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Two Essays on the Airbnb Market

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TWO ESSAYS ON THE AIRBNB MARKET

by

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ABSTRACT

This dissertation analyses the Airbnb market in Orange County, FL to provide insight on the performances of short-term vacation rentals listed on the platform. In the first essay we examine the factors affecting the demand and supply of this real estate sector before and after the Covid-19 pandemic, using occupancy, pricing and revenue models. The results identify the aspects of the Airbnb peer-to-peer sharing model that do and those that do not recover quickly after local covid restrictions are lifted. In particular, host experience, professional management, and proximity to major tourist attractions are some of the key factors that generate greater Airbnb unit occupancy, revenue, and prices. The effects are stronger in the post-covid period. On the other hand, Airbnb consumers appear to steer clear of rentals with popular reviews from previous tenants, located in high-income areas, and in ethnic neighborhoods during the post-covid period. Traditional hotel rooms participating in the Airbnb market exhibit different post-pandemic responses than found for other properties. In addition, there is evidence that, while hotel participation directly competes with other properties, these effects are mediated by shopping externalities created by greater search traffic from hotels on the platform.

In the second essay we use a choice theoretic approach to identify factors driving the Airbnb unit owner's choice of management form and the effect of that choice on the unit rentals performance. Property owners looking to let their real-estate assets on a short-term basis on the Airbnb platform can choose between two forms of day-to-day management: owner managed (OM) and third party managed (TPM). Incentives theory shows that asset owners must weigh the input mix inefficiency arising from the incentive structure of TPM against possibly greater TPM management ability. The empirical model reveals that management structure affects pricing and occupancy rates of these units in both the full sample and when controlling for endogenous management form selection using matched sample methods. Airbnb data for Orange County, Florida, over 2014-2022 reveals higher prices and occupancy for TPM units in both cases. Interestingly, TPM fails to outperform OM when the number of units managed for the owner are sufficiently high, consistent with effort-thinning associated with rising marginal management costs for TPM firms. In addition, professional management outcomes vary significantly across property types, with lower prices and occupancy rates for high density apartments and condominiums relative to comparable OM units. Furthermore, TPM hosts' response to the declining demand for vacation properties during the pandemic is found to be stronger than OM hosts.

This dissertation is dedicated to my father who taught me to imagine beyond the boundaries of the commonplace.

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First, I would like to express my sincere gratitude to my advisor, Dr. Geoffrey K. Turnbull, who believed in me, guided me and continuously supported all my endeavors throughout my doctoral studies. I am also extremely grateful to the rest of my dissertation committee, Dr. Ann Marie Whyte, Dr. David Harrison, and Dr. Gregory Trompeter, for their mentorship, crucial suggestions on my dissertation, without which it would be impossible for me to complete this dissertation.

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“অন্তর মম বিকশিত করো অন্তরতর হে–

নির্মল করো, উজ্জ্বল করো, সুন্দর করো হে ॥

জাগ্রত করো, উদ্যত করো, নির্ভয় করো হে।

মঙ্গল করো, নিরলস নিঃসংশয় করো হে ॥ “

~Rabindranath Tagore

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CHAPTER 1 : INTRODUCTION

In October 2007, Brian Chesky and Joe Gebbia came up with the idea of putting an air mattress in their living room and turning it into a bed and breakfast in San Francisco. They put together a website that offered short-term living quarters and breakfast for those who were unable to book a hotel in the saturated market. The site Airbedandbreakfast.com officially launched on August 11, 2008. The founders had their first customers in the summer of 2008, during the Industrial Design Conference held by Industrial Designers Society of America, where travelers had a hard time finding lodging in the city. 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 and had served 9,000,000 guests with nearly 250,000 listings by 2013, even adding travel guides for travelers. Airbnb first became profitable during the second half 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. [1]

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 crafted 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

[1] Institutional details on Airbnb are drawn from various sources including Wikipedia: "https://en.wikipedia.org/wiki/Airbnb", City of Orlando: "https://www.orlando.gov/Building-Development"

interests of guests or hosts. Despite these efforts, Airbnb has been subjected to heavy criticisms for possibly enabling increases in home rents and by the hotel industry for not being subject to fair regulations. Many governments have passed laws requiring that Airbnb provide guest information so that local regulations can be enforced, and hotel taxes are collected. Regulation of short-term rentals are highly localized and are segmented based on building, city and zoning standard. It can include requirements for hosts to have business licenses, payment of business tax receipts like hotels. In addition to government-imposed restrictions, many homeowner associations also limit short term rentals. [2]

Orlando hosts around 75 million tourists every year making it a lucrative location for setting up a vacation rental business. It is no surprise therefore that Airbnb rentals are thriving in this area. The average monthly revenues of Airbnb in Orlando are 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 the US, which is only 48%. 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. The City of Orlando website provides several resources regarding taxations, zoning laws and registration requirements. 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 several thousand in 2018. Although Airbnb has consistently warned hosts to be mindful

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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 consistently claim they do not consider listings platforms such as Airbnb a viable threat to their occupancy rates, citing the number of rooms in the region and their price range. In addition, guests also pay the Orange County Tourist Development Tax. Florida's transient rental tax is 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, home sharing allows hosts to rent up to half the bedrooms on the property, but only in residential zones with the homeowner or tenant being present for the duration of the rental. Orange County requires that properties rented in their entirety be licensed by the Department of Business and Professional Regulation, be located in O-3, MU district, or AC districts, and obtain a Business Tax Receipt. [3]

Our analysis studies the Airbnb platform as a short-term rental market, but we recognize that Airbnb does not represent the entire short-term rental segment. Although Airbnb may be the most popular, other short term vacation rental (STVR) platforms owned by large travel companies, such as Expedia, Priceline, and TripAdvisor, also provide some peer-to-peer (P2P) short-term rental services. Unlike Airbnb, which offers private and shared rooms as well as small studios and apartments and entire homes catering to a large variety of clients, the other platforms and services tend to provide much larger spaces (Geminiani and DeLuca, 2018). For instance, approximately 70% of vacation rental listings on major STVR booking platforms, such as VRBO and HomeAway, are two- or more-bedroom properties with an average capacity of six

[3] Source:" https://www.airbnb.com/help/article/2371"

people—and 87% of their guests travel with a family member (Vacation Rental Management Association, 2020), greater proportions than found on Airbnb.

Vacation housing acts as a spot market where prices are driven by current demand conditions. Airbnb is a relatively new vacation product, not yet extensively studied in the real estate literature and may or may not function like other vacation housing or short-term rentals. This study offers the first rigorous analysis of the Airbnb market. Airbnb, unlike traditional hotels and other vacation rental properties, is heterogeneous in nature, with atomized supply and free entry and exit conditions. Nonetheless we observe a large volume of transactions taking place on a daily basis. It is therefore no surprise that Airbnb has become a popular short-term rental booking platform bringing together vacation and business renters with small scale property owners. So, what happens when this fast-expanding innovation gets disrupted by an exogenous shock like the covid-19 pandemic that has exerted significant pressure on the revenue model of tourism that Airbnb is founded on?

The survival of these vacation rentals has been highly speculated in the media, and yet the Airbnb market has shown surprising resilience in bouncing back from the temporary slumber. The pandemic provides us with a unique opportunity to examine how this market operates in terms of temporary shifts in pricing and occupancy, to get a better picture of its' differences from the general short-term vacation rental market. While most of the current research focuses on the tourism aspect of Airbnb market, this paper develops a real estate management model based on Sirmans et al (1999) that provide additional insight on the roles of neighborhood and platform characteristics in driving unit prices and occupancy in the Airbnb market. This paper also examines the effect of the pandemic on these platform amenities valued by potential clients and its subsequent effect on the unit performance.

Secondly, Airbnb rentals have been long criticized as having destructive consequences on the hotel industry. The early success of what is essentially a search market platform created some concern that the venue creates the opportunity for atomistic vacation property owners to offer renters attractive alternatives to traditional hotel rooms, especially those in small- and medium scale chain hotels and independent hotels. Hotels are characterized by important fixed costs (Aznar & Sayeras, 2015). The cost structure of these businesses makes their profitability vulnerable to any adverse shock in demand. Airbnb platform on the other hand, offers a similar, but cheaper alternative, with a structure of new suppliers with no significant fixed costs and may not be as vulnerable in terms of profitability. So, it is not surprising that some of these hotels now list rooms on Airbnb, creating a competitive presence on the platform. What is not known is how these hotels on Airbnb affect competing rental units ranging from single rooms to entire houses. This paper offers the first rigorous empirical evidence regarding this issue.

Furthermore, the growth of Airbnb to a hundred-billion-dollar industry in the past ten years has made it an increasingly important part of a unique real estate market segment. The company that initially started out under the banner of a simple peer-to-peer sharing platform has slowly outgrown this status and molded into a more professionalized lodging corporation. Growing demand from travelers using the platform has attracted more property owners and increased 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 inventory, providing standardized experiences, etc.

Nonetheless, recent studies have shown that the capability to create value on Airbnb platform is unequally distributed across host types, (Deboosere et al., 2019; Wachsmuth and Weisler, 2018). As a result, some property owners who possesses neither the acumen nor the resources required to provide high quality travel experiences to guests naturally rely on third-party property management companies to host their rentals. These new standardized offerings have the potential to create significantly large value for Airbnb owners. They make up almost half of Airbnb's business revenue while the sharing economy model has taken a backseat. This motivates us to investigate the effect of management form on the profitability of Airbnb units.

CHAPTER 2 : THE AIRBNB MARKET, COVID-19 PANDEMIC, AND RECOVERY: EVIDENCE FROM ORLANDO, FLORIDA

1. Introduction

Vacation housing acts as a spot market where prices are driven by current demand conditions. Airbnb is a relatively new vacation product, not yet extensively studied in the real estate literature and may or may not function like other vacation housing or short-term rentals. This study offers the first rigorous analysis of the Airbnb market. The use of technology to create a one-stop shop for sellers of available space to reach potential clientele, who then sorts through prices and characteristics of the properties to make renting decisions, is what sets this business model apart from competing products. Airbnb, unlike traditional hotels and other vacation rental properties, is heterogeneous in nature, with atomized supply and free entry and exit conditions. Nonetheless we observe a large volume of transactions taking place on a daily basis.

It is therefore no surprise that Airbnb has become a popular short-term rental booking platform bringing together vacation and business renters with small scale property owners. So, what happens when this fast-expanding innovation gets disrupted by an exogenous shock like the covid-19 pandemic that has exerted significant pressure on the revenue model of tourism that Airbnb is founded on? The survival of these vacation rentals has been highly speculated in the media, and yet the Airbnb market has shown surprising resilience in bouncing back from the temporary slumber. While most of the current research focuses on the tourism aspect of Airbnb market, this paper studies the effect of the pandemic on Airbnb as a real-estate product.

The pandemic provides us with a unique opportunity to examine how the market operates in terms of temporary shifts in pricing and occupancy, to get a better picture of its' differences from the general short-term vacation rental market. We develop a real estate management model based on Sirmans et al (1999) that help us gain additional insight on the roles of neighborhood and platform characteristics in driving unit prices and occupancy in the Airbnb market. We extend this model to further examine the effect of the pandemic on these platform amenities valued by potential clients and its subsequent effect on the unit performance. Our first research question is then to identify if certain property, listing and neighborhood amenities that are known to affect the prices of traditional housing products like single family detached houses, condominiums, apartments etc. also affect the Airbnb market, which consists of a sizable portion of similar real estate assets. Additionally, how has the pandemic altered the effects, if any? We find that an important feature of Airbnb's P2P business model i.e., home sharing, underperformed during and after the pandemic. We also find that neighborhood characteristics such as median income and concentration of ethnic residents have a negative effect on pricing and occupancy of Airbnb units. On the positive side, host experience, professional management, and clustering in tourist areas contributes to the superior performance of these rentals during the global health crisis.

Secondly, Airbnbs have been long criticized as having destructive consequences on the hotel industry. The early success of what is essentially a search market platform created some concern that the venue creates the opportunity for atomistic vacation property owners to offer renters attractive alternatives to traditional hotel rooms, especially those in small- and medium-scale chain hotels and independent hotels. Hotels are characterized by important fixed costs (Aznar & Sayeras, 2015). The cost structure of these businesses makes their profitability vulnerable to any adverse shock in demand. Airbnb platform on the other hand, offers a similar, but cheaper alternative, with a structure of new suppliers with no significant fixed costs and may not be as vulnerable in terms of profitability. So, it is not surprising that some of these hotels now list rooms on Airbnb, creating a competitive presence on the platform. What is not known is how these hotels on Airbnb affect competing rental units ranging from single rooms to entire houses. This paper offers the first rigorous empirical evidence regarding this issue. Our first step is to identify listing amenities on the Airbnb platform that drive the performance of these hotel rooms. We find that host experience, professional management, popularity, and clustering of listings are some of the key factors that positively affected the performance of hotels during and after the pandemic, while high-income neighborhoods with higher percentage of ethnic population affected their prices and occupancy rates negatively.

Despite claims that the Airbnb platform is a mere supplement to hotels' services (Gallagher, 2017), the goal of our analysis is to explain why the effect is more complex than just supplementing the supply of rooms. Previous studies like Gutiérrez, et al (2017), Heo et al. (2019) have emphasized both positive and negative influence of Airbnb in generating demand and business opportunities for hotels. But the literature is not quite in agreement regarding these questions. Nonetheless, we argue that this debate overlooks the question that is just as important to the broader short-term rental market, the role of hotel participation in the Airbnb market platform on the performance of Airbnb residential rentals. Our sample has a substantial proportion of residential properties listed on Airbnb that tend to be clustered around the popular tourist attractions and other tourism properties like hotels and resorts, (Figures 2.12, 2.13, 2.14). This creates a perfect setting to evaluate the hotel effects on surrounding non-hotel properties. To implement this we control 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. The empirical results 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. This is consistent with weak search synergy or shopping externality effects from nearby hotels that are not strong enough to offset the competition effect on the occupancy rate.

At its inception, Airbnb was a P2P sharing economy, with most hosts renting out a single property. However, Airbnb's growth over the past few years has been stimulated by providers who offer multiple units on the platform, often within the same building or local area. Multi-unit hosts and hosts offering entire home listings now generate the majority of Airbnb's revenues, Dogru et al (2020). Evidence in this paper also point to the fact that professional management is a key driver of survival and recovery of Airbnb amidst the health crisis. Hu and Lee (2020), (Zervas et al, 2017), Boto- Garcia (2022) document that skilled hosts adjust prices to local COVID-19 cases more aggressively during worst phases of the pandemic. Therefore, our last and final question examines the pricing strategies of multi-unit hosts managing residential units and conclude that while these strategies do increase revenue, it fails to increase occupancy rates. In contrast, these strategies have a negative effect on the performance of Airbnb units in the post pandemic time.

2. Airbnb Industry Overview

In October 2007, Brian Chesky and Joe Gebbia came up with the idea of putting an air mattress in their living room and turning it into a bed and breakfast in San Francisco. They put together a website that offered short-term living quarters and breakfast for those who were unable to book a hotel in the saturated market. The site Airbedandbreakfast.com officially launched on August 11, 2008. The founders had their first customers in the summer of 2008, during the Industrial Design Conference held by Industrial Designers Society of America, where travelers had a hard time finding lodging in the city. 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 and had served 9,000,000 guests with nearly 250,000 listings by 2013, even adding travel guides for travelers. Airbnb first became profitable during the second half 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. [4]

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 crafted 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 possibly enabling increases in home rents and by the hotel industry for not being subject to fair regulations. Many governments have passed laws requiring that Airbnb provide guest information so that local regulations can be enforced, and hotel taxes are collected. Regulation of

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Central Florida hoteliers consistently claim they do not consider listings platforms such as Airbnb a viable threat to their occupancy rates, citing the number of rooms in the region and their price range. In addition, guests also pay the Orange County Tourist Development Tax. Florida's transient rental tax is 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, home sharing allows hosts to rent up to half the bedrooms on the property, but only in residential zones with the homeowner or tenant being present for the duration of the rental. Orange County requires that properties rented in their entirety be licensed by the Department of Business and Professional Regulation, be located in O-3, MU district, or AC districts, and obtain a Business Tax Receipt. [5]

3. Literature Review

While there are several studies that investigate Airbnb listing amenities individually, on the performance of short-term rentals during the pandemic, this is the first paper that develops a real-estate management model based on Sirmans et al (1999) to link potential clients' preference for listing, neighborhood, and host characteristics to Airbnb unit pricing, revenue and occupancy. For example, results from four Italian cities have shown that areas that have increased their Airbnb supply are limited while large, clustered, contiguous portions of these cities have reversed the exponential growth trend of recent years (Romano, 2021). Other studies like Kourtit et al (2022) find hardships for the Airbnb market as a whole in most cities. Results from four cities in Austria document shift in the operations of the short-term rentals while finding no shifts in rent (Kadi et al., 2020). Hu and Lee (2020) find private rooms experience 20% more cancellations than entire homes, while the supply side, remain stable. Choi & Choi (2022) find that messaging format impact travelers' intention to book Airbnb spaces. Miguel et al (2022) document that short-term rental platforms adopted high level of communication with stakeholders and a temporary switch from short-term rental to long-term rental market in some

[5] Source:" https://www.airbnb.com/help/article/2371"

countries. In the U.S, properties that are perceived to be clean had higher revenue and occupancy during covid, while prices for these properties did not increase post covid, Shen and Sean (2022). Wong et al. (2021) finds evidence of seasonal, spatial, and pricing effects on the supply of Airbnb listings. Wee and Liow (2022) undertakes a comparative study of millennials choice between small hotels and Airbnb rentals and reveal price and reviews to be their common pull motivations when making accommodation choices while factors such as location, service quality, facilities and amenities, safety, and security associated with small hotels do not appear to significantly influence the millennials' choices.

Internationally, there is a plethora of evidence that examines the performance of Airbnb rentals during COVID-19. (Vietnam; Lower revenue, Capetown; no change, Sydney; lower revenue in comparison to company, Budapest; decreased revenue and listings). Most of these studies discuss the business strategy of Airbnb as a possible cause for the inferior performance, while several others like Muschter, et al. (2022) who study community perceptions of short-term rentals in top tourist destinations advocate the use of regulatory strategies for the sustainable future of Airbnbs. Our paper identifies specific listing features of Airbnb platform as well as neighborhood characteristics that drive the profitability in this market during the global health crisis.

This paper also contributes to the ongoing debate on the effect of the Airbnb market on the hotel industry. Studies argue that Airbnb plays an alternative or substitutive role for conventional accommodations because it offers similar products and services in direct competition with hotels (Blal et al., 2018; Dogru et al., 2019, Kwok & Xie, 2019). Other scholars posit, however, that based on its territorial distribution of listings and competitive prices, Airbnb is supplementary or complementary to the hotel industry (Dogru et al., 2017; Gutierrez et al., 2017). Hoesli and Malle (2021) report that hospitality properties have been affected the most by COVID-19, while the residential and industrial sectors have been less affected by the crisis. We tackle this debate from a different angle and show that hotels, who voluntarily marketed themselves on the Airbnb platform boosted their performance by taking advantage of several listing amenities of the platform. This paper also finds a net competitive effect of increasing hotel prices on the prices of nearby competing residential Airbnb units. The direct effect of hotels on the occupancy rates of these units however, is asymmetric and reveals a shopping externality effect that has not yet been documented in the existing literature.

Previous literature also report that price positioning and dynamic pricing positively affect the revenue of Airbnb units especially for multi-unit hosts (Kwok and Xie, 2019). We show that professionalization of Airbnb hosts and their ability to revise prices as a key factor that has had profound effects on the profitability of Airbnb listings in the pre-pandemic era, consistent with previous studies.

This paper also contributes to the general literature focusing on the resilience of real estate markets to economic shocks. A big data analysis of all house listings in the city of Vilinius by reveals that real estate is quite resilient to pandemics. Tanrıvermiş (2020), Bhoj (2020) as well as Jovanovic et al. (2020), Sequera et al (2022) document transitionary shifts in demand or supply of international real estate markets like Turkey, India, China, Great Britain, Serbia, Spain and Italy. However, Carlsson-Szlezak et al. (2020) points out that future of real estate markets is not straight forward and characterizing the shape of the recovery like might not be adequate or effective. The findings in this paper identifies host efforts and inputs, and co-location in areas close to tourist spots as the main factors that contributed to the pliability of the vacation rental market. We also attribute the survival and recovery of this market partially to the shorter-term restrictions that were in effect in the State of Florida as compared to other regions in the country.

