborhood level.

The coefficients β measure the marginal valuation of each amenity (Rosen 1974; Black 1999; Bayer et al. 2007). By including fixed effects at the municipality-time level, we are only using variation in listing prices from listings within the same municipality to estimate these marginal valuations β. Our identification assumption is that conditional on these fixed effects plus the effects δ_{jn}, the amenity variables X_{ijnt} are uncorrelated with the error term. This assumption may be untenable if there are unaccounted remaining unobservables in equation (1), or if individuals sort across Airbnb listings (Bayer et al. 2007; Faye 2021; Jang et al. 2021). We argue that our models have high explanatory power, so any remaining unobservables are unlikely to change the coefficients by a large amount (Oster 2019).

5. These effects are not perfectly collinear with the country-wide effects θ_t because the set of municipalities in the sample changes in some months.

We estimate equation (1) for both the pre-pandemic and the pandemic periods and separately for beach and non-beach municipalities. To evaluate if the marginal valuation changed in the pandemic, we test whether the coefficients β change across periods. We also estimate (1) month by month to see how the marginal valuation of amenities evolves.

Changes in prices associated with an amenity may not be due to the changing tastes of tourists but to changes in the supply composition of Airbnb listings. Indeed, figure 1 shows that the number of listings changed substantially at the beginning of the pandemic. Banco de México (2021) shows that the supply of listings changed during the pandemic, with hosts offering more cleaning and remote-work-related amenities. To control for these supply composition changes, we also estimate equation (1) on a sample of "stable" listings that appear on the platform at least once before the pandemic and at least once during the pandemic. While the valuation of amenities in these listings may be different from the valuation of amenities in the overall listing sample, the evolution of the valuation of these listings over time allows us to look at changes in consumer willingness to pay while isolating changes in supply composition.

4 Results

This section shows our results about the changing valuation of amenities during the pandemic from the estimation of equation (1).[6] First, we show estimations where we pool the pre-pandemic and pandemic period observations. These show that the valuation of amenities related to working from home, access to open spaces, and reduced contact increased during the pandemic. We also show month-by-month estimates highlighting that the valuation changes start precisely at the beginning of the pandemic and seem to persist during the recovery. Last, we show how the valuation changes differ for beach and non-beach municipalities.

Pre-pandemic and pandemic estimates. Table 3 shows estimates of the coefficients β from equation (1) for selected amenities. Columns (1) and (2) show the results for the complete sample. Columns (4), (5), (7), and (6) show estimates separating between beach and non-beach municipalities. We show both the coefficients β and the percentage contribution to the ADR price $e^{\beta} - 1$.

Column (1) shows that at the national level, five out of the six selected amenities had a statistically significant effect on the prices of Airbnb listings before the pandemic. Listings with a gym or a pool were respectively 5.2% and 33.3% more expensive than other listings. Elevators and access to a waterfront also had a positive effect on listing prices. On the other

6. We use the R package "fixest" from Bergé (2018) for all the estimations.

Table 3: Effect of amenities on log average daily rate of Airbnb listings: selected amenities

	National			Beach			Non-beach		
Variable	(1) Pre pandemic	(2) Pandemic	(3) Diff.	(4) Pre-pandemic	(5) Pandemic	(6) Diff.	(7) Pre-pandemic	(8) Pandemic	(9) Diff.
Gym	0.051***	0.075***	0.025***	0.104***	0.138***	0.033***	-0.021	-0.018	0.003
	(0.013)	(0.014)	[0.002]	(0.015)	(0.015)	[0.002]	(0.013)	(0.013)	[0.735]
Workspace	-0.018***	-0.009*	0.010***	-0.012*	-0.003	0.009**	-0.021***	-0.011**	0.010**
	(0.004)	(0.005)	[0.002]	(0.006)	(0.007)	[0.043]	(0.005)	(0.005)	[0.014]
Pool or jacuzzi	0.303***	0.318***	0.015**	0.316***	0.327***	0.011	0.289***	0.313***	0.024***
	(0.011)	(0.010)	[0.025]	(0.014)	(0.012)	[0.295]	(0.015)	(0.014)	[0.002]
Elevator	0.171***	0.147***	-0.024**	0.185***	0.146***	-0.039***	0.150***	0.138***	-0.012
	(0.010)	(0.009)	[0.016]	(0.014)	(0.012)	[0.003]	(0.009)	(0.011)	[0.348]
Waterfront	0.068***	0.091***	0.023***	0.074***	0.104***	0.030***	0.053***	0.058***	0.004
	(0.010)	(0.010)	[0.002]	(0.012)	(0.011)	[0.000]	(0.018)	(0.020)	[0.710]
Private living room	0.009	0.029**	0.021*	0.017	0.039*	0.022	0.013	0.030**	0.017
	(0.010)	(0.012)	[0.062]	(0.023)	(0.021)	[0.25]	(0.011)	(0.013)	[0.167]
Percentage contribution to ADR $e^{\beta} - 1$									
Gym	5.222***	7.838***	2.616***	10.991***	14.751***	3.760***	-2.068	-1.757	0.311
Workspace	-1.833***	-0.851*	0.982***	-1.184*	-0.303	0.881**	-2.112***	-1.079**	1.033**
Pool or jacuzzi	35.368***	37.473***	2.105**	37.181***	38.697***	1.515	33.487***	36.725***	3.237***
Elevator	18.667***	15.842***	-2.825**	20.264***	15.668***	-4.596***	16.171***	14.843***	-1.328
Waterfront	7.058***	9.549***	2.491***	7.640***	10.965***	3.325***	5.480***	5.944***	0.464
Private living room	0.866	2.979**	2.112*	1.670	3.969*	2.299	1.310	3.071**	1.761
Fit statistics									
Observations	1,692,091	1,217,031		621,401	434,334		1,070,690	782,697	
R^2	0.80	0.80		0.78	0.78		0.78	0.80	
Within R^2	0.60	0.60		0.65	0.65		0.59	0.58	
# of properties	178,859	173,056		62,598	60,039		116,261	113,017	
# of neighborhoods	15,504	15,651		1,719	1,748		13,785	13,903	
# of municipalities	958	944		20	20		938	924	
# of periods	26	18		26	18		26	18	
Fixed-effects									
Neighborhood	Yes	Yes		Yes	Yes		Yes	Yes	
Month-year	Yes	Yes		Yes	Yes		Yes	Yes	
Municipality-month-year	Yes	Yes		Yes	Yes		Yes	Yes	

Source: AirDNA, author's calculations. The top panel shows OLS estimates of the β coefficients in equation (1) for selected amenities. The bottom panel shows the percentage contribution to the ADR. "Pre-pandemic" estimates are for January 2018 - February 2020. The "Pandemic" estimates are for March 2020 - August 2021. "Beach" estimates are for touristic beach municipalities. "Non-Beach" estimates are for municipalities without touristic beaches. Standard errors clustered at the neighborhood level in parentheses. "Diff" columns correspond to the difference in the coefficients between the pre-pandemic and the pandemic period. The p-value for a test of whether these differences are zero are reported in brackets. The omitted categories for listing type, property type and cancellation policy are entire home, single family home, and flexible-moderate, respectively. *p<0.1; **p<0.05; ***p<0.01.

hand, the presence of a workspace slightly negatively impacted the price of a listing. This finding coincides with that of Faye (2021) and may be due to consumers perceiving these listings as more cramped.

