MICHIGAN ROSS

Working Paper

Pros vs. Joes: Agent Pricing Behavior in the Sharing Economy

Jun Li
Stephen M. Ross School of Business
University of Michigan

Antonio Moreno
Department of Managerial Economics and Decision Sciences (MEDS)
Northwestern University

Dennis J. Zhang
Olin Business School
Washington University in St. Louis

Ross School of Business Working Paper Series
Working Paper No. 1298
August 2016

Pros vs Joes: Agent Pricing Behavior in the Sharing Economy

Jun Li

Ross School of Business, University of Michigan, Ann Arbor, Michigan, MI 48109, junwli@umich.edu

Antonio Moreno

Kellogg School of Management, Northwestern University, Evanston, IL 60208, a-morenogarcia@kellogg.northwestern.edu

Dennis J. Zhang

Olin Business School, Washington University in St. Louis, St. Louis, MO 63130, denniszhang@wustl.edu

One of the major differences between markets that follow a "sharing economy" paradigm and traditional two-sided markets is that the supply side in the sharing economy often includes individual nonprofessional decision makers, in addition to firms and professional agents. Using a data set of prices and availability of listings on Airbnb, we find that there exist substantial differences in the operational and financial performance of professional and nonprofessional hosts. In particular, properties managed by professional hosts earn 16.9% more in daily revenue, have 15.5% higher occupancy rates, and are 13.6% less likely to exit the market compared with properties owned by nonprofessional hosts, while controlling for property and market characteristics. We demonstrate that these performance differences between professionals and nonprofessionals can be partly explained by pricing inefficiencies. Specifically, we provide empirical evidence that nonprofessional hosts are less likely to offer different rates across stay dates based on the underlying demand patterns, such as those created by major holidays and conventions. We develop a parsimonious model to analyze the implications of having two such different host groups for a profit-maximizing platform operator and for a social planner. While a profit-maximizing platform operator should charge lower prices to nonprofessional hosts, a social planner would charge the same prices to professionals and nonprofessionals.

Key words: Platforms, two-sided market, sharing economy, behavioral economics, revenue management, hospitality, amateurs, professionals.

---

1. Introduction

> Uber, the world's largest taxi company, owns no vehicles. Facebook, the world's most popular media owner, creates no content. Alibaba, the most valuable retailer, has no inventory. And Airbnb, the world's largest accommodation provider, owns no real estate. Something interesting is happening."
>
> —*Tom Goodwin, in "The Battle is for the Customer Interface" (Goodwin 2015).*

The widespread adoption of Internet infrastructure and smartphones has reduced the transaction costs associated with individuals sharing and trading their idle resources and capacity. This has enabled innovative business models that provide services using distributed capacity contributed by independent contractors. In some cases, the agents ultimately providing the service are nonprofessional individuals who share their spare resources, giving rise to the trend often referred to as "the sharing economy", which revolutionized various industries in the past years.

Most of the sharing economy business models, such as Uber (https://www.uber.com/) and Airbnb (http://www.airbnb.com), are based on digital platforms (Parker et al. 2016) that connect individuals who possess excess resources with individuals who need resources, creating two-sided markets (Parker and Van Alstyne 2005, Eisenmann et al. 2006). On one side of the market, the platform "contracts" the service with the customers. On the other side, independent service providers deliver the service using their own assets. Frequently, the platform simply acts as an intermediary and does not directly employ the service providers nor has any ownership or control of the assets that are used to provide the service.

Without the need to invest on physical assets or maintain a large internal workforce, many of the sharing-economy platforms scale up quickly. In December 2014, Airbnb had a global portfolio of one million listings, exceeding the capacity of the largest hotel groups in the world—Hilton, InterContinental and Marriott.[1] On the other hand, platforms are limited in the tools they can use to manage their capacity. While Marriott can decide how many rooms are offered at which prices in each market, Airbnb cannot make that type of decisions. The independent providers (hosts, in this case) decide whether they want to offer their properties to the market as well as the quantity and price. This represents a change of paradigm from traditional service models where such decisions are made within the boundaries of the firm by professional decision makers. This paper studies the implications of this change of paradigm represented by the sharing economy.

In particular, we focus on one of the critical differences between sharing economies and some of the traditional two-sided markets (e.g., credit card markets, software markets), which is that in the sharing economy the supply side often consists of both professional (experienced) players and nonprofessional (inexperienced) players. For example, on Airbnb.com, there are professional rental service providers as well as "amateurs" who rent out their apartments occasionally.[2] Studies in behavioral economics have found that nonprofessionals are more likely to suffer from behavioral biases such as loss aversion (Mayer 2001), limited attention (DellaVigna and Pollet 2009), and overconfidence (Malmendier and Tate 2008). These behavioral anomalies often change the prediction of traditional models based on complete rationality, as seen in recent operations management modeling literature (e.g., see Su 2008 and Huang et al. 2013). If the paradigm of the sharing economy involves a shift towards services provided more and more by nonprofessionals, it is crucial to

[1] Airbnb will soon be booking more rooms than the worlds largest hotel chains. Quartz. January 20, 2015.

[2] Airbnb in the city. New York State Office of General Attorney. October, 2014.

understand how their biases translate into market outcomes, and what interventions may improve market efficiency. In this paper, we empirically study the performance and behavioral differences between professional and nonprofessional agents, and we explore their implications for the delivery of services using business models that are based on the sharing economy.

We develop a software procedure to scrape listing data from Airbnb.com for all stay dates in a four-month period from December 1, 2012 to March 31, 2013 in the Chicago area. We classify hosts according to the number of properties they list on the site. We call *nonprofessional hosts* those who only list one property through Airbnb, and *professional hosts* those who list multiple properties, which represent 18% of hosts in our sample. We then compare the performance of professional and nonprofessional hosts using performance metrics commonly used in the hospitality industry, including average daily revenue, occupancy rate and price. We find substantial discrepancies between professional and nonprofessional hosts. All else being equal, a property managed by a professional host earns 16.9% higher average daily revenue, and has a 15.5% higher occupancy rate, despite being offered for the same number of days per week at similar average price.

To understand the stability of the market, we ping the URLs of these listings one and half year later and find a high turnover rate: 49% of previously available listings have exited the market. In particular, properties managed by non-professional hosts are 13.6% more likely to exit the market, everything else being equal.

We then explore the source of these discrepancies. We show that they are in part explained by the pricing inefficiencies of nonprofessional hosts. While professional hosts are more likely to offer different prices across stay dates based on the underlying demand level, which results in higher occupancy rates and revenues, nonprofessional hosts fail to do so. In particular, nonprofessionals fail to respond to surges in demand by charging higher prices for major holidays such as Christmas and major conventions occurring during the period of analysis, such as the Chicago Auto Show. During the Christmas and the Chicago Auto Show periods, total sales in the area were up by 98% and 23%, respectively, compared with other dates in the same month, and the occupancy rate went up by 84% and 21%, respectively. During those periods, nonprofessionals failed to offer higher prices and earned less. The price increases of non-professionals were 8.5% and 2.1% lower than those of professionals during the Christmas and Chicago Auto show periods respectively, controlling property-level fixed effects. The revenue increases of non-professionals were 19.8% and 11.8% lower during the Christmas and Chicago Auto show periods respectively.

We also find that both professional and nonprofessional hosts engage in minimal dynamic price adjustments across the booking horizon. That is, they almost never adjust prices upward nor downward even when the property is not rented out a few days prior to the stay date. Note that this is in contrast to the common practice in the hotel industry, where the prices for a given stay date often experience substantial changes along the booking horizon based on time left and changes in customer willingness-to-pay.

The inferior performance and high exit rate of nonprofessional hosts can pose a long-term threat to the sustainable growth of sharing economy platforms. To understand the impacts and potential remedies, we incorporate our empirical findings into a classic two-sided market revenue management model (Armstrong 2006). We show that under standard assumptions about demand functions, the platform should charge a lower fee to nonprofessional hosts to induce more supply-side participants and to optimize profit. In contrast, the social planner's optimal strategy would be to charge the same price to both professional and nonprofessional agents, because lowering prices will make the platform's serving costs overweight the customers' utility gains. Moreover, the optimal profit of the platform decreases in the operational discrepancy between professional and nonprofessional agents. This suggests that the platform could consider interventions that assist hosts adjust their prices more efficiently, such as the price recommendation tool recently launched by Airbnb.

2. Literature Review and Hypothesis Development

2.1. Literature Review

Sharing economy business models are capturing an increasing attention from the academic community. Recent work has studied what drives owning vs sharing (Benjaafar et al. 2015, Horton and Zeckhauser 2016), how to create successful matches in the sharing economy (Cullen and Farronato 2014), how to manage distributed, self-scheduling capacity (Cachon et al. 2015 , Gurvich et al. 2015), or how to design and operate urban bike sharing programs (Kabra et al. 2015).

Within in this line of research, some has explored the context created by Airbnb, one of the most prominent platforms in the sharing economy. For example, Zervas et al. (2014) study the effects of Airbnb on hotel revenues, Fradkin (2014) analyzes the consequences of search frictions using internal data from Airbnb, and Edelman et al. (2015) study racial discrimination using a field experiment on Airbnb. Our work contributes to this emerging stream of literature.

As a new form of two-sided market, sharing economy business models inherit important traits from the traditional two-sided markets: network externalities. That is, each side of the market benefits from the presence of the other (David 1985, Farrell and Saloner 1985, Katz and Shapiro 1985, and Parker and Van Alstyne 2005). However, sharing economy markets can be less efficient due to the presence of nonprofessional service providers, who are more likely to be subject to behavioral constraints. The focus of our work is on understanding the differences in behavior of professional and nonprofessional service providers, and the consequences for the market.

Behavioral differences between amateurs and professional players have received a considerable amount of attention in the behavioral economics literature. For example, using observational data, Mayer (2001) show that investors outperform homeowners in the real estate market because homeowners exhibit larger loss aversion in pricing their properties. List (2003) demonstrates, with a series of field experiments, that professional players outperform amateurs in the card-trading market due to endowment effects. List (2004) later shows that this performance gap shrinks when nonprofessional players gain more experiences in the market. DellaVigna (2009) surveys the empirical literature on behavioral anomalies and the resulting performance discrepancies between professional and nonprofessional players. Our work considers similar discrepancies between professionals and nonprofessionals and their impacts, but in the context of the sharing economy. Given that the sharing economy represents a general paradigm shift towards nonprofessional service providers, it is particularly important to understand the implications of their behavioral differences on market outcomes.

