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The Hidden Price Effect: Partitioned Pricing and Host Accommodation Strategies on Airbnb

Shaohui Gao[1] & Yiming He[2]

[1] School of Accounting, Guangzhou College of Technology and Business, Guangzhou, China

[2] Department of Tourism Management, South China University of Technology, Guangzhou, China

Correspondence: Yiming He, Department of Tourism Management, South China University of Technology, Guangzhou, 510006, China.

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Abstract

This paper investigates the relationship between various room types and partitioned pricing strategies under the theoretical framework of market equilibrium between guests and hosts on an online short-term rental platform. Using Beijing Airbnb listing data from April 2018 to October 2020, we use the (log) cleaning-fee-to-price ratio to measure partitioned pricing. A predicted instrumental variable method is used to address endogeneity issues. Empirical results show that an increase in partitioned pricing intensity reduces room-type privacy, implying hosts are more likely to offer shared rooms. This negative relationship is robust to alternative fixed-effects specifications. The findings provide empirical evidence linking partitioned pricing to hosts' strategic supply decisions.

Keywords: Airbnb Pricing Strategy, Shared-Room Service, Sharing Economy

1. Introduction

The scope of the Airbnb market has expanded across metropolitan areas worldwide since 2008 (Farronato & Fradkin, 2022). Hence, this paper collects data from Airbnb listings in Beijing, China, spanning from April 2018 to October 2020. Beijing is one of the world's biggest metropolises and the capital city of China. Therefore, the dataset from the Beijing metropolitan area provides a sample for investigating the effects of the host's partitioned pricing strategies on Airbnb room types.

In addition, geographic environments and historical landmarks can significantly affect the development of metropolitan Airbnb communities. Therefore, this paper conducts endogeneity tests to assess the causal link between partitioned pricing intensity and room type by constructing a predicted distance variable between properties and historical landmarks in our regression models. To quantify the prediction that the host's partitioned pricing intensity affects short-term room type, this paper develops a theoretical framework for the short-term rental equilibrium market to characterize this effect. Meanwhile, this paper uses the two-stage least squares (2SLS) method to address the potential endogeneity issues between the host's partitioned pricing intensity and room type.

Overall, the motivation of this paper is to develop a short-term rental market equilibrium model on the Airbnb platform by exploring a conceptual framework that predicts opposite-signed causal effects of the host's partitioned pricing intensity on room type and by providing a real-world example that forms the basis for estimating related coefficients.

The paper is organized as follows. Section 2 provides a literature review. Section 3 presents a theoretical framework that derives a testable hypothesis. Section 4 introduces the data source and empirical strategies. Section 5 reports the main empirical results, discusses robustness checks and endogeneity tests, and presents sensitivity tests. Section 6 provides further discussion. Section 7 concludes.

2. Literature Review

In this paper, we examine the differences in room types chosen by hosts who implement partitioned pricing strategies and those who do not. We investigate whether room-type choices are affected by distances to properties and historical landmarks, or by other determinants. In carrying out this research, we contribute to the growing empirical literature on the Airbnb platform (Gunter 2018, Luo and Tang 2019, Moreno-Izquierdo, L., Ramón-Rodríguez, A. B., Such-Devesa, M. J., & Perles-Ribes, J. F. 2019). We highlight the heterogeneous responses in the effect of partitioned pricing intensity on room type across districts over time. In contrast to these studies, our empirical analysis examines that effect by

constructing predicted distances between properties and historical tourist attractions across districts and over time, thereby contributing to the literature on spatial effects within the sharing economy.

Our study relates to and contributes to four strands of literature. The first body of literature pertains to Airbnb pricing research. Several notable studies—including those by Adamiak (2022), Cai, Y., Zhou, Y., Ma, J., & Scott, N. (2019), Barron, K., Kung, E., & Proserpio, D (2020), Nieuwland and van Melik (2020), and Holtz, D., Lobel, F., Lobel, R., Liskovich, I., & Aral, S (2025)—address regulations and development in pricing dynamics for Airbnb properties. We take a different approach, focusing instead on the effects of hosts' partitioned pricing strategy on room-type provision, and we integrate a predicted instrumental variable (IV) approach. We provide findings that connect the partitioned pricing strategy, room-type provision, and the predicted distance variable to the properties and historical landmarks. We provide a detailed proof, and the results suggest that our theoretical explanation facilitates efficient causal inference in Airbnb studies.

Second, Barnes (2021), Barnes and Kirshner (2021), Banerjee, S., Lens, M., & Pal, A. (2022), Zhang, S., Lee, D., Singh, P. V., & Srinivasan, K. (2022), Zhang, H., Zach, F. J., & Xiang, Z. (2023), Li, H., Wang, Q., Li, G., & Cai, D. (2023),Zhang, H., Zach, F. J., & Xiang, Z. (2024a), Zhang, H., Zach, F. J., & Xiang, Z. (2024b), and Bai, S., Huang, X., Han, C., Yang, M., Yu, D., & Bi, X. (2024) conduct empirical research on Airbnb operations management using empirical approaches. For instance, Zhang et al. (2022) develop a difference-in-differences model to estimate the causal effect of property photo quality on property demand. Zhang et al.'s approach fails to account for how room types are affected by the partitioned pricing strategy in the high-dimensional fixed-effects regressions. Additionally, Gao & He (2026) investigate the effects of contractual cancellation policies on Airbnb prices. Based on it, we use a two-stage least squares (2SLS) approach to identify the effect of partitioned pricing on Airbnb room type, controlling for high-dimensional fixed effects.