4. Model

The theoretical framework draws from the real estate management model developed in Sirmans et al (1999). This version suppresses management structure issues addressed in the more general model in order to focus on 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 $q(m, n)$ of owner-supplied management and maintenance inputs, m, as well as the surrounding neighborhood amenities, indexed by n. 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.

$$p = p(q(m, n), s) \tag{2.1}$$

The price is increasing in q ($p_q > 0$, using subscripts to denote derivatives). Therefore, the price effect of neighborhood characteristics fully reflect 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

$$x = x(p, q(m, n), s) \tag{2.2}$$

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 and quality constant, directly reflects whether the characteristics are desirable ($x_n > 0$) or not ($x_n \leq 0$).

The property owner's expected profit for the unit per period is.

$$\pi = E[p(q(m,n),s)x(p,q(m,n),s)] - c(m) \qquad (2.3)$$

where $c(m)$ is the cost of owner supplied inputs m for the rental unit, with increasing marginal cost ($c' > 0, c'' > 0$). The owner's input choice maximizing (2.3) can be expressed as the implicit solution $m^* = m(n)$. Substituting this into (2.1) and (2.2) and solving for the equilibrium price and occupancy rates yields the reduced forms describing the equilibrium outcomes

$$p^* = f(n) \qquad (2.4)$$

$$x^* = g(n) \qquad (2.5)$$

Where,

$$\frac{dp^*}{dn} = p_q q_n \gtreqless 0 \text{ as } q_n \gtreqless 0 \qquad (2.6)$$

$$\frac{dx^*}{dn} = x_n + x_p\left(\frac{dp^*}{dn}\right) \qquad (2.7)$$

Result (2.6) draws the direct connection between desirable neighborhood attributes and unit rent. As revealed in (2.7), 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 (2.7)) and the second being the indirect effect through change in rent (the second term in (2.7)). The indirect price effect implies that even neighborhood attributes highly prized by potential tenants may not be reflected in higher occupancy rates.

Empirically, we observe for Airbnb properties the Average Daily Rate (ADR) per month, and the occupancy rate of these units per month. To test our hypothesis, we implement the following seemingly unrelated regression (SUR) models:

$$\begin{cases} \log(ADR) = \beta_0 + \beta_1 X + \beta_2 Z + \varepsilon_{ADR} \\ \mathrm{OCC} = \alpha_0 + \alpha_1 X + \alpha_2 Z + \varepsilon_{OCC} \end{cases} \quad (2.8)$$

$$\begin{cases} \log\,(\mathrm{RevPAR}) = \mu_0 + \mu_1 X + \mu_2 Z + \varepsilon_{rev} \\ \mathrm{OCC} = \gamma_0 + \gamma_1 X + \gamma_2 Z + \varepsilon_{OCC} \end{cases} \quad (2.9)$$

Where Z represents quarter and census tract fixed effects and ε indicates the error terms. Alternatively, we run Ordinary Least Squares (OLS) regressions on the following extended models which are now redefined to take into account the effects of the pandemic.

$$\log(ADR) = \beta_0 + \beta_1 covid + \beta_2 X + \beta_3 X \times covid + \beta_4 Z + \varepsilon_{ADR} \quad (2.10)$$

$$\mathrm{OCC} = \alpha_0 + \alpha_1 covid + \alpha_2 X + \alpha_3 X \times covid + \alpha_4 Z + \varepsilon_{OCC} \quad (2.11)$$

$$\log(RevPAR) = \mu_0 + \mu_1 covid + \mu_2 X + \mu_3 X \times covid + \mu_4 Z + \varepsilon_{rev} \quad (2.12)$$

$$ListingDEN = \gamma_0 + \gamma_1 covid + \gamma_2 X + \gamma_3 X \times covid + \gamma_4 Z + \varepsilon_{OCC} \quad (2.13)$$

We use OLS approach in this section as the dependent variable *ListingDEN*, denoting supply of Airbnb units is calculated at the census tract level while the other dependent variables are calculated at the unit level. SUR estimates for dependent variables that have different levels of aggregation may not be reliable. Since it is important to examine the effect of the pandemic om the supply of Airbnb at the neighborhood level, we implement a standard OLS regression technique to empirically test our hypothesis.

5. Data and Methodology

We obtain Airbnb from AirDNA, a company that provides data and analytics to entrepreneurs, investors, and academic researchers, for the period January 2014 through June 2022. The data pertain to Orange County, Florida, which encompasses the major tourist attractions at the heart of the Orlando-Kissimmee-Sanford Metropolitan Statistical Area. Schuetz and Sarah (2021) identify the area as a top location in the U.S. in terms of both hotel room supply and Airbnb supply. Our analysis studies the Airbnb platform as a short-term rental market, but we recognize that Airbnb does not represent the entire short-term rental segment. Although Airbnb may be the most popular, other short term vacation rental (STVR) platforms owned by large travel companies, such as Expedia, Priceline, and TripAdvisor, also provide some peer-to-peer (P2P) short-term rental services. Unlike Airbnb, which offers private and shared rooms as well as small studios and apartments and entire homes catering to a large variety of clients, the other platforms and services tend to provide much larger spaces (Geminiani and DeLuca, 2018). For instance, approximately 70% of vacation rental listings on major STVR booking platforms, such as VRBO and HomeAway, are two- or more-bedroom properties with an average capacity of six people—and 87% of their guests travel with a family member (Vacation Rental Management Association, 2020), greater proportions than found on Airbnb.

The data comprises Airbnb listings where property types are mostly classified residential, (e.g., Apartments, Bungalows, Condominiums, single family detached houses, guest houses attached to larger residential units, Lofts, Rental Housing, Townhouses and Villas) as well as those classified as traditional lodging properties (e.g., vacation homes, apartment-hotels, serviced and corporate apartments, resorts, bed and breakfast, boutique hotels, and hotels.) We construct several unit performance measures. The logarithm of monthly revenue per available unit (*RevPAR*) is a popular performance indicator that reflects the simultaneous effect of demand and supply. In addition to *RevPAR*, we also use the monthly average daily rate (*ADR*)[6] and monthly occupancy rate (*OCC*) as dependent variables to sort out competition and search synergy effects of hotel listings on other properties.

The measure of Airbnb supply, the variable *ListingDEN*, is the total number of listings available during a month in the census tract, including entire homes, private rooms, and shared rooms, divided by total number of housing units in the census tract. Some Airbnb listings are not "Active," that is, some listings created in the Airbnb platform are not available for rent. To account for this, we only include listings that are active at least once within the past twelve months in the *ListingDEN* measure.

Data are available monthly and we require listings to be active at least three months since inception to be included in the sample. In addition, we obtain information on property characteristics such as the number of bedrooms and bathrooms. We use the latitude, longitude and zip code information provided on Airbnb to map properties into census tracts, which we define as the neighborhood. We use the number of reviews and overall rating of listings to create control variables indicating the popularity (*Popularity*) and identify highly rated hosts (*Demand*). We also include dummy variables for various host characteristics like *Experience* (hosts given the SuperHost badge reported on Airbnb). For residential Airbnb units we also use additional dummies for the listing type description to define an indicator variable for units available as a

[6] 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 schemes.

shared space, *Shared-listing* and *Multi-unit* for hosts that offer multiple listings in the sample period.

To control for neighborhood characteristics, we collect tract-level information for each rental unit address from the US Census Bureau[7]. The American Community Survey (ACS) supplements the decadal census count data with vital information for the population across the country every year. The ACS provides 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. Since the above information is only available till 2020, we use 2020 demographic values to proxy for neighborhood characteristics in years 2021 and 2022. In addition to the above information, we also create a measure of proximity to sightseeing spots to indicate if Airbnb listings cluster near major tourist attractions. We identify three major tourist attractions in Orange County—Walt Disney World, Universal Studios, and downtown Orlando—and calculate the straight-line distance in miles between the property and these locations (SeaWorld, another major theme park, lies between Universal and Disney and so does not affect this measure). The median distance is about six miles, so we define the variable *Clustered* to identify Airbnb units located within 6 miles of any of the above three sites.

Data description—To summarize demand and supply trends in the Orange County Airbnb market, we create a quarterly price index based on the monthly ADR of hotel and residential listings from 2014 to 2022 and similar indices for monthly occupancy rates, revenues and listing density. Figures 2.1-2.3 portray the indices. Figures 2.4-2.11 display the raw values of these variables over time. From Figure 2.1, it is seen that that the price levels of Airbnb

[7] Data obtained from "https://data.census.gov/"

residential units are well above the general housing prices in Orlando for a major part of our sample, although it started dipping when the shutdown orders hit during the second quarter of 2020. Surprisingly, prices in the STR market coincided with the housing market during this time. Subsequently the prices in the housing market started rising, while rents in the STR market continued to decline. Figure 2.1 also shows a steep decline in average daily prices of hotel listings since the start of the sample period in 2014, in contrast with the pattern of steadily rising housing prices. Prices remain steady during 2016-2018 and drop sharply during the pandemic. The price index for hotel listings shows stable pricing once the covid restrictions are lifted. Figure 2.2 provides a different picture of hotel listings performance over time. While revenue and occupancy have generally moved in the same direction in the pre-pandemic period, a major shift is evident when the pattern reverses post-pandemic. At the same time, it is interesting to note that the hotel listing density index in Figure 2.3 shows un upward trend beginning in 2020 and continuing through the pandemic and leveling off in the post-pandemic period. Clearly, hotels have a greater presence on the Airbnb platform after the pandemic. Hotel participation appears to be a permanent feature of Airbnb going forward. This emphasizes the need to understand the relationship between hotels and Airbnb residential units.

In terms of listing activity, we find an increase in active listings during early months of 2021 following the slow easing of shutdown orders in Florida. This is also seen in Figures 2.16, 2.17 which plots the creation dates of Airbnb listings and “Active” status of listings over time. We find that following a record number of delisting in March 2020 when the first wave of the pandemic hit US (Figure 2.15), the number of new listings added to the platform started to increase only after November 2020. We note that the statuses of most listings, however, become active following the first month of 2021. Based on these activity patterns as well as news articles searches that mention reopening of theme parks and other businesses, we define the time period prior to second quarter of 2020 as pre-pandemic; the second and third quarter of 2020 is deemed as peak pandemic period and any observation falling in the first quarter of 2021 as post pandemic. We refer to the fourth quarter of 2020 as a transition quarter. We then define *covid* dummy in our analysis as the second and third quarter of 2020, while *post-covid* dummy is defined to be one for every quarter following the transitionary quarter.

Figures 2.12-2.14 provide a clear picture of the location characteristics of Airbnb listings in Orange County. Figure 2.12 reveals evenly spread residential units over the county in the pre-pandemic period. Figure 5 shows that Airbnb listings thinned out during the peak pandemic period, with surviving listings tending to cluster in areas closer to major tourist attractions like theme parks, downtown Orlando and the well-established hotel corridor on International Drive in south-central Orange County. Nonetheless, it is interesting to note that the number of hotel listings grew during this period. Although limited to certain areas of the city due to zoning laws, the number of hotel units active on the platform rose from 1,444 listings pre-pandemic to 3,436 listings during the peak pandemic period, rising further to 4,754 listings post-pandemic. Residential units, on the other hand, range from 5,185 listings pre-pandemic, to 3,586 during the pandemic and 6,332 units post-pandemic. A zip code level analysis of supply and demand variables is also available in the Appendix for pre, peak and post pandemic times.

Table 2.1 presents the summary statistics for the data. From this table we see that that the occupancy rate for residential units in our full sample is higher than that of hotel rooms (8% vs 13%), while the average daily rents for hotel rooms are higher than that of residential Airbnb units. This explains why the monthly revenue for the latter, is higher. In general, the number of blocked days, Airbnb host experience, overall ratings, location clustering, property and neighborhood characteristics are similar across the two segments of listing. The differences are stark when it comes to the number of reviews (average of five reviews per hotel listing vs 18 reviews per residential listing) indicating higher popularity of residential rentals; and in terms of the type of space available to rent (77% of residential listings offer a shared space).

6. Results

6.1.Probit Analysis

To motivate our initial intuition that the performance of Airbnb rentals is driven by the potential clients' preference for certain property, listing, host and neighborhood characteristics, we first construct four different categories of listings based on their activity on Airbnb platform in the pre, peak and post pandemic environment. Category 1 consists of listings that failed during the pandemic. A listing is defined to have failed if it stops listing during March and April of 2020 and never lists the property again till the end of our sample period i.e., April 2022, or becomes "Inactive" for every month since the third quarter of 2020. Category 2 consists of units that were listed throughout the entire sample period under study and were active at least one month during the second and third quarter of 2020. Category 3 consists of listings that started advertising their properties on the Airbnb website during peak covid times i.e., the second and third quarter of 2020 and continued to list the rentals even after restrictions were eased. We require listings to be "active" at least a month after its inception to be included in the sample. And finally, Category 4 consists of units that stopped listing either by removing their posting from the website or by becoming "inactive", when shut-down orders and travel bans effectively choked the demand in the hospitality sector. These are also the collection of listings that resurfaced in the fourth quarter of 2020. We use the following multinomial probit model to examine the differences in the characteristics of these listings.

$$ListingCAT = \beta_0 + \beta_1 X + \beta_2 H + \beta_3 Z + \varepsilon_S \qquad (2.14)$$

Where *ListingCAT* is a categorical variable taking the values 1, 2,3 and 4 representing the four different collection of listing types.

From table 2.2, we find that the coefficients of *shared* dummy and *log (population)* is positive and significant for *ListingCAT* 1 and 4, which indicates that the sample of listings that failed or stopped listing during covid have a higher likelihood of being a shared space and are from neighborhoods with higher population density. These listings also have a greater probability of being in a neighborhood with higher proportion of ethnic residents and are less likely to be hosted by an experienced or multi-unit host. They tend to have a lower likelihood of being in a high-income neighborhood or to be clustered around points of tourist attractions. In contrast, coefficients of *shared* dummy for *ListingCAT* 2 and 3 are negative and significant indicating that the listings that were active throughout the pandemic and the ones that started during pandemic are less likely to be shared rooms, more likely to be from experienced hosts, less likely to be the popular or in-demand listings and have lower probability of being clustered in areas closer to tourist attractions. The negative and statistically significant coefficients on *log (income)*, and *log (population)* variables tell us that these listings have a lower likelihood of belonging to a neighborhood with high population density or high income and has a higher chance of being from a tract with a higher percentage of white residents. This is consistent with Chmielewska, Mateusz & Małgorzata (2022) who show that there is an apparent trend of increasing demand for residential properties away from parts of cities with the highest density of social infrastructure sites in favor of urban edge areas and areas close to green spaces. *ListingCAT* 4 contains listings that are more likely to be located in the vicinity of tourist spots and high-income neighborhoods, and also have a higher probability of being popular that justifies their comeback. They are less likely to be managed by experienced hosts.

These differences in the characteristics of Airbnb properties provide a solid motivation for the pre and post covid analysis in the following section that examines, if these are indeed the factors that affected the demand and the supply of Airbnb properties during the pandemic.

6.2.Residential Rentals' performance on Airbnb platform

To understand how the listing, host, and neighborhood amenities affect the demand and supply of Airbnb rentals, we first run a seemingly unrelated regression (SUR) for the empirical models defined in equations (2.8) and (2.9). Table 2.3 reports the results from this regression analysis. We conclude from the coefficients of *experience, demand, multi-unit, clustered, %Old, %Educated* variables in column (1) that units that are higher in demand (defined by higher overall ratings), managed by multi-unit, and experienced hosts, clustered around sightseeing spots and are in neighborhoods with higher percentage of senior and educated residents tend to have higher prices. Shared-space listings, popular listings, and listings in neighborhoods with a higher percentage of Asian and young residents seem to have a negative effect on the average daily prices. Similarly, experience of host, popularity, and clustering of listing, management by professional or multi-unit host, and a neighborhood with higher percentage of White and educated population have a positive influence on *OCC* or occupancy rates of Airbnb rentals.

In columns (3) and (4) of table 2.3, seemingly unrelated regression (SUR) analysis of *log (RevPAR)* and *OCC* show that experience, popularity, demand, clustering and being managed by a multi-unit host has positive effect on the revenue of the listing, while higher listing density, and percentage of Hispanic residents in the census tract have a negative influence on the revenue of the listings. On the occupancy model, results are similar to that of the previous section. In addition, higher population density in the neighborhood affects occupancy rates negatively.

To take into account the effects of the covid period, we run alternative specifications of our baseline model defined in eq (2.10), (2.11). (2.13) and (2.14). In the first specification, we study the effect of the worst phases of covid on Airbnb performance by interacting the control variables with the *covid* dummy. In the second specification we examine the performance of Airbnb rentals in a post covid setting. We interact the control variables with the *post-covid* dummy. A cross-equation test of coefficients of the interaction terms in the simultaneous equation is conducted for the SUR regressions. Results from the F-test are statistically significant rejecting the null hypothesis that coefficients are equal to zero across equations. This confirms our motivation that covid indeed affected these characteristics that drives the performance of Airbnb rentals. Results from this SUR analysis is available in the online Appendix.

We run OLS regressions for our modified models. The regressions results presented in column (1) of table 2.4 show that the coefficients for the *shared-listing*×*covid*, *popular*×*covid*, and *log(income)*×*covid* interaction terms are negative and significant for the price equation. This indicates that shared-space listings, listings with higher volume of reviews and listings in high income areas had lower prices during the pandemic. This is justified as health concerns were of primary importance during this time and travelers perceived the pre-established popularity of rentals to act as signals that are likely to attract more reservations and hence more vulnerable to disease transmission. Higher listing density in the neighborhood exerts a downward pressure on the revenues of rentals as does high-income neighborhoods and neighborhoods with a higher proportion of popular rentals. Column (3) report the results for the occupancy equations. The coefficient of *popular* dummy is negative and significant indicating that listings with popular reviews had lower number of reservations during the worst phases of the pandemic. Units that are clustered and managed by multi-unit hosts had higher occupancy rates during this time. The coefficient for *covid* dummy is negative and significant for all dependent variables, indicating a decrease in prices, revenue and occupancy rates, as is expected. The results in column (4) of table 2.4 indicate that overall supply is lower during pandemic, although the *ListingDEN* is higher in high-income neighborhoods, and in neighborhoods with a higher percentage of White residents. *ListingDEN* is lower in neighborhoods with lower proportion of multi-unit hosts.

In the post pandemic scenario (Table 2.5), shared space listings, listings with higher number of reviews, and listings in high income neighborhood have lower prices while prices of Airbnb rentals are overall higher in post pandemic quarters. It is also evident that multi-unit hosts and listings that are clustered near sightseeing spots like theme parks and downtown Orlando had higher prices post pandemic. This is shown in column (1) of table 2.5. Similarly, from column (3) we observe that multi-unit hosts and clustering increase the occupancy rates of these units, while pre-established popularity of listings still has a negative effect on occupancy rate in post pandemic environment. The overall occupancy rates for all listings show a positive shift after shut-down orders were lifted. The results in column (4) indicate that overall supply is lower after the pandemic, although *ListingDEN* is higher for neighborhoods with higher proportion of experienced hosts, in high income neighborhoods, and in neighborhoods with a higher percentage of White residents. There seems to be no overall significant effect on the monthly revenue in post pandemic quarters, although the signs of the coefficients are as expected.

6.3.Hotel Performance on Airbnb platform

The pandemic severely affected the profitability of the hospitality industry. Even with post-pandemic operations returning to normal and the boom in the housing market, the performance of the hotel industry has yet to fully recover pre-pandemic levels. Although Airbnb is expected to emulate the hotel industry in some regards, there are important differences, not the least being the ease of comparing hotel and non-hotel listings on Airbnb. It is therefore useful to focus on Airbnb listings for rooms in small to midsize independent hotels and hotel chains to see if performance is influenced by the same factors as non-hotel listings. The focus is on Airbnb amenities affecting hotel listing pricing, occupancy and revenue as well as systematic changes induced by the pandemic.

