Property Management Technology Adoption in the Short-Term Housing Rental Market

Sophia Göppinger* Jaime Luque†

December 20, 2021

Abstract

Following the recent and growing literature that focuses on the eruption of Airbnb on the short-term rental housing market, this paper studies the impact of a new technology that provides information on market trends using Airbnb's scrapped data. We collected a sample of 5,392 housing units available on Airbnb in Madrid, Spain. We exploit a natural experiment whereby 14% of the properties in the sample were managed by property managers that adopted the technology at different points in time. We use Propensity Score Matching to estimate the effect of adopting this technology on the occupancy rate, the average daily price, and revenue. We find that enhanced market transparency through this technology adoption led to a 23% increase in occupancy, 525% increase in average daily price, and 289% increase in revenue. We conducted robustness checks using Augmented Inverse Propensity Weighting (AIPW), which showed effects of similar signs but smaller magnitudes. We discuss the implications of these results for the consolidation and competition in this market.

Keywords: short-term rental market, information technology adoption, market transparency, PropTech

*sophia.goeppinger@edu.escp.eu; ESCP Business School
†jluque@edu.escp.eu; ESCP Business School

1 Introduction

Real estate is the world's most valuable asset class, and it is a prime component of the global physical capital. Yet, the real estate sector has been slow to adopt new technologies relative to other income-producing asset classes (Goldstein et al. (2019)). Dismayed by the inefficiencies present in the real estate industry, a vast array of start-ups and more mature technology development companies have recognized the opportunities in the digital transformation of this market.[1] There is now a plethora of new technologies driving this transformation, and the term PropTech has been coined to characterize them (see Braesemann and Baum (2020) and Baum et al. (2020)).

One sector of the real estate industry that is particularly affected by PropTech is the short-term rental (STR) housing market. By the end of 2019, a total investment volume of over USD 64.8 Billion was recorded with an even distribution of investment across the PropTech companies in the STR market. This represents an increase of USD 5.33 Billion as compared to 2014. With the disruptive impact of PropTech companies targeting the STR market and the investment linked to these firms, the STR market has been on a steady growth trajectory.[2]

The STR market consists of housing units for rental for short periods (usually between 1 and 7 days). The supply side is typically property managers (PMs) and independent hosts. Independent hosts are individuals who rent out their homes when they are out of town or are willing to vacate their house to get an additional stream of income. The demand side consists of consumers (most commonly travelers). While independent hosts typically participate in the market for financial, social, and cultural reasons, PMs are essentially intermediary firms seeking to maximize profits. The supply-side barriers to entry are low because a landlord does not need to own a property. The low barriers to market entry and exit have resulted in a highly independent host turnover rate and volatility in supply, as well as intense competition

[1] From 2014 to 2019, a total of 319 startups entered the industry across 34 countries and raised USD 86.5 Billion in funding. Data source: Venture Scanner.

[2] The growth rate of start-ups creation was 56% between 2014 and 2019. Data source: Venture Scanner.

and high market fragmentation. Given the difficulty in gathering data on market rates and occupancy levels that helps understand the quick changes that STRs experience on a daily basis, there is a significant lack of market transparency in this sector. Therefore, operational and strategic decisions such as revenue maximization and occupancy optimization remain a significant challenge for PMs in the STR market (Gibbs et al. (2018)).

In this paper, we bring light to the question of how information acquisition by PMs on the performance of the STR housing market – in terms of market rates and demand – can impact their revenues and occupancy levels. In particular, our goal is to quantify the effects of adopting a PropTech technology solution that provides such information to PMs. The information technology in question is a market intelligence data dashboard used by PMs in the STR market. PMs who use this PropTech platform gain visibility over STR market trends and pricing algorithm's suggestions do not bias them. Hence, PMs with this information technology are better equipped to make informed and tailored decisions about pricing, investment, and listing their properties.

As the PropTech solution of interest, we gained access to data from the market intelligence data dashboard provided by the company Transparent Intelligence Inc, which tracks and analyses over 34 million daily STR listings globally. The company systematically consolidates this data in the form of a dynamic dashboard for its clients. The dashboard allows those clients, in particular PMs, to monitor and optimize future rates and occupancy, track demand and their competitor's portfolio, and effectively grow their inventory.

Since the STR market is highly segmented regarding location and property characteristics, we focus on a given city for our study. In particular, we investigate the impact of Transparent Intelligence Inc.'s dashboard on the performance of STR PMs operating in Madrid, Spain. Madrid is a significant and vibrant metropolis that is interesting for our purposes. Its population is around 6.5 million residents, of which 3.2 million live in the city of Madrid. As of July 2018, Madrid had 22,292 properties for STR usage with an average daily rate (ADR) of 126 Euros downtown. About two-thirds (66%) of the properties in the STR market in Madrid are apartments, followed by guest houses which make up approximately 6.84%, and homes with about 4.44%. Our data sample consists of 5,392 STR properties listed on Airbnb, managed by 179 property managers (PMs) over 18 months starting from July 2018.

In our panel data set, we observe occupancy rates, revenue, property defining characteristics, and subscription status to Transparent Intelligence Inc.'s services. The unit of analysis is defined as a combination of property and month. The outcome variables are defined as the occupancy rate and revenue generated at the level of each property and each month, while the treatment is defined as a PM's subscription to Transparent Intelligence Inc.'s dashboard services. The treatment group amounts to 14% of the 5,392 properties in our sample. There is some covariate imbalance between the treatment and controls groups, but we can control for most of the confounding variables given the richness in the data.

Our identification strategy is based on observing a natural experiment in the STR market in Madrid, where we observe different PMs subscribing to Transparent Intelligence Inc.'s services (treatment) at different points in time. We observe the treated units before and after the treatment and the control units for the same periods. This variation in treatment status allows us to identify the natural experiment in the data. The natural experiment in the setting is akin to an event study research design. We defined the treatment and control groups based on adopting the new technology. Given that the adoption of new technology was done at the PM level, we assign the treatment status to all properties of a PM from the time that PM subscribed to the new technology till the end of the sample period. All observations of those properties before adopting this technology by the same PM are counted in the control group. All properties whose PMs never adopted the new technology are counted in the control group throughout the sample period.

To estimate the Average Treatment Effect on the Treated (ATT), we used Propensity Score Matching. The set of matching variables is reasonably large, making simple matching estimation methods computationally infeasible. In the first stage of the estimation procedure, we reduce the dimension of the matching variables set by using the Propensity Score Model to estimate the probability of the treatment variable as a function of all the matching variables. This was done using a Logit model. Given the estimated model, we can estimate the probability of each observation for receiving treatment or not. In the second stage of the estimation procedure, we use the estimated propensity scores to do the matching. As reported in Table 3, the treatment group is much smaller than the control group, so the matching process involved searching for a match for each observation in the treatment group to many observations in the control group. This allowed us to construct for 1-to-many matches.

