Competition and Investment: Empirical Evidence from Hotel Industry in Taiwan*

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Abstract

This paper studies the relationship between competition and investment incentives in the Taiwanese hotel industry. Using detailed firm-level investment, revenue, and sales data, I estimate a discrete choice model for consumer demand, then incorporate these estimates into a dynamic model for investment and entry. This model is then used to evaluate the welfare effects of competition policies. Counterfactual analysis shows that a 20% reduction in entry costs leads to more hotels and lower prices; however, investments decrease by 13%, and thus the overall average quality of hotels decreases. This indicates that consumers may not actually benefit from more competitive market structures.

Keywords: Investment, Hotel, Competition, Discrete Choice Demand, Dynamic Model

JEL Classification: L13, L50, L83

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1 Introduction

Within economics, there are different views on the relationship between competition and investment. On the one hand, an increase in competitive pressure creates investment incentives for incumbents to avoid competition or to block potential entrants (Arrow 1962). On the other hand, though, more competitors could reduce potential returns from investments, thereby weakening investment incentives (Schumpeter 1942). The combined effects could also result in an inverted-U shape relationship (Aghion et al. 2005). This ambiguous relationship further complicates the welfare effects of competition policies with endogenous decisions regarding investment and entry and means that it is possible consumers could benefit or suffer depending on the specific changes that occur in investment incentives.

This paper considers this relationship and its potential welfare effects specifically within the Taiwanese hotel industry. Previous literature has often relied on cross-industry variations and instrumental variables to identify the casual relationship.[1] However, the impact of competition on investment depends both on precise competition measures and the types of investments at stake. Lack of industry-specific and demand-side estimates makes it difficult to interpret results and determine policy implications. In this study, I focus on only one industry and exploit cross-market variations. Moreover, I model product market competition and dynamic investment decisions in a structural model. The structural approach allows me to evaluate potential policy effects.

I have chosen to consider the specific setting of the hotel industry in Taiwan for three reasons. First, hotel investments directly affect product quality. Although investments can help firms in many different dimensions, such as cost structures, production processes, capacities, patents, or product characteristics, it is always difficult to model the impact of investments even within an industry.[2] In my dataset, investment information refers to the amounts hotels spend on durable goods and fixed assets. These expenditures affect product quality as well as consumers' utility, because the product in this industry is a night's stay in a hotel room. Hotels can upgrade amenities in hotel rooms by replacing old ones. Major renovations also change the interior designs as well as room qualities. This results in a relatively straightforward mechanism for investment decisions to impact demand, revenues,

[1] This research builds on numerous prior studies of competition and investment (e.g., Aghion et al. 2005; Aghion et al. 2009; Gutierrez and Philippon 2017). These have mostly relied on instrumental variables and cross-industry variations to establish identification.

[2] Capacity, or the number of rooms in a hotel, is largely fixed based on initial construction (Kalnins 2006). This rules out the possibility that market structure or concentration is affected by capacity-expanding investments.

and prices. Second, competition in this industry is local. The locations of hotels determine the places of consumption. Consumers need to be physically present to stay at hotels. Therefore, competition is limited to other hotels in the neighborhood. Third, competition policies are relevant in the hotel industry. Suzuki (2013) noted that land-use regulations could be a major determinant of entry costs for hotels. Changing or relaxing land-use regulations would be equivalent to a policy that reduces entry costs. Therefore, in the counterfactual experiment, I consider a 20% reduction in entry costs.

This study uses a unique dataset containing information on investment expenditures and financial performance from hotels in Taiwan during 2009–2016. Descriptive analysis shows that markets with more competing hotels tend to have lower investments. However, results from regressions do not account for potential unobserved demand shocks or market beliefs about future demand that drive both investments and entries. The negative correlation between investment and competition is not causal. To endogenize entry and investment decisions, I take a structural approach.

The structural model combines static consumer demand with a dynamic model. I have used a dynamic model because investments affect future product quality. Entry decisions also depend on market structures and expected future flow profits. Consumer demand and pricing decisions are static in this model. I use the discrete choice framework developed by Berry, Levinsohn and Pakes (1995), hereafter abbreviated as BLP, for consumer demand. Because investments from hotels affect product quality for consumers, I allow investments to directly impact consumer demand and have persistent effects through unobserved characteristics. In each period, incumbent hotels make static decisions on prices and dynamic decisions on investments. Potential entrants decide whether to enter the market depending on entry costs and discounted future expected profits.

Consumer demand is estimated from data on market shares, prices, and product characteristics in the hotel industry. I find that investments increase demand and that their effects are persistent. On the supply side, unlike previous literature that used dynamic models (e.g. Ryan 2012; Collar-Wexler 2013, Maican and Orth 2018), I do not estimate the dynamic parameters of interest, investments costs and entry costs, because I can calibrate the cost parameters with direct industry cost information. With the demand and dynamic parameters, I use the dynamic model to analyze equilibrium investment strategies and market outcomes.

Based on demand estimates and cost information, I conduct a counterfactual analysis in which entry costs are lowered by 20%. The proposed policy weakens investment incentives because more hotels are competing in a market. Average investments are lowered by 13%, and thus, average unobserved qualities decrease. Consumers still benefit from increased product variety and lower prices. The net changes in consumer surplus are positive. However, ignoring the negative competition effects on investments will overestimate consumer surplus under such a policy.

This study bridges and builds on two separate bodies of literature. First, it is related to the literature on market structure and endogenous product characteristics. Previous studies such as Mazzeo (2002) and Fan (2013) have focused on static models. In contrast, my study takes a dynamic approach to allow firms to change qualities through investment decisions. There have been a few studies, including Sweeting (2013), Leyden (2017), and Goettler and Gordon (2011), that have focused on dynamic endogenous product characteristics. Sweeting (2013) modeled radio station format changes in a dynamic model, and Leyden (2017) studied smartphone application updates. As in these two studies, in my model, firms make discrete choices that could impact consumer demand. My study, however, is most closely related to Goettler and Gordon (2011), and Hashmi and Biesebroeck (2016). They considered the same margins as I do in this study, and they studied endogenous innovation and examined competition effects on innovation in the CPU industry and automobile industry. But whereas this study allows for potential entries into a market, their studies did not allow for potential policy impact, and focused on exogenous change to the number of firms in a market.

This study also contributes to the literature on the hotel industry. Lewis and Zervas (2016) estimated consumer demand and evaluated the welfare effects of online ratings. Hollenbeck (2017) considered the cost and revenue explanations for chain affiliation. Suzuki (2013) and Ruan (2017) both studied the impact of land use regulations in Texas with a dynamic entry and exit model. My study differs from these previous ones in that it estimates the impact of investments on consumer demand and endogenizes investment decisions in a dynamic framework.

The remainder of this paper is organized as follows. Section 2 introduces the data and the sample I use in the empirical analysis. Section 3 presents a descriptive analysis using regressions. In Section 4, I develop a model of consumer and firm behavior for the hotel industry. Section 5 explains the estimation methodology. Section 6 lays out the empirical results. In Section 7, I conduct a counterfactual simulation and analyze how investment behavior and welfare changes when entry costs are reduced by 20%. Finally, in Section 8 I discuss the conclusions of my study.

2 The Hotel Industry in Taiwan

My primary dataset for this study is a monthly panel of Taiwanese hotels' financial performance between 2009–2016. In 2008, the Bureau of Tourism started collecting information about revenues, sales, employment, number of rooms, customer types, and investments in fixed assets and durable goods for all the legitimate hotels in Taiwan. The dataset covers over 95% of hotels operating in any given month.[3] Using the number of room-nights sold and room revenues, I can calculate average daily rates for every hotel.

I also supplement this data with a panel of consumer ratings from major online review platforms: TripAdvisor, Agoda, Expedia, and Bookings.com. This data contains consumers' stay dates, review dates, and ratings. Following Lewis and Zervas (2016), I aggregate ratings across platforms to construct average ratings for hotels.

I restrict my analysis to five-star hotels only. Five-star hotels are identified based on the star ratings given by the Bureau of Tourism and online travel agencies. The government star rating program, which is voluntary for hotels, was introduced in 2011. It is very similar to the AAA diamond rating system in the United States. Essentially, the ratings range from one to five stars for participating hotels. Hotels need to renew their ratings every 3 years. As the rating program is voluntary, some up-scale luxury may choose not to participate in the program. Therefore, I also consider star ratings given by online booking platforms.[4]

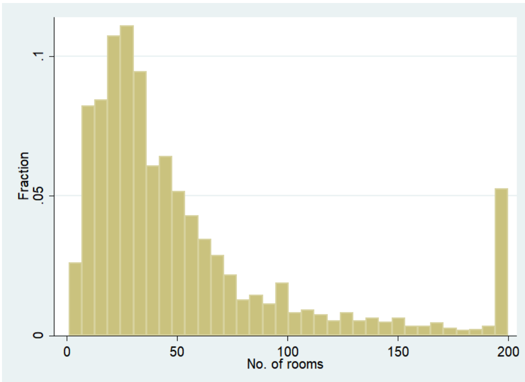
There are three reasons for choosing to narrow the sample in this way. First, hotels compete within different tiers. In general, hotels can be classified into different tiers based on star ratings, services and amenities, or prices. Competition is stronger among hotels within the same tier, since consumers view them as close substitutes. Focusing within a particular tier thus allows me to capture direct competitive pressures from close competitors.

Second, small hotels are more likely to face liquidity constraints or to have higher credit costs than large hotels, and their investment decisions could be affected by variations in unobserved heterogeneity of accessing capital. This issue becomes more severe when the market consists of a large number of small hotels. Figure 1(a) shows the histogram of hotel sizes. The distribution is skewed right: most hotels have less than 50 rooms. Figure 1(b) shows that five-star hotels are significantly larger than other hotels. Moreover, average quarterly investment expenditure per room is around \$900 for five-star hotels, and \$300

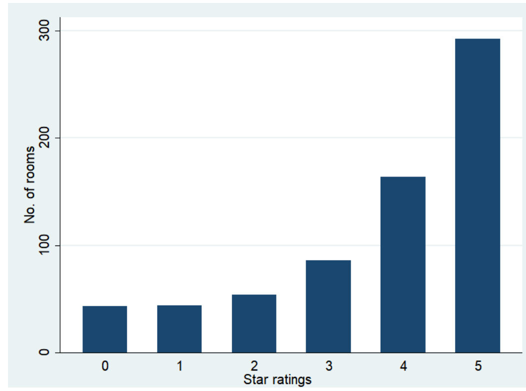
[3] Total number of hotels from 2009 to 2016 is shown in Table A.1 in the Appendix.