Using the same model specifications defined in equations (2.10-2.14), we run OLS regressions and report the regression coefficients for *log (RevPAR), log (ADR), OCC* and *ListingDEN* of hotel rooms in tables 2.7 and 2.8. Note that *ListingDEN*, our measure of the supply of Airbnb units the listing density variable constructed for hotels includes only Airbnb listed hotel rooms in the census tracts as a ratio of total housing units in the tract. Since the computation of this variable is at the census tract level while the other dependent variables are calculated at the individual listing level, SUR is not appropriate when dependent variables have different levels of aggregation. Hence these models are estimated using OLS. And since it is important to consider pandemic induced changes on the supply of Airbnb listings at the neighborhood level, we include interaction terms to pick up differential effects associated with the pandemic periods. We run SUR regressions for the hotel and other property subsamples and conduct a cross-equation test of coefficients for all interaction terms in the simultaneous equations. Results from the F-tests are statistically significant, rejecting the null hypothesis that coefficients are zero across equations.

Table 2.6 reports the coefficients of the SUR models (2.8) and (2.9) of all hotel rooms listed. The hotel subsample shows that host experience is a key determinant of higher overall prices and occupancy, while higher overall rating of hotel rooms by customers does not necessarily ensure higher prices, although it does increase the occupancy rate. While higher listing density of hotels leads to higher occupancy rates, the effect on pricing is opposite. Column (3) shows that higher listing density, and higher percentage of white residents in the neighborhood lead to higher revenue while greater popularity has a negative effect on the revenue of hotel rooms.

The key estimates of the OLS regression reported in tables 2.7 show the overall effect of covid on prices, occupancy, revenue and listing density is insignificant for all hotel listings in our sample. The *clustered* dummy coefficient is positive and significant in column (2), indicating that location is an important factor that increases hotel revenues during the pandemic. The post pandemic analysis in table 2.8 reveals that hotels perform better in terms of revenue and occupancy in the post pandemic environment. Interestingly, greater concentrations of some ethnic residents and higher income neighborhoods are associated with lower hotel revenues and occupancy. Higher ratings do not seem to affect occupancy rates. Additionally, unlike residential rentals, pre-established popularity of hotel room listings increases price and occupancy of hotel rooms, particularly in the post covid period. Host experience has a positive effect on prices and occupancy in the post-pandemic time period.

Drawing the results in this section together, we identify host experience, professional management, popularity and clustering to be some of the key features of the Airbnb platform that lead to greater hotel listing performance.

6.4.Spillover Effects

Airbnb reduces search and matching costs for both renters and property owners. A critical mass creates search synergies for both sides of the market that increase the attractiveness of the platform to both parties. 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 centers on hotel effects on surrounding residential listings.

The ability to distinguish hotel type listings from residential listings in our sample provides us with a unique opportunity to analyze the relationship between Airbnb and the traditional lodging industry. 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 in the vicinity of competing Airbnb unit generates on the demand and supply of the target unit. We first tackle this question empirically by computing a statistic that measures this effect. We compute a proxy for hotel participation, using distance weighted average daily room rates (*wtprc*) of hotels within one mile available on Airbnb at the same time as the competing residential unit. We include *log*(*wtprc*) as an independent variable in the empirical models and report key parameter estimates for the subsample of non-hotel properties in table 2.9. The *log(wtprc)* coefficient estimate is significantly negative in the *OCC* equation and significantly positive in the *log(ADR)* equation for the overall sample, as seen in columns (1) and (4) respectively. The coefficients in the occupancy and rental price equations provide evidence of substitute goods effects but no evidence of search synergy effects; higher hotel room rates increase the demand and prices for other Airbnb units. The occupancy equation result follows the net effect of higher prices; the negative coefficient does not provide insight into the direct hotel room rate effect on occupancy. Nonetheless, when taking into consideration covid and post covid time periods separately, the coefficients on the interactions of *log(wtprc)* variable with *covid* and *post-covid* dummies reveal stronger hotel substitute goods effects in both occupancy and price equations during and after the pandemic. The pandemic experience significantly altered the demand relationship between hotel rooms and other properties on Airbnb.

To establish a sound theoretical background for this effect, we now extend the original model in section 4 to consider how nearby hotel participation on the Airbnb platform affects surrounding properties. The framework incorporates two possible channels: hotel rooms as competing substitute goods for other properties listed on Airbnb and as a source of shopping externalities arising from search synergies on the platform arising from increased traffic from buyers drawn to the site primarily to search for hotel rooms.

As before, unit quality is q is an increasing quasiconcave function $q(m, n)$ of owner-supplied management and maintenance inputs, m, and neighborhood amenities, n. The rental price p of the unit is a function of the unit quality, q, the presence of nearby hotels, h, and the realization of the stochastic state indexed by s

$$p = p(q(m, n), h, s) \tag{2.15}$$

The price is increasing in q ($p_q > 0$). We use the prices of nearby hotel units to measure hotel participation h. The sign of p_h is determined by two possibly offsetting effects on the demand for nearby Airbnb properties. At root, hotel rooms are substitute goods for the listed Airbnb unit, which by itself leads to a positive relationship between hotel room prices and the price that can be obtained by the listed Airbnb unit, or $p_h > 0$. At the same time, however, we allow for the possibility that the availability of nearby hotel rooms may create shopping externalities for other nearby properties listed on Airbnb from search synergies. If lower priced hotel rooms increase search traffic for nearby properties as well, then this search synergy or shopping externality by itself increases prices of nearby properties, so that $p_h < 0$. The net effect of nearby hotel participation on other properties therefore reflects the relative strength of the substitute demand relationship and possible search synergy effects. As the former implies $p_h > 0$, it follows that observing $p_h \leq 0$, provides evidence of search synergies or shopping externalities that are strong enough to overshadow the demand substitutes relationship between hotel rooms and other properties on Airbnb.

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

$$x = x(p, q(m, n), h, s) \qquad (2.16)$$

Recall $x_p < 0$ and $x_q > 0$. What is new here is the relationship between occupancy and nearby hotel prices, holding unit price and quality constant, directly reflects whether nearby hotels are net substitute goods for the property ($x_h > 0$) or generate shopping externalities strong enough to offset the demand substitutes effect on occupancy ($x_h \leq 0$).

The property owner's expected profit for the unit per period is

$$\pi = E[p(q(m, n), h, s)x(p, q(m, n), h, s)] - c(m) \qquad (2.17)$$

The input choice maximizing (2.17) is given by the implicit solution $m^* = m(n, h)$. Substituting this into (2.15) and (2.16) and solving for the equilibrium price and occupancy rates yields the reduced forms describing the equilibrium outcomes.

$$p^* = f(n, h) \tag{2.18}$$

$$x^* = g(n, h) \tag{2.19}$$

The comparative static properties for n are the same as before. For hotel price effects, on the other hand, we find

$$\frac{\partial p^*}{\partial h} = p_h \tag{2.20}$$

$$\frac{\partial x^*}{\partial h} = x_h + x_p(\frac{\partial p^*}{\partial h}) \tag{2.21}$$

Taking a closer look at the competition and search synergy effects from nearby hotel participation on the booking platform, from (2.20) we see that a strong substitute goods relationship between hotel rooms and other properties implies the standard result that higher hotel room rates increase the demand hence rents for other nearby Airbnb properties, $p_h > 0$. To the extent that lower hotel room rates draw search traffic and generate shopping externalities, observing a nonpositive relationship between hotel room rates and the other property rents, $p_h \leq 0$, indicates the presence of a shopping externality that is sufficiently strong to fully offset the usual competition effect between substitute goods.

As in the case of neighborhood amenities, the hotel room rate affects the other property occupancy rate through two channels, the direct effect reflecting substitutes or shopping externality for given rent (the first term in (2.21)) and the indirect effect from how the hotel room rate affects the unit rent (the second term in (2.21)). Therefore, the net hotel room rate effect on unit rent and occupancy need not be symmetric. Looking at the first term (2.21), $x_h > 0$ is expected for substitute goods so that observing $x_h \leq 0$ indicates the presence of a strong shopping externality. Of course, the combined direct and indirect hotel price effect $\frac{\partial x^*}{\partial h}$ is what is observed when estimating the reduced form equations (2.18) -(2.19). Nonetheless, as explained later, the empirical modeling can be adapted to obtain separate estimates of the x_h term capturing the direct effect of hotel room rates on other property occupancy.

The model shows that, while hotel rooms are substitutes for other properties, the competitive effect on prices and occupancy in this regard may be mediated or fully offset by the associated shopping externalities generated for non-hotel properties by the Airbnb participation of nearby hotels. Competition from nearby hotels implies that higher hotel prices lead to higher prices for other nearby listings while shopping externalities lead to lower non-hotel prices. The predicted relationship with the occupancy rate is more complicated, as the occupancy rate is also directly affected by the price of the listing itself as well as competition and shopping externalities from nearby hotels. Controlling for the effect of listing price on occupancy, competition and shopping externalities from nearby hotels imply that higher hotel prices lead to higher and lower non-hotel occupancy rates, respectively. In any case, the effect of hotel price on both listing price and occupancy rate is tested empirically as follows:

For our empirical design, we first estimate the price function and obtain the residuals Δ for each listed property. In the second step we include Δ as a control additional variable in the occupancy equation:

$$\log(ADR) = \beta_0 + \beta_1 H + \beta_2 X + \beta_3 Z + \varepsilon_{ADR} \qquad (2.22)$$

The estimated price equation is then

$$\log \widehat{(AD}R) = \beta_0 + \beta_1 H + \beta_2 X + \beta_3 Z + \Delta \qquad (2.23)$$

The ex-post price is $\log(ADR) = \log \widehat{(AD}R) + \Delta$, where $\Delta = \log(p) - \widehat{\log(p)}$ is regression residual, The structural occupancy rate equation (un-estimated) is

$$\text{OCC} = \alpha_0 + \alpha_1 H + \alpha_2 \log(ADR) + \alpha_3 X + \alpha_4 Z + \varepsilon_{OCC} \tag{2.24}$$

Substitute for $\log(ADR) = \beta_0 + \beta_1 H + \beta_3 X + \beta_4 Z + \Delta$ to get:

$$OCC = \alpha_0 + \alpha_1 H + \alpha_2(\beta_0 + \beta_1 H + \beta_3 X + \beta_4 Z + \Delta) + \alpha_3 X + \alpha_4 Z + \varepsilon_{OCC} \tag{2.25}$$

Simplifying,

$$OCC = (\alpha_0 + \alpha_2\beta_0) + (\alpha_1 + \alpha_2\beta_1)H + \alpha_2\Delta + (\alpha_3 + \alpha_2\beta_3)X + (\alpha_4 + \alpha_2\beta_4)Z + \varepsilon_{OCC} \tag{2.26}$$

Denoting the estimated coefficient on H in the price equation as β_1 and the estimated coefficient on H in the occupancy equation as Θ, and the estimated coefficient on Δ in the occupancy equation as α_2; the direct effect of hotel on occupancy holding the price of the listing constant is therefore $\alpha_1 = \Theta - \beta_1\alpha_2$. This is the term we need to evaluate to ascertain if shopping externality is strong enough to outweigh competition effect on occupancy. The standard error for this term is (Proof in Online Appendix)

$$s.e(\alpha_1) = \sqrt{Var(\Theta) + Var(\beta_1)Var(\alpha_2) + Var(\beta_1)[E(\alpha_2)]^2 + Var(\alpha_2)[E(\beta_1)]^2}$$

To evaluate if the effect of the pandemic alters the hotel effect, we add a dummy C representing covid period to the price equation:

$$\log(ADR) = \beta_0 + \beta_1 H + \beta_2 X + \beta_3 Z + \beta_4 Covid + \beta_5(H \times Covid) + \varepsilon_{ADR} \tag{2.27}$$

The estimated price equation is therefore,

$$\widehat{\log(ADR)} = \beta_0 + \beta_1 H + \beta_2 X + \beta_3 Z + \beta_4 Covid + \beta_5(H \times Covid) + \Delta \tag{2.28}$$

Following above, adding the estimated Δ to the occupancy equation we obtain,

$$\begin{aligned} OCC = {} & \alpha_0 + \alpha_1 H + \alpha_2(\beta_0 + \beta_1 H + \beta_2 X + \beta_3 Z + \beta_4 Covid + \beta_5(H \times Covid) + \Delta) + \\ & \alpha_3 X + \alpha_4 Z + \alpha_5 Covid + \alpha_6(H \times Covid) + \varepsilon_{OCC} \end{aligned} \tag{2.29}$$

Simplifying,

$$OCC = (\alpha_0 + \alpha_2\beta_0) + (\alpha_1 + \alpha_2\beta_1)H + \alpha_2\Delta + (\alpha_3 + \alpha_2\beta_3)X + (\alpha_4 + \alpha_2\beta_4)Z + (\alpha_5 + \alpha_2\beta_4)Covid + (\alpha_6 + \alpha_2\beta_5)H \times covid + \varepsilon_{OCC} \qquad (2.30)$$

Denoting the estimated coefficient on $H \times Covid$ as $\Phi = \alpha_6 + \alpha_2\beta_5$, the direct effect of hotel on occupancy during the pandemic, holding the price of the listing constant is therefore $\alpha_6 = \Phi - \alpha_2\beta_5$. The standard error is calculated in a similar manner explained previously.

A simple OLS regression is implemented for models defined in (2.22) and (2.26) and coefficients of key parameters of interest are reported in table 2.10. The coefficient of the *log(wtprc)* variable is positive and significant for *log(ADR)* in Panel A column (1), consistent with a substitute demand relationship. However, using the formula derived earlier, we find $\alpha_1 = \Theta - \beta_1\alpha_2 = -0.065 - (0.209 \times -0.104) = -0.043$ so the estimated direct effect of hotel room rates on other unit occupancy rates is -0.043 and significant.[8] Higher hotel prices decrease search traffic and occupancy of surrounding properties, holding rental rates constant, evidence of search synergy or shopping externality effects.

In addition, the effect of nearby hotels on residential unit prices is stronger during and after the pandemic, indicating a stronger demand substitution relationship. The computed incremental direct effect of hotel pricing on the occupancy rates during the peak covid lockdown period is -0.030 but insignificant.[9] In contrast, in the post-covid period the calculated coefficient is -0.128 and statistically significant at 5% level.[10] This indicates stronger shopping externalities in the post-pandemic period. This pattern is consistent with search synergy or shopping externality effects from nearby hotels, but effects that are not strong enough to offset the competition effect on price and through price on the occupancy rate. The two-stage structural model approach is essential for identifying shopping externalities here.

[8] Calculated as $\alpha_1 = \Theta - \beta_1\alpha_2 = -0.065 - (0.209 \times -0.104) = -0.043$; $s.e\ (\alpha_1) = 0.008$; $tstat = -5.37$

[9] Calculated as $\alpha_6 = \Phi - \alpha_2\beta_5 = -0.065 - (0.209 \times -0.104) = -0.030$; $s.e\ (\alpha_6) = 0.063$; $tstat = -0.47$

[10] Calculated as $\alpha_6 = \Phi - \alpha_2\beta_5 = -0.065 - (0.209 \times -0.104) = -0.043$; $s.e\ (\alpha_6) = 0.016$; $tstat = -8.00$.

Overall, hotel rooms are substitute goods for other listed Airbnb units, reflected in the positive relationship between hotel room prices and the price that can be obtained by the listed Airbnb unit. On the other hand, consistent with the theoretical result, the hotel relationship with the occupancy need not mirror the effect on price, as the occupancy rate is directly affected by the price of the listing itself as well as competition and shopping externalities from nearby hotels. It turns out that the two-stage estimation approach exploiting the structural model from the theory allows us to deduce the presence of a shopping externality, but one that is not sufficiently strong to offset the hotel effect on occupancy through unit rental price. Our results show that by controlling for the effect of listing price on occupancy, shopping externalities from nearby hotels lead to lower non-hotel occupancy rates. The unique approach and evidence presented here is what sets this paper apart from contemporary studies overlooking the offsetting roles of competition and search synergies in the Airbnb market platform.

6.5.Pricing Strategies of multi-unit hosts

Results from section 6.4. emphasize the role of multi-unit hosts in generating income in the Airbnb market even amidst a major economic crisis. While hotels are known to engage in dynamic pricing strategies, one may wonder if the decision of professional hosts managing residential listings to revise prices affects the performance of these listings differently than other Airbnb rentals. To investigate the dynamic pricing strategies of multi-unit hosts managing residential properties, we first count the number of changes in prices in a quarter. Since data is available at the monthly level, we are only able to observe changes in prices across months. We define a variable *#Pchange* that counts the number of times average daily prices are changed in the three months defining that quarter, where counts are included only for price changes that are greater than the median change in prices across all quarters in that year for that particular unit. Next, we take the logarithm value of *#Pchange* variable and interact it with the *multi-unit* dummy in Equation (2.9). We then run our baseline regression model for the *log (RevPAR)* and *OCC* dependent variables. The results from this regression are presented in table 2.11.

For the *log (RevPAR)* dependent variable in column (1) the coefficient of the interaction term is positive and significant for both hotels and residential listings indicating that a multi-unit host strategically changing the price of his/her listing frequently and accordance to current conditions may benefit more than hosts managing a single or handful of units, The *log(#Pchange)* variable itself has no significant effect on the revenues earned by residential listings, but has a positive effect on revenues earned by hotel listings. For the *OCC* response variable, the *log(#Pchange)* variable has a positive effect on occupancy rate, while the coefficient on the interaction term with *multi-unit* dummy in Column (3) is negative and significant. This means that multi-unit hosts engaged in dynamic pricing are unable to increase occupancy rates. The effect is only significant for residential properties. This makes sense as the original popularity of traditional Airbnb listings hosted by small scale homeowners was due to affordable and stable pricing strategies. A possible explanation for higher revenues may be due to higher prices charged for completed reservations in these multi-unit host operated rentals. In unreported results we find similar evidence during the worst phases of the pandemic.

To see if the effect persists in the post covid period, the *log(#Pchange*) variable is now interacted with *post-covid dummy.* A triple interaction term between multi-unit hosts, *post-covid* and the *log(#Pchange)* variable is also added. From the coefficients of *post-covid*×*log (#Pchange)* and *post-covid*×*multi-unit*×*log(#Pchange)* terms, in columns (2) and (4), it is evident that the effect vanishes in the post covid period. Dynamic pricing has a negative effect on both revenue and occupancy of residential listings in the post pandemic period. This suggests that residential Airbnb customers were reluctant to pay prices different from those charged in the pre pandemic market.

7. Conclusion

Kostynets et al (2021) observe the realization of pent-up demand in Airbnb bookings during the period of partial easing of restrictions on the movement of tourists, starting July 2020. Given that Florida was one of the first few states in the United States that eased restrictions, one would expect the pressure of this pent-up demand to be more visible in the Airbnb activity happening in the area. This paper examines property, neighborhood, listing and host characteristics that affected the demand and supply of Airbnb listings in Orange County Florida, pre and post pandemic. A multinomial probit analysis of the listing, property, host and neighborhood amenities of units that were active before, during and post pandemic times on the Airbnb platform reveal significant differences in features of listings in each category.

Taking into account the effect of local restrictions, we observe that, although supply fell dramatically when the shut-down orders hit, units that are managed by experienced and professional hosts and are clustered in sightseeing areas of the city had higher prices, occupancy and revenues. Occupancy, price, and revenues are lower during the worst phases of the pandemic, for listings that are shared spaces, have high number of existing reviews and are in high income neighborhoods with high concentrations of ethnic residents. This is consistent with Liang et al (2020) who find that reservation rates decrease during the pandemic.

Results from the hotel listings indicate that hotels do benefit by drawing in on the demand for the Airbnb platform. Higher listing density of hotels on this platform during and post pandemic, have a positive effect on the revenue and occupancy of hotel rooms. One could also argue that the resilience of Airbnb industry is very well due to this collaboration. Results from the analysis of effect of hotel units on the price and occupancy of geographically proximate residential listings suggest that incremental prices of hotel rooms increase prices of these units both during and post pandemic indicating a substitute goods relationship between the two products. The relationship with the occupancy rates is more complicated and suggests weak search synergy or shopping externality effects from nearby hotels that are not strong enough to offset the competition effect on the occupancy rate.

