

Third-Party vs Owner Management in the Vacation Rental Market: Evidence from Airbnb

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Abstract. Owners looking to let their real-estate assets on a short-term basis on the Airbnb platform choose one of two forms of day-to-day management: owner managed (OM) or third party managed (TPM). Incentives theory identifies factors driving the choice of management form and the implications for asset performance. Owners must weigh input mix inefficiency arising from the TPM incentive structure against possibly greater TPM management ability. Controlling for endogenous management form selection using matched sample methods, data for Orange County, Florida, over 2014-2022 shows TPM productivity advantages sufficiently strong to overcome inefficient input mix effects on price and occupancy as well as effort-thinning from rising marginal management costs. Outcomes vary significantly across property types. Further, TPM and OM host responses to the decline in vacation property demand during the pandemic differ significantly. In addition, third-party managers react strongly to shopping externalities arising out of greater search traffic for neighborhood hotels participating on the Airbnb platform.

Keywords: Third party management; Principal–agent relationship; Short-Term Rentals; Airbnb Market.

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A. Introduction

Airbnb has grown from startup to a hundred-billion-dollar platform over the past decade to become an important part of the vacation rental market. Initially started as a peer-to-peer sharing platform, the company has evolved to encompass a professional lodging market platform. Growing search traffic from travelers continues to attract additional property owners, increasing the range of offerings on the booking platform. Some owners now offer more than one listing on the platform and many are becoming increasingly sophisticated in terms of pricing, managing their property, providing standardized experiences, etc. The mix of properties being offered on Airbnb now resembles other real estate markets in terms of management form, with some owner managed and some third party managed. What is not known is what underpins this mix in this setting and what it means for the vacation housing product. These are the questions addressed here.

Recent studies show that different hosts have uneven ability to create value on the Airbnb platform (Deboosere et al., 2019; Wachsmuth and Weisler, 2018). As a result, some property owners who possess neither the acumen nor the resources required to provide high quality travel experiences to guests rely on third-party property management companies to host their rentals. The new standardized offerings have significant potential. They are now responsible for almost half of Airbnb's business revenue while the person-to-person sharing economy model takes a backseat.

Individuals or firms owning real estate typically manage their assets using one of two types of management schemes, owner management (OM), in which the firm or individual owner conducts all basic and day-to-day management functions, or third-party management (TPM) wherein the owner hires a property management company to provide and monitor a number of

services such as collecting rents, tenant selection, repair and maintenance quality control, security, and other daily activities for which they are rewarded with a significant percentage of revenue generated from the property. The literature identifies several key factors that drive the choice of management form for real estate assets in general (Glascock and Turnbull, 1994; Sirmans et al., 1999). First, high owner opportunity costs make them less likely to rely on the OM form of management. This is particularly relevant for small scale operations. Second, professional management may enjoy productivity advantages that allow them to provide services more cheaply than owner managed firms due to greater ability or economies of scale. Finally, the principal-agent problem inherent in third-party management increase costs as the format leads to less efficient use of their own time, effort and resources as opposed to the inputs supplied by the owner. While the theory identifies these advantages and disadvantages of TPM rationalizing a mix of both management forms in real estate markets, the empirical evidence is scant in general and nonexistent for short-term vacation rental markets. This paper begins to fill this gap, focusing on the choice of management form and asset performance consequences for properties participating on the Airbnb platform.

Glascock and Turnbull (1994) analyze rental houses and apartment property owners' propensity to supply labor to their own rental firm as opposed to hiring outside labor, focusing on the characteristics of the employment relation in the principal-agent form of organization as a key determinant of the owner's decisions in this regard. Sirmans et al. (1999) find that management form affects apartment rents, but they are unable to test the effect of the choice of management form on occupancy due to unavailability of data. In their theoretical model, the occupancy rate is also a market-determined stochastic function of both the level of service

provided and the rent, implying separate simultaneous management form effects on price and occupancy.

We apply the Sirmans et al. (1999) property management model to the Airbnb setting. The Airbnb data allow us to observe both prices and occupancy rates for each unit, providing a unique opportunity to examine factors prompting Airbnb owners to choose OM or TPM to host their properties and the effects of this choice on price and occupancy. Stochastic demand means that observed price and occupancy outcomes are not sufficient statistics for unobservable third-party management efforts, thereby precluding first-best incentives. This application of incentives theory shows that a property owner must weigh the possibly greater TPM management ability against the input mix inefficiency arising from the TPM incentive structure. Our study not only provides new insights into the structure and performance of the Airbnb industry, it also contributes empirical evidence to the broader real estate literature dealing with management and asset performance.

The original Airbnb market offered products tied to the residential real estate rental market, comprising small-scale individual suppliers with only a few units to rent on a short-term basis. It has since evolved to include larger real estate firms with substantial holdings in multiple units. Hence, the empirical results offered here provide additional insights about the short-term rental market not captured in the existing literature. Furthermore, as theory reveals that management form is endogenous, the empirical study must address possible sample selection issues. To this end we use propensity score matched samples to control for self-selection bias associated with management form, comparing results with full sample results to assess the empirical effects attributable to the possible sample selection bias.

The seemingly unrelated regression (SUR) model of prices and occupancy on the full sample reveals that TPM often obtain higher prices than OM in the Airbnb market. According to the underlying theory, this implies that the greater productivity of the professional hosts outweighs the inherent input mix inefficiency arising in the TPM form. Comparing estimates between the full sample and matched sample results reveals that selection bias does affect some of the key full sample results.

Third party management effects are not uniform across the Airbnb market. Professional hosts managing high density real estate properties generate lower prices and occupancy rates, indicating that whatever the productivity advantages enjoyed by TPM providers, they are not sufficiently strong to offset the input mix inefficiency identified in the theory for these properties. Moreover, the occupancy rate is lower for properties managed by firms that have a greater number of total units under management locally. Whether the result of management effort thinning analogous to that identified earlier by Bian et al. (2015) for real estate agents or decreasing returns to scale in management, this result also illustrates the relevance of the inefficient input mix effects inherent in the TPM form even when the professional manager has greater ability.

Looking at the effects from local pandemic restrictions shows that TPM properties exhibit stronger price and occupancy responses than OM units during the most restrictive phase of the crisis when the demand for vacation properties fell dramatically. The strength of these differences, however, vary across property types. TPM hosts respond more aggressively to the lifting of local restrictions, raising prices relative to OM hosts. The surge in post pandemic demand also increases occupancy rates for both types of properties.

The adverse effect of Airbnb on hotel revenues has been well documented in the literature. Dogru, Tarik, et al. (2022) argue that multi-unit or professional hosts are the primary driving force for this effect. Dey and Turnbull (2023) show that higher prices of nearby hotel Airbnb rooms increase the unit prices and decrease occupancy rates of competing residential units both before and after the pandemic period. Their results are consistent with the notion of search synergy or shopping externality effects from nearby hotels that are not strong enough to offset the competition effect on the occupancy rate. The goal of our analysis here is to examine any difference in this effect that may arise due to the choice of management form. We evaluate the hotel effects on surrounding TPM managed non-hotel properties by controlling for the distance weighted average price of hotels located within a one-mile radius of the competing residential Airbnb unit, in our regression models. We also examine if the effect is altered by the pandemic experience. Results show that TPM hosts respond strongly to competition from nearby hotel prices, as opposed to OM hosts by decreasing the rents of the units they manage. This leads to a demand substitution effect on the occupancy rates of these units. Results hold in the post covid period but are insignificant during the covid lock-down.

Airbnb Industry Overview

In October 2007, roommates Brian Chesky and Joe Gebbia, finding it difficult to afford their San Francisco apartment, came up with the brilliant idea of putting an air mattress in their living room. They created a simple website with blog and maps and turned their home into short-term living quarters for travelers who were unable to book a hotel in the saturated market. The site which was originally named Airbedandbreakfast.com officially launched on August 11, 2008 with the help of their third co-founder Nathan Blecharczyk. They had their first customers in the

summer of 2008, during the Industrial Design Conference held by Industrial Designers Society of America, where three attendees unable to find accommodation agreed to pay \$80 each to spend the night on air mattresses. By March 2009, the site had 10,000 users and 2,500 listings with entire rooms and properties. It continued to raise money from private investors and venture capitalists and finally went international in October 2011, when Airbnb established an office in London. Airbnb continued its expansion globally undergoing several upgrades and served 9,000,000 guests with nearly 250,000 listings by 2013. As it continued to grow, Airbnb started offering more sophisticated amenities like travel guides and customized experiences for travelers. Airbnb first became profitable during the third quarter of 2016. Airbnb's revenue grew more than 80% from 2015 to 2016. By October 2019, two million people were staying with Airbnb each night and the company went public in December 2020.

While Airbnb faced several challenges in its journey to become ubiquitous, the company has made substantial efforts in evolving in terms of guest and host needs. In July 2016, Airbnb implemented an anti-discrimination policy and on March 30, 2020, the company pledged \$250 million in payouts to host to compensate them for guest cancellations due to the pandemic, a move that set it apart from its competitors like Vrbo that faced criticism due to its lack of protection of the interests of guests or hosts. Despite these efforts, Airbnb has been subjected to heavy criticisms for allegedly enabling increases in home rents, housing prices and by the hotel industry for not being subject to similar taxation and regulation. Several regional authorities have taken the initiative to pass laws that require Airbnb to provide guest information so that local regulations can be enforced, and proper taxes are collected. Nevertheless, regulation of these short-term rentals remains highly localized and are segmented based on building, city and zoning standard. Some of these regulations include business licenses for hosts to operate as vacation

rental managers of their property, payment of business tax receipts like hotels. In addition to government-imposed restrictions, many homeowner associations also have their own set of regulations for short term rentals.

Orlando hosts around 75 million tourists every year making it a lucrative location for setting up a vacation rental business. The average monthly revenues of Airbnb in Orlando is approximately \$2,609, with an average daily rate of \$200 with an average occupancy rate of 70%. This far exceeds the occupancy rates for the rest of US which is only 48%. In Orange County, Florida, prior to July 1, 2018, homes zoned as R-3 transient residential could legally operate as vacation rental that can be rented or leased for 30 days or less. Short-term rentals are defined as rented for between 31 and 179 days. While only 4.1 percent of Orange County is zoned for legal Airbnb operations the number of Airbnb listing was close to a thousand in 2018. Although Airbnb has consistently warned hosts to be mindful of local regulations, the number of illegal rentals on Airbnb continues to rise creating a disruption for the large number of hotel and traditional lodging properties located in the area. Central Florida hoteliers have consistently said they don't consider listings platforms such as Airbnb a viable threat to their occupancy rates, citing the number of rooms in the region and the price range they're offered in. Guests booking Airbnb rentals are also required to pay Orange County Tourist Development Tax, Florida's transient rental tax is currently 6% of the listing price (including cleaning fee) for reservations shorter than 182 nights. As of July 2018 the city of Orlando allows home sharing subject to registration, approval from HOA and/or landlords and permit fees and sales tax. In addition, hosts are only allowed to rent up to half the bedrooms on the property, only in residential zones with the homeowner or tenant being present at the time of rental. For renting out an entire property Orange County requires such properties to be licensed by the Department of Business

and Professional Regulation, be located in O-3, MU district, or AC districts and must obtain a Business Tax Receipt.