The estimation results of the Propensity Score Matching model show that the ATT of using the market data intelligence platform was an increase of 22.9% on occupancy, an increase of 525% on average daily price, and an increase of 289% on revenue. All these effects are statistically significant at the 99% confidence level. We also estimated the Propensity Score Model with different matches and found similar results. These results clearly show that adopting this new technology was beneficial to the property managers to increase occupancy and revenue. The effect on prices indicates that the PMs used dynamic pricing to achieve these gains in revenue and occupancy. These results further infer that this new technology improved market transparency, reducing asymmetric information. Because the surplus for property managers, tourists, and the platform owner increased, the adoption of this new technology was welfare-enhancing.

We conducted robustness checks with the same method, i.e., Propensity Score Matching, with varying specifications and number of neighbors used in the matching process, and got similar results. We also used an alternative but similar method, called Augmented Inverse Propensity Weighting, as a robustness check. We found that the coefficients were of the same sign with the new method, but their magnitudes were smaller. We aregue that this could be because of the differences in the estimation of the ATE using the new method instead of the ATT. These robustness checks corroborate our main results from Propensity Score Matching by establishing the invariance to alternative model specifications and methods.

Furthermore, we conducted a sub-sample analysis to investigate further groups in our data where the treatment effect might have been different from the average. This exercise was guided by intuition on the definition of dynamic pricing. The property managers are likely to increase prices when the demand is high, such as holiday periods. Similarly, the property managers are likely to decrease prices when occupancy is relatively low. Given this argument, it should follow that the effects of a revenue management technology that facilitates the implementation of dynamic pricing based on new market-level information would be higher in times of high or low occupancy than when occupancy is already at average levels. We split the sample into three subsets based on the existing occupancy level to test this. The first subset contained observations with 75th percentile or higher occupancy, the second with observations in the interquartile range of occupancy, and the third with 25th percentile or lower occupancy.

The subset analysis shows that while the new technology had statistically significant effects on occupancy for all subsets, revenue and prices were primarily driven from the subset where occupancy level was below the 25th quantile. This result sheds further light on our primary analysis to explain the large effects on revenue and prices relative to the small effect on occupancy. It further supports our argument that property managers use this new technology to engage in dynamic pricing, and this activity bears fruits particularly well when the demand for short-term housing is low.

Our paper contributes to different strands of the literature on real estate technology adoption, information systems, and market transparency in the STR housing market. The first of these strands – real estate technology adoption or PropTech – is quite a recent and understudied phenomenon (see e.g. Baum et al. (2020), Baum and Dearsley (2017), Buchak et al. (2018), and Porter et al. (2019)).[3] PropTech has been credited with improving

[3]Recent research has focused on highlighting the emergence of PropTech as a new class of technologies and their role in digitizing the real estate market. Buchak et al. (2020) study the trading behavior of iBuyers (non-bank intermediaries) in the online real estate market and show how their entry improves liquidity in the market. See also Buchak et al. (2018) for evidence of how technology can dampen capital requirements

efficiency and facilitating real estate activities, including buying, selling, leasing, managing, appraising, financing, marketing, developing, designing, building, and investing, among other things. Below in Section 2, we deliver powerful market data insights on the evolution of this market using novel data acquired from Venture Scanner data vendors. We also provide contextual data of the PropTech landscape and focus on technological solutions specific to the STR market.

The STR market is highly fragmented, and this situation is aggravated by the volatility of supply and lack of data on market prices, demand, and supply levels. This has led to opacity in the market, which hampers PMs in operational and strategic decision-making. A change in market transparency can have positive or negative effects on market participants depending on the resulting information structure. For instance, Li and Zhu (2020) showed how a reduction in information transparency in the online market for daily deals led to a reduction in seller side multi-homing and also a reduction in the profitability of the uninformed marketplace platform. Ghose et al. (2012) show how market transparency can be reduced by using data from social media platforms to incorporate into demand estimation models to improve the rankings in product search engines. Furthermore, the literature on the STR market suggests that the application of data analytics potentially leads to substantial efficiency gains (Braesemann and Baum (2020)) and superior organizational performance of firms that are aware and exploit the value of data generated in renting, buying, and managing real estate (Ghasemaghaei (2012)). We contribute to this literature by empirically demonstrating that PMs in the STR market see their revenues and occupancy levels significantly increased after the adoption of a technology that increases transparency in a market previously lacking reliable data for strategic and operational decision-making.

By addressing the performance differences in terms of occupancy and revenue between the PMs who adopt market information technology and those who do not, we demonstrate that PMs who are at the forefront of the digital transformation of the STR market can gain

in mortgage lending.

a competitive edge in their regional markets. These results are noteworthy because previous literature exclusively investigates the significant difference in the performance of single-unit and multi-unit hosts[4] (Aznar et al. (2018) and Gibbs et al. (2018)), but not the wide spectrum of technology adoptions by professional PMs operating in the STR market who are essentially profit-driven. STR supply providers that are engaging with digital technologies have a higher survival rate in the market (Leoni (2020), Li et al. (2015)) and are expected to prosper by achieving substantial efficiency gains, raising the bar in customer experience and engagement, innovation and workforce productivity (Siniak et al. (2020)).[5]

We also extend previous findings on revenue management and optimal pricing of STR supply providers – exhaustively analyzed within the context of dynamic pricing and price positioning of Airbnb hosts[6] – by investigating the effect of adopting an information technology solution which guides PMs in setting their optimal prices to maximize occupancy and revenue. Our research shows that without a technology adoption that increases market transparency in the STR market, independent hosts are underperforming with respect to more informed market players. Possible explanations for the lack of rates adjustments[7] by Airbnb hosts are a lack of motivation, professionalization (measured in terms of the number

[4]i.e., owners who own multiple listings are more likely to be professional PMs.

[5]It comes as no surprise that single-unit hosts are outperformed in terms of revenue and occupancy by multi-unit hosts. The discrepancy in the performance of single-unit and multi-unit hosts presumably exists because among the multi-unit hosts some operate as professional PMs who are profit-maximizing firms. In contrast, single-unit hosts are motivated not only by financial incentives but also by potential social interactions (e.g., enjoying meeting new people) and sharing one's world by utilizing unused space (Karlsson and Dolnicar (2015), Visser et al. (2017), Ladegaard (2018)). Thus, they are not expected to professionalize and grow their business consciously. The significance of having a competitive edge over competitors is shown Leoni (2020) who analyses the survival rate of Airbnb listings in Ibiza – measured by the number of listings and longevity on the platform. She concludes that an Airbnb host's strategies and technological tools affect the probability of abandoning the platform.