Finally, pricing strategies of multi-unit hosts operating residential properties increase the revenue of these units but has no effect on the occupancy rates. An opposite effect is observed in the post pandemic period. In conclusion, similar to traditional real-estate markets, amenities associated with properties listed on the Airbnb platform are found to drive the performance of the Airbnb rentals as well. Whether these effects are transitionary or permanent is a question of future research.

Figures

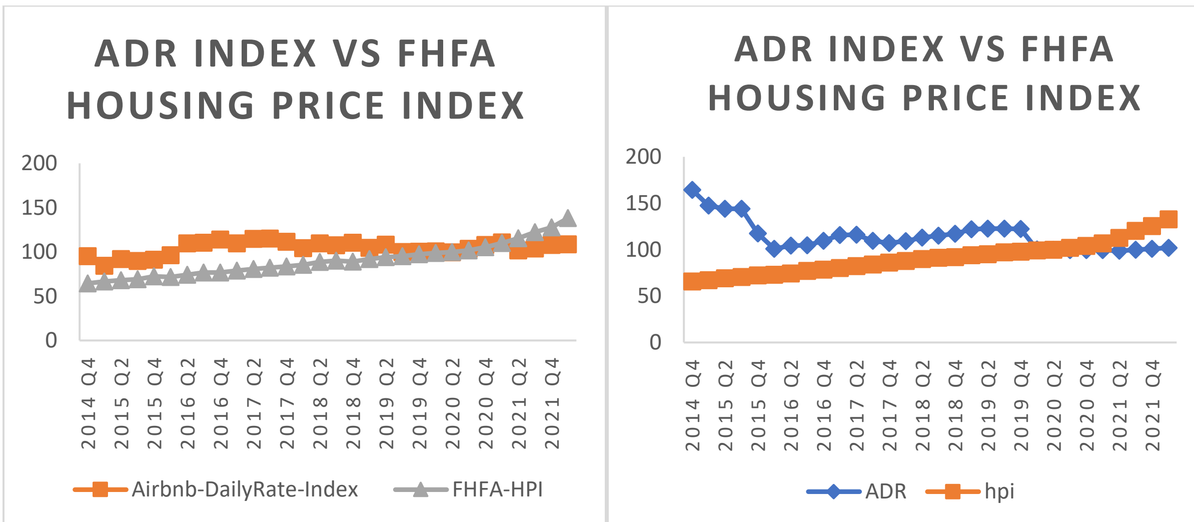

Figure 2.1: Airbnb Daily Price Index vs. Housing Price Index

Figures represent the average daily rate indices of residential (left) and hotel units (right) for each quarter over 2014-2022 plotted against the FHFA published quarterly housing price index for the Orlando-Kissimmee-Sanford MSA.

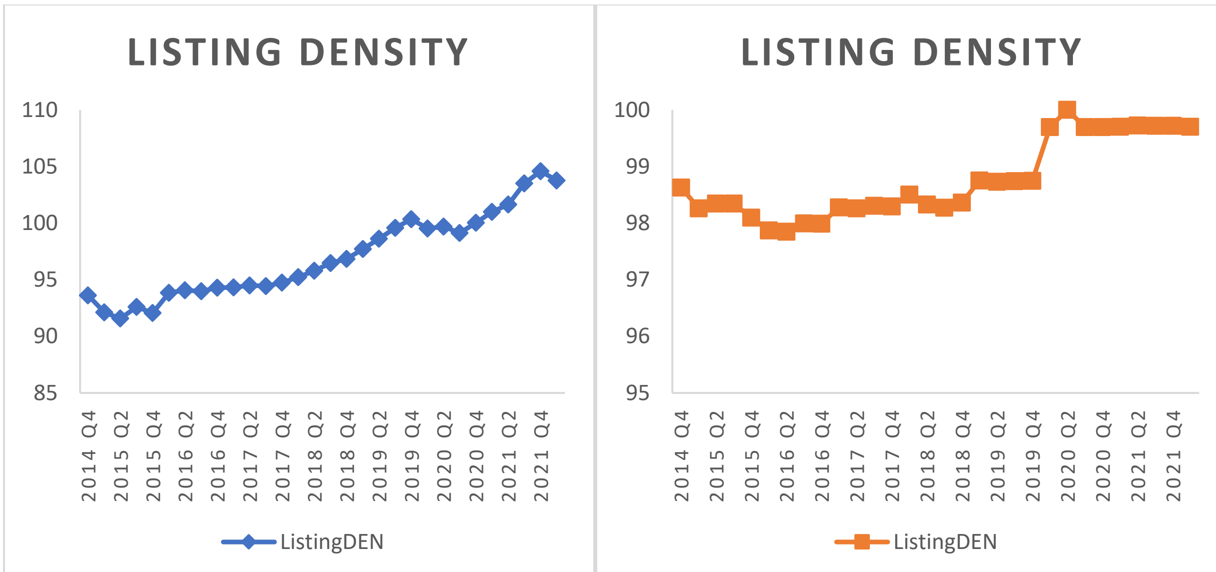

Figure 2.2: Residential and Hotel Airbnb Listing Index

Figures represent listing density index of residential (left) and hotel units (right) for each quarter over 2014-2022

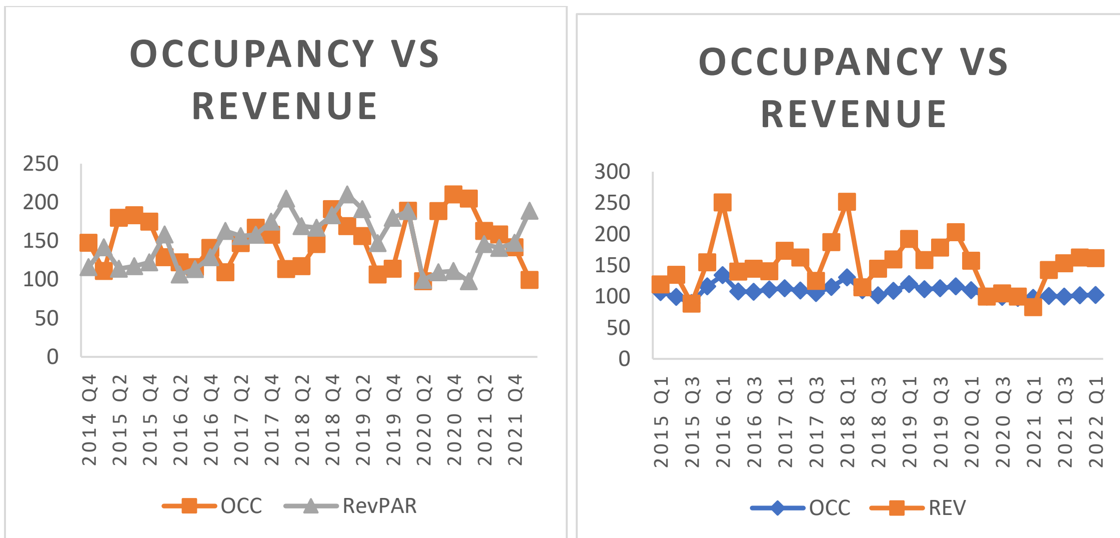

Figure 2.3: Occupancy Index vs. Revenue Index

Figures represent the occupancy rate indices of residential (left) and hotel units (right) for each quarter over 2014-2022 plotted against revenue indices of residential and hotel units.

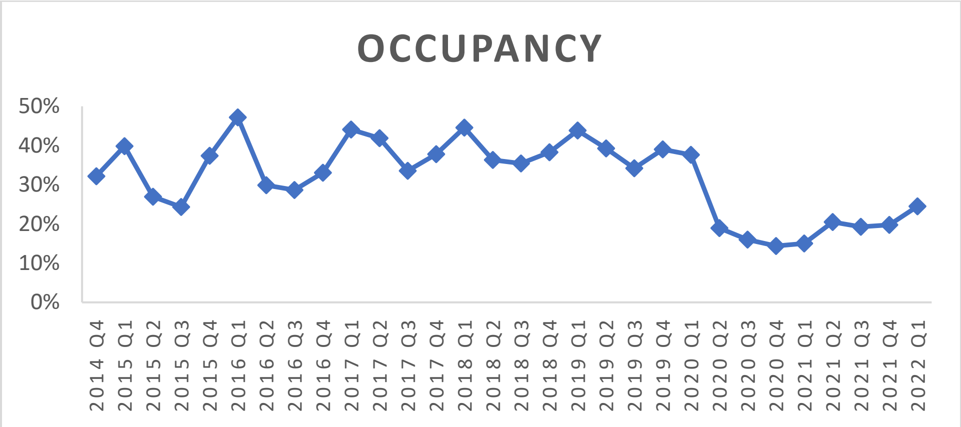

Figure 2.4: Raw Occupancy Rates of Residential Airbnb

Figure represents the raw average occupancy rates for residential units in each quarter from 2014-2022

Figure 2.5: Raw Prices of Residential Airbnb

Figure represents the raw average daily rates (ADR) for residential units in each quarter from 2014-2022

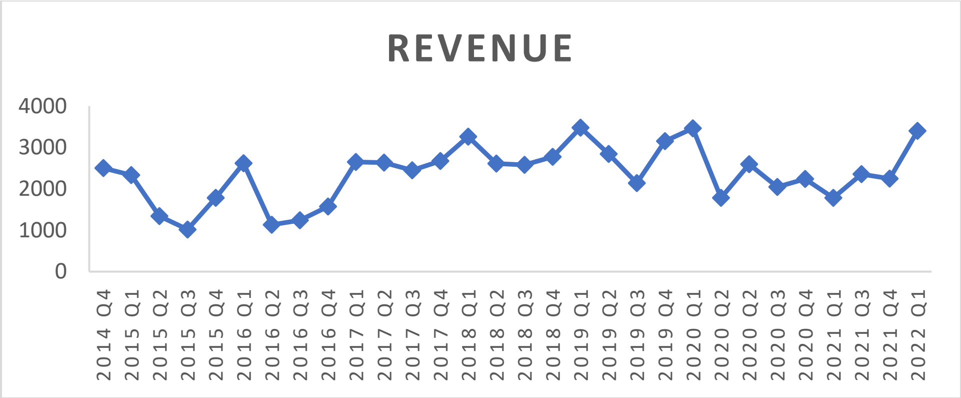

Figure 2.6: Raw Revenues of Residential Airbnb

Figure represents the raw average revenues for residential units in each quarter from 2014-2022

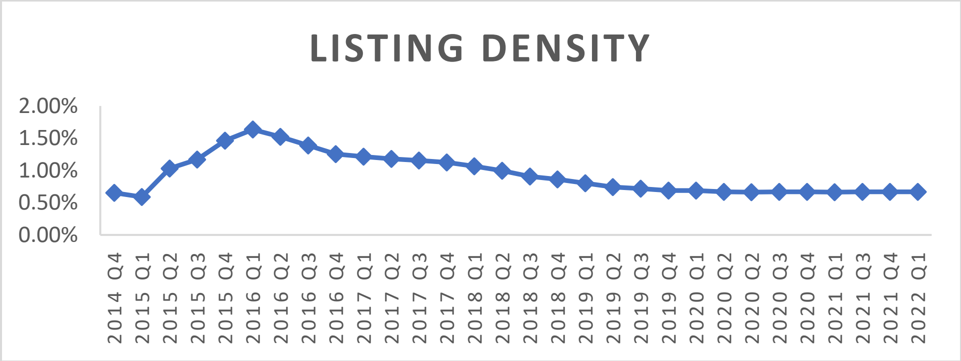

Figure 2.7: Listing Density of Residential Airbnb

Figure represents the listing density for residential units in each quarter from 2014-2022

Figure 2.8: Prices of Hotel Units

Figure represents the raw average daily rates (ADR) for hotel units in each quarter from 2014-2022

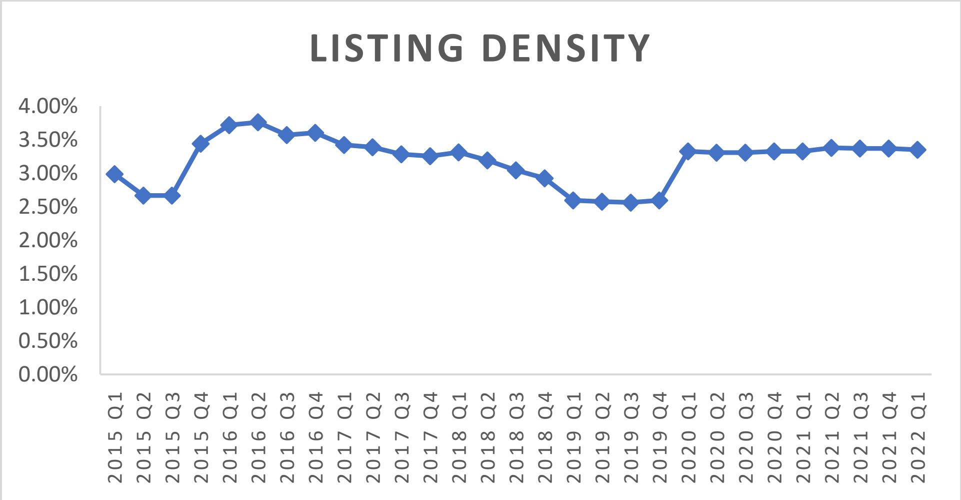

Figure 2.9: Listing Density of Hotel Units

Figure represents the listing density for hotel units in each quarter from 2014-2022

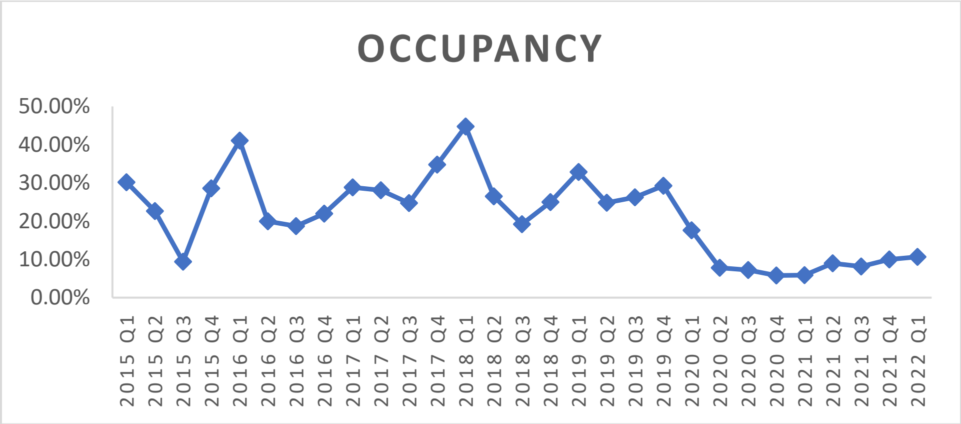

Figure 2.10: Raw Occupancy Rates of Hotel Units

Figure represents the raw average occupancy rates for hotel units in each quarter from 2014-2022

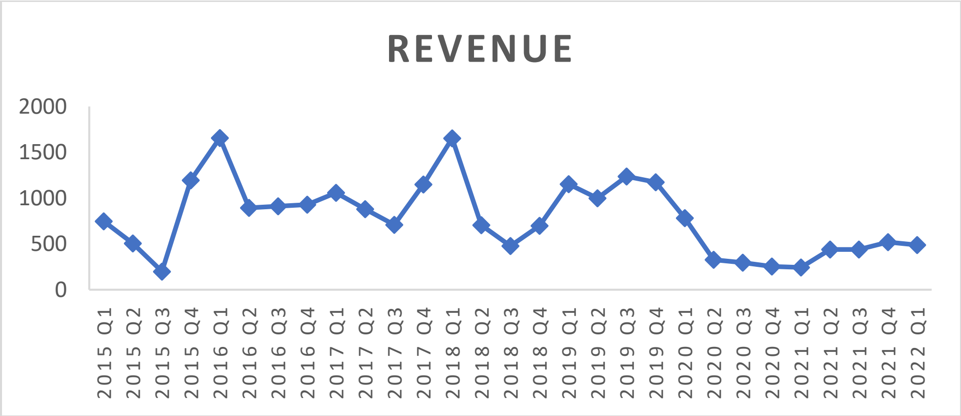

Figure 2.11: Raw Revenues of Hotel Units

Figure represents the raw average revenues for hotel units in each quarter from 2014-2022

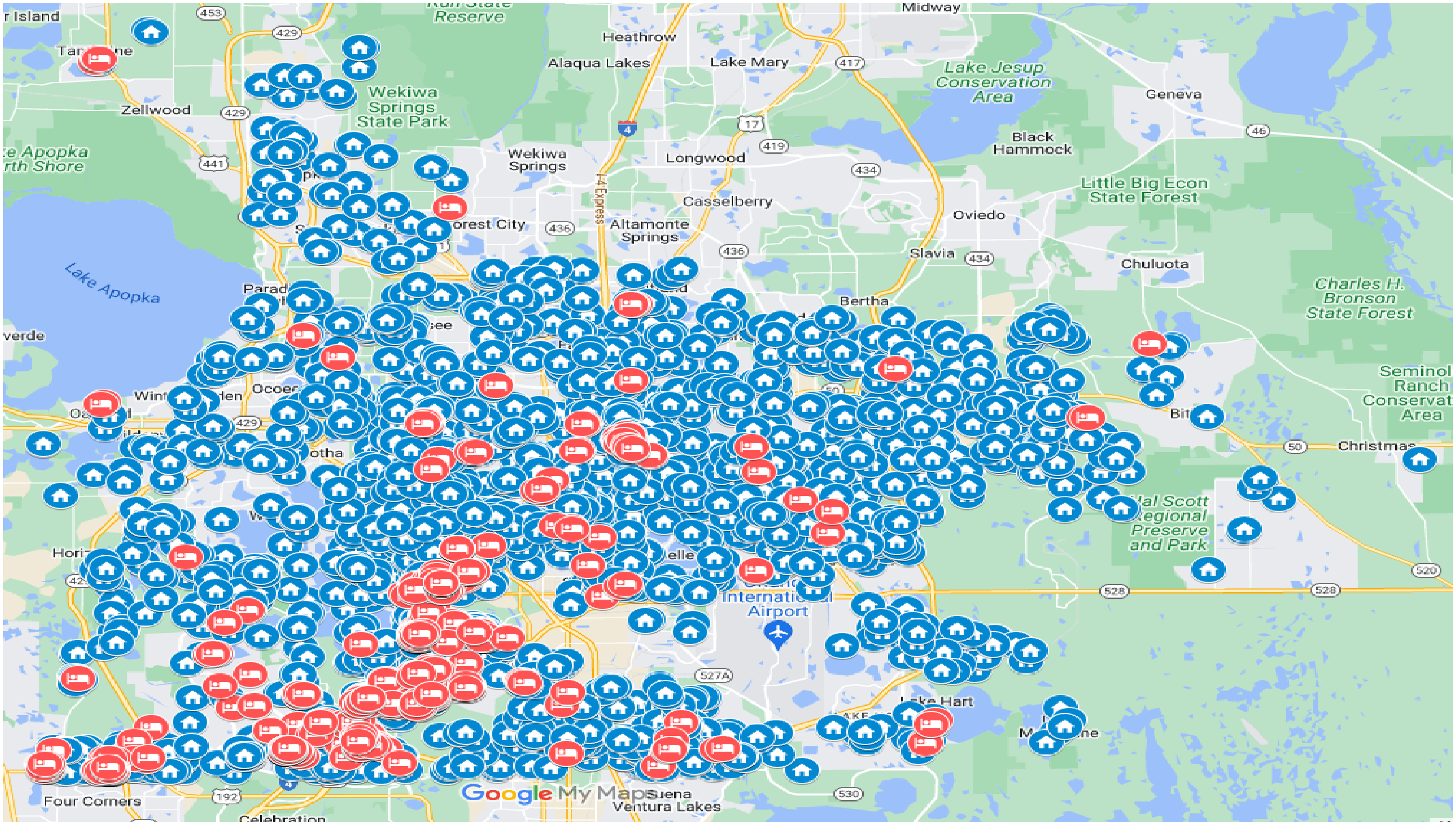

Figure 2.12: Pre-Covid Map of Orange County Airbnb Listings

Red markers represent hotels while blue markers represent residential properties. Hotels are restricted to commercial, industrial and mixed zones.