[4] In Figure A.1, I present a screenshot of five-star hotels from Expedia.com. Essentially, these star ratings from booking platforms are given to consumers in order to refine their searches and facilitate their purchases.

Figure 1: Hotel Sizes (2016 Jan.)



(a) Histogram of hotel sizes



(b) Average hotel sizes across stars

Notes: For Figure 1 (a), the maximum number of rooms is top coded at 200. For Figure 1 (b), 0 means no star rating.

for other hotels. This indicates that five-star hotels are capable and willing to make large investments. Therefore, focusing on these five-star hotels would provide more meaningful analysis.

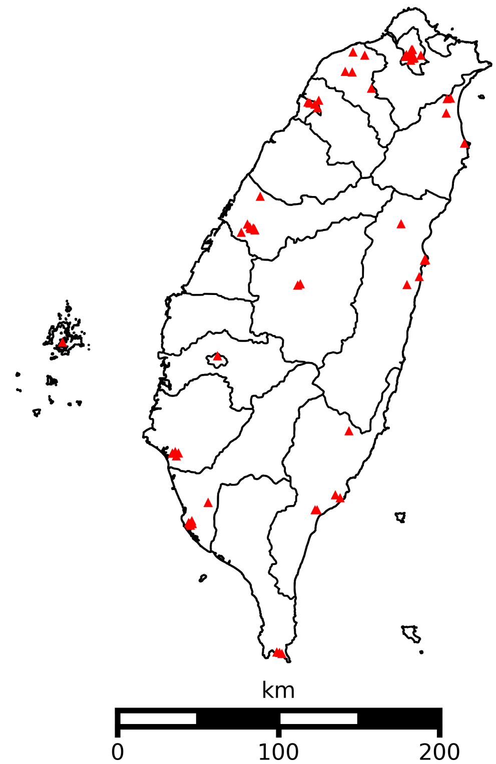
Finally, the total number of hotels is too large to for a dynamic model. If I define a market as a county, the number of hotels in each market is on average around 140, but in major cities such as Taipei, there are over 500 hotels in a single market. The number of firms in major cities' markets is too large for the dynamic framework developed by Ericson and Pakes (1995) under the Markov-perfect equilibrium concept.[5]

After narrowing my sample to only five-star hotels, it consists of a total 67 hotels in 15 counties in 2016. Since 2009, 26 hotels have entered the markets. Figure 2 displays the geographic distribution of five-star hotels in 2016; as expected, hotels are geographically concentrated within counties.[6] Therefore, I consider each county as a local market. As these five-star hotels are geographically close to each other, vertical differentiation within same tier becomes very important. The dynamics of hotel qualities are driving consumer

[5] Weintraub et al. (2008) developed a new solution concept called oblivious equilibrium to approximate Markov-perfect equilibrium with large number of firms. Oblivious equilibrium is not subject to the curse of dimensionality because each firm's strategy only depends on its own states and the long-run average industry state; current industry state is ignored. However, this solution concept is not applicable here since I am interested in how changes in current competition pressure affect investment behaviors. For more details about oblivious equilibrium, please see Weintraub et al. (2008) and Weintraub et al. (2010).

[6] For more details on geographic concentration, see Chung and Kalnins (2001), in which they investigate agglomeration effects on hotel performance in Texas's lodging industry.

Figure 2: Geographic Distribution of Five Star Hotels (2016 Q2)



Notes: Each triangle is a location of a five star hotel. The black lines are county borders.

choices. Table 1 reports summary statistics of market structures, hotel performances, and hotel characteristics. On average, a market had 4 hotels in 2016, and Taipei had 12 five-star hotels. The average size of these hotels is approximately 300 rooms, and they hire nearly the same number of employees as their number of rooms, meaning that the average number of employees is also around 300 for each hotel. The average daily rate is around \$130 dollars. Dividing a given hotel's total sales in a quarter by its total number of room-nights available in that time period gives me its occupancy rate. Five-star hotels on average sell 65% of their total capacity. One common measure of hotel performance is daily revenue per available room, or "RevPar." This can be computed by simply multiplying a hotel's average price by its occupancy rate. On average, RevPar is around \$85 dollars. In a quarter, the average revenue generated by a room is \$7,605 dollars. The number for investment represents the total amounts spent in fixed assets and durable goods in a quarter. The expenditure is adjusted by the number of rooms to account for different hotel sizes. More than 40% of the investment observations are zero, which is common for most investment data in other

Table 1: **Summary Statistics**

	Mean	S.D.	P25	P50	P75
Market Structure					
No. of hotels	4.47	3.27	1.00	4.00	5.50
Firm variables					
No. of rooms	300.31	143.48	202.00	257.00	358.00
No. of employees	318.26	191.66	200.67	267.67	366.33
Price ($)	132.26	66.08	87.33	110.77	159.07
Occupany rate (%)	65.37	15.55	57.77	67.72	75.86
Inv. per room ($)	943.43	5988.09	0.00	179.78	490.00
Online ratings	8.40	0.76	8.03	8.46	8.87

Notes: This table presents summary statistics on market and hotel characteristics. Number of hotels is as of the second quarter in 2016. Firm variables are of quarter-firm level. I aggregate the monthly data into quarterly data since the major renovations could take up to several months.

industries.[7] The distribution of investments has a long-right tail as the median of investments is around $180 dollars, and average investment is $943 dollars per room. The investment expenditures account for around 12.4% of the revenues.[8] Online ratings were scraped from online review platforms. Since some websites use five points scale, and some use ten points scale. I aggregate the consumer ratings in ten points scale. For example, ratings of 4 out of 5 will be converted into 8 points. The ratings do not show much variation, since these hotels are coming from the same (high) tier. Most five-star hotels have consumer ratings of 8 and above.

3 Descriptive Analysis

I first explore the empirical relationship between investments and competition, measured by number of hotels in a market, by running simple regressions. Results from regressions

[7] Figure A.2 in the appendix shows the investment time-series for two randomly selected hotels. Essentially, the investment pattern is lumpy, with occasional spikes, and most of the observations are either very small or zero. The small amounts may reflect regular maintenance.

[8] Dividing the average investments, $943 dollars, by the average revenue generated by a room, $7,605 dollars, gives me the percentage for investments.

indicate that competition are negatively associated with more investment. Specifically, I consider the following model:

$$Inv_{jt} = x_{jt}\beta + \phi \cdot Comp_{mt} + \alpha_j + \delta_t + \epsilon_{jt}$$

where j indexes incumbents, m indexes markets, and t indexes times . Inv_{jt} is a measure of investments, in this case investments per room. It is calculated from dividing the total investments made in a quarter by the number of rooms. x_{jt} are controls for hotel characteristics, including age, number of employees, occupancy rates, and prices. $Comp_{mt}$ is a measure of competition intensity. For this, I use the number of competing hotels in a market to indicate competition intensity. The coefficient of interest is ϕ, because it captures the impact of additional five-star hotel in a market. I also include firm fixed effects, α_j, and time fixed effects, δ_t.

The impact of market structure on investment incentives is ambiguous. A more competitive market may spur firms to provide better quality through investments.[9] But having more competitors also reduce their potential returns from investments since consumers have more options to choose from. Moreover, a competitive market will drive both market shares and prices down, potentially limiting hotels' ability to make investments due to decreased revenues.

Regression results are presented in Table 2. The first column shows results where the number of hotels in a market is used as the only regressor, controlling for firm fixed-effects and time fixed-effects. The coefficient of interest is negative and significant at the 10% level. The result is interesting because potential bias can arise due to unobserved demand shocks. Specifically, positive demand shocks can drive both entries and investments in a positive direction (e.g. Gutierrez and Philippon 2017). Therefore, the direction of bias is positive, which indicates that the true coefficient could be more negative. The second column controls firm-specific characteristics and market sales since hotels' performance will affect their ability to make investments. Market size is also important for both entries and investments. The coefficient of interest is still negative and significant at the 10% level, and occupancy rate is negatively correlated with investments. The intuition behind this is that during high seasons , investments induce additional opportunity costs since rooms under renovation would be unavailable for occupancy. Hence, these potential losses in revenues weaken investment incentives. In column 3, I add two period lead variables to

[9] Mazzeo (2003) and Matsa (2011) both find that competitive markets drive firms to provide better qualities of their products.

Table 2: OLS results between Market Structures and Investments

	Investments per room ($)		
	(1)	(2)	(3)
No. of hotels	-334.61^{**}	-551.36^{**}	-731.04^{**}
	(147.03)	(228.11)	(301.39)
Price ($)		-11.95	-5.77^{**}
		(8.32)	(2.75)
Occupancy rate		-8319.13^{**}	-5359.946^{**}
		(3508.51)	(2646.69)
No. of employees		-13.61	-19.32^{***}
		(9.63)	(5.01)
Market sales (thous.)		11.95	-4.47
		(14.44)	(21.73)
Onlin ratings		-377.45	-137.77
		(396.46)	(204.09)
Two periods lead controls	No	No	Yes
Hotel FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R^2	0.33	0.35	0.53
Observations	1,563	1,563	1,421

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. They are robust and clustered at the market level. An observation is a hotel-quarter combination. The full table is provided in Table A.2. Other measures of investments are also used, and results are shown in Table A.3.

control for future demand shocks that would affect both entry and investment decisions. One notable difference between column 2 and column 3 is that R-squared increases by 0.18, which indicates that investments could be explained by future demand shocks.

