

Regulating Asymmetric Competition of Platform Owners: Evidence from the Korean Accommodation Market

Sung Kwan Lee¹, Liu Ming¹, Chen Tang²

¹School of Management and Economics, ²School of Data Science, Chinese University of Hong Kong (Shenzhen)

July 2024



香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

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Motivation

Many large platform owners are entering the market by running their own business.



Taobao entered the market by operating Tmall.

Taobao entered the market by running Great Value.

- The platform owner can have an advantage in information;
- What's more, the platform can recommend its own products in priority;

The government can alleviate this unfairness through directives that urging the platform owner to compete fairly. One question arises:

How can we identify the effects of the policy?

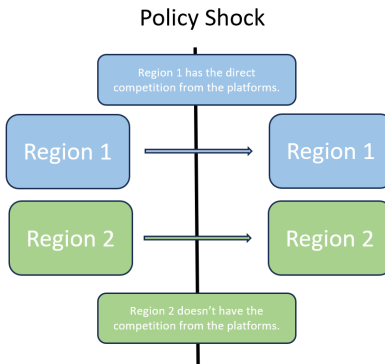
Hospitality Market Provide Oppourtunaties

Sadly, we can barely identify the effect using the data from the E-commerce platform.

But

We can draw upon insights from platforms in other industries.

- If there is a hospitality platform owner entering the market in only a fraction of the regions, we can identify the effects of the 'soft policy' using DiD.



Background: Yanolja in South Korea

- Yanolja is the largest hospitality platform in South Korea.

There are two types of hotels and homestay properties on the platform:

- ① **Self-owned**: some brands of hotels that have been acquired by Yanolja;
- ② **Third-party**: other hotels and homestays.

The platform has unfair contracts, coupons, and advertisement activity between self-owned and third-party hotels.

- In February 2022, the FTC required Yanolja and some other large platforms to revise the unfair contract.
- Yanolja platform revised the contract and claimed they'd immediately improved the unfair advertising activities.

This allows us to identify the effect of the regulation on the third-party hotels' operating conditions.

Literature Review:

Past research has focused on:

- ① The motivation and impact of the platform owner's entry;
- ② The entry strategy for platform owners;
- ③ Asymmetric competition between the platform owner and the third-party firms;
- ④ Literature on the accommodation industry.

Our most similar study is [Rong et al., 2024], which examines the effect of China's antitrust platform regulation on entrepreneurship and new investment.

To the best of our knowledge,
this is the first paper to study the impact of regulation against the platform's
asymmetric competition **within the platform ecosystem.**

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Original Data

- Our main datasets are sourced from the Korean government's official public data;
- It includes the operational records of every accommodation listing across the entire country:
 - Name of the property;
 - Specific Location of the property;
 - Opening month and closing month (if any) of each hotel.

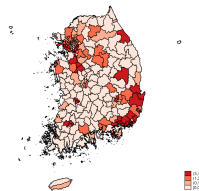
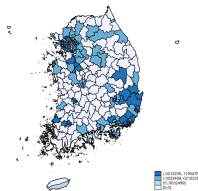
How to identify whether one hotel belongs to the platform owner:

- The hotels acquired by Yanolja are large chain hotels;
- They usually have the same prefixes, such as 'Hound', 'Brown Dotv', 'No. 25'.
- In Korea, there are three tiers of administrative locations: city (province), district, and town;
- The location information of each property has been granulated to the specific **district**.

Data Description

The variable $Treatment_i$ for each district is defined as:

- ① $Treatment = 1$: the platform owner has already established a presence in this district;
- ② $Treatment = 0$: the platform owner has not established a presence in this district;



By the end of 2022, there were **390** Yanolja-operated hotels, compared to **52,400** third-party hotels.