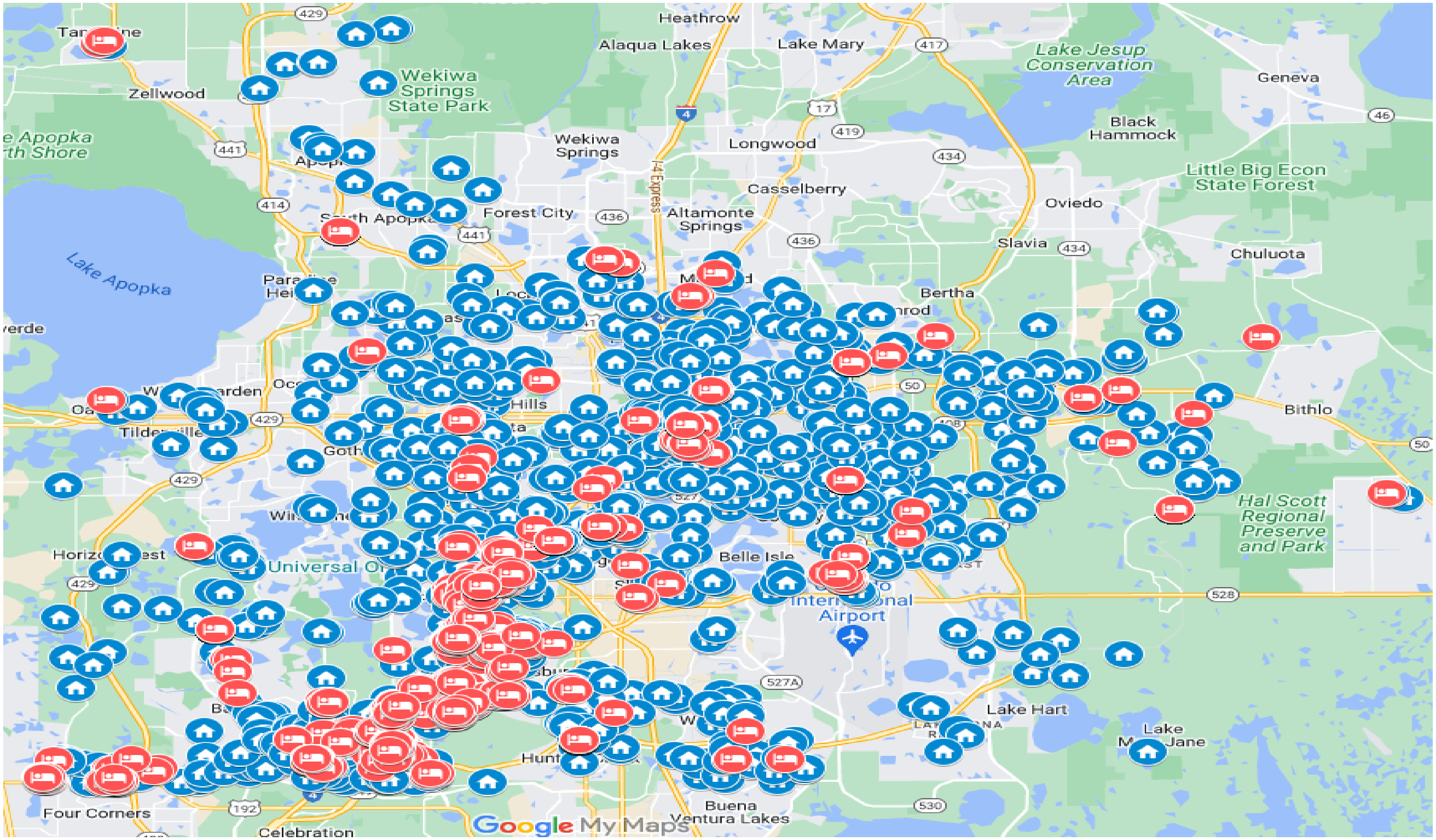

Figure 2.13: Peak covid Map of Orange County Airbnb Listings

Red markers represent hotels while blue markers represent residential properties. Hotels are restricted to commercial, industrial, and mixed zones. The density of residential listings is significantly less towards the western edge and central downtown part of the city

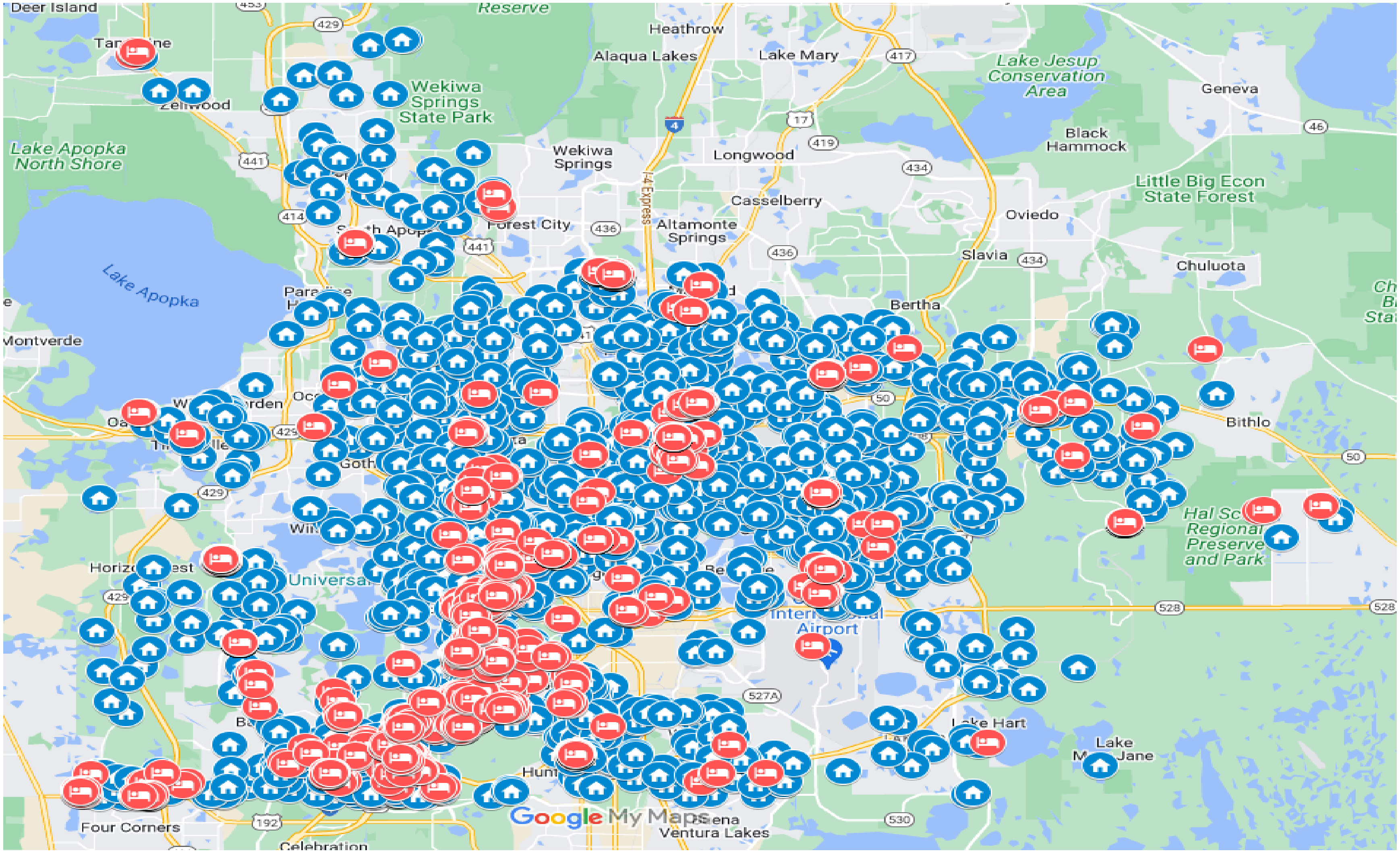

Figure 2.14: Post covid Map of Orange County Airbnb Listings

Red markers represent hotels while blue markers represent residential properties. Hotels are restricted to commercial, industrial and mixed zones. While listings seemed to have return at city center, the western edge of the city remains thin in supply

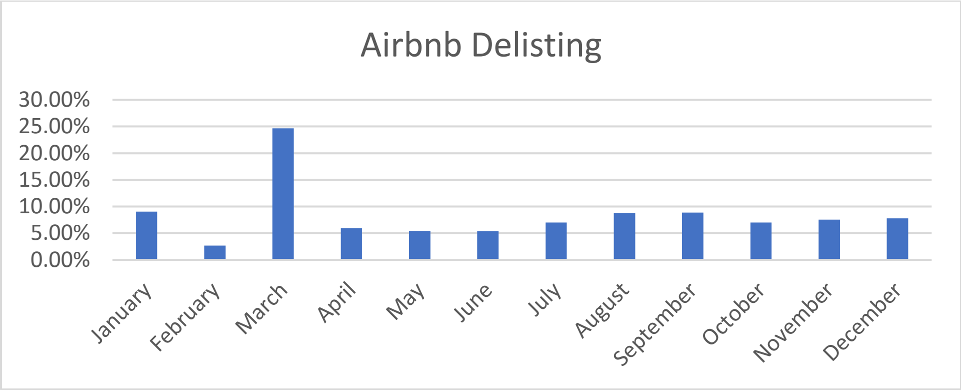

Figure 2.15: Airbnb Delisting

Figure represents the percentage of Airbnb units out of total listings in the county in that month that were delisted in each month of the year 2020 when the pandemic first hit the US. About 25% of the listings were deleted during March 2020.

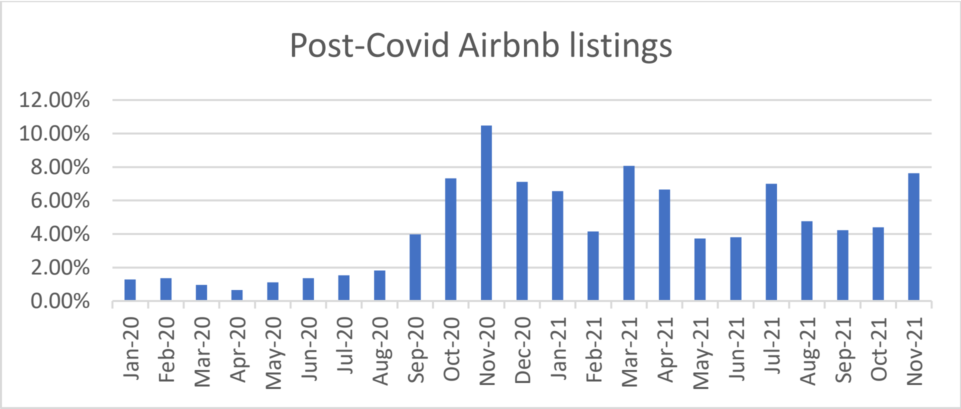

Figure 2.16: Post-Covid Airbnb Listings

Figure represents percentage of new listings added to the platform out of total listings already existent in the county for each month in the years 2020 and 2021. Addition of new listings picked up in November of 2020 and continued through 2021 in response to covid cases.

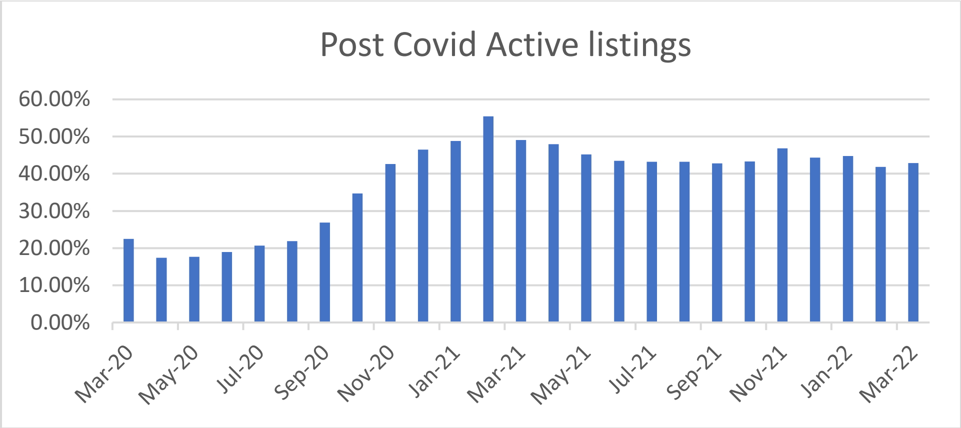

Figure 2.17: Post Covid Active Listings

Figure represents percentage of Airbnb listings that were active in each month since the first wave of the pandemic. Activity started picking up in November 2020 and was highest during March 2021.

Tables

Table 2.1: Summary Statistics of Key Variables in the Full Sample.

Variables	Hotels		Residential	
	Mean	*SD*	*Mean*	*Std Dev*
RevPAR	750.25	872.19	1037.64	1666.52
ADR	220.42	301.56	167.89	279.67
OCC	0.08	0.14	0.23	0.26
Available Days	17.76	11.41	13.30	10.15
Blocked Days	10.40	11.68	10.98	10.71
Shared-listing	0.57	0.50	0.77	0.42
Experience	0.07	0.26	0.07	0.25
Reviews	4.81	32.32	17.88	46.81
Rating	91.55	15.92	91.69	13.49
multi-unit hosts	0.80	0.40	0.67	0.47
clustered	0.47	0.50	0.50	0.50
ListingDEN	0.08	0.06	0.13	0.19
BA	1.61	0.70	1.70	0.91
BR	1.65	0.86	1.87	1.25
Max guests	5.42	2.63	5.17	2.94
Total population ('000)	5399.08	2461.46	6742.23	5133.71
Median age	33.80	5.02	34.41	5.61
Median income ($)	36397.77	14425.43	33274.44	13115.90
%Male	48.43	5.43	48.73	4.95
%Young	78.33	7.45	77.05	7.27
%Old	9.90	5.83	10.56	5.69
%White	63.67	15.41	61.45	17.96
%Black	15.41	16.52	18.48	19.20
%Asian	3.61	2.43	3.69	2.71
%Indian	3.46	4.58	2.66	4.08
%Hispanic	30.01	15.61	30.02	15.81
Married	0.42	0.19	0.41	0.17
Educated	0.30	0.09	0.27	0.10
Total Housing Units	3068.74	1322.56	3379.51	2194.20
N	5,645		11,665	

Table 2.2**:** Multinomial Probit Regression Marginal Probability Estimates.

	ListingCAT (1)		ListingCAT (2)		ListingCAT (3)		ListingCAT (4)	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Shared-listing	0.148**	0.021	-0.003**	0.004	-0.005*	0.037	0.146***	0.028
Experience	-0.043***	0.006	0.001***	0.001	0.002***	0.011	-0.043*	0.008
Popular	-0.172	0.024	-0.003*	0.004	0.006**	0.043	0.169**	0.033
Demand	-0.014	0.002	-6.E-04**	0.000	0.001	0.004	0.014**	0.003
Clustered	-2.E-04*	0.000	-3.E-04*	0.000	-2.E-04*	0.000	4.E-04**	0.000
Multi-unit	-0.100**	0.014	-0.002	0.003	-0.004	0.025	0.098	0.019
Log (population)	0.129***	0.018	-0.003***	0.003	-0.005***	0.032	-0.127	0.025
Log (age)	0.022	0.003	0.000	0.001	-0.001	0.005	-0.021	0.004
Log (income)	-0.200***	0.028	-0.004***	0.005	-0.007**	0.050	0.197**	0.038
Male%	-0.001	0.000	-1.E-04	0.000	-1.E-04	0.000	0.001	0.000
Young%	0.002	0.000	2.E-04	0.000	2.E-04	0.001	-0.002	0.000
Old%	0.001	0.000	4.E-04	0.000	4.E-04	0.000	-0.001	0.000
White%	0.006	0.001	4.E-04	0.000	4.E-04	0.001	-0.005	0.001
Black%	0.003**	0.000	2.E-04	0.000	3.E-04	0.001	-0.003	0.001
Asian%	0.015	0.002	0.010	0.000	-0.018*	0.004	-0.015	0.003
Indian%	0.014*	0.002	-1.E-04*	0.000	4.E-04	0.003	-0.013	0.003
Hispanic%	-0.001	0.000	-1.E-04	0.000	4.E-04	0.000	0.001	0.000
Educated	-0.409*	0.058	-0.008*	0.010	0.015*	0.101	0.403*	0.078

Marginal probability estimates of multinomial probit regression of listing category on property, listing and host characteristics as well as neighborhood features; *ListingCAT* is defined as *ListingCAT* 1: Failed during covid; *ListingCAT* 2: Listed throughout; *ListingCAT* 3: Started during covid; *ListingCAT* 4: Stopped listing during covid.

Table 2.3: Seemingly Unrelated Regression (SUR) of Price and Occupancy and Revenues and Occupancy of Residential Units

parameter	Log (ADR)	OCC	Log (RevPAR)	OCC
Intercept	4.903*** (0.537)	0.231 (0.510)	4.565*** (1.558)	0.683 (0.495)
Shared-listing	-0.476*** (0.011)	-0.087*** (0.011)	-0.826*** (0.034)	-0.072*** (0.011)
Experience	0.062*** (0.009)	0.143*** (0.008)	0.288*** (0.025)	0.132*** (0.008)
Popular	-0.219*** (0.006)	0.187*** (0.006)	0.146*** (0.019)	-0.161*** (0.006)
Demand	0.333*** (0.009)	-0.013 (0.008)	0.261*** (0.027)	0.018** (0.008)
Multi-unit	0.183*** (0.007)	0.071*** (0.006)	0.066*** (0.020)	0.081*** (0.006)
Clustered	0.060*** (0.006)	0.056*** (0.006)	0.099*** (0.019)	0.043*** (0.006)
ListingDEN	1.842 (5.225)	-0.554 (4.963)	-2.938* (15.640)	-6.894 (4.967)
BA	0.063*** (0.006)	-0.012** (0.005)	0.052*** (0.016)	-0.010** (0.005)
BR	0.051*** (0.005)	0.010** (0.005)	0.182*** (0.014)	-0.003 (0.005)
Guests	0.071*** (0.002)	-0.003 (0.002)	0.012** (0.006)	-0.001 (0.002)
Log(population)	0.031 (0.035)	-0.062* (0.033)	-0.094 (0.102)	-0.088*** (0.032)
Log(age)	-0.038 (0.092)	0.037 (0.088)	0.514* (0.274)	0.009 (0.087)
Log(income)	-0.013 (0.029)	0.053* (0.027)	0.017 (0.087)	0.065** (0.028)
Male%	-0.001 (0.002)	-0.003** (0.001)	-0.007 (0.005)	-0.003** (0.001)
young%	-0.009*** (0.002)	0.003** (0.002)	-0.004 (0.005)	0.003* (0.002)
Old%	0.008*** (0.002)	-0.002 (0.002)	0.001 (0.007)	0.000 (0.002)
White%	0.003** (0.001)	0.004*** (0.001)	0.007* (0.004)	0.003** (0.001)
Black%	0.003* (0.002)	-0.001 (0.002)	0.004 (0.005)	-0.002 (0.002)
Asian%	-0.011*** (0.003)	-0.003 (0.003)	0.010 (0.009)	-0.002 (0.003)
Indian%	-0.003 (0.004)	0.001 (0.003)	0.000 (0.011)	0.001 (0.003)
Hispanic%	-0.001 (0.001)	-0.002* (0.001)	-0.007** (0.003)	-0.002** (0.001)
Married%	0.060 (0.068)	0.084 (0.064)	0.533*** (0.204)	-0.038 (0.065)
Educated%	0.366*** (0.090)	0.440*** (0.085)	0.757*** (0.266)	0.380*** (0.084)

parameter	Log (ADR)	OCC	Log (RevPAR)	OCC
R^2	0.32		0.28	
N	188,686			

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

Table 2.4: OLS analysis of Residential Airbnb Performances During Covid

parameter	Log (ADR)	Log (RevPAR)	OCC	ListingDEN
covid	-0.523***	-0.664***	-0.087***	-1.351***
	(0.018)	(0.063)	(0.011)	(0.091)
Shared-listing×covid	-0.119**	-0.048	-0.019	0.009
	(0.050)	(0.180)	(0.032)	(0.008)
Experience×covid	0.007	0.124	-0.026	0.005
	(0.039)	(0.142)	(0.025)	(0.008)
Popular×covid	-0.168***	-0.215*	-0.129***	-0.003
	(0.031)	(0.111)	(0.019)	(0.006)
Demand×covid	-0.011	0.007	0.042*	-0.006
	(0.040)	(0.142)	(0.025)	(0.009)
Multi-unit×covid	-0.038	0.321***	0.095***	0.011*
	(0.030)	(0.106)	(0.019)	(0.007)
Clustered×covid	0.036	0.319***	0.120***	0.017**
	(0.029)	(0.103)	(0.018)	(0.007)
ListingDEN×covid	-0.021	-1.177***	-0.416	
	(0.040)	(0.143)	(1.063)	
Old%×covid	-0.170**	-0.547**	-0.053	0.399***
	(0.076)	(0.273)	(0.048)	(0.082)
Young%×covid	0.000	0.001	0.003**	0.005**
	(0.003)	(0.009)	(0.002)	(0.003)
White%×covid	-0.004	-0.012	-0.002	0.006*
	(0.003)	(0.010)	(0.002)	(0.003)
Black%×covid	0.003	0.024**	-0.002	0.009***
	(0.003)	(0.010)	(0.002)	(0.003)
Asian%×covid	0.001	0.010	-0.002	-0.016
	(0.003)	(0.011)	(0.002)	(0.003)
Indian%×covid	0.004	0.005	0.003	0.009
	(0.006)	(0.021)	(0.004)	(0.007)
Hispanic%×covid	0.004	0.028	0.003	0.003
	(0.005)	(0.018)	(0.003)	(0.006)
Log (income) ×covid	-0.002	-0.003	-0.001	0.008***
	(0.002)	(0.005)	(0.001)	(0.002)
Education%×covid	-0.124	-1.335	0.068	-0.272
	(0.238)	(0.856)	(0.149)	(0.266)
N		*188,636*		

Dependent variables are log (RevPAR), log (ADR), Occupancy and *ListingDEN*. Table reports OLS estimates for host, listing and neighborhood characteristics; *covid* dummy defined as one for second and third quarter of 2020 and zero otherwise. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Regressions controlled for Quarter and location FE; Aggregation for price, revenue and occupancy at listing level per month, and for listing density at census tract level quarterly.