The results above indicate that having more competitors is associated with lower investment amounts.[10] I also use other measures of investments in the regression model. The results are qualitatively similar to Table 2. Another concern is that the investment data

[10] I also consider the possibility that hotels respond to entry by improving service qualities instead of upgrading physical amenities. Regression results for this scenario are shown in Table A.5 in the Appendix.

contains a lot of zeros. Zeros account for more than 40% of the total observations. To deal with this issue, I aggregate the quarterly data into annual data to reduce the number of zero investments and capture effects in longer horizon. The results also indicate negative correlation between investments and number of competitors in a market. The detail estimates are reported in Table A.3 and Table A.4 in the Appendix. In general, the estimates of interest are negative but insignificant. These correlations cannot be interpreted as causal. Potential endogeneity issues still apply here. Therefore, I next pursue a structural approach to analyze the relationship.

4 Model

I develop a model for consumer and hotel behaviors in the hotel industry in two steps. First, I present a static demand model to analyze product-market competition and evaluate the impact of investments. I then combine the static demand model with a dynamic model of investment and entry to model hotel behaviors. This model allows me to capture changes in investment incentives from product-market competition.

4.1 A Discrete Choice Model of Demand in Hotel Industry

Following the large body of literature on discrete choice demand system (e.g. Berry 1994; Berry, Levinsohn and Pakes 1995), I use a random-coefficient discrete choice model to describe consumer demand for hotel rooms as a function of product characteristics and prices. Specifically, consumer i receives indirect utility u_{ijt} from staying at hotel j at time t,

$$u_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt} \tag{1}$$

where $j = 1, ..., J_t$. x_{ijt} is a vector of observable hotel characteristics. p_{jt} is the price of staying at hotel j, and ξ_{jt} is the mean unobservable consumer utility from other characteristics that are known to consumers and firms but are unobserved to econometricians. α_i and β_i are individual-specific coefficients. Finally, ϵ_{ijt} is the random taste shock of consumer i for hotel j at time t.[11]

To allow for consumer heterogeneity, I assume that the distribution of consumer prefer-

[11] I also consider market fixed effects and time fixed effects in the indirect utility. For simplicity of the model, I suppress the fixed effects.

ences over prices and product characteristics follows a multivariate normal distribution:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Sigma\nu_i, \ \nu \sim N(0, I_{n+1}) \tag{2}$$

Consumer i's taste consists of α and β, which are common across consumers, and ν_i, which is a vector of unobserved random tastes that affects purchasing decisions. The matrix of Σ allows for different variances and covariances between product characteristics. These random coefficients generate more realistic substitution patterns by allowing interactions between consumer tastes and product characteristics.

Consumer utility can be decomposed into δ_{jt}, mean utility associated with hotel j at time t that is common across consumers, and μ_{jt}, an idiosyncratic deviation from the mean utility.

$$\begin{aligned} u_{ijt} &= x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{jt} \\ \delta_{jt} &= x_{jt}\beta - \alpha p_{jt} + \xi_{jt} \\ \mu_{ijt} &= [p_{jt}, x_{jt}] \ \Sigma\nu_i \end{aligned}$$

In the model, consumer i decide to stay at hotel j at time t if and only if

$$\delta_{jt} + \mu_{ijt} + \epsilon_{ijt} \geq \delta_{kt} + \mu_{ikt} + \epsilon_{ikt} \ \forall k \neq j$$

Consumers may decide not to purchase any of the inside options, here I consider five-star hotels in the specification. Therefore, I introduce an outside good, which is staying at hotels other than five-star hotels. The indirect utility from this outside option is

$$u_{i0t} = \xi_{0t} + \epsilon_{i0t}$$

where ξ_{0t} is the mean utility. I use the log of total number rooms from other hotels in outside option to capture the change of outside option.[12] The idea is that as there are more hotel rooms in outside option, the attractiveness of inside option may be lower. I normalize the mean utility of outside option to zero by subtracting the log of total number rooms from other hotels from utilities of inside products.

I assume that ϵ_{ijt} follows an i.i.d. Type I Extreme Value distribution. This assumption

[12] This is an ad hoc way to model the change of outside option. In future work, I plan to try nested-logit model, in which consumers are choosing among different tiers of hotels.

admits a closed form solution for the probability that consumer i choose to stay at hotel j in period t:

$$s_{ijt} = \frac{\exp(x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} - \xi_{0t} + \epsilon_{ijt})}{1 + \sum_{k \in J_t} \exp(x_{kt}\beta_i - \alpha_i p_{kt} + \xi_{kt} - \xi_{0t} + \epsilon_{ikt})} \tag{3}$$

Even when they exhibit the same observed characteristics on paper, hotels are highly differentiated because of variations in designs, locations, services, amenities, and room sizes. ξ_{jt} captures a wide variety of these unobserved characteristics, and it will not vary from period to period in an i.i.d. way. More importantly, these unobserved characteristics can reflect a hotel's investment decisions endogenously. Therefore, similar to Sweeting (2013), I assume that ξ_{jt} evolves according to ρ and follows the AR(1) process:

$$\xi_{jt} = \rho\xi_{jt-1} + \gamma \cdot 1(\iota_{jt-1} \geq I) + \eta_{jt} \tag{4}$$

where the unobserved characteristics are correlated over time according to ρ and subject to an i.i.d. innovation, $\eta_{jt} \sim N(0, \sigma_\eta^2)$. The coefficient for investment, γ, captures the impact of investment in the last period . γ serves as a vertical shift on ξ. Through the AR(1) process, investments can have persistent effects over time. Consumers are short-lived and only observe ξ_{jt}, and do not observe past investments. Therefore, they cannot use change in ξ to infer past investments.

Investment decisions are modeled as a dummy variable. I only consider investments above a threshold, I, because investment amounts are lumpy, and most of the observations are zero or very small. The small amounts usually represent regular maintenance, which is related to unobserved shocks to quality and is different from major renovations. Potentially, in future studies I could allow for multiple levels of investment as discrete choices, and multiple parameters to capture these differential effects. But here I consider only binary investment choices for simplicity.

Equation (3) can be re-written as:

$$s_{ijt} = \frac{\exp(\tilde{\delta}_{jt} + \mu_{ijt})}{1 + \sum_{k \in J_t} \exp(\tilde{\delta}_{kt} + \mu_{ikt})} \tag{5}$$

where $\tilde{\delta}_{jt} = \delta_{jt} - \xi_{0t}$. Integrating over the distribution of unobserved consumer tastes, ν_i, the predicted aggregate market share for hotel j is given by:

$$s_{jt}(p_{jt}, x_{jt}, \xi_{jt}, \theta) = \Pr(u_{ijt} \geq u_{ikt},\ \forall k = 0, 1, ..., J_t) \tag{6}$$

$$= \int_{\nu} s_{ijt} dP_{\nu}(\nu) \tag{7}$$

4.2 A Dynamic Model of Investment and Entry

In this section, I present a dynamic model of entry and investment following the dynamic framework developed by Ericson and Pakes (1995). There are N_m hotels competing in a local market $m \in \{1, 2, ..., M\}$. Hotels are either incumbents or potential entrants. Time is discrete, and the decision period is a quarter. Incumbents choose action $a_{jt} \in A = \{0, 1\}$ for each period $t = 0, ..., \infty$ in order to maximize

$$\sum_{t=0}^{\infty} \beta^t \big(\pi(a_{jt}, S_{jt}) + \epsilon_{jt}(a_{jt})\big) \tag{8}$$

where per-period payoffs can be written as

$$\pi(a_{jt}, S_{jt}) + \epsilon_{jt}(a_{jt}) = R_{jt}(S_{jt}) - \mu \cdot 1\{a_{jt} = 1\} + \epsilon_{jt}(a_{jt})$$

$R(S_{jt})$ is the revenue hotel j makes given state, S_{jt}. Hotels are competing in a spot market. I model the spot equilibrium as Bertrand-Nash in prices. The static action, prices, and quantities don't affect influence the evolution of the state variables. Specifically,

$$R_{jt}(S_{jt}) = \max_{p_{jt}} (p_{jt} - mc_j) \cdot M_t \cdot s_{jt}(S_{jt}) \tag{9}$$

where mc_j is constant marginal costs, M_t is market size, and s_{jt} is market share for hotel j. Marginal costs are assumed to be constant over time, and are estimated from demand estimation. Optimal pricing decisions are obtained by solving a system of first order conditions for competing hotels.

In addition to $R(S_{jt})$, hotels make investment if $a_{jt} = 1$, and pay a fixed cost of investment, μ. Hotels receive an i.i.d. private payoff shock $\epsilon_{jt}(a_{jt})$ in each period. These shocks follow a Type 1 Extreme value distribution.

I assume hotel j's strategy is characterized by a pure Markov strategy $\sigma_j : (S_j, \epsilon_j) \rightarrow a_j$

Following Bellman's principle of optimality, the value function can be expressed:

$$V_j^{I\sigma}(S_j, \epsilon_j) = \max_{a_j} \left\{ \pi(a_j, S_j) + \epsilon_j(a_j) + \beta \int V_j^{\sigma}(S_j') g(S_j' | a, \sigma_{-j}, S_j) dS_j' \right\} \tag{10}$$

Entrant's problem can be summarized:

$$V_j^{E\sigma}(S_j, \epsilon_j) = \max_{e_j} \left\{ \epsilon_j(e_j = 0), -EC + \beta \int V_j^{I\sigma}(S_j') g(S_j' | a = 0, \sigma_{-j}, S_j) dS_j' + \epsilon_j(e_j = 1) \right\} \tag{11}$$

where EC is the entry cost entrant draw from a distribution. Entrant simply compare cost of entry and expected value function as an incumbent. With the distribution of ϵ, an optimal strategy of investment can be expressed as conditional choice probability:

$$P^{\sigma_j}(a, S_j, \sigma_{-j}) = \frac{\exp(v_j^{\sigma}(a, S_j, \sigma_{-j}))}{\sum_{a' \in A} \exp(v_j^{\sigma}(a', S_j, \sigma_{-j}))} \tag{12}$$

where $v_j(\cdot)$ is the choice-specific value function:

$$v_j^{\sigma}(a, S_j, \sigma_{-j}) = \pi(a_j, S_j) + \beta \int V_j^{\sigma}(S_j') g(S_j' | a, \sigma_{-j}, S_j) dS_j' \tag{13}$$

The strategy profile $\sigma = (\sigma_j, \sigma_{-j})$ form a Markov Perfect Equilibrium if for all states, all value functions $V(\cdot)$, and all possible strategies $\tilde{\sigma_j}$:

$$V(S, \sigma_j, \sigma_{-j}, \epsilon) \geq V(S, \tilde{\sigma_j}, \sigma_{-j}, \epsilon) \tag{14}$$

5 Estimation

Now let us consider the estimation procedures for consumer demand. First, I solve for the mean utilities, $\tilde{\delta}_{jt}$, via contraction mapping given observed market shares, s_{jt}, and a guess of nonlinear taste parameters (Berry 1994; BLP 1995).[13] Second, I construct quasi-differenced moments on mean utilities by subtracting $\rho\tilde{\delta}_{jt-1}$ from $\tilde{\delta}_{jt}$, which results in[14]

$$\tilde{\delta}_{jt}(\Sigma, s_{jt}) - \rho\tilde{\delta}_{jt-1}(\Sigma, s_{jt-1}) = (x_{jt} - \rho x_{jt-1})\beta - \alpha(p_{jt} - \rho p_{jt-1}) + \gamma \cdot 1(\iota_{jt-1} \geq I) + \eta_{jt} \tag{15}$$

[13] I provide more details on the computation of mean utilities in the Appendix.