Literature Review

Incentives theory argues that the TPM agreements are a market response to the principal-agent problem that exists in an asymmetric information environment. The predominance of gross rent share contracts for third-party management can be viewed as a motivating mechanism. There are several studies that show that revenue sharing can often be an efficient response to the agency problem (Holmstrom, 1982), especially when demand or production is stochastic (Stiglitz, 1974; Drago and Turnbull, 1991), conditions which typify the real estate rental market. For example, Elliott, et al. (1980) analyze maintenance efforts of the professional landlord while Elliott, et al. (1985) test the link between the maintenance behavior of large-scale landlords and neighborhood succession; Smith and Tomilson (1981), Hohm (1983), and Mann and Veseth (1983) examine the relationship between rent controls and rental housing values; and Read (1988; 1991), Rosen and Smith (1983), and Wheaton (1990) study vacancy behavior.

Sirmans and Sirmans (1991) provide empirical evidence that information asymmetries between landlord and tenants can be overcome by signals provided by the landlord, such as employing professional management companies holding professional designations, resulting in higher visibility of the expected management quality for the tenant. In a different vein, Sirmans et al. (1999) investigate the choice of two asset management forms by apartment building owners, namely owner manager or third party managed, and provide empirical evidence that owner management results in higher apartment rents and that profit considerations affect the

choice of management form. Other studies like Jaffe (1976) confirm that the structure of the agent compensation is central to aligning divergent objectives.

Rosenberg and Corgel (1990) examine agency costs implicit in standard property management contracts. Their empirical results indicate that these costs for property management contracts are significant and are higher for institutional owners due to fact that ownership is more dispersed, similar to conclusions in the general management literature (Jensen and Meckling, 1976; Rozeff, 1982; Lease et al., 1983; Kim and Sorensen, 1986). Fama (1980), on the other hand provides evidence that competition for property management has no impact on agency costs. Their analysis shows that agency costs are the highest for institutional owners related to the property management company and lowest for similarly related private owners, who have superior ownership control and knowledge. Rosenberg and Corgel (1990) also conclude that existing property management contracts should be adjusted to improve the alignment of manager and owner interests. Despite their conclusion, by industry convention, management compensation for small properties continues to be based on rental collections and not on net operating income or similar measures. Agency problems arising from outsourcing corporate real estate functions are investigated by Gibler and Black (2004). They conclude that an optimal balance of staffing/outsourcing could possibly be achieved by keeping all strategic functions in house. Munneke, et al. (2015), however, show that unobservable worker effort coupled with uncertain demand preclude first-best incentives for both inside employees and outsourced workers.

Theoretical Model

The theoretical framework draws from the real estate management model developed in Sirmans et al. (1999), extending it to include the connection between neighborhood amenities and the demand for properties listed on Airbnb. Without loss of generality, consider a single unit listed on Airbnb.

Unit quality is q , a measure of the expected vacation service enjoyed by occupants. Unit quality is an increasing quasi-concave function $q(m, z, n)$ of management effort, m , and maintenance and other operating, z , as well as the surrounding neighborhood amenities, indexed by n . Demand is uncertain ex ante. The rental price p of the unit is a function of the unit quality, q , and the realization of the stochastic state indexed by s .

$$p = p(q(m, z, n), s) \quad (1)$$

The price is increasing in unit quality ($p_q > 0$, using subscripts to denote derivatives). Therefore, the price effect of neighborhood characteristics fully reflects their desirability to potential tenants indicated by the sign of q_n .

The occupancy rate, x , for the unit is a function of price, unit quality, and the realized state

$$x = x(p, q(m, z, n), s) \quad (2)$$

The occupancy rate is decreasing in price ($x_p < 0$) reflecting the law of demand and increasing in quality ($x_q > 0$). The relationship between occupancy and neighborhood characteristics, holding unit price constant, directly reflects whether potential tenants find the characteristics desirable ($x_q q_n > 0$) or not ($x_q q_n \leq 0$).

Owner Management. Under owner management, the property owner's expected profit for the unit per period is

$$\pi^{OM} = E[p(q(m, z, n), s)x(p, q(m, z, n), s)] - wm - vz \quad (3)$$

where w and v are the costs of management effort and maintenance inputs, respectively. The owner's input choice maximizing (3) is the implicit solution $\{m^* = m(n); z^* = z(n)\}$ to the marginal conditions

$$\frac{\partial \pi^{OM}}{\partial m} = E[MR]q_m - w = 0 \quad (4)$$

$$\frac{\partial \pi^{OM}}{\partial z} = E[MR]q_z - v = 0 \quad (5)$$

denoting the marginal revenue of q as $MR = [p_q x + x_q p]$. We assume realized revenue is concave in inputs so that both realized and expected marginal revenue are decreasing in q , as usually depicted, which ensures all second order conditions are fulfilled.

Figure (1) portrays the locus defined by conditions (4) and (5) in input space. The owner's input choices satisfy the cost minimizing or efficient input mix condition $MRTS_{z,m} = \frac{w}{v}$ satisfied along the efficient production locus aa in the figure. Substitute the input choices $\{m^*, z^*\}$ into the unit quality production function to obtain the indirect output function

$$q^* = q(m(n), z(n), n) = Q(n) \quad (6)$$

for which $Q_n > 0$.

Inputs are not observable in the data, but unit rental price and vacancy rate are. Substitute (6) into (1) and (2) and differentiate the resultant system to find the observable neighborhood effects on price and occupancy rate

$$\frac{\partial p^*}{\partial n} = p_q Q_n > 0 \quad (7)$$

$$\frac{\partial x^*}{\partial n} = x_q Q_n + x_p \frac{\partial p^*}{\partial n} \quad (8)$$

Result (7) draws the direct connection between desirable neighborhood attributes and unit rent. As revealed in (8), however, the net effect of neighborhood amenities on unit occupancy comprises two offsetting influences, the first being the direct effect on occupancy for given rent (the first term in (8)) and the second being the indirect effect through change in rent (the second term in (8)). This indirect price effect implies that even neighborhood attributes highly prized by potential tenants may not be reflected in higher occupancy rates, an otherwise counter-intuitive result.

Third Party Management. The alternative to owner management is for the owner to hire a professional management firm to operate the property. The management firm is typically paid a proportion of revenue, α (generally 10%-20% in this market), while the owner is responsible for non-management maintenance and operating inputs, z . The stochasticity of demand for the unit, reflected in the stochastic term s , precludes the owner from directly monitoring manager effort; while price and occupancy realizations are observable, they are not sufficient statistics to infer management effort or capability. Carmichael (1983) describes this as an agent-agent setting, the equilibrium for which is Nash.

The manager and owner expected profits in the TPM scheme are, respectively,

$$\pi^{TPM} = \alpha E[p(q(m, z, n), s)x(p, q(m, z, n), s)] - wm \quad (9)$$

$$\pi^O = (1 - \alpha)E[p(q(m, z, n), s)x(p, q(m, z, n), s)] - vz \quad (10)$$

Management effort maximizes (9) while owner supplied inputs maximize (10). The equilibrium $\{m^{**}, z^{**}\}$ satisfies the Nash conditions

$$\frac{\partial \pi^{TPM}}{\partial m} = \alpha E[MR]q_m - w = 0 \quad (11)$$

$$\frac{\partial \pi^O}{\partial z} = (1 - \alpha)E[MR]q_z - v = 0 \quad (12)$$

Sirmans et al. (1999) conclude that the TPM incentive structure elicits an inefficient input mix, which is easily seen here from the above conditions: $MRTS_{z,m} > \frac{w}{v}$ and the input mix lies on the locus labeled bb above the efficient input mix locus aa in figure 1. This, by itself, suggests that the OM and TPM outcomes differ, with professional managers relying on relatively more non-management inputs than is first best.

But more can be said. It can be shown that the locus of points satisfying (11) in figure 1 lies to the left of that satisfying (4) and the locus satisfying (12) lies to the right of (5). As a consequence, $m^{**} < m^*$ and $z^{**} < z^*$ and the vacation quality from a given unit is lower under TPM than OM, $q^{**} < q^*$. Therefore, from (1) it follows that,

*Proposition 1: TPM leads to a lower unit rental price than OM: $p^{**} < p^*$*

The effect of TPM on occupancy, however, is not as straightforward. By (2), $x^{**} = x(p^{**}, q^{**}, s)$ and $x^* = x(p^*, q^*, s)$, so that : $p^{**} < p^*$ increases x^{**} relative to x^* but at the same time $q^{**} < q^*$ reduces x^{**} relative to x^* , so that *the net TPM effect on occupancy relative to OM is ambiguous.*

It is straightforward to verify that the effects of neighborhood amenities, n , exhibit the same comparative static properties as found in the OM model. Nonetheless, the above results make it clear that TPM effects on price and occupancy, like those of neighborhood characteristics, will not in general take the same sign.

One potential advantage of TPM over OM may be that professional managers are better at what they do. This may be due to experience, economies of scale in managing multiple units, or lower opportunity costs. Indeed, the productivity advantage is likely what makes TPM

attractive in the first place. Using the same approach taken for neighborhood amenities in the OM model, it can be shown that greater management ability that yields a factor neutral increase in input productivity increases input employment from f to k along locus bb in figure 1.² As drawn, the greater TPM productivity shifts input usage out to k , but this is only one possibility, the movement along bb reflecting the extent of the productivity advantage relative to OM. Regardless, greater productivity has the same qualitative effect on vacation quality, rental price, and occupancy as greater neighborhood amenity found earlier:

*Proposition 2. Greater TPM productivity increases TPM price, p^{**} , and has an ambiguous effect on occupancy, x^{**} .*

Thus, when compared with the OM solution, since the inefficient input mix effect of TPM reduces price, we can conclude the following:

*Proposition 3. Observing higher prices under TPM than OM ($p^{**} > p^*$) implies greater TPM productivity strong enough to offset the TPM inefficient input mix effect.*

Because the rental price and quality of services provided by the unit both affect occupancy, the empirical condition identified above is key to inferring the presence of TPM productivity advantages.

² Not shown in the diagram are the outward shifts in the Nash conditions loci from greater TPM productivity that yield the new intersection at k . The factor neutrality of the productivity shift ensures the new equilibrium lies on the original locus bb .