Table 2.5: OLS Analysis of Residential Airbnb Performances Post Covid

parameter	Log (ADR)	Log (RevPAR)	OCC	ListingDEN
post-covid	1.713** (0.854)	3.431 (3.063)	0.414 (0.535)	-4.410*** (0.923)
Shared-listing×post-covid	-0.119** (0.050)	-0.046 (0.180)	-0.020 (0.032)	0.091 (0.094)
Experience×post-covid	0.008 (0.039)	0.124 (0.142)	-0.026 (0.025)	0.162** (0.073)
Popular×post-covid	-0.167*** (0.031)	-0.215* (0.111)	-0.129*** (0.019)	0.073 (0.062)
Demand×post-covid	-0.012 (0.040)	0.0060 (0.142)	0.042* (0.025)	0.021 (0.076)
Multi-unit×post-covid	0.038 (0.030)	0.321*** (0.106)	0.095*** (0.019)	-0.023 (0.057)
Clustered×post-covid	0.037 (0.029)	0.319*** (0.103)	0.120*** (0.018)	0.080 (0.053)
ListingDEN×post-covid	-0.016 (0.017)	0.019 (0.061)	-0.005 (0.011)	
Old%×post-covid	-0.168** (0.076)	-0.539** (0.273)	-0.055 (0.048)	0.363*** (0.083)
Young%×post-covid	0.000 (0.003)	0.001 (0.009)	0.003** (0.002)	0.002 (0.003)
White%×post-covid	-0.004 (0.003)	-0.012 (0.010)	-0.002 (0.002)	0.004 (0.003)
Black%×post-covid	0.003 (0.003)	0.024** (0.010)	-0.002 (0.002)	0.002 (0.003)
Asian%×post-covid	0.001 (0.003)	0.010 (0.011)	-0.002 (0.002)	0.011 (0.003)
Indian%×post-covid	0.004 (0.006)	0.005 (0.021)	0.003 (0.004)	-0.006 (0.006)
Hispanic%×post-covid	0.004 (0.005)	0.028 (0.018)	0.003 (0.003)	-0.007 (0.005)
Log (income) ×post-covid	-0.002 (0.002)	-0.003 (0.005)	-0.001 (0.001)	0.003** (0.002)
Education%×post-covid	-0.127 (0.238)	-1.335 (0.855)	0.069 (0.149)	-0.062 (0.256)
N		188,686		

Dependent variables are log (RevPAR), log (ADR), Occupancy and *ListingDEN*. Table reports OLS estimates for host, listing and neighborhood characteristics; *covid* dummy defined as one for second and third quarter of 2020 and zero otherwise. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Regressions controlled for Quarter and location FE; Aggregation for price, revenue and occupancy at listing level per month, and for listing density at census tract level quarterly.

Table 2.6: Seemingly Unrelated Regression (SUR) of Price, Occupancy and Revenues of Hotel Units

Parameter	log (ADR)	OCC	Log (RevPAR)	OCC
Intercept	3.962 (3.147)	-1.826 (1.415)	-11.103 (23.317)	-2.984 (6.765)
Experience	0.288*** (0.019)	0.018** (0.009)	0.331*** (0.071)	0.103*** (0.021)
Popular	-0.401*** (0.014)	0.387*** (0.006)	0.491*** (0.041)	0.260*** (0.012)
Demand	-0.064*** (0.008)	0.013*** (0.004)	0.086** (0.035)	0.025** (0.010)
Clustered	0.183*** (0.021)	0.009 (0.009)	0.258** (0.104)	0.029 (0.030)
ListingDEN	-4.210* (22.931)	6.072*** (10.309)	2.671*** (97.586)	7.897** (28.314)
BA	-0.003 (0.010)	-0.018*** (0.004)	-0.178*** (0.050)	-0.068*** (0.014)
BR	0.140*** (0.009)	-0.022*** (0.004)	0.029 (0.042)	-0.057*** (0.012)
Guests	0.068*** (0.003)	0.010*** (0.001)	0.129*** (0.013)	0.033*** (0.004)
Log(population)	-0.063 (0.171)	0.472*** (0.077)	1.905 (1.307)	0.277 (0.379)
Log(age)	0.483 (0.492)	0.420* (0.221)	2.719 (4.077)	1.899 (1.183)
Log(income)	0.042 (0.153)	-0.118* (0.069)	-0.711 (0.702)	-0.464** (0.204)
Male%	-0.007 (0.012)	0.004 (0.005)	0.064 (0.097)	0.055** (0.028)
young%	-0.007 (0.013)	-0.039*** (0.006)	-0.135** (0.068)	-0.067*** (0.020)
Old%	-0.003 (0.012)	0.012** (0.006)	-0.053 (0.054)	-0.021 (0.016)
White%	0.009 (0.007)	0.004 (0.003)	0.024 (0.033)	0.013 (0.009)
Black%	0.005 (0.008)	0.000 (0.003)	-0.010 (0.037)	0.000 (0.011)
Asian%	0.011 (0.016)	0.015** (0.007)	-0.060 (0.082)	-0.029 (0.024)
Indian%	0.012 (0.019)	0.000 (0.008)	0.196* (0.102)	0.045 (0.029)
Hispanic%	0.000 (0.005)	-0.006*** (0.002)	0.030 (0.027)	0.002 (0.008)
Married%	0.598 (0.399)	0.145 (0.179)	2.306 (1.680)	1.012** (0.487)
Educated%	-0.500 (0.386)	1.133*** (0.174)	3.846** (1.798)	1.874*** (0.522)
R^2		0.32		0.30

Parameter	log (ADR)	OCC	Log (RevPAR)	OCC
N		198,719		

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

Table 2.7: OLS Analysis of Hotel Airbnb Performances During Covid

parameter	log (ADR)	log(RevPAR)	OCC	ListingDEN
Covid	-0.318 (1.201)	-5.724 (4.877)	-0.122 (0.537)	-0.229 (0.319)
Experience×covid	0.058 (0.056)	0.370* (0.201)	-0.025 (0.025)	0.000 (0.002)
Popular×covid	0.048 (0.048)	0.084 (0.118)	-0.229*** (0.022)	0.000 (0.001)
Demand×covid	0.003 (0.026)	-0.027 (0.088)	-0.016 (0.012)	0.000 (0.001)
Clustered×covid	-0.011 (0.040)	0.513*** (0.161)	-0.013 (0.018)	0.000 (0.000)
ListingDEN×covid	-0.002 (0.005)	0.036** (0.018)	0.002 (0.002)	
Old%×covid	0.000 (0.004)	-0.031** (0.013)	-0.003* (0.002)	0.000 (0.001)
Young%×covid	-0.002 (0.004)	0.029* (0.015)	0.002 (0.002)	-0.001 (0.001)
White%×covid	-0.002 (0.005)	-0.037** (0.018)	0.004* (0.002)	0.000 (0.001)
Black%×covid	0.002 (0.013)	0.066 (0.054)	0.004 (0.006)	0.000 (0.001)
Asian%×covid	-0.005 (0.008)	0.050 (0.031)	0.001 (0.003)	-0.002 (0.002)
Indian%×covid	-0.002 (0.003)	0.017* (0.010)	0.001 (0.001)	0.000 (0.002)
Hispanic%×covid	0.057 (0.126)	-0.789 (0.513)	-0.008 (0.056)	0.000 (0.001)
Log (income) ×covid	-0.168 (0.392)	2.163* (1.159)	0.563*** (0.175)	-0.063 (0.077)
N		198,719		

Dependent variables are log (RevPAR), log (ADR), Occupancy and *ListingDEN*. Table reports OLS estimates for host, listing and neighborhood characteristics; *covid* dummy defined as one for second and third quarter of 2020 and zero otherwise. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Regressions controlled for Quarter and location FE; Aggregation for price, revenue and occupancy at listing level per month, and for listing density at census tract level quarterly.

Table 2.8: OLS Analysis of Hotel Airbnb Performances Post Covid

Parameter	log (ADR)	log(RevPAR)	OCC	ListindDEN
post-covid	-0.213 (0.879)	11.505*** (4.129)	1.536*** (0.393)	0.027 (0.171)
Experience×post-covid	0.125*** (0.028)	0.649*** (0.067)	0.110*** (0.016)	-0.002 (0.005)
Popular×post-covid	0.039** (0.017)	0.167*** (0.061)	0.102*** (0.012)	0.005*** (0.001)
Demand×post-covid	0.062*** (0.017)	0.140** (0.061)	-0.016** (0.008)	-0.065*** (0.013)
Clustered×post-covid	-0.470 (1.292)	-14.360* (7.507)	0.030** (0.013)	-0.029** (0.014)
ListingDEN×post-covid	-0.004 (0.003)	-0.055*** (0.019)	0.008*** (0.002)	
Old%×post-covid	0.000 (0.003)	-0.058*** (0.011)	-0.002** (0.001)	-0.006*** (0.001)
Young%×post-covid	0.002 (0.003)	0.030*** (0.011)	0.003** (0.001)	0.002*** (0.001)
White%×post-covid	-0.001 (0.004)	-0.039*** (0.014)	-0.002 (0.002)	0.003 (0.001)
Black%×post-covid	0.006 (0.009)	-0.046 (0.042)	-0.003 (0.004)	0.005 (0.001)
Asian%×post-covid	-0.002 (0.005)	-0.073*** (0.026)	-0.008*** (0.002)	0.002 (0.002)
Indian%×post-covid	0.000 (0.002)	-0.022** (0.010)	0.001 (0.001)	0.000 (0.000)
Hispanic%×post-covid	0.021 (0.091)	-1.211** (0.481)	-0.168*** (0.041)	0.077** (0.034)
Log (income) ×post-covid	-0.403 (0.278)	6.002*** (1.148)	0.181 (0.124)	0.153*** (0.031)
N		198,719		

Dependent variables are log (RevPAR), log (ADR), Occupancy and *ListingDEN*. Table reports OLS estimates for host, listing and neighborhood characteristics; *post-covid* dummy defined as one for all quarters beginning 2021 and zero otherwise. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Regressions controlled for Quarter and location FE; Aggregation for price, revenue and occupancy at listing level per month, and for listing density at census tract level quarterly.

Table 2.9: Spillover Effect of Nearby Hotel Prices on Performance of Competing Residential Units

Parameter	OCC			Log (ADR)			Log (RevPAR)		
	Full Sample	*Covid*	*Post-covid*	*Full Sample*	*Covid*	*Post-covid*	*Full Sample*	*Covid*	*Post-covid*
Covid/post-covid		-0.097***	0.431		-0.529**	1.529**		-0.668*	2.962
		(0.009)	(0.533)		(0.020)	(0.86)		(0.063)	(3.049)
log (wtprc)	-0.127***	-0.129***	-0.088***	0.205***	0.201***	0.192***	0.049	0.080**	-0.011
	(0.017)	(0.017)	(0.023)	(0.018)	(0.019)	(0.025)	(0.035)	(0.035)	(0.048)
Covid-dummy × *log (wtprc)*		4.E-04	-0.085***		0.095**	0.057**		-0.442	0.101**
		(0.042)	(0.024)		(0.047)	(0.026)		(0.095)	(0.051)

Dependent variables are log (RevPAR), log (ADR) and OCC. Table reports OLS estimates for key characteristics only; *covid-dummy* is equal *covid* for peak covid scenario and is equal *post-covid* for post covid scenario. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Regressions controlled for Quarter and location FE; Aggregation for prices, revenue and occupancy at listing level per month.

Table 2.10: Spillover Effect of Nearby Hotel Prices on Performance of Competing Residential Units (Structural Model)

Panel A: Overall Sample		
Parameter	Log (ADR)	OCC
residual		-0.104*** (0.006)
log(wtpr)	0.209*** (0.012)	-0.065* (0.008)
Panel B: Covid period		
residual		-0.103*** (0.006)
covid	-0.629 (0.677)	0.529 (0.425)
log(wtpr)	0.211*** (0.013)	0.013 (0.008)
*covid*log(wtpr)*	0.111 (0.099)	-0.041 (0.062)
Panel B: Post Covid period		
residual		-0.101*** (0.006)
post-covid	-0.155 (4.710)	-2.380 (2.976)
log(wtpr)	0.127*** (0.021)	0.012*** (0.014)
*post-covid*log(wtpr)*	0.117*** (0.026)	-0.140*** (0.016)

Dependent variables are log (RevPAR), log (ADR) and OCC. Table reports OLS estimates for key characteristics only; *covid-dummy* is equal *covid* for peak covid scenario and is equal *post-covid* for post covid scenario. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Regressions controlled for Quarter and location FE; Aggregation for prices, revenue and occupancy at listing level per month

Table 2.11: Pricing Strategy of Professional Hosts

Panel A: Residential				
Parameter	log (RevPAR)		OCC	
Multi-unit hosts	0.093*	0.021	0.157***	0.147***
	(0.052)	(0.058)	(0.024)	(0.027)
log (#Pchange)	-0.020	0.002	0.098***	0.117***
	(0.024)	(0.024)	(0.011)	(0.011)
Multi-unit × log (#Pchange)	0.076***	0.127***	-0.113***	-0.075***
	(0.024)	(0.026)	(0.011)	(0.012)
post-covid		-0.464		-0.295
		(0.708)		(0.335)
Multi-unit × post-covid		0.247***		0.104***
		(0.067)		(0.030)
Multi-unit × post-covid × log (#PChange)		-0.143***		-0.114***
		(0.029)		(0.013)
Panel B: Hotels				
Multi-unit hosts	-0.087	-0.150**	-0.011**	-0.008
	(0.054)	(0.062)	(0.005)	(0.016)
log (#Pchange)	0.213***	0.208***	0.097***	0.004***
	(0.028)	(0.028)	(0.004)	(0.090)
Multi-unit × log (#Pchange)	0.056*	0.084**	-0.002	0.005
	(0.033)	(0.036)	(0.004)	(-0.011)
post-covid		0.097		0.374***
		(1.702)		(0.854)
Multi-unit × post-covid		0.147*		0.009
		(0.082)		(-0.031)
Multi-unit × post-covid × log (#PChange)		-0.062		0.005
		(0.039)		(-0.012)

Dependent variables are log (RevPAR) and OCC. Table reports OLS estimates for key characteristics only; *post-covid* dummy defined as one for all quarters beginning 2021 and zero otherwise. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Regressions controlled for Quarter and location FE; Aggregation for revenue and occupancy at listing level per month

Appendix

Table 2.12: List of Variables and Definitions

Variable	*Definition*
RevPAR	Revenue of each unit per month
ADR	Average daily rate (ADR) of booked nights in USD. ADR = Total Revenue of the month / Booked Nights. The monthly rate is then calculated as ADR X Available Days in the month for booking.
OCC	Occupancy Rate per month of each unit
Available Days	Number of Days Airbnb is available to book
Blocked Days	Number of Days Airbnb is blocked for reservations to book in a month
Shared-listing	Dummy =1 If the listing is a shared room/shared space in a property type
Experience	Dummy =1 if host has a “SuperHost” badge on Airbnb
popular	Dummy=1 if Number of reviews in that month>median
Demand	Dummy=1 if overall rating out of 100 for the Airbnb unit is at least 90
multi-unit hosts	Dummy =1 If the host listing the Airbnb has more than one listing
clustered	Dummy =1 If listing is within six miles of points of attraction in the city
ListingDEN	Number of listings in a month in a census tract/total housing units in the census tract in that year
BA	Number of Bathrooms of unit
BR	Number of Bedrooms of unit
Max guests	Maximum number of guests allowed in the rental
Total population ('000)	Population of census tract
Median age	Median age of census tract
Median income ($)	Median Income in inflated Dollars of census tract
%Male	Percentage of males in census tract
%Young	Percentage of people below the age of 25 in census tract
%Old	Percentage of people above the age of 65 and below 85 in census tract
%White	Percentage of Whites in census tract
%Black	Percentage of African Americans in census tract
%Asian	Percentage of Asians in census tract
%Indian	Percentage of Indian in census tract
%Hispanic	Percentage of Hispanics in census tract
%Married	Percentage of people married in census tract
%Educated	Percentage of people college educated in census tract
Total Housing Units	Number of housing units in census tract

Table 2.13**:** Summary Statistics for Listing Characteristics by Property Type

Property Type	*#Listings*	*ADR*	*Reservations/Month*	*Max Guests*	*Shared*	*Multi-unit Hosts*	*Superhosts*
			Panel A: Pre-covid				
Apartment	867	146.28	2	5	70.82%	61.94%	8.65%
Bungalow	35	169.06	1	4	54.29%	48.57%	0.00%
Condominium	1318	187.57	1	6	84.90%	66.54%	5.84%
Guest House	158	99.00	3	3	83.75%	65.31%	6.40%
House/Residential Home	1370	140.08	2	4	68.35%	50.59%	12.43%
Loft	21	104.10	3	3	34.01%	44.93%	19.05%
Rental unit	373	174.11	2	5	81.77%	51.24%	18.98%
Townhouse	303	155.97	2	6	65.35%	65.35%	10.29%
Villa	214	303.81	1	7	90.65%	56.54%	1.40%
			Panel B: Peak Covid				
Apartment	808	145.94	1	5	71.04%	62.25%	8.54%
Bungalow	35	132.25	1	4	60.00%	60.00%	2.86%
Condominium	1685	184.14	1	6	89.73%	72.52%	6.41%
Guest House	187	109.49	3	3	79.68%	47.06%	22.99%
House/Residential House	1369	123.72	1	4	40.32%	53.32%	9.72%
Loft	19	106.71	1	3	84.21%	57.89%	15.79%
Rental unit	469	166.49	2	5	81.88%	55.01%	8.10%
Townhouse	332	154.65	2	7	73.49%	73.49%	8.43%
Villa	225	296.02	1	8	92.89%	59.11%	6.22%
			Panel C: Post Covid				
Apartment	512	161.69	0	4	75.00%	62.11%	7.03%
Bungalow	29	148.72	2	4	65.52%	55.17%	20.69%
Condominium	2607	157.79	2	5	92.44%	75.49%	5.64%
Guest House	308	115.35	4	3	84.42%	45.13%	21.43%
House/Residential Home	1673	125.44	2	5	47.52%	53.68%	7.95%
Loft	34	202.29	3	4	88.24%	47.06%	8.82%
Rental unit	1156	158.35	3	5	86.16%	58.39%	5.36%
Townhouse	464	165.13	3	7	82.76%	79.09%	6.47%
Villa	207	276.05	2	8	88.89%	56.52%	6.76%