Our work is also closely related to 1) service operations literature which considers human interactions in service contexts (e.g., Buell et al. 2015, Frei and Morriss 2012); 2) behavioral operations literature which studies bounded rationality and its implications on operational decisions (e.g., Su 2008 and Huang et al. 2013); and 3) revenue management literature which studies theory and practice of demand- and capacity-based revenue management (Netessine and Shumsky 2005, Talluri and Van Ryzin 2006, Jerath et al. 2010), particularly in the hospitality industry (Anderson and Xie 2011, Bodea et al. 2009, Lederman et al. 2014). We find that there are substantial differences in the way revenue management tools are implemented by professional and nonprofessional agents, which translate into significant differences in market outcomes.

2.2. Hypotheses Development

As mentioned above, past research in behavioral economics shows that professional players have superior financial and operational performance compared to nonprofessionals in traditional markets. We hypothesize that nonprofessionals will have inferior financial and operational performance in the Airbnb market as well. In particular, we define our metrics as follows. Let Revenue_{it} represent the total revenue that property i collects for stay dates within time interval t. We can write Revenue_{it} as

$$\text{Revenue}_{it} = \text{NumDaysOffered}_{it} \times \text{DailyRevenue}_{it},$$

where $\text{NumDaysOffered}_{it}$ is the number of stay days that property i is offered during time interval t, often determined exogenously before pricing decisions are made. DailyRevenue_{it} measures average daily revenue *conditional on being offered.* We use DailyRevenue_{it} to measure property i's host's financial performance, as opposed to total revenue, i.e., Revenue_{it}, because we do not want to penalize a host merely because he decides to offer the property for fewer days. Note that our definition of DailyRevenue_{it} is parallel to the Revenue Per Available Room (RevPAR), a performance metric commonly used by hotels. RevPAR is defined as total room revenue divided by the number of rooms available and the number of days available during the period under consideration. We hypothesize that:

HYPOTHESIS 1. *A property managed by a professional host has higher average daily revenue than a property managed by a nonprofessional host, everything else being equal.*

If Hypothesis 1 is supported, we are also interested in identifying the main channel through which professionals earn higher daily revenue. It could be that professional hosts have higher occupancy rates, or that they can charge higher average rent prices (controlling for property and market characteristics), or both. We can rewrite the daily revenue as the combination of those channels, and test them independently:

$$\text{DailyRevenue}_{it} = \text{OccupancyRate}_{it} \times \text{AverageRentPrice}_{it}$$

where $\text{OccupancyRate}_{it}$ is the occupancy rate for property i in time interval t, calculated as the number of days occupied divided by the total number of days offered, and $\text{AverageRentPrice}_{it}$ is the average price at which property i is rented out during time interval t (which is calculated using the prices listed on the days in which the property was rented).

Several past studies have shown that one of the major differences between professional and nonprofessional agents in traditional markets is that professional agents are more likely to reach a deal (Mayer 2001 and List 2003). This allows us to hypothesize as follows.

HYPOTHESIS 2. *A property managed by a professional host has a higher occupancy rate than a property managed by a nonprofessional host, everything else being equal.*

Similarly, Hypothesis 1 can also be driven by the fact that professional hosts have a higher average rent price, i.e., average price when a property is rented out. This could be true, for example, if being a professional host signals better service quality. Consequently, we hypothesize that:

HYPOTHESIS 3. *A property managed by a professional host has a higher average rented price than a property managed by a nonprofessional host, everything else being equal.*

Besides merely testing whether the direction established in Hypotheses 2 and 3 is supported by the data, we are interested in their relative magnitude so that we can identify the main driver of better revenue performance of professional hosts, if Hypothesis 1 is supported. The following equation sums up our three hypotheses:

$$\text{Revenue}_{it} = \text{NumDaysOffered}_{it} \times \underbrace{\overbrace{\text{OccupancyRate}_{it}}^{\text{Hypothesis 2}} \times \overbrace{\text{AverageRentPrice}_{it}}^{\text{Hypothesis 3}}}_{\text{Hypothesis 1}}.$$

Finally, we are interested in not only the temporary operational and financial performance of different hosts, but also the consequences of such differences on market dynamics in the long term. As suggested by the economics literature (e.g., Ellison and Fudenberg 2003), one of the important long-term metrics of two-sided markets in defining market efficiency is the number of suppliers in the platform, which, in our case, is closely related to agents' exiting behavior. Since nonprofessional agents may suffer from behavioral anomalies and receive lower than expected revenues, they are probably more likely to exit the market, possibly in favor of other options, for instance, selling the property in the real estate market or renting the property in the long-term rental rather than short-term rental market.[3] Therefore, we hypothesize that:

Hypothesis 4. *A property managed by a professional host is less likely to exit the market than a property managed by a nonprofessional host, everything else being equal.*

3. Empirical Setting and Data

3.1. Empirical Setting: The Airbnb Platform

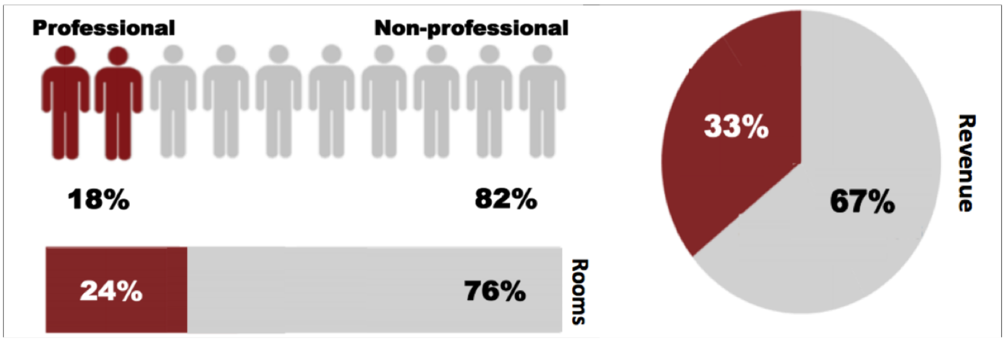
To study the differences in behavior between professionals and nonprofessionals, we use data from Airbnb. Airbnb is a sharing-economy platform that connects hosts with empty rooms to potential renters. Hosts on Airbnb list their spare rooms or apartments/houses and determine their own daily prices for rentals. Users visit the Airbnb website to search for desirable accommodations. Founded in 2008, the Airbnb's marketplace has experienced tremendous growth in the last few years. As of 2014, there are more than one million properties worldwide and 30 million guests who use the service. Like other traditional two-sided markets, Airbnb earns revenues from both sides. In particular, guests pay a 9% to 12% service fee on average for each reservation, depending on the length of stay and the location, while hosts pay a 3% service fee to cover the cost of processing payments by Airbnb. Currently, Airbnb's business model operates with little to no regulation in most locations. As a result, it becomes a major concern, for some local governments such as New York City, that professional rental businesses use Airbnb to avoid taxes, and this has been the subject of intense policy debates.[4] The main focus of our study is not to contribute to the ongoing debate about regulation in Airbnb, but to use data from the platform as an example to study differences in behavior between professionals and nonprofessionals that can be relevant in other sharing-economy platforms as well.

We classify Airbnb hosts in two types: 1) inexperienced individuals who list their spare rooms or apartments/houses for rent, which we denote as **nonprofessional hosts**, and 2) professional

[3] We restrict our attention to properties offered as entire apartments or houses and exclude those properties where the hosts also reside, so that we focus on a relatively homogeneous group of hosts with similar levels of mobility.

[4] "Airbnb, New York State Spar Over Legality Of Rentals." NPR. October 16, 2014.

Figure 1: Percentage of Professional Hosts in Our Sample and Their Revenue.



The first row shows that 18% of all hosts list two or more properties (entire apartments) on Airbnb in our data. These hosts are classified as professional hosts. Those hosts account for 24% of all properties in our sample and earn 33% of the total revenue across all properties in our sample period.

agents who manage multiple properties at the same time, which we denoted as **professional hosts**. In this paper, we define professional hosts as those who offer two or more unique units on Airbnb. Our results do not change qualitatively if we follow the definition by New York State Attorney General's office and define hosts as professional hosts if they hold three or more unique units.[5] Figure 1 shows that, in our sample, among hosts who offer entire apartments for rent, 18% are professional hosts with at least two properties. The professionals who constitute these 18% hold 24% of all properties in our sample and account for 33% of all revenue in our sample period.[6]

3.2. Airbnb Data: Listings and Transactions

To conduct this study, we developed a software procedure to scrape listings around the Chicago area on Airbnb.com for stay dates ranging from December 1, 2012 to March 31, 2013. This time horizon has the advantage that it is not affected by the presence of automatic pricing tools that have been developed more recently, so it is adequate to study differences in agent behavior. The procedure works as follows: (1) the program logs on to Airbnb.com to search for available rooms in the Chicago area; (2) the program then follows the link to each listing and records the information about that listing, such as location, room type, number of bedrooms, number of bathrooms, guest reviews, identify of the host, etc.; (3) for each listing, the crawler searches for availability and price of all stay dates during the four-month travel period. To capture at least one month worth of availability and price history for each listing on each stay date, the program was run on a daily basis from November 1, 2012 until March 31, 2013. In order to study the entry and exit of Airbnb

[5] "Airbnb In The City". New York State Office of The Attorney General. October, 2014.

[6] Note that there are professional hosts who own properties in multiple cities but only one of them is in our sample, which covers the Chicago area. Those hosts are still classified as professional hosts. This explains why the percentage of properties in our sample owned by professional hosts (24%) is lower than $2 * 18\% = 36\%$.

Table 1: Summary Statistics of Listings

	N	Mean	St. Dev.	Min	Max
Price ($)	24,845	149.99	79.65	10	600
Rented	24,845	0.27	0.45	0	1
NumReviews	24,845	10.99	15.23	0	150
AvgRating	17,179	9.61	0.55	8	10
NumBathrooms	23,055	1.29	0.62	1	5
NumBedrooms	24,140	1.58	0.89	1	6

hosts, we re-scraped Airbnb.com 18 months later, in August 2014. Since Airbnb does not reuse the host ID, we can identify hosts who had delisted their properties and exited the market.

We restrict our attention to offerings of an entire house or apartment and exclude those offerings with just a part of a property. This is because hosts who provide just a room or a bed in their house or apartment tend to have different demographics, incur different costs of renting and sometimes rent their rooms out for different reasons (such as social reasons). We also focus only on listings targeting short-term stays rather than long-term stays (listings with minimum length of stay less than a week).

Documenting differences in listings between different types of hosts is informative in itself, but we also use calendar listings to impute bookings from dynamic changes in listing availability. Based on descriptions on Airbnb's website, when a property is unavailable for a stay date, either booked or not offered, the price is not displayed in the calendar. For example, if we observe on December 10th that a property is available at $149 for the night of December 11th, it means that it has not been booked for the stay on December 11th and it is available as of December 10th. On the other hand, if a price was displayed on booking date December 9th for a stay on the 11th, but it is no longer displayed on December 10th, it implies that the property was booked for December 11th on December 10th.