[6]Oskam et al. (2018) found that hosts who adjusted prices more frequently performed better in terms of occupancy levels and daily rates. Li et al. (2015) identify that in Chicago multi-unit hosts have a 16.9% and 15.5% higher ADR and OCC rate, respectively, as compared to those with single units due to pricing inefficiencies of the latter. Magno et al. (2018) show evidence of a strategic pricing behavior for Airbnb hosts, as these hosts increased prices in response to an increase in demand. Aznar et al. (2018) and Gibbs et al. (2018) showed that the volatility in host prices on Airbnb was much lower than the volatility in prices charged by professional hotels.

[7]The Transparent Intelligence Inc. market intelligence data dashboard does not include a dynamic pricing tool that suggests rate changes to PMs and implements them upon request. However, the market transparency provided by this dashboard allows PMs to change prices more frequently and better informed than usual.

of properties under management, see Li et al. (2015), and Oskam et al. (2018)), experience and an extensive Airbnb pricing tool (see Hill (2015)). Our study provides evidence that using market data intelligence by PMs leads to significant increases in occupancy and revenue.

The rest of the paper is organized as follows. Section 2 explains the setting and describes the data used for our analysis. In Section 3, we develop the empirical model, define the identification strategy and report the results from the estimated model. Section 4 concludes with a discussion of results and their policy implications.

2 Setting and Data

In this section, we provide an overview of the PropTech revolution and discuss the eruption of STR PropTech technologies. We also give details about the local STR housing market in Madrid, Spain, and provide information about Transparent Intelligence Inc., its market data intelligence platform and the summary statistics of the sample data used for the subsequent empirical analysis.

2.1 The PropTech Revolution

The real estate industry is far from agreeing on a universally accepted definition of PropTech. Various industry experts have cultivated their definitions and boundaries to what comprises PropTech independently. This paper will refer to PropTech as software, tools, platforms, apps, websites, and other digital solutions employed by real estate practitioners. PropTech encompasses Contech (construction technology) and CREtech (commercial real estate) and overlaps with Fintech. Proptech has been credited with improving efficiency and facilitating real estate activities, including buying, selling, leasing, managing, appraising, financing, marketing, developing, designing, building, and investing.

The application of technology and innovation to real estate came relatively late compared to other industries involved in the global digital revolution. This delay is attributed to the success and profitability of the old commission-based business model. Another reason is the hyper-local nature and high real estate market regulation, primarily involving private assets. Additionally, homebuyers and renters are wary of using new and unaccustomed methods for what is likely to be the acquisition of their most valuable asset. Above all, the illiquidity of properties made it hard for the real estate market to keep up with the era of fast-paced liquid transactions online. All the above reasons contributed to a tendency of resistance against change and innovation by the different stakeholders in the real estate market. However, the conservative sector has become a fertile ground for innovative tech start-ups, startled by the time-consuming and inefficient offline processes, and a magnet for investors. The delay in innovation has led to an incredibly dynamic change in PropTech as it is catching up with the other digital industries and taking the investment world by storm.

2.2 PropTech in the Short Term Rental Housing Market

The surge of technology targeting the Short Term Rental (STR) housing market has important implications on the functioning of this market. PropTech companies like Airbnb and Booking.com have increased the asset's utilization rates for physical capital and, in doing so, have made existing physical capital more productive Calder-Wang (2020) and Gutiérrez et al. (2017)). The emergence of STR marketplace platforms also has spillover effects in other sectors of the economy. Alyakoob and Rahman (2018) estimate the impact of Airbnb activity on local restaurant employment, a complimentary local service. With the advent of such PropTech companies, an independent host can rent out a spare room in his house with a few simple clicks in a matter of minutes.

The recent proliferation of new technology impacts all sectors and actors of the real estate industry. The STR market is at the forefront of this change. PropTech companies targeting the STR market have been successful in attracting investments. Here we provide evidence about the growth of the STR PropTech sector in terms of companies creation, funds raised, investor composition, and the distribution of STR PropTech companies' headquarters across the globe. To this end, we collected data from Venture Scanner.

There was a surge of new companies starting in 2005 in the US and later in 2010 in other countries. This lends credence to our earlier discussion that the real estate industry has slowly adopted new technologies. Since 2010 the STR housing market has become a breeding space for new start-ups. The growth rate of start-ups creation in this sector exceeded 200 percent in major markets such as the US, China and the EU. A large fraction of these companies originated in the United States, but there was also a significant number of STR PropTech start-ups that emerged in the United Kingdom and the European Union. A large fraction of these companies serve clients worldwide.

As prompted by the change in how real estate is suddenly practiced, investors gradually found STRs as a profitable alternative to their usual ventures. Investment started to sky-rocket in 2014. Within just one year, the investment amount doubled from approximately \$20 Billion to \$40 Billion. By the end of 2019, more than \$60 Billion were invested in these companies.

The two booking platforms Airbnb and OYO, stand out as the major players leading by a large margin with investments of approximately \$4.5 Billion and \$3.2 Billion, respectively. Even though these are large amounts, the sum only makes up a fraction of over \$60 Billion invested in all the PropTech companies in the STR market together. The relatively small share of investment in the top two firms compared to the total volume suggests that the investments are not highly concentrated on a minimal number of companies, but are distributed fairly uniformly across the market participants.

2.2.1 The Short Term Rental Housing Market in Madrid, Spain

Our empirical analysis below focuses on the STR housing market in Madrid, Spain. This region has 6.5 million residents, of which 3.2 million live in the city of Madrid. This city has a vibrant downtown area with a high population density and a more open outer city where the population density drops slightly. The STR market in Madrid boasts different types of housing properties. About two-third (66%) of the properties in the STR market are apartments, followed by guest houses which make up approximately 6.84%, and houses with about 4.44%.[8]

On the supply side, as of July 2018, there was a capacity of 74,743 bedrooms for STR use in the city of Madrid. About 54% (40,343) of these bedrooms were located in the city's downtown area, while the remaining 46% (34,309) were located outside the downtown area. The total number of properties available for STR purposes was 22,292 of which 51% (11,385) were in the downtown area and the remaining 49% (10,907) were located in the rest of the city[9]. While both the downtown area and the rest of the city have almost the same number of properties, the properties in the downtown area make up a larger fraction of the total capacity available. Such a difference might stem from travelers who opt for such housing units may prefer to stay downtown. Another potential explanation is that people living in the downtown district may be more receptive to renting out a spare room given the higher cost of living in the center of Madrid. In July 2018, the average daily rate (ADR) of a room in the downtown area was 126 Euros, while in the rest of the city, it was approximately 107 Euros.