Table 2.14: OLS Analysis for During and Post Covid Scenarios: Residential

Parameter	log(ADR)	log (RevPAR)	OCC	ListingDEN
covid	-1.603***	0.428	0.475	-1.394**
	(0.866)	(0.563)	(0.539)	(0.088)
Post-covid	1.741***	3.843	0.539	-2.937
	(0.855)	(3.008)	(0.542)	(0.778)
Shared-listing×covid	-0.005	0.136**	0.003	-0.003
	(0.014)	(0.058)	(0.007)	(0.002)
Experience × covid	0.034	0.151**	-0.059***	-0.001
	(0.023)	(0.061)	(0.012)	(0.005)
Popular × covid	-0.045**	-0.343***	-0.167***	-0.010***
	(0.020)	(0.044)	(0.010)	(0.003)
Demand × Covid	0.024	0.233***	0.017	-0.006*
	(0.016)	(0.057)	(0.009)	(0.003)
Multi-unit × covid	-0.011	0.121**	-0.034***	0.001
	(0.013)	(0.049)	(0.007)	(0.002)
clustered × covid	0.042***	0.194***	0.017**	0.004
	(0.013)	(0.041)	(0.007)	(0.003)
Occupancy × covid	0.334***	0.210***		-0.095
	(0.031)	(0.062)		(0.105)
Log (income) × covid	-0.024	-0.256**	0.000	-0.092
	(0.041)	(0.123)	(0.021)	(0.066)
%Young × covid	0.002**	0.001	0.001	0.000
	(0.001)	(0.004)	(0.001)	(0.002)
%Old × covid	-0.002	-0.011**	0.000	0.002
	(0.001)	(0.004)	(0.001)	(0.002)
%White × covid	0.004***	0.011***	0.001	-0.004*
	(0.001)	(0.004)	(0.001)	(0.002)
%Black × Covid	0.003**	0.005	0.001	-0.001
	(0.002)	(0.005)	(0.001)	(0.002)
%Asian × covid	0.003	0.022**	0.002	-0.007
	(0.003)	(0.009)	(0.002)	(0.004)
%Indian × Covid	0.002	-0.004	0.001	0.004
	(0.003)	(0.008)	(0.001)	(0.005)
%Hispanic × covid	-0.001	-0.006***	0.000	0.003***
	(0.001)	(0.002)	(0.000)	(0.001)
%Educated × covid	-0.350***	-0.505	-0.068	1.184***
	(0.126)	(0.379)	(0.066)	(0.212)
Shared × post-covid	-0.095***	-0.094***	0.023***	0.007***
	(0.007)	(0.016)	(0.004)	(0.001)
Experience × post-covid	0.088***	0.096***	-0.008	-0.003
	(0.012)	(0.020)	(0.006)	(0.003)
Popular × post-covid	0.062***	-0.043***	0.046***	-0.032***
	(0.010)	(0.015)	(0.005)	(0.002)
Demand × post-covid	0.072***	0.021	0.030***	-0.016***
	(0.008)	(0.017)	(0.004)	(0.002)
Multi-unit × post-covid	-0.021***	-0.061***	-0.035***	-0.004***
	(0.007)	(0.014)	(0.003)	(0.001)
clustered × post-covid	0.031***	0.043***	0.018***	0.005***
	(0.006)	(0.012)	(0.003)	(0.001)
Occupancy × post-covid	-0.082***	0.199***		0.135***
	(0.010)	(0.019)		(0.041)

Parameter	log(ADR)	log (RevPAR)	OCC	ListingDEN
Income × post-covid	0.107***	-0.064	0.049***	-0.030
	(0.026)	(0.059)	(0.013)	(0.037)
%Young × post-covid	0.002***	0.001	0.001***	0.001
	(0.001)	(0.002)	(0.000)	(0.001)
%Old × post-covid	-0.003***	-0.006***	-0.001*	0.001
	(0.001)	(0.002)	(0.000)	(0.001)
%White × post-covid	0.001	0.005***	0.002***	-0.003**
	(0.001)	(0.002)	(0.000)	(0.001)
%Black × post-covid	0.001	0.005***	0.002***	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
%Asian × post-covid	0.001	0.010**	0.000	-0.005*
	(0.002)	(0.004)	(0.001)	(0.003)
%Indian × post-covid	0.000	-0.002	0.001	0.004
	(0.002)	(0.004)	(0.001)	(0.003)
%Hispanic × post-covid	-0.001***	-0.001	0.001***	0.005***
	(0.000)	(0.001)	(0.000)	(0.001)
%Educated × post-covid	-0.581***	0.231	-0.030	1.195***
	(0.080)	(0.180)	(0.041)	(0.125)

Dependent variables are log (RevPAR), log (ADR), OCC and *ListingDEN*. Table reports OLS estimates for key characteristics only; *covid* dummy defined as one for second and third quarter of 2020 and zero otherwise; *post-covid* dummy defined as one for all quarters beginning 2021 and zero otherwise. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Regressions controlled for Quarter and location FE; Aggregation for revenue and occupancy at listing level per month and for listing density at census tract level quarterly

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CHAPTER 3 : THIRD-PARTY VS OWNER MANAGEMENT IN VACATION RENTAL MARKET: EVIDENCE FROM AIRBNB

1. 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 possesses 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.

2. Airbnb Industry Overview

In October 2007, Brian Chesky and Joe Gebbia came up with the idea of putting an air mattress in their living room and turning it into a bed and breakfast in San Francisco. They put together a website that offered short-term living quarters and breakfast for those who were unable to book a hotel in the saturated market. The site Airbedandbreakfast.com officially launched on August 11, 2008. The founders had their first customers in the summer of 2008, during the Industrial Design Conference held by Industrial Designers Society of America, where travelers had a hard time finding lodging in the city. 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 and had served 9,000,000 guests with nearly 250,000 listings by 2013, even adding travel guides for travelers. Airbnb first became profitable during the second half 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. [11]

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 crafted 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

[11] Institutional details on Airbnb are drawn from various sources including Wikipedia: "https://en.wikipedia.org/wiki/Airbnb", City of Orlando: "https://www.orlando.gov/Building-Development"

for possibly enabling increases in home rents and by the hotel industry for not being subject to fair regulations. Many governments have passed laws requiring that Airbnb provide guest information so that local regulations can be enforced, and hotel taxes are collected. Regulation of short-term rentals are highly localized and are segmented based on building, city and zoning standard. It can include requirements for hosts to have business licenses, payment of business tax receipts like hotels. In addition to government-imposed restrictions, many homeowner associations also limit short term rentals.

Orlando hosts around 75 million tourists every year making it a lucrative location for setting up a vacation rental business. It is no surprise therefore that Airbnb rentals are thriving in this area. The average monthly revenues of Airbnb in Orlando are 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%. The City of Orlando website provides several resources regarding taxations, zoning laws and registration requirements. 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 consistently claim they do not consider listings platforms such as Airbnb a viable threat to their occupancy rates, citing the number of rooms in the region and their price range. In addition, guests also pay the Orange County Tourist Development Tax.

Florida's transient rental tax is 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, home sharing allows hosts to rent up to half the bedrooms on the property, but only in residential zones with the homeowner or tenant being present for the duration of the rental. Orange County requires that properties rented in their entirety be licensed by the Department of Business and Professional Regulation, be located in O-3, MU district, or AC districts, and obtain a Business Tax Receipt. [12]

3. 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.

[12] Source:" https://www.airbnb.com/help/article/2371"

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.

4. Model

The theoretical framework draws from the real estate management model developed in Sirmans et al (1999). This version suppresses management structure issues addressed in the more general model in order to focus on 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 and maintenance inputs, m and z, as well as the surrounding neighborhood amenities, indexed by n. For notation convenience, we include physical characteristics of the property in the amenity index. Neighborhood amenities n are assumed to have factor-neutral effects on unit quality.[13] 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.

$$p = p(q(m, z, n), s) \qquad (3.1)$$

The price is increasing in q ($p_q > 0$, 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.

[13] Factor neutrality implies that *n* does not affect the marginal rate of technical substitution between inputs *m* and *z* in the production of *q*.

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

$$x = x(p, q(m, z, n), s) \qquad (3.2)$$

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

$$\pi^{OM} = E[p(q(m, z, n), s)x(p, q(m, z, n), s)] - wm - vz \qquad (3.3)$$

where w and v are the costs of management effort and maintenance inputs, respectively. The owner's input choice maximizing (3.3) is the implicit solution $\{m^* = m(n);\ z^* = z(n)\}$ to the marginal conditions

$$\frac{\partial \pi^{OM}}{\partial m} = E[MR]q_m - w = 0 \qquad (3.4)$$

$$\frac{\partial \pi^{OM}}{\partial z} = E[MR]q_z - v = 0 \qquad (3.5)$$

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

Figure (3.1) portrays the locus defined by conditions (3.4) and (3.5) 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.

$$q^* = q(m(n), z(n), n) = Q(n) \qquad (3.6)$$

for which $Q_n > 0$.

Inputs are not observable, but unit price and the vacancy rate are. Substitute (3.6) into (3.1) and (3.2) and differentiate the resultant system to find the observable neighborhood effects on price and occupancy rate

$$\frac{\partial p^*}{\partial n} = p_q Q_n > 0 \qquad (3.7)$$

$$\frac{\partial x^*}{\partial n} = x_q Q_n + x_p \frac{\partial p^*}{\partial n} \qquad (3.8)$$

Result (3.7) draws the direct connection between desirable neighborhood attributes and unit rent. As revealed in (3.8), 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 (3.8)) and the second being the indirect effect through change in rent (the second term in (3.8)). The presence of 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 management effort. Therefore, 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,

$$\pi^{TPM} = \alpha E[p(q(m,z,n),s)x(p,q(m,z,n),s)] - wm \quad (3.9)$$

$$\pi^{O} = (1-\alpha)E[p(q(m,z,n),s)x(p,q(m,z,n),s)] - vz \quad (3.10)$$

Management effort maximizes (3.9) while owner supplied inputs maximize (3.10). The equilibrium $\{m^{**}, z^{**}\}$ satisfies the Nash conditions

$$\frac{\partial \pi^{TPM}}{\partial m} = \alpha E[MR]q_m - w = 0 \quad (3.11)$$

$$\frac{\partial \pi^{O}}{\partial z} = (1-\alpha)E[MR]q_z - v = 0 \quad (3.12)$$

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 (3.1). This, by itself, suggests that the OM and TPM outcomes differ, with professional managers relying on relatively more non-management inputs than first best.

But more can be said. The locus of points satisfying (3.11) in figure (3.1) lies to the left of that satisfying (3.4) and the locus satisfying (3.12) lies to the right of (3.5). 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 (3.1) it follows that,

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

The effect of TPM on occupancy, however, is not as straightforward. By (3.2), $x^{**} = x(p^{**}, q^{**}, s)$ 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 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 may be what makes TPM attractive in the first place (Glascock et al. 1994). 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 (3.1)[14]. As drawn, the greater TPM productivity shifts input usage out to *k*, but this is only one possibility, the movement 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 q^{**} and p^{**} and has an ambiguous effect on x^{**}.

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

Proposition3. observing higher prices under TPM ($p^{**} > p^{*}$) implies greater productivity strong enough to offset the 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.

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[14] 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, and that choice is driven by expected profit. 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. Nonetheless, the implication is that any empirical comparison of OM and TPM outcomes must take into account the possible selection bias arising from the owner's underlying choice of form.

To empirically test that rent prices and occupancy rates are higher under TPM, when the economies of scale are sufficiently large as in the case of Airbnb market, we implement the following seemingly unrelated regression (SUR) models:

$$\log(ADR) = \beta_0 + \beta_1 Profman + \beta_2 X + \beta_3 Z + \varepsilon_{ADR} \tag{3.13}$$

$$\mathrm{OCC} = \alpha_0 + \alpha_3 Profman + \alpha_2 X + \alpha_3 Z + \varepsilon_{OCC} \tag{3.14}$$

Where X represents the property and listing characteristics including *Mngd* (the number of units managed by an Airbnb host and *Attached*, a dummy for attached property type), *Profman* represents the type of management scheme, Z represents quarter and census tract fixed effects and ε indicates the error terms. Alternatively, we define two other SUR model specifications to consider the effects of different property types and the scale of management for the professional host.

$$\begin{cases} \log(ADR) = \beta_0 + \beta_1 Profman + \beta_2 X + \beta_3 Profman \times Mngd \\ \quad + \beta_4 PROFMAN \times ATTACHED + \beta_5 Z + \varepsilon_{ADR} \\ \mathrm{OCC} = \alpha_0 + \alpha_1 Profman + \alpha_2 X + \alpha_3 Profman \times Mngd \\ \quad + \alpha_4 Profman \times Attached + \alpha_5 Z + \varepsilon_{rev} \end{cases} \tag{3.15}$$

To empirically test the effect of COVID-19 on management choice of Airbnb rentals we define the following models,

$$\log(ADR) = \beta_0 + \beta_1 Profman + \beta_2 X + \beta_3 covid + \beta_4 Profman \times covid + \beta_5 Z + \varepsilon_{ADR} \quad (3.16)$$

$$OCC = \alpha_0 + \alpha_1 Profman + \alpha_2 X + \alpha_3 covid + \alpha_4 Profman \times covid + \alpha_5 Z + \varepsilon_{OCC} \quad (3.17)$$

In a modified specification, we extend the above models (3.16-3.17) to investigate how the pandemic altered the effects of different property types and the scale of management for the professional host on Airbnb prices and occupancy rates found previously.

5. Data and Methodology

5.1. 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, Florida,[15] 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

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

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 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 3.1 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 of dummy variable. We use the natural log of monthly Airbnb average daily rate (ADR)[16] and monthly occupancy rate (Occupancy) as our price and occupancy dependent variables to analyze the performance of Airbnb rentals under the two management. 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.

[16] 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 schemes.

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 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 (*Demand*). We also include information about how hosts operate their businesses. We define dummy variables indicating highly responsive hosts (*Response*), whether the host has a flexible cancelation policy (*Flexibility*) 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 (*Minstay*), maximum number of occupants (*Max guests*), and the number of listings that hosts on the Airbnb platform manage locally (*Mngd*) to control inventory management effects or economies of scale.

We obtain additional host information by scraping host profiles on the Airbnb website. Sites contain the 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. The American Community Survey (ACS) supplements the US Census[17] 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 *Clustered* 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 *Clustered* dummy identifies Airbnb units located within 6 miles of any of the above sightseeing spots.

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 selfselection 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.

[17] Data obtained from "https://data.census.gov/"

5.2. Propensity Score Matching (PSM)

Matching members of a treatment group (cases) to members of a no treatment group (controls) is often used in observational studies to reduce bias and approximate a randomized trial. There is often a trade-off when matching cases to controls and two different types of bias can be introduced. First, while trying to maximize exact matches, cases may be excluded due to incomplete matching. Second, while trying to maximize cases, inexact matching may result. Bias is introduced by both incomplete matching and inexact matching. Propensity scores are used in observational studies to reduce bias. Research shows matching on propensity scores calculated from predicted probabilities of the dependent variable in a logistic regression can result in similar matched solutions. This single score (between 0 and 1) then represents the relationship between multiple characteristics and the dependent variable as a single characteristic. In our sample, the management scheme is therefore the dependent variable while the listing, neighborhood and property characteristics are our dependent variables. We run the following logit regression to calculate the propensity scores of each Airbnb unit.

$$Profman = \gamma_0 + \gamma_1 X + \gamma_2 Z + \varepsilon_S \tag{3.18}$$

We create a propensity score matched sample using k-nearest neighbor greedy matching techniques. A greedy algorithm is frequently used to match cases to controls in observational studies. In a greedy algorithm, a set of X Cases is matched to a set of Y Controls in a set of X decisions. Once a match is made, the match is not reconsidered. That match is the best match currently available. The presented algorithm also uses the nearest available pair matching method. The cases are ordered and sequentially matched to the nearest unmatched control. If more than one unmatched control matches to a case, the control is selected at random. Good matched-pair samples contain both closely matched individual pairs and balanced case and control groups. A pair is closely matched if the distance between the case and the control is small. When a single covariate is used to match, the distance can be viewed as the absolute difference in the values. When several covariates are used, distances must be determined in more complex ways. When several covariates are represented as a single propensity score, the distance can more simply be viewed as the absolute difference in the propensity score of the case and the control. Matching on propensity score can create good matched pairs.

Matching on the propensity score can also balance case and control groups or create covariate balance. The algorithm used in this paper presented here makes "best" 5-digit case-control match on propensity score first and "next-best" matches next, in a hierarchical sequence until no more matches can be made. Best matches are those with the highest digit match on propensity score. The algorithm proceeds sequentially to the lowest digit match on propensity score. Goodness of matched pairs is defined as those with the least absolute difference in matched propensity score.

5.3.Data Description

Table 3.2 and 3.3 present the summary statistics of key parameters. For the overall sample we find that on an average, hosts manage about 5-6 listings at a time while the proportion of third-party managed listings in our sample is about 45%. Out of the unique 2,477 hosts that mange listings on Airbnb in the Orlando area, only about 6% of them have a “SuperHost” Badge that signifies experience, reliability, and expertise. About 53% of our listings are in properties that are considered attached-type housing like Apartments, Condominiums, Townhouses etc. What is even more surprising is that the majority of listings in our sample are shared space listings indicating that most of the traditional Airbnb rentals tend to be private room or rooms in high density real estate properties which became a cause for concern during the pandemic in 2020.

Interestingly, the characteristics of listings vary considerably across the two management types (table 3.3). TPM listings tend to be more clustered around tourist attractions (54% vs 47%), have higher response rates (93% vs 85%), managed less of attached type real estate properties (47% vs 59%), and allows higher number of guests in their properties (average of 6 guests per rental vs 4 guests per rental). Most of the listings offered by TPM tend to be entire properties (62% vs 95%), while hosts from property management companies tend to be less flexible, popular or in demand, and require minimum stay periods that are higher than OM hosts (5 days vs 11 days). The average number of listings managed by TPM hosts are about 23 while that of OM hosts are about 5 units. The ADR and occupancy rates of TPM properties are also higher than that of owner managed properties. The neighborhood characteristics of properties under both management schemes appear to be similar.

6. Empirical Results

To provide a benchmark of how the self-selection bias affects our results we present results from the Seemingly Unrelated Regression (SUR) analysis of unmatched samples in table 3.4[18]. In the first two columns we run our baseline regression models in Eq (3.13) and (3.14). 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.

[18] 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.

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, *Demand*, *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 (3.15) in table 3.4 add interaction terms $Profman \times Attached$ and $Profman \times Mngd$. 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 than other TPM units. Similarly, the coefficient on $Profman \times Mngd$ 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.

To evaluate if the results in the previous section are due to self-selection bias, we implement a bias correction technique that matches the sample of professionally managed listings with the sample of owner managed listings on property, host and listing characteristics. The matching is done based on k-nearest neighbor propensity scores of each management type's choices for different characteristics. A total of 5,706 unique listings are matched using this technique and the analysis is repeated for equations (3.13) and (3.14). Results are reported in table 3.5.

The negative marginal effects indicate that *Shared-listing* units and those with *Experience*, *Popular*, and *Demand* hosts are less likely to be TPM. Interestingly, *Clustered* 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 3.6 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×Mngd*, 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.