Table 1 gives a summary of all offerings, where an offering is defined as the combination of property and stay date. Price is the last observed price along a 30-day booking horizon prior to the date of stay. Rented is equal to 1 if the property is rented out for the stay date. The table also displays observable property characteristics, including number of reviews, average ratings, number of bathrooms, and number of bedrooms.

Inferring availability and transactions from the calendar data has some potential limitations and requires some assumptions. First, a property could become unavailable in the calendar and be classified as "booked" because the host no longer wants to offer the property for a particular night, and not because the property has been booked. Even though one cannot completely rule out such possibility, we believe that imputing transactions in this way offers a reasonable proxy for real bookings. Given that we focus on listings for an entire house or apartment rather than a single room or bed at a property, the chance that a property owner delists a property due to personal reasons is significantly reduced because the owner does not reside at the property. Moreover, given that we focus only on short-term rentals and Airbnb is the leading existing short-term rental marketplace for individual properties, the chance that a property is rented out through other channels is also greatly reduced.[7] Second, a property could appear as "available" from the calendar but could actually be unavailable. This could happen, for example, when the host has not updated the calendar to reflect the actual availability of the property, in what Fradkin (2014) refers to as a "stale vacancy". Note that having access to internal data would not solve this problem.

Because the focus of this paper is to understand the differences between the behavior of professional and nonprofessional hosts, the aforementioned issues could be problematic if they affected professional and nonprofessional hosts differently. In the next subsection we present a comparison of professional and nonprofessional hosts and we report the results of two tests that suggest that these issues do not affect the two types of hosts differently.

3.3. Comparison of Professional and Nonprofessional Hosts

Table 2 displays summary statistics at the weekly level for professional and nonprofessional hosts, respectively. The first part of the table simply shows the variables summarized in Table 1, for professional and nonprofessional hosts, aggregated at the weekly level. The second part of the table includes additional variables calculated at the weekly level. We do not observe any significant difference in the number of days offered per property per week between professional and nonprofessional hosts. It appears clear though, even before conducting any statistical analysis, that properties managed by professional hosts on average earn more per week, obtain a higher occupancy rate, and are less likely to exit the market. However, such discrepancies in performance can be driven by the fact that professional hosts offer more spacious properties (more bedrooms and more bathrooms), have more reviews (though they are not necessarily rated higher), and perhaps even are located in more popular districts. The rest of the paper studies this performance discrepancy systematically, introducing the relevant control variables in the analysis.

As discussed above, although calendar listings are measured accurately (and are interesting on their own), bookings and availability inferred from them could be misrepresented. If this phenomenon affected professionals and nonprofessionals differently, this could bias some of our results. To alleviate this concern, we describe evidence from two additional analyses that suggest that this is not the case.

[7] In Section 5, we focus on the subset of hosts who make their properties available more than four days per week (50% of the time). Because of the high availability of their properties, it is less likely that these hosts will cancel availability for other reasons. We do not find any qualitative differences in our results by focusing on this subsample.

Table 2: Summary Statistics for Professional and Nonprofessional Hosts at Weekly Level

	Professional Hosts		**Nonprofessional Hosts**	
	Mean	St. Dev.	Mean	St. Dev.
Average Price ($)	167.87	83.35	146.94	99.5
Occupancy Rate	0.31	0.38	0.27	0.35
NumReviews	12.63	15.47	11.39	17.26
AvgRating	9.36	0.63	9.69	0.51
NumBathrooms	1.45	0.88	1.24	0.52
NumBedrooms	2.02	1.19	1.47	0.78
Daily Revenue ($)	44.66	63.91	34.22	65.04
NumDays Offered	5.89	1.94	5.79	2.02
NumWeekdays Offered	4.22	1.56	4.12	1.64
NumWeekends Offered	1.67	0.54	1.67	0.54
Exit	0.28	0.45	0.57	0.50

† Exits are measured 18 months later from the original data collection period.

First, we have partnered with PriceLabs, a provider of pricing tools for vacation rentals, to study anonymized records from a random sample of 300 Airbnb listings belonging to both professional and nonprofessional hosts. The data includes actual bookings as well as availability updates, which allows us to compare actual bookings with bookings inferred from availability changes. For each property in the sample, we measure the calendar inaccuracy rate as the fraction of days where the calendar data would suggest there was a booking but there was no actual booking. While the bookings inferred from the calendar information are not always accurate, there is no statistical difference in the accuracy for professional and nonprofessional hosts.

Second, Cui et al. (2016) conduct a randomized field experiment in which they send accommodation requests to a random set of listings in Chicago, and track the hosts' responses. While the purpose of that experiment is to study discrimination, analysis of the data using the available (and exogenous) variation in the host status (professional vs nonprofessional) does not indicate a statistically significant difference in calendar misrepresentation for professional and nonprofessional hosts in their sample.

Based on these two analyses, we believe that, even though there may be a mismatch between actual and imputed bookings, our results are not subject to systematic biases (either towards professional or nonprofessional hosts) due to such mismatch.

4. Performance of Professional vs Nonprofessional Hosts: Econometric Specifications and Results

In this section we describe the overall methodology of our analysis, the construction of our variables, and the corresponding empirical results. We follow the order in which we develop the hypotheses, starting with the analysis of daily revenue (Hypotheses 1), and following with the occupancy rate and average rent price (Hypotheses 2 and 3, respectively), and the assessment of the robustness of the results. Finally, we analyze the effects on exit probability (Hypothesis 4).

4.1. Daily Revenue

In Hypothesis 1, we would like to understand how the daily revenue from renting out a property depends on whether the property is managed by a professional or a nonprofessional host. We focus on the daily revenue, DailyRevenue_{it}, which we average at the weekly level. There are two reasons why we construct our revenue measure in this way. First, as mentioned above, normalizing total revenue by the number of days each host makes their properties available allows us to tease out the effect of predetermined availability and focus on the performance metric driven by endogenous decisions such as pricing. Second, we choose the aggregation level at the weekly level because we want to construct our measure in a relative homogeneous period for each host and, at the same time, average out the day-of-week effect. We use a family of reduced-form specifications and model daily revenue as,

$$log(\text{DailyRevenue}_{it}) = C_0 + \alpha_1 \text{Professional}_i + \beta X_{it} + v_m + v_t + \epsilon_{it}$$

where $log(\text{DailyRevenue}_{it})$ is the natural log transformation of daily revenue for property i in week t, Professional_i denotes whether the property is owned by a professional host. We control for various confounding factors that may potentially correlate with both the daily revenue (i.e., the dependent variable) and the host status (i.e., the treatment). First, we use zip-code-level and week-level fixed effects, v_m and v_t, to control for the possibility that certain markets are more attractive to travelers and meanwhile are also populated with more professional hosts.[8] Second, we control for the characteristics of an offering, denoted by X_{it}, which includes the physical characteristics of the property (i.e.,the number of bedrooms and bathrooms) and the quality of service (i.e., the number of guest reviews, the average review ratings, and the average response time of the host). Moreover, we control for the rank of an offering in the search result. If a host's professional status (or factors correlated with it) is used as an input to the Airbnb's search-engine ranking algorithm, then professional-host status can be correlated with performance through rank.

Hypothesis 1 holds if $\alpha_1 > 0$, which indicates that properties managed by professionals have higher daily revenue than those managed by nonprofessionals. The value of the coefficient α_1 gives the magnitude of the impact of the host type on daily revenue. Since we control for zip-code-level and week-level fixed effects, the identification of α_1 is enabled by the variation of daily revenue among all properties within a zip-code and a week, while controlling for offering characteristics.

Table 3 shows the estimates obtained under different sets of control variables. Column 1 only has market and time fixed effects. Column 2 controls for the physical characteristics of the properties

[8] Ideally, we would like to use a fixed-effect model to control for a listing's specific characteristics. However, since our independent variable of interest (i.e., whether a property is managed by a professional or a nonprofessional host) is time-invariant, including fixed effects in our model would absorb the effect of the variable of interest.

Table 3: Hypothesis 1 (Revenue)

	Dependent variable:		
	LogDailyRevenue		
	(1)	(2)	(3)
Professional	0.233^{***}	0.217^{***}	0.169^{**}
	(0.072)	(0.074)	(0.073)
NumWeekends	-0.232^{***}	-0.236^{***}	-0.147^{**}
	(0.061)	(0.061)	(0.061)
NumBathrooms		0.070	0.209^{***}
		(0.074)	(0.074)
NumBedrooms		0.018	−0.028
		(0.051)	(0.050)
NumReviews			0.020^{***}
			(0.002)
Rank			-0.001^{***}
			(0.0002)
Observations	4,297	4,297	4,297
R^2	0.142	0.143	0.185
Note:			*p<0.1; **p<0.05; ***p<0.01
			ResponseTime, Week-level and zip-code-level dummy included

in addition to the fixed effects. Column 3 further includes the quality of service in the control variables.[9] All three columns show that α_1 is significantly greater than zero. Hence, our empirical evidence is consistent with Hypothesis 1. Properties managed by professional hosts on average earn higher daily revenue than properties managed by nonprofessional hosts, with the magnitude being 16.9% in the specification reported in Column 3.

4.2. Occupancy Rate and Average Rent Price

The fact that professional hosts earn higher daily revenue (Hypothesis 1) can be attributed to them having a higher occupancy rate (Hypothesis 2), or a higher rent price (Hypothesis 3), or both. In this section, we evaluate the two channels and discuss their relative importance.

We start by testing our second hypothesis, which suggests that a property managed by a professional host will have a higher weekly occupancy rate than one managed by a nonprofessional host. We employ the same model specifications as in the previous section:

$$log(\text{Occupancy}_{it}) = C_0 + \alpha_2 \text{Professional}_i + \beta X_{it} + v_m + v_t + \epsilon_{it},$$

where $log(\text{Occupancy}_{it})$ is the log transformation of the weekly occupancy rate of property i in week t, and all the other variables are defined as before.

[9] We did not find a significant effect of average rating due to its lack of variation. Moreover, average rating is missing when there is no review available, which will limit the number of observations when included. Therefore, we decide to drop average rating in our analyses.