DiD Design

We employed a Difference in Difference framework to identify the effects of interest using the data 11 months prior and after the policy shock:

$$\begin{aligned} survival_rate_{i,t} = & \alpha_0 + \alpha_1 treatment_i + \gamma treatment_i * policy_t + \\ & \lambda * Control_Variables_{i,t} + \tau_t + \eta_i + \epsilon_{it} \end{aligned} \quad (1)$$

- ① $survival_rate_{i,t}$: the survival rate of the **third-party** hotels for each district;
- ② $policy_t$: whether the current time period falls before or after February 2022 (the policy shock);
- ③ $Control_Variables_{i,t}$: quarterly district-level GDP and population;
- ④ τ_t, η_i : time and district fixed effects respectively.

Pre-treatment Parallel Examination

We verified that the control group $Treatment = 0$ and the treatment group $Treatment = 1$ have the same trend before the abrupt exogenous policy:

We follow the steps in [Zhang et al., 2022]:

$$\begin{aligned}
 survival_rate_{i,t} = & \alpha_0 + \alpha_1 treatment_i \\
 & + \sum_{j=1}^{11} \gamma_j (PRE_t(j) * treatment_i) \\
 & + \lambda * Control_Variables_{i,t} + \tau_t + \eta_i + \epsilon_{it}
 \end{aligned}
 \quad (2)$$

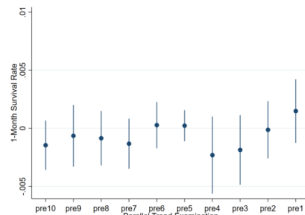
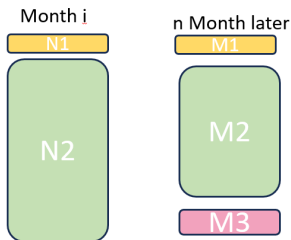


Figure 3 Confidence interval of pre-treatment effects

none of the γ_j is statistically different from zero.

Regression Details

Calculation of the survival rate:



- $N1$ are the newly-entered hotels at month i , $N2$ are the old survival hotels at month i ;
- $M1$ are the newly-entered hotels at month $i + n$, $M3$ are the hotels entering from month i to month $i + n - 1$, $M2 \subset N2$ are the old survival hotels at month i .
- The survival rate is calculated by $\frac{M2}{N2}$.

- We only run the regression using the third-party samples;

Regression Results

Main regression results:

Table 2 Main Regressions

| | (1) survival_rate | (2) survival_rate |
|--------|-----------------------|-------------------------|
| t_13 | 0.00388 (2.32) | 0.00392 (2.18) |
| t_10 | 0.00123 (1.08) | 0.00122 (0.97) |
| t_7 | 0.000839 (1.07) | 0.000840 (0.99) |
| t_4 | 0 (.) | 0 (.) |
| t_zero | 0.00395** (4.37) | 0.00397** (3.48) |
| t3 | 0.00450** (3.80) | 0.00450** (3.47) |
| t6 | 0.00429** (4.46) | 0.00429** (3.93) |
| GDP | | 0.000000117 (0.32) |
| Pop | | -4.30e-08** (-24.78) |
| _cons | 0.990*** (3224.74) | 0.990*** (2768.59) |
| N | 1516 | 1516 |

t statistics in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001

The robustness check calculates the 11-month survival rate of each district:

Table 3 Robustness Check

| | (1) survival_rate | (2) survival_rate |
|----------------|---------------------------|-------------------------|
| post | -0.00311284 (-1.18) | -0.0030436 (-0.96) |
| treatment | 0.0018372 (0.09) | 0.0017867 (0.09) |
| post#treatment | 0.0108796 *** (2.84) | 0.0107138 *** (0.99) |
| GDP | | 0.0022265 (0.35) |
| Pop | | 0.0567317 (0.37) |
| _cons | 0.9689238 *** (101.39) | 0.2853409 (0.16) |
| N | 434 | 434 |

t statistics in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001

- We also regress including the newly-entered hotels, the identification results are the same.

Conclusions

- The policy, although soft, can have a **significant positive** effect on the third-party hotel's operational condition;
- The policy increases the third-party hotels' 11-month survival rate by 1%;
- This research extends beyond the hospitality industry and has broader implications for other platforms where the owner has employed an entry strategy;
- We are acquiring the **pricing** data (average at the district level) to evaluate the impact of regulation on **social welfare**.

Q& A

Any Questions?

Thanks!

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