

Research on the Impact of Dynamic Pricing on Revenue Based on Airbnb Data

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Abstract: Airbnb, as a globally leading short-term rental platform, faces unique challenges in pricing due to the diversity of its listings, including variations in location, amenities, and host preferences. To address these challenges, Airbnb has introduced a calendar-based visualization tool and a machine learning-driven tool to maximize hosts' revenue. However, the empirical impact of dynamic pricing—particularly its differential effects across room types—remains understudied. To get figure out that, this research used linear regression to quantify the impact of dynamic pricing on revenue and find out how it had differential effects across room types. This study addressed two core questions: How significant is the revenue gap between dynamic pricing and fixed pricing strategies? Does dynamic pricing exert varying impacts on revenue across different room types? Taking Chicago as an example, the article finds that dynamic pricing can increase annual income by 30% and shows no significant difference in the degree to which different room types affect income from dynamic pricing.

1 INTRODUCTION

Recently, advancements in the use of dynamic pricing have benefited multiple industries, especially driven by digitalization and real-time data analysis technology. In a saturated market, dynamic pricing ensures hosts remain price-competitive, avoiding lost bookings due to overpricing or profit erosion from underpricing. Its flexibility and profitability advantages make it a core strategy for many enterprises. Despite extensive research on theoretical research in economics, little attention has been paid to specific quantitative research on the extent to which dynamic pricing can improve revenue. Airbnb, which plays an important role in short-term rental market, adopts a dynamic pricing model of landlord's independent selection and algorithm recommendation. Airbnb's dynamic pricing is semi-automated, with hosts having the final decision-making power, but algorithmic tools have become an important tool for increasing revenue. Its success depends on a deep understanding of the local market, rather than simply being driven by technology. However, detailed regulations and algorithms of smart dynamic pricing are not available. More research is required for the

definition and judgment on dynamic pricing. This study seeks to address this gap by constructing an original method to define dynamic pricing and analysing data in Chicago on Airbnb to quantify the revenue impact of dynamic pricing and explore its heterogeneous effects across room types.

This article provides practical insights for landlords and operators of Airbnb and has reference significance for other industries such as shared office, car rental, hotels, and catering. Meanwhile, it provides theoretical implications for academic research in Price Theory and Market Mechanism, Algorithm and Data Science, and Sharing Economy and Policies. With its original dynamic pricing definition, this article breaks through traditional dynamic pricing theory, filling academic gaps to a certain extent, and promoting the development of pricing theory. Besides, developing original dynamic pricing definitions has significant commercial value to guide business practices and enhance market competitiveness. On the other hand, studying the specific quantitative impact of dynamic pricing on revenue can help support decision-making, optimize resource allocation, conduct risk management, and strategic value assessment.

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2 LITERATURE REVIEW

With the Literature Review, the author finds that research on Airbnb is mostly focusing on travelling tourism, such as customers' optional motivation, development of hotel business, impact on tourist destinations, etc. Some studies in the Economics aspect include pricing factors and local revenues affected by Airbnb. However, in these discussions from an economic perspective, a key issue has been relatively overlooked-Airbnb, as a typical representative of the sharing economy, lacks systematic research on the decision-making mechanism and market impact of its hosts' dynamic pricing strategies. For example, an empirical analysis of short-term rental platforms.

