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Property management technology adoption in the short-term housing rental market

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Abstract
We show evidence of the impact providing information on market conditions (supply growth, demand patterns, pricing trends, and competitor rates) on pricing in the short-term rental market. Using a sample of 2196 housing units over 18 months available on Airbnb in Madrid, Spain, we observe property managers' adoption of this technology at different points in time for 16% of our observations. Our propensity score matching estimates support the evidence of greater market transparency obtained through the adoption of this technology, with a significant increase in revenues obtained through a reduced average daily price and increased occupancy. Our results are robust to several model selections dealing with a potential endogeneity issue. We also show some preliminary evidence of property managers increasingly engaging in dynamic pricing after adopting this technology. Mainly, revenue growth seems to be generated through a small price drop leading to a rise in occupancy at the top end of the price distribution rather than at the bottom end, where a significant and much higher price drop is not able to generate the necessary occupancy growth to obtain an overall increase in revenues.

KEYWORDS
short-term rental market, information technology, market transparency, PropTech

1 INTRODUCTION

Real estate is the world's most valuable asset class and a prime component of global physical capital. However, 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 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] A plethora of new technologies, collectively called PropTech, are currently driving this transformation (Braesemann & Baum, 2020; Baum et al., 2020; Luque, 2020).

One of the most affected real estate sectors by PropTech is the short-term rental (STR) housing market, and the disruption caused by Airbnb is now well known (Barron et al., 2020; Garcia-López et al., 2020). By the end of 2020, a total investment volume of over USD 74.2 billion was recorded, with an even distribution of investment across PropTech companies in the STR market. This represents an increase of USD 14.73 billion as compared to 2014. With the disruptive impact of PropTech companies targeting this market and their relative investments, the STR market has been on a steady growth trajectory.[2]

This market consists of housing units for rental for short periods (usually between 1 and 7 days). The supply side is typically composed of property managers (PMs) and independent hosts. Independent hosts are individuals who let their homes when they are out of town or are willing to vacate their houses to create an additional income stream. The demand side consists of consumers (most commonly travelers). While independent hosts typically participate in the market for financial, social, and cultural reasons, PMs essentially operate as 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 supply volatility, intense competition, and high market fragmentation. Given the difficulty in gathering data on market rates and occupancy levels to 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 significant challenges for PMs in the STR market (Gibbs et al., 2018).

In this paper, we analyze how information acquisition by PMs on the performance of STR housing markets (e.g., market rates and demand) can impact their occupancy levels, daily pricing, and revenues. In particular, we aim to quantify the effects of adopting a PropTech 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 knowledge of STR market trends, and the pricing algorithm's suggestions do not bias them. Hence, PMs with access to this information technology should be better equipped to make informed and tailored decisions about their properties' pricing, investment, and listing.

[1] See the 2020 PropTech Global Trends Barometer.

[2] The growth rate of start-up creation was 47% between 2014 and 2020. Data source: Venture Scanner.

To test this hypothesis, we gained access to data from the market intelligence data dashboard provided by TII, which tracks and analyzes over 34 million daily STR listings globally. The company is a global leader and systematically presents these data in the form of a dynamic dashboard for its clients—in particular PMs—to monitor and optimize future rates and occupancy, track demand and their competitors' portfolios, and effectively grow their inventory.

Since the STR market is highly segmented according to location and property characteristics, we focus on a given city for our study. In particular, we investigate the impact of TII's dashboard on the performance of STR PMs operating in Madrid, Spain. Madrid is a significant and vibrant metropolis that represents an appropriate laboratory for our purpose. The metropolitan area's population is around 6.5 million, 3.2 million of whom live in the city. As of July 2018, Madrid had 22,292 properties for STR usage with an average daily rate (ADR) of 126 euros in the downtown area. Our data sample consists of 2196 STR properties listed on Airbnb, managed by 63 PMs over 18 months, starting from July 2018 and ending in December 2019.

In our panel dataset, we observe occupancy rates, revenue, property-defining characteristics, and subscription status to TII'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. In contrast, the treatment is defined as a PM's subscription to TII's dashboard services. The treatment group amounts to 16% of the 2196 properties in our sample. There is some covariate imbalance between the treatment and control groups, but we can control for most of the confounding variables, given the richness of the data.

Our identification strategy is based on observing the choice of PMs' subscriptions to TII's services (treatment) in the STR market in Madrid at different points in time. We observe the treated units before and after the treatment and the control units during the same periods. This variation in treatment status allows us to identify a quasi-natural experiment in the data. This setup could also be thought of as an event study research design. We define the treatment and control groups based on the adoption of this new technology. As the adoption of new technology is chosen at the PM level, we assign the treatment status to all properties of a PM from when the PM in question subscribed to the new technology until the end of the sample period or until their subscription withdrawal. All observations for properties whose PMs never adopted the new technology throughout our sample period form the control group, alongside all observations of properties managed by platform-subscribing PMs before their subscription.

To estimate the average treatment effect on the treated (ATT), we use propensity score matching (PSM). The set of matching variables is reasonably large, making simple matching estimation methods computationally infeasible. In the first stage of the estimation procedure, we use a Probit model and reduce the dimension of the matching variables set by using the PSM model to estimate the probability of the treatment variable as a function of all the matching variables. In particular, we estimate, for each observation, the probability of receiving the treatment. In the second stage, we use the estimated propensity scores to perform the matching, with the treatment group tending to be smaller than the control group, as the matching process allows for one-to-many matches.

The estimation results of the PSM model show that the ATT of using the market data intelligence platform is an increase of 13.3% in occupancy, alongside a decrease of 15.1% in the average daily price and an overall 11.6% increase in revenues. We also estimate the PSM model with different matches. For instance, we can use five and one rather than four neighbors as in the main table. Regardless, our findings do not change. These results strongly suggest that PMs can benefit from the adoption of this new technology as they manage to achieve an increase in revenues by reducing the average pricing to obtain a higher occupancy. The effect on prices indicates that the PMs used dynamic pricing to achieve these gains in revenue and occupancy. Particularly, we found that the revenue increase was obtained in the higher part of the price distribution rather than the lower part. These results further infer that this new technology improved market transparency, reducing asymmetric information. Because the surplus for PMs, tourists, and the platform owner increased, the adoption of this new technology was welfare-enhancing.

Furthermore, we conduct a series of robustness tests using alternative methods, such as augmented inverse propensity weighting (AIPW), as well as the lagged dependent variable model, the Heckman two-stage model, and the quasi difference-in-difference model. As a robustness check, our main findings are confirmed both in significance and magnitude. We find that coefficients had matching signs and magnitude in line with our main results in the PSM table. A higher coefficient (in absolute terms) in the AIPW model could be due to the differences in estimating the average treatment effects (ATE). These robustness checks corroborate our main results from PSM by establishing the invariance to alternative model specifications and methods.

We further investigate the pricing behavior in the STR market by quantifying the difference between the volatility in prices of the treatment versus the control group. We find that the volatility in the prices of treated properties is higher than the price volatility of properties in the control group. This was true across all PMs who adopted the TII platform. From this evidence, we infer that the PMs subscribing to the TII services probably entered into a more dynamic pricing strategy by changing the prices of their properties more often than PMs not joining the TII platform. Moreover, our estimation at different ranges of the price distributions reveals that the increase in revenues is mainly achieved at the high end of the price distribution, where a small reduction in price manages to increase occupancy significantly. On the contrary, at the low end of the price distribution, we find that a significant reduction in price does not manage to increase occupancy enough to obtain an overall increase in revenues.