Table 4: Hypothesis 2 (Occupancy Rate)

	Dependent variable:		
	LogOccupancyRate		
	(1)	(2)	(3)
Professional	0.173^{**}	0.193^{***}	0.155^{**}
	(0.068)	(0.070)	(0.070)
NumWeekends	-0.283^{***}	-0.279^{***}	-0.191^{***}
	(0.058)	(0.058)	(0.058)
NumBathrooms		-0.048	0.078
		(0.070)	(0.070)
NumBedrooms		-0.034	-0.076
		(0.048)	(0.047)
NumReviews			0.020^{***}
			(0.002)
Rank			-0.0004^{**}
			(0.0002)
Observations	4,297	4,297	4,297
R^2	0.143	0.144	0.186
Note:			*p<0.1; **p<0.05; ***p<0.01
			ResponseTime, Week-level and zip-code-level dummy included

Table 4 shows the estimates obtained under different sets of specifications. In all columns, α_2 is significantly greater than 0, which supports Hypothesis 2. Specifically, properties managed by professional hosts achieve 15.5% higher occupancy rates than properties managed by nonprofessional hosts, based on the estimates reported in Column 3.

Besides higher occupancy rate, do professional hosts also charge higher prices? We next evaluate the difference of rented price between professional and nonprofessional hosts. We adopt the same specification structure as above, changing the dependent variable to AvgRentPrice_{it}:

$$log(\text{AvgRentPrice}_{it}) = C_0 + \alpha_3 \text{Professional}_i + \beta X_{it} + v_m + v_t + \epsilon_{it}.$$

Table 5 shows the estimates with different specifications. In Columns 2 and 3, α_3 is not significantly greater than 0, and the magnitude of the point estimates are small as well, therefore Hypothesis 3 is not supported. That is, professional hosts do not seem to charge a higher rental price on average. Since the dependent variable is calculated using the prices of properties that are rented, our results indicate that customers do not have a higher willingness-to-pay for properties managed by professional after controlling for the quality of the property and the service offered. This also alleviates potential concerns regarding to omitted variable biases.

Recall that Column 3 of Table 3 indicated that professional hosts on average earn 16.9% more revenue, controlling for property and market characteristics. We have shown that the additional revenue primarily comes from higher occupancy rates rather than higher rented prices.

Table 5: Hypothesis 3 (Average Rent Price)

	Dependent variable:		
	LogRentPrice		
	(1)	(2)	(3)
Professional	0.108^{***}	0.032	0.022
	(0.023)	(0.021)	(0.022)
NumWeekends	0.092^{***}	0.082^{***}	0.078^{***}
	(0.019)	(0.017)	(0.018)
NumBathrooms		0.240^{***}	0.245^{***}
		(0.022)	(0.022)
NumBedrooms		0.115^{***}	0.113^{***}
		(0.015)	(0.015)
NumReviews			-0.001^{**}
			(0.001)
Rank			-0.0003^{***}
			(0.0001)
Observations	2,313	2,313	2,313
R^2	0.288	0.438	0.444
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
	ResponseTime, Week-level and Zip-code-level dummy included		

4.3. Robustness Tests for Model Specifications and Endogeneity

In this section, we formally address the potential concern of omitted variable bias, even though it seems unlikely from the previous results on rented price. One may argue that, for example, properties managed by professional hosts might be closer to transportation stations and therefore are more likely to be rented. Although some of these effects are accounted for by controlling for guest reviews, there may still be unobserved variables that are correlated with both the host type and the performance of a property, and hence lead to biased estimates. Moreover, the linear specification may not be accurate either.

We perform two major tests to alleviate concerns related to model specification and endogeneity. First, we use a propensity score matching estimator to address concerns related to our linear specification. Second, in addition to using our matching estimator, we conduct Rosenbaum bound sensitivity analysis (Rosenbaum 2002). This analysis studies how the estimates would change in presence of unobserved confounding factors of varying magnitudes. This allows us to determine how strongly an unmeasured confounding factor must affect the selection into treatment in order to undermine the conclusions about causal effects from a matching analysis, and in turn addresses concerns related to potential omitted variable bias.

We construct a matching estimator based on propensity scores with a generic search algorithm to optimally balance covariates (Sekhon 2008). In particular, for Hypotheses 1 and 2, the two hypotheses supported by previous empirical analyses, we match observations based on the characteristics of offerings and their locations (zip-codes). Table 6 shows the results. Each column of

Table 6: Matching Estimator and Rosenbaum Bounds

	Daily Revenue (Hypothesis 1)	Occupancy Rate (Hypothesis 2)
Original Treatment Effect	0.169^{**}	0.155^{**}
	(0.072)	(0.068)
Matching Treatment Effect	0.315^{***}	0.338^{***}
	(0.096)	(0.091)
Lower Bound for $\gamma = 1.5$	0.116	0.154
Upper Bound for $\gamma = 1.5$	0.516	0.554
Tipping γ	2.0	2.0
Note:		**p<0.05; ***p<0.01

Table 6 corresponds to one hypothesis. For each hypothesis, we present the original estimator of the treatment effect and our propensity-score-based matching estimator. The direction and significance level of the matching estimator do not differ significantly from original ordinary least-squared estimator. The magnitudes are even higher when we use the propensity score matching approach. Therefore, we conclude that our results are very unlikely to arise from the specific choice of model presented in Sections 4.1 and 4.2.

We then perform the Rosenbaum sensitivity analysis suggested by Rosenbaum (2002). The underlying idea is to measure how the estimated effect changes when an omitted confounding factor is present in the treatment selection. Given a certain level of odds ratio of treatment selection, we compute the upper and lower bounds of the average treatment effect. Table 6 shows how our matching estimator could change if two units with similar observed covariates could differ in their *odds* of receiving the treatment (i.e., having a professional host), when the unobserved confounding factor drives as much as 50% of the treatment selection (i.e., $\gamma = 1.5$). The table shows that in all cases the lower and upper bounds of the matching estimators have the same sign as the original estimators, which shows that even a hidden confounding factor that drives 50% of the treatment selection will not alter our conclusion. We present the tipping point of the treatment selection parameter γ, which is defined as the lowest γ such that the measured treatment effect would have its sign flipped. In this case, the hidden confounding factors have to make selection into the treatment twice as likely as into the control group in order to alter the support for our hypotheses, which is highly unlikely. Besides the Rosenbaum bounds, we also estimate the Heckman endogenous treatment model (Heckman 1976 and Wooldridge 2010) that allows selection into treatment to be based on unobservables and we arrive at the same conclusion that the discrepancy we see between professionals and nonprofessionals is not likely driven by unobserved confounding factors.

4.4. Exit Probability

Given that the performance of nonprofessional hosts is inferior to that of their professional counterparts, are properties managed by nonprofessional hosts also more likely to exit the market after

Table 7: Hypothesis 4 (Exit)

	Dependent variable:		
	Exit		
	(1)	(2)	(3)
Professional	-0.744^{***}	-0.632^{**}	-0.599^{**}
	(0.283)	(0.290)	(0.299)
NumBathrooms		0.026	-0.043
		(0.312)	(0.319)
NumBedrooms		-0.330	-0.302
		(0.207)	(0.211)
NumReviews			-0.019^{*}
			(0.010)
Rank			-0.0002
			(0.001)
Observations	317	317	317
Note:			*p<0.1; **p<0.05; ***p<0.01
			ResponseTime, Zip-code-level dummy inlcuded

a certain period of time? The literature on the two-sided markets suggests that the revenue of the platform and the social welfare depend critically on the size of the supply side (Armstrong 2006). Therefore, exit probability is an important measure to consider in analyzing the health and growth of any sharing-economy marketplace. We use a family of Logit specifications to test this hypothesis. In particular, we model the exit rate of a property as:

$$\text{Exit}_i = logit(C_0 + \alpha_4 \text{Professional}_i + \beta X_i + \upsilon_m + \epsilon_i),$$

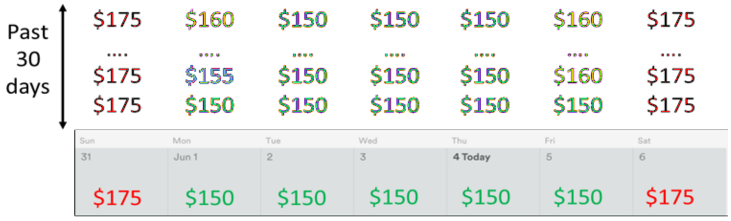
where Exit_i indicates whether property i has exited Airbnb's market 18 months after the original sample period. All the other variables are as previously defined.

Table 7 shows the results. Under all three specifications the estimates of α_4 are statistically significantly negative, which supports Hypothesis 4. Computing the marginal effects from estimates in Column 3, we conclude that a property owned by a professional host is on average 13.6% less likely to exit the market after one and half years, measured by marginal effect at the means.

5. Understanding the Differences in Performance

In Section 4 we provided empirical evidence that properties managed by professional agents have higher daily revenue as well as occupancy rates, and are less likely to exit a market compared with those managed by nonprofessional hosts. In this section we examine the source of these differences in performance. We do so by analyzing the potential pricing inefficiencies of nonprofessional hosts, including insufficient price adjustments and inadequate response to well-known demand shocks. We then test whether alternative explanations are plausible for the observed performance discrepancy.

Figure 2: Example: Number of Price Levels Offered Across Stay Dates and Booking Dates



In the example, last observed prices for stay dates in the week are either \$150 or \$175, therefore StayDateRateCnt=1. Along the 30-day booking horizon, there are three price levels for Monday night stay (\$160, \$155 and \$150), two price levels for Friday night stay (\$160 and \$150), and one price level for all other stay dates. Therefore, BookingDateRateCnt=0+2+0+0+0+1+0=3.

5.1. Intensity of Pricing Activity

The revenue management (RM) literature (Talluri and Van Ryzin 2006, Gallego and Van Ryzin 1994, and Bitran and Caldentey 2003) has extensively documented the use and impact of various RM techniques in an array of industries providing perishable products or services, one of which being the hotel industry (Zhao and Zheng 2000). According to this literature, there are two RM tools widely adopted by hotels when setting room rates: (1) variable room rates across stay dates (Talluri and Van Ryzin 2006): hotels offer different room rates based on the day of the week, the season, or other observable factors affecting total demand; (2) variable room rates across booking dates (Su 2007): hotels offer different room rates based on time left to the stay date. We therefore define two measures of the intensity of pricing activity: (1) **StayDateRateCnt**$_{it}$, calculated as the total number of last observed price levels for all stay dates in week t minus 1. The last observed price equals to the rented price if a property is rented out eventually, or the listing price last observed along the booking horizon otherwise. $\text{StayDateRateCnt}_{it} = 0$, for example, means that there is no price variation across stay dates in week t because the last observed prices are constant. (2) **BookingDateRateCnt**$_{it}$. We first calculate the number of price levels along the 30-day booking horizon for each stay date in week t minus 1. We then take the sum of this measure over all stay dates in week t. $\text{BookingDateRateCnt}_{it} = 0$ indicates no price variation across booking dates for any stay date in week t, as listing prices are constant. Figure 2 provides an example of how these two measures are calculated.