Gallego and Ryzin studied on dynamic pricing problem of inventory within a limited time. They found that dynamic pricing was more valuable when the market demand was equivocal (Gallego and Ryzin, 1994). Victor Araman and René Caldentey studied how to use dynamic pricing to maximise long-term average profit (Victor Araman and René Caldentey, 2009). Gabriel Bitran and René Caldentey researched pricing models in revenue management and provided the theoretical basis and practical guidance for enterprises to formulate pricing strategies (Gabriel Bitran and René Caldentey, 2003). Kelly and William concluded that, in consumers' opinion, price changes within the short term are more unfair than those in the long term. Moreover, when consumers get equal or more discounts in business, the sense of price fairness and purchase satisfaction rate is higher (Kelly and William, 2006). Georgios Zervas, Davide Proserpio, and John W. Byers proved that Airbnb has a great effect on hotel revenue and different types of hotels are affected to varying degrees (Georgios Zervas, Davide Proserpio, and John W. Byers, 2016). Martin Falk and Miriam Scaglione found that regulations could significantly affect Airbnb's lease performance (Martin Falk and Miriam Scaglione, 2024). He, Qiu, and Cheng studied the effect on labour supply from dynamic pricing on Uber. They analysed the data from Uber and explored drivers' responses to dynamic pricing. The results can be used to study Airbnb's users' response to dynamic pricing (He, Qiu, and Cheng, 2022). Gallego and Ryzin prepared the theoretical framework in a changing market, and Victor Araman and René Caldentey further extended to maximize long-term average profits. Theoretical preparation provided support for deeper and broader research. Later, more factors like consumer behavior, regulations effect and supply were taken into consideration.

The research on the impact of dynamic pricing on Airbnb revenue mainly focuses on technical application and strategy differences. Machine learning is used to mimic the progress of dynamic pricing and provides pricing suggestions. Wang (2024) highlighted the complexity of Airbnb's machine learning algorithms, which process thousands of data points-including historical bookings, seasonal trends, and competitor prices-to generate real-time pricing recommendations. A study on strategy differences shows dynamic pricing on Airbnb can increase revenue. Kwok and Xie (2019) compared pricing behaviours between single-property and multi-property hosts, finding that multi-property hosts adopting dynamic pricing achieve significantly higher revenue than fixed-pricing counterparts. However, there is no study on how much can dynamic pricing increase revenue. Moreover, considering that the definition of pricing method and algorithm are non-public, how to use limited public data to define dynamic pricing and fixed pricing is also a worthwhile research aspect. The author established original data filtering rules and definition methods. By doing this, a specific number was calculated to show how dynamic pricing affect Airbnb's revenue.

3 METHODOLOGY

3.1 Modeling

To analyse the impact of dynamic pricing on Airbnb's revenue, this article used linear regression to analyse the pre-processed data. The regression model used was:

$$\begin{aligned} \text{Revenue} = & \beta_0 + \beta_1 \times \text{Dynamic} \\ & + \beta_2 \times \text{Income} + \beta_3 \times \text{Room type} \\ & + \beta_4 \times (\text{Room type} \times \text{Dynamic}) + \epsilon \end{aligned} \quad (1)$$

Independent variable in this equation showed in Table1.

In the original data, "price" represents daily price in local currency and "reviews per month" reflects guests' occupancy rates and feedback. This article used a review rate of 0.78 to estimate the annual income of each room. The review rate is from Julia's research: about 78% of guests leave reviews of their accommodation. This provides a revenue estimation that is closer to the actual booking volume. Thus:

$$\begin{aligned} & \text{Estimated Annual Income} \\ = & \text{price} \times \text{reviews per month} \times 12/78 \end{aligned} \quad (2)$$

Table 1: Independent variable Meanings

Independent variable	Meaning
Dynamic	Binary independent variable indicating whether dynamic pricing is used in this room. (Dynamic price =1, Fixed price=0)
Income	Estimated Annual Income.
Room type	Categorical variable representing different types of rooms. (Entire home, Hotel room, Private room, Shared room)
Room type $\times$ dynamic	Interaction term intended to test whether the effectiveness of dynamic pricing varies by room type.
ϵ	The residual error.

3.2 Data Introduction

The data used in this article was downloaded from inside Airbnb. The author chose data from Chicago, USA, presented on the Internet. The original data includes approximately 8700 sets, consisting of more than 10 variables: id (user), name (user), host id, hostname, neighbourhood (more than 80), latitude, longitude, room type (Entire home/apt, Private room, Shared room, Hotel room), price, minimum nights, number of reviews, last review, reviews per month, calculated host listings count, availability 365, number of reviews, license. The primary variables utilized in the data processing included Host ID, Room type, neighbourhood, Price, and Reviews per Month. The neighbourhood parameter denotes the geographical community in which the rental property is situated.