Third, there is a large literature on Airbnb pricing strategy, including Chen and Xie (2017), Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., & Goodwill, A. (2018), Chattopadhyay and Mitra (2019), Tang, L. (Rebecca), Kim, J., & Wang, X (2019), Falk, M., Larpin, B., & Scaglione, M. (2019), Lawani, A., Reed, M. R., Mark, T., & Zheng, Y. (2019), Lorde, T., Jacob, J., & Weekes, Q. (2019), Zhang and Fu (2020), Boto-García, D., Mayor, M., & De la Vega, P (2021), Sainaghi, R., Abrate, G., & Mauri, A. (2021), and Leoni and Nilsson (2021). Related to our paper are the estimated determinants of Airbnb prices from Casamatta, G., Giannoni, S., Brunstein, D., & Jouve, J (2022), Wang and Rasouli (2022), and Milone, F. L., Gunter, U., & Zekan, B. (2023). Here, the papers by Tan, H., Su, T., Wu, X., Cheng, P., & Zheng, T. (2024), Wang (2025), Lin, L., Hu, M., Li, H., & Liu, M (2024), and Lin and Yang (2024) are most closely related to ours in terms of empirical paradigm. Lin and Yang (2024) and Lin et al. (2024) investigate the effects of guests' comments and property cover image scenes on Airbnb listing prices, respectively. But they do not consider applying the predicted IV approach to estimate Airbnb pricing effects. The AI methodologies of Tan et al. (2024) and Wang (2025) do not predict the causal effects of the partitioned pricing strategy on room type, which is central to our research.

Finally, in studies of P2P platforms, some scholars have investigated the impact of friendships on online P2P lending (Liu, D., Brass, D. J., Lu, Y., & Chen, D 2015). The risk of such a platform is affected by the platform's design and other organizational factors (Bao, T., Ding, Y., Gopal, R., & Möhlmann, M. 2024). Furthermore, Klein, G., Shtudiner, Z., & Zwilling, M. (2023) explain the reasons for the failure of P2P platforms. Currently, scholars on online platforms are beginning to use facial recognition algorithms in computer vision to detect smiles (Prithi & Tamizharasi, 2024). For instance, Sheng et al. (2025) find that anchors' positive facial expressions encourage consumer purchasing behavior. Ramya et al. (2025) design a hands-free selfie system to detect smiles using machine learning algorithms. Actually, perceived technology security encourages positive perceptions and intentions towards facial recognition payment (Lim et al., 2025). Nevertheless, those papers do not establish a formal model to identify the effects of partitioned pricing.

Overall, the motivation for this study is to develop a formal model of market equilibrium that incorporates consumers' optimal leasing demand and the host's optimal pricing strategies. This includes theoretical links between consumers' privacy and the demand for leasing optimal short-term apartments within the utility-maximization framework. In addition, this study provides a concrete, real-world example (e.g., Airbnb share contracts between hosts and the platform) that forms the basis for justifying various parameters and assumptions in the host's pricing model.

While share contracts are common in the real world, standard share contract models assume that prices are not involved in the share contracts or that there is only one equilibrium share rate in sharecropping. Against this background, our study aims to answer the following questions: (1) How does the consumer's privacy preference affect the host's partitioned pricing strategy through the profit maximization problem under share contracts? (2) How to identify and examine the causal effects of room type on partitioned pricing by the instrumental variable approach through constructing a predicted distance variable between the property and the eight 5A tourist attractions?

To be sure, our study's contributions are both theoretical and empirical. Our theoretical framework (1) develops a

formal model of short-term rental market equilibrium through a Peer-to-Peer (P2P) platform to identify the causal effect of partitioned pricing intensity on room type. In addition, it (2) derives a theoretical hypothesis to predict the relationship between the implementation of a partitioned pricing strategy and room type. Empirically, meanwhile, (1) we show that the host's partitioned pricing intensity encourages the provision of shared-room service, and (2) we construct the predicted distance variable as a candidate for an efficient instrumental variable (IV) for the partitioned pricing intensity variable to identify the causal effects of the partitioned pricing strategy on room type.

3. Theoretical Model

To begin, we establish a representative consumer's utility-maximization model to demonstrate the relationship between room type or privacy (RT) and partitioned pricing intensity or the cleaning fee-to-price ratio (PPS). The representative consumer's preference is captured by the following utility function:

$$\mathrm{u} = \beta^{RT} dc,$$

where d denotes the consumer's demand for the property and c represents the consumption of a composite commodity. The guest's income is I, so his budget constraint is given by

$$I = c + (\bar{p} + f)d + g(RT),$$

where $\bar{p}$ denotes rental prices, f denotes the cleaning fee ($f > 1$), β denotes the base service intensity per unit of physical space ($\beta > 1$), and RT represents the type of room or the level of privacy (e.g., $RT = 1$ for shared room or low level of privacy; $RT = 2$ for private room or moderate level of privacy; and $RT = 3$ for entire apartment or high level of privacy). In addition, we assume the consumer's cost of privacy $g(RT) = aRT^2$ is a convex function. It implies that as the level of privacy rises (from a shared room (RT=1) to an entire apartment (RT=3)), the property must provide greater space exclusivity. As a result, the consumer has to pay much more for a higher level of privacy.

Therefore, the consumer can choose among d, c, and RT to maximize his utility under the budget constraint. To solve this maximization problem, we set up the Lagrangian function:

$$L(d, c, RT) = \beta^{RT} dc + \lambda[I - c - (\bar{p} + f)d - aRT^2].$$

The first-order conditions for this problem require that

$$\frac{\partial L}{\partial d} = \beta^{RT} c - \lambda(\bar{p} + f) = 0,$$

$$\frac{\partial L}{\partial c} = \beta^{RT} d - \lambda = 0,$$

$$\frac{\partial L}{\partial RT} = \beta^{RT} ln\beta dc - \lambda 2aRT = 0.$$

Thus, the consumer's optimal choice is to rent the property $d^* = \frac{2aRT}{(\bar{p}+f)ln\beta}$.