We first test in our context whether the use of such RM tools, as captured by the aforementioned variables, indeed leads to higher revenue. In particular, we hypothesize that a property's weekly revenue is higher if it has higher StayDateRatesCnt and BookingDateRatesCnt for that week. We test the hypothesis with the following model specifications:

$$log(\text{DailyRevenue}_{it}) = C_0 + \theta_1 \text{StayDateRateCnt}_{it} + \theta_2 \text{BookingDateRateCnt}_{it}$$

Table 8: Impact and Use of Revenue Management Techniques

	Dependent variable:			
	LogRevenue	LogOccupancyRate	StayDateRateCnt	BookingDateRateCnt
	OLS	*OLS*	*Poisson*	*Poisson*
	(1)	(2)	(3)	(4)
Professional			0.124**	−0.217
			(0.053)	(0.133)
StayDateRateCnt	0.328***	0.038***		
	(0.048)	(0.006)		
BookingDateRateCnt	0.002	−0.0002		
	(0.007)	(0.001)		
NumBathrooms	0.151**	−0.001	0.178***	0.109
	(0.069)	(0.009)	(0.063)	(0.143)
NumBedrooms	0.005	−0.002	−0.159***	−0.126
	(0.045)	(0.006)	(0.042)	(0.095)
NumReviews	0.022***	0.003***	0.005***	0.009**
	(0.002)	(0.0002)	(0.002)	(0.004)
Rank	−0.0004**	−0.00000	−0.0005***	−0.002***
	(0.0002)	(0.00002)	(0.0001)	(0.0003)
Observations	4,743	4,743	4,743	4,743
R^2	0.134	0.127		

Note: *p<0.1; **p<0.05; ***p<0.01
Response Time, Week-level and Zip-code-level dummy included

$$+\beta X_{it} + v_m + v_t + \epsilon_{it},$$

$$log(\text{OccupancyRate}_{it}) = C_0 + \theta_3 \text{StayDateRateCnt}_{it} + \theta_4 \text{BookingDateRateCnt}_{it}$$
$$+\beta X_{it} + v_m + v_t + \epsilon_{it},$$

All variables are as previously defined. The coefficients of interest are $\theta_1, \theta_2, \theta_3$, and θ_4. $\theta_1 > 0$ and $\theta_2 > 0$ suggest that variable rates by stay date and by booking date lead to higher daily revenue respectively, while $\theta_3 > 0$ and $\theta_4 > 0$ suggest variable rates by stay date and by booking date lead to higher occupancy rates respectively. Columns 1 and 2 of Table 8 show that a more intense pricing activity results in higher daily revenue and occupancy rates, controlling for property and market characteristics. The effect is mainly driven by the use of variable rates by stay date. We did not find significant revenue and occupancy effects of variable rates by booking date, which can be partially driven by lack of adoption of this practice — we observe that 75% of listings did not adjust their prices at all along the booking horizon and 95% of them adjust their prices at most once along the booking horizon.

Given that a more intense pricing activity leads to better performance, the next question is whether professional hosts indeed engage more in such practice and earn higher revenues in turn. In order to test this, we use Poisson model to analyze the levels of pricing sophistication:

$$\text{StayDateRatesCnt}_{it} = Poisson(C_0 + \theta_5 \text{Professional}_i + \beta X_{it} + v_m + v_t + \epsilon_{it}),$$

$$\text{BookingDateRatesCnt}_{it} = Poisson(C_0 + \theta_6 \text{Professional}_i + \beta X_{it} + v_m + v_t + \epsilon_{it}),$$

Column 3 of Table 8 shows that θ_5 is positive and significant, which indicates professional hosts vary property prices more often based on the date of stay. Computing the marginal effect, we find that properties managed by professional hosts vary prices 4.9% more frequently, calculated as marginal effect at mean. Since θ_6 is non-distinguishable from zero in Column 4, it indicates that professional hosts do not necessarily adjust their prices more often along booking dates, which may be driven by the lack of engagement in dynamic pricing across *booking dates* by all hosts.

Overall, we have shown that a more intense pricing activity results in higher occupancy rates and higher daily revenue. The fact that professional hosts are more likely to engage in intense pricing activity may partially explain their superior performances in this market. The evidence so far provides a mechanism (more intense price adjustments) through which Hypothesis 1 and 2 (higher daily revenue and occupancy rates for properties managed by professionals) may hold.

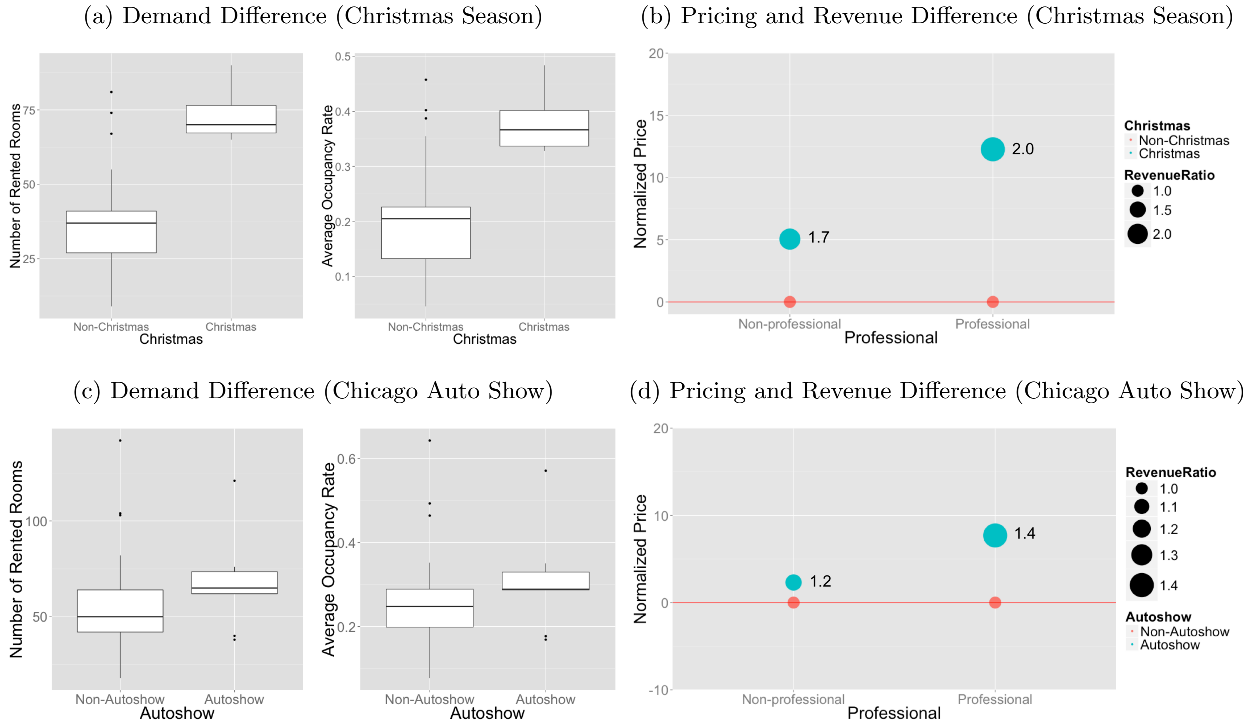
5.2. Response to Specific Demand Shocks

The results indicates that there are likely opportunities missed (i.e., revenue lost) by nonprofessional hosts, because they offer a relatively constant price across stay dates and do not respond to demand changes in the market as often as they should. To verify this conjecture more concretely, we identify specific, well-known demand shocks during our sample period. In particular, we focus on major holidays and events that all hosts could be equally aware of, including Christmas and the Annual Chicago Auto Show. In those periods, we first verify that demand is indeed higher. We then test whether professional hosts and nonprofessional hosts react to such *predictable* demand surges differently. In other words, do nonprofessional hosts fail to raise their prices for high-demand travel dates, and how much do they sacrifice in revenue as a consequence?

Christmas Season: We define Christmas season as Dec 24th to Dec 31th and non-Christmas season as the rest of December. We first note that demand during Christmas is indeed higher than that during the non-Christmas season. The upper-left panel of Figure 3 shows that during the Christmas season, average daily sales and average occupancy rate (that is, demand relative to supply) are nearly twice as high as those during the non-Christmas season in the Chicago area.

According to the classic RM practice in the hotel industry (Talluri and Van Ryzin 2006), hosts should charge higher prices during the Christmas season and obtain higher daily revenue as the demand is higher. The upper-right panel of Figure 3 shows the average prices of properties managed by professionals and nonprofessionals during the Christmas and non-Christmas seasons. For illustration purpose, we subtract all average prices by the average prices during the non-Christmas season for professional and nonprofessional hosts, respectively. The chart shows that, on average, both professional and nonprofessional hosts charge higher prices during the Christmas season,

Figure 3: Demand Signal: Christmas Season and Chicago Auto Show



Panels (a) and (c) show the total number of rented properties and average occupancy rates across all hosts for the different stay days in our sample. Panel (a) compares the days during the Christmas Season (Dec 24th to Dec 31th, 2012) with the other days in December 2012 (Dec 1st to Dec 23rd, 2012), while Panel (c) shows the days during the 2013 Chicago Auto Show (Feb 8th to Feb 19th, 2013) and the other days in February 2013 (Feb 1st – Feb 7th and Feb 19th – Feb 28th, 2013). The positions of the green dots in Panel (b) show the average price differences between the days during Christmas season and the other days in December 2012 across all professional hosts and nonprofessional hosts, respectively. The sizes of the dots represent the ratio of daily revenue during the Christmas season over daily revenue during other days in December 2012. Panel (d) is equivalent to Panel (b), but is used to describe the Chicago Auto Show period relative to other days in February, 2013.

which is consistent with RM theory and practice. However, the chart also indicates that the price differences between the Christmas and non-Christmas periods are larger for rooms managed by professionals. Moreover, we compute the average ratios of daily revenue during the Christmas and non-Christmas seasons for each property, indicated by the size of the dots in Figure 3. It is clear that professional hosts are not only more likely to adjust prices in response to higher demand during Christmas, but they also earn more revenue compared with nonprofessional hosts.

Chicago Auto Show: Another type of demand signals that hotel revenue managers commonly track is major events in town. One of the largest events in Chicago every year is the Chicago Auto Show — the largest in North America, held annually in February in downtown Chicago. The

2013 Chicago Auto Show spanned from February 8th to February 19th. If nonprofessional hosts fail to react to this demand surge as well, we expect to observe similar patterns as we did for the Christmas season. The bottom-left panel of Figure 3 shows that both the average daily sales and the average occupancy rates are higher during the Chicago Auto Show period. Moreover, the bottom-right panel demonstrates that, on average, properties managed by professional hosts are more likely to be charged a higher price during the Chicago Auto Show period, and earns higher revenue as well.