Finally, the owner decides whether to operate as OM or TPM, weighing the expected profitability of each. The inefficient input mix of TPM reduces expected profit but greater management ability or productivity increase TPM profit relative to OM. Clearly, the compensation paid to the management firm reduces owner profit under TPM. Thus, neither form dominates the other in all situations, yielding the mix of types observed in the market. Regardless, the model implies that any empirical comparison of OM and TPM outcomes must take into account possible selection bias arising from the owner's underlying choice of management form.

Data

We obtain the Airbnb data from AirDNA, a company that provides data and analytics to entrepreneurs, investors, and academic researchers, for the period between January 2014 through June 2022. The geographical region considered is Orange County, Florida³, which spans the entire Orlando-Kissimmee-Sanford Metropolitan Statistical area. Schuetz and Sarah (2021) document that Orlando being heavily dependent on tourism and hospitality industries, is one of top performing cities in the U.S. in terms of both hotel room supply and Airbnb supply. Since our analysis studies Airbnb market as a short-term rental product, the question naturally arises if Airbnb represents the entire short-term rental segment. A second concern may be that of Airbnb mechanically excluding the needs of travelers who would otherwise stay at hotels. Although Airbnb may be the most popular, other on-line platforms owned by large travel companies, such as Expedia, Priceline, and TripAdvisor, also provide similar peer-to-peer (P2P) short-term rental services. However, Airbnb offers private and shared rooms as well as small studios and

³ The total population of Orange County, FL in 2021 was 1.43 million while that of Orlando MSA is 2.69 million.

apartments and has the capacity to cater to a large variety of clients, while the others tend to provide larger spaces with more offerings (Geminiani & DeLuca, 2018). For example, about 70% of vacation rental listings on major short term vacation rental booking platforms, like VRBO and HomeAway, have two or more bedroom and an average capacity of six people—and 87% of their guests travel with a family member (Vacation Rental Management Association, 2020). Airbnb represents a wider range of property types and is a significant part of the broader vacation rental market.

Table 1 provides a complete list of variables and definitions. The traditional Airbnb listings are mostly classified residential, for example, apartments, bungalows, condominiums, single family detached houses, guest houses attached to larger residential units, lofts, townhouses and villas as well as traditional rental housing. We identify apartment, condominium and townhouse properties with the *Attached* type dummy variable. We use the natural log of monthly Airbnb average daily rate (*ADR*)⁴ and monthly occupancy rate (*Occupancy*) as our price and occupancy dependent variables to analyze the performance of Airbnb rentals under the two management schemes. We also construct a measure of Airbnb supply in the census tract, *Listing Density*, as the total number of Airbnb listings available during that month in the census tract, including entire homes, private rooms, and shared rooms, divided by the total number of housing units in the tract.

Some Airbnb listings are not always active, created in Airbnb platform but not available for rent over some periods. Therefore, we only include Airbnb listings that are active at least

⁴ Average daily rate of booked nights in USD equals total revenue for the month divided by booked nights. The monthly average daily rate *ADR* is then calculated as the average daily rate multiplied by the number of available days in the month of each individual booking.

once within the previous twelve months. Observations are monthly and we do not include listings that have not been active for at least three months since inception.

We include property characteristics such as the number of bedrooms (*BR*) and bathrooms (*BA*). We use the location and zip code information provided by Airbnb to map properties into census tracts, which we define as the neighborhood. We also construct an indicator for units available in their entirety versus as a shared space (*Shared Listing*). We identify units that have a greater than average number of reviews (*Popular*) and higher than average ratings (*High Rating*). We also include information about how hosts operate their businesses. We define dummy variables indicating highly responsive hosts (*Responsive*), whether the host has a flexible cancellation policy (*Flexible*) and whether the host has a designated “Superhost” badge on Airbnb platform (*Experience*). Other variables summarize restrictions on minimum number nights that can be booked (*Min-stay*), maximum number of occupants (*Max-guests*), and the number of listings that hosts on the Airbnb platform manage locally (*Units Managed*) to control inventory management effects or economies of scale.

We obtain additional host information by scraping host profiles on the Airbnb website. Sites contain name of the host, their current location, number of listings, a section describing the host, languages spoken by host, where the host works and when the host joined Airbnb platform. We note that not all items on this list are available for each host. We use the host name or information about a property management company or details about host’s workplace or the number of listings the host manages across Airbnb to identify units under third-party management (TPM). The dummy variable *Profman* indicates these units.

We define neighborhoods as census tracts and draw neighborhood characteristics from US Census data.⁵ The American Community Survey (ACS) supplements the US Census count data for non-census years, providing information about population, median age of the community, employment status, educational attainment, gender distribution, age distribution, household income, number of housing units, and the concentration of different ethnic groups in the community. This ACS data is only available through 2020, so we extrapolate 2020 values to proxy neighborhood characteristics in years 2021 and 2022.

In addition to the above information, we also create an indicator *Proximity* for Airbnb listings near major tourist attractions. We identify three major tourist destinations within the Orlando metropolitan area namely, Disney, Universal and downtown Orlando, and calculate the straight-line distance in miles between the property and these locations. The median distance is about 6 miles. The *Proximity* dummy identifies Airbnb units located within 6 miles of any of the above 3 sightseeing spots.

Sample Description. Tables 2 and 3 present summary statistics of key variables for the full sample and the management firm subsamples, respectively. In the full sample, table 2 indicates each host manages about 5 listings on average. About 45% of listings are third-party managed. Of the unique 2,477 hosts managing listings on Airbnb in Orange County, only about 6% have been awarded the super host distinction signifying experience, reliability, and expertise (indicated by the dummy variable *Experience*). About 53% of the listings are for attached housing like apartments, condominiums, and townhouses. The majority of listings in our sample are shared space listings, which is consistent with the early history of Airbnb rentals as private

⁵ Census data is drawn from <https://data.census.gov>

rooms or rooms in high density real estate properties. These unit are likely less desirable during the pandemic and in its immediate aftermath.

Table 3 compares the subsamples for the two management forms. TPM listings tend to cluster around the major tourist attractions (54% vs 47%), have higher response rates (93% vs 85%), less likely to be in attached type real estate properties (47% vs 59%), and tend to allow a higher number of guests (average of 6 guests per rental vs 4 guests per rental). Most of the listings offered by TPM are entire properties (95% vs 62%), as well as less flexible, popular or have high ratings, and require longer minimum stays than required by OM hosts (11 days vs 5 days). The average number of listings managed by TPM hosts is about 23 while that of OM hosts is about 5 units. The *ADR* or rental rate and occupancy rates of TPM properties are also higher than those of owner managed properties. The neighborhood characteristics of properties under each management scheme appear to be similar.

Empirical Results

To examine how TPM affects rent prices and occupancy rates, we use the following empirical reduced form system as our base model

$$\log(ADR) = \beta_0 + \beta_1 Profman + \beta_2 \mathbf{X} + \beta_3 \mathbf{FE} + \varepsilon_{ADR} \quad (13)$$

$$Occupancy = \alpha_0 + \alpha_3 Profman + \alpha_2 \mathbf{X} + \alpha_3 \mathbf{FE} + \varepsilon_{OCC} \quad (14)$$

where \mathbf{X} is the vector of property and listing characteristics, *Profman* indicates TPM units, \mathbf{FE} is a vector of quarter and census tract fixed effects and the ε are error terms. *ADR* and *Occupancy* are simultaneously determined in equilibrium and affected by the same realizations of the

underlying stochastic demand, giving rise to possible cross equation correlation in the error terms. Seemingly Unrelated Regression (SUR) yields asymptotically efficient coefficient error estimates in such situations.

Table 4 provides benchmark SUR estimates on the indicated unmatched samples.⁶ The first two columns report results of the baseline price and occupancy models (13)-(14). Of central interest, the coefficient of *Profman* is positive and significant in both equations indicating that professional management yields higher rents and occupancy rates than owner management. While the number of managed properties and proximity to major tourist venues have positive effects on both price and occupancy, minimum lease period and attached property type have negative effects on price and occupancy. *Popular* listings and high host *Response* rates have a positive effect on occupancy but a negative effect on price. These results are not surprising in light of the underlying theory explaining why factors affecting vacation quality need not have the same effects on price and occupancy. On the other hand, *High Rating*, *Max-guests*, and cancellation *Flexibility* lead to higher average daily rents of Airbnb rentals and lower occupancy rates. Finally, the coefficient estimates of *Attached* are significantly negative in both equations, indicating stronger demand for detached than attached property types.

Taking a closer look at differences in performance across property types and the number of properties managed locally by hosts, the models (3) and (4) in table 4 add interaction terms *Profman* \times *Attached* and *Profman* \times *Units Managed*. The estimates indicate third-party managed listings of attached properties have lower prices and occupancy rates than owner managed attached properties and attached units under TPM have lower prices and occupancy

⁶ Results in this section are corroborated by running simple OLS regressions for price and occupancy separately for both matched and unmatched sample and are available in the Appendix.

than other TPM units. Similarly, the coefficient on *Profman*×*Units Managed* is positive and insignificant on the price equation and negative and significant on the occupancy equation. While the number of units managed by TPM has no significant effect on the rental prices of these properties, handling more units reduces occupancy rates. The occupancy results are consistent with professional management effort thinning from spreading effort across a larger inventory of units.

Matched Sample Analysis. The theory emphasizes the need to address possible self-selection bias when including the management form in empirical rent and occupancy equations. The two stage methods by Heckman (1976), Lee (1978) and others are not always ideal for correcting self-selection bias because the selection decision is often difficult to identify econometrically, as it is in this case. Therefore, we apply a propensity score matching (PSM) technique to create a sample matching each TPM unit with a similar OM unit, controlling for differences in characteristics correlated with management form in order to approximate a randomized trial.

The dependent variable is the management form indicator *Profman* in the first stage logit estimation on listing, neighborhood and property characteristics for the full sample of Airbnb units:

$$Profman = \beta_0 + \beta_1\mathbf{X} + \beta_2\mathbf{T} + \varepsilon_S \quad (16)$$

Using the predicted logit value as the propensity score for each observation, each TPM observation is matched with a corresponding OM observation using a k-nearest neighbor greedy matching technique that matches OM to TPM observations without replacement. Good

matched-pair samples contain both closely matched individual pairs and balanced case and control groups. The matched sample comprises 5,706 unique listings. Table 5 reports estimated marginal effects from the logit estimation on the full sample.

The negative marginal effects indicate that *Shared-listing* units and those with *Experience*, *Popular*, and *High Rating* hosts are less likely to be TPM. Interestingly, *Proximity* shows that locations near tourist hot spots are neither more nor less likely to be TPM. Property owners located in areas with heavy tourist footfall may not see how third party management can improve their outcomes. On the other hand, detached housings like single family residential houses, villas, bungalows rented out in their entirety require more extensive maintenance, preparation between renters, and upkeep and are therefore less likely self-managed by small scale owners.