The STR housing market is highly fragmented. The fragmentation stems from the fact that the supply side ranges from a sheer number of independent hosts willing to vacate their homes for a few days to professional PMs with multiple units under management. As individuals do not have to own a property to put a bedroom up for rental within a matter of minutes, it allows anyone to participate in this market. This results in a crowded STR market with multiple independent hosts who occasionally rent out their properties. While there were 5,041 multi-unit hosts (including hosts with more than one property and professionally operating PMs) active in Madrid in July 2018, more than double this number was single-

[8]Data source: Transparent Intelligence Inc.'s client report.

[9]The number properties is much smaller than the capacity because on average a property has multiple bedrooms available

unit hosts (10,357). However, when comparing the supply of both market players, multi-unit hosts overtake the 10,357 properties provided by the single-unit hosts, offering 11,818 active properties on the market. The supply provided by independent hosts is volatile and difficult to quantify.

On the demand side, most travelers who decided to rent out a property in the Madrid STR market came from outside of Spain making up about 81% of the total guests, while the rest (19%) were domestic guests as of July 2018. Travelers from the United States represented the largest share of guests in Madrid with 23%, followed by domestic travelers, representing 13 % of total visitors. The domestic guests comprise primarily Spanish travelers from outside Madrid. A significant number of travelers come from neighboring European countries such as the United Kingdom (9%), France (8%), Germany (4%), and Italy (3%). Other major markets include Mexico (4%), Australia (3%), Argentina (3%), Canada (3%), and Brazil (2%).

2.3 Transparent Intelligence Inc.

As a provider of market intelligence data, Transparent Intelligence Inc. monitors and analyses over 34 million STR listings worldwide and their activity on the booking platforms Airbnb, Vrbo, and Booking.com by scraping their data at the daily frequency.[10] During the scraping process, Transparent Intelligence Inc. indexes the three booking platforms, by the order in which their listings are browsed by potential guests to obtain all publicly available data, such as the property type, property subtype, the average daily rate, host identifier (when available), and the address of the property (when available). As these platforms often use different names to refer to the same variables, Transparent Intelligence Inc. standardizes and unifies these listings and data variables into a single clean database.

Additionally, it maintains a proprietary database of over 100,000 reservations tracked

[10]By data scraping, we mean the process of extracting and combining contents of interest from the web in a systematic way (Gonzalez-Peña et al. 2013). Scraping may be subject to errors, though. For instance, it's well known that Airbnb slightly perturbs the location of a property to ensure host privacy. See Wachsmuth and Weisler (2018) who show that perturbation is between 0 and 500 feet.

by month to collect historical performance data of those STR properties. The aggregation of proprietary and publicly available data from major booking platforms allows Transparent Intelligence Inc. to provide its clients in the STR market with information on market conditions, such as supply growth, demand patterns, pricing trends and competitor rates. Information is provided through the data-powered product Smart Rental PRO Data Dashboard (Smart Rental PRO). This platform enables Transparent Intelligence Inc.'s clients to make smarter and more efficient data-driven decisions and save time and effort in tracking and benchmarking competitors manually from public sites.

As the STR market is becoming increasingly professionalized, it is crucial for PMs to understand market behavior to develop a well-informed strategy that is based on the performance of their competitors. Without the insights shared by data intelligence providers such as Transparent Intelligence Inc., gathering of data is a very arduous task, performed manually by PMs, making it both expensive and time-consuming, not to mention likely inaccurate due to incomplete data, covering only a part of the market. Transparent Intelligence Inc. service allows PMs to replace previous manual processes with its integrated platform of market trends which is constantly updated, and ready for analysis.

The dynamic information provided on the platform allows PMs to track their competitors' portfolio and make more reasoned decisions related to pricing, inventory growth, and listing of properties on booking platforms[11] to maximize revenue. To equip PMs with the necessary knowledge to make informed decisions on these parameters, Transparent Intelligence Inc. provides clean tabulated data and visualizations using interactive maps and graphs on its dashboard. The data is accessible on a market and competitor levels in all indicators.

For PMs to optimize their pricing, Transparent Intelligence Inc. provides information on seasonal trends and shocks to the supply and demand of housing units. Given the dynamic nature of the STR market, the demand of a given property fluctuates frequently. By tracking such changes PMs can react proactively. Smart Rental PRO gives PMs a clear picture of

[11] By listing, we refer to both resource allocation (active and passive listings) as well as listing creation.

their pricing positions relative to the market, enabling them to adjust their rates when they deviate significantly from the market average, i.e., changing the ADR upward when it is set below the market average to optimize revenue or adjust it downwards when it exceeds the market average significantly so that it does not impact occupancy negatively.

Furthermore, in a differentiated product market like the STR market, PMs must set their properties against similar attributes (number of bedrooms, capacity, etc.) listed in the market. To help with this, Transparent Intelligence Inc. allows for comparing similar properties by using benchmarks in terms of closest matches of a given property in terms of location, the number of bedrooms, amenities, and services offered. PMs, find this kind of customizable comparison information extremely valuable. As revenue maximization is subject to the relationship between ADR and occupancy, PMs can monitor the availability together with demand and rates. This enables them to profit from low availability during a surge in demand or adjust for low demand when occupancy is low.

Transparent Intelligence Inc. employs advanced analytics to calculate occupancy rates based on the public and proprietary data sets it collects. This is essential because calculating occupancy is more complex while data on prices are publicly available from the booking platforms. As Oskam et al. (2018) note in their study, Airbnb does not disclose whether an unavailable night is due to paid occupancy (i.e., an actual booking) or blocked by the owner for personal use or maintenance. For this purpose, Transparent Intelligence Inc. uses proprietary data on reservations and combines it with listings data to calculate accurate estimates of occupancy of each property in the market. Furthermore, to understand stay controls, the platform displays the average minimum length of stay[12] of the market for every day in the future.

To support its clients in effective inventory growth, Transparent Intelligence Inc. employs interactive maps, which PMs can leverage to discover potential business development opportunities and maximize inventory, as well as keep track of the densest areas of the market

[12] i.e., the minimum number of days the STR is to be rented for by the guest.

and their competitor's location of growth. Transparent Intelligence Inc. also allows PMs to get detailed information on each property including owner, review scores, and property attributes (number of bedrooms, amenities, etc.). It also provides a ranking of all PMs to reflect their performance. Such information serves PMs as a valuable source of leads for the acquisition of new inventory, as they can easily search for properties that fit their portfolio requirements.

Finally, PMs have the opportunity to peruse the top reviewed listings from competitors, allowing them to understand the importance of factors such as picture positioning, suitable titles, descriptions, and amenities. The data obtained from Transparent Intelligence Inc.'s dashboard can be exported to integrate with other property technologies, such as a channel manager or a dynamic pricing tool, to capitalize on the market intelligence gained.