We define the cleaning fee-price ratio $PPS = \frac{f}{\bar{p}}$ ($0 < PPS < 1$) and let α be the Airbnb platform service rate ($0 < \alpha < 1$). We assume the host's cost function of charging a cleaning fee is $C_h(f) = \frac{f^2}{2}$, and the host's cost function of operating various types of rooms $k(RT)$ is convex ($k''(RT) > 0$), and then the host's profit maximization problem is given by ($\bar{p} + f = \bar{p}(1 + PPS)$):

$$\max_{\{RT,PPS\}} \pi_h = [(1-\alpha)\bar{p} + f - C_h(f)]d^* - k(RT) = \bar{p}[(1-\alpha) + PPS - \frac{\bar{p}(PPS)^2}{2}]\frac{2aRT}{\bar{p}(1+PPS)ln\beta} - k(RT) = [(1 -$$

$$\alpha) + PPS - \frac{\bar{p}(PPS)^2}{2}]\frac{2aRT}{(1+PPS)ln\beta} - k(RT).$$

The first-order condition with respect to RT is given by:

$$\frac{d\pi_h}{dRT} = \frac{2a}{ln\beta}\frac{[1-\alpha+PPS-\frac{\bar{p}(PPS)^2}{2}]}{(1+PPS)} - k'(RT) = 0.$$

Therefore, we obtain

$$k'(RT) = \frac{2a}{ln\beta}\frac{[1-\alpha+PPS-\frac{\bar{p}(PPS)^2}{2}]}{(1+PPS)}. \quad (1)$$

We differentiate equation (1) with respect to PPS:

$$\frac{d[k'(RT)]}{dRT}\frac{dRT}{dPPS} = \frac{2a}{ln\beta}\frac{(1-\bar{p}PPS)(1+PPS)-\left[1-\alpha+PPS-\frac{\bar{p}(PPS)^2}{2}\right]}{(1+PPS)^2} = \frac{2a}{ln\beta}\frac{[\alpha-f\left(1+\frac{PPS}{2}\right)]}{(1+PPS)^2}.$$

Thus,

$$\frac{dRT}{dPPS} = \frac{1}{k''(RT)}\frac{2a}{ln\beta}\frac{[\alpha-f\left(1+\frac{PPS}{2}\right)]}{(1+PPS)^2} < 0, \text{ because } k''(RT) > 0, \frac{2a}{ln\beta} > 0, \text{ and } f\left(1+\frac{PPS}{2}\right) > 1 > \alpha.$$

As a result, we obtain:

$$\frac{dRT}{dlnPPS} = PPS\frac{dRT}{dPPS} < 0 \quad (2).$$

PROPOSITION 1: An increase in the host's partitioned pricing intensity reduces privacy.

Proposition 1 implies that if the cleaning fee increases relative to the base rent, the consumer's total leasing cost rises. According to the law of demand, when the effective price increases, the quantity demanded of a good with a high level of privacy decreases. In anticipation of this demand shock, hosts adjust their room-type provision strategies toward lower-privacy accommodations.

Hence, we propose a theoretical hypothesis:

Hypothesis 1: *An increase in the partitioned pricing intensity leads to a rise in the provision of shared room service.*

This hypothesis also implies that implementing a partitioned pricing strategy encourages the host to offer more shared rooms. Thus, in the next section (e.g., equation (3)), we test this hypothesis, according to comparative statics from formula (2).

4. Empirical Evidence

Based on the theoretical framework, we derive a hypothesis predicting the negative effect of partitioned pricing intensity on room type. Therefore, we conduct empirical research to provide some evidence to test and support it.

4.1 Data Sources

Our data come from Inside Airbnb for Beijing, China, covering the period from April 2018 to October 2020. For each Airbnb listing, we collected information on the property's location, average rent, host ID, and all reviews from guests who have stayed there. In addition, to estimate causal effects, we construct a predicted instrumental variable using information on the locations of 5A tourist attractions, then merge Airbnb listing data with Beijing 5A tourist attractions data using district names.

A tourist attraction rating standard (GBT 17775-2003) was established in China in 2003. This standard divides tourist attractions into five levels, from 1A to 5A (AAAAA), with 5A as the highest level (Lin, Y. X., Lin, B. S., Chen, M. H., & Su, C. H. 2020). The Beijing 5A tourist attractions data come from the open platform of the Beijing city public data platform. This dataset records eight 5A tourist attractions in Beijing, including Prince Gong's Mansion, Badaling Great Wall, Temple of Heaven, Mutianyu Great Wall, the Palace Museum, Old Summer Palace, Summer Palace, and Imperial Tombs of the Ming and Qing Dynasties. We obtain the latitudes and longitudes of the centroids of the 5A tourist attractions from ZIP codes and addresses using ArcGIS.

4.2 Econometric Models and Specifications

This section uses high-dimensional fixed-effects (HDFE) models to estimate the impact of the host's partitioned pricing intensity on room type in our Airbnb samples. To address potential endogeneity issues, we use the two-stage least squares (2SLS) method (Angrist, 2001). Thus, the 2SLS-HDFE regression function can be expressed as follows:

$$RT_{ijtk} = a_t + \delta_j + \varphi_k + b\text{PPS}_{ijtk} + \theta X_{ijtk} + e_{ijtk}, \quad (3)$$

where RT_{ijtk} represents the room type for the ith listing at wave t in community j with property type k, PPS_{ijtk} denotes the (log) host's partitioned pricing intensity for the ith listing at wave t in community j with property type k, and