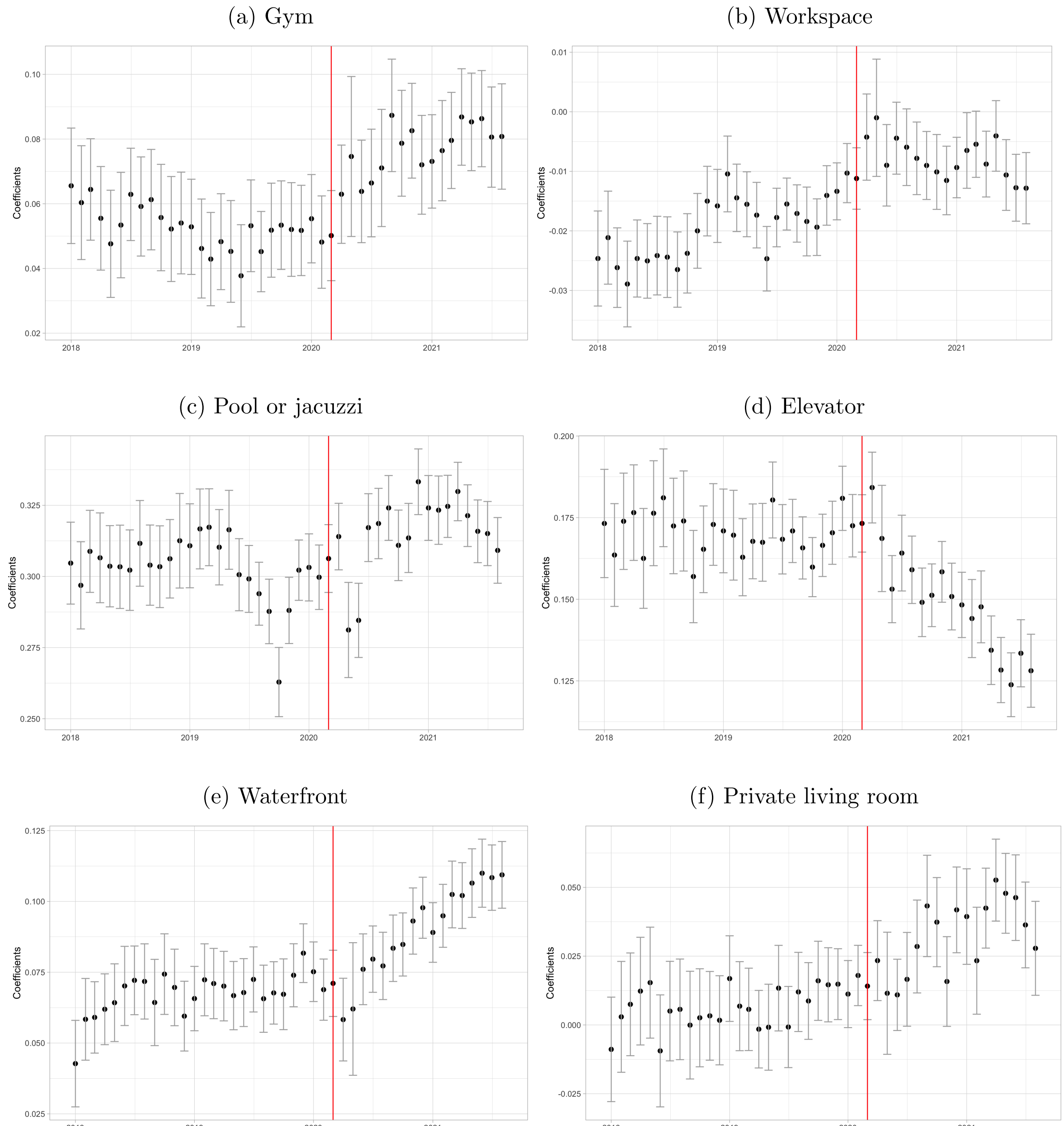
Amenity valuations during the pandemic appear in column (2), and the difference between pandemic and pre-pandemic appears in column (3). The valuation for a workspace increased by 0.98 p.p., consistent with an increasing demand for listings for remote work. Valuation for amenities related to open spaces, such as a waterfront or access to a pool or jacuzzi, increased by 2.1 and 2.4 p.p., respectively. We also observe changes in amenity values consistent with an increasing willingness to pay for reduced contact with other people. Since gyms were closed at the beginning of the pandemic, and presumably because attending a large gym may involve a risk of SARS-COVID-19 contagion, customers increased their valuation for access to a gym. They also reduced their valuation for listings with elevators and increased their valuation for having private living rooms.

Columns (4),(5),(7), and (8) show how the valuation of amenities differs between beach municipalities and non-beach municipalities. There is a higher willingness to pay for gyms, pools, and waterfronts in beach destinations. For example, before the pandemic, access to a gym was associated with a listing price 10.9% higher in beach destinations. In contrast, it did not have a statistically significant effect on listings prices in non-beach municipalities.

The valuation changes during the pandemic are also different between the beach and non-beach destinations, as shown in columns (6) and (9). The valuation of gyms increased by 3.7 p.p. in the pandemic period relative to before in beach municipalities, but it did not change in non-beach places. Access to a pool or jacuzzi became more valuable during the pandemic in non-beach destinations, but this valuation did not increase in beach destinations. This difference between beach municipalities and the rest is consistent with the valuation for open spaces increasing in places where open space was not widely available. The only amenity that shows a similar valuation increase in both types of destinations is the presence of a workspace.

Month-by-month estimates. Figure 2 shows results of estimating cross-sectional equivalents of equation (1) separately for every month. These regressions do not have time or municipality-time fixed effects, but they capture the cross-sectional differences in ADR between listings with different amenities within the same municipality. These estimates illustrate how the cross-sectional estimates of amenity valuations change over time. For gyms, elevators, waterfronts, and private living rooms, the time series of the estimated coefficients show a stable valuation in the pre-pandemic period and a clear change in trend that coincides with the beginning of the pandemic. Evidence for changes in the valuation trend for workspaces and pools or jacuzzis is less clear than other amenities. However, there are clear differences in the averages in the pandemic and pre-pandemic periods.

Figure 2: Effect of amenities on log average daily rate of Airbnb listings for selected amenities. Month-by-month estimates, national sample



(a) Gym

(b) Workspace

(c) Pool or jacuzzi

(d) Elevator

(e) Waterfront

(f) Private living room

Source: AirDNA, author's calculations. The points are coefficient estimates of a cross-sectional analog of equation (1) by month. The vertical bars are 95% confidence intervals. Standard errors clustered by neighborhood. The omitted categories for listing type, property type and cancellation policy are entire home, single family home, and flexible-moderate, respectively. The vertical line marks the beginning of the pandemic.

In Appendix figures A.1 and A.2 we also estimate month-by-month specifications for beach and non-beach municipalities. The heterogeneity in the time evolution of the coefficients for beach and non-beach municipalities follows the patterns shown in table 3. The changes in valuation for gyms and waterfronts are noteworthy in beach municipalities, but it is not evident for non-beach municipalities. Valuation for pools and jacuzzis shows a trend change at the beginning of the pandemic only for non-beach places.

Robustness and discussion. We conduct two additional exercises to gauge the robustness of our results. First, we re-estimate equation (1) on a sample of stable listings observed at least once in the pre-pandemic period and once in the post-pandemic period. We do this to avoid valuation changes arising from supply shifts due to the changing composition of Airbnb listings, especially in the first months of the pandemic. Appendix table A.1 shows the full results for the complete and restricted stable listings samples. The changes in amenity valuations are similar across samples. These results suggest that the changes in valuation we observe are not due to the change in the percentage of listings that offer each amenity type during the pandemic.

We also estimate equation (1) on a restricted period starting in 2019 instead of 2018. We do this because figure 2 shows that the time series of amenity valuations does show lower levels for some amenities in 2018, arising concerns about trending unobservables. Table A.2 in the Appendix shows that amenity valuations still exhibit statistically significant changes with this more limited pre-pandemic period.

Biases from unobservable selection. Because our hedonic price models estimate the effects of several attributes on Airbnb prices without quasi-experimental variation, a valid concern is that unobservables may be driving our results. To address this issue we follow Oster 2019 and calculate statistics that are indicative of how serious the bias from unobservables need to be to invalidate our results under a proportional selection assumption.

In Table 4, we show coefficients from equation (1) without and with fixed effects by neighbourhood and municipality time, along with the R-squared values for both regressions. We do this for the pre-pandemic and pandemic periods. Then, we calculate the degree of selection in unobservables that would be needed to drive these valuation coefficients to 0. In the pre-pandemic period, for the valuation of gyms to be 0, unobservables would need to bias the coefficient in the opposite direction as the bias from fixed effects, and would need to be as important as the unobservables captured by fixed effects. In the pandemic period, unobservables would need to be three times as important as observables in determining the variance of prices. Our results for the valuation of pools, elevators and private living rooms is also quite robust to unobservable selection. We also show bounds on the coefficient estimates assuming that unobservables were as important as observables.