[14] I suppress the outside option, ξ_{0t}, and fixed-effects just to maintain the clarity of the equations.

ξ_{jt} is differenced out by the AR(1) assumption, $\xi_{jt} = \rho\xi_{jt-1} + \gamma \cdot 1(\iota_{jt-1} \geq I) + \eta_{jt}$. η_{jt} can be written as a function of parameters:

$$\begin{aligned}\eta_{jt} &= \tilde{\delta}_{jt}(\Sigma, s_{jt}) - \rho\tilde{\delta}_{jt-1}(\Sigma, s_{jt-1}) - (x_{jt} - \rho x_{jt-1})\beta + \alpha(p_{jt} - \rho p_{jt-1}) - \gamma \cdot 1(\iota_{jt-1} \geq I) \\ &= \eta_{jt}(\alpha, \beta, \gamma; \rho, \Sigma)\end{aligned}$$

η_{jt} is the structural error from demand side. Moments can be written as:

$$E\big(Z'\eta_{jt}(\alpha, \beta, \gamma; \rho, \Sigma)\big) = 0 \tag{16}$$

where Z is a set of instruments. Finally, let $\theta = [\alpha, \beta, \gamma; \rho, \Sigma]$. The GMM estimates are recovered by minimizing the GMM objective function:

$$\hat{\theta} = \arg\min_{\theta} \eta(\theta)'Z\Omega^{-1}Z'\eta(\theta) \tag{17}$$

where Ω is a consistent estimate of $E(Z'\eta(\theta)\eta(\theta)'Z)$. Similar to Nevo (2000), given values for nonlinear parameters ρ and Σ, linear parameters α, β, and γ can be estimated via a linear regression with $\tilde{\delta}_{jt} - \rho\tilde{\delta}_{jt-1}$ as the dependent variable. In addition, note that $\eta_{jt} \sim N(0, \sigma_\eta^2)$, σ_η^2 is estimated from the residuals in the previous regression.

The price endogeneity issue still exists even with the AR(1) assumption, and the quasi-difference on ξ. This is because prices can be adjusted quickly in response to unobserved quality shocks, η, especially when hotels adopt revenue management. Therefore, I use BLP-style instruments, competitors' product characteristics, to identify the parameters. The identifying assumption here is that the innovation η is orthogonal to product characteristics excluding prices. Competitors' product characteristics, however, do not respond to firm-specific shocks, and cannot be changed immediately, but will affect prices in equilibrium.

Mean utility parameters β are identified by correlating observed product characteristics and market shares under the identifying assumption. The impact of investments, γ, is identified using the timing assumption of innovation, η. When making investment decisions, hotels do not observe the unobserved quality shocks in next period . Identification of random coefficients Σ relies on changes in market shares when new hotels enter, or existing hotels change their product characteristics. Finally, ρ, the parameter in the AR(1) process, is identified via persistence in market shares across periods.

6 Empirical Results

6.1 Primary Specification

Since I focus only on five-star hotels, the amenities and services provided by these hotels are very similar. For example, most of these hotels provide gyms, business centers, parking, laundry services, and full-service restaurants. In-room amenities are also close to identical. These characteristics are mostly time-invariant. Therefore, including these characteristics does not create much differentiation between hotels or across time. Instead, I allow them to enter the characteristics unobserved by econometricians and vary according to an AR(1) process.

In addition to prices, I use a hotel's age, distance to city center, number of rooms, online ratings, and number of employees per room as its product characteristics. I also control for market fixed effects and time fixed effects to account for unobserved demand shocks.

For prices, I use the average price in each quarter. I calculate prices by dividing quarterly room revenues by total number of room-nights sold. This is not a perfectly precise measure for prices since hotels usually adopt price discrimination based on booking dates, stay dates, room types, and consumer types. Consumers may be offered varying prices in practice and have different price sensitivities.[15] Therefore, a random coefficient is needed for prices to capture consumer heterogeneity.

Hotels' ages are measured in years since exact opening dates for many incumbent hotels are not readily available. I found that age does not impact consumer demand in a clear direction. While newly-opened hotels would show few or no signs of wear and tear, older hotels in the five-star tier often have well-established reputations that new hotels have not yet developed. I expect that consumers have varying tastes regarding a hotel's age and reputation; to account for this variation, I have added a random coefficient.

Distance is constructed by measuring the distance between the locations of a hotel and the center of the city it is located in, usually either the downtown area or a major train station. This variable is included because it captures probably the only horizontal differentiation of hotels, and it is often shown on online booking platforms. Consumers often factor a hotel's location into their decision-making process, and different locations are preferred depending on each consumer's needs.

[15] One common way to capture heterogeneity in prices is to include income information. However, since hotels often serve both foreign visitors and local residents, and seasonality affects both occupancy rate and type of visitors, it is not clear how income is distributed for consumers.

The number of rooms is included in the specification because hotels operate under capacity constraints. When hotels are fully booked up on some days, their observed market shares are smaller than predicted market shares . This is an ad hoc way to deal with capacity constraints since daily sales data is not available, meaning it is not possible to directly model unavailability.

I also consider hotel brands, online ratings and number of employees per room to control for hotel quality. Hotel brands is a dummy variable, which is set equal to 1 if a hotel is affiliated with a major hotel group, such as SPG, IHG, or Hyatt. This variable reflects brand values and reputations based on hotel brand names. Consumers are more likely choose these hotels if they have had previous experience with the same brand. Online ratings and number of employees per room are also important. Most consumers now use online booking platforms to reserve hotel rooms, and online ratings play an important role while consumers are choosing between hotels (Lewis and Zervas 2016). And the number of employees a hotel has per room provides a measure of service quality. Having sufficient personnel speeds up the check-in and check-out processes, and makes sure rooms are ready when consumers arrive.

Changes in outside options—other, smaller and/or lower quality, hotels—are important in my model since the product I am studying is relatively homogeneous, and consumers can easily substitute outside options if they are willing to stay in hotels of lower quality. Therefore, I include the logarithm of total rooms available in each market to account for this possibility and control for the evolution of outside options. If there are more alternatives in outside options, consumers are less likely to choose five-star hotels.[16]

One main purpose for the demand estimation is to recover the impact of investments on consumer demand. In the primary specification, I use an investment cutoff of $500 per room per quarter. Any investment expenditure above $500 is considered as an investment action. Any amount lower than $500 will not count as investment. Small amounts may reflect regular maintenance, and may not reflect on consumer demand.

6.2 Demand Estimates

Table 3 presents the demand estimates from the primary specification. The first column contains the parameter estimates and standard errors from the logit model , and the sec-

[16] Admittedly, using other non five-star hotels as consumers' outside option may not be realistic if consumers strongly prefer upscale luxury hotels, and do not consider cheap hotels. Their outside option could only be four star hotels, or some three star hotels. In future work, I plan to vary the definition of outside good as robustness checks.

ond column provides the results of the random coefficient logit model. The logit model does not include either transition processes or investment effects. Overall, estimates fit my expectations and most of them are statistically significant.

The results indicate that consumers are more price-sensitive in the RC logit model than in the logit model, with average own price elasticity around -1.04 for the logit model and -2.42 for the RC logit model. This difference may result from serially correlated unobserved qualities and investment decisions, as they are positively correlated with prices. Therefore, the RC logit model is the preferred model.

These estimates show that prices and ages impact consumer utilities negatively. Random coefficients for these two variables also are significant. This indicates that consumers have a great deal of heterogeneity in their preferences regarding a hotel's prices and age. On average, consumers prefer hotels with higher online ratings, more rooms, and more employees, and strongly value brand names. Increases in supply from outside options reduces the probability that consumers will choose five-star hotels. Estimates for distance are insignificant and close to zero; this likely reflects the fact that, as shown in Figure 2, similar hotels tend to be clustered in similar, and geographically close, neighborhoods. Horizontal differentiation does not play an important role in the model.

There is strong persistence in unobserved qualities, $\hat{\rho} = 0.9035$, as each period is a quarter , and investments positively impact consumer utility through unobserved qualities. Dividing estimates of product characteristics by the price coefficient, I can measure the impact of other characteristics in monetary terms. On average, the effect of investment on utility is around \$26. If hotels can charge \$26 more per room-night following a major investment, holding everything else constant, then on average hotels can recover investment costs of around \$3,300 per room in three quarters.

I also use other cutoff values, \$300 and \$1000 per room per quarter. These results are reported in Table A.6. Essentially, the estimates are qualitatively similar to those in Table 3. Perhaps unsurprisingly, investment impact is larger when I use \$1000 as cutoff value, and smaller when \$300 is used. Estimates from these two cutoffs both require around three quarters to fully recover the investment costs.