e_{ijtk} represents the error term. The vector X_{ijtk} includes covariates such as the (log) number of rooms, (log) number of bathrooms, (log) number of bedrooms, and (log) number of beds. The HDFE strategy enables us to control for the entire set of wave fixed effects (a_t), property fixed effects (φ_k), and community fixed effects (δ_j). For instance, $RT_{ijtk} = 1$ for shared usage rights of the room (a shared room in an Airbnb, so guests share the sleeping area with others in a private bedroom), $RT_{ijtk} = 2$ for private usage rights of the room (a private room in a shared home, so guests have a private bedroom but share common areas outside the bedroom), and $RT_{ijtk} = 3$ for private usage rights of the entire apartment (an entire house, so guests have exclusive access to the whole property). In the real world, the practices from Airbnb's standard categories confirm the room as the base unit, with apartments as multi-room extensions: (1) shared room: a single room in a shared space (e.g., a bunk bed or shared bedroom in a house); (2) private room: a single room in a multi-room apartment with private access (e.g., a private bedroom in a shared apartment) and the guests share common areas; (3) entire house: the full apartment with multiple rooms (e.g., a full three-bedroom unit).

4.3 Identification of Instrumental Variable

In this subsection, we first construct a predicted instrumental variable following Lipscomb, M., Mushfiq Mobarak, A., & Barham, T. (2013). Specifically, we first calculate each property's suitability score for adopting a partitioned pricing strategy using a probit model with the actual geographical distances to eight 5A tourist attractions in Beijing as exogenous regressors. Based on such a score, we construct the predicted instrumental variable (IV) by computing the product of the suitability score and the predicted adoption indicator, and then capture the relevant condition: Airbnb properties near 5A tourist attractions face higher visitor demand, enabling higher base prices and reducing the incentive to implement a partitioned pricing strategy. Therefore, the predicted distance variable is positively associated with partitioned pricing intensity.

On the other hand, these 5A tourist attractions, which are cultural and historical landmarks, predate the modern Airbnb market by centuries, ensuring that the predicted distance variable reflects only the exogenous spatial cost structure rather than any strategic decisions made by hosts. These landmarks were established as significant tourist destinations long before the emergence of peer-to-peer accommodation platforms. Their locations are determined by historical, cultural, and political factors that are entirely exogenous to contemporary Airbnb hosts' partitioned pricing decisions and room-type choices. Hence, after controlling for community, property, and time fixed effects, distance to historical tourist attractions is plausibly exogenous with respect to unobserved determinants of room-type decisions. It means that this predicted distance variable satisfies the exclusion condition.

Overall, we select the predicted distance variable as a candidate for the efficient IV for the host's partitioned pricing intensity (see Figure 1). This choice addresses potential endogeneity issues between the host's partitioned pricing intensity variable and the dependent variable (room type) in equation (3). As a result, we use the following equation as the first-stage regression for equation (3):

$$\mathrm{PPS}_{ijtk} = a_t + \delta_j + \varphi_k + \rho \mathrm{PD}_{ijtk} + \gamma X_{ijtk} + \varepsilon_{ijtk}\,, \tag{4}$$

where X_{ijtk} is exogenous and PD_{ijtk} serves as the instrumental variable for PPS_{ijtk}. To save space, we report only the coefficients of the host's partitioned pricing intensity or the implementation of such a pricing strategy in the second-stage panel.

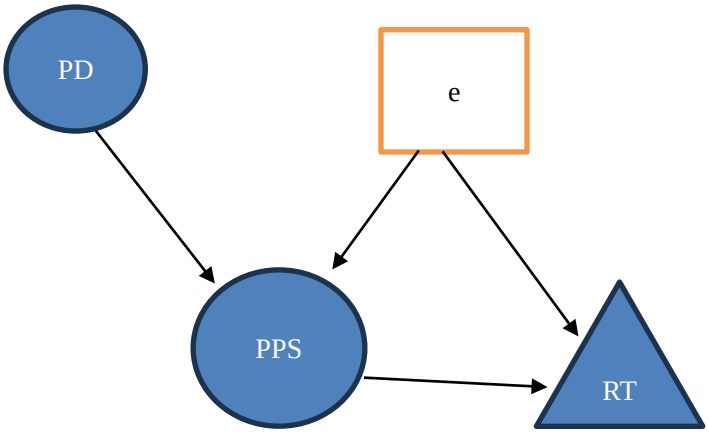

Figure 1. Causal diagram of IV

4.4 Quantile Regression

Furthermore, we use quantile regression (QR) as an alternative estimation method (Koenker & Bassett, 1978) to replace OLS (Koenker & Hallock, 2001). The QR estimates are more robust to outliers than OLS (Koenker, 2017). Hence, we express the quantile regression in the form of the location-scale model developed by Rios-Avila et al. (2024) as follows:

$$Q_{RT}(\tau|\mathrm{X}) = \mathrm{X}B + X\ell(\tau) \quad (5),$$

where X denotes explanatory variables, $Q_{RT}(\tau|\mathrm{X})$ denotes the τ-th conditional quantile of RT (room type), B denotes the location parameter vector, and $\ell(\tau)$ denotes the scale parameter vector as a function of τ.

5. Empirical Results

Table A1 shows the symbols, measurements, and data resources for major variables in this paper.

Table A1. Major Variables, Measurements, and Data Sources

Variable	Symbol	Measurement	Data Source
Room Type / Privacy Level	RT	Ordinal variable: 1 = Shared room (low privacy), 2 = Private room (moderate privacy), 3 = Entire apartment (high privacy)	Airbnb listing data
Partitioned Pricing Intensity	PPS	(log) Cleaning-fee-to-price ratio: ln(Cleaning Fee / Nightly Price)	Airbnb listing data
Predicted Distance	PD	Actual geographical distance from property to the nearest of eight 5A tourist attractions in Beijing	ARCGIS / open platform of Beijing city public data

5.1 Benchmark Specification

Table 1. OLS Regression Results of Partitioned Pricing Strategic Effects on Airbnb Room Type

VARIABLES	RT			
	(1)	(2)	(3)	(4)
PPS	-0.1709926***	-0.1868403***	-0.1869952***	-0.1844525***
	(0.0538395)	(0.0586055)	(0.0585203)	(0.0582616)
Covariates	YES	YES	YES	YES
Time FE	YES	YES	NO	NO
Property FE	NO	YES	YES	NO
Community FE	YES	YES	NO	YES
Time*Community FE	NO	NO	YES	NO
Time*Property FE	NO	NO	NO	YES
Observations	679,547	676,571	676,571	676,511
R-squared	0.1635	0.2390	0.2398	0.2416

Notes:

1.***p<0.01,**p<0.05,*p<0.1.