In the bottom panel, we also show the degree of selection in unobservables needed for the pandemic coefficients to be equal to their pre-pandemic estimated counterparts. This is an imperfect test because the pre-pandemic coefficient estimates may be biased themselves. Nevertheless, our findings for several of the amenities are robust. The selection in unobservables would need to be as important as selection for observables to rule out changes in the valuations of gyms, elevators and private living rooms.

Table 4: Unobservable selection diagnostics

	No FE	**FE**	**Sel. for coef = 0**	**Bound**
Pre-Pandemic				
Gym	0.0231	0.051	-1.2	0.093
Workspace	-0.0455	-0.018	0.4	0.024
Pool	0.3261	0.303	8.7	0.268
Elevator	0.1846	0.171	8.3	0.150
Waterfront	0.1864	0.068	0.4	-0.111
Private Living Room	0.0201	0.009	0.5	-0.008
R-squared	0.800	0.668		

Pandemic	**No FE**	**FE**	**Sel. for coef = 0**	**Bound**	**Sel. for coef = pre**
Gym	0.0583	0.075	-2.8	0.102	-0.91
Workspace	-0.042	-0.009	0.2	0.043	-0.17
Pool	0.3685	0.318	4.0	0.238	0.19
Elevator	0.1573	0.147	9.0	0.131	-1.47
Waterfront	0.2171	0.091	0.5	-0.109	0.11
Private Living Room	0.0399	0.029	1.7	0.012	-1.42
R-squared	0.800	0.674			

Source: AirDNA, author's calculations. Coefficient estimates and unobservable selection statistics for the Pre-Pandemic and Pandemic periods. Column "No-FE" shows estimates from (1) without neighborhood and municipality-time fixed effects. Column "FE" shows estimates including fixed effects. "Sel for coef = 0" shows the degree of unobservable selection needed for the true coefficient to be 0, assuming selection on unobservables is proportional to selection in observables. A value of 1 implies that unobservables need to be as important as observables in determining the variance of the dependent variable. Column "Bound" shows the coefficient estimate assuming that unobservables are as important as observables, i.e. assuming that the degree of selection from the "Sel. for coef=0" is 1. In the bottom panel. the "Sel for coef=pre" column shows the degree of selection on unobservables neeeded for the pandemic coefficients to be equal to their pre-pandemic estimates.

5 Concluding remarks

We test if the valuation of amenities in Airbnb short-term rental listings changed in Mexico during the COVID-19 pandemic. We show that some amenities change valuation in patterns consistent with possible effects of changing tastes for open spaces, remote work, and close-quarters contact. Specifically, we show that the valuation for gyms, waterfronts, pools, workspaces, private living rooms, and elevators display substantial changes. These valuation changes are heterogeneous across beach and non-beach municipalities.

Our results suggest that the pandemic has permanently changed the taste for amenities in touristic destinations. Remote-work opportunities and preferences for open space seem to have induced a shift in consumer behavior that may have longer-run consequences in the market for touristic rentals. Nevertheless, these changes may not be present in other markets outside Mexico. They may not generalize to changes in the preferences for amenities in permanent housing nor to taste for amenities in traditional hotel rooms.

Other research designs, such as estimation of discrete choice models of consumer behavior (Berry et al. 1995; Bayer et al. 2007), are alternative strategies to examine these changing valuations while imposing additional structure on taste variation across consumers, allowing for richer conclusions regarding the effects of sorting. Nevertheless, our results provide a first approximation to how COVID-19 has changed amenity valuations.

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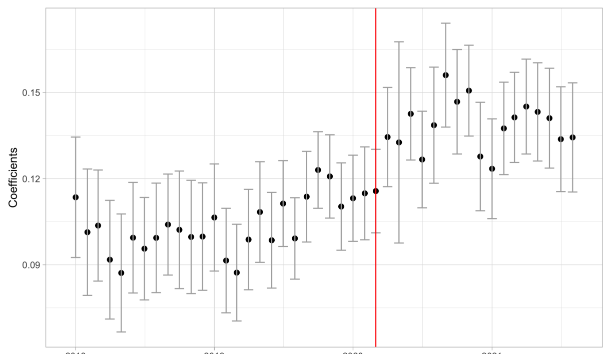
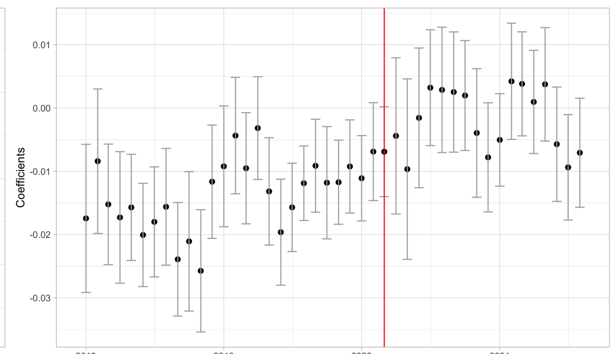
Appendix

Figure A.1: Effect of amenities on log average daily rate of Airbnb listings for selected amenities. Month-by-month estimates, beach municipalities