2.4 Data

To conduct our empirical analysis, we collected data on the short-term accommodation rental housing market in Madrid, Spain. The primary source of this data set is Transparent Intelligence Inc. We collected a sample of 5,392 housing units, managed by 179 PMs for a time the period starting from July 2018 and ending in December 2019, constituting 18 months of data in total[13] The data set contains monthly frequency information about the housing unit's occupancy rate, revenue generated and defining features like the number of bedrooms and bathrooms, size, and the type of building, among others. The data set has a panel structure where a housing unit is a cross-sectional unit and a month is a longitudinal unit. Consequently, the primary unit of analysis for our empirical analysis will be the combination of a housing unit and a month.

The data set also has information about the property manager of each housing unit and whether it adopted Transparent Intelligence Inc.'s market data intelligence system. We precisely defined the treatment variable by using market data intelligence system adoption

[13] The 179 PM were identified and confirmed to be professionals operating in Madrid during the time mentioned above period by Transparent Intelligence Inc.

dates. This information was instrumental in recognizing and exploiting the natural experiment in the market. The market data intelligence system by Transparent Intelligence Inc. was adopted by a subset of all managers at different points in time within the sample period. As explained later in section 3, this natural experiment generated variation akin to an event study, and we used Propensity Score Matching to estimate the ATT. We further conducted robustness checks using the Augmented Inverse Propensity Weighting method.

Table 1 reports the summary statistics of the two outcome variables – occupancy rate and revenue – and the covariate balance between the control and treatment groups. We observe 65,343 combinations of housing units and months. Out of these 65,343 observations, 60,650 (92%) are in the control group and 4,693 (8%) are in the treatment group (corresponds to 14% of all housing units in our sample). Columns 1 and 2 of Table 1 report the means of the variables broken down by the control and treatment groups, respectively. Column 3 reports the difference in the means of the treated and controls groups, and column 4 reports the p-value to measure the statistical significance of the mean difference reported in column 3. These statistical significance checks were done using the Wilcox t-test for comparing the means of two variables.

According to the estimates reported in Table 1, the control and treatment groups differ on several quantifiable dimensions. The occupancy in the treated units is 10% higher on average than in the control group. The revenue in the treatment group is also higher than the control group by $515 on average. Both differences in means are statistically significant at a 99% confidence level. However, it is unclear whether the treatment caused this result or if it was pre-existing from this simple comparison.

An interesting point to note here is that on average, the housing units in the treatment, the group have fewer essential amenities than those in the control group. Amenities like breakfast, a doorman, free internet, and a pool is more likely to be available in the control group housing units than those in the treatment group. This might be indicative of the effectiveness of the market data intelligence system in helping property managers to set

Table 1: Summary statistics and covariate balance

Variable	Control (1)	Treatment (2)	Difference (3)	P-Value (4)
Occupancy	0.67	0.78	0.10	0.00
	[0.35]	[0.27]		
Revenue ($)	3,246.78	3,762.07	515.29	0.00
	[6,829.7]	[2,993.03]		
Avg. Daily Price ($)	146.4	156.03	9.63	0.00
	[325.8]	[111.06]		
Bedrooms	1.23	1.51	0.28	0.00
	[1.11]	[1.29]		
Beds	1.95	2.17	0.22	0.00
	[1.78]	[1.87]		
Bathrooms	1.13	1.19	0.06	0.00
	[0.89]	[0.88]		
Capacity (bedrooms)	3.43	4.06	0.63	0.00
	[2.53]	[2.93]		
Min. stay (days)	2.61	1.87	-0.75	0.00
	[7.77]	[5.36]		
Air conditioning	0.68	0.73	0.04	0.00
Instant bookable	0.61	0.63	0.02	0.00
Breakfast	0.01	0.00	-0.01	0.00
Doorman	0.07	0.00	-0.06	0.00
Gym	0.01	0.00	-0.01	0.00
Heating	0.73	0.73	-0.00	0.84
Internet available	0.28	0.01	-0.27	0.00
Pool	0.03	0.01	-0.02	0.00
Event suitability	0.02	0.00	-0.01	0.00
TV	0.73	0.72	-0.01	0.26
Wheelchair accessible	0.03	0.03	0.00	0.99
Observations	60,650	4,693	65,343	65,343

prices optimally, leading to higher revenues and occupancy rates of inferior products.

In Table 1 we can also observe that the units in the treated group are likely to have a shorter minimum stays than the units in the control group do. This could also be indicative of the effectiveness of the market data intelligence system in helping the PMs renting out properties to a larger group of potential tenants who need a housing unit for a shorter time.

When compared to the control group, the listings of the treated units also appear more likely to be instantly bookable; thus, the housing the unit can be booked without a precedent approval from the PM. This could also indicate usage of the revenue management technology by the PM, which lends credence to our findings that the new technology is utilized by the PMs.

In Table 1 we also see that the treated units have a higher number of bedrooms, beds, bathrooms, the capacity of guests, and are more likely to have air conditioning. Furthermore, both the treated and control units are equally likely to have wheelchair accessibility, a television set, and heating. Except for wheelchair accessibility, television set, and heating, these mean differences are significant at the 95% confidence level.

The covariate imbalance reported in Table 1 motivates the inclusion of all these confounding variables in our Propensity Score model in order to remove any bias they may have created if they were excluded from the model. The richness of the data set allows us to control for these effects as there is significant variation in these confounding variables. This motivates the inclusion of confounding variables in our model.

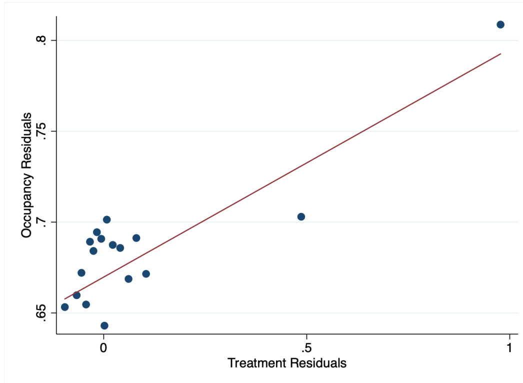

Figure 1: Binscatter plot of Occupancy by Treatment

Before continuing to the empirical strategy section, we show the visual relationships between our outcome variables of interest and the treatment variable. We used the binned scatter plots while eliminating the effects of the matching/confounding variables, which we will later use to estimate Propensity Score Matching and Augmented Inverse Propensity Weighting methods. These visualizations are presented in Figures 1, 2, and 3. These figures show preliminary visual evidence of the positive effects of the treatment on all the outcomes of interest. In particular, the effects seem to be rather large for revenue and price, which are log-transformed. It should also be noted that the results seem to be driven primarily by the observations in the last two bins for all the outcome variables.