2. Robust standard errors in () are clustered at the community level.

Table 1 reports the baseline results of the effect of partitioned pricing intensity on Airbnb room type. Table 1 presents the OLS regression results for the high-dimensional FE model that includes the host's partitioned pricing intensity variable. Model (1) of Table 1 shows a negative and statistically significant relationship between the host's partitioned pricing intensity and Airbnb room type, controlling for time and community fixed effects. The estimated coefficient of the host's partitioned pricing intensity is -0.1709926, with a robust standard error of 0.0538395. In model (2) of Table 1, we control for the time fixed effects, the property fixed effects, and the community fixed effects. The host's partitioned pricing intensity variable remains negative and statistically significant, with a coefficient of -0.1868403. In addition, in the third model of Table 1, when controlling for the property fixed effects and the interactive fixed effects of time*community, the effect of the host's partitioned pricing intensity remains significantly negative, with an estimated coefficient close to that in model (2). Hence, the relationship between the host's partitioned pricing intensity and room type remains robust when controlling for the alternative high-dimensional fixed effects in the third model of Table 1.

Overall, the results in Table 1 document a negative association between the host's partitioned pricing intensity and room type. These empirical findings could be explained by our hypothesis above.

5.2 Endogeneity Tests

As we know, Table 1 documents a statistically significant relationship between the host's partitioned pricing intensity and room type. Nevertheless, such a linkage does not necessarily correspond to the causal effect of the host's partitioned pricing intensity on room type. In Table 2, we report findings from an IV estimation that addresses endogeneity between the host's partitioned pricing intensity and room type.

Table 2. Results of 2SLS Estimates

Panel A Second-stage	RT			
	(1)	(2)	(3)	(4)
PPS	-6.099171***	-4.129603***	-4.08568***	-4.195388***
	(1.925995)	(0.7390695)	(0.7265197)	(0.7647728)
Covariates	YES	YES	YES	YES
Time FE	YES	YES	NO	NO
Property FE	NO	YES	YES	NO
Community FE	YES	YES	NO	YES
Time*Community FE	NO	NO	YES	NO
Time*Property FE	NO	NO	NO	YES
Observations	679,547	676,571	676,571	676,511
R-squared	-1.1177	-0.4508	-0.4377	-0.4743
Panel B First-stage	PPS			
	(5)	(6)	(7)	(8)
PD	0.0055697***	0.0062256***	0.0062503***	0.0062942***
	(0.0014005)	(0.0013487)	(0.0013652)	(0.0013792)
Cragg-Donald Wald F statistic	929.348	1150.985	1154.361	1174.562
Kleibergen-Paap rk Wald F statistic	15.816	21.306	20.960	20.826

Notes:

1.***p<0.01,**p<0.05,*p<0.1.

2. Robust standard errors in () are clustered at the community level.

In Panel A of Table 2, we present the link between the host's partitioned pricing intensity and Airbnb room type, using the predicted distance variable as an IV. In model (1) of Panel A of Table 2, we control for the time fixed effects and the community fixed effects. Comparing this to model (1) of Table 1, the overall pattern remains similar despite changes in the effect of the host's partitioned pricing intensity, with a larger negative estimated coefficient (-6.099171). Model (2) of Panel A of Table 2 includes the property fixed effects in the specification from model (1) of Panel A of Table 2. The coefficient of the host's partitioned pricing intensity retains the same sign as in model (1) of Panel A of Table 2, and the effect remains negative and statistically significant. It's important to emphasize that, even though the deviation in Airbnb room types differs, the sign pattern remains consistent when controlling for interactive high-dimensional fixed effects. Model (3) of Panel A of Table 2 replaces the regression model in model (2) of Panel A of Table 2 by controlling for the property fixed effects and the interactive fixed effects of time*community. The estimated coefficient of the host's partitioned pricing intensity is similar to that in model (2) of Panel A of Table 2.

Obviously, Panel A of Table 2 presents our 2SLS specification, which includes the predicted distance variable. This instrumental variable controls for various spatial characteristics that positively correlate with the host's partitioned pricing intensity. The second-stage estimate shows a statistically significant negative effect of the host's partitioned pricing intensity on room type. It not only confirms Hypothesis 1 but also provides supporting evidence for the findings in Table 1.

5.3 Robustness Checks: Alternative Measurement of Partitioned Pricing Decisions

Even though our results show that the host's partitioned pricing intensity is statistically significantly associated with the room type of an Airbnb, we need to continue examining whether this association also holds for an alternative measure of the host's partitioned pricing strategy. Hence, we design a binary treatment variable (PPST) that compares any active cleaning fee decision with non-engagement with partitioned pricing.