Table 3: Demand Estimates

	Logit	RC Logit
Mean Utility		
Price ($ 100)	-0.8455^{***}	-2.2621^{***}
	(0.1238)	(0.1335)
Age	0.0075^{***}	-0.2229^{***}
	(0.0020)	(0.0111)
Distance	0.0029	−0.0010
	(0.0025)	(0.0071)
No. of rooms (hundreds)	0.2636^{***}	0.3753^{***}
	(0.0121)	(0.0238)
Brand	0.1629^{**}	0.9229^{***}
	(0.0632)	(0.0676)
Online ratings	0.0219^{***}	0.0338^{***}
	(0.0050)	(0.0104)
No. of employees per room	0.4380^{***}	0.8748^{***}
	(0.0629)	(0.1084)
Log of total room supply	-1.1089^{***}	-0.4859^{***}
	(0.0992)	(0.0503)
Constant	5.9834^{***}	2.0231^{***}
	(1.2308)	(0.3983)
S.D.		
Price		0.4054^{***}
		(0.1431)
Age		0.2318^{***}
		(0.0110)
Distance		0.0058
		(0.1014)
Constant		0.0264
		(0.1522)
Transition Process		
ρ		0.9035^{***}
		(0.0072)
σ_η		0.8172^{***}
		(0.0036)
γ		0.5855^{***}
		(0.2089)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Result based on 1,563 observations and 5,000 simulation draws in each period. Robust standard errors in parentheses.

6.3 Calibration of Cost Parameters

I use cost data to calibrate cost parameters in my dynamic model. Most papers using dynamic models pursue dynamic estimation to recover parameters governing strategies.[17] Here I take a different approach because my dataset provides me with direct information on cost parameters.

For investment costs, I observe the amounts hotels spend on durable goods and fixed assets. As I only consider investments above certain levels, I compute the investments using the threshold of spending \$500 or more per room in a quarter. The average investment cost is around \$3,300 per room. Specifically, μ in the dynamic model equals \$3,300 multiplied by the number of rooms in a given hotel. I do not incorporate cost shocks just to simplify the model.

For entry costs, I utilize information on development costs for potential entrants whose properties are under construction obtained from the Bureau of Tourism.[18] This cost information is available because these potential entrants are applying for International Tourism Hotel certification.[19] In general, these properties are built to operate as upscale, or luxury, hotels. Therefore, their development costs can be considered similar to those for five-star hotels. Figure 3 contains a scatter plot showing the development costs and number of rooms for 33 potential entrants . A quadratic fitted line is also shown. This figure indicates that for a hotel with 300 rooms and an average size for five-star hotels in this market , the average development cost is around \$100 million. For this study, I compute the average development costs per room and form an empirical distribution. Entry cost is drawn from this distribution and be multiplied by the number of rooms.

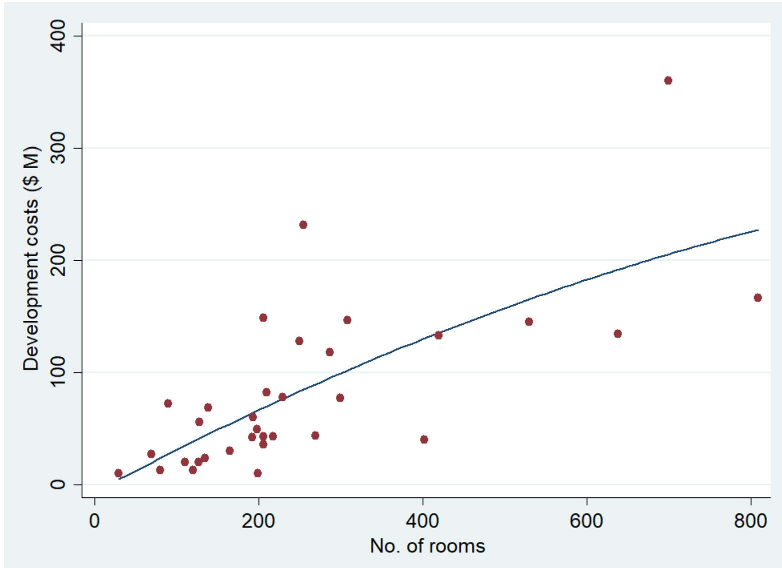
Using this cost information to calibrate cost parameters avoids intensive dynamic estimation. However, this approach has its own drawbacks. These costs are accounting costs, which obviously do not reflect opportunity costs. Major investments could reduce the total

[17] The commonly used two-step approach developed in Bajari, Benkard, and Levin (2007) reduces computation burdens considerably, and facilitates many applications of dynamic models (e.g. Ryan 2012, Collar-Wexler 2013, Suzuki 2013, Hashmi and Biesebroeck 2016, Hollenbeck 2017, Maican and Orth 2018). However, computations regarding simulations of valuation functions and perturbation of alternative strategies are still very intensive.

[18] Though these properties are under construction, they are not necessarily committed to operate as hotels. Some of the properties that have been completed since the data was collected ended up as commercial buildings or residential properties.

[19] International Tourism Hotel is a government certification for high-end hotels. It has been implemented for more than 40 years. The intention of this certification is to provide high-quality accommodations for foreign visitors by enforcing certain construction requirements. For example, to obtain certification, a hotel must meet minimum requirements for the number of elevators, area of their lobby and restaurant(s), and number of room types.

Figure 3: Development costs



Notes: This scatter plot is based development costs from 33 potential entrants.

number of rooms available for sale at a given time. Hotels often make investments in slow seasons. Therefore, investment costs could be lower than the true investment costs. For entry costs, the calibration relies on the assumption that development costs for these existing hotels resemble the cost distributions for potential five-star hotels currently under construction. The direction of these biases could go either way. In the future, I plan to estimate the cost parameters in my dynamic model and compare estimates with cost information.

7 Conterfactual Exercises

7.1 Welfare under Different Market Structures

The primary purpose of my structural model is to understand how market structures affect investments and compare welfare effects across different market structures. Using cost parameters and demand estimates in my structural model, I can find counterfactuals with different number of hotels in a market. The counterfactuals will resolve long-run equilibrium with both static and dynamic strategic interactions, prices and investments.

In this section, I am holding the number of hotels in each market exogenous. In the next section, I will consider endogenous market structures through entry decisions. For the counterfactual experiment, I first select a mid-size market with four hotels in 2016. In 2009, there were only two incumbent hotels. Later, two new hotels entered the market. I use the product characteristics of these four hotels as well as market characteristics for my simulation.[20] Then I solve the model and obtain value functions and policy functions associated with the Markov Perfect Equilibrium. Last, based on the above value and policy functions, I simulate investment decisions, and market outcomes for 100 periods, which is equivalent to 25 years.

Instead of using the full solution method developed in Pakes and McGuire (1994), I adopt the stochastic algorithm of Pakes and McGuire (2001) and Collar-Wexler (2013) to approximate the value functions and strategies. The main reason for this choice is the large state space, as the average number of firms in my dataset is around 4, and the state variable, ξ, is a continuous variable, which will be discretized in the computation.[21]

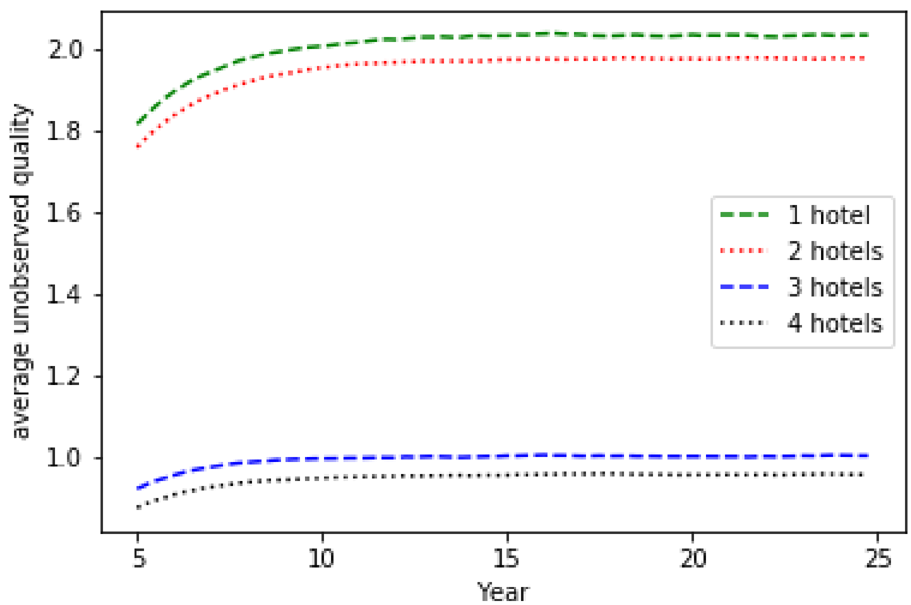
The simulation results are summarized in Figure 4. The results are based on 500,000 simulations. Figure 4 shows the path of average unobserved qualities in four different market structures. Monopoly has the highest average unobserved qualities, as duopoly has sightly lower ones. When there are three or four hotels, average investment per hotel decreases by 50% and average unobserved qualities are significantly lower than those of monopoly and duopoly. The significant drop in unobserved qualities is resulted from the fact that the third and fourth hotel possesses more attractive product characteristic, age.[22] Hotels cut back

[20] Some product characteristics are time-varying. For example, age of a hotel will increase over time. I fix the product characteristics as those in 2016 to simplify the computation of Markov Perfect Equilibrium. Market size is fixed at the level in 2016.

[21] See Appendix A.2.2 for more computation details for Markov Perfect Equilibrium.

[22] I will conduct similar analysis with symmetric hotels to see if the gap between two and three hotels is smaller.

Figure 4: Simulation Results under Different Market Structures

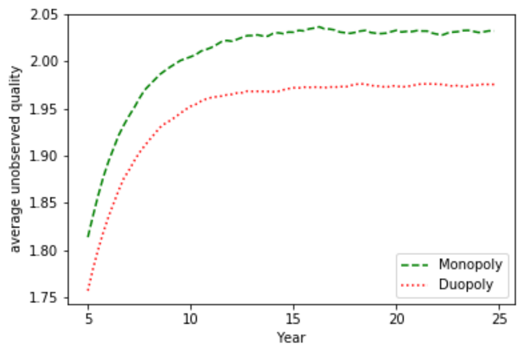


Notes: I use 500,000 simulations for the counterfactual experiment. Lines reflect the average unobserved qualities different number of hotels in the market.