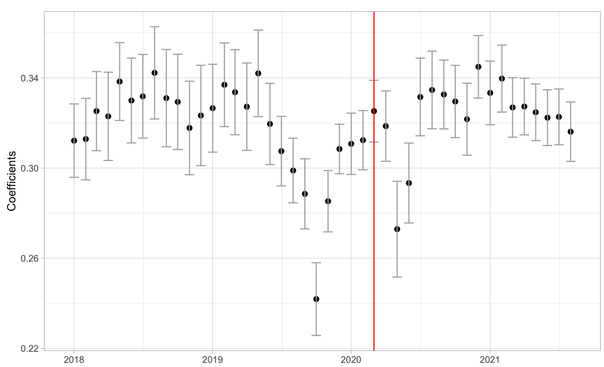
(a) Gym



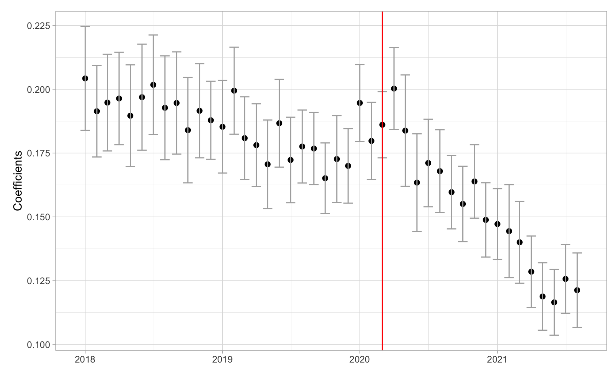
(b) Workspace



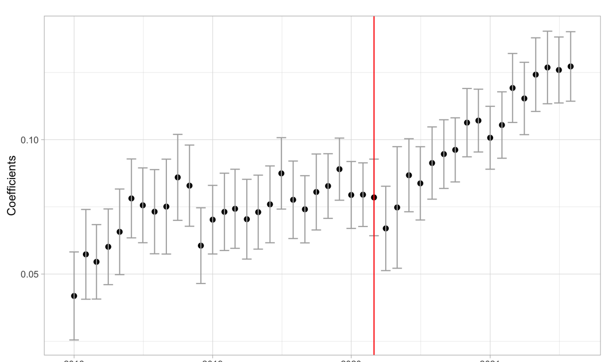
(c) Pool or jacuzzi



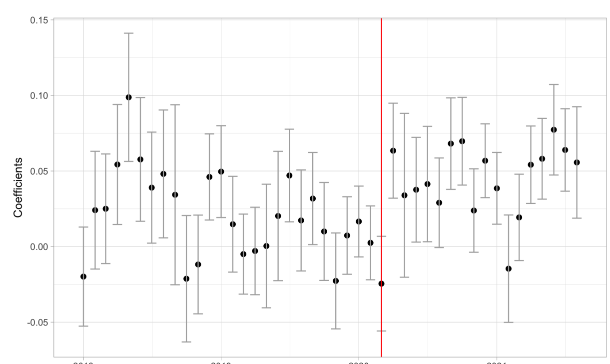
(d) Elevator



(e) Waterfront



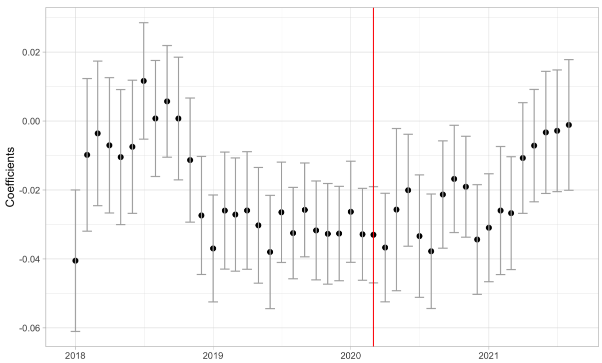
(f) Private living room



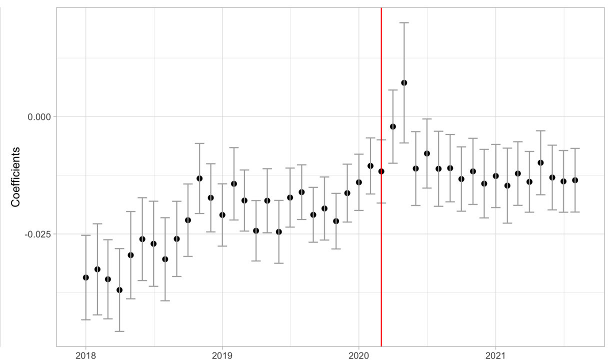
Source: AirDNA, author's calculations. The points are coefficient estimates of a cross-sectional analog of equation (1) by month on the sample of beach municipalities. The vertical bars are 95% confidence intervals. Standard errors clustered by neighborhood. The omitted categories for listing type, property type and cancellation policy are entire home, single family home, and flexible-moderate, respectively. The vertical line marks the beginning of the pandemic.

Figure A.2: Effect of amenities on log average daily rate of Airbnb listings for selected amenities. Month-by-month estimates, non-beach municipalities

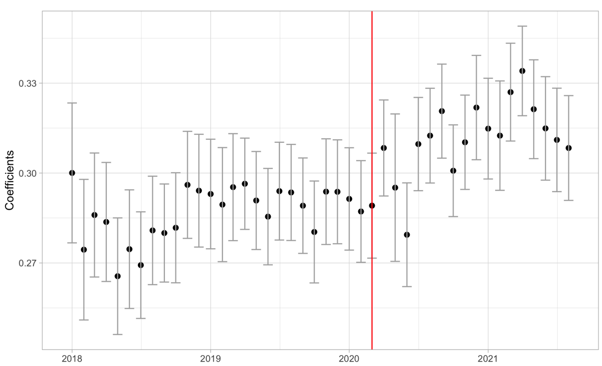
(a) Gym



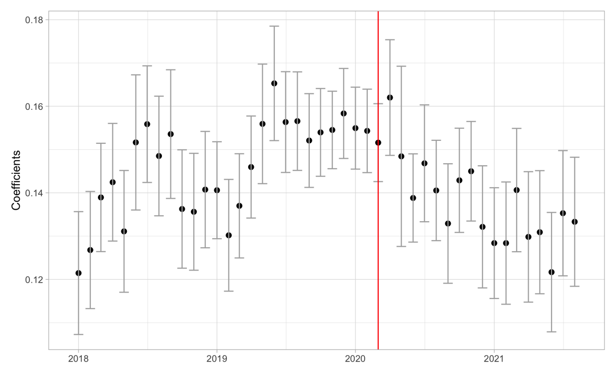
(b) Workspace



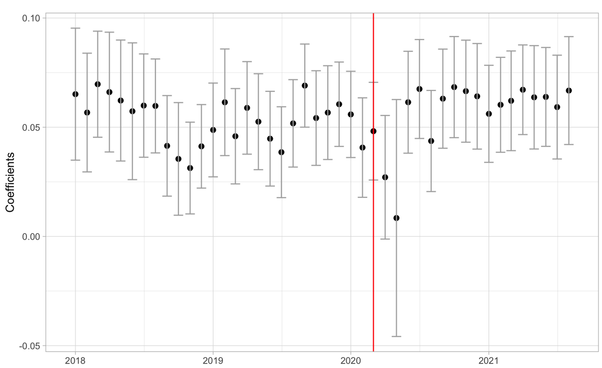
(c) Pool_or_jacuzzi



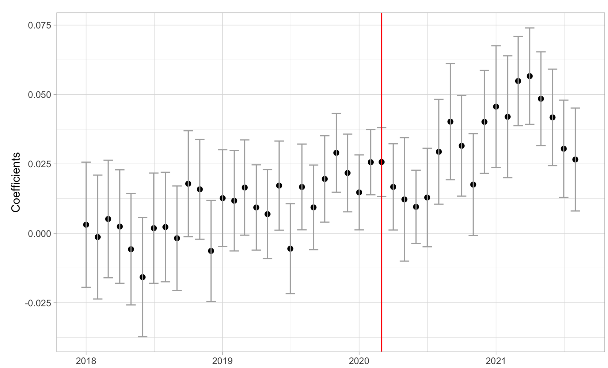
(d) Elevator



(e) Waterfront



(f) Private_living_room



Source: AirDNA, author's calculations. The points are coefficient estimates of a cross-sectional analog of equation (1) by month on the sample of non-beach municipalities. The vertical bars are 95% confidence intervals. Standard errors clustered by neighborhood. The omitted categories for listing type, property type and cancellation policy are entire home, single family home, and flexible-moderate, respectively. The vertical line marks the beginning of the pandemic.

Table A.1: Effect of amenities on log average daily rate of Airbnb listings. All amenities, all listings and stable listings.