Table 3. Robustness Checks Results

Panel A Second-stage	RT			
	(1)	(2)	(3)	(4)
PPST	-0.859794**	-0.6060815***	-0.5893741***	-0.6205163***
	(0.3480861)	(0.1683298)	(0.1520159)	(0.173689)
Covariates	YES	YES	YES	YES
Time FE	YES	YES	NO	NO
Property FE	NO	YES	YES	NO
Community FE	YES	YES	NO	YES
Time*Community FE	NO	NO	YES	NO
Time*Property FE	NO	NO	NO	YES
Observations	679,599	676,623	676,623	676,563
R-squared	-0.4452	-0.1780	-0.1615	-0.1935
Panel B First-stage	PPST			
	(5)	(6)	(7)	(8)
PD	0.0394764***	0.0423579***	0.0432679***	0.0425022***
	(0.0073324)	(0.0082907)	(0.0076859)	(0.008154)
Cragg-Donald Wald F statistic	2535.641	2916.550	3033.371	2935.534
Kleibergen-Paap rk Wald F statistic	28.985	26.103	31.691	27.170

Notes:

1.***p<0.01,**p<0.05,*p<0.1.

2. Robust standard errors in () are clustered at the community level.

Therefore, we assess the effect of implementing the partitioned pricing strategy on Airbnb room types in this subsection. In Panel A of Table 3, we present 2SLS estimates of the causal effect of implementing the partitioned pricing strategy. Model (1) of Table 3 shows that the coefficient on the PPST variable is statistically significant and negative. In addition, the coefficients of that variable in models (2), (3), and (4) of Table 3 remain statistically significant. Hence, the effect of implementing the partitioned pricing strategy is also robust. Finally, the estimated coefficients in Panel B of Table 3 remain statistically significant and positive.

Overall, these results also indicate that the average effect of implementing a partitioned pricing strategy on room type is significantly negative and statistically robust.

5.4 Sensitivity Tests

Another way to support our empirical findings from the investigation on the impact of the host's partitioned pricing intensity on room type is to conduct sensitivity tests by restricting our sample to various listing groups. Panel A of Table 4 presents the results for the host's partitioned pricing intensity by room type across different subsamples.

Table 4. Heterogeneous Test Results

Panel A Second-stage	RT			
	(1) non-host identification verified	(2) host identification verified	(3) non-super host	(4) super host
PPS	-6.656113***	-5.520661	-5.06554***	-54.0092
	(1.819326)	(7.390147)	(1.503024)	(80.05189)
Covariates	YES	YES	YES	YES
Time FE	YES	YES	NO	NO
Community FE	YES	YES	NO	YES
Observations	528,921	150,626	518,919	160,628
R-squared	-1.3398	-0.8969	-0.7177	-98.1948
Panel B First-stage	PPS			
	(5)	(6)	(7)	(8)
PD	0.0061614***	0.00196	0.0064941***	0.0006985
	(0.0018246)	(0.0013166)	(0.0017941)	(0.0010503)
Cragg-Donald Wald F statistic	901.959	24.805	916.805	4.321
Kleibergen-Paap rk Wald F statistic	11.404	2.216	13.102	0.442

Note: 1.***p<0.01,**p<0.05,*p<0.1. 2. Robust standard errors in () are clustered at the community level.

3. The super host and host-identification-verified subsamples are reported for completeness only. Negative R-squared values can arise in 2SLS and should not be interpreted as OLS-style model fit.

Model (1) in Panel A of Table 4 shows that the host's partitioned pricing intensity variable is negatively and

significantly associated with room type for listings without verified host identification. In addition, model (2) of Panel A of Table 4 shows that the average effect of the host's partitioned pricing intensity for the listings with host identification verified becomes statistically non-significant. Nevertheless, model (3) in Panel A of Table 4 shows a statistically significant negative link between the host's partitioned pricing intensity and Airbnb room type for non-superhost listings.

5.5 Further Discussion: Alternative Approach with Quantile Regression

Although RT has only three categories, quantile regression remains informative because it reveals effect heterogeneity across the distribution that is masked by OLS. The coefficients indicate whether partitioned pricing has a stronger effect on properties near the shared-room end (low quantiles), the private-room middle (median), or the entire-apartment end (high quantiles). This heterogeneity is policy-relevant and cannot be captured by the conditional mean alone.

Table 5. Quantile Regression Results of Partitioned Pricing Strategic Effects on Airbnb Room Type

VARIABLES	RT			
quantile	(1)	(2)	(3)	(4)
	(quantile=20%)	(quantile=40%)	(quantile=60%)	(quantile=80%)
PPS	-0.0859524	-0.1330123**	-0.2419809***	-0.2744339***
	(0.0755633)	(0.0610187)	(0.0597728)	(0.0710051)
Covariates	YES	YES	YES	YES
Time FE	YES	YES	NO	NO
Community FE	YES	YES	NO	YES
Observations	679,547	679,547	679,547	679,547

Notes:
1.***p<0.01,**p<0.05,*p<0.1.
2. Robust standard errors in () are clustered at the community level.

The average effects of the host's partitioned pricing intensity on Airbnb room type, with quantile regression (QR) used as an alternative to OLS, are presented in Table 5. Although the fixed effects are specified for OLS, the QR estimates control for the same fixed effects and covariates that may correlate with quantiles. Our results show that the coefficient of PPS is non-significant in model (1) of Table 5; however, we do find statistical significance in the primary estimators in models (2), (3), and (4). Figure 2 visualizes the results of these estimates.