One may be concerned that the discrepancy in price and revenue may simply be driven by the fact that professional hosts manage more spacious properties or are located in more popular areas. In order to formally test whether professionals are more likely to adjust prices in response to demand signals and as a result earn higher revenue than nonprofessionals, we introduce the following empirical specifications with property fixed effects:

$$\begin{aligned}
log(\text{ListPrice}_{it}) &= C_0 + \kappa_1 \text{Professional}_i \times \text{DemandSignal}_t + \alpha_1 \text{DemandSignal}_t \\
&\quad + \beta X_{it} + v_i + \epsilon_{it}, \\
log(\text{DailyRevenue}_{it}) &= C_0 + \kappa_2 \text{Professional}_i \times \text{DemandSignal}_t + \alpha_2 \text{DemandSignal}_t \\
&\quad + \beta X_{it} + v_i + \epsilon_{it},
\end{aligned}$$

where $log(\text{ListPrice}_{it})$ and $log(\text{DailyRevenue}_{it})$ are the log of listed price and revenue of property i on day t, DemandSignal_t indicates whether day t belongs to a particular demand signal, the Christmas season or Chicago Auto Show. X_{it} includes the weekend dummy and the time-varying characteristic, i.e., rank. v_i is the fixed-effect of property i.

Results are shown in Table 9, with Columns 1 and 2 for Christmas season and Columns 3 and 4 for Auto Show. Column 1 shows that the price difference for properties managed by professional hosts during the Christmas versus non-Christmas season is 8.5% greater than that for properties managed by nonprofessional hosts. Column 2 shows that the revenue difference of properties managed by professional hosts during Christmas and non-Christmas seasons is 19.8% higher than that of properties managed by nonprofessionals. Similarly, Column 3 shows that the price and revenue differences between the Chicago Auto Show period and the rest of the month is 2.1% and 11.8% greater for properties managed by professional hosts.

In summary, professionals vary prices more frequently across different stay dates according to variations in demand. Note that, as summarized in Table 5, there is no systematic price difference between properties rented by professionals and nonprofessionals on average, across all dates. Our analysis of the Christmas period and the Chicago Auto Show period suggest professionals are better at matching prices with specific demand situations. Thanks to this superior pricing ability, professionals are able to obtain on average a 16.9% higher daily revenue.

Table 9: Response to Demand Shocks (Christmas and Autoshow)

	Dependent variable:			
	Dec 2012		Jan - Feb 2013	
	LogListPrice	LogRevenue	LogListPrice	LogRevenue
	(1)	(2)	(3)	(4)
Christmas	0.014^{***}	0.405^{***}		
	(0.005)	(0.039)		
Professional:Christmas	0.085^{***}	0.198^{***}		
	(0.009)	(0.071)		
Autoshow			-0.002	0.131^{***}
			(0.003)	(0.025)
Professional:Autoshow			0.021^{***}	0.118^{**}
			(0.006)	(0.050)
Weekend	0.028^{***}	-0.014	0.023^{***}	0.0001
	(0.003)	(0.025)	(0.002)	(0.017)
Rank	-0.0001^{***}	-0.002^{***}	0.00003	-0.002^{***}
	(0.00003)	(0.0002)	(0.00002)	(0.0001)
Observations	5,714	5,714	12,803	12,803
R^2	0.049	0.070	0.011	0.014

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Property-level fixed-effect included

5.3. Alternative Explanations

We test two alternative explanations for professional hosts outperforming their counterparts.

5.3.1. Heterogeneous Renting Costs

One could argue that the operational performance discrepancy between professional and nonprofessional hosts could be mainly driven by the difference in the costs they incur when renting a unit. In particular, if nonprofessional hosts incur higher costs of renting, they will charge higher prices and in turn have lower occupancy rates and revenues in equilibrium. It could be also be that some nonprofessionals with very high rental costs are only offering their units when demand is very high and they can charge a high price. Recall, however, that there is actually no significant difference in the number of days a unit is offered per month between professional and nonprofessional hosts according to Table 2. Nevertheless, we conduct an additional test to assess whether our estimates are affected by the possible difference in rental costs.

If the differences in renting costs were indeed the main driver, we would expect the operational performance discrepancy between professional and nonprofessional hosts to be substantially reduced when the analysis is restricted to a subsample of units with more homogeneous renting costs. We now focus on units that are rented more than 50% of the time on average (i.e., 4 days or more per week).[10] This is likely to eliminate hosts with high renting costs and makes the sample more homogeneous.

[10] For exposition purposes, we show the results for the 50% cutoff point; our conclusion does not change qualitatively if we increase the cutoff to 70%.

Table 10: Tests of Alternative Explanations: Renting Costs

	Dependent variable:		
	LogRevenuePerDay	LogOccupancyRate	LogRentPrice
	(1)	(2)	(3)
Professional	0.164^{**}	0.156^{**}	0.008
	(0.074)	(0.069)	(0.021)
NumWeekends	-0.194^{***}	-0.229^{***}	0.070^{***}
	(0.062)	(0.059)	(0.017)
NumBathrooms	0.187^{**}	0.061	0.237^{***}
	(0.073)	(0.069)	(0.021)
NumBedrooms	-0.017	-0.067	0.116^{***}
	(0.050)	(0.047)	(0.015)
NumReviews	0.019^{***}	0.019^{***}	-0.001^{***}
	(0.002)	(0.002)	(0.001)
Rank	-0.001^{***}	-0.0004^{***}	-0.0003^{***}
	(0.0002)	(0.0002)	(0.0001)
Observations	4,116	4,116	2,227
R^2	0.144	0.146	0.389
Note:			*p<0.1; **p<0.05; ***p<0.01
	ResponseTime, Weekday-level, week-level and zipcode-level dummy included		

We retest Hypotheses 1, 2 and 3 with this more homogeneous sample, using the same model specification as before. As shown in Table 10, our hypotheses that units managed by professional hosts achieve higher revenue and a higher occupancy rate are still supported. Moreover, the magnitude of the effects are comparable with the results from the whole sample, i.e., a 16.4% higher revenue compared with 16.9% previously, a 15.9% higher occupancy rate compared with 15.5% previously. Therefore, we do not seem to find empirical evidence that the difference in rental costs between professional and nonprofessional hosts could be the main driver of the observed performance discrepancy.

5.3.2. Learning

Another possible explanation for the difference in performance between professionals versus nonprofessionals could be different rates of learning. List (2004) finds that consumers learn to overcome the endowment effect as they accumulate more market experience. In our context, as professional hosts manage more properties, it is also likely that they observe more demand information in a given period of time. Hence, professional hosts can learn how to price optimally faster than nonprofessional hosts, and they in turn perform better operationally and financially.

In order to test whether professional hosts learn faster than nonprofessional hosts, we first define a measure of learning: the speed at which the expected daily revenue improves over time. Let μ_i denote the rate at which property i's expected revenue increases per day. If daily revenues improve, this variable will be greater than 0. It can be decomposed into two components: 1) a constant rate caused by changes in the market, μ, and 2) a room-specific rate ε_i, which can be influenced

Table 11: Tests of Alternative Explanations: Learning

	Dependent variable: LogRevenue			
	All Hosts		Hosts New to Airbnb	
	(1)	(2)	(3)	(4)
DayNumber	0.007^{***}	0.007^{***}	0.008^{***}	0.009^{***}
	(0.0004)	(0.0004)	(0.001)	(0.001)
DayNumber:Professional		-0.0002		-0.007^{***}
		(0.001)		(0.001)
Observations	24,845	24,845	10,204	10,204
R^2	0.018	0.018	0.022	0.024
Note:			*p<0.1; **p<0.05; ***p<0.01	
			Month-level dummy, fixed effect.	

by host experience. That is, $\mu_i = \mu + \varepsilon_i$. If professional hosts learn faster than nonprofessional hosts, we expect to observe $\mu_P = E[\mu_i|i \in P] - E[\mu_i|i \in NP] > 0$, where P represents the set of professional hosts, and NP represents the set of nonprofessional hosts. In other words, we would expect the revenues of properties listed by professional hosts to improve at a higher rate. We test this hypothesis with the following fixed-effect model:

$$log(\text{DailyRevenue}_{it}) = C_0 + \mu t + \mu_P t \times \text{Professional}_i + \alpha \text{Professional}_i + \beta F_i + v_t + \epsilon_{it}$$

where $log(\text{DailyRevenue}_{it})$ is the log of the revenue for property i on day t.[11] t is measured as the number of days elapsed from the start of our sample, Dec 1st, 2012. The coefficient of interest is μ_P. $\mu_P > 0$ would suggest that properties managed by professional hosts have a higher rate of learning.[12]

Table 11 offers the result. Column 1 estimates the baseline specification without the interaction. It shows that hosts do learn over time. However, Column 2 shows that properties managed by professional hosts do not have a higher increasing rate of revenue.

We have assumed so far that the learning rate of each host is constant over time, that is, regardless of how long a host has been in the market. If professional hosts have operated in the market for a longer time, then their learning rate will slow down as the learning curve plateaus. In this case, professional hosts will appear to have a slower learning rate compared with nonprofessional hosts. In order to address this, we focus on a subsample of hosts who are relatively new to the market. We use the number of total reviews of a host across his properties as a proxy for his time in the Airbnb market. By focusing on a subsample of hosts with fewer than 5 reviews when they first appear in our sample, we restrict our attention to new participants in the market.

[11] We add 1 to all $Revenue_{it}$ to avoid infinity after the log transformation.

[12] If we exclude the Christmas and Chicago Auto Show periods, the results do not change qualitatively.

Columns 3 and 4 of Table 11 show the results. We can see that new market participants on average learn faster (0.8% revenue increase per day) compared with all participants (0.7% revenue increase per day). However, the interaction effect in Column 4 shows that new nonprofessional participants actually learn faster than new professional participants over time. This result is consistent with the result from List (2004), who shows that nonprofessional traders can correct their loss aversion biases over time. To sum up, we do not find empirical evidence to support the conjecture that the better performance of professional hosts is explained by a higher rate of learning.

6. Implications for Platform Owners and the Social Planner

6.1. A Parsimonious Model

Having shown that there are important differences between professionals and nonprofessionals in terms of behavior and outcomes, we turn our attention to exploring the consequences of these differences. In particular, we propose a parsimonious model to understand how the difference between professional and nonprofessional hosts affects the optimal prices charged by the profit-maximizing platform holder or by a social planner. We use a well-established two-sided market model from Armstrong (2006) to describe the sharing economy.