Dependent Variable:	log(ADR)											
	National				Beach				Non-beach			
			Stable				Stable				Stable	
Model:	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid
Bedrooms	0.0274***	0.0324***	0.0273***	0.0368***	0.0299*	0.0522***	0.0219	0.0536***	0.0208***	0.0208***	0.0230***	0.0254***
	(0.0058)	(0.0056)	(0.0075)	(0.0064)	(0.0173)	(0.0149)	(0.0199)	(0.0182)	(0.0039)	(0.0049)	(0.0048)	(0.0053)
Bathrooms	0.0495***	0.0665***	0.0538***	0.0681***	0.0928***	0.1213***	0.0954***	0.1196***	0.0277***	0.0401***	0.0320***	0.0414***
	(0.0061)	(0.0061)	(0.0076)	(0.0066)	(0.0142)	(0.0094)	(0.0170)	(0.0107)	(0.0055)	(0.0058)	(0.0069)	(0.0066)
Gym	0.0509***	0.0755***	0.0503***	0.0640***	0.1043***	0.1376***	0.1047***	0.1327***	-0.0209	-0.0177	-0.0255	-0.0415***
	(0.0130)	(0.0139)	(0.0136)	(0.0157)	(0.0146)	(0.0154)	(0.0144)	(0.0155)	(0.0131)	(0.0134)	(0.0156)	(0.0161)
Workspace	-0.0185***	-0.0085*	-0.0196***	-0.0082	-0.0119*	-0.0030	-0.0111	-0.0057	-0.0213***	-0.0108**	-0.0233***	-0.0085
	(0.0041)	(0.0046)	(0.0050)	(0.0056)	(0.0061)	(0.0071)	(0.0072)	(0.0081)	(0.0048)	(0.0054)	(0.0060)	(0.0067)
Pool_or_jacuzzi	0.3028***	0.3183***	0.3042***	0.3104***	0.3161***	0.3271***	0.3194***	0.3218***	0.2888***	0.3128***	0.2929***	0.3017***
	(0.0114)	(0.0100)	(0.0119)	(0.0111)	(0.0145)	(0.0117)	(0.0154)	(0.0128)	(0.0153)	(0.0145)	(0.0167)	(0.0161)
Tv	0.0808***	0.0607***	0.0758***	0.0568***	0.0585***	0.0375***	0.0529***	0.0364***	0.0876***	0.0693***	0.0829***	0.0642***
	(0.0057)	(0.0062)	(0.0069)	(0.0070)	(0.0090)	(0.0105)	(0.0106)	(0.0120)	(0.0070)	(0.0072)	(0.0084)	(0.0082)
Wifi	-0.0255***	-0.0069	-0.0277***	-0.0078	-0.0329**	-0.0036	-0.0377**	-0.0099	-0.0228**	-0.0140	-0.0235*	-0.0109
	(0.0089)	(0.0079)	(0.0097)	(0.0092)	(0.0146)	(0.0121)	(0.0154)	(0.0136)	(0.0108)	(0.0097)	(0.0121)	(0.0114)
Free_parking	0.0198***	0.0222***	0.0197***	0.0162**	-0.0040	0.0191	0.0026	0.0122	0.0306***	0.0248***	0.0283***	0.0200**
	(0.0058)	(0.0069)	(0.0067)	(0.0074)	(0.0091)	(0.0143)	(0.0098)	(0.0145)	(0.0070)	(0.0069)	(0.0081)	(0.0082)
Elevator	0.1711***	0.1471***	0.1649***	0.1608***	0.1845***	0.1456***	0.1763***	0.1662***	0.1499***	0.1384***	0.1455***	0.1459***
	(0.0101)	(0.0086)	(0.0109)	(0.0096)	(0.0138)	(0.0125)	(0.0146)	(0.0149)	(0.0094)	(0.0105)	(0.0110)	(0.0103)
Waterfront	0.0682***	0.0912***	0.0798***	0.0858***	0.0736***	0.1040***	0.0863***	0.0949***	0.0534***	0.0577***	0.0635***	0.0629***
	(0.0101)	(0.0099)	(0.0103)	(0.0102)	(0.0116)	(0.0106)	(0.0114)	(0.0109)	(0.0183)	(0.0204)	(0.0193)	(0.0206)
Breakfast	0.0804***	0.0781***	0.0808***	0.0745***	0.0678***	0.0531***	0.0596***	0.0461**	0.0906***	0.0900***	0.0913***	0.0883***
	(0.0109)	(0.0106)	(0.0131)	(0.0128)	(0.0204)	(0.0183)	(0.0217)	(0.0218)	(0.0116)	(0.0117)	(0.0151)	(0.0143)
Washing_machine	0.0176***	0.0273***	0.0178***	0.0254***	0.0464***	0.0569***	0.0477***	0.0523***	-0.0052	0.0032	-0.0055	0.0032
	(0.0061)	(0.0065)	(0.0064)	(0.0066)	(0.0093)	(0.0091)	(0.0093)	(0.0092)	(0.0060)	(0.0068)	(0.0070)	(0.0078)
Patio_or_balcony	0.0272***	0.0174***	0.0276***	0.0172***	0.0309***	0.0212***	0.0282***	0.0180**	0.0302***	0.0211***	0.0330***	0.0235***
	(0.0046)	(0.0053)	(0.0054)	(0.0062)	(0.0074)	(0.0074)	(0.0084)	(0.0084)	(0.0053)	(0.0068)	(0.0063)	(0.0078)
Garden_or_backyard	-0.0368***	-0.0300***	-0.0340***	-0.0301***	-0.0360***	-0.0254***	-0.0319***	-0.0236**	-0.0328***	-0.0340***	-0.0308***	-0.0353***
	(0.0063)	(0.0060)	(0.0070)	(0.0072)	(0.0085)	(0.0087)	(0.0099)	(0.0100)	(0.0087)	(0.0082)	(0.0098)	(0.0101)
Kitchen	-0.0018	0.0089	0.0036	0.0046	0.0265	0.0376**	0.0318*	0.0335*	-0.0118	0.0017	-0.0044	-0.0027
	(0.0073)	(0.0080)	(0.0084)	(0.0089)	(0.0165)	(0.0153)	(0.0180)	(0.0175)	(0.0072)	(0.0092)	(0.0088)	(0.0101)
Private_living_room	0.0086	0.0294**	0.0150	0.0369***	0.0166	0.0389*	0.0025	0.0397*	0.0130	0.0302**	0.0230*	0.0415**
	(0.0105)	(0.0116)	(0.0125)	(0.0140)	(0.0230)	(0.0209)	(0.0285)	(0.0230)	(0.0114)	(0.0131)	(0.0133)	(0.0161)
Dryer	0.0982***	0.0833***	0.1007***	0.0868***	0.0865***	0.0810***	0.0906***	0.0860***	0.1031***	0.0806***	0.1046***	0.0832***
	(0.0066)	(0.0070)	(0.0080)	(0.0083)	(0.0098)	(0.0108)	(0.0118)	(0.0114)	(0.0083)	(0.0089)	(0.0101)	(0.0110)
Coffee_machine	0.0568***	0.0456***	0.0568***	0.0491***	0.0530***	0.0286***	0.0537***	0.0310***	0.0601***	0.0580***	0.0607***	0.0619***
	(0.0059)	(0.0070)	(0.0069)	(0.0080)	(0.0079)	(0.0096)	(0.0098)	(0.0104)	(0.0067)	(0.0082)	(0.0078)	(0.0093)
Ac	0.1012***	0.0955***	0.0996***	0.0959***	0.1377***	0.0955***	0.1289***	0.0947***	0.1017***	0.1074***	0.1017***	0.1096***
	(0.0069)	(0.0073)	(0.0078)	(0.0082)	(0.0179)	(0.0130)	(0.0180)	(0.0145)	(0.0088)	(0.0091)	(0.0102)	(0.0105)
Cable	0.0081*	0.0009	0.0117**	0.0037	0.0053	-0.0012	0.0078	0.0030	0.0091	0.0041	0.0138**	0.0056
	(0.0047)	(0.0050)	(0.0051)	(0.0054)	(0.0073)	(0.0078)	(0.0077)	(0.0085)	(0.0058)	(0.0060)	(0.0065)	(0.0065)
Hot_water	-0.0387***	-0.0347***	-0.0448***	-0.0360***	-0.0297***	-0.0398***	-0.0352***	-0.0406***	-0.0418***	-0.0312***	-0.0492***	-0.0327***
	(0.0047)	(0.0054)	(0.0056)	(0.0062)	(0.0066)	(0.0087)	(0.0074)	(0.0099)	(0.0063)	(0.0065)	(0.0078)	(0.0076)
Heating	0.0449***	0.0556***	0.0459***	0.0561***	0.0231**	0.0325***	0.0233**	0.0349***	0.0495***	0.0615***	0.0500***	0.0595***
	(0.0062)	(0.0068)	(0.0067)	(0.0074)	(0.0090)	(0.0100)	(0.0098)	(0.0111)	(0.0072)	(0.0077)	(0.0081)	(0.0087)

Table A.1: Effect of amenities on log average daily rate of Airbnb listings. All amenities, all listings and stable listings. *(continued)*