6.1.Effect of Pandemic

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 quarters of 2020, the period during which business restrictions were imposed locally, and zero otherwise. Table 3.7 columns (1) and (2) report estimates for the extended model (3.16)-(3.17) interacting *Profman* and *Mngd* variables with the *Covid* dummy. The model also includes triple interaction terms *Covid*×*Profman*×*Mngd* and *Covid*×*Profman*×*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 3.7 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×Mngd* 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 3.7 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 3.8 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 3.8. As before, the conclusions resemble those from the unmatched sample. We note, however, that the coefficient of *Post-covid×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.

7. 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.

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 29 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.

Figure

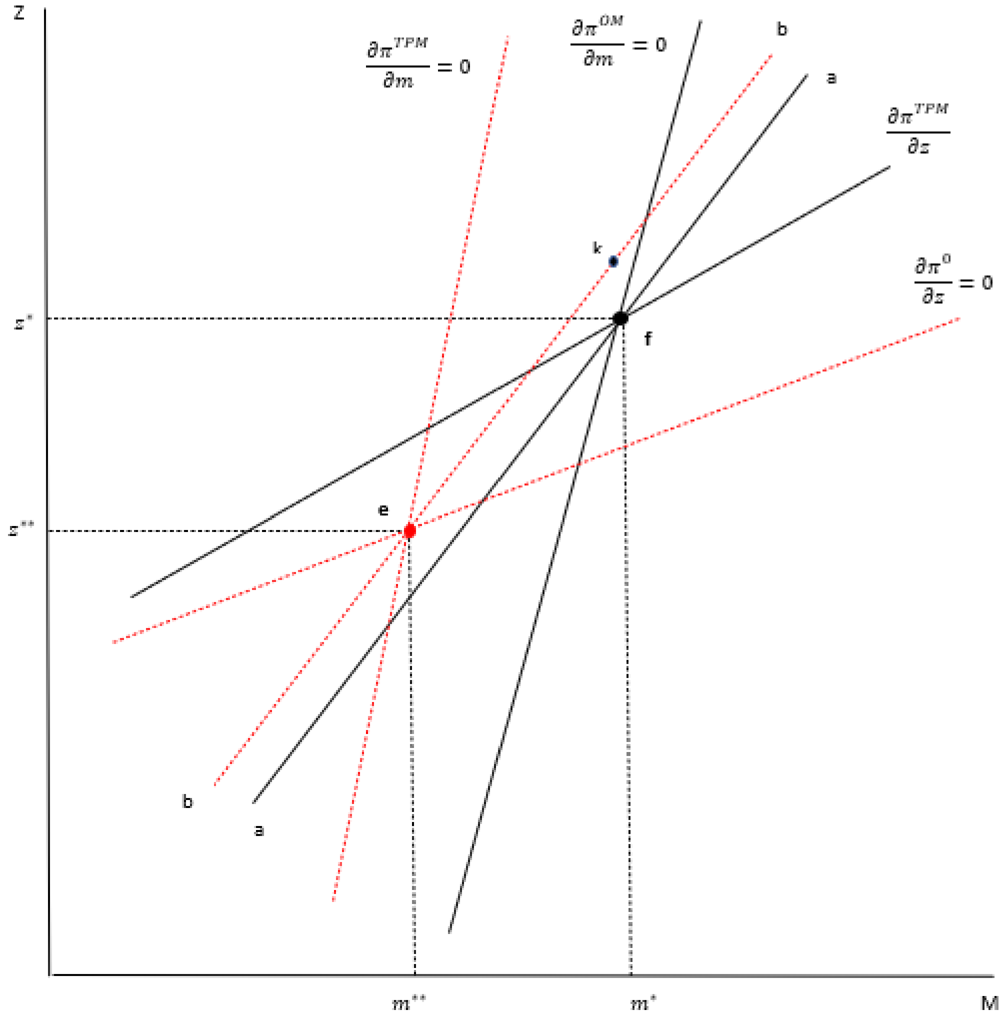

Figure 3.1: OM and TOM Equilibria

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

Tables

Table 3.1: List of Variables

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

Table 3.2: Summary Statistics of Key Variables

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

Table 3.3: Summary Statistics of Key Variables by Management Type

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

Table 3.4: Seemingly Unrelated Regression (SUR) Estimates of Price and Occupancy (Unmatched Sample)

Parameter	log (ADR)	OCC	log (ADR)	OCC
Intercept	3.888*** (0.624)	0.273 (0.346)	3.887*** (0.622)	0.266 (0.345)
Profman	0.100*** (0.004)	0.059*** (0.002)	0.175*** (0.006)	0.133*** (0.003)
Shared-listing	0.684*** (0.004)	0.007*** (0.002)	0.687*** (0.004)	0.010*** (0.002)
Mngd	0.002*** (0.002)	0.020*** (0.001)	0.002 (0.002)	0.023*** (0.001)
Experience	0.066*** (0.006)	0.056*** (0.003)	0.064*** (0.006)	0.054*** (0.003)
Popular	-0.164*** (0.005)	0.313*** (0.003)	-0.160*** (0.005)	0.312*** (0.003)
Demand	0.034*** (0.004)	-0.014*** (0.002)	0.029*** (0.004)	-0.015*** (0.002)
Clustered	0.014*** (0.003)	0.013*** (0.002)	0.015*** (0.003)	0.016*** (0.002)
Attached	-0.052*** (0.003)	-0.034*** (0.002)	0.016*** (0.004)	-0.001 (0.002)
Response	-0.002*** (0.000)	0.001*** (0.000)	-0.002*** (0.000)	0.001*** (0.000)
Flexibility	0.047*** (0.004)	-0.072*** (0.002)	0.039*** (0.004)	-0.071*** (0.002)
Minstay	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
BA	-0.006* (0.003)	-0.017*** (0.002)	-0.004 (0.003)	-0.017*** (0.002)
BR	0.061*** (0.003)	0.046*** (0.001)	0.061*** (0.003)	0.047*** (0.001)
Max-Guests	0.089*** (0.001)	-0.003*** (0.001)	0.089*** (0.001)	-0.003*** (0.001)
ListingDEN	-0.337*** (0.052)	0.262*** (0.029)	-0.346*** (0.052)	0.261*** (0.029)
Profman × Attached			-0.171*** (0.006)	-0.081*** (0.004)
Profman × Mngd			0.002 (0.002)	-0.023*** (0.001)

Parameter	log (ADR)	OCC	log (ADR)	OCC
Neighborhood Controls	*Y*	*Y*	*Y*	*Y*
Quarter and Census FE	*Y*	*Y*	*Y*	*Y*
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. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Table 3.5: Marginal Effects of Owner Managed Versus Third Party Managed Apartments.

Parameter	Non-Matched Sample	Matched Sample
	Profman = 1	*Profman* =1
Shared-listing	-0.285*** (0.095)	-0.039** (0.002)
Experience	-0.075*** (0.025)	0.050*** (0.002)
Popular	-0.042*** (0.014)	0.158*** (0.007)
Demand	-0.101*** (0.034)	0.100*** (0.005)
Clustered	0.003 (0.001)	-0.033*** (0.002)
Attached	-0.126*** (0.042)	-0.066*** (0.003)
Response	0.001*** (0.000)	-0.001*** (0.000)
Flexibility	-0.273*** (0.092)	0.040*** (0.002)
Minstay	0.001*** (0.000)	-0.001*** (0.000)
BA	0.012* (0.004)	0.009*** (0.000)
BR	0.024 (0.008)	-0.014 (0.001)
Max-Guests	0.001*** (0.000)	-0.008*** (0.000)
ListingDEN	-0.007* (0.002)	-0.010*** (0.000)
log (population)	-0.083 (0.028)	-0.169*** (0.008)
log (income)	0.006 (0.002)	-0.026 (0.001)
%Male	0.001 (0.000)	0.003*** (0.000)
%Young	-0.001 (0.000)	0.001*** (0.000)
%Old	-0.001 (0.000)	0.001 (0.000)
%White	-0.003** (0.001)	-0.003*** (0.000)
%Black	-0.002 (0.001)	-0.002*** (0.000)
%Asian	-0.005** (0.002)	-0.003*** (0.000)

Parameter	Non-Matched Sample	Matched Sample
%Indian	-0.001 (0.000)	-0.004*** (0.000)
%Hispanic	-3.E-05** (0.000)	-0.001*** (0.000)
%Educated	-0.150 (0.050)	0.027*** (0.001)
Quarter and Census FE	N	N
R2	0.35	0.25
N	11,348	5706

Marginal effects of logit regression; Dependent variable 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 3.6: Seemingly Unrelated Regression (SUR) Estimates of Price and Occupancy (Propensity Score Matched Sample)

Parameter	log (ADR)	OCC	log (ADR)	OCC
Intercept	3.764*** (0.673)	-1.017*** (0.382)	3.900*** (0.670)	-0.960** (0.381)
Profman	0.099*** (0.004)	0.061*** (0.002)	0.227*** (0.008)	0.129*** (0.004)
Shared-listing	0.789*** (0.008)	0.017*** (0.004)	0.789*** (0.007)	0.018*** (0.004)
Mngd	0.025*** (0.003)	0.018*** (0.002)	0.026*** (0.003)	0.020*** (0.002)
Experience	0.089*** (0.007)	0.043*** (0.004)	0.083*** (0.007)	0.040*** (0.004)
Popular	-0.192*** (0.006)	0.322*** (0.003)	-0.192*** (0.006)	0.322*** (0.003)
Demand	0.039*** (0.005)	-0.003 (0.003)	0.030*** (0.005)	-0.006** (0.003)
Clustered	0.015*** (0.004)	0.005** (0.002)	0.016*** (0.004)	0.006*** (0.002)
Attached	-0.065*** (0.004)	-0.031*** (0.002)	0.024*** (0.006)	0.006* (0.003)
Response	-0.001*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
Flexibility	0.099*** (0.007)	-0.073*** (0.004)	0.092*** (0.007)	-0.074*** (0.004)
Minstay	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
BA	0.038*** (0.004)	-0.024*** (0.002)	0.039*** (0.004)	-0.024*** (0.002)
BR	0.108*** (0.003)	0.049*** (0.002)	0.106*** (0.003)	0.048*** (0.002)
Max-Guests	0.069*** (0.001)	-0.005*** (0.001)	0.069*** (0.001)	-0.005*** (0.001)
ListingDEN	-0.424*** (0.067)	0.634*** (0.038)	-0.393*** (0.067)	0.650*** (0.038)
Profman × *Attached*			-0.185* (0.008)	-0.075*** (0.005)
Profman × *Mngd*			-0.025*** (0.003)	-0.020*** (0.002)

Parameter	log (ADR)	OCC	log (ADR)	OCC
Neighborhood Controls	*Y*	*Y*	*Y*	*Y*
Quarter and Census FE	*Y*	*Y*	*Y*	*Y*
R^2	0.4		0.41	
N	81,119			

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

Table 3.7: SUR Estimates of Price and Occupancy for Covid Period

	Unmatched		Matched	
Parameter	log (ADR)	OCC	log (ADR)	OCC
Intercept	4.561*** (0.622)	0.286 (0.345)	3.900*** (0.669)	-0.962** (0.381)
Profman	0.170*** (0.006)	0.138*** (0.003)	0.225*** (0.008)	0.132*** (0.004)
Shared-listing	-0.686*** (0.004)	-0.011*** (0.002)	0.788*** (0.007)	0.018*** (0.004)
Mngd	0.002 (0.002)	0.025*** (0.001)	0.026*** (0.003)	0.021*** (0.002)
Experience	0.066*** (0.006)	0.055*** (0.003)	0.085*** (0.007)	0.042*** (0.004)
Popular	-0.161*** (0.005)	0.312*** (0.003)	-0.192*** (0.006)	0.321*** (0.003)
Demand	0.028*** (0.004)	-0.015*** (0.002)	0.028*** (0.005)	-0.007** (0.003)
Clustered	0.014*** (0.003)	0.015*** (0.002)	0.014*** (0.004)	0.006** (0.002)
Attached	0.015*** (0.004)	-0.002 (0.002)	0.024*** (0.006)	0.005 (0.003)
Response	-0.002*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
Flexibility	0.039*** (0.004)	-0.070*** (0.002)	0.092*** (0.007)	-0.075*** (0.004)
Minstay	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
BA	-0.004 (0.003)	-0.017*** (0.002)	0.039*** (0.004)	-0.024*** (0.002)
BR	0.061*** (0.003)	0.047*** (0.001)	0.106*** (0.003)	0.049*** (0.002)
Max-Guests	0.089*** (0.001)	-0.004*** (0.001)	0.069*** (0.001)	-0.005*** (0.001)
ListingDEN	-0.343*** (0.052)	0.263*** (0.029)	-0.379*** (0.067)	0.659*** (0.038)
Profman × Attached	-0.168*** (0.007)	-0.082*** (0.004)	-0.180*** (0.008)	-0.077*** (0.005)
Profman × Mngd	-0.002 (0.002)	-0.025*** (0.001)	-0.026*** (0.003)	-0.021*** (0.002)
covid	-0.034* (0.019)	-0.030*** (0.010)	0.111 (0.069)	-0.226*** (0.040)
covid × Profman	-0.037 (0.023)	-0.150*** (0.013)	-0.082*** (0.030)	-0.114*** (0.017)
covid × Profman × Mngd	0.001 (0.008)	0.028*** (0.005)	0.017 (0.011)	0.021*** (0.006)

	Unmatched		Matched	
Parameter	log (ADR)	OCC	log (ADR)	OCC
covid × Profman × Attached	0.033 (0.028)	0.067*** (0.015)	-0.018 (0.033)	0.064*** (0.019)
covid × Mngd	0.001 (0.008)	-0.027*** (0.005)	-0.015 (0.011)	-0.020*** (0.006)
covid × Attached	0.005 (0.015)	0.013 (0.008)	-0.021 (0.021)	0.011 (0.012)
Neighborhood Controls	Y	Y	Y	Y
Quarter and Census FE	Y	Y	Y	Y
R^2	0.45		0.39	
N	143,558		81,119	

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

Table 3.8: SUR Estimates of Price and Occupancy for Post-Covid Period

	Unmatched		Matched	
Parameter	log (ADR)	OCC	log (ADR)	OCC
Intercept	4.781*** (0.619)	0.397 (0.346)	3.947*** (0.669)	-0.849** (0.385)
Profman	0.124*** (0.009)	0.087*** (0.005)	0.154*** (0.011)	0.110*** (0.006)
Shared-listing	-0.677*** (0.004)	-0.011*** (0.002)	0.785*** (0.007)	0.021*** (0.004)
Mngd	0.002 (0.003)	0.024*** (0.002)	0.030*** (0.004)	0.022*** (0.002)
Experience	0.085 (0.006)	0.057*** (0.003)	0.102*** (0.007)	0.041*** (0.004)
Popular	-0.174*** (0.005)	0.310*** (0.003)	-0.206*** (0.006)	0.317*** (0.003)
Demand	0.027*** (0.004)	-0.015*** (0.002)	0.029*** (0.005)	-0.005* (0.003)
Clustered	0.015*** (0.003)	0.015*** (0.002)	0.017*** (0.004)	0.007*** (0.002)
Attached	0.025*** (0.006)	-0.023*** (0.003)	0.032*** (0.008)	-0.015*** (0.005)
Response	-0.002*** (0.000)	0.001*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)
Flexibility	0.030*** (0.004)	-0.069*** (0.002)	0.097*** (0.007)	-0.066*** (0.004)
Minstay	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
BA	0.000 (0.003)	-0.015*** (0.002)	0.041*** (0.004)	-0.022*** (0.002)
BR	0.062*** (0.003)	0.045*** (0.001)	0.106*** (0.003)	0.047*** (0.002)
Max-Guests	0.088*** (0.001)	-0.004*** (0.001)	0.068*** (0.001)	-0.005*** (0.001)
ListingDEN	-0.279*** (0.052)	0.278*** (0.029)	-0.130** (0.066)	0.817*** (0.038)
Profman × Attached	-0.158*** (0.009)	-0.069*** (0.005)	-0.156*** (0.012)	-0.078*** (0.007)
Profman × Mngd	0.001 (0.003)	-0.023*** (0.002)	-0.027*** (0.004)	-0.022*** (0.002)
post-covid	-0.027 (0.055)	-0.186*** (0.031)	0.259*** (0.066)	-0.138*** (0.038)
post-covid × Profman	-0.028** (0.012)	0.063*** (0.006)	0.047*** (0.015)	0.022** (0.009)
post-covid × Profman × Mngd	-0.003 (0.004)	0.001 (0.002)	0.006 (0.006)	0.004 (0.003)

Parameter	Unmatched		Matched	
	log (ADR)	OCC	log (ADR)	OCC
post-covid × *Profman* × *Attached*	0.027** (0.013)	-0.020*** (0.007)	-0.021 (0.016)	0.010 (0.009)
post-covid × *Mngd*	0.000 (0.004)	-0.001 (0.002)	-0.008 (0.006)	-0.005 (0.003)
post-covid × *Attached*	-0.031*** (0.008)	0.045*** (0.004)	-0.012 (0.011)	0.050*** (0.006)
Neighborhood Controls	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 OLS estimates for host, listing and neighborhood characteristics. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month

Appendix

Table 3.9: OLS Estimates of Price and Occupancy (Unmatched Sample)

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

Parameter	log (ADR)	OCC	log (ADR)	OCC
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. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing level per month.

Table 3.10: OLS Estimates of Price and Occupancy (Matched Sample)

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

Parameter	log (ADR)	OCC	log (ADR)	OCC
Neighborhood Controls	*Y*	*Y*	*Y*	*Y*
Quarter and Census FE	*Y*	*Y*	*Y*	*Y*
R2	0.4		0.41	
N	81119			

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

Table 3.11: SUR Estimates of Price and Occupancy for Property Types (Matched Sample)

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

Parameter	*Attached*=1		*Attached*=0	
	log (ADR)	OCC	log (ADR)	*OCC*
Quarter and Census FE	*Y*	*Y*	*Y*	*Y*
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. Standard errors in parenthesis. *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Aggregation at listing per month

Table 3.12: Probit Estimates of Owner Managed Versus Third Party Managed Apartments

Parameter	Unmatched Sample	Matched Sample
	Profman = 1	*Profman* =1
Intercept	-0.462 (6.841)	-2.039 (1.426)
Shared-listing	-1.563*** (0.094)	-0.062** (0.031)
Experience	-0.462*** (0.112)	0.204*** (0.030)
Popular	-0.434*** (0.113)	0.631*** (0.022)
Demand	-0.564*** (0.070)	0.436*** (0.021)
Clustered	0.045 (0.053)	-0.123*** (0.016)
Attached	-0.758*** (0.055)	-0.279*** (0.017)
Response	0.008*** (0.001)	0.007*** (0.000)
Flexibility	-1.691*** (0.086)	0.144*** (0.026)
Minstay	0.005*** (0.002)	-0.008*** (0.001)
BA	0.015* (0.057)	0.066*** (0.016)
BR	0.002 (0.042)	0.036*** (0.012)
Max-Guests	0.058*** (0.016)	-0.441*** (0.005)
ListingDEN	-0.712* (1.028)	-2.004*** (0.262)
log (population)	-0.916* (0.491)	-0.320** (0.126)
log (income)	0.517 (0.389)	0.429*** (0.100)
%Male	0.013 (0.021)	0.026*** (0.005)
%Young	-0.006 (0.025)	0.015** (0.005)
%Old	-0.017 (0.032)	0.005 (0.009)
%White	-0.036** (0.018)	-0.043*** (0.004)
%Black	-0.010 (0.021)	-0.067*** (0.005)
%Asian	-0.083** (0.041)	-0.034*** (0.009)

Parameter	Unmatched Sample	Matched Sample
	Profman = 1	*Profman* =1
%Indian	-0.043 (0.047)	-0.060*** (0.011)
%Hispanic	-0.040** (0.016)	-0.055*** (0.004)
%Educated	-0.934 (1.145)	-1.512*** (0.314)
Quarter and Census FE	N	N
R2	0.35	0.25
N	11,348	5706

Parameter estimates of probit regression; Dependent variable 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.

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