Suppose that there are two groups of agents, denoted as 1 and 2. Group 1 represents the hosts in the market, while Group 2 represents the buyers. As in the previous sections, hosts can be further divided into two subgroups: professional hosts, denoted as P, and nonprofessional hosts, or NP. The utility of an agent, following the classic two-sided models (Rochet and Tirole 2003 and Armstrong 2006), is determined in the following way: if the platforms attracts n_1^P professional hosts, n_1^{NP} nonprofessional hosts, and n_2 customers, the utilities of the hosts and customers are, respectively,

$$u_1^P = \alpha_1 n_2 - p_1^P;\ u_1^{NP} = \beta(\alpha_1 n_2) - p_1^{NP}\ ;\ u_2 = \alpha_2(n_1^P + n_1^{NP}) - p_2, \tag{1}$$

where p_1^P, p_1^{NP}, and p_2 are the prices charged by the platform to professional hosts, nonprofessional hosts, and customers, respectively. For exposition purposes, we assume those are membership fees that hosts and customers pay to have access to the platform. In practice, Airbnb charges hosts and customers per transaction (i.e., a usage model). Rochet and Tirole (2006) have shown the equivalence of these two models. All the subsequent conclusions, though developed under the membership model, hold under the usage model as well. The parameter α_1 represents how the utility derived by hosts depends on the number of customers (a reasonable assumption being that $\alpha_1 > 0$, which implies that hosts obtain a higher utility when there are more customers in the market). Based on our empirical estimates, nonprofessional hosts obtain less utility for the same platform characteristics, given that their performance is lower. We use β to represent, in general, the performance difference between professional and nonprofessional hosts regardless of the behavioral driving forces. The higher the β, the better the nonprofessional hosts perform, relative to the performance of the professional hosts. Based on Table 2, β is around 80% in our empirical setting.

The number of participating hosts and customers is determined by the agents' participating utilities in the two-sided market as follows:

$$n_1^P = \phi_1(u_1^P) \ ; \ n_1^{NP} = \phi_1(u_1^{NP}) \ ; \ n_2 = \phi_2(u_2),$$

where $\phi_1(\cdot)$ and $\phi_2(\cdot)$ are increasing and concave demand functions.

Last, we define the cost structure for the platform. Suppose that the platform incurs a marginal cost f_1 for serving each host, both professional and nonprofessional, and f_2 for serving each customer.[13] The platform's profit can be written as

$$\pi = n_1^P(p_1^P - f_1) + n_1^{NP}(p_1^{NP} - f_1) + n_2(p_2 - f_2),$$

which is equivalent to

$$\begin{aligned}\pi(u_1^P, u_1^{NP}, u_2) =& \phi_1(u_1^P)[\alpha_1\phi_2(u_2) - u_1^P - f_1] + \\ & \phi_1(u_1^{NP})[\beta(\alpha_1\phi(u_2)) - u_1^{NP} - f_1] + \\ & \phi_2(u_2)[\alpha_2(\phi_1(u_1^P) + \phi_1(u_1^{NP})) - u_2 - f_2]. \end{aligned} \tag{2}$$

Suppose that the hosts' and customers' surpluses are $v_1^P(u_1^P)$, $v_1^{NP}(u_1^{NP})$, and $v_2(u_2)$ such that the envelope condition is satisfied: $v_1^{P\prime}(u_1^P) = \phi_1(u_1^P)$, $v_1^{NP\prime}(u_1^{NP}) = \phi_1(u_1^{NP})$, and $v_2'(u_2) = \phi_2(u_2)$. The total social welfare can be defined as

$$w = \pi(u_1^P, u_1^{NP}, u_2) + v_1^P(u_1^P) + v_1^{NP}(u_1^{NP}) + v_2(u_2).$$

For the above system, we derive the optimal prices that the platform and the social planner should charge to maximize profit.

6.2. Profit-Maximizing Platform

The following proposition gives the structure of the optimal prices that a profit-maximizing platform would set.

Proposition 1. *Given the number of hosts and customers in the market, the profit-maximizing price satisfies the following equation:*

$$p_1^P = f_1 - \alpha_2 n_2 + \frac{\phi_1(u_1^P)}{\phi_1'(u_1^P)} \ ; \ p_1^{NP} = f_1 - \alpha_2 n_2 + \frac{\phi_1(u_1^{NP})}{\phi_1'(u_1^{NP})} \ ; \ p_2 = f_2 - \alpha_1 n_1 + \frac{\phi_2(u_2)}{\phi_2'(u_2)}.$$

[13] Again, these can be interpreted as "membership costs," but a model that considers costs per transaction (i.e., a usage model) would yield the same conclusions, following Rochet and Tirole (2006).

The structure of optimal prices is similar to that of traditional two-sided market models: the price of each group i depends on the cost of serving that group, f_i, the network externalities of that group, $\alpha_j n_j$, and the elasticity of group participation, $\frac{\phi_i(u_i)}{\phi_i'(u_i)}$. For example, for customers, their serving costs are f_2, their network externalities are $\alpha_1 n_1$ (i.e., the benefit of an additional customer to all hosts), and their elasticities of participation are $\frac{\phi_2(u_2)}{\phi_2'(u_2)}$.

Whether the platform should charge a lower price to the group that is at disadvantage (i.e., nonprofessionals) depends on the elasticity of group participation (which depends on the demand function). Specifically, if $\frac{\phi_1(x)}{\phi_1'(x)}$ is an increasing function of x (which would happen if the demand were increasing and concave), then $p_1^{NP} < p_1^P$. In other words, under a standard increasing and concave demand function, the platform's optimal strategy is to lower the prices for nonprofessional hosts. The main intuition is that since both professional and nonprofessional hosts are equally attractive to customers, the platform wants to charge a lower price to nonprofessional hosts, given that they are less likely to participate (or more likely to exit after trial-out period as we shown in our data) due to their lower performance.

Moreover, since $u_1^P(n_2,p) - u_1^{NP}(n_2,p) = \alpha_1(1-\beta)n_2$, it is not surprising that the price difference increases as β decreases. When the performance of the nonprofessional hosts is worse, the platform has to compensate nonprofessional hosts more, assuming that the demand function is increasing and concave in utilities. Note that a simple two-part tariff system, in which each host is charged a base fee for participating and an add-on fee for each additional property, could help the platform compensate for the performance differences between professional and nonprofessional hosts.

Finally, if the platform can reduce the performance discrepancy between professional and nonprofessional players (i.e., by helping nonprofessional agents become more competitive in the market), how much could they benefit from this? Since we cannot characterize the profit improvement in a closed form for general demand functions, we assume a simple and widely used linear demand model:

$$\phi_1(u) = k_1 u - k_2 \ ; \ \phi_2(u) = k_3 u - k_4. \tag{3}$$

LEMMA 1. *Given that the demand functions for both hosts and customers are linear, the platform's profit is increasing in β. In particular,*

$$\frac{\partial \pi^*}{\partial \beta} = \frac{\alpha_1 n_2^* n_1^*}{2},$$

where n_1^* and n_2^* are the optimal number of hosts and customers in the system, independent of β.

It is not surprising that the optimal profit is increasing in β: if the nonprofessional hosts perform better (i.e., β increases), the platform can charge higher prices to nonprofessional hosts and in turn collect higher profits. This suggests that Airbnb could consider interventions that help nonprofessional hosts dynamically adjust their prices more efficiently, such as the price tip tool launched by Airbnb on June 4th, 2015.[14] The rate at which optimal profit increases with β depends on the attractiveness of customers to hosts α_1 and the size of the system n_1^* and n_2^*. The intuition is that, when customers become more and more attractive, the loss in the number of nonprofessional hosts due to the operational discrepancy is larger.

6.3. Welfare-Maximizing Social Planner

From the perspective of a social planner, we can characterize the welfare-maximizing prices as follows.

Proposition 2. *Given the number of hosts and customers in the market, the welfare-maximizing price satisfies the following equation:*

$$p_1^P = f_1 - \alpha_2 n_2 \ ; \ p_1^{NP} = f_1 - \alpha_2 n_2 \ ; \ p_2 = f_1 - \alpha_1 n_1.$$

Surprisingly, the social planner's optimal strategy is to charge the same price to both professional and nonprofessional agents regardless of the operational discrepancy. The intuition behind this result is that the social planner, when deciding prices for one type of host, cares the platform's profits as well as hosts' and customers' utilities from participating. Since hosts' and customers' aggregated utilities is decreasing in prices, the social planner should lower the prices until the increment gain on participants' utilities cannot overweigh the increment loss on firms' costs, even when β is equal to one. Therefore, when β is less than one, the social planner cannot further lower prices to nonprofessional hosts since the incremental gain from doing so cannot overweigh the incremental loss on the platform's costs. Therefore, the social planner should not charge differentiated prices to professional and nonprofessional hosts when there is an operational discrepancy.

In sum, there are several insights obtained from combining our empirical results with a well-established two-sided market model. First, our analysis shows that, under mild assumptions on demand functions, the platform has incentives to charge different prices to professional and nonprofessional agents. Specifically, the platform's optimal strategy is to lower the price for nonprofessional agents to compensate for their loss in the competition. With a conventional linear demand system, we show that the optimal profit increases in β monotonically. In particular, the increasing rate depends on the attractiveness of customers to hosts (α_1) and the size of the systems (n_1^* and n_2^*). Second, our results show that the social planner, contrary to our intuition, does not want to charge different prices for different type of hosts.

[14] "Using Data to Help Set Your Price." Airbnb Blog June 4, 2015.

7. Conclusion

The sharing-economy business model comes with an increase in the use of nonprofessional labor. We have used Airbnb as the empirical setting to study the implications of this shift towards using nonprofessional service providers.

We have documented substantial discrepancies between professional and nonprofessional hosts. All else being equal, a property managed by a professional host earns more than a 16.9% higher average daily revenue, has a 15.5% higher occupancy rate. Moreover, properties managed by professional hosts are 13.6% less likely to exit the market compared with properties owned by nonprofessional hosts, controlling for property and market characteristics. We have shown that these discrepancies can be rationalized by the pricing inefficiencies of nonprofessional hosts, such as less frequent price adjustments and inadequate response to instances of high demand.

Finally, we have combined our empirical results with traditional two-sided market models to show that platforms like Airbnb should charge a lower price to nonprofessional hosts to compensate for their lower performance or, alternatively, could try to assist nonprofessionals with their pricing and capacity-management decisions. An example of this is the pricing that Airbnb is currently providing to its hosts or the "heat maps" that Uber shows their drivers, to indicate areas where they are more likely to find a customer. Such actions help inexperienced hosts and drivers make more money, and are also likely to increase the profits of the platform.

Although our empirical analysis has focused on Airbnb, we believe that our results provide meaningful insights that go beyond this specific setting. Other platforms such as Uber also use a combination of professionals (e.g., a full-time driver offering a "black car" service) and nonprofessionals (e.g., a student occasionally driving for Uber via their "UberX"). We expect that our findings, which point to a lower efficiency of nonprofessionals, could play similarly in a service like Uber. Furthermore, as innovative business models are finding new ways of shifting risks to different parts of the value chain including final customers (Girotra and Netessine 2014), the inefficiencies that we observe arising from the use of nonprofessionals could become even more important.