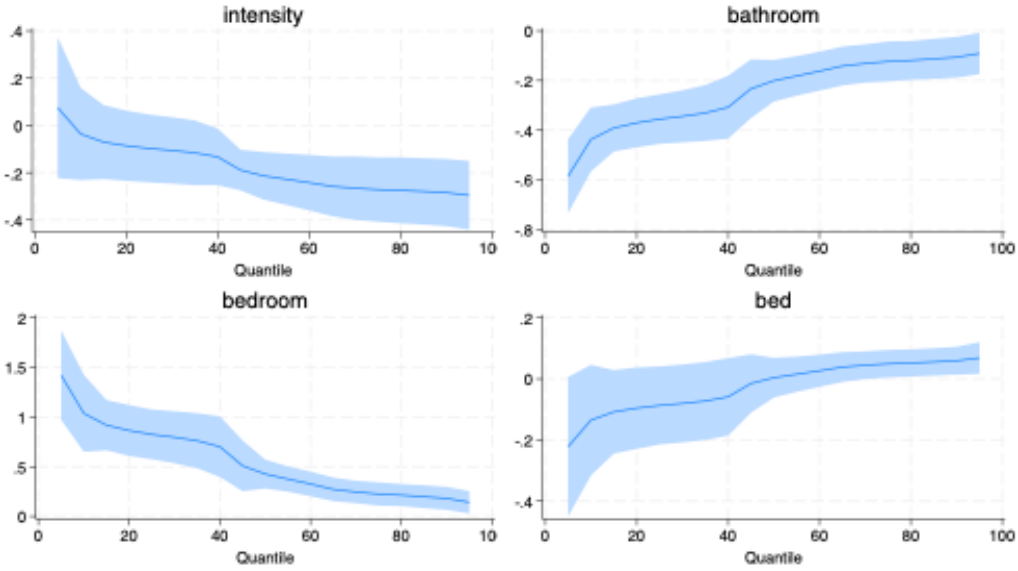

Figure 2. Quantile Coefficients Controlling for Time and Listing Fixed Effects

6. Further Discussion

To be sure, our proposition depends on assumptions about the utility function and budget constraints, but we have

provided an Airbnb example using the IV method to confirm the hypothesis derived from it. In this section, we present alternative forms of the utility function and the budget constraint. Indeed, in order to solve for the optimal rental prices, we now consider an alternative utility function as follows:

$$\mathrm{U} = \alpha\mathrm{RT} + \gamma lnd + \delta lnc.$$

In addition, to investigate the effect of RT on optimal rental prices, we assume a representative guest's budget constraint is

$$\mathrm{I} = c + (\bar{p} + f)d + g(RT),$$

where $g(RT) = aRT^2$ is supposed to be convex: $g'(RT) = 2aRT > 0$, $g''(RT) = 2a > 0$, and $g'''(RT) = 0$.

Thus, the Lagrangian function is expressed as follows:

$$\mathcal{L}_G(d, c, RT) = \alpha\mathrm{RT} + \gamma lnd + \delta lnc + \lambda_G[\mathrm{I} - c - (\bar{p} + f)d - g(RT)]$$

The FOCs with respect to d, c, and RT are as follows:

$$\frac{\partial \mathcal{L}_G}{\partial d} = \frac{\gamma}{d} - \lambda_G(\bar{p} + f) = 0,$$

$$\frac{\partial \mathcal{L}_G}{\partial c} = \frac{\delta}{c} - \lambda_G = 0,$$

$$\frac{\partial \mathcal{L}_G}{\partial RT} = \alpha - \lambda_G g'(RT) = 0.$$

Therefore, the consumer's optimal choice to rent the property is given by:

$$d^{**} = \frac{\gamma g\prime(RT)}{\alpha(\bar{p}+f)}.$$

Again, the host's profit maximization problem is given by:

$$\max_{\{RT,PPS\}} \pi_h = [(1-\alpha)\bar{p} + f - \frac{\bar{p}(PPS)^2}{2}]d^{**} - k(RT) = \bar{p}[(1-\alpha) + PPS - \frac{\bar{p}(PPS)^2}{2}]d^{**} - k(RT) = \bar{p}[(1-\alpha) +$$

$$PPS - \frac{\bar{p}(PPS)^2}{2}]\frac{\gamma g\prime(RT)}{\alpha(\bar{p}+f)} - k(RT) = \bar{p}[(1-\alpha) + PPS - \frac{\bar{p}(PPS)^2}{2}]\frac{\gamma g\prime(RT)}{\alpha\bar{p}(1+PPS)} - k(RT) =$$

$$[(1-\alpha) + PPS - \frac{\bar{p}(PPS)^2}{2}]\frac{\gamma g\prime(RT)}{\alpha(1+PPS)} - k(RT).$$

Thus,

$$\frac{d\pi_h}{dRT} = \frac{\gamma g''(RT)}{\alpha(1+PPS)}[(1-\alpha) + PPS - \frac{\bar{p}(PPS)^2}{2}] - k'(RT) = 0.$$

Therefore, we obtain

$$k'[RT(PPS)] = \frac{\gamma g''(RT)}{\alpha(1+PPS)}\left[(1-\alpha) + PPS - \frac{\bar{p}(PPS)^2}{2}\right] = \frac{\gamma g''(RT)}{\alpha}[\frac{(1-\alpha)+PPS-\frac{\bar{p}(PPS)^2}{2}}{1+PPS}],$$

and then

$$\frac{d[k'(RT)]}{dPPS} = \frac{d[k'(RT)]}{dRT}\frac{dRT}{dPPS} = k''(RT)\frac{dRT}{dPPS} = \frac{d}{dPPS}\left\{\frac{\gamma g''(RT)}{\alpha}\left[\frac{(1-\alpha) + PPS - \frac{\bar{p}(PPS)^2}{2}}{1+PPS}\right]\right\}$$

$$= \frac{\gamma g''(RT)}{\alpha}\frac{(1-\bar{p}PPS)(1+PPS)-\left(1-\alpha+PPS-\frac{\bar{p}(PPS)^2}{2}\right)}{(1+PPS)^2} = \frac{\gamma g''(RT)}{\alpha}\frac{1+PPS-\bar{p}PPS-\bar{p}(PPS)^2-1+\alpha-PPS+\frac{\bar{p}(PPS)^2}{2}}{(1+PPS)^2} = \frac{\gamma g''(RT)}{\alpha}\frac{\alpha-\bar{p}PPS-\frac{\bar{p}(PPS)^2}{2}}{(1+PPS)^2} =$$

$$\frac{\gamma g''(RT)}{\alpha}\frac{\alpha-\bar{p}PPS(1+\frac{PPS}{2})}{(1+PPS)^2}=\frac{\gamma g''(RT)}{\alpha}\frac{\alpha-f(1+\frac{PPS}{2})}{(1+PPS)^2}.$$