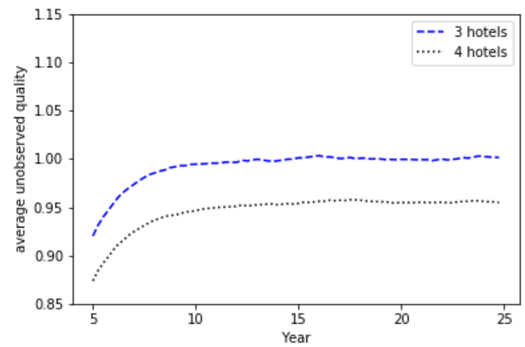
on their investments not only due to competition effects but also due to more attractive product characteristics for third and fourth hotels. In Figure 5, I show closer look between differences in ξ in different market structures.

Welfare comparisons are shown in Table 4. In general, competition is beneficial to consumers. Consumer surplus increases with the number of hotels. Consumer surplus for two and three hotels are relatively close because average qualities are lower in the three hotels case. Consumers benefit from lower prices, and more product varieties from more hotels. However, the product qualities are also lower. Without the adverse effects of competition on investment in quality, the numbers for welfare could be larger. When computing producer surplus, I only consider investment costs, but not upfront entry costs since I treat the number of hotels in a market as exogenous. The welfare changes from adding additional hotel into the market are small when consider that the average entry cost is \$ 64 million dollars. Especially, when the number of hotels increase from 2 to 3, the welfare gains are less than \$ 10 million dollars. This indicates that more hotels in a market might not be socially efficient

Figure 5: Difference in Unobserved Qualities



(a) 1 and 2 hotels



(b) 3 and 4 hotels

Notes: I use 500,000 simulations for the counterfactual experiment. The lines reflect the average unobserved qualities for existing hotels in each period.

Table 4: Welfare Effects under Different Market Structures

	1 hotel	2 hotels	3 hotels	4 hotels
Consumer Surplus	\$ 36.27 M	\$ 65.15 M	\$ 67.93 M	\$ 91.12 M
Producer Surplus	\$ 24.91 M	\$ 36.66 M	\$ 40.98 M	\$ 48.04 M

Notes: The number reflect net present values over 100 periods with discount factor equal to 0.98.

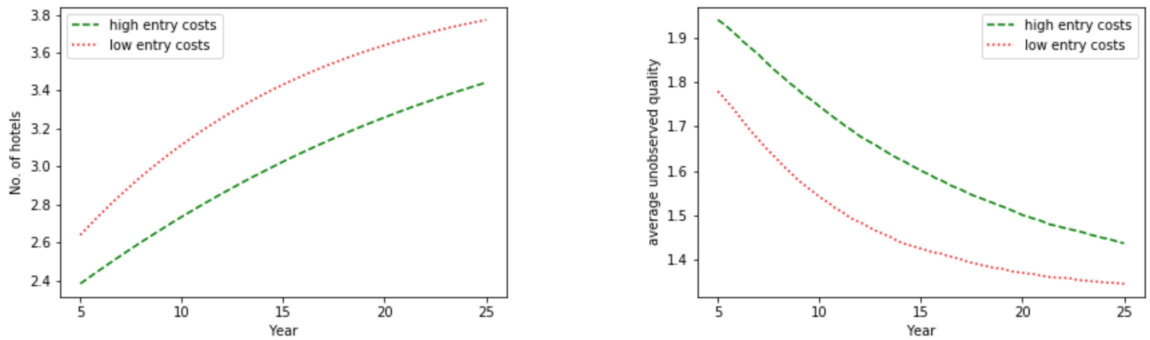
because of the upfront entry costs required for establishing a new hotel.[23]

7.2 Reduction in Entry Cost

In this section, I perform a counterfactual experiment based the estimated demand system and costs data. The goal of this analysis is to examine how competition affects equilibrium investment decisions and welfare changes. This analysis consists of two steps. First, I solve the model and obtain value functions and policy functions associated with the Markov Perfect Equilibrium. Second, based on the above value and policy functions, I simulate market structures, investment decisions, and market outcomes for 100 periods.

[23] In the counterfactual simulation, I fixed market size to capture the effect of changes in market structures. However, growing market sizes would increase both consumer surplus and producer surplus. In that case, a new entry might be socially beneficial. I will consider changes in market sizes and outside options later.

Figure 6: Simulation Results for Reducing Entry Cost



(a) Number of Hotels over time **(b) Average quality over time**

Notes: I use 500,000 simulations for the counterfactual experiment. Red dotted line is based on counterfactual policy with 20% reduction in entry costs. Figure 6a shows the average number of hotels over time. In Figure 6b, the lines reflect the average unobserved qualities for existing hotels in each period.

My counterfactual experiment considers a policy which reduces entry costs by 20%. This policy is similar to the more lenient land use regulations studied in Suzuki (2013). In this counterfactual experiment, I examine a small market from my dataset to illustrate competition's effects on investments. The chosen market had two incumbents at the beginning of 2009, and two firms entered the market during the study period, for total four hotels in this market in 2016. I simulate investment and entry decisions for incumbents and potential entrants.

In each period, a potential entrant shows up and draws its product characteristics, and entry cost from empirical distribution. The distribution of product characteristics is formed by using the product characteristics from five-star hotels in the sample.[24] Incumbents choose the optimal prices in each period by solving static pricing game. Investment decisions are based on the policy functions which are functions of current states.

The simulation results are summarized in Figure 6. The results are based on 500,000 simulations over 100 periods, equivalent to 25 years. In Figure 6a, the average number of firms in the market grows over time, and markets with higher entry costs have lower average numbers of entrants. Figure 6b shows the path for the average of unobserved qualities in the market over time. Markets with higher entry costs have higher average hotel quality. The gap between the two lines in Figure 6b is around 1.5 in absolute value. The 20% reduction in

[24] Age, unlike other characteristics, is set to zero when the entrant first enter the market.

Table 5: **Welfare Effects with Different Entry Costs**

	+20%	Baseline	-20%	Δ
Consumer Surplus	\$85.32 M	\$87.60 M	\$92.93 M	+\$5.33 M
Producer Surplus	\$18.09 M	\$20.53 M	\$22.48 M	+\$1.95 M

Notes: The number reflect net present values over 100 periods with discount factor equal to 0.98.

entry costs is causing an 8–10% decrease in average quality over time, as a result of the lower investment frequencies. In this scenario, hotels are reducing the amounts they are investing by an average of 13% because there are more competitors in the market.

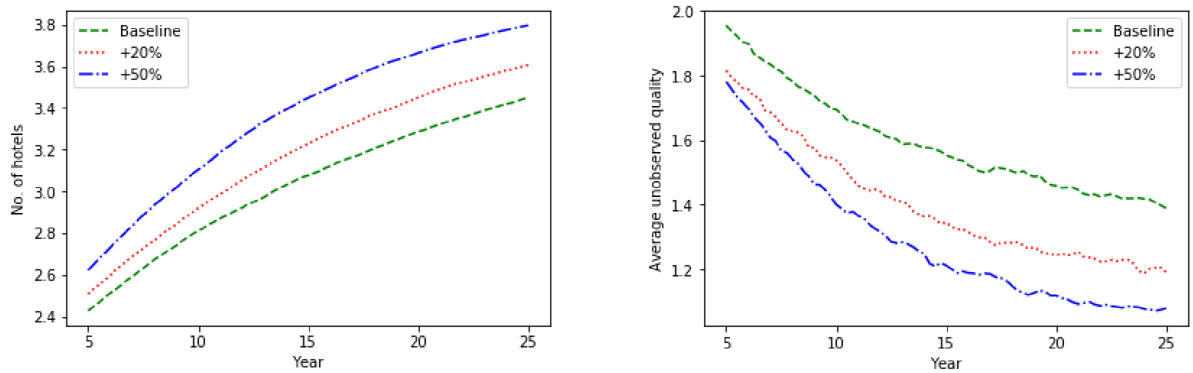
Table 5 summarizes the differences in welfare between two cases . Overall, the reduction in entry costs yields positive welfare effects, and the consumer surplus increases by around \$5 million. The results are driven by two opposite forces: greater product variety and lower prices increase the consumer surplus, while lower average quality reduces it. The combined effects are still positive overall, though. Ignoring the competition effect on investment incentives will overestimate consumer surplus. Producer surplus increases in this counterfactual experiment; however, incumbents' surpluses decrease due to the higher number of competitors.

The results in counterfactual experiment are qualitatively similar to Goettler and Gordon (2011), in which they find that excluding AMD in the market leads to more innovation from Intel, but consumers are worse off. Both studies indicate that more competitive environments spur investments, but consumer surpluses are higher when there are more firms in the markets. My study adds to the literature by consider oligopoly market structures and policies which affect market structures through entry decisions.

7.3 Changes in Market Size

In this section, I consider the impact of market sizes on entry and investment. Increasing market sizes has ambiguous effects on potential return on investment. On the one hand, larger market sizes will increase return to investment because there are more consumers from demand side. On the other hand, bigger market will also attract more entries, which would reduce potential return to investment as more competitors are sharing the total market. The combined effects on investment and average unobserved qualities do not have a clear

Figure 7: Simulation Results for Different Market Sizes



(a) Number of Hotels over time **(b) Average quality over time**

Notes: I use 500,000 simulations for the counterfactual experiment. I consider three market sizes. Figure 7a shows the average number of hotels over time. In Figure 7b, the lines reflect the average unobserved qualities for existing hotels in each period.

direction.