It can be concluded that this method defines the pricing type of rooms in the same neighbourhood of the same house host, considering that house hosts choose the same pricing type for the same room type in the same neighbourhood.

The following selection and processing steps were performed on the data:

First of all, to calculate the necessary metrics, the author selected only those Host IDs that repeat at least four times, avoiding sample bias and making sure of proper judgment.

Second, since a single Host ID may correspond to multiple listings, i.e., a house host has several rooms or houses for rent on Airbnb, the author grouped all listings by Host ID. Listings with the same Room type and neighbourhood under the same Host ID were assigned to the same Room ID. Each Room ID is considered as a single research subject. To minimize

randomness, the author filtered out Room IDs that repeated less than three times and got 321 groups of Room IDs in total.

Third, the author used the average price for each Room ID as a baseline and calculated the relative price deviation for all listings within the same group (volatility value = $|\text{price} - \text{average price}| / \text{average price}$). The maximum volatility value's corresponding price was selected as the representative value for that Room ID.

Finally, among the representative values of all groups, the author selected the top 50% with the higher representative values to be classified as dynamic pricing, while the remaining 50% were classified as fixed pricing.

The author conducted the data compute processing using MATLAB R2023a and set the dynamic pricing and the fixed price, with the code provided in the Appendix. The result shows that when the representative volatility rate for a room ID exceeds a certain threshold ($= 29.55\%$), the group is assigned dynamic pricing; otherwise, it is assigned fixed pricing. Among the 321 groups of Room IDs, 161 groups were set as dynamic pricing. The MATLAB calculation of the critical volatility rate is displayed in Table 2.

Table 2: MATLAB operation results display

Type of variables	
Dynamic room id	161 sets
Total room id	321 sets
Threshold	29.55%

The above operation is based on the situation of the data itself. After calculating the multiple distribution ratio, the author selected the most suitable screening criteria for this situation. For more different data, the same definition method in this article can be used, but setting unique standards according to different situations is necessary.

4 RESULT ANALYSIS

4.1 Descriptives

After data Preprocessing, there are 321 sets of room IDs in total. Among them, 161 groups were set as dynamic pricing and the other 160 groups were set as

fixed pricing, as shown in Table 3. Because shared rooms were all set at fixed pricing, the author does not analyse it here. Classifying according to different room types, dynamic pricing increases income compared to fixed pricing in the entire house, private room, and hotel rooms. The analysis results show that the entire house has the highest dynamic pricing rate and then there is a hotel room. The entire house has the most reviews per month, which indicates that the occupancy rate of the entire house is relatively high, and guests are more willing to leave reviews. Moreover, the standard error of the entire house's annual estimated income is the lowest, implying that the revenue from the entire house is stable and sustainable. It might be related to its high rate of using dynamic pricing and show support for sustainable revenue from dynamic pricing.

Table 3: Descriptive statistical analysis

	Entire room	Private room	Hotel room
Average annual income of dynamic pricing	6434\$	2312\$	5784\$
Average annual income of fixed pricing	6322\$	2245\$	5778\$
Dynamic pricing rate	78.4%	36.0%	60.7%
Reviews per month	1.87	1.58	0.94
Standard error of annual estimated Income	264.9	279.9	990.3

4.2 Regression Results

Using Fixed pricing as the control group and Entire Home as the control group for regression analysis, the results show that dynamic pricing can increase annual income by more than \$1,000, with a p-value less than 0.05, indicating that the increase in income due to dynamic pricing is statistically significant. Moreover, when Entire Home is used as the control group, the five p-values are all greater than 0.05, suggesting that the impact of dynamic pricing on income is not affected by the room type. Here, can only conclude that Private Rooms, Hotel Rooms, and Shared Rooms are not significantly distinguished from Entire Rooms.