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 & Dearsley, 2017; Buchak et al., 2018; Fields, 2019).[3] 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, among other things. This paper provides contextual data on the PropTech landscape and focuses on technological solutions specific to the STR market.

The STR market is highly fragmented, being further aggravated by the volatility of supply and the 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, J. Li et al. (2016) showed how a reduction in information transparency in the online market for daily deals led to a reduction in seller-side multihoming and also a reduction in the profitability of the marketplace platform with less transparency. Ghose et al. (2012) show how market transparency can be reduced by using data from social media platforms to incorporate into demand estimation models and 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 & Baum, 2020) and superior

[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. (2021) study the trading behavior of iBuyers (nonbank 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 in mortgage lending.)

organizational performance of firms that are aware of and exploit the value of data generated in renting, buying, and managing real estate (Ghasemaghaei, 2020). We contribute to this literature by empirically demonstrating that PMs in the STR market see their revenues and occupancy levels significantly increase after adopting 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 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 multiunit hosts[4] (Aznar et al., 2018; Gibbs et al., 2018), but not the wide spectrum of technology adoption 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; H. Li and Zhu, 2021) 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 effects of adopting an information technology solution that guides PMs in setting their optimal prices to maximize occupancy and revenue. Our research shows that independent hosts are underperforming with respect to more informed market players because they have not adopted technology that increases market transparency in the STR market. Possible explanations for the lack of rate adjustments[7] by Airbnb hosts are a lack of motivation, professionalization (measured in terms of the number of properties under management; see H. Li and Zhu, 2021, and Oskam et al., 2018), experience, and an extensive Airbnb pricing tool (see Hill, 2015). Our study provides evidence that the use of 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 Sections 3 and 4, we develop the empirical model, define the

[4] That is, 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 multiunit hosts. The discrepancy in the performance of single-unit and multiunit hosts presumably exists because among the multiunit 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 (2016), Visser et al. (2017), and 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 by Leoni (2020), who analyzes 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. H. Li and Zhu (2021) identify that in Chicago, multiunit hosts have a 16.9% and 15.5% higher ADR and OCC (Occupancy) 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 TII 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 in a better informed than usual.

identification strategy, and report the results from the estimated models and robustness tests. Section 5 concludes with a discussion of results and their policy implications.

2 | SETTING AND DATA

In this part of the paper, we provide information about TII and its market data intelligence platform in Section 2.1, and we present the summary statistics of the data sample used for our empirical analysis in Section 2.2). In the Appendix, we also provide details about the changing nature of the STR market due to the introduction of PropTech (Section A.1), while we describe the local STR market in Madrid, Spain (Section A.2).

2.1 | Transparent Intelligence, Inc.

The TII dashboard platform first entered the STR market in Madrid, Spain, at the end of 2017/beginning of 2018. Its existence and availability became very well known within few months and its subscription rate was such that it was affordable even for PMs managing a small number of properties. The subscription is more economical for larger PMs, but the dashboard is not aimed at either very large (c.ca 500+ assets under management)—which would need a lot of raw data with in-house built visualization tools built in-house—or the very small ones (c.ca 5 or less assets under management). The annual fee of 250 euros per month for a basic service (with a premium service at 500 euros per month offered from September 2021) is not significant as it represents a flat annual fee of 3000 euros for each PM.

Most of the ones they targeted had +25 units as the conversion would be higher in this market segment. The ideal spot is between 25 units and 500 units (the tool is not effective PMs that are too large either, as they would require more raw data; they have their own Business Intelligence (BI) stack and do not want to have an external tool for visualization but rather their own system, therefore only needing raw data as they probably already have a data team to develop proprietary visualization tools).

As a provider of market intelligence data, TII monitors and analyzes over 34 million STR listings worldwide and their activity on the booking platforms Airbnb, Vrbo, and Booking.com by scraping their data on a daily basis.[8]

During the scraping process, TII indexes the three booking platforms by the order in which potential guests browse their listings to obtain all publicly available data, such as property type and subtype, average daily rate, host identifier (when available), and property address (when available). As these platforms often use different names to refer to the same variables, TII 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 by month to collect historical performance data of those STR properties. The aggregation of proprietary and publicly available data from the most significant booking platforms allows TII to provide its clients in the STR market with information on market conditions, such as supply growth,

[8] 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. For instance, it is well known that Airbnb slightly alters the location of a property to ensure host privacy. (See Wachsmuth and Weisler, 2018, who show that number of properties is between 0 and 500 ft.)

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 TII'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 their competitors performance. Without the insights shared by data intelligence providers such as TII, 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. TII's service allows PMs to replace 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' portfolios and make more reasoned decisions related to pricing, inventory growth, and listing of properties on booking platforms[9] to maximize revenue. To equip PMs with the necessary knowledge to make informed decisions on these parameters, TII provides clean tabulated data and visualizations using interactive maps and graphs on its dashboard. The data are accessible on a market and competitor level in all indicators.

For PMs to optimize their pricing, TII 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 for a given property fluctuates frequently. By tracking such changes, PMs can react proactively. Smart Rental PRO gives PMs a clear picture of their pricing positions relative to the market, enabling them to adjust their rates when they deviate significantly from the market average, that is, 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 (the number of bedrooms, capacity, etc.) listed in the market. To help with this, TII allows for comparing similar properties by using benchmarks in terms of the 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 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.

TII employs advanced analytics to calculate occupancy rates based on the public and proprietary datasets 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, TII uses proprietary data on reservations and combines it with listing 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[10] of the market for every day in the future.

To support its clients in effective inventory growth, TII 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 and their competitors' locations of growth.

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

[10] That is, the minimum number of days the STR is to be rented for by the guest.

TII also allows PMs access to detailed information on each property, including current 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 TII'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.

2.2 | 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 dataset is TII. We collected a sample of 2196 housing units managed by 63 PMs for a time period starting from July 2018 and ending in December 2019, constituting 18 months of data in total.[11] The dataset contains monthly frequency information about the housing unit's occupancy rate, pricing, generated revenues, and defining features, such as the number of bedrooms and bathrooms, size, and building type, among other important details. The dataset has a panel structure whereby 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 dataset also has information about the PM of each housing unit and whether they adopted the TII market data intelligence system. PM-specific variables include their past profit margin, number of employees, and total assets. We collected these data from the Orbis and Registro Mercantil databases in February and March 2022. These variables help us account for any variation in the outcome variable related to PM-specific variables, even if we also estimate models with PM-fixed effects to consider other unobservable characteristics. For the treatment variable, we precisely define it by using market data intelligence system adoption dates by the PMs. This information was instrumental in recognizing and exploiting this quasi-natural experiment in the market. The market data intelligence system by TII was adopted by a subset of all PMs at different points in time within the sample period. As explained later in Section 3, this quasi-natural experiment generated variation akin to an event study, and we used PSM to estimate the ATT. We further conducted robustness checks using the AIPW 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 22,320 combinations of housing units and months. Out of these 22,320 observations, 18,799 (84%) are in the control group and 3521 (16%) are in the treatment group. Columns 1 and 2 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 control 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 to compare the means of two variables.

[11] The 63 PMs were identified and confirmed by TII to be professionals operating in Madrid during the time period mentioned above

TABLE 1 Summary statistics and covariate balance.