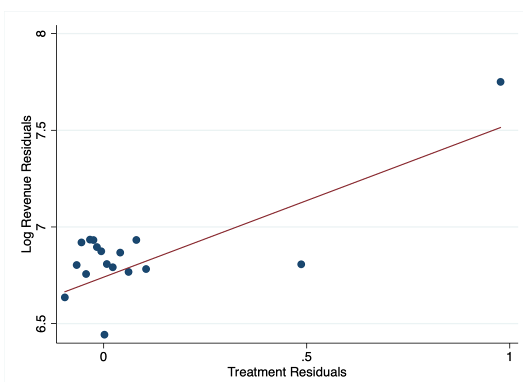

Figure 2: Binscatter plot of Log Revenue by Treatment

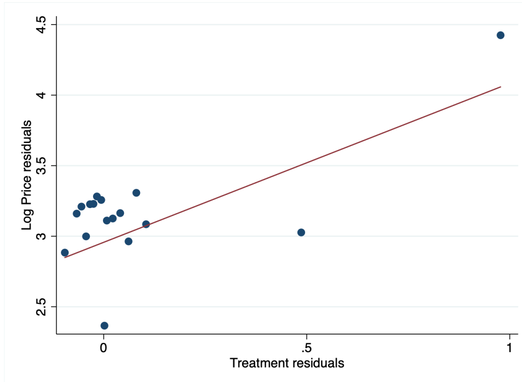

Figure 3: Binscatter plot of Log Price by Treatment

3 Empirical Strategy

Our objective is to estimate the Average Treatment Effect on Treated (ATT) of adopting a market data intelligence system on the occupancy and revenue of the housing units in the STR housing market. In this regard, our focus is on the population of all the housing units available for STR can potentially adopt this technology. We note that the population of housing units we are interested in can receive the treatment. The treatment variable is defined as the incidence of adopting a market data intelligence system by the entity responsible for renting out the housing unit. The outcome variables of interest are the occupancy rate and the revenue generated from the housing unit in the time of a month. The population estimands of interest are the ATTs of the above-defined treatment on each outcome variable.

As noted in the section 2, the sample we collected to estimate the ATT is a balanced panel data of housing units from the STR market in Madrid, Spain, for a period of 18 months starting from July 2018 to December 2019. As noted before, we observe 5,392 individual housing units operated by 179 PMs for each of the 18 months in the sample period. The unit of analysis is defined as the combination of a housing unit and a month. For each housing unit, we observe the total monthly revenue, occupancy, and a set of housing specific features, for example, number of bedrooms, pool availability, heating status, etc.[14]

Our sample is representative of the population, as defined above, and is therefore ideal for this analysis. The market comprises differentiated products, and the usual market forces determine the prices and allocations in this market. In this regard, the market operates to allow for the free exchange of goods and services and free movement of prices and information revelation.

We assume that PMs can also use the market data intelligence dashboard to make better decisions. According to Gibbs et al. (2018), Hunt and Morgan (1997), and Oskam et al. (2018) a resource only provides a competitive advantage if the organization has the internal capabilities to use it.

Furthermore, we should note here that while we know about the adoption of Transparent Intelligence Inc., market data intelligence dashboard, we do not have information about a different provider of such information. Here we assume that the information provided by Transparent Intelligence Inc. has a clear advantage over any other source of aggregated information available to PMs in the STR market of Madrid, Spain.

3.1 Propensity Score Matching Model

The natural experiment in the setting warrants an event-study design. We defined the treatment and control groups based on adopting the new technology. Given that the adoption of new technology was done at the PM level, we assign the treatment status to all properties of a PM from the time that PM subscribed to the new technology till the end of the sample period. All observations of those properties before adopting this technology by the same PM are counted in the control group. Furthermore, all properties whose PMs never adopted the new technology were counted in the control group throughout the sample period.

To estimate the Average Treatment Effect on the Treated (ATT), we used Propensity Score Matching. The set of matching variables is reasonably large, making simple matching

[14]A complete list of these variables can be found in Table 1.

estimation methods computationally infeasible. In the first stage of the estimation procedure, reduce the dimension of the matching variables set by using the Propensity Score Model to estimate the probability of the treatment variable as a function of all the matching variables. This was done using a Probit model. Given the estimated model, we can estimate the probability of each observation for receiving treatment or not. In the second stage of the estimation procedure, we use the estimated propensity scores to do the matching. As reported in Table 1, the treatment group is much smaller than the control group, so the matching process involved searching for a match for each observation in the treatment group to many observations in the control group. This allowed us to construct for 1-to-many matches.

We chose Propensity Score Matching to estimate the ATT because it is well-suited to exploit the natural experiment in a window-study design explained above. The treatment variable is such that a subset of observations after a particular point in time receive the treatment. Furthermore, we observe a rich set of variables for which are potential confounders of the treatment effect, i.e., they likely affect both the treatment status and the outcome variables of interest, namely occupancy, price, and revenue. To remove the bias created from these potential confounding variables, we directly reduce their dimension to a single variable, the estimated propensity score, as explained above. This empirical strategy is motivated by the selection of observables.

One caveat here is that there could be other unobservable confounding variables that we do not consider while estimating the propensity score. We note here that while it is certainly possible that such unobservable variables may exist, it is unlikely that they will have significant effects on both the treatment and outcome variables to create significant bias. This is because the set of matching variables is already so large and contains significantly rich information that it may help most explain most of the variation in the outcome variables of interest. Hence, it is likely that the remaining unobservable variables will not be different from pure noise.

Common Support

To use Propensity Score Matching estimation, we first checked the common support of the matching variables between the treatment and control groups. As can be seen in 4, there was a small right tail region in the distribution of the propensity scores where we had observations in the treatment group but not in the control group. A standard solution is to trim the data set by dropping the observations in that region of uncommon support and only use the observations in the region of common support of the propensity score distribution.

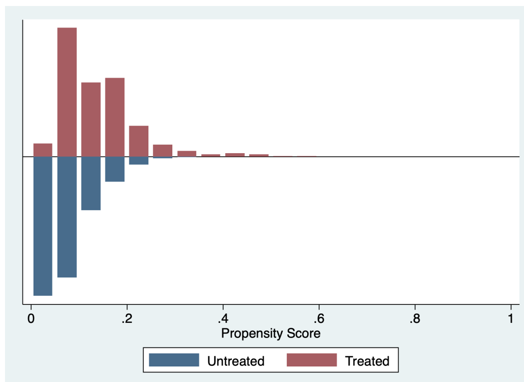

Figure 4: Common Support

Covariate Balance

Table reftab:covariate-balance reports the covariate balance after successful matching based on the estimated propensity scores. Compared to Table 1, we can observe a much-balanced panel in the matched data set. The mean differences between the treatment and control groups are much lower for most variables. Additionally, the mean differences are statistically insignificant for most variables in the matched panel, unlike in the starting sample data set, where most mean differences are statistically significant.