Dependent Variable:	log(ADR)											
	National				Beach				Non-beach			
			Stable				Stable				Stable	
Model:	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid
Bbq_area	-0.0022	0.0041	-0.0014	0.0027	-0.0094	0.0004	-0.0096	-0.0037	0.0022	0.0046	0.0031	0.0058
	(0.0067)	(0.0076)	(0.0076)	(0.0086)	(0.0085)	(0.0100)	(0.0097)	(0.0111)	(0.0093)	(0.0103)	(0.0106)	(0.0120)
Family_friendly	-0.0433**	-0.1281***	-0.0168	-0.1450***	-0.0284	-0.0470	0.1532	-0.0497	-0.0975***	-0.1662***	-0.2262***	-0.1801***
	(0.0190)	(0.0434)	(0.1163)	(0.0462)	(0.0265)	(0.0588)	(0.1689)	(0.0645)	(0.0257)	(0.0523)	(0.0737)	(0.0549)
Doorman	-0.0052	-0.0140	-0.0019	-0.0132	-0.0238*	-0.0384**	-0.0207	-0.0317*	0.0074	0.0055	0.0094	0.0021
	(0.0075)	(0.0096)	(0.0090)	(0.0101)	(0.0129)	(0.0176)	(0.0149)	(0.0177)	(0.0075)	(0.0086)	(0.0089)	(0.0096)
Host_checkin	-0.0151***	-0.0110**	-0.0127***	-0.0117**	-0.0172**	-0.0094	-0.0098	-0.0098	-0.0163***	-0.0161**	-0.0183***	-0.0180***
	(0.0040)	(0.0049)	(0.0047)	(0.0053)	(0.0067)	(0.0064)	(0.0075)	(0.0071)	(0.0047)	(0.0065)	(0.0058)	(0.0070)
Private_entrance	0.0133***	0.0058	0.0132***	0.0100**	0.0094**	0.0045	0.0112**	0.0080	0.0143***	0.0043	0.0125**	0.0087
	(0.0035)	(0.0040)	(0.0041)	(0.0041)	(0.0047)	(0.0051)	(0.0057)	(0.0054)	(0.0046)	(0.0053)	(0.0056)	(0.0056)
Bed_linens	-0.0134***	-0.0101*	-0.0180***	-0.0153***	-0.0109	-0.0113	-0.0175**	-0.0165*	-0.0110**	-0.0073	-0.0132**	-0.0115*
	(0.0045)	(0.0057)	(0.0052)	(0.0059)	(0.0069)	(0.0086)	(0.0077)	(0.0089)	(0.0055)	(0.0065)	(0.0064)	(0.0070)
Bathtub	0.0342***	0.0395***	0.0290**	0.0470***	0.0450**	0.0576***	0.0451**	0.0608***	0.0167	0.0177	0.0095	0.0271
	(0.0121)	(0.0119)	(0.0131)	(0.0140)	(0.0177)	(0.0167)	(0.0183)	(0.0189)	(0.0151)	(0.0161)	(0.0175)	(0.0197)
Gas_detector	-0.0053	0.0081	0.0044	0.0105	-0.0251**	-0.0046	-0.0185*	-0.0103	0.0072	0.0147	0.0168	0.0221*
	(0.0075)	(0.0074)	(0.0081)	(0.0089)	(0.0097)	(0.0110)	(0.0104)	(0.0129)	(0.0095)	(0.0094)	(0.0104)	(0.0114)
Toys	-0.0338***	-0.0373***	-0.0357***	-0.0328***	-0.0442***	-0.0375**	-0.0491***	-0.0362**	-0.0234**	-0.0328***	-0.0246*	-0.0258*
	(0.0085)	(0.0100)	(0.0097)	(0.0109)	(0.0119)	(0.0157)	(0.0130)	(0.0166)	(0.0111)	(0.0122)	(0.0130)	(0.0138)
Cooking_basics	-0.0298***	-0.0214***	-0.0301***	-0.0268***	-0.0335***	-0.0242**	-0.0362***	-0.0258**	-0.0276***	-0.0181***	-0.0256***	-0.0270***
	(0.0064)	(0.0061)	(0.0075)	(0.0074)	(0.0107)	(0.0105)	(0.0123)	(0.0121)	(0.0080)	(0.0069)	(0.0092)	(0.0093)
Crib	0.0629***	0.0563***	0.0643***	0.0536***	0.0555***	0.0485***	0.0570***	0.0498***	0.0726***	0.0685***	0.0744***	0.0593***
	(0.0083)	(0.0098)	(0.0090)	(0.0105)	(0.0083)	(0.0127)	(0.0099)	(0.0130)	(0.0133)	(0.0140)	(0.0142)	(0.0160)
Dishes	-0.0551***	-0.0433***	-0.0565***	-0.0408***	-0.0540***	-0.0349***	-0.0516***	-0.0352***	-0.0517***	-0.0473***	-0.0568***	-0.0425***
	(0.0064)	(0.0061)	(0.0077)	(0.0074)	(0.0090)	(0.0090)	(0.0106)	(0.0107)	(0.0083)	(0.0075)	(0.0099)	(0.0094)
Dishwasher	0.0963***	0.0906***	0.1019***	0.0953***	0.0964***	0.0963***	0.1025***	0.0947***	0.0809***	0.0633***	0.0852***	0.0755***
	(0.0095)	(0.0088)	(0.0103)	(0.0096)	(0.0129)	(0.0109)	(0.0130)	(0.0119)	(0.0125)	(0.0128)	(0.0145)	(0.0141)
Extra_pillows	-0.0232***	-0.0181***	-0.0238***	-0.0158**	-0.0152**	-0.0089	-0.0170**	-0.0086	-0.0328***	-0.0282***	-0.0334***	-0.0244***
	(0.0050)	(0.0057)	(0.0056)	(0.0064)	(0.0076)	(0.0084)	(0.0085)	(0.0094)	(0.0060)	(0.0068)	(0.0068)	(0.0079)
Fire_extinguisher	0.0360***	0.0326***	0.0351***	0.0358***	0.0248***	0.0219***	0.0196***	0.0221***	0.0461***	0.0421***	0.0480***	0.0466***
	(0.0042)	(0.0045)	(0.0049)	(0.0055)	(0.0059)	(0.0058)	(0.0066)	(0.0077)	(0.0058)	(0.0060)	(0.0065)	(0.0073)
Hair_dryer	0.0168**	0.0282***	0.0160**	0.0296***	0.0301***	0.0377***	0.0267**	0.0403***	0.0019	0.0188**	0.0027	0.0183*
	(0.0065)	(0.0064)	(0.0077)	(0.0076)	(0.0090)	(0.0088)	(0.0109)	(0.0102)	(0.0079)	(0.0082)	(0.0096)	(0.0094)
Hangers	0.0106**	0.0099*	0.0145**	0.0105*	0.0141*	0.0102	0.0135	0.0158*	0.0076	0.0081	0.0136*	0.0059
	(0.0049)	(0.0051)	(0.0057)	(0.0057)	(0.0072)	(0.0078)	(0.0084)	(0.0086)	(0.0061)	(0.0061)	(0.0071)	(0.0069)
High_chair	0.0362**	0.0335**	0.0384**	0.0435**	0.0387**	0.0427**	0.0505**	0.0564***	0.0192	0.0085	0.0135	0.0121
	(0.0157)	(0.0160)	(0.0174)	(0.0178)	(0.0191)	(0.0175)	(0.0212)	(0.0180)	(0.0208)	(0.0251)	(0.0236)	(0.0301)
Iron	-0.0102**	-0.0194***	-0.0135***	-0.0181***	-0.0217***	-0.0297***	-0.0266***	-0.0301***	-0.0017	-0.0112*	-0.0033	-0.0092
	(0.0043)	(0.0048)	(0.0049)	(0.0057)	(0.0070)	(0.0081)	(0.0075)	(0.0090)	(0.0054)	(0.0058)	(0.0064)	(0.0070)
Bedroom_door_lock	-0.0893***	-0.0926***	-0.1074***	-0.0965***	-0.1224***	-0.1232***	-0.1418***	-0.1358***	-0.0719***	-0.0756***	-0.0878***	-0.0737***
	(0.0081)	(0.0089)	(0.0102)	(0.0110)	(0.0177)	(0.0188)	(0.0187)	(0.0232)	(0.0074)	(0.0085)	(0.0102)	(0.0102)
Microwave	0.0071	-0.0012	0.0044	0.0008	0.0173**	0.0118	0.0106	0.0094	0.0003	-0.0096	0.0017	-0.0042
	(0.0054)	(0.0058)	(0.0066)	(0.0072)	(0.0080)	(0.0085)	(0.0120)	(0.0108)	(0.0069)	(0.0075)	(0.0082)	(0.0096)
Oven	0.0372***	0.0374***	0.0365***	0.0368***	0.0303***	0.0324***	0.0373***	0.0347***	0.0358***	0.0333***	0.0314***	0.0329***