Variable	Control (1)	Treatment (2)	Difference (3)	*p*-Value (4)
Occupancy	0.72	0.78	0.06	0.000
Revenue	3181.86	3458.86	277.00	0.000
Average daily price	150.81	149.92	−0.89	0.710
Air conditioning	0.90	0.97	0.07	0.000
Breakfast	0.02	0.00	−0.02	0.000
Doorman	0.08	0.00	−0.08	0.000
Gym	0.01	0.00	−0.01	0.000
Heating	0.93	0.98	0.05	0.000
Internet	0.33	0.01	−0.32	0.000
Pool	0.04	0.01	−0.03	0.000
Suitable for events	0.02	0.00	−0.02	0.000
TV	0.95	0.96	0.01	0
Wheelchair access	0.04	0.03	−0.01	0.070
Bedrooms	1.61	2.01	0.40	0
Beds	2.56	2.89	0.33	0
Bathrooms	1.49	1.59	0.10	0
Capacity	4.42	5.41	0.99	0
Minimum stay	2.57	2.49	−0.08	0.450
Instant bookable	0.84	0.84	0.00	0.940
Review count	19	6.36	−12.64	0
Review score	2.74	2.25	−0.49	0
Total assets	2,320,121.49	4,433,628.21	2,113,506.72	0
Profit margin	4.66	0.78	−3.88	0
Number of employees	24.51	64.63	40.12	0
N	18,799	3,521		

Note: This table reports, before matching, average values for control and treatment groups in the first two columns, and the test for differences between means and its *p*-values, respectively in columns 3 and 4. The first three variables represent the key dependent variables used in our estimation models: occupancy rates (in percentage), monthly revenue (in euros), and average daily price (in euros). Other variables reflect the characteristics of housing units and PMs and they are used as controls to account for heterogeneity in all our estimation models.

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 6% higher, on average than in the control group. The revenue in the treatment group is also higher than that of the control group by $277 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 preexisting from this simple comparison.

An interesting point to note here is that, on average, the housing units in the treatment group have fewer essential amenities than those in the control group. Amenities like breakfast, a doorman, free Internet, and a swimming pool are more likely to be available in the control group housing units than the treatment group. This might be indicative of the effectiveness of the market data intelligence system in helping PMs set 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 stay than those in the control group. This could also indicate the effectiveness of the market data intelligence system in helping PMs to rent out properties to a larger group of potential tenants who need a housing unit for a shorter time.

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

In Table 1, we also see that the treated units have a higher number of bedrooms, beds, bathrooms, and 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. Another source of bias can arise from differences at the level of PMs which may affect their decisions to adopt the new technology and also the occupancy, revenue, and prices charged by the PM on its properties. It is possible that some of the variation in the outcome variables that is explained by the treatment variable is actually the variation in PM ability, effort, usage, growth ambition, or some other characteristics. To account for any such differences, we collected additional data on PMs past profit margins, number of employees, and total assets. We find these variables (alongside the inclusion of timing, location, PM fixed effects, and further robustness tests) to be useful in reducing the concern of a potential bias in our estimates of the treatment effect caused by PM heterogeneity. However, we also acknowledge that we may not have a perfect identification strategy, and our approach may suffer some limitations due to the PSM sources of identification being based on the selection of observables. Unfortunately, such limitation is also due to data availability, and we could not fully deal with it in this study. We hope that several robustness tests presented in this paper mitigate the concern and offer further reassurance of the important economic impact technology has in the formation and setting of real estate asset pricing.

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 dataset allows us to control for these effects as there is significant variation in these confounding variables.

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 PSM and AIPW methods. These visualizations are presented in Figure 1, with panels (a), (b), and (c), respectively, representing occupancy, revenues and price. Essentially, these graphs show how the outcome variable changes when the treatment variable switches from 0 to 1, after eliminating any variation in the outcome variable due to any confounding variables. The difference from left to right can be viewed as a preliminary visual indication of the causal effect. Low (close to 0) values of residualized treatment refer to the control group, while high (close to 1) values of this variable refer to the treatment group. The number of bins in the treatment group appears small because, as noted in Table 1, there are fewer observations in the treatment group than in the control group.

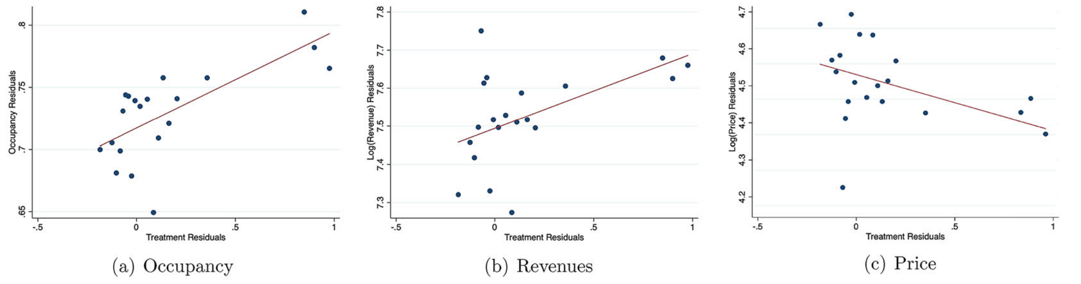


FIGURE 1 Binscatter plot by treatment for occupancy (a), revenues (b), and price (c). The three scatter plots show the change in the outcome variable—occupancy rate in panel (a), revenues in (b), and daily price in (c)—when a property manager subscribes to the TII platform—i.e. the treatment changes from 0 to 1. [Color figure can be viewed at wileyonlinelibrary.com]

All these three graphs show initial anectodal (and correlational in nature) evidence of the potential positive effects of technology on occupancy (a) and revenues (b) and the negative impact on pricing (c). We will formally test these relationships in the remaining part of our paper.

Another source of variation in the properties that may lead to a bias in the coefficient of the treatment variable is the variation in property micro-locations (as different roads may differ). The occupancy, price, and revenue of a property are likely factors of its micro- (and not only broader) location in the city in terms of distance to the city center or quality of the neighborhood, and these factors could affect the decision of the PM to subscribe to the services of TII. Furthermore, even if we control for macro-location (broad administrative areas within the city), we do not, unfortunately, have access to the micro-(road level-)location information to construct such measures. To mitigate this issue, we remind the reader that we observe a rich set of other defining features of properties (see Table 1), which should capture (at least partially) the effects of location to a significant extent. It is reasonable to assume that there are some property-defining features that are different between properties in the downtown and properties in the suburbs. For example, properties in the downtown area have less area, smaller or fewer rooms, less capacity, access to a gym, etc.

It is also important to note that our sample dataset is taken entirely from Airbnb, and we claim that it is representative of the entire STR market in Madrid. While it is unlikely that all properties available for STRs will have listings on Airbnb, we argue that the ones that are not, are likely to be small in number. Their absence from the prevalent online marketplace already excludes them from competing with the other properties. To the extent that we do not count large hotel chains in our target population, which prefer not to make listings on Airbnb, it is reasonable to assume that our sample, which consists of all the listings for the city of Madrid for the period stated above, is a representative sample of the target population. Hence, any descriptive statistics and estimates from the empirical analysis should be interpreted as valid empirical counterparts of the true population parameters and estimands.

To mitigate the concern about potential effects of unobservable efforts of PMs that may have led to bias in our estimates of the ATT of the treatment, we present Figure A.1 (see the Appendix), which shows the changes in a number of properties and revenues by the sample of treated and untreated PMs over time. These two panels give evidence of a similar behavior for the two groups in both metrics, with panel (b) showing a narrower gap between the two, probably due to the increase in revenues obtained after joining the TII platform. Furthermore, Figure A.2 (see the

Appendix) shows the changes in the number of properties owned by the treated and untreated PMs over time. These graphs clearly show that none of the major changes coincided with the time of treatment as indicated by the red line in panels (a), (b), and (c), with the number of properties managed by PM2 remaining the same for much of the sample, while those managed by PM1 and PM3 initially increasing and later decreasing slightly. Moreover, even if the identity of the PMs is unknown to the authors for confidentiality reasons, the TII platform has verified that no change of management in the treated PMs has happened over the 18-month period of our sample. These information should reduce the concern of unobservable PM characteristics affecting the PM strategies and therefore leading to a change in pricing, occupancy, and revenues.