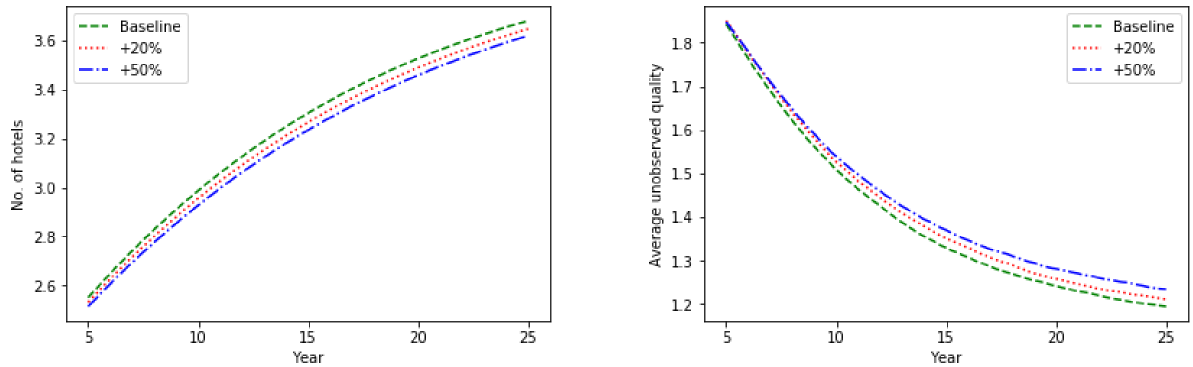
This counterfactual experiment also considers the market used in previous sections. I solve for Markov Perfect equilibria with entry and investment policies under three different market sizes. I increase the baseline market size by 20% and 50% to compare their effects. The simulation procedures are similar with those in the previous section, in which I consider entry and investment as policy functions. The results are also based on 500,000 simulations over 100 periods. Figure 7 shows paths of average number of firms for three different market sizes. Intuitively, market with more consumers have on average more hotels.

The 20% and 50% increase in market size lead to an 10% to 16% and 10% to 28% decrease in average quality over time. The results indicate that the investment decisions are mainly driven by negative competition effects from entries. Larger markets do not necessarily provide more incentives to invest in qualities due to more competitors.

7.4 Changes in Outside Options

In my demand specification, I use the total number of rooms supplied by other non-five-star hotels as outside option for consumers. Increase in outside options makes inside goods less favorable and creates incentives to change investment policies in response to outside competition pressure. In this section, I investigate the effects in a counterfactual exercise.

Figure 8: Simulation Results for Changes in Outside Option



(a) Number of Hotels over time **(b) Average quality over time**

Notes: I use 500,000 simulations for the counterfactual experiment. Figure 8a shows the average number of hotels over time. In Figure 8b, the lines reflect the average unobserved qualities for existing hotels in each period.

The experiment is relevant for policy regarding the lodging industry as Airbnb and other supplies of rooms are competing with traditional hotels. Platforms featuring "sharing economy" provide home owners additional channel to maximize revenues generated from their properties. This creates increase in total supply when consumers are looking for a place to stay. Hotels are affected by this new type of competition. Zervas et al (2017) studies the impact of Airbnb on the hotels in Texas. They find the presence of Airbnb causes approximately 8-10% reduction in quarterly revenue for hotels. Policy makers are also concerned about increased supply of accommodations for travelers. For example, in 2018, Japanese government enforced a law requiring all B&Bs to be registered before listing on platforms like Airbnb. The regulation immediately resulted in 80% decreases of total supply on B&Bs. The effects of regulating or restricting some of consumers' choices are unclear. Consumer can benefit more if the increase in outside option create a positive effects on investment and entry of hotels in inside options.

In Figure 8, the simulation results for three different outside options are presented. I find that competitive pressure from outside options actually creates positive effects on investment through lower entry rates. The intuition is that markets with more supply in outside options are less favorable for potential entrants as consumers can easily find a place in outside option to stay in those markets. This causes lower entry rate and less competitors in a market, which would result in more investments. However, the effects are small mainly because the competitive pressure is not coming from close substitute, as I consider five-star hotels in inside options. 20% increase in outside options only lead to 0-2% increase in average qualities.

8 Conclusion

Competition effects on investments are important because policy makers can often affect market structures through regulations, or policies. This paper has studied the relationship between competition and investment in the hotel industry using a structural dynamic model of investment and entry. I conduct several counterfactual experiments. The results show that more competitive environment negatively impacts investments in quality. Based on my analysis, 20% reduction in entry costs leads to 13% decrease in investments, and 10% lower in average qualities. Although change in consumer surplus is still positive because of lower prices and more product varieties, ignoring the competition effects on investments biases the welfare effects. Increase in market sizes would lead to lower average qualities. Changes in outside options do not have significant impact on investment and entry decisions.

There are few extensions for this paper. First, I plan to pursue a dynamic estimation of entry cost using two-step approach developed by Bajari, Benkard, and Levin (2007). Calibration of cost parameters avoids intensive dynamic estimation. However, the cost information does not reflect opportunity cost. Therefore, I would like to conduct a comparison between dynamic estimates and cost information. Second, I restrict my attention to the market structure with less than five firms in a market. In the future, I would like to extend my analysis by considering more firms in a market.

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A Appendix

A.1 Additional Results

Figure A.1: Screenshot of five star hotels on Expedia.com

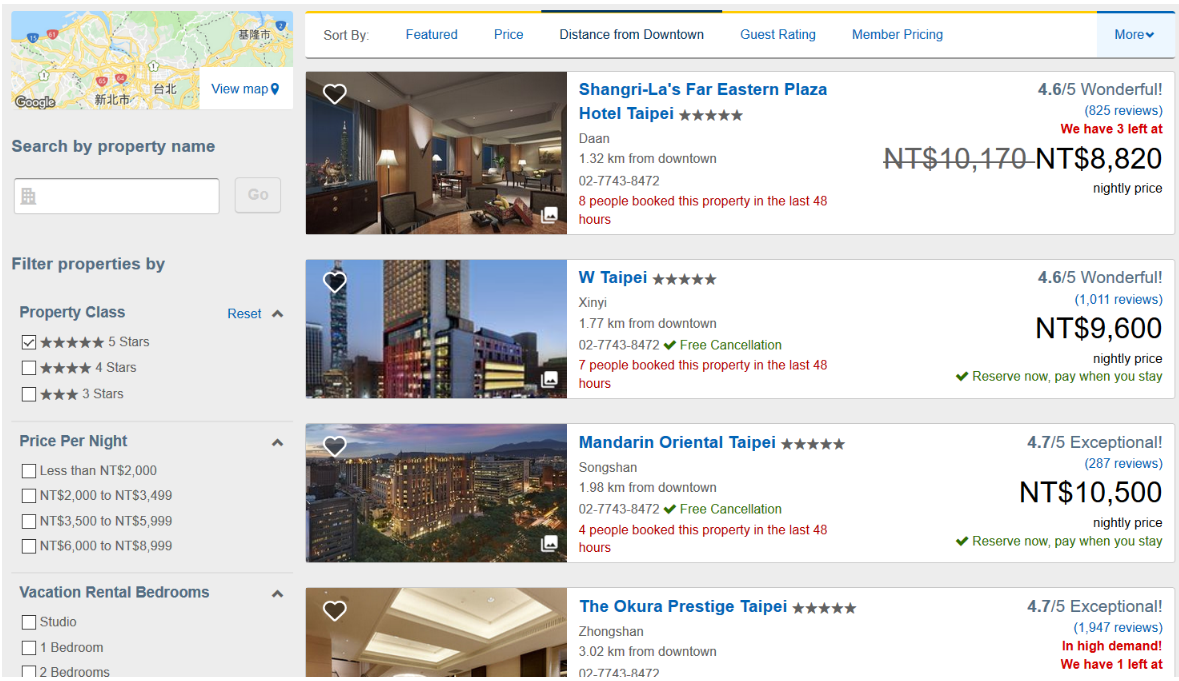
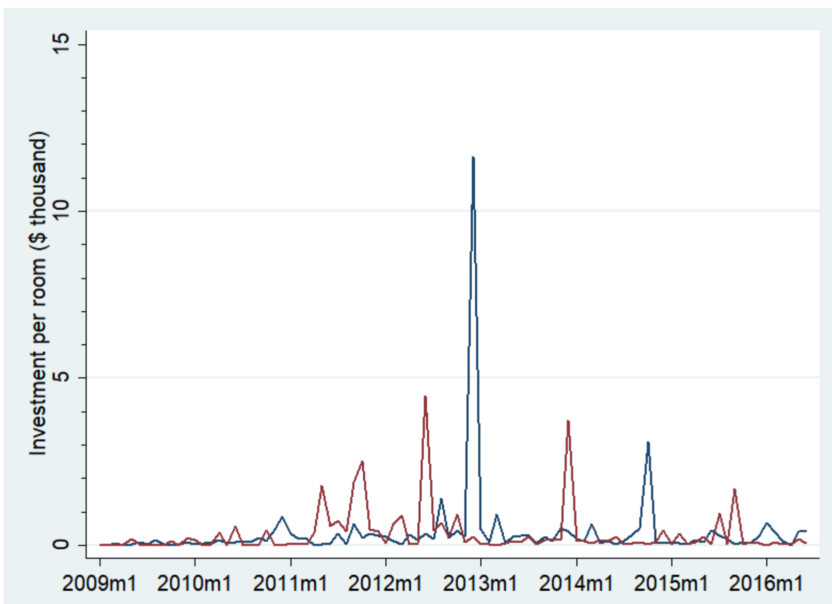


Table A.1: Total Number of Hotels

Year	No. of Hotels
2009	2680
2010	2678
2011	2692
2012	2746
2013	2810
2014	2899
2015	3010
2016	3115

Figure A.2: Lumpy Investment Patterns



Notes: This figure shows the monthly investment amounts for two randomly selected five-star hotels in my sample.