Table 6 reports the SUR price and occupancy model results for the matched sample. Most of the estimates resemble those from the unmatched sample, suggesting that the full sample conclusions are not being driven by selection effects. The coefficient of *Profman* \times *Units Managed*, however, does change significantly in the matched sample. While the unmatched sample finds an insignificant price effect of number of properties managed by professional hosts, the matched sample result indicates that a greater number of properties managed by TPM hosts lead to both lower rents and occupancy. This indicates greater effort thinning from an increasing marginal cost of managing additional units for TPM than OM. Thus, while greater inherent productivity makes TPM outperform OM firms in terms of price and occupancy outcomes, stronger effort thinning reduces the productivity advantage of TPM as manager handles more units. The observed net effect of professional management on price and occupancy rates

nonetheless indicates that greater inherent TPM productivity offsets the inefficient input mix from the TPM incentives structure over the relevant range of management firm sizes.

Covid-19 Pandemic Effects. The covid-19 pandemic created an unprecedented external shock to the tourism industry. We consider whether this event in the Orange County Airbnb market creates differences in TPM and OM responses. We repeat the SUR analysis with additional interaction terms that account for the worst phases of the pandemic as well as the post pandemic period.

The *Covid* dummy equals one for the second and third quarter of 2020, the period during which business restrictions were imposed locally, and zero otherwise. Table 7 columns (1) and (2) report estimates for the extended model interacting *Profman* and *Units Managed* variables with the *Covid* dummy. The model also includes triple interaction terms $Covid \times Profman \times Units Managed$ and $Covid \times Profman \times Attached$ to examine differences in TPM and OM behavior during this pandemic period. The second specification reported in columns (3) and (4) examine the performance of Airbnb rentals in what we label the post-covid setting, interacting the variables of interest described above with the *Post-covid* dummy for quarters during and after 2021 after the many local restrictions were lifted. For both extended models, cross-equation tests of the interaction terms reject the null hypothesis that coefficients are equal to zero across equations. Clearly, the COVID-19 restrictions and the aftermath affected Airbnb rental performance.

Results from the SUR analysis of the unmatched full sample presented in table 7 reveal significant differences in how OM and TPM forms respond during the *Covid* period. The estimates show both lower prices and occupancy during the most severe wave of the pandemic for OM properties, although the coefficient of the *Covid* dummy is significant only in the occupancy

equation reported in the second column. The significantly negative coefficient of *Covid* × *Profman* shows TPM units have lower occupancy than OM units during this time. The effect on price, on the other hand, is not significant. The coefficients on the triple interaction terms *Covid* × *Profman* × *Units Managed* and *Covid* × *Profman* × *Attached* in the second column further reveal that TPM hosts who manage more units locally or manage attached type properties obtain higher occupancy rates even when local restrictions are in place. Taken together, the period during which local restrictions are imposed changed both OM and TPM behavior, but their responses differ. This points to another difference in the two management forms, how they react to external market shocks.

Table 7 columns 3 and 4 report the results for the matched sample. The conclusions are the same as for the unmatched sample, with one difference. The coefficient of *Covid* × *Profman* interaction term in the price equation in column 3 is now negative and significant. This reinforces the conclusion that TPM and OM respond differently to the demand shock, with TPM obtaining both lower prices and lower occupancy during the worst phase of the health crisis. TPM hosts appear to respond more strongly than OM hosts to this situation by reducing price more aggressively but also enduring lower occupancy.

Table 8 reports estimates dealing with what we identify as the post-pandemic period. The *Post-covid* coefficient in column 2 indicates lower OM occupancy rates after restrictions are lifted. The interaction term *Post-covid* × *Profman* shows TPM Airbnb rentals have higher occupancy rates. In addition, the coefficients of the interaction terms *Post-covid* × *Attached* and *Post-covid* × *Profman* × *Attached* in columns 1 and 2 show OM attached properties obtain lower prices and greater occupancy while TPM managed attached properties have even higher prices but lower occupancy rates than OM units in the post pandemic environment. This is additional

evidence of differences between TPM and OM responses to changes in market demand conditions.

Results for the matched sample are in columns 3 and 4 of Table 8. As before, the conclusions resemble those from the unmatched sample. We note, however, that the coefficient of $Post-covid \times Profman$ in both the price and occupancy equations are now significantly positive, indicating a stronger TPM effect relative to OM rentals. It appears that professional management does a better job exploiting the demand surge for vacation rentals in the post covid period.

Spillover Hotel Effects. Dey and Turnbull (2023) argue that from the property owner's perspective, greater buyer search traffic stimulated by nearby listings can create shopping externality effects, localized search synergies that benefit all listings in the area. Our question in this section centers on the effect of hotel rooms listed on the Airbnb platform on surrounding third-party managed residential listings.

To delve deeper into this, we focus on the residential units that are located in close proximity to hotels and estimate their performance during and after the pandemic. The motivation behind this analysis is to find evidence of the influence that the presence of hotels run by experts, generates on competing professionally managed Airbnb unit. We tackle this question empirically by computing a statistic that measures this effect. We calculate the distance weighted average ADR ($wtprc$) of the hotels that are listed on Airbnb in the same month as the competing residential unit and are located within a mile of this unit. We use this variable as a proxy to capture what we define here as the hotel effect. We then interact the logarithmic value of this variable, $\log(wtprc)$ with the *Profman* dummy in all our regression specifications and report the results in Table 9.

From Panel A, the coefficient of the $Profman \times \log(wtprc)$ variable is positive and significant for occupancy rates in both unmatched and matched samples, as seen in columns (2) and (4) respectively. The coefficient of $Profman \times \log(wtprc)$ on the price equation is negative and significant for the matched sample while the effect is negligible for the unmatched sample. This indicates that TPM hosts respond strongly to competition from nearby hotel prices, as opposed to OM hosts by decreasing the prices of the units they manage. This leads to a demand substitution effect on the occupancy rates of these units.

To take into consideration covid and post covid time periods, we interact the $\log(wtprc)$ variable with *covid* and *post-covid* dummies and add triple interaction terms $covid \times Profman \times \log(wtprc)$ and $post-covid \times Profman \times \log(wtprc)$ to determine the joint effect of the pandemic and nearby hotels on TPM Airbnb units. From Panel B, we do not observe evidence of any significant effect of increasing prices of nearby hotels on the performance of TPM units during the shutdown period. Results are consistent with previous findings and are typical in regard to prices and occupancy rates of professionally managed units and the performance of all Airbnb rentals during this time. Results in the post-covid setting are similar to those obtained in Panel A. The coefficient of $post-covid \times Profman \times \log(wtprc)$ is negative and significant on the price equation and positive and significant on the occupancy equation as seen in Panel C. This points to the fact that following the easing of restrictions, TPM hosts reverted back to their original strategy of decreasing the rents of Airbnb units directly competing with nearby hotels. This strategy resulted in higher occupancy rates for these units.

The findings lead us to the conclusion that the net effect of hotel rooms on TPM Airbnb rentals is purely competitive and is reflected in the positive relationship between rising hotel room prices and occupancy rates of professionally managed Airbnb units. This is not a surprise

as hoteliers often consider professionally managed rentals to be the real threat. In fact, the third party managers response to competition from hotels are stronger than owner managed rentals and fully offset the shopping externality effect generated for non-hotel properties by the Airbnb participation of nearby hotels. Results are consistent with Farronato and Fradkin (2018) develop a model of competition between peer hosts and hotels who provide differentiated products. Empirical analysis shows that professional hosts are more responsive to market conditions and exert downward pressure on hotel prices down as a result.

Conclusion

This paper applies incentives theory to study Airbnb rental owner choice of management form and the effects of the choice on asset performance. Airbnb began as a simple sharing model that has evolved into a broad search platform offering a wide range of vacation experiences. It has expanded to include specialized hosts providing a wider array of services that are sometimes beyond the capabilities of many small-scale homeowners renting out single rooms or even their entire properties on Airbnb on a short-term basis. The literature identifies these skilled hosts as one of the key factors now driving Airbnb revenues. Nonetheless, while many hosts are affiliated with professional property management firms, the platform still includes a substantial number of individual owner managed properties.

This paper is the first to consider the mix of management forms observed for Airbnb properties, examining factors prompting owners to forego hosting and instead turn to professional management firms to handle their properties listed on Airbnb. The theoretical model shows that asset owners weigh the inefficient input mix arising from the TPM incentive structure against possibly greater TPM management ability. Indeed, preliminary analysis identifies

differences in management style; cancellation flexibility, responsiveness to customers, and host experience are all more likely associated with units under third party management than owner management.

We apply the management choice model to Airbnb platform data for all residential listings over 2014-2022 in Orange County, Florida. A simultaneous SUR model of prices and occupancy rates reveals that the effect of TPM on prices and occupancy depend on property characteristics. While prices and occupancy are generally higher for many property types, TPM leads to lower prices and occupancy rates for high density properties. Moreover, the occupancy rate is lower for TPM firms who manage a greater number of units locally, a pattern consistent with management effort thinning or decreasing returns to scale.

Since the choice of management form may also be subject to self-selection bias, we also use propensity score matched samples to control for the possible bias and find that selection effects do not appear to be driving the full sample results. We also find significant differences in how OM and TPM forms respond to local pandemic restrictions and the surge in vacation demand after they are lifted. The results vary across property types and differ during and after the period in which local restrictions are in place.

Results from the analysis of effect of hotel units on the price and occupancy of geographically proximate residential listings managed by third-party hosts suggest that increasing prices of hotels exerts a downward pressure on prices of these units. However, the demand substitutes relationship between hotel prices and occupancy rates of TPM Airbnb is strong and overcomes any associated shopping externality effect generated for non-hotel properties by the Airbnb participation of nearby hotels. The hotel effect on occupancy rates is

therefore direct and competitive in nature. Results hold in the post covid period but are insignificant during the covid lock-down.

In any case, as indicated by the theory, greater net productivity in the form of higher rents or greater occupancy does not always yield greater owner profitability, as third-party management firms typically receive up to 20% of gross revenue. This explains the mix of management forms observed for units offered on the Airbnb platform; the TPM firm revenue share makes the more productive TPM less profitable for some owners, who instead choose to rely on the OM format. The Airbnb market is a short-term vacation rental market with high turnover requiring both greater upkeep and constant bookings than needed for long-term rentals. Nonetheless, comparing our results with Sirmans et al. (1999) study of traditional apartment rentals yields additional insights. Our ability observe occupancy allows us to verify another aspect of the theory, that greater third-party management productivity reflected in higher rents need not yield greater occupancy. Further, we are also able to show that the strength of TPM productivity advantages vary across property types in the vacation rental market.