3 | EMPIRICAL STRATEGY

Our objective is to estimate the 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 that can 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 span of a month. The population estimands of interest are the ATTs of the above-defined treatment on each outcome variable.

As noted in 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 spanning from July 2018 to December 2019. As noted previously, we observe 2196 individual housing units operated by 63 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, the number of bedrooms, swimming pool availability, heating status, etc.[12]

We also observe some PM-specific characteristics. As a flat fee is applied to the subscribers, even if this fee is very small compared to PMs revenues, we may still observe that larger PMs are more likely to subscribe as the fee can be spread across more properties. In addition, we can also reasonably find that less profitable PMs may see joining the platform as a potential success factor, which is not necessarily believed to be a priority for PMs that are already more successful. For this reason, in fact, Table 1 shows that PMs with a larger amount of total assets, smaller profit margins, and a larger number of employees are more likely to choose to subscribe to the TII platform. As a result, we include PM-related variables to the matching criteria in our PSM model to correct for this potential self-selection bias and heterogeneity in the PM ability, growth ambition, and effort level. Reduced distances between treatment and control groups are observed in Table 2. Furthermore, PSM results suggest that, if we compare the likelihood of PMs with similar total assets, profit margins, and employee numbers to join the platform, we still find a positive impact (lower prices, higher occupancy, and greater revenues) from the adoption of this technology.

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 the free movement of prices and information revelation.

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

TABLE 2 Covariate balance.

Variable	Treatment	Control	Bias	*t*-stat
Air conditioning	0.9662	0.9571	3.7	1.94
Breakfast	0.0006	0.0000	0.7	1.41
Doorman	0.0015	0.0009	0.3	0.71
Gym	0.0039	0.0003	4.2	3.21
Heating	0.9761	0.9866	−5.1	−3.19
Internet	0.0143	0.0160	−0.5	−0.55
Pool	0.0090	0.0026	4.3	3.43
Suitable for events	0.0015	0.0020	−0.5	−0.51
TV	0.9621	0.9669	−2.3	−1.07
Wheelchair access	0.0329	0.0256	3.9	1.78
Bedrooms	2.0114	2.0876	−7.1	−2.80
Beds	2.9172	2.9933	−4.8	−1.93
Bathrooms	1.5967	1.6513	−7.3	−3.50
Capacity	5.4765	5.4407	1.7	0.73
Minimum stay	1.4831	1.2450	4.5	4.35
Instant bookable	0.8781	0.8755	0.7	0.33
Review count	6.5820	5.1054	4.7	6.51
Review score	2.3279	2.1722	6.9	2.86
PM profit margin	1.0760	1.0178	0.3	0.35
log(PM total assets)	15.2920	15.3070	−1.3	−3.08
log(PM number of employees)	4.1604	4.1809	−2.1	−3.78
N	18,799	3,521		

Note: This table reports, after matching, average values for control and treatment groups in the first two columns, and the test for differences between means and its *p*-values, respectively in columns 3 and 4. The variables reflect the characteristics of housing units and property managers (PMs), and they are used as controls to account for heterogeneity in all our estimation models.

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 TII's market data intelligence dashboard, we do not have information about a different provider of such information. TII is the global leader in providing data intelligence for the STR industry, so we assume that the information provided by TII has a clear advantage over any other source of aggregated information available to PMs in the STR market of Madrid, Spain.

3.1 | PSM model

The quasi-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 the PM subscribed to the new technology until 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 ATT, we used PSM. 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 Probit model. Given the estimated model, we can estimate the probability of each observation of receiving treatment. In the second stage of the estimation procedure, we use the estimated propensity scores to coordinate the match. 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 one-to-many matches.

We chose PSM to estimate the ATT because it is well-suited to exploit this quasi-natural experiment in a window-study design explained above. The treatment variable is such that a subset of observations after a particular time receives the treatment. Furthermore, we observe a rich set of variables that are potential confounders of the treatment effect; that is, they likely affect both the treatment status and the outcome variables of interest, namely occupancy, price, and revenue. To remove the bias created by 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 is that there could be other unobservable confounding variables 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 explain most variation in the outcome variables of interest. Hence, it is likely that the remaining unobservable variables will not be different from pure noise.

3.2 | Common support and covariate balance

To use PSM estimation, we first check the common support of the matching variables between the treatment and control groups. Figure 2 shows a small right tail region in the distribution of the propensity scores, where we have observations in the treatment group but not in the control group. A standard solution is to trim the dataset 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.

Table 2 reports the covariate balance after successful matching based on the estimated propensity scores. Compared to Table 1, we can observe a more balanced panel in the matched dataset. The mean differences between the treatment and control groups are significantly lower for most variables. Additionally, the mean differences are statistically insignificant for most (albeit not all) variables in the matched panel, unlike for the starting sample dataset, where most mean differences are statistically significant.

4 | ESTIMATION RESULTS

Table 3 reports the estimates of the PSM model. The ATT of subscribing to TII's technology was both statistically and economically significant for revenues (11.6%). This outcome was mainly

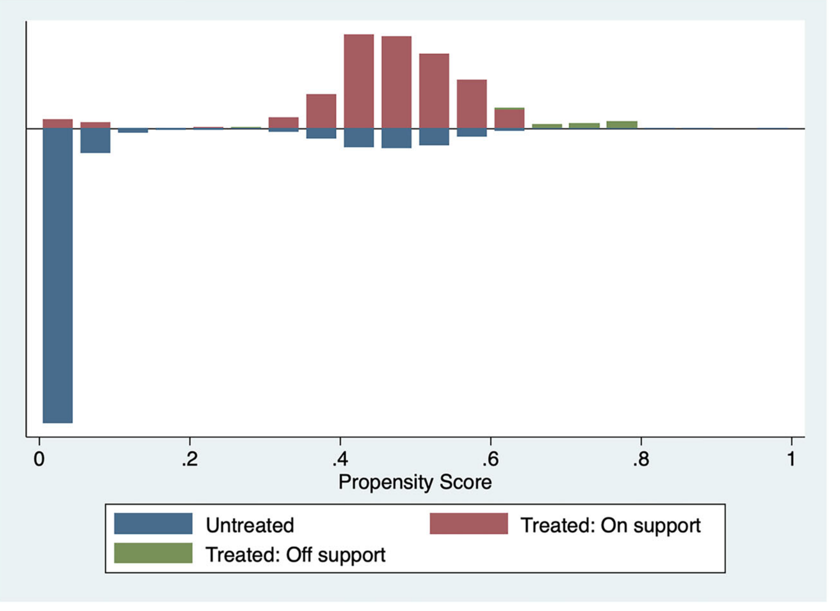


FIGURE 2 Common support. This figure shows the common support of the matching variables and the potential need to trim the data when observations in the treatment group are not supported by observations in the control group. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 PSM estimates ($n = 4$).

Variables	Occupancy	Revenue	Price
ATT	0.133***	0.116**	−0.151***
	(0.009)	(0.052)	(0.021)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
Observations	18,799	18,799	21,579
Treated	16%	16%	16%
Control	84%	84%	84%

Note: This table presents the estimates of a propensity score matching (PSM) model with four nearest neighbors, where we estimate the effect of the subscription to the Transparent Intelligence, Inc. platform on occupancy, revenue stream, and average daily price. Robust standard errors are in parentheses. The heterogeneous characteristics of the individual unit (Property vars.) and property manager (PM vars.) are included in all models.
The significance of coefficients is represented as follows: ***p <0.01, **p <0.05, * p < 0.1

driven by an increase in occupancy associated with a decrease in pricing (−15.1%) and an increase in occupancy by 13.3%.