Thus,

$$\frac{dRT}{dPPS}=\frac{1}{k''(RT)}\frac{\gamma g''(RT)}{\alpha}\frac{[\alpha-f\left(1+\frac{PPS}{2}\right)]}{(1+PPS)^2}<0, \text{ because } k''(RT)>0, \frac{\gamma g''(RT)}{\alpha}>0, \text{ and } f\left(1+\frac{PPS}{2}\right)>1>\alpha.$$

As a result, we obtain:

$$\frac{dRT}{dlnPPS}=PPS\frac{dRT}{dPPS}<0 \quad (6).$$

Thus, formula (6) is consistent with formula (2). It implies that our testable hypothesis and empirical strategy are not determined by the utility function's form. It is important to note that, although RT is observed as a discrete variable in the empirical section, it is treated as a continuous latent privacy index for the purpose of deriving comparative statics. The three-room categories are discrete manifestations of this underlying continuous index. Additionally, our model represents a market equilibrium rather than a sequential game. The consumer's optimization determines the demand-side equilibrium condition, while the host's optimization determines the supply-side equilibrium condition. The comparative static results in Proposition 1 and equation (6) characterize how the market equilibrium shifts when partitioned pricing intensity changes, rather than implying that the host dictates consumer choices.

Compared to the Airbnb literature that pertains to our study, we first provide a formal model to identify the effect of partitioned pricing on Airbnb room type.

Furthermore, such studies typically focus on the determinants of pricing on the Airbnb platform. For example, Kourtit, K., Nijkamp, P., Östh, J., & Turk, U. (2022) find that hardships in the Airbnb market are associated with high price volatility. Boto-García (2022) finds that professional hosts have adjusted prices to a greater extent during the COVID-19 pandemic. Only a few previous studies have focused on optimal pricing strategies in this context (Filippas, A., Horton, J. J., & Zeckhauser, R. J. 2020, Zheng, Q., Ke, D., & Li, X. 2023). However, our paper takes the opposite approach, investigating the effects of pricing rather than the determinants of pricing.

Additionally, earlier studies used the AirDNA dataset, while more recent ones have used listing-level data from Inside Airbnb, which contains only information on short-term rentals (Rossi 2024). Our dataset allows us to investigate the effect of the host's partitioned pricing strategies on room type in the Airbnb marketplace.

Therefore, the policy implications of this paper are that implementing partitioned pricing strategies affects market equilibrium by increasing consumers' effective transaction costs. This results in increased demand for low-privacy accommodations and prompts hosts to shift toward shared-room listings. That is to say, the existence of the sharing economy in such a short-run rental market equilibrium could be characterized by the suppliers' pricing decisions.

Finally, we discuss the impact of the predicted distance variable on the host's partitioned pricing intensity. Especially, we discuss the service rate of the Airbnb platform in the host's profit function. Therefore, a general equilibrium model that connects the Airbnb platform, consumers, and hosts is a particularly central area for future research. In addition, our results show that several empirical patterns are useful when considering the predicted instrumental variable for the partitioned pricing strategy. However, we should further consider alternative algorithms to construct the predicted function of IV using spatial analysis in future research.

7. Concluding Remarks

In this paper, we study the effect of partitioned pricing on Airbnb room types in a microdata set from Beijing, China. Our theoretical proposition predicts that the host's partitioned pricing intensity encourages the provision of shared room services. Furthermore, empirical results show that an increase in partitioned pricing intensity leads to a decrease in the room-type privacy scale. In addition, after constructing the predicted distance variable between the property and one of the eight 5A tourist attractions, we confirm our theoretical hypothesis based on these predictions.

Therefore, according to the theoretical framework and empirical results above, our contributions are as follows:

First, to address the endogeneity issue between partitioned pricing intensity and room type, this paper calculates each property's suitability score for adopting a partitioned pricing strategy using a probit model with distances to eight 5A tourist attractions in Beijing as exogenous regressors. Empirical results show that the predicted distance variable has a positive effect on partitioned pricing intensity.

Second, this paper presents several robustness checks using high-dimensional fixed-effects models and quantile regression models. This paper applies 2SLS regression and controls for wave, property, and community fixed effects. However, the literature has paid limited attention to examining the effects of partitioned pricing intensity on Airbnb

room types across interactive fixed effects. Moreover, there is no literature on specifying quantile regression for such an impact. Therefore, this paper introduces quantile regression in the form of the location-scale model to test our theoretical hypothesis regarding the relationship between the host's partitioned pricing strategies and Airbnb room type.

Third, this paper provides a formal model to identify the effect of the host's partitioned pricing strategies on Airbnb room type. Basically, this paper derives a theoretical proposition: an increase in the host's partitioned pricing intensity reduces privacy. Furthermore, this paper develops a testable hypothesis. That is, an increase in the intensity of partitioned pricing leads to a rise in the provision of shared room service.

Finally, our empirical findings suggest that charging higher cleaning fees and more strictly implementing partitioned pricing strategies may require hosts to offer more shared rooms. In contrast, reducing cleaning-fee intensity could induce hosts to offer fewer shared rooms.

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Author contributions

Dr. S.G was responsible for study design and revising. Prof. Y.H was responsible for data collection. Prof. Y.H drafted the manuscript and Prof. S.G revised it. All authors read and approved the final manuscript.

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Data sharing statement

No additional data are available.

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