Table A.2: OLS results between Market Structures and Investments

	Investments per room (\$)		
	(1)	(2)	(3)
No. of hotels	-334.61^{**}	-551.36^{**}	-731.04^{**}
	(147.03)	(228.11)	(301.39)
Price (\$)		-11.95	-5.77^{**}
		(8.32)	(2.75)
Price $t+1$ (\$)			-1.01
			(3.72)
Price $t+2$ (\$)			-5.24^{*}
			(3.07)
Occupancy rate		-8319.13^{**}	-5359.946^{**}
		(3508.51)	(2646.69)
Occupancy rate $t+1$			99.62
			(1945.38)
Occupancy rate $t+2$			-3019.18^{**}
			(1215.906)
No. of employees		-13.61	-19.32^{***}
		(9.63)	(5.01)
No. of employees $t+1$(%)			8.96^{*}
			(4.91)
No. of employees $t+2$(%)			6.61^{*}
			(3.79)
Market sales (thous.)		11.95	-4.47
		(14.44)	(21.73)
Market sales $t+1$(%)			23.50
			(15.15)
Market sales $t+2$(%)			5.91
			(10.40)
Online ratings		-377.45	-137.77
		(396.46)	(204.09)
Online ratings $t+1$(%)			64.06
			(84.20)
Online ratings $t+2$(%)			-49.96
			(105.04)
Hotel FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R^2	0.33	0.35	0.53
Observations	1,563	1,563	1,421

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: OLS Results from Different Measures of Investments

	Dependent Variable			
	log(inv.+1)	1(inv.$\geq$\$300)	1(inv.$\geq$\$500)	1(inv.$\geq$\$1000)
No. of hotels	-0.1680	-0.0197	-0.0055	-0.0419^{**}
	(0.1455)	(0.0248)	(0.0243)	(0.0195)
Hotel FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.75	0.42	0.29	0.26
Observations	1,421	1,421	1,421	1,421

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The specifications are the same as Column 3 in Table 2. The first column uses logarithm of investments in a quarter. The last three columns use dummy variables equal 1 when investments in a quarter are above certain cutoffs. These dummies allow me to focus on major investments only and ignore small investments, possibly for maintenance purposes.

Table A.4: OLS results using annual investments

	Investments per room ($)		
	(1)	(2)	(3)
No. of hotels	−23 471.54	−29 018.79*	−60 195.37**
	(16 446.03)	(17 175.05)	(24 981.43)
Price ($)		−56.51*	−96.71***
		(26.01)	(22.60)
Price $t+1$ ($)			−25.94
			(23.75)
Price $t+2$ ($)			40.19*
			(23.48)
Occupancy rate		−638 018.41***	−422 413.47***
		(159 536.43)	(2646.69)
Occupancy rate $t+1$			223 179.00
			(210 361.82)
Occupancy rate $t+2$			−452 821.83**
			(207 139.91)
No. of employees		−365.50	−723.64
		(607.21)	(526.22)
No. of employees $t+1$(%)			1589.256**
			(658.37)
No. of employees $t+2$(%)			588.70
			(607.19)
Market sales (thous.)		16.74	348.33
		(22.78)	(206.48)
Market sales $t+1$(%)			849.07**
			(419.26)
Market sales $t+2$(%)			91.87
			(16.66)
Online ratings		−13 158.67	−11 791.53**
		(8464.81)	(4822.64)
Online ratings $t+1$(%)			1134.93
			(7607.61)
Online ratings $t+2$(%)			15 441.78
			(11 814.62)
Hotel FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R^2	0.51	0.55	0.54
Observations	434	434	297

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: OLS results between Market Structures and Employment

	Employees per room		
	(1)	(2)	(3)
No. of hotels	0.0004	0.0173^{**}	0.0288^{**}
	(0.0048)	(0.0077)	(0.0110)
Price (\$)		0.0009^{***}	0.0007^{***}
		(0.0002)	(0.0002)
Price $t+1$ (\$)			0.0002
			(0.0002)
Price $t+2$ (\$)			0.0003^{*}
			(0.0001)
Occupancy rate (%)		0.2587^{***}	0.2207^{**}
		(0.0709)	(0.0788)
Occupancy rate $t+1$(%)			0.0535
			(0.0482)
Occupancy rate $t+2$(%)			0.0417
			(0.0576)
Market sales (thous.)		-0.0013^{**}	-0.0007
		(0.0005)	(0.0004)
Market sales $t+1$(%)			-0.0008^{**}
			(0.0003)
Market sales $t+2$(%)			-0.0001
			(0.0003)
Online ratings		0.0094^{**}	0.0067^{**}
		(0.0041)	(0.0035)
Online ratings $t+1$(%)			0.0141^{**}
			(0.0056)
Online ratings $t+2$(%)			0.0146^{*}
			(0.0070)
Hotel FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
R^2	0.93	0.94	0.94
Observations	1,563	1,563	1,421

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The specifications are similar to Table 2 except that I use the number of employees per room as a dependent variable. The results indicate a positive relationship between employment and competitive intensity. The coefficient of interest is statistically significant but not economically significant, however, since this represents an increase in employment of less than 3%, only about 9 employees for an average hotel.

Table A.6: Demand estimates using other investment measures

	1(inv.≥$300)	1(inv.≥$1000)
Mean Utility		
Price ($ 100)	-1.8067^{***}	-2.3553^{***}
	(0.1207)	(0.1440)
Age	-0.1504^{***}	-0.2637^{***}
	(0.0135)	(0.0137)
Distance	-0.0455^{***}	-0.0003
	(0.0166)	(0.0005)
No. of rooms	0.2880^{***}	0.5275^{***}
	(0.0188)	(0.0317)
Online ratings	0.0396^{***}	0.0410^{***}
	(0.001)	(0.0103)
Brand	0.7043^{***}	0.5597^{***}
	(0.0613)	(0.0694)
No. of employees per room	0.7048^{***}	1.2935^{***}
	(0.1062)	(0.1388)
Log of total room supply	-0.4543^{***}	-0.6766^{***}
	(0.0368)	(0.0578)
Constant	1.9136^{***}	3.2100^{***}
	(0.3105)	(0.4724)
S.D.		
Price	0.3592	0.2658
	(0.2513)	(0.2538)
Age	0.1676^{***}	0.2759^{***}
	(0.0184)	(0.0089)
Distance	0.0792^{***}	0.0052
	(0.0213)	(0.1225)
Constant	0.0179	0.0577
	(0.5225)	(0.4571)
Transition Process		
ρ	0.8955^{***}	0.8893^{***}
	(0.0082)	(0.0076)
σ_ρ	0.7032^{***}	0.8932^{***}
	(0.0042)	(0.0061)
γ	0.3814^{**}	0.9209^{**}
	(0.1538)	(0.3529)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Result based on 1,563 observations and 5,000 simulation draws in each period. Robust standard errors in parentheses. Mean elasticities are -2.13 and -2.69 for the two specifications.

A.2 Computation Details

A.2.1 Demand Estimation

In this section, I provide details about simulated market shares and contraction mapping for mean utilities. For random-coefficient model predicted market shares is calculated by integrating over the distribution of unobserved consumer tastes. Following Nevo (200), I approximate the integral by simulation. Specifically,

$$s_{jt}(p_{jt}, x_{jt}, \delta_{jt}, \theta) = \frac{1}{ns}\sum_{i=1}^{ns} s_{ijt} = \frac{1}{ns}\sum_{i=1}^{ns} \frac{\exp(\delta_{jt} + \sum_{m=1}^{M} x_{jt}^{m}\nu_i^m \sigma_m)}{1 + \sum_{k\in J_t}\exp(\delta_{kt} + \sum_{m=1}^{M} x_{kt}^{m}\nu_i^m \sigma_m)} \tag{18}$$

where ν are draws from $P_\nu(\nu)$, and ns is the number of simulation draws. I use 5,000 simulation draws in the estimation. After simulating the predicted market shares, I can solve for the mean utilities using contraction mapping proposed by BLP:

$$\delta_{jt}^{h+1} = \delta_{jt}^{h} + \ln s_{jt} - \ln s_{jt}(p_{jt}, x_{jt}, \delta_{jt}^{h}, \theta) \tag{19}$$

where s_{jt} is the observed market shares, and $s_{jt}(\cdot)$ is the predicted market shares just computed. h is the number of iteration. The computation of this fixed point iteration will stop when the difference between δ^H and δ^{H-1} is smaller than some tolerance level. I use 1e$-$15 for tolerance level in the estimation. This is the most computationally intensive part of the estimation procedures because for every guess of parameters, the estimation needs to solve for a new vector of fixed points. This is also called the "inner loop" of BLP estimation. As the outer loops search for parameters minimizing the GMM objective function, the inner loops solve for fixed points for mean utilities. To speed up the fixed point iteration, I use squared polynomial extrapolation method (SQUAREM).[25]

[25] For more details about this method, please see Varadhan and Roland (2008) and Reynaerts et al. (2012).

A.2.2 Stochastic Algorithm

I adapt stochastic algorithm of Pakes and McGuire (2001) and Collard-Wexler (2013) to compute policy functions associated with MPE. Similar to Collard-Wexler (2013), the action is a discrete choice in my model. Therefore, I closely follow his Discrete Action Stochastic Algorithm (DASA). In each iteration, only one state is updated. An iteration follows these steps:

1. Start with a state-action pair (S^k, a_j^k), with values of choice specific value functions v^k stored in memory.

2. Given the state, draw actions a_{-j}^k from policy functions for other players. And draw a state in the next period S^{k+1} based on action profile a^k.

3. Compute the value of action a_j^k, R, given the state and policy functions.

4. Update the old v^k with R based on some weights.[26] Because policy functions are functions of v^k, policy functions are also changed.

5. Draw a new action a_j^{k+1} according to new policy functions, and go back to step 1 with (S^{k+1}, a_j^{k+1})

There is one main difference in my model in contrast to model in Pakes and McGuire (2001) and Collard-Wexler (2013). I do not model exit of incumbents as I do not observe exit in my dataset. So, as iteration moves forward, the number of hotels in the state will grow and stuck at the maximum number of hotels allowed. I deal with this problem by resetting the state to initial number of firms for every hundreds of iterations.

The stopping rule for this algorithm is based on Fershtman and Pakes (2012) and Collard-Wexler (2013). Only a subset of the states visited in the last million steps of the algorithm are used in the computation of stopping rule. Essentially, the choice-specific value functions of these states are approximated by one step forward simulation. Then if the differences between simulated choice-specific value functions and the choice-specific value functions obtained by previous iterations are small enough, iteration can be stopped. Otherwise, the iteration continues. One check of the convergence is very computational intensive as it requires forward simulations for a large number of states visited in last a million iterations. As suggested by Collard-Wexler (2013), I only check convergence after 50 million of iterations.

[26] Collard-Wexler (2013) provides useful tips on how to set the weights.