The estimates hereby reported show clear evidence that the new technology proved to be beneficial to PMs who managed to increase occupancy and, therefore, revenues with a downward pricing adjustment. The positive and significant effects of the new technology on prices suggest that PMs increased prices significantly, where possible, and subsequently, they experienced revenue increases. The overall results, therefore, show that PMs could utilize the information provided by the new technology to market their properties on Airbnb more effectively, setting a price that maximizes occupancy and revenues.

At first sight, it may appear that the more considerable magnitude of price drop compared to the increase in occupancy should lead to an overall decrease in revenues (especially because occupancy is also quite high on average, above 70%). However, these values only represent average outcomes, and they do not necessarily reflect the actual picture. PMs typically apply a range of prices during the year, depending upon the level of demand (e.g., high and low season). Therefore, a percentage drop from high prices leads to a different impact on revenues if we compare it to the same percentage drop from low prices. Therefore, PMs may actually benefit from the information gathered on the TII platform and apply price changes to increase occupancy heterogeneously across the price range of each property. For example, a bigger percentage drop in price may be deemed to be necessary more at low-price levels (in low season) and less so at high-price levels (high season). Moreover, for the latter case, PMs may even increase prices if they believe that the high demand and their competitive position (e.g., as they were previously charging lower prices than their competitors) allow them to do so. In this case, on average, we may still record a drop in prices, but, at the same time, we may also report an increase in revenues (as the occupancy levels are increasing and maybe even more so for high-price ranges). In fact, the percentage drop from low prices would result in a smaller impact on revenues, and overall the amount of revenues may still increase because, during high demand (and normally associated high prices), the need to reduce the pricing is weaker. This argument will also be strengthened by our discussion on the dynamic pricing PMs may enter, thanks to the better information they access when they subscribe to the TII platform.

These results also indicate a level of opacity in the market, and, by providing more information about the market, platforms such as TII should improve market transparency. The very fact that PMs are 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 that is functioning inefficiently due to asymmetric information.

With the additional market information, PMs can learn to distinguish high-value tourists from low-value ones and change prices accordingly to increase the occupancy and revenue generated from their properties by changing prices accordingly. In economic terms, this situation leads to an increase in producer surplus. On the other hand, as occupancy increases, more of the consumer demand for housing is met, thereby increasing the consumer surplus. It should be noted that, in this case, the primary decision in the hand of a PM is that of pricing and we infer that by changing prices more frequently in response to market demand, the PM engages in dynamic pricing, leading to an improved outcome. As subscription expenses are relatively small, the overall net gain should still be positive.

The STR is a multisided 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 PMs, we must also consider the platform owner's interest. The platform generates revenues 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 revenues. With increases in the surpluses of PMs, tourists, and the platform, one can conclude that adopting this technology also improves the total welfare.

4.1 | Robustness tests

To check the robustness of our estimates reported in Table 3, we hereby present a series of results we obtained with several other estimation models and procedures.

TABLE 4 PSM estimates with different numbers of neighbors.

Variables	Occupancy	Revenue	Price
Panel A: Five neighbors			
ATT	0.128***	0.101**	−0.160***
	(0.009)	(0.049)	(0.020)
Panel B: One neighbor			
ATT	0.163***	0.339***	−0.141***
	(0.018)	(0.115)	(0.038)
Information for both panels			
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
N (treated)	3,521 (15.8%)		
N (control)	18,799 (84.2%)		

Note: This table presents the estimates of a propensity score matching (PSM) model with five (panel A) and one (panel B) nearest neighbors, where we estimate the effect of the subscription to the Transparent Intelligence, Inc. platform on occupancy, revenue stream, and average daily price. Robust standard errors are in parentheses. The heterogeneous characteristics of the individual unit (Property vars.) and property manager (PM vars.) are included in all models.
The significance of coefficients is represented as follows: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.1.1 | PSM with different numbers of neighbors

First, we also estimate our PSM model using five nearest neighbors instead of four as in the baseline model. The magnitude, sign, and statistical significance of coefficients are very similar to the estimates reported in Table 3, with a decrease in the positive impact on revenues (0.101 vs. 0.116) driven by both a relatively stronger decrease in price (−0.160 vs. −0.151) and a slightly lower increase in occupancy (0.128 vs. 0.133)—see Table 4. Moreover, we stress test our model by using only one neighbor and therefore assuming the presence of thin markets (or a small platform with not enough units to generate enough neighbors for the matching), and our main results still hold. Revenues increase more significantly (0.339) due to a slightly lower decrease in price (−0.141) and a much higher increase in occupancy (0.163).

4.1.2 | Augmented inverse propensity weighting

As an additional robustness check, we estimate the policy's ATE on the outcomes of interest using AIPW. This new method is similar to PSM except it can utilize the complete sample instead of just the matched sample. It certainly includes observations that have propensity scores bounded away from 0 and 1. However, unlike PSM, it still assigns nonzero weights to observations with propensity scores close to 0 or 1. Another desirable property is a built-in bias correction, and many researchers use both of these estimation methods to support their analyses. For reference, see Glynn and Quinn (2009).

In estimating AIPW, we used the same set of matching variables for AIPW as we used for the PSM method. The difference here is that we could only estimate the ATE of the policy instead of its ATT. The results of AIPW estimation are provided in Table 5. We found that the signs of the effects were the same, but the magnitudes were significantly larger. The effect on occupancy was statistically significant at 14.1%, which is only slightly more than the 14.1% effect estimated by

TABLE 5 AIPW estimates.

Variables	Occupancy	Revenue	Price
ATE	0.141***	0.304***	−0.126***
	(0.003)	(0.016)	(0.019)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
N (treated)	3,521 (15.8%)		
N (control)	18,799 (84.2%)		

Note: This table presents the estimates of an augmented inverse propensity weighting (AIPW) model, where we estimate the average treatment effect of the subscription to the Transparent Intelligence, Inc. platform on occupancy, revenue stream, and average daily price. Robust standard errors are in parentheses. The heterogeneous characteristics of the individual unit (Property vars.) and property manager (PM vars.) are included in all models.
Abbreviations: ATE, average treatment effects; PM, property manager.
The significance of coefficients is represented as follows: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

PSM. The greater significant difference was in the effect of the treatment on revenue. We found the AIPW estimation yielded an effect of 30.4% on revenue, which is much bigger than the 11.6% effect using PSM. Lastly, the effect on level price was a 12.6% reduction, in line with the 15.5% in our baseline model. Overall, the AIPW coefficients confirm the robustness of our results as they are all statistically significant and comparable (both in sign and order of magnitude) with the ones from the main PSM model in Table 3.

4.1.3 | Lagged dependent variable model

To further corroborate our results, we use a value-added model commonly used in labor and educational studies, which is an ordinary least squares (OLS) estimation with lagged dependent variables and property and time fixed effects:

$$y_{it} = a_{it} + \beta \times TIItechnology_{it} + \lambda \times controls_{it} + \theta \times y_{it-1} + v_i + \mu_t + \epsilon_{it} \tag{1}$$

where y_{it} represents occupancy (occ_{it}), revenue (rev_{it}), and price ($price_{it}$) in the separate three regressions; y_{it-1} is its lag; $TIItechnology_{it}$ is a dummy equal to one if the property manager is registered on the platform for unit i at time t and zero otherwise; $controls_{it}$ are a set of control variables representing the characteristics of both unit and property manager; v_i, μ_t, and ϵ_{it} represents the unit and time fixed effects and error term, respectively. This approach can inform the readers about whether the subscription to TII's dashboard platform can explain any changes in the outcome variable, having adjusted for the autocorrelation pattern and value of past information.