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Figures

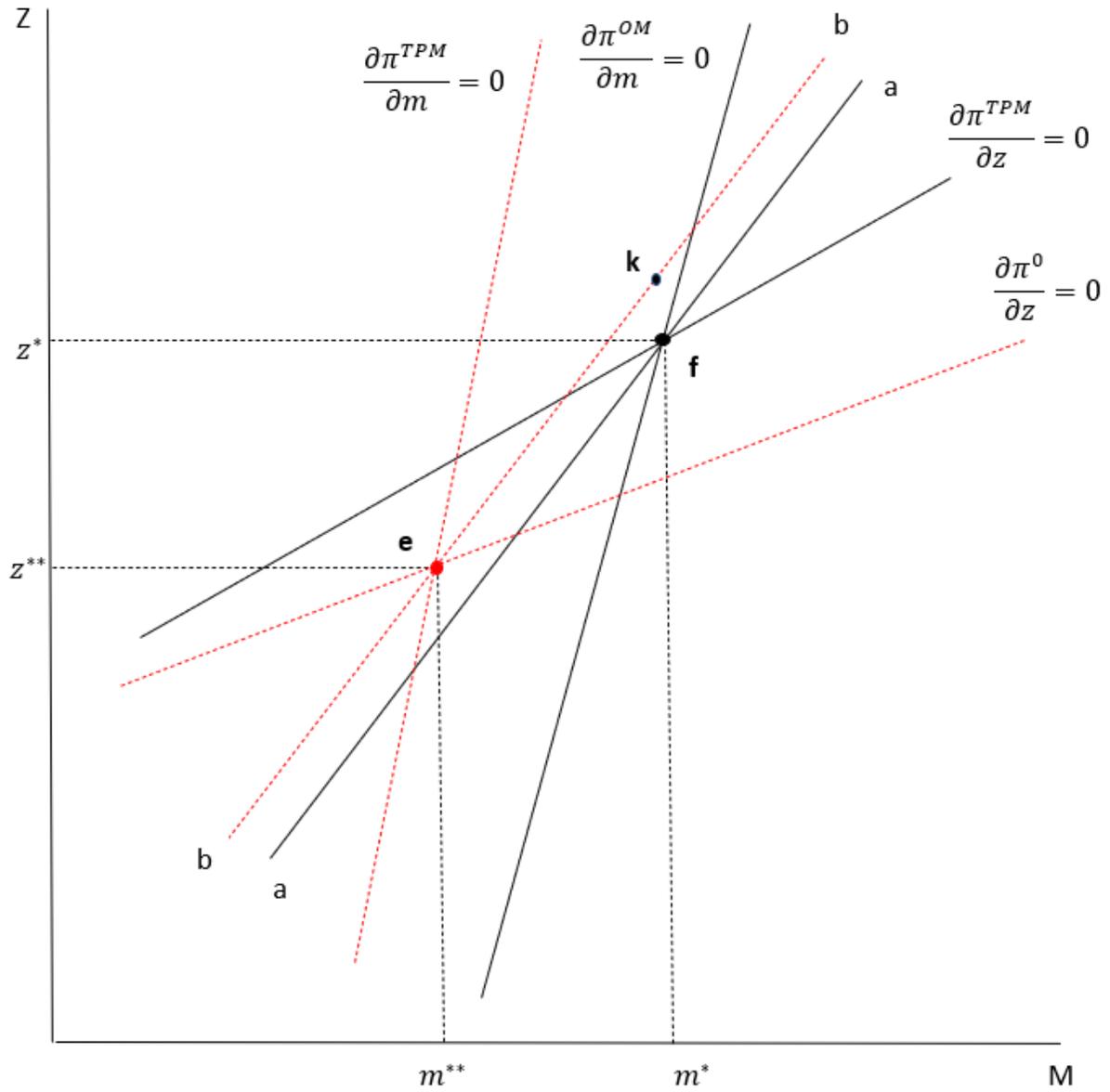


Figure 1: Comparing OM $\{m^*, z^*\}$ and TPM $\{m^{**}, z^{**}\}$ equilibria.

Tables

Table 1: List of Variables

<i>Variable</i>	<i>Definition</i>
<i>ADR</i>	Average daily rate of Airbnb rental available monthly
<i>OCC</i>	Occupancy rate per month of Airbnb Rental
<i>Profman</i>	Dummy =1 if property is managed by third-party management
<i>Units Managed</i>	Number of units managed by Owner or Third-Party Management
<i>Attached</i>	Dummy =1 if property is attached type property like apartments, condominiums, Townhouses and zero otherwise
<i>Popular</i>	Dummy=1 if listing has higher than median number of reviews of all listings
<i>High Rating</i>	Dummy =1 if listing has higher than median overall rating of all listings
<i>Experience</i>	Dummy=1 if Host has “Superhost” badge
<i>Flexibility</i>	Dummy = 1 if host has flexible cancellation policy
<i>Response</i>	Response Rate of Host
<i>Shared-listing</i>	Dummy =1 If the listing is a shared room/shared space in a property type
<i>Listing Density</i>	Number of listings in a month in a census tract/total housing units in the census tract in that year
<i>Proximity</i>	If listing is within six miles of points of attraction in the city
<i>Log(wtprc)</i>	Logarithmic value of weighted average daily rates of all hotels located within a mile of competing Airbnb unit
<i>Max-guests</i>	Maximum number of guests allowed in the rental
<i>Min-stay</i>	Minimum Lease Length
<i>BA</i>	Number of Bedrooms
<i>BR</i>	Number of Bathrooms
<i>%Asian</i>	Percentage of Asians in census tract
<i>%Black</i>	Percentage of African Americans in census tract
<i>%Educated</i>	Percentage of residents thar college educated in census tract
<i>%Hispanic</i>	Percentage of Hispanics in census tract
<i>%Indian</i>	Percentage of Indian in census tract
<i>%Male</i>	Percentage of males in census tract
<i>%Married</i>	Percentage of residents married in census tract
<i>%Old</i>	Percentage of people above the age of 65 and below 85 in census tract
<i>%White</i>	Percentage of Whites in census tract
<i>%Young</i>	Percentage of people below the age of 25 in census tract
<i>Log (Age)</i>	Logarithmic value of the median age of census tract
<i>Log (income)</i>	Logarithm value of median income in the tract (2020 Inflated dollars)
<i>Log (Population)</i>	Logarithmic value of the population of census tract

Table 2: Summary Statistics of Key Variables

<i>Parameter</i>	Mean	SD
<i>ADR</i>	169.86	283.33
<i>Occupancy</i>	0.23	0.26
<i>Profman</i>	0.45	0.50
<i>Units Managed</i>	5.21	36.60
<i>Attached</i>	0.53	0.50
<i>Popular</i>	0.09	0.29
<i>High Rating</i>	0.17	0.37
<i>Experience</i>	0.06	0.25
<i>Flexibility</i>	0.20	0.40
<i>Response</i>	89.28	25.20
<i>Shared-listing</i>	0.77	0.42
<i>Listing Density</i>	0.05	0.08
<i>Proximity</i>	0.50	0.50
<i>Minstay</i>	7.56	18.63
<i>Max-guests</i>	5.21	2.95
<i>BR</i>	1.89	1.26
<i>BA</i>	1.71	0.92
<i>%Asian</i>	3.70	2.73
<i>%Black</i>	18.95	19.85
<i>%Educated</i>	0.26	0.11
<i>%Hispanic</i>	29.58	15.83
<i>%Indian</i>	2.64	4.08
<i>%Male</i>	48.74	4.89
<i>%Married</i>	0.41	0.17
<i>%Old</i>	10.44	5.65
<i>%White</i>	61.78	18.02
<i>%Young</i>	76.93	7.30
<i>Log (Age)</i>	3.52	0.16
<i>Log (income)</i>	10.33	0.35
<i>Log (Population)</i>	8.63	0.58
<i>N</i>		11,348

Table 3: Summary Statistics of Key Variables by Management Type

<i>Parameter</i>	<i>OM</i>		<i>TPM</i>	
	Mean	STD	Mean	STD
<i>ADR</i>	145.83	315.09	205.17	224.18
<i>OCC</i>	0.21	0.25	0.25	0.26
<i>Units Managed</i>	1.68	0.95	23.55	43.67
<i>Attached</i>	0.59	0.49	0.47	0.50
<i>Popular</i>	0.10	0.30	0.08	0.28
<i>High Rating</i>	0.21	0.41	0.12	0.32
<i>Experience</i>	0.08	0.27	0.05	0.21
<i>Flexibility</i>	0.31	0.46	0.06	0.23
<i>Response</i>	85.68	29.57	93.39	18.15
<i>Shared-listing</i>	0.95	0.49	0.62	0.23
<i>Listing Density</i>	0.05	0.08	0.05	0.08
<i>Proximity</i>	0.47	0.50	0.54	0.50
<i>Minstay</i>	5.03	18.18	10.66	18.72
<i>Max-guests</i>	4.56	2.86	6.02	2.85
<i>BR</i>	1.67	1.07	2.16	1.40
<i>BA</i>	1.54	0.78	1.92	1.03
<i>%Asian</i>	3.75	2.77	3.64	2.69
<i>%Black</i>	19.27	20.17	18.55	19.45
<i>%Educated</i>	0.26	0.11	0.27	0.11
<i>%Hispanic</i>	29.34	15.73	29.88	15.95
<i>%Indian</i>	2.62	4.11	2.66	4.05
<i>%Male</i>	48.73	4.75	48.76	5.06
<i>%Married</i>	0.41	0.17	0.41	0.17
<i>%Old</i>	10.46	5.59	10.42	5.72
<i>%White</i>	61.79	18.22	61.77	17.78
<i>%Young</i>	76.74	7.34	77.16	7.24
<i>Log (Age)</i>	3.53	0.16	3.52	0.16
<i>Log (income)</i>	10.32	0.36	10.35	0.34
<i>Log (Population)</i>	8.65	0.60	8.60	0.57
<i>N</i>	6,253		5,095	