3.2 Estimation Results

Table 3 reports the estimates of the Propensity Score Matching Model. The ATT of subscribing to Transparent's technology was positive and statistically significant for Occupancy,

Table 2: Covariate Balance

Variable	Treated	Control	Bias (%)	t-test
Air Conditioning	0.726	0.711	3.2	1.59
Breakfast	0.000	0.000	-0.0	0.00
Doorman	0.001	0.001	-0.2	-0.40
Gym	0.003	0.003	-0.4	-0.26
Heating	0.733	0.725	1.9	0.90
Internet	0.010	0.011	-0.1	-0.14
Pool	0.006	0.003	2.6	2.24
Event Suitable	0.001	0	1.2	2.24
TV	0.721	0.705	3.9	1.86
Wheelchair Acc.	0.026	0.022	2.6	1.29
Bedrooms	1.508	1.456	4.2	1.91
Beds	2.170	2.083	4.9	2.26
Bathrooms	1.193	1.147	5.1	2.51
Capacity	4.058	3.895	5.9	2.70
Min. Stay	1.865	1.677	3.4	1.90
Instant Bookable	0.633	0.629	0.9	0.46
Review Count	4.774	4.264	2.3	2.94
Review Score	1.691	1.693	-0.1	-0.04

Revenue, and Average Daily Price. The effect on occupancy was 22.9%, but the effects on revenue and price were much larger at 289% and 525%, respectively.

The estimates reported in Table 3 show clear evidence that the new technology proved beneficial to the property managers in terms of increasing occupancy and revenue. The positive and large effect of the new technology on prices suggests that property managers increased prices significantly, where possible, and subsequently, they experienced revenue increases. The increase in occupancy shows that the property managers could utilize the information provided by the new technology to market their properties on Airbnb better.

These results also indicate a level of opacity in the market, and by providing more information about the market, market transparency improves. The very fact that property managers were able to use dynamic pricing in response to changing market conditions is indicative of the benefits of this revenue management technology in improving market transparency. In conventional economic theory, this would be equivalent to reducing asymmetric information in a market functioning inefficiently due to asymmetric information. With addi-

Table 3: Propensity Score Matching Estimates (n=4)

Variables	Occupancy	Log(Revenue)	Log(Price)
ATT	0.229***	1.431**	2.3**
	(0.038)	(0.504)	(0.936)
N		63,819	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

tional information about tourist demands and types, the property managers can distinguish the high-value tourists from low-value tourists and change prices accordingly to increase producer surplus. It can also be inferred that the tourist (consumer) surplus also goes up with the adoption of this revenue management technology. With dynamic pricing, property managers also reduce prices when demand is not high, so low-value tourists can rent a property, increasing consumer surplus.

The STR is a multi-sided platform, where the platform owner, Airbnb, is also a private agent in the market. Since we are evaluating the impact of this new technology on the welfare of tourists and property managers, we must also consider the platform owner's interest. The platform generates revenue by charging a fractional fee for each transaction, so the payoffs for the platform are directly proportional to the transaction volume. It is easy to infer that the transaction volume increased because we see evidence of increased revenue. With increases in the surpluses of property managers, tourists, and the platform, one can conclude that adopting this technology improves total welfare.

Robustness Check

To check the robustness of our estimates reported in Table 3, we also estimated the propensity score matching model using five nearest neighbors instead of 4 in the main estimation. The magnitudes, signs, and statistical significance of the coefficients are very similar to the estimates reported in Table 3. Hence, the results in Table 4 corroborate the results reported in Table 3.

As an additional robustness check, we estimate the policy's Average Treatment Effects (ATE) on the outcomes of interest using Augmented Inverse Propensity Weighting Esti-

Table 4: Propensity Score Matching Estimates (n=5)

Variables	Occupancy	Log(Revenue)	Log(Price)
ATT	0.237***	1.526**	2.482**
	(0.031)	(0.407)	(0.757)
N		63,819	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Augmented Inverse Propensity Weighting Estimates

Variables	Occupancy	Log(Revenue)	Log(Price)
ATE	0.122***	0.824***	0.933***
	(0.005)	(0.038)	(0.052)
N		63,819	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

mation (AIPW). This new method is similar to Propensity Score Matching, except it can utilize the complete sample instead of just the matched sample. It certainly gives observations that have propensity scores bounded away from 0 and 1. However, unlike Propensity Score Matching, it still offers non-zero weights to observations with propensity scores close to 0 or 1. Another desirable property is a built-in bias correction, and many researchers prefer both of these estimation methods. For reference, see Glynn and Quinn (2010).

In estimating AIPW, we used the same set of matching variables for AIPW as we used for the Propensity Score Matching method. The difference here is that were could only estimate ATE of the policy instead of ATT. The results are of AIPW estimation are provided in Table 5. We found that the signs of the effects were the same, but the magnitudes were reduced significantly. The effect on occupancy was statistically significant at 12%, which is less than the 23% effect estimated by Propensity Score Matching (PSM). The more significant difference was in the effects on revenue and average daily price. We found the AIPW estimation yielded effects of 128% on revenue and 154% on average daily price. These effects are still large, but they are smaller than those estimated using PSM, at 289% and 525% for revenue and average daily price, respectively.

Sub-sample analysis

We also conducted a sub-sample analysis for further insights into the effects of the new technology. We divided the sample into three subsets based on the level of occupancy. The first subset consisted of observations with at least 75th percentile of occupancy, the second subset consisted of the interquartile range of occupancy, and the third consisted of observations below the 25th percentile. We conducted this sub-sample analysis to test if the magnitude of the effect of technology differed when occupancy was low, medium, or high. The intuition behind this analysis was that if the occupancy is already very high or very low, there might be more potent effects on revenue and price in those subsamples than when occupancy levels were medium.

We report the results of this sub-sample analysis in Table 6 which shows that the effect of the new technology on revenue and prices was more pronounced when occupancy was below the 25th percentile. However, the effects on revenue and prices were not statistically significant in the other two subsets when the occupancy was higher. The effects on occupancy were positive and statistically significant for all subsets of the complete sample. This consistent positive effect on occupancy could indicate that there might be a power issue due to which the effects on revenue and prices were not statistically significant in subsets where occupancy was relatively high.

These results shed further light on our primary analysis to explain the large effects on revenue and prices relative to the small effect on occupancy. It further supports our argument that property managers use this new technology to engage in dynamic pricing, and this activity bears fruits particularly well when the demand for short-term housing is low.