Table 6 presents the results for our value-added model. Columns (1), (2), and (3), present the results for occupancy, revenues, and price, respectively. The lagged dependent variable (that can also be seen as an autoregressive coefficient) is positive and falls within the range 0–1 as expected. Consistently with our PSM and AIPW model, we find that PMs' subscription to the platform ($TIItechnology$) has a positive effect (0.164) on revenues driven by a downward adjustment in price (−0.081) leading to a higher level of occupancy (0.100). All coefficients are significant at the 99% level and they are similar to the ATT coefficients shown in Tables 3–5.

TABLE 6 Lagged dependent model estimates.

Variables	Occupancy	Revenue	Price
TII technology	0.100***	0.164***	−0.081***
	(0.005)	(0.016)	(0.008)
lagged dependent	0.173***	0.050***	0.238***
	(0.005)	(0.016)	(0.008)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
Adj. R-squared.	0.467	0.520	0.812
Observations.	20,124	20,124	19,233

Note: This table presents the estimates of a lagged dependent model, where we estimate the effect of the subscription to the TII platform on occupancy, revenue stream, and average daily price by adjusting for the autocorrelation pattern and value of past information. Robust standard errors are in parentheses. The heterogeneous characteristics of the individual unit (Property vars.) and property manager (PM vars.) are included in all models.
Abbreviations: PM, property managers; TTI, Transparent Intelligence, Inc.
The significance of coefficients is represented as follows: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

TABLE 7 Heckman two-stage model estimates.

Variables	Occupancy	Revenue	Price
TII technology	0.017**	−0.037	−0.039**
	(0.008)	(0.032)	(0.015)
imr	−0.004	0.025	0.021
	(0.005)	(0.016)	(0.015)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
Adj. R-squared.	0.449	0.517	0.811
Observations.	6,988	6,988	6,964

Note: This table presents the estimates of the second-stage regression in a Heckman two-stage model, where we estimate the effect of the subscription to the TII platform on occupancy, revenue stream, and average daily price by correcting for the potential omitted variable bias. Robust standard errors are in parentheses. The heterogeneous characteristics of the individual unit (Property vars.) and property manager (PM vars.) are included in all models.
Abbreviations: imr, inverse mills ratio; PM, property managers; TTI, Transparent Intelligence, Inc.
The significance of coefficients is represented as follows: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.1.4 | Heckman two-stage model

Our results may be driven by an omitted variable bias. To control for this potential bias, we use a Heckman two-stage model. In the first stage, we estimate a probit model with the dependent variable as the treatment on a set of controls and an instrument, which is represented by the average of the past three prices (price3). We compute the inverse mills ratio (IMR) in the first stage and include it in our second-stage estimation. In the second stage, we regress the three variables of interest—occupancy (occ_{it}), revenue (rev_{it}), and price ($price_{it}$)—on the treatment variable ($TIItechnology_{it}$), a set of controls, and the IMR. If omitted variable bias has been dealt with, the IMR should be insignificant.

In Table 7, we report the second-stage results of our Heckman procedure for the three variables of interest occupancy, revenues, and price, respectively. The coefficients of our key variable

TABLE 8 Quasi-DiD model estimates.

Variables	Occupancy	Revenue	Price
post	0.061***	0.144***	−0.057***
	(0.006)	(0.038)	(0.009)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
Adj. R-squared.	0.489	0.510	0.829
Observations.	22,320	22,320	21,579

Note: This table presents the estimates of a quasi difference-in-difference (DiD) model, where we estimate the posttreatment effect of the subscription to the Transparent Intelligence, Inc platform on occupancy, revenue stream, and average daily price. Robust standard errors are in parentheses. The heterogeneous characteristics of the individual unit (Property vars.) and property manager (PM vars.) are included in all models.
The significance of coefficients is represented as follows: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

TIItechnology—i.e., PMs' registration to the platform—are found to be slightly smaller than the ones in our baseline results, with revenues only being marginally significant. The *imr* coefficient is insignificant, suggesting that our models are not subject to an omitted variable bias and our results are robust and consistent with our main findings. The number of observations is smaller than the original one used in our baseline model because of the construct of the instrument in the first stage, which requires the existence of the previous three prices.

4.1.5 | Quasi-difference-in-differences

Until now, our estimations have controlled for endogeneity arising from observable and omitted variables bias. It could also be that our models suffer from endogeneity arising from unobservable bias. To further corroborate our results, we perform a quasi-difference-in-differences (DiD) estimation as follows:

$$y_{it} = a_{it} + \beta \times post_{it} + \lambda \times controls_{it} + v_i + \mu_t + \epsilon_{it}, \tag{2}$$

where y_{it} represents occupancy (occ_{it}), revenue (rev_{it}), and price ($price_{it}$) in the separate three regressions; $post_{it}$ is a dummy equal to one post the treatment period and zero before the treatment at time t; $controls_{it}$ are a set of control variables representing the characteristics of both unit and property manager; v_i, μ_t and ϵ_{it} represent the unit and time fixed effects and error term respectively.

Table 8 presents the results of our quasi-DiD estimation. Consistent with our previous findings and after controlling for unobservable bias, we find that the treatment has a positive and significant effect on revenues with a magnitude (0.144) that remains similar to our baseline and other robustness models. This improvement in revenues is still achieved by an increase in occupancy (0.061), which is higher than a decrease in price (−0.057), with both coefficients slightly lower in absolute terms than the one obtained in our baseline model.

4.1.6 | PMs self-selection and fixed effects

Even if access to the TII platform should not be affected by the relative size of PMs due to a relatively modest flat joining fee, one may wonder if there are characteristics making the subscription

TABLE 9 Model estimates including property manager fixed effects.

Variables	Occupancy	Revenue	Price
Panel A: Propensity score matching			
ATT	0.131***	0.182**	−0.132***
	(0.010)	(0.056)	(0.021)
Observations	18,799	18,799	21,579
Treated	16%	16%	16%
Control	84%	84%	84%
Panel B: Lagged dependent variable			
TII technology	0.078***	0.112***	−0.066***
	(0.005)	(0.026)	(0.008)
lagged dependent	0.352***	0.214***	0.603***
	(0.006)	(0.005)	(0.005)
Adj. R-squared.	0.403	0.434	0.772
Observations.	20,124	20,124	19,233
Panel C: Basic OLS estimation			
TII technology	0.101***	0.097***	−0.110***
	(0.006)	(0.034)	(0.010)
Adj. R-squared.	0.274	0.302	0.610
Observations.	22,320	22,320	21,579
Panel D: Variables in all models above			
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
PM fixed effect	Yes	Yes	Yes

Note: This table presents the results of several models, where we include property managers (PM) fixed effects and estimate the effect of the subscription to the TII platform on occupancy, revenue stream. and average daily price: propensity score matching with four nearest neighbors (panel A), lagged dependent variable model (panel B), basic OLS (panel C). Robust standard errors are in parentheses. The heterogeneous characteristics of the individual unit (Property vars.) and property manager (PM vars.), alongside PM fixed effects, are included in all models (panel D).
Abbreviations: ATT, average treatment effect on the treated; OLS, ordinary least squares; TII, Transparent Intelligence, Inc.
The significance of coefficients is represented as follows: ***p<0.01, **p<0.05, *p<0.1.

more or less likely. As the descriptive statistics in Table 1 suggest that bigger PMs with more assets and smaller profit margins may be more likely to be in the treatment group, we use these characteristics in the matching process within our PSM estimation. At the same time, other characteristics not captured in our database may also have an impact and therefore we also estimate models including PM fixed effects to mitigate this concern.