**Table 4: Seemingly Unrelated Regression (SUR) estimates of Price and Occupancy
(Unmatched Sample)**

<i>Parameter</i>	<i>Model (1)</i>		<i>Model (2)</i>	
	log (ADR)	OCC	log (ADR)	OCC
<i>Intercept</i>	3.900*** (0.670)	-0.960** (0.381)	3.887*** (0.622)	0.266 (0.345)
<i>Profman</i>	0.227*** (0.008)	0.129*** (0.004)	0.175*** (0.006)	0.133*** (0.003)
<i>Profman × Attached</i>			-0.185*** (0.008)	-0.075*** (0.005)
<i>Profman × Units Managed</i>			-0.025*** (0.003)	-0.020*** (0.002)
<i>Units Managed</i>	0.026*** (0.003)	0.020*** (0.002)	0.002 (0.002)	0.023*** (0.001)
<i>Attached</i>	-0.052*** (0.003)	-0.034*** (0.002)	0.016*** (0.004)	-0.001 (0.002)
<i>Popular</i>	-0.167*** (0.005)	0.328*** (0.002)	-0.164*** (0.005)	0.328*** (0.002)
<i>High Rating</i>	0.034*** (0.004)	-0.014*** (0.002)	0.029*** (0.004)	-0.015*** (0.002)
<i>Experience</i>	0.066*** (0.006)	0.056*** (0.003)	0.064*** (0.006)	0.054*** (0.003)
<i>Flexibility</i>	0.047*** (0.004)	-0.072*** (0.002)	0.039*** (0.004)	-0.071*** (0.002)
<i>Response</i>	-0.002*** (0.000)	0.001*** (0.000)	-0.002*** (0.000)	0.001*** (0.000)
<i>Shared-listing</i>	0.684*** (0.004)	0.007*** (0.002)	0.687*** (0.004)	0.010*** (0.002)
<i>Listing Density</i>	-0.337*** (0.052)	0.262*** (0.029)	-0.346*** (0.052)	0.261*** (0.029)
<i>Proximity</i>	0.014*** (0.003)	0.013*** (0.002)	0.015*** (0.003)	0.016*** (0.002)
<i>Minstay</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Max-Guests</i>	0.089*** (0.001)	-0.003*** (0.001)	0.089*** (0.001)	-0.003*** (0.001)
<i>BA</i>	-0.006* (0.003)	-0.017*** (0.002)	-0.004 (0.003)	-0.017*** (0.002)
<i>BR</i>	0.061*** (0.003)	0.046*** (0.001)	0.061*** (0.003)	0.047*** (0.001)

Table Continued

<i>Neighborhood Controls</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
<i>Quarter and Census FE</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
R^2	0.45		0.39	
N		143,558		

Dependent variables are log (ADR) and Occupancy. Table reports SUR estimates for host, listing and neighborhood characteristics for full sample. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Table 5: Marginal Effects of Owner managed versus Third-party managed apartments

<i>Parameter</i>	<i>Matched Sample</i>
	<i>Profman =1</i>
<i>Attached</i>	-0.066*** (0.003)
<i>Popular</i>	0.158*** (0.007)
<i>High Rating</i>	0.100*** (0.005)
<i>Experience</i>	0.050*** (0.002)
<i>Flexibility</i>	0.040*** (0.002)
<i>Response</i>	-0.001*** (0.000)
<i>Shared-listing</i>	-0.039** (0.002)
<i>Listing Density</i>	-0.010*** (0.000)
<i>Proximity</i>	-0.033*** (0.002)
<i>Minstay</i>	-0.001*** (0.000)
<i>Max-Guests</i>	-0.008*** (0.000)
<i>BA</i>	0.009*** (0.000)
<i>BR</i>	-0.014 (0.001)
<i>%Asian</i>	-0.003*** (0.000)
<i>%Black</i>	-0.002*** (0.000)
<i>%Educated</i>	0.027*** (0.001)
<i>%Hispanic</i>	-0.001*** (0.000)
<i>%Indian</i>	-0.004*** (0.000)
<i>%Male</i>	0.003*** (0.000)
<i>%Old</i>	0.001 (0.000)
<i>%White</i>	-0.003*** (0.000)
<i>%Young</i>	0.001*** (0.000)

Table Continued

<i>log (income)</i>	-0.026 (0.001)
<i>log (population)</i>	-0.169*** (0.008)
<i>Quarter and Census FE</i>	N
<i>R</i> ²	0.25
<i>N</i>	5706

Table reports parameter estimates of probit regression; Dependent variable *Profman* is a 0–1 binary variable indicating whether an apartment is owner-managed (0) or third-party managed (1). Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

**Table 6: Seemingly Unrelated Regression (SUR) estimates of Price and Occupancy
(Propensity Score Matched Sample)**

<i>Parameter</i>	<i>Model (1)</i>		<i>Model (2)</i>	
	log (ADR)	OCC	log (ADR)	OCC
<i>Intercept</i>	3.764*** (0.673)	-1.017*** (0.382)	3.900*** (0.670)	-0.960** (0.381)
<i>Profman</i>	0.099*** (0.004)	0.061*** (0.002)	0.227*** (0.008)	0.129*** (0.004)
<i>Profman × Attached</i>			-0.185*** (0.008)	-0.075*** (0.005)
<i>Profman × Units Managed</i>			-0.025*** (0.003)	-0.020*** (0.002)
<i>Units Managed</i>	0.025*** (0.003)	0.018*** (0.002)	0.026*** (0.003)	0.020*** (0.002)
<i>Attached</i>	-0.065*** (0.004)	-0.031*** (0.002)	0.024*** (0.006)	0.006* (0.003)
<i>Popular</i>	-0.170*** (0.006)	0.332*** (0.003)	-0.169*** (0.006)	0.332*** (0.003)
<i>High Rating</i>	0.039*** (0.005)	-0.003 (0.003)	0.030*** (0.005)	-0.006** (0.003)
<i>Experience</i>	0.089*** (0.007)	0.043*** (0.004)	0.083*** (0.007)	0.040*** (0.004)
<i>Flexibility</i>	0.099*** (0.007)	-0.073*** (0.004)	0.092*** (0.007)	-0.074*** (0.004)
<i>Response</i>	-0.001*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
<i>Shared-listing</i>	0.789*** (0.008)	0.017*** (0.004)	0.789*** (0.007)	0.018*** (0.004)
<i>Listing Density</i>	-0.424*** (0.067)	0.634*** (0.038)	-0.393*** (0.067)	0.650*** (0.038)
<i>Proximity</i>	0.015*** (0.004)	0.005** (0.002)	0.016*** (0.004)	0.006*** (0.002)
<i>Minstay</i>	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Max-Guests</i>	0.069*** (0.001)	-0.005*** (0.001)	0.069*** (0.001)	-0.005*** (0.001)
<i>BA</i>	0.038*** (0.004)	-0.024*** (0.002)	0.039*** (0.004)	-0.024*** (0.002)

Table Continued

<i>BR</i>	0.108*** (0.003)	0.049*** (0.002)	0.106*** (0.003)	0.048*** (0.002)
<i>Neighborhood Controls</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
<i>Quarter and Census FE</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
<i>R</i> ²		0.4		0.41
<i>N</i>			81,119	

Dependent variables are log (ADR) and Occupancy. Table reports SUR estimates for host, listing and neighborhood characteristics for matched sample. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Table 7: SUR Estimates of Price and Occupancy for Pre covid period

<i>Parameter</i>	<i>Unmatched</i>		<i>Matched</i>	
	log (ADR)	OCC	log (ADR)	OCC
<i>Intercept</i>	4.561*** (0.622)	0.286 (0.345)	3.900*** (0.669)	-0.962** (0.381)
<i>Profman</i>	0.170*** (0.006)	0.138*** (0.003)	0.225*** (0.008)	0.132*** (0.004)
<i>Profman × Attached</i>	-0.168*** (0.007)	-0.082*** (0.004)	-0.180*** (0.008)	-0.077*** (0.005)
<i>Profman × Units Managed</i>	-0.002 (0.002)	-0.025*** (0.001)	-0.026*** (0.003)	-0.021*** (0.002)
<i>covid</i>	-0.034* (0.019)	-0.030*** (0.010)	0.111 (0.069)	-0.226*** (0.040)
<i>covid × Profman</i>	-0.037 (0.023)	-0.150*** (0.013)	-0.082*** (0.030)	-0.114*** (0.017)
<i>covid × Profman × Units Managed</i>	0.001 (0.008)	0.028*** (0.005)	0.017 (0.011)	0.021*** (0.006)
<i>covid × Profman × Attached</i>	0.033 (0.028)	0.067*** (0.015)	-0.018 (0.033)	0.064*** (0.019)
<i>covid × Units Managed</i>	0.001 (0.008)	-0.027*** (0.005)	-0.015 (0.011)	-0.020*** (0.006)
<i>covid × Attached</i>	0.005 (0.015)	0.013 (0.008)	-0.021 (0.021)	0.011 (0.012)
<i>Units Managed</i>	0.002 (0.002)	0.025*** (0.001)	0.026*** (0.003)	0.021*** (0.002)
<i>Attached</i>	0.015*** (0.004)	-0.002 (0.002)	0.024*** (0.006)	0.005 (0.003)
<i>Popular</i>	-0.161*** (0.005)	0.312*** (0.003)	-0.192*** (0.006)	0.321*** (0.003)
<i>High Rating</i>	0.028*** (0.004)	-0.015*** (0.002)	0.028*** (0.005)	-0.007** (0.003)
<i>Experience</i>	0.066*** (0.006)	0.055*** (0.003)	0.085*** (0.007)	0.042*** (0.004)
<i>Flexibility</i>	0.039*** (0.004)	-0.070*** (0.002)	0.092*** (0.007)	-0.075*** (0.004)
<i>Response</i>	-0.002*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
<i>Shared-listing</i>	-0.686*** (0.004)	-0.011*** (0.002)	0.788*** (0.007)	0.018*** (0.004)
<i>Listing Density</i>	-0.343*** (0.052)	0.263*** (0.029)	-0.379*** (0.067)	0.659*** (0.038)
<i>Proximity</i>	0.014*** (0.003)	0.015*** (0.002)	0.014*** (0.004)	0.006** (0.002)
<i>Minstay</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Max-Guests</i>	0.089*** (0.001)	-0.004*** (0.001)	0.069*** (0.001)	-0.005*** (0.001)

Table Continued

<i>BA</i>	-0.004 (0.003)	-0.017*** (0.002)	0.039*** (0.004)	-0.024*** (0.002)
<i>BR</i>	0.061*** (0.003)	0.047*** (0.001)	0.106*** (0.003)	0.049*** (0.002)
<i>Neighborhood Controls</i>	Y	Y	Y	Y
<i>Quarter and Census FE</i>	Y	Y	Y	Y
<i>R</i> ²		0.45		0.39
<i>N</i>		143,558		81,119

Dependent variables are log (ADR) and Occupancy. Table reports SUR estimates for host, listing and neighborhood characteristics during the peak covid period defined as the second and third quarters of year 2020. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Table 8: SUR Estimates of Price and Occupancy for Post-covid period