References

Anderson, C. and Xie, X. (2011). A choice-based dynamic programming approach for setting opaque prices. *Production and Operations Management*, 21(3):590–605.

Armstrong, M. (2006). Competition in two-sided markets. *The RAND Journal of Economics*, 37(3):668–691.

Benjaafar, S., Kong, G., Li, X., and Courcoubetis, C. (2015). Modeling and analysis of collaborative consumption in peer-to-peer car sharing. *University of Minnesota, Working Paper.*

Bitran, G. and Caldentey, R. (2003). An overview of pricing models for revenue management. *Manufacturing & Service Operations Management*, 5(3):203–229.

Bodea, T., Ferguson, M., and Garrow, L. (2009). Choice-based revenue management: Data from a major hotel chain. *Manufacturing & Service Operations Management*, 11(2):356–361.

Buell, R. W., Kim, T., and Tsay, C.-J. (2015). Creating reciprocal value through operational transparency. *Harvard Business School Technology & Operations Mgt. Unit Working Paper*, (14-115).

Cachon, G. P., Daniels, K. M., and Lobel, R. (2015). The role of surge pricing on a service platform with self-scheduling capacity. *Working Paper*.

Cui, R., Li, J., and Zhang, D. J. (2016). Mitigating digital discrimination with reviews in the sharing economy: Field evidence from airbnb. *Working Paper*.

Cullen, Z. and Farronato, C. (2014). Outsourcing tasks online: Matching supply and demand on peer-to-peer internet platforms. *Working Paper*.

David, P. A. (1985). Clio and the economics of qwerty. *The American Economic Review*, pages 332–337.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, 47(2):315–72.

DellaVigna, S. and Pollet, J. M. (2009). Investor inattention and friday earnings announcements. *The Journal of Finance*, 64(2):709–749.

Edelman, B. G., Luca, M., and Svirsky, D. (2015). Racial discrimination in the sharing economy: Evidence from a field experiment. *Harvard Business School NOM Unit Working Paper*, (16-069).

Eisenmann, T., Parker, G., and Van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard business review*, 84(10):92.

Ellison, G. and Fudenberg, D. (2003). Knife-edge or plateau: When do market models tip? *The Quarterly Journal of Economics*, pages 1249–1278.

Farrell, J. and Saloner, G. (1985). Standardization, compatibility, and innovation. *The RAND Journal of Economics*, pages 70–83.

Fradkin, A. (2014). Search frictions and the design of online marketplaces. *NBER Working Paper*.

Frei, F. and Morriss, A. (2012). Uncommon service. *Harvard Business Review Press, Boston*.

Gallego, G. and Van Ryzin, G. (1994). Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Management science*, 40(8):999–1020.

Girotra, K. and Netessine, S. (2014). *The risk-driven business model: Four questions that will define your company*. Harvard Business Press.

Goodwin, T. (2015). The battle is for the customer interface. `http://techcrunch.com/2015/03/03/in-the-age-of-disintermediation-the-battle-is-all-for-the-customer-interface`.

Gurvich, I., Lariviere, M., and Moreno, A. (2015). Operations in the on-demand economy: Staffing services with self-scheduling capacity. *Northwestern University, Working Paper*.

Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In *Annals of Economic and Social Measurement, Volume 5, number 4*, pages 475–492. NBER.

Horton, J. J. and Zeckhauser, R. J. (2016). Owning, using and renting: Some simple economics of the" sharing economy". Technical report, National Bureau of Economic Research.

Huang, T., Allon, G., and Bassamboo, A. (2013). Bounded rationality in service systems. *Manufacturing & Service Operations Management*, 15(2):263–279.

Jerath, K., Netessine, S., and Veeraraghavan, S. K. (2010). Revenue management with strategic customers: Last-minute selling and opaque selling. *Management Science*, 56(3):430–448.

Kabra, A., Belavina, E., and Girotra, K. (2015). Bike-share systems: Accessibility and availability. *Chicago Booth Research Paper*, (15-04).

Katz, M. L. and Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, pages 424–440.

Lederman, R., Olivares, M., and Ryzin, G. V. (2014). Identifying competitors in markets with fixed product offerings. Columbia Business School Research Paper No. 14-10.

List, J. A. (2003). Does market experience eliminate market anomalies? *The Quarterly Journal of Economics*, 118(1):41–72.

List, J. A. (2004). Neoclassical theory versus prospect theory: Evidence from the marketplace. *Econometrica*, 72(2):615–625.

Malmendier, U. and Tate, G. (2008). Who makes acquisitions? ceo overconfidence and the market's reaction. *Journal of Financial Economics*, 89(1):20–43.

Mayer, C. (2001). Loss aversion and seller behavior: Evidence from the housing market. *Quarterly Journal of Economics.*

Netessine, S. and Shumsky, R. A. (2005). Revenue management games: Horizontal and vertical competition. *Management Science*, 51(5):813–831.

Parker, G., Van Alstyne, M., and Choudary, S. (2016). Platform revolution.

Parker, G. G. and Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management science*, 51(10):1494–1504.

Rochet, J.-C. and Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, 1(4):990–1029.

Rochet, J.-C. and Tirole, J. (2006). Two-sided markets: a progress report. *The RAND Journal of Economics*, 37(3):645–667.

Rosenbaum, P. R. (2002). *Observational studies.* Springer.

Sekhon, J. S. (2008). Multivariate and propensity score matching software with automated balance optimization: the matching package for r. *Journal of Statistical Software, Forthcoming.*

Su, X. (2007). Intertemporal pricing with strategic customer behavior. *Management Science*, 53(5):726–741.

Su, X. (2008). Bounded rationality in newsvendor models. *Manufacturing & Service Operations Management*, 10(4):566–589.

Talluri, K. T. and Van Ryzin, G. J. (2006). *The theory and practice of revenue management*, volume 68. Springer Science & Business Media.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

Zervas, G., Proserpio, D., and Byers, J. (2014). The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. *Boston U. School of Management Research Paper*, (2013-16).

Zhao, W. and Zheng, Y.-S. (2000). Optimal dynamic pricing for perishable assets with nonhomogeneous demand. *Management science*, 46(3):375–388.

Appendix

A. Proof of Proposition 1

Since both $\phi_1(\cdot)$ and $\phi_2(\cdot)$ are concave and increasing, the first order condition is necessary for optimal pricing. Due to envelope theorem, the first order condition of the value function respect to u_1^P should be 0:

$$\frac{\partial \pi}{\partial u_1^P} = -\phi_1(u_1^P) + \phi_1'(u_1^P)[\alpha_1\phi_2(u_2) - u_1^P - f_1] + \phi_2(u_2)[\alpha_2\phi_1'(u_1^P)] = 0.$$

Substituting Equation 1:

$$p_1^P = f_1 - \alpha_2 n_2 + \frac{\phi_1(u_1^P)}{\phi_1'(u_1^P)}.$$

Similarly, using envelope theorems on the value function respect to u_1^{NP} and u_2, we can derive:

$$p_1^{NP} = f_1 - \alpha_2 n_2 + \frac{\phi_1(u_1^{NP})}{\phi_1'(u_1^{NP})} \ ; \ p_2 = f_2 - \alpha_1 n_1 + \frac{\phi_2(u_2)}{\phi_2'(u_2)}.$$

■

B. Proof of Proposition 2

Since both $\phi_1(\cdot)$ and $\phi_2(\cdot)$ are concave and increasing, the first order condition is necessary for optimal pricing. Based on our assumption that , the optimization problem of the social welfare satisfies the envelope theorem. Therefore, taking the first order condition of the value function respect to u_1^P:

$$\frac{\partial w}{\partial u_1^P} = -\phi_1(u_1^P) + \phi_1'(u_1^P)[\alpha_1\phi_2(u_2) - u_1^P - f_1] + \phi_2(u_2)[\alpha_2\phi_1'(u_1^P)] + \phi_1(u_1^P) = 0,$$

which implies that

$$\alpha_1\phi_2(u_2) - u_1^P - f_1 + \phi_2(u_2)[\alpha_2\phi_1'(u_1^P)] = 0.$$

Re-arranging equations and substituting Equation 1:

$$p_1^P = f_1 - \alpha_2 n_2.$$

Similarly, using envelope theorems on the value function respect to u_1^{NP} and u_2, we can derive:

$$p_1^{NP} = f_1 - \alpha_2 n_2 \; ; \; p_2 = f_1 - \alpha_1 n_1.$$

■

C. Proof of Lemma 1

Based on Proposition 1, it is easy to see that the difference between optimal prices charged on professional and nonprofessional hosts are constant: $p_1^{P*} - p_1^{NP*} = (1-\beta)\alpha_1 n_2$. Therefore, solving the optimal prices is equivalent to solving the following linear system:

$$\begin{bmatrix} p_1^* \\ p_2^* \\ n_1^* \\ n_2^* \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & \frac{\alpha_1-\alpha_2}{2} \\ 0 & 0 & \frac{\alpha_2-\alpha_1}{2} & 0 \\ -2k_1 & 0 & 0 & 2\alpha_1 k_1 \\ 0 & -k_3 & \alpha_2 k_3 & 0 \end{bmatrix} \times \begin{bmatrix} p_1^* \\ p_2^* \\ n_1^* \\ n_2^* \end{bmatrix} + \begin{bmatrix} \frac{f_1}{2} - \frac{k_2}{2k_1} \\ \frac{f_2}{2} - \frac{k_4}{2k_3} \\ -2k_2 \\ k_4 \end{bmatrix} \tag{4}$$

where $p_1^* = p_1^{P*}$ and $n_1^* = n_1^{P*} + n_1^{NP*}$.

Based on Equation 4 can be seen that (1) the optimal prices charged to the professional host p_1^* and customers p_2^* do not depend on β and (2) the optimal numbers of hosts and customers (i.e., n_1^* and n_2^*) do not depend on β. Moreover, notice that since the difference in optimal prices charged to professional and nonprofessional hosts are constant, it is easy to see that $n_1^{P*} = n_1^{NP*}$ regardless of β. Therefore,

$$\pi^* = \frac{n_1^*}{2}(p_1^{P*} + p_1^{NP*}) - n_1^* f_1 + n_2^*(p_2^* - f_2) = n_1^*(p_1^* - f_1) + n_2^*(p_2^* - f_2) - \frac{(1-\beta)\alpha_1 n_2^* n_1^*}{2}$$

Hence,

$$\frac{\partial \pi^*}{\partial \beta} = \frac{\alpha_1 n_2^* n_1^*}{2}.$$

■