Table A.1: Effect of amenities on log average daily rate of Airbnb listings. All amenities, all listings and stable listings. *(continued)*

Dependent Variable:	log(ADR)											
	National				Beach				Non-beach			
			Stable				Stable				Stable	
Model:	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid
	(0.0052)	(0.0059)	(0.0060)	(0.0064)	(0.0077)	(0.0082)	(0.0086)	(0.0091)	(0.0061)	(0.0065)	(0.0073)	(0.0074)
Refrigerator	-0.0646***	-0.0476***	-0.0669***	-0.0536***	-0.0708***	-0.0626***	-0.0755***	-0.0637***	-0.0614***	-0.0382***	-0.0631***	-0.0476***
	(0.0062)	(0.0063)	(0.0074)	(0.0079)	(0.0090)	(0.0102)	(0.0113)	(0.0122)	(0.0077)	(0.0081)	(0.0090)	(0.0102)
Room_shades	0.0023	-0.0008	0.0021	-0.0015	-0.0038	-0.0039	0.0013	-0.0008	0.0072	0.0031	0.0033	-0.0002
	(0.0050)	(0.0051)	(0.0057)	(0.0061)	(0.0070)	(0.0075)	(0.0077)	(0.0090)	(0.0068)	(0.0066)	(0.0080)	(0.0081)
Smoke_detector	0.0247***	0.0318***	0.0200***	0.0269***	0.0228**	0.0386***	0.0196*	0.0317**	0.0250***	0.0249***	0.0195**	0.0220**
	(0.0065)	(0.0067)	(0.0075)	(0.0083)	(0.0103)	(0.0101)	(0.0113)	(0.0123)	(0.0077)	(0.0083)	(0.0091)	(0.0102)
Stove	0.0036	0.0075	0.0045	0.0067	-0.0001	0.0080	0.0005	0.0092	0.0066	0.0093	0.0077	0.0074
	(0.0051)	(0.0053)	(0.0057)	(0.0060)	(0.0085)	(0.0091)	(0.0096)	(0.0101)	(0.0061)	(0.0061)	(0.0068)	(0.0070)
First_aid_kit	-0.0299***	-0.0208***	-0.0282***	-0.0216***	-0.0271***	-0.0207***	-0.0245***	-0.0182***	-0.0280***	-0.0166***	-0.0274***	-0.0201***
	(0.0042)	(0.0041)	(0.0046)	(0.0050)	(0.0062)	(0.0058)	(0.0063)	(0.0065)	(0.0049)	(0.0055)	(0.0061)	(0.0069)
Pets_allowed	-0.0385***	-0.0316***	-0.0328***	-0.0338***	-0.0490***	-0.0443***	-0.0474***	-0.0459***	-0.0273***	-0.0200***	-0.0197***	-0.0217***
	(0.0056)	(0.0055)	(0.0063)	(0.0063)	(0.0094)	(0.0091)	(0.0105)	(0.0101)	(0.0061)	(0.0063)	(0.0068)	(0.0071)
Private_room	-0.3888***	-0.3567***	-0.3611***	-0.3540***	-0.2196***	-0.2157***	-0.1844***	-0.1971***	-0.4630***	-0.4140***	-0.4347***	-0.4193***
	(0.0160)	(0.0135)	(0.0164)	(0.0153)	(0.0224)	(0.0184)	(0.0240)	(0.0222)	(0.0119)	(0.0130)	(0.0128)	(0.0141)
Shared_room	-1.080***	-0.9870***	-1.110***	-0.9950***	-1.137***	-1.048***	-1.109***	-1.009***	-1.072***	-0.9597***	-1.114***	-0.9854***
	(0.0365)	(0.0374)	(0.0463)	(0.0427)	(0.0837)	(0.0518)	(0.0982)	(0.0684)	(0.0399)	(0.0463)	(0.0513)	(0.0521)
Seniority	0.0048***	0.0037***	0.0045***	0.0039***	0.0052***	0.0036***	0.0049***	0.0039***	0.0046***	0.0038***	0.0044***	0.0041***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Overall_rating	0.0032***	0.0033***	0.0039***	0.0041***	0.0027***	0.0031***	0.0033***	0.0040***	0.0034***	0.0033***	0.0042***	0.0040***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Num_of_reviews	-0.0023***	-0.0023***	-0.0023***	-0.0023***	-0.0029***	-0.0028***	-0.0029***	-0.0027***	-0.0020***	-0.0021***	-0.0021***	-0.0022***
	(0.0001)	(0.00009)	(0.0001)	(0.00009)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.00009)	(0.0001)	(0.00009)
Num_of_photos	0.0024***	0.0024***	0.0022***	0.0023***	0.0021***	0.0019***	0.0018***	0.0018***	0.0026***	0.0028***	0.0024***	0.0026***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Response_rate	-0.0004***	-0.0005***	-0.0006***	-0.0006***	-0.0004***	-0.0007***	-0.0006***	-0.0009***	-0.0004***	-0.0004***	-0.0005***	-0.0005***
	(0.00008)	(0.00008)	(0.00010)	(0.00008)	(0.00009)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Superhost	0.0415***	0.0270***	0.0341***	0.0275***	0.0390***	0.0256***	0.0331***	0.0256***	0.0413***	0.0261***	0.0341***	0.0271***
	(0.0044)	(0.0041)	(0.0048)	(0.0045)	(0.0070)	(0.0074)	(0.0075)	(0.0077)	(0.0056)	(0.0045)	(0.0061)	(0.0053)
Professional	0.0347***	0.0058	0.0289***	0.0099**	0.0260***	0.0024	0.0173**	0.0077	0.0384***	0.0092**	0.0347***	0.0118**
	(0.0040)	(0.0036)	(0.0046)	(0.0042)	(0.0062)	(0.0061)	(0.0068)	(0.0068)	(0.0046)	(0.0041)	(0.0056)	(0.0049)
Maximum_guests	0.0822***	0.0792***	0.0818***	0.0777***	0.0813***	0.0693***	0.0820***	0.0680***	0.0817***	0.0823***	0.0811***	0.0810***
	(0.0021)	(0.0018)	(0.0027)	(0.0022)	(0.0064)	(0.0043)	(0.0078)	(0.0052)	(0.0019)	(0.0018)	(0.0022)	(0.0022)
Extra_people_fee	0.00003***	0.00005***	0.00003***	0.00005***	0.00003***	0.00004***	0.00003***	0.00004***	0.00003***	0.00007***	0.00003***	0.00007***
	(0.000005)	(0.00001)	(0.000007)	(0.00001)	(0.000007)	(0.00001)	(0.000009)	(0.00001)	(0.000007)	(0.00002)	(0.000010)	(0.00002)
Security_deposit	0.000005***	0.000008***	0.000006***	0.000008***	0.000008***	0.00001***	0.000009***	0.00001***	0.000003***	0.000004***	0.000003***	0.000004***
	(0.0000008)	(0.0000010)	(0.000001)	(0.0000010)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.0000007)	(0.0000009)	(0.000001)	(0.0000009)
Minimum_stay	0.0003	0.0003	0.0002	0.0003	0.0008***	0.0008***	0.0007***	0.0008***	-0.0007***	-0.0004*	-0.0010***	-0.0005**
	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Exact_location	-0.0056	0.0024	-0.0034	-0.0017	0.0032	0.0063	0.0048	0.0010	-0.0088	0.0019	-0.0072	-0.0022
	(0.0054)	(0.0056)	(0.0062)	(0.0061)	(0.0065)	(0.0072)	(0.0076)	(0.0072)	(0.0077)	(0.0078)	(0.0088)	(0.0086)
Instantbook	-0.0288***	-0.0625***	-0.0243***	-0.0605***	-0.0263***	-0.0844***	-0.0240***	-0.0809***	-0.0262***	-0.0489***	-0.0207***	-0.0473***
	(0.0036)	(0.0044)	(0.0045)	(0.0044)	(0.0059)	(0.0075)	(0.0068)	(0.0075)	(0.0046)	(0.0047)	(0.0059)	(0.0049)