<i>Parameter</i>	<i>Unmatched</i>		<i>Matched</i>	
	log (ADR)	OCC	log (ADR)	OCC
<i>Intercept</i>	4.781*** (0.619)	0.397 (0.346)	3.947*** (0.669)	-0.849** (0.385)
<i>Profman</i>	0.124*** (0.009)	0.087*** (0.005)	0.154*** (0.011)	0.110*** (0.006)
<i>Profman × Attached</i>	-0.158*** (0.009)	-0.069*** (0.005)	-0.156*** (0.012)	-0.078*** (0.007)
<i>Profman × Units Managed</i>	0.001 (0.003)	-0.023*** (0.002)	-0.027*** (0.004)	-0.022*** (0.002)
<i>post-covid</i>	-0.027 (0.055)	-0.186*** (0.031)	0.259*** (0.066)	-0.138*** (0.038)
<i>post-covid × Profman</i>	-0.028** (0.012)	0.063*** (0.006)	0.047*** (0.015)	0.022** (0.009)
<i>post-covid × Profman × Units Managed</i>	-0.003 (0.004)	0.001 (0.002)	0.006 (0.006)	0.004 (0.003)
<i>post-covid × Profman × Attached</i>	0.027** (0.013)	-0.020*** (0.007)	-0.021 (0.016)	0.010 (0.009)
<i>post-covid × Units Managed</i>	0.000 (0.004)	-0.001 (0.002)	-0.008 (0.006)	-0.005 (0.003)
<i>post-covid × Attached</i>	-0.031*** (0.008)	0.045*** (0.004)	-0.012 (0.011)	0.050*** (0.006)
<i>Units Managed</i>	0.002 (0.003)	0.024*** (0.002)	0.030*** (0.004)	0.022*** (0.002)
<i>Attached</i>	0.025*** (0.006)	-0.023*** (0.003)	0.032*** (0.008)	-0.015*** (0.005)
<i>Popular</i>	-0.174*** (0.005)	0.310*** (0.003)	-0.206*** (0.006)	0.317*** (0.003)
<i>High Rating</i>	0.027*** (0.004)	-0.015*** (0.002)	0.029*** (0.005)	-0.005* (0.003)
<i>Experience</i>	0.085 (0.006)	0.057*** (0.003)	0.102*** (0.007)	0.041*** (0.004)
<i>Flexibility</i>	0.030*** (0.004)	-0.069*** (0.002)	0.097*** (0.007)	-0.066*** (0.004)
<i>Response</i>	-0.002*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
<i>Shared-listing</i>	-0.677*** (0.004)	-0.011*** (0.002)	0.785*** (0.007)	0.021*** (0.004)
<i>Listing Density</i>	-0.279*** (0.052)	0.278*** (0.029)	-0.130** (0.066)	0.817*** (0.038)
<i>Proximity</i>	0.015*** (0.003)	0.015*** (0.002)	0.017*** (0.004)	0.007*** (0.002)
<i>Minstay</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Max-Guests</i>	0.088*** (0.001)	-0.004*** (0.001)	0.068*** (0.001)	-0.005*** (0.001)

Table Continued

<i>BA</i>	0.000 (0.003)	-0.015*** (0.002)	0.041*** (0.004)	-0.022*** (0.002)
<i>BR</i>	0.062*** (0.003)	0.045*** (0.001)	0.106*** (0.003)	0.047*** (0.002)
<i>Neighborhood Controls</i>	Y	Y	Y	Y
Quarter and Census FE	Y	Y	Y	Y
R^2		0.4		0.41
N		143,558		81,119

Dependent variables are log (ADR) and Occupancy. Table reports SUR estimates for host, listing and neighborhood characteristics during the post covid period defined as all quarters following January 2021. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Table 9: Effect of Third-Party managed Airbnb on neighborhood Hotels

<i>Parameter</i>	<i>Unmatched</i>		<i>Matched</i>	
	log (ADR)`	OCC	log (ADR)	OCC
<i>Panel A: Full sample</i>				
<i>Profman</i>	0.327*** (0.118)	-0.296*** (0.080)	1.054*** (0.141)	-0.367*** (0.104)
<i>Profman</i> × <i>log(wtpr)</i>	0.006 (0.021)	0.093*** (0.014)	-0.119*** (0.025)	0.092*** (0.019)
<i>log(wtpr)</i>	0.196*** (0.017)	-0.034*** (0.011)	0.263*** (0.022)	-0.019 (0.016)
<i>Panel B: During Covid</i>				
<i>Profman</i>	0.215* (0.118)	-0.273*** (0.078)	1.127*** (0.142)	-0.497*** (0.098)
<i>Profman</i> × <i>log(wtpr)</i>	0.031 (0.021)	0.076*** (0.014)	-0.135*** (0.025)	0.113*** (0.017)
<i>log(wtpr)</i>	0.184*** (0.017)	-0.017 (0.011)	0.290*** (0.022)	-0.033** (0.015)
<i>covid</i> × <i>Profman</i> × <i>log(wtpr)</i>	-0.175 (0.129)	0.042 (0.085)	-0.248* (0.145)	0.096 (0.100)
<i>covid</i> × <i>log(wtpr)</i>	0.139 (0.085)	0.025 (0.056)	0.217** (0.111)	-0.062 (0.076)
<i>covid</i>	-2.020** (0.916)	-0.059 (0.600)	-1.253* (0.677)	-0.397 (0.465)
<i>covid</i> × <i>Profman</i>	1.125 (0.689)	-0.298 (0.451)	1.369* (0.777)	-0.519 (0.534)
<i>Panel C: Post covid</i>				
<i>Profman</i>	0.084 (0.194)	0.264** (0.130)	1.144*** (0.219)	0.456*** (0.151)
<i>Profman</i> × <i>log(wtpr)</i>	0.103*** (0.034)	-0.017 (0.023)	-0.101*** (0.039)	-0.050* (0.027)
<i>log(wtpr)</i>	0.137*** (0.031)	0.106*** (0.021)	0.239*** (0.037)	0.162*** (0.025)
<i>post-covid</i> × <i>Profman</i> × <i>log(wtpr)</i>	-0.183*** (0.042)	0.148*** (0.028)	-0.097* (0.050)	0.279*** (0.035)
<i>post-covid</i> × <i>log(wtpr)</i>	0.107*** (0.035)	-0.162*** (0.023)	0.141*** (0.043)	-0.277*** (0.030)
<i>post-covid</i>	-0.984 (0.800)	1.237** (0.534)	-0.520 (0.375)	1.875*** (0.259)
<i>post-covid</i> × <i>Profman</i>	0.556** (0.238)	-0.815*** (0.159)	0.233 (0.280)	-1.592*** (0.193)
<i>Neighborhood Controls</i>	Y	Y	Y	Y

Table Continued

<i>Quarter and Census FE</i>	Y	Y	Y	Y
R^2		0.42		0.48
N		143,558		81,119

Dependent variables are log (ADR) and Occupancy. Table reports key estimates for SUR model, specifically, interactions between third-party managed Airbnb rentals and our measure of competition from neighborhood hotel listings $\log(wtprc)$ defined as logarithm value of weighted price of all hotels listed within 1 mile of target rental unit. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Appendix

Table 1A: OLS Estimates of Price and Occupancy (Unmatched Sample)

<i>Parameter</i>	log (ADR)	OCC	log (ADR)	OCC
<i>Intercept</i>	3.972*** (0.298)	-0.014 (0.157)	3.988*** (0.297)	0.006 (0.157)
<i>Profman</i>	0.098*** (0.004)	0.051*** (0.002)	0.173*** (0.006)	0.120*** (0.003)
<i>Profman × Attached</i>			-0.174*** (0.006)	-0.084*** (0.003)
<i>Profman × Units Managed</i>			0.002 (0.002)	-0.020*** (0.001)
<i>Units Managed</i>	0.000*** (0.000)	0.000*** (0.000)	0.002 (0.002)	0.020*** (0.001)
<i>Attached</i>	-0.049*** (0.003)	-0.029*** (0.002)	0.020*** (0.004)	0.005** (0.002)
<i>Popular</i>	-0.167*** (0.005)	0.328*** (0.002)	-0.164*** (0.005)	0.328*** (0.002)
<i>High Rating</i>	0.030*** (0.004)	-0.004** (0.002)	0.026*** (0.004)	-0.005** (0.002)
<i>Experience</i>	0.065*** (0.006)	0.051*** (0.003)	0.063*** (0.006)	0.049*** (0.003)
<i>Flexibility</i>	0.043*** (0.004)	-0.062*** (0.002)	0.036*** (0.004)	-0.061*** (0.002)
<i>Response</i>	-0.002*** (0.000)	0.001*** (0.000)	-0.002*** (0.000)	0.001*** (0.000)
<i>Shared-listing</i>	0.687*** (0.004)	0.008*** (0.002)	0.690*** (0.004)	0.012*** (0.002)
<i>Listing Density</i>	-0.280*** (0.052)	0.222*** (0.027)	-0.290*** (0.052)	0.221*** (0.027)
<i>Proximity</i>	0.014*** (0.003)	0.013*** (0.002)	0.016*** (0.003)	0.015*** (0.002)
<i>Minstay</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Max-Guests</i>	0.089*** (0.001)	-0.002*** (0.000)	0.089*** (0.001)	-0.002*** (0.000)
<i>BA</i>	-0.001 (0.003)	-0.015*** (0.002)	0.001 (0.003)	-0.014*** (0.002)
<i>BR</i>	0.059*** (0.003)	0.041*** (0.001)	0.058*** (0.003)	0.042*** (0.001)
<i>Neighborhood Controls</i>	Y	Y	Y	Y
<i>Quarter and Census FE</i>	Y	Y	Y	Y

Table Continued

R^2	0.54	0.49	0.55	0.48
N	143,558			

Dependent variables are log (ADR) and Occupancy. Table reports OLS estimates for host, listing and neighborhood characteristics for full sample. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Table 2A: OLS Estimates of Price and Occupancy (Propensity Score Matched Sample)