4 Conclusion

In this paper, we estimated the Average Treatment Effect on Treated (ATT) of adopting a market data intelligence platform by PMs in the STR market on the occupancy and revenue of properties. We exploited a natural experiment in the STR market of Madrid, Spain,

Table 6: Subsample analysis based on Occupancy

Occupancy Sub-group	Occupancy	Log(Revenue)	Log(Price)
Top 25%	-0.001**	0.564	-0.129
(N = 15,784)	(.0003)	(0.327)	(0.141)
Middle 26%-74%	0.032***	0.030	-0.033
(N = 31,132)	(0.005)	(0.024)	(0.026)
Botton 25%	0.061***	1.084**	2.286***
(N = 16,534)	(0.008)	(0.141)	(0.274)

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

where a new market data intelligence platform was introduced and was adopted by a subset of PMs at different points in time. After the adoption, all the properties managed by a PM who adopted the new technology were considered treated. The natural experiment was akin to an event-study research design, and we used Propensity Score Matching to estimate the ATT using a rich set of matching variables. We found that the adoption of this market data intelligence system lead to a 22.9% increase in occupancy, 535% increase in average daily price, and a 289% increase in revenue.

We argue that these results can be attributed to a reduction in the opacity of the STR market for PMs who adopted the new system. As mentioned above, this opacity is caused by the high fragmentation of the supply side. Using a market data intelligence system that provides information about market trends, competition, and seasonal shocks in supply and demand, the PMs could make better pricing decisions, rent out properties, and design listings. Ultimately, these better decisions lead to significant increases in occupancy and revenue at the property level.

Given the fragmentation and high level of competition in the STR market, the supply side is ripe for consolidation. Low-performing PMs might be challenged by PMs leveraging information technology to scale quickly or leave the market altogether. Future research on the survival rate of PropTech adopting and non-PropTech adopting PMs in the STR market could provide valuable insights into the ramifications of adopting new information technologies. The setting of Covid-19 lends itself to such an undertaking. PMs using technology to track market trends are expected to react quickly to changes in travel patterns. Less technology-oriented Without any tools to support them in noticing changes in customer behavior and the flexibility to act, PMs might have difficulties finding guests. While some might keep their heads above water, others are potentially pushed out of the market.

References

Alyakoob M, Rahman M (2018) The Heterogeneous Impact of Airbnb on Restaurant Employment Growth, Working Paper

Aznar P, Sayeras JM, Segarra G, Claveria J (2018) AirBnB Competition and Hotels' Response: The Importance of Online Reputation. Athens J. Tour. 5(1).

Baum A, Dearsley J What is PropTech? A definition, including a sector and region overview. Retrieved (January 20, 2021), https://www.unissu.com/proptech-resources/what-is-proptech.

Baum A, Saull A, Braesemann F (2020) PropTech 2020: the future of real estate, Saïd Business School, Oxford University

Braesemann F, Baum A (2020) PropTech: Turning Real Estate Into a Data-Driven Market? SSRN Electron. J.

Buchak G, Matvos G, Piskorski T, Seru A (2018) Fintech, regulatory arbitrage, and the rise of shadow banks. J. financ. econ. 130(3).

Buchak G, Matvos G, Piskorski T, Seru A (2020) Why is Intermediating Houses So Difficult? Evidence from IBuyers. Work. Pap. (November 2019):1–76.

Calder-Wang S (2020) The Distributional Impact of the Sharing Economy on the Housing Market. Working Paper

Chetty R, Friedman JN, Saez E (2013) Using differences in knowledge across neighborhoods to uncover the impacts of the EITC on earnings. Am. Econ. Rev. 103(7):2683–2721.

Ghasemaghaei M (2020) Improving Organizational Performance Through the Use of Big Data. J. Comput. Inf. Syst. 60(5).

Ghose A, Ipeirotis PG, Li B (2012) Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. Mark. Sci. 31(3):493–520.

Gibbs C, Guttentag D, Gretzel U, Yao L, Morton J (2018) Use of dynamic pricing strategies by Airbnb hosts. Int. J. Contemp. Hosp. Manag. 30(1).

Glynn A, Quinn K (2010) An Introduction to the Augmented Inverse Propensity Weighted Estimator. Political Analysis. 18:36-56

Goldstein I, Jiang W, Karolyi GA (2019) To FinTech and beyond. Rev. Financ. Stud. 32(5).

Gutiérrez J, García-Palomares JC, Romanillos G, Salas-Olmedo MH (2017) The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. Tour. Manag. 62.

Hill D (2015) How much is your spare room worth? IEEE Spectr. 52(9).

Hunt SD, Morgan RM (1997) Resource-advantage theory: A snake swallowing its tail or a general theory of competition? J. Mark. 61(4).

Karlsson L, Dolnicar S (2016) Someone's been sleeping in my bed. Ann. Tour. Res. 58.

Ladegaard I (2018) Hosting the comfortably exotic: Cosmopolitan aspirations in the sharing economy. Sociol. Rev. 66(2).

Leoni V (2020) Stars vs lemons. Survival analysis of peer-to-peer marketplaces: the case of Airbnb. Tour. Manag. 79.

Li J, Moreno A, Zhang DJ (2015) Agent Behavior in the Sharing Economy: Evidence from Airbnb. SSRN Electron. J.

Li H, Zhu F (2020) Information Transparency, Multihoming, and Platform Competition: A Natural Experiment in the Daily Deals Market. Manage. Sci. (October).

Magno F, Cassia F, Ugolini MM (2018) Accommodation prices on Airbnb: effects of host experience and market demand. TQM J. 30(5).

Oskam J, van der Rest JP, Telkamp B (2018) What's mine is yours—but at what price? Dynamic pricing behavior as an indicator of Airbnb host professionalization. J. Revenue Pricing Manag. 17(5):311–328.

Porter L, Fields D, Landau-Ward A, Rogers D, Sadowski J, Maalsen S, Kitchin R, Dawkins O, Young G, Bates LK (2019) The politics of digital transformations of housing. Plan. Theory Pract. 20(4):575–603.

Saull A, Baum A, Braesemann F (2020) Can digital technologies speed up real estate transactions? J. Prop. Invest. Financ. 38(4).

Siniak N, Kauko T, Shavrov S, Marina N (2020) The impact of proptech on real estate industry growth. IOP Conf. Ser. Mater. Sci. Eng.

Visser G, Erasmus I, Miller M (2017) Airbnb: The emergence of a new accommodation type in Cape Town, South Africa. Tour. Rev. Int. 21(2).

Wachsmuth D, Weisler A (2018) Airbnb, and the Rent Gap: Gentrification Through the Sharing Economy Forthcoming in Environment and Planning A: Economy and Space. Environ. Plan. A Econ. Sp. 50(6).