Table 9 reports the main results for three different models, which include PM fixed effects alongside property- and PM-related control variables already included in previous estimations (panel D). For our PSM model with four neighbors, panel A shows coefficients that are consistent with our main findings in Table 3, with a slightly smaller price reduction leading to an even higher improvement in revenues. In panel B, our lagged dependent variable model confirms our main results in Table 6, with coefficients, in general, showing a slightly smaller magnitude (mostly negligible difference). Finally, we also present a basic OLS estimation as a simple benchmark model to further mitigate concerns of a potential self-selection bias. As coefficients remain consistent

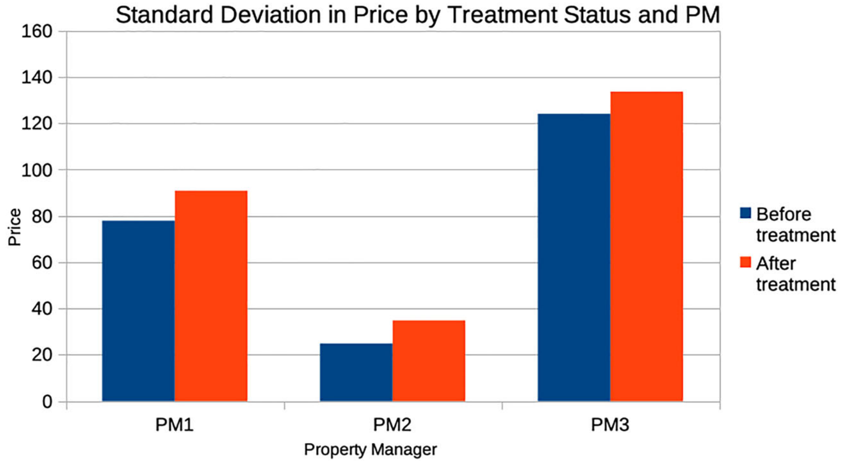


FIGURE 3 Standard deviation in price by treatment status and treated PM. This graph reports the standard deviation of prices applied by three PMs before and after treatment. [Color figure can be viewed at wileyonlinelibrary.com]

throughout our estimations suggesting a 10–15% increase in revenues obtained through the adoption of technology, we believe that the self-selection bias should only marginally lead to a small overestimation of our results.

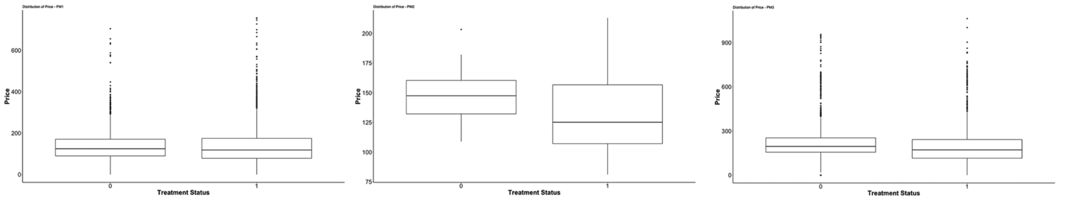
Overall, several robustness tests have been applied, and our results hold, confirming the main finding of our study: the use of technology improves market transparency through information sharing, and the reduced information asymmetry allows PMs to engage in dynamic pricing by lowering the price to obtain a higher occupancy and, as a result, to unlock the potential to increase revenues, therefore maximizing their objective function.

4.2 | Dynamic pricing

In this section, we investigate the dynamic pricing mechanism through which the PMs can leverage the information attained from TII to make better pricing decisions. We document the differences in the volatility of prices for treated PMs before and after receiving the treatment. As we work with aggregate data at a monthly frequency, we do not observe PM's choices of individual prices set at each point in time. Instead, we observe the average price for a given property over a month. Furthermore, we do not observe the actual information that a PM receives by subscribing to TII's services. We assume that all treated PMs receive the same information, and we believe that this represents a fairly reasonable assumption because TII had a single subscription service during our sample period.

With the above-mentioned data restrictions, we focus on the standard deviation of prices of treated properties before and after the treatment and report in Figure 3 three examples, grouped by the PM. We see evidence that the standard deviation of prices increases for each PM after they receive the treatment. Therefore, we find evidence that the subscription to TII and the acquisition of information through the platform led the PMs to engage in dynamic pricing even more.

As a further test for the potential engagement in more proactive dynamic pricing, we take the same three treated PMs as an example, we observe the entire distribution of prices and we present



(a) PM 1 (b) PM 2 (c) PM 3

FIGURE 4 Box-plot of prices of three treated PMs. This graph reports the range of prices applied by three PMs before (left bar in each graph) and after (right bar) treatment.

TABLE 10 PSM estimates for the top and bottom 30th percentiles.

Variables	Occupancy	Revenue	Price
Panel A: Price in the top 30th percentile			
ATT	0.102***	0.274***	−0.028***
	(0.012)	(0.033)	(0.019)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
Number of observations	6,378		
Panel B: Price in the bottom 30th percentile			
ATT	0.144***	0.042	−0.221***
	(0.018)	(0.061)	(0.022)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
Number of observations	4,304		

Note: This table presents the estimates of a propensity score matching model with four nearest neighbors, where we estimate the effect of the subscription to the TII platform on occupancy, revenue stream, and average daily price. Panels A and B, respectively, report the results for the top and bottom 30th percentile of prices. Robust standard errors are in parentheses. Property-related (Property vars.) and property-manager-related variables (PM vars.) are included in all models.
Abbreviations: ATT, average treatment effect on the treated; PM, property manager.
The significance of coefficients is represented as follows: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$, $+p < 0.15$.

the interquartile range as an indication of price dispersion in Figure 4. Clearly, interquartile ranges are wider for each of the three PMs after they receive the treatment. Therefore, we interpret this as further evidence of higher price dispersion among the treated properties.[13]

Furthermore, we attempt to shed light upon the different actions taken by the platform subscribers at the high end and bottom end of the price range, which should correspond to the pricing applied during holidays and high seasons and relatively quiet periods. This also allows us to further explore how dynamic pricing is applied using the information provided by the TII platform. We create two samples for the top and bottom 30th percentiles of the price range of our properties (leaving out the middle four deciles). We then estimate a PSM model similar to our main empirical analysis and report the findings in Table 10. Our results suggest that the increase in revenues is clearly generated from the top of the price distribution (27.4%) through a significantly higher

[13] Further study of how PMs compete on price or possibly collude is beyond the scope of this paper, and we leave that for further research. To answer such questions, one needs to take a different empirical approach that involves structural models of consumer demand and sellers' competition.

TABLE 11 Lagged dependent model estimates.