<i>Parameter</i>	log (ADR)	OCC	log (ADR)	OCC
<i>Intercept</i>	4.530*** (0.409)	-0.908*** (0.233)	4.672*** (0.408)	-0.855*** (0.232)
<i>Profman</i>	0.095*** (0.004)	0.061*** (0.002)	0.222*** (0.008)	0.129*** (0.004)
<i>Profman × Attached</i>			-0.189*** (0.008)	-0.076*** (0.005)
<i>Profman × Units Managed</i>			-0.023*** (0.003)	-0.020*** (0.002)
<i>Attached</i>	-0.061*** (0.004)	-0.031*** (0.002)	0.030*** (0.006)	0.006* (0.003)
<i>Units Managed</i>	0.000*** (0.000)	0.000*** (0.000)	0.024*** (0.003)	0.019*** (0.002)
<i>Popular</i>	-0.199*** (0.006)	0.322*** (0.003)	-0.199*** (0.006)	0.322*** (0.003)
<i>High Rating</i>	0.035*** (0.005)	-0.003 (0.003)	0.026*** (0.005)	-0.006** (0.003)
<i>Experience</i>	0.089*** (0.007)	0.043*** (0.004)	0.083*** (0.007)	0.040*** (0.004)
<i>Flexibility</i>	0.104*** (0.007)	-0.073*** (0.004)	0.098*** (0.007)	-0.074*** (0.004)
<i>Response</i>	-0.001*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
<i>Shared-listing</i>	0.796*** (0.008)	0.017*** (0.004)	0.796*** (0.008)	0.018*** (0.004)
<i>Listing Density</i>	-0.410*** (0.067)	0.633*** (0.038)	-0.379*** (0.067)	0.649*** (0.038)
<i>Proximity</i>	0.018*** (0.004)	0.005** (0.002)	0.019*** (0.004)	0.006*** (0.002)
<i>Minstay</i>	-0.002*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
<i>Max-Guests</i>	0.069*** (0.001)	-0.005*** (0.001)	0.069*** (0.001)	-0.005*** (0.001)
<i>BA</i>	0.045*** (0.004)	-0.024*** (0.002)	0.045*** (0.004)	-0.024*** (0.002)
<i>BR</i>	0.103*** (0.003)	0.049*** (0.002)	0.101*** (0.003)	0.048*** (0.002)
<i>Neighborhood Controls</i>	Y	Y	Y	Y

Table Continued

<i>Quarter and Census FE</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
R^2	0.4		0.41	
N		81119		

Dependent variables are log (ADR) and Occupancy. Table reports OLS estimates for host, listing and neighborhood characteristics for matched sample. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Table 3A: SUR Estimates of Price and Occupancy for different Property Types (Matched Sample)

<i>Parameter</i>	<i>ATTACHED=1</i>		<i>ATTACHED=0</i>	
	log (ADR)	OCC	log (ADR)	OCC
<i>Intercept</i>	13.582*** (0.857)	-1.167** (0.468)	3.547*** (0.815)	0.306 (0.503)
<i>Profman</i>	0.053*** (0.010)	0.070*** (0.005)	0.166*** (0.009)	0.098*** (0.006)
<i>Units Managed</i>	0.030*** (0.004)	0.020*** (0.002)	0.021*** (0.004)	0.021*** (0.002)
<i>Attached</i>	-0.002*** (0.000)	0.002*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
<i>Popular</i>	-0.091*** (0.009)	0.323*** (0.005)	-0.248*** (0.008)	0.304*** (0.005)
<i>High Rating</i>	0.065*** (0.009)	-0.045*** (0.005)	-0.009 (0.007)	0.003 (0.004)
<i>Experience</i>	0.092*** (0.012)	0.129*** (0.006)	0.060*** (0.010)	0.000 (0.006)
<i>Flexibility</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.003*** (0.000)	-0.002*** (0.000)
<i>Response</i>	0.074*** (0.010)	-0.083*** (0.005)	0.097*** (0.009)	-0.058*** (0.005)
<i>Shared-listing</i>	0.807*** (0.010)	0.018*** (0.005)	0.762*** (0.012)	0.040*** (0.007)
<i>Listing Density</i>	-0.627*** (0.097)	0.797*** (0.053)	-0.159* (0.089)	0.624*** (0.055)
<i>Proximity</i>	-0.016*** (0.006)	0.018*** (0.003)	0.010* (0.005)	-0.004 (0.003)
<i>Minstay</i>	-0.030*** (0.004)	-0.020*** (0.002)	-0.020*** (0.004)	-0.021*** (0.002)
<i>Max-Guests</i>	0.057*** (0.002)	-0.005*** (0.001)	0.071*** (0.002)	-0.006*** (0.001)
<i>BA</i>	0.118*** (0.006)	-0.015*** (0.003)	-0.031*** (0.006)	-0.025*** (0.004)
<i>BR</i>	0.091*** (0.004)	0.043*** (0.002)	0.119*** (0.005)	0.050*** (0.003)
<i>Neighborhood Controls</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>
<i>Quarter and Census FE</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>	<i>Y</i>

Table Continued

R^2	0.49	0.38
N	39161	43693

Dependent variables are log (ADR) and Occupancy. Table reports OLS estimates for host, listing and neighborhood characteristics for property type subsample. ATTACHED=0 indicates all low density detached property types defined in the text; ATTACHED=1 indicates all attached properties like apartment condominiums etc. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing per month

Table 4A: Probit Estimates of Owner managed versus Third Party managed apartments

<i>Parameter</i>	<i>Matched Sample</i>
	<i>Profman =1</i>
<i>Intercept</i>	-2.039 (1.426)
<i>Attached</i>	-0.279*** (0.017)
<i>Popular</i>	0.631*** (0.022)
<i>High Rating</i>	0.436*** (0.021)
<i>Experience</i>	0.204*** (0.030)
<i>Flexibility</i>	0.144*** (0.026)
<i>Response</i>	0.007*** (0.000)
<i>Shared-listing</i>	-0.062** (0.031)
<i>Listing Density</i>	-2.004*** (0.262)
<i>Proximity</i>	-0.123*** (0.016)
<i>Minstay</i>	-0.008*** (0.001)
<i>Max-Guests</i>	-0.441*** (0.005)
<i>BA</i>	0.066*** (0.016)
<i>BR</i>	0.036*** (0.012)
<i>%Asian</i>	-0.034*** (0.009)
<i>%Black</i>	-0.067*** (0.005)
<i>%Educated</i>	-1.512*** (0.314)
<i>%Hispanic</i>	-0.055*** (0.004)
<i>%Indian</i>	-0.060*** (0.011)
<i>%Male</i>	0.026*** (0.005)
<i>%Old</i>	0.005 (0.009)
<i>%White</i>	-0.043*** (0.004)

Table Continued

<i>%Young</i>	0.015** (0.005)
<i>log (income)</i>	0.429*** (0.100)
<i>log (population)</i>	-0.320** (0.126)
<i>Quarter and Census FE</i>	N
<i>R²</i>	0.25
<i>N</i>	5706

Parameter estimates of probit regression; ; Dependent variable *Profman* is a 0–1 binary variable indicating whether an apartment is owner-managed (0) or third-party managed (1). Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 5A: SUR Estimates of Price and Occupancy for all Covid specifications

<i>Parameter</i>	<i>Unmatched</i>		<i>Matched</i>	
	log(ADR)	OCC	log(ADR)	OCC
<i>Intercept</i>	3.749*** (0.298)	-0.031 (0.166)	3.837*** (0.667)	-0.960** (0.380)
<i>Profman</i>	0.116*** (0.009)	0.105*** (0.005)	0.157*** (0.012)	0.125*** (0.007)
<i>Profman × Attached</i>	-0.161*** (0.010)	-0.075*** (0.006)	-0.155*** (0.012)	-0.088*** (0.007)
<i>Profman × Units Managed</i>	0.001 (0.003)	-0.027*** (0.002)	-0.030*** (0.004)	-0.026*** (0.003)
<i>Units Managed</i>	0.002 (0.003)	0.027*** (0.002)	0.033*** (0.004)	0.026*** (0.003)
<i>Attached</i>	0.026*** (0.006)	-0.028*** (0.003)	0.036*** (0.008)	-0.020*** (0.005)
<i>covid</i>	-0.089 (0.057)	-0.139*** (0.032)	0.140** (0.070)	-0.226*** (0.040)
<i>post-covid</i>	-0.021 (0.055)	-0.181*** (0.031)	0.259*** (0.066)	-0.138*** (0.038)
<i>covid × Profman</i>	0.018 (0.024)	-0.116*** (0.014)	-0.017 (0.031)	-0.106*** (0.018)
<i>covid × Attached</i>	-0.008 (0.016)	0.039*** (0.009)	-0.033 (0.022)	0.037*** (0.013)
<i>covid × Units Managed</i>	0.001 (0.008)	-0.029*** (0.005)	-0.021* (0.012)	-0.025*** (0.007)
<i>covid × Profman × Units Managed</i>	-0.002 (0.008)	0.030*** (0.005)	0.021* (0.012)	0.026*** (0.007)
<i>covid × Profman × Attached</i>	0.030 (0.028)	0.060*** (0.016)	-0.039 (0.034)	0.074*** (0.019)
<i>post-covid × Profman</i>	-0.021* (0.012)	0.046*** (0.007)	0.038** (0.016)	0.000 (0.009)
<i>post-covid × Attached</i>	-0.032*** (0.008)	0.051*** (0.005)	-0.025** (0.011)	0.047*** (0.006)
<i>post-covid × Units Managed</i>	0.000 (0.004)	-0.005** (0.002)	-0.012** (0.006)	-0.009*** (0.003)
<i>post-covid × Profman × Units Managed</i>	-0.003 (0.004)	0.004* (0.002)	0.010* (0.006)	0.009*** (0.003)
<i>post-covid × Profman × Attached</i>	0.031** (0.013)	-0.014* (0.007)	-0.021 (0.016)	0.020*** (0.009)
<i>Popular</i>	-0.175*** (0.005)	0.310*** (0.003)	-0.202*** (0.006)	0.321*** (0.003)
<i>High-Rating</i>	0.028*** (0.004)	-0.015*** (0.002)	0.028*** (0.005)	-0.006** (0.003)
<i>Experience</i>	0.086*** (0.006)	0.056*** (0.003)	0.104*** (0.007)	0.043*** (0.004)
<i>Flexibility</i>	0.029*** (0.004)	-0.070*** (0.002)	0.091*** (0.007)	-0.072*** (0.004)

Table Continued

<i>Response</i>	-0.002*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
<i>Shared-listing</i>	0.676*** (0.004)	0.011*** (0.002)	0.779*** (0.007)	0.016*** (0.004)
<i>Listing Density</i>	-0.268*** (0.052)	0.276*** (0.029)	-0.313*** (0.066)	0.669*** (0.038)
<i>Proximity</i>	0.015*** (0.003)	0.015*** (0.002)	0.016*** (0.004)	0.007*** (0.002)
<i>Minstay</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
<i>Max-Guests</i>	0.088*** (0.001)	-0.004*** (0.001)	0.068*** (0.001)	-0.005*** (0.001)
<i>BA</i>	0.000 (0.003)	-0.015*** (0.002)	0.041*** (0.004)	-0.022*** (0.002)
<i>BR</i>	0.061*** (0.003)	0.045*** (0.001)	0.106*** (0.003)	0.047*** (0.002)
<i>Neighborhood Controls</i>	Y	Y	Y	Y
<i>Quarter and Census FE</i>	Y	Y	Y	Y
<i>R²</i>		0.43		0.49
<i>N</i>		143,558		81,119

Dependent variables are log (ADR) and Occupancy. Table reports SUR estimates for host, listing and neighborhood characteristics for full model consisting of covid and post covid period. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month