It is important to note that all Shared Room listings are classified under Fixed pricing, so the regression analysis results for Shared Room show

anomalies in terms of values (the p-value is NUM and the others are all zeros), but this does not affect the overall conclusion. The results of Regression 1 are shown in Table 4.

Furthermore, to examine the difference in the impact of dynamic pricing between Private Rooms and Hotel Rooms, the author performed another regression with Private Rooms as the control group. The p-value of the Hotle Dummy and Shared Dummy are all greater than 0.05. This shows that there is no significant difference between these room types and the Private Room. Meanwhile, the p-value of the interaction terms, i.e. f_d*HD and f_d*SD , are greater than 0.05. This shows that room type has no significant effect on how dynamic pricing increases avenue.

Table 4: Regression 1

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	LL 95.0%	UL 95.0%
Intercept	517138.7	265769.7	1.945815	0.051809	-4057.95	1038335	-1.2×10^7	12754095
Hotel Dummy	440.4479	1032.579	0.426551	0.669749	-1584.53	2465.421	-47103.1	47983.95
Private Dummy	-586.002	391.2381	-1.49781	0.13433	-1353.25	181.2484	-18600	17427.95
Shared Dummy	-1851.6	1078.308	-1.71713	0.086101	-3966.25	263.0533	-51500.6	47797.41
f d*HD	-2436.22	1306.753	-1.86433	0.062413	-4998.87	126.4299	-62603.6	57731.18
f d*PD	-833.688	507.064	-1.64415	0.100294	-1828.08	160.7069	-24180.7	22513.29
f d*SD	0	0	65535	#NUM!	0	0	0	0

The results confirm that the impact of dynamic pricing on income remains unaffected by room type. The outcomes of Regression 2 are shown in Table 5.

Table 5: Regression 2

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	LL 95.0%	UL 95.0%
Hotel Dummy	1717.556	1606.371	1.069215	0.285094	-1432.67	4867.783	-1432.67	4867.783
Entire Dummy	1060.904	599.2701	1.770326	0.076816	-114.315	2236.122	-114.315	2236.122
f d*HD	-2548.14	2070.527	-1.23067	0.218582	-6608.62	1512.334	-6608.62	1512.334
f d*ED	1300.124	791.8715	1.641837	0.100772	-252.802	2853.05	-252.802	2853.05

The f_d represents the Dynamic variable. ED represents entire house dummy. HD represents hotel room dummy. PD represents private room dummy. SD represents Shared room dummy.

It is noteworthy that intrinsic price differentials exist across distinct Room Type categories (e.g., Entire Home versus Private Room). Consequently, coefficients associated with Room Type and its interaction terms, when modelled as independent variables, may exhibit negative values in regression analyses.

5 CONCLUSION

In conclusion, this research investigated how significant the revenue gap is between dynamic pricing and fixed pricing strategies and whether dynamic pricing exerts varying impacts on revenue across different room types or not by linear regression. The results demonstrate that dynamic pricing can increase annual income by more than \$1,000 in Chicago, supporting the hypothesis that dynamic pricing can increase annual income by 30%. Besides, it shows that there is no significant difference in the degree to which different room types affect income

from dynamic pricing. These findings not only contribute to the short-term rental market but also have an impact on economics, tourism management, data science, and consumer behaviour. The implications of the current study are significant for both Airbnb and its hosts. Firstly, the research provides evidence for the notion that dynamic pricing is more than just a technological convenience. Additionally, no significant difference in different room types indicates the need for tailored dynamic pricing algorithms.

Airbnb's dynamic pricing not only improves the revenue management model of the tourism industry, but also promotes the development of interactive research between data science and economics. It optimizes short-term rental market prices through intelligent algorithms, while triggering policy discussions on platform regulation and algorithm fairness. This technology has promoted innovation in the theory of the sharing economy and provided rich cases for interdisciplinary research. Further attention needs to be paid to its long-term impact on the housing market and social equity in the future.

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