Table A.1: Effect of amenities on log average daily rate of Airbnb listings. All amenities, all listings and stable listings. *(continued)*

Dependent Variable:	log(ADR)											
	National				Beach				Non-beach			
			Stable				Stable				Stable	
Model:	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid	pre_covid	covid
Competition	-0.0002***	-0.0001***	-0.0002***	-0.0001**	-0.0001**	-0.00007	-0.00007	-0.00005	-0.00008	0.00005	-0.0001**	0.00002
	(0.00004)	(0.00005)	(0.00005)	(0.00005)	(0.00004)	(0.00005)	(0.00006)	(0.00005)	(0.00005)	(0.00008)	(0.00006)	(0.00008)
Dist_centroid	0.0129*	0.0125**	0.0153**	0.0144**	0.0354**	0.0426***	0.0377***	0.0420***	-0.0113*	-0.0113**	-0.0103	-0.0116**
	(0.0070)	(0.0058)	(0.0060)	(0.0062)	(0.0146)	(0.0132)	(0.0125)	(0.0119)	(0.0066)	(0.0045)	(0.0064)	(0.0055)
Multifamily_home	-0.0828***	-0.0966***	-0.0807***	-0.0982***	-0.0829***	-0.0977***	-0.0905***	-0.1056***	-0.0789***	-0.0904***	-0.0728***	-0.0894***
	(0.0075)	(0.0084)	(0.0079)	(0.0082)	(0.0141)	(0.0129)	(0.0146)	(0.0134)	(0.0080)	(0.0099)	(0.0089)	(0.0097)
Villa	0.1211***	0.1102***	0.1183***	0.1057***	0.1384***	0.1270***	0.1437***	0.1234***	0.0653***	0.0585***	0.0558***	0.0539***
	(0.0169)	(0.0148)	(0.0182)	(0.0149)	(0.0241)	(0.0226)	(0.0276)	(0.0216)	(0.0127)	(0.0132)	(0.0149)	(0.0147)
B&B	-0.0454***	-0.0618***	-0.0490***	-0.0608***	-0.0782***	-0.1082***	-0.0926***	-0.1165***	-0.0444***	-0.0560***	-0.0473***	-0.0534***
	(0.0096)	(0.0115)	(0.0114)	(0.0131)	(0.0181)	(0.0249)	(0.0223)	(0.0256)	(0.0112)	(0.0131)	(0.0128)	(0.0152)
Hotel	0.2191***	0.1864***	0.2105***	0.1859***	0.1110***	0.1246***	0.0958***	0.1062***	0.2626***	0.2059***	0.2492***	0.2117***
	(0.0181)	(0.0214)	(0.0186)	(0.0209)	(0.0254)	(0.0311)	(0.0259)	(0.0323)	(0.0213)	(0.0267)	(0.0223)	(0.0260)
Firm-strict	0.0415***	0.0377***	0.0409***	0.0421***	0.0423***	0.0298***	0.0362***	0.0345***	0.0398***	0.0447***	0.0442***	0.0491***
	(0.0046)	(0.0049)	(0.0056)	(0.0055)	(0.0078)	(0.0080)	(0.0094)	(0.0093)	(0.0052)	(0.0059)	(0.0058)	(0.0062)
Superstrict	0.3318***	0.3338***	0.3296***	0.3259***	0.2721***	0.2315***	0.2553***	0.2224***	0.3416***	0.3806***	0.3732***	0.3971***
	(0.0401)	(0.0351)	(0.0432)	(0.0364)	(0.0405)	(0.0379)	(0.0454)	(0.0385)	(0.0593)	(0.0432)	(0.0463)	(0.0445)
Lux_policy		1.136***		1.136***		0.9366***		0.9483***				
		(0.0827)		(0.1208)		(0.0894)		(0.1259)				
Fixed-effects												
Neighborhood	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality-month-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	1,692,091	1,217,031	1,301,075	935,425	621,401	434,334	474,741	338,595	1,070,690	782,697	826,334	596,830
R^2	0.79725	0.80430	0.80803	0.80979	0.77994	0.78382	0.78760	0.78749	0.77907	0.79623	0.79278	0.80236
Within R^2	0.60408	0.59807	0.60840	0.60247	0.64650	0.64665	0.64996	0.64849	0.58969	0.58002	0.59462	0.58579

Source: AirDNA, author's calculations. OLS estimates of the β coefficients in equation (1) "Pre_covid" estimates are for January 2018 - February 2020. "Covid" estimates are for March 2020 - August 2021. "Beach" estimates are for touristic beach municipalities. "Non-Beach" estimates are for municipalities without touristic beaches. "Stable" estimates are for properties that are observed at least once in the pre-pandemic period and once in the pandemic period. Standard errors clustered at the neighborhood level in parentheses. The omitted categories for listing type, property type and cancellation policy are entire home, single family home, and flexible-moderate, respectively. *p<0.1; **p<0.05; ***p<0.01.

Table A.2: Effect of amenities on log average daily rate of Airbnb listings: selected amenities, restricted pre-pandemic period

Variable	(1) Pre Pandemic 2018	(2) Pre Pandemic 2019	(3) Pandemic	Diff. 2018	Diff. 2019
Gym	0.051***	0.049***	0.075***	0.025***	0.025***
	(0.013)	(0.013)	(0.014)	[0.002]	[0.000]
Workspace	-0.018***	-0.016***	-0.009***	0.010***	0.008**
	(0.004)	(0.004)	(0.005)	[0.002]	[0.017]
Pool_or_jacuzzi	0.303***	0.300***	0.318***	0.015**	0.018***
	(0.011)	(0.011)	(0.010)	[0.025]	[0.002]
Elevator	0.171***	0.170***	0.147***	-0.024**	-0.023***
	(0.010)	(0.009)	(0.009)	[0.016]	[0.006]
Waterfront	0.068***	0.070***	0.091***	0.023***	0.021***
	(0.010)	(0.010)	(0.010)	[0.002]	[0.002]
Private_living_room	0.009	0.009	0.029*	0.021*	0.020*
	(0.010)	(0.011)	(0.012)	[0.062]	[0.053]
Percentage contribution to ADR $e^{\beta}-1$					
Gym	5.222***	5.012***	7.838***	2.616***	2.826***
Workspace	-1.833***	-1.592***	-0.851***	0.982***	0.741**
Pool_or_jacuzzi	35.368***	35.020***	37.473***	2.105**	2.454***
Elevator	18.667***	18.543***	15.842***	-2.825**	-2.701***
Waterfront	7.058***	7.240***	9.549***	2.491***	2.309***
Private_living_room	0.866	0.918	2.979*	2.112*	2.061*
Fit statistics					
Observations	1,692,091	1,103,331	1,217,031		
R^2	0.80	0.80	0.80		
Within R^2	0.60	0.60	0.60		
# of properties	178,859	157,821	173,056		
# of neighborhoods	15,504	14,673	15,651		
# of municipalities	958	928	944		
# of periods	26	14	18		
Fixed-effects					
Neighborhood	Yes	Yes	Yes		
Month-year	Yes	Yes	Yes		
Municipality-month-year	Yes	Yes	Yes		

Source: AirDNA, author's calculations. The top panel shows OLS estimates of the β coefficients in equation (1) for selected amenities. The bottom panel shows the percentage contribution to the ADR. "Pre pandemic 2018" estimates are for January 2018 - February 2020. "Pre pandemic 2019" estimates are for January 2019 - February 2020. The "Pandemic" estimates are for March 2020 - August 2021. "Beach" estimates are for touristic beach municipalities. "Non-Beach" estimates are for municipalities without touristic beaches. Standard errors clustered at the neighborhood level in parentheses. "Diff" columns correspond to the difference in the coefficients between the pre-pandemic and the pandemic period. The p-value for a test of whether these differences are zero are reported in brackets. The omitted categories for listing type, property type and cancellation policy are entire home, single family home, and flexible-moderate, respectively. *p<0.1; **p<0.05; ***p<0.01.