Variables	Occupancy	Revenue	Price
Panel A: Price in the top 30th percentile			
TII technology	0.048***	0.060*	−0.025**
	(0.010)	(0.031)	(0.012)
Lagged dependent	0.149***	0.097***	0.053***
	(0.013)	(0.007)	(0.012)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
Adj. R-squared.	0.482	0.418	0.796
Observations.	5,919	5,919	5,825
Panel B: Price in the bottom 30th percentile			
TII technology	0.080***	0.028	−0.121***
	(0.013)	(0.039)	(0.017)
Lagged dependent	0.188***	0.034***	0.149***
	(0.011)	(0.005)	(0.009)
Property vars.	Yes	Yes	Yes
PM vars.	Yes	Yes	Yes
Adj. R-squared.	0.580	0.655	0.737
Observations.	5,887	5,887	5, 610

Note: This table presents the estimates of a model including the autoregressive component of the dependent variable. Panels A and B, respectively, report the results for the top and bottom 30th percentile of prices. Robust standard errors are in parentheses. Property-related (Property vars.) and property-manager-related variables (PM vars.) are included in all models.
Abbreviations: PM, property manager; TTI, Transparent Intelligence, Inc.
The significance of coefficients is represented as follows: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*} < 0.1$.

occupancy (10.2%) achieved with a small reduction in prices (2.8%, almost four times smaller than the achieved increase in occupancy). At the bottom end of the price distribution, instead, a much bigger reduction in prices (22.1%) is applied to try to obtain an increase in occupancy (14.4%) that is, however, not able to generate a significant improvement in revenues.

Similar results are found if we apply a lagged dependent variable model as reported in Table 11, with prices decreasing by 2.5% and 12.1%, respectively, for top and bottom 30th percentiles, and occupancy increasing by 5% and 8%. Finally, these findings are also consistent and give statistical evidence to the data represented in Figure 4, where the top part of the range only slightly moves downwards, while the bottom price of the box plots moves downwards significantly, hence extending the range of prices after the treatment.

5 | CONCLUSION

In this paper, we estimated the ATT of adopting a market data intelligence platform by PMs in the STR market on the occupancy and revenue of properties. We exploited a quasi-natural experiment in the STR market of Madrid, Spain, where a subset of PMs introduced and adopted a new market data intelligence platform at different points in time. After the adoption, all the properties managed by a PM who adopted the new technology were considered treated. The quasi-natural experiment was akin to an event-study research design, and we used PSM to estimate the ATT using a rich set of matching variables. We find that the adoption of this market data intelligence system led to an 11.6% increase in revenues due to a 13.3% increase in occupancy obtained through a 15.8% decrease in price. We also show that the rise in revenues is primarily driven by the high end of the price distribution, where a slight price reduction leads to a more significant increase in occupancy.

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, PMs could make better decisions regarding pricing, renting out properties, and designing listings. Ultimately, these more informed 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. PMs who are less technology-oriented and not equipped with the tools to support them in noticing changes in customer behavior and the flexibility to act might have difficulties finding guests. While some might keep their heads above water, others may be pushed out of the market.

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APPENDIX A

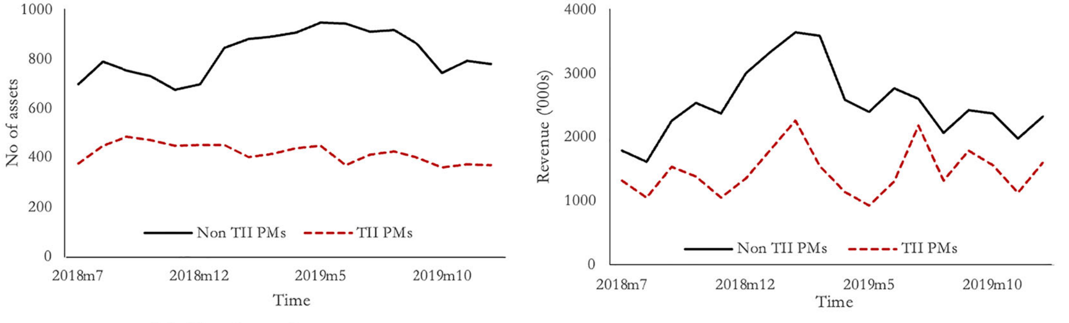
This appendix contains figures for the size of treatment and control groups and a description of the short rental market housing market in Madrid, Spain, and the impact of Proptech.

A.1 | PropTech revolution and the STR housing market

The real estate industry is far from agreeing on a universally accepted definition of PropTech. Various industry experts have cultivated their definitions and boundaries as to what comprises PropTech independently. We 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 technology) and overlaps with Fintech (financial technology). 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 sector's 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 the different stakeholders in the real estate market resisting change and innovation. 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.

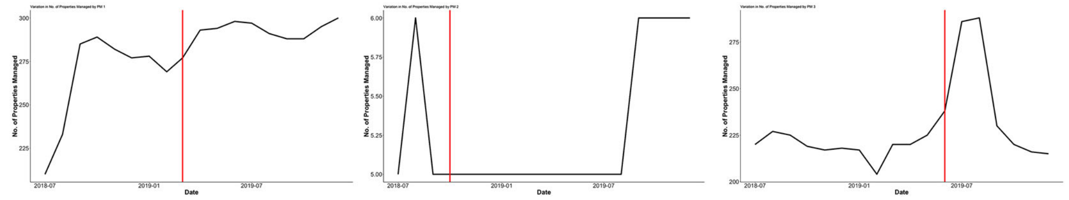
The surge of technology targeting the STR housing market has significant implications for the functioning of this market. PropTech companies such as Airbnb and Booking.com have increased the asset utilization rates for physical capital and, in doing so, have made existing physical capital more productive (Calder-Wang, 2021; Gutiérrez et al., 2017). The emergence of STR marketplace platforms also has spillover effects on other sectors of the economy. Alyakoob and Rahman (2022)



(a) Number of assets

(b) Revenue

FIGURE A.1 Number of assets (a) and revenues (b) for treated and control PMs. These graphs report the sum of the number of assets, (panel a) and revenues (panel b, managed by PMs subscribing to the TII platform (treated PMs, red dotted line) and the one of nonsubscribers (control, black solid line) PMs. [Color figure can be viewed at wileyonlinelibrary.com]



(a) Treated PM 1 (b) Treated PM 2 (c) Treated PM 3

FIGURE A.2 Growth in size for treated PMs. These graphs report the growth in size for treated PMs. The red vertical line shows the treatment event for each of the three treated PMs. [Color figure can be viewed at wileyonlinelibrary.com]

estimate the impact of Airbnb activity on local restaurant employment, a complementary local service. With the advent of such PropTech companies, an independent host can rent out a spare room in their 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 investment. Here, we provide evidence about the growth of the STR PropTech sector in terms of company 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 United States and later in 2010 in other countries. This lends credence to our earlier observation that the real estate industry has slowly adopted new technologies. Since 2010 the STR housing market has become a breeding ground for new start-ups. The growth rate of start-up creation in this sector exceeded 200% in major markets such as the United States, China, and the European Union. A large proportion 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 proportion of these companies serve clients worldwide.

As prompted by the sudden change in how real estate is suddenly practiced, investors gradually found STRs as a profitable alternative to their usual ventures. Investment started to skyrocket in 2014. Within just one year, the investment volume doubled from approximately \$20 billion to \$40 billion. By the end of 2020, more than \$74 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 \$6 billion and \$3.4 billion, respectively. Even though these are large amounts, the sum only makes up a fraction of the over \$60 billion invested in all the PropTech companies in the STR market combined. The relatively small share of investment in the top two firms compared to the total volume suggests that investment is not highly concentrated in a minimal number of companies but is distributed fairly uniformly across the market participants.

A.2 | The STR 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 is comprised of different types of housing properties.

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.[14] 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 the preference of travelers who opt for such housing units 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 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. This 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 rent 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 5041 multiunit hosts (including hosts with more than one property and professionally operating PMs) active in Madrid in July 2018, single-unit hosts constituted more than double this number (10,357). However, when comparing the supply of both market players, multiunit 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. 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%).

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