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Land Use Regulation as a Barrier to Entry: Evidence from the Texas Lodging Industry

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Abstract

This paper examines the anticompetitive effects of land use regulation using micro-data on mid-scale chain hotels in Texas. I construct a dynamic entry-exit model that endogenizes hotel chains' reactions to land use regulation. Estimation results indicate that imposing stringent regulation increases costs considerably. Hotel chains nonetheless enter highly regulated markets even if entry probabilities are lower, anticipating fewer rivals and hence greater market power. Consumers incur the costs of regulation indirectly in the form of high prices. (JEL: R3, L1, L5)

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1 Introduction

In many countries, zoning is the primary means by which local governments regulate private land use within their boundaries. Zoning governs private land use in a host of different ways: prohibiting commercial activity in certain areas, limiting the height of buildings, specifying minimum lot sizes, requiring the presence of private parking and specifying the type of materials for building exterior. The main rationale for such local government intervention is to prevent problems due to market failure. For example, restricting the size of commercial signs may be a sound policy in order to deliver the public good of uncluttered streets. However, zoning may have undesirable consequences.

One possible negative side effect of land use regulations relates to their impact on local competition by increasing costs of local businesses and hence discouraging entry. For instance, some regulations require local businesses to use expensive materials such as brick for the exterior of their buildings, or to deviate from a prototype building design. Although business owners can request re-zoning or special exceptions, these requests need to go through processes that could involve city administration or politics, often giving rise to considerable additional expense.

Such anticompetitive effects of land use regulation have been at the heart of several law suits and are therefore well-known among legal scholars.[1] However, these effects have attracted little attention from economists and their quantitative importance is not well-understood. The goal of this paper is to fill this gap by assessing the actual cost impacts of land use regulation and its consequence on the intensity of local competition.

Anticompetitive effects of land use regulation are relevant to various industries in which firms compete locally. Numerous retail industries such as supermarkets, gas stations and hotels are typical examples. Furthermore, some manufacturing industries that produce time-sensitive materials such as concrete also belong to this category. Among these industries, this

[1] Legal scholars have debated as to whether municipalities are immune from antitrust liability arising from their local ordinances. See Sullivan (2000) for a summary of these arguments and a discussion of several influential cases.

paper focuses on the hotel lodging industry in Texas by taking advantage of the accessibility to rich microdata.

Several facts draw attention to the anticompetitive effects of land use regulation in the lodging industry. First, land use regulation appears to be among the major determinants of cost structure, and hence it plays a part in the entry decisions of hotels. This industry is capital-intensive[2] and its primary capital input is undoubtedly buildings. Therefore, it is natural to expect that regulations on buildings should have a significant cost impact. Second, competition in this industry is fairly local. Because of the nature of their product, hotels must locate at the place of consumption; they cannot sell their product without first having a physical location inside a market. As a result, competitors are limited to other hotels in the neighborhood and entry decisions of local rivals are among the primary determinants of their market power. Third, it appears that people in the lodging industry realize that local land use regulation can act as an entry barrier for their competitors. This is indicated by the following quote from a hotel developer:

> There's a short answer to why certain hotel developers choose projects encumbered with difficult zoning or environmental challenges. It's because once those hurdles are cleared, they're often left with a hotel with desirable barriers to entry. Cruz (2003)

One of the major obstacles facing empirical studies of land use regulation is measuring. Complicated rules and discretion in the actual implementation of these regulations indicate that no single index provides a definitive measure of the stringency of land use regulation. Acknowledging this difficulty, I employ various measures based on the written survey collected and summarized by Gyourko et al. (2008). Some of these measures are based on institutional features (e.g., the presence of particular regulations) while some other measures are based on the results of actual implementation (e.g., the average time length to

[2] According to an example shown in Powers (1992), the capital cost of a typical 120-room hotel accounts for about 20 percent of its total expenditure. This ratio is about twice as much as that of a suburban restaurant.

obtain a building permit). Realizing that the focus of these indices is residential land use regulation, I check the robustness of my estimation results by using different sets of indices including one that has more direct relationship with commercial land use regulation.

Reduced-form analyses indicate that markets under stringent land use regulation tend to have fewer hotels. However, these regressions do not distinguish the cost impact of land use regulation from its impact on demand. The impact of stringent land use regulation on travel demand is ambiguous. For example, it may attract more leisure travelers by preserving some scenic views while it may decrease business travelers by discouraging the construction of commercial buildings. Therefore, the observed negative correlation in reduced-form analyses may overestimate or underestimate the actual cost impact of land use regulation. To avoid this drawback, I pursue a structural estimation approach.

Specifically, I construct a dynamic entry-exit model of hotel chains in which they maximize their expected profits by choosing the number of hotels to open or close in a local market every period. The revenue of a mid-scale chain hotel is allowed to depend on market characteristics, chain characteristics and the number of other hotels present in the same market. Since a new hotel cannibalizes the revenue of other hotels in the same chain, the marginal revenue of opening an additional hotel monotonically decreases. Hotel chains incur entry costs and exit costs when they open a new hotel and close an existing hotel, respectively, while they need to pay the operating costs at every period until the hotel closes down. I assume that each hotel chains' entry cost and exit cost are stochastic and the actual sizes of these shocks are observable to this chain only. Therefore, each hotel chain's decision is based on its belief about its competitors' decisions. In a Markov Perfect equilibrium, its belief must be consistent with the actual decisions of its rival chains.

Estimation of this model proceeds in three stages. I first estimate the parameters of a hotel-level revenue function. Exploiting the longitudinal structure of the dataset, I identify market-specific revenue shifters that may be attributable to both observable and unobservable time-invariant factors. Taking the revenue function estimates as given, I next recover structural cost parameters by finding a set of parameters that rationalizes both the revenue function estimates and the observed entry-exit decisions over time. These cost parameters are chain-market specific. To take into account the interacting decisions of competing hotel chains while mitigating the computational burden, I employ the estimation method developed by Bajari et al. (2007). Finally, I regress the recovered cost parameter estimates on land use regulation indices along with other control variables.

Three key results emerge, consistent with the hypothesis that stringent land use regulation lessens the intensity of competition by increasing the costs. First, an increase in the stringency of land use regulation by one standard deviation increases operating costs and entry costs by 8 percent and 10 percent, respectively. Second, these cost increases discourage entry, decreasing the equilibrium number of hotels by 15 percent. Third, as a consequence of lessened competition, revenue per room, a good proxy for the price, increases by 5 to 6 percent.

This paper makes several contributions to the existing literature. First, to the best of my knowledge, it is the first to recover the actual cost impacts of land use regulation on local business markets by controlling its impacts on the demand side. Most economic studies of land use regulation have focused on its impacts on housing and land markets.[3] Few studies have looked at its cost impacts on business.[4] Next, in relation to the literature on empirical industrial organization, this paper belongs to the literature on firms' entry decisions that originated from papers by Bresnahan and Reiss (1990) and Berry (1992).[5] Among

[3]For example, see McMillen and McDonald (1991b) for land price, Wu and Cho (2007) and Saiz (2010) for land development, McConnell et al. (2006) for density and Glaeser et al. (2005), Glaeser and Ward (2009) and Quigley and Raphael (2005) for housing markets. For a recent survey of empirical studies in this area, see Evans (1999) and Quigley (2007). *Regional Science and Urban Economics* published a special issue featuring studies of land use regulation. For a summary of these papers, see Cheshire and Sheppard (2004).

[4]One exception is Nishida (2010). In his study on competition between two convenience store chains in Japan, he includes a dummy variable for zoning as a cost factor by presuming it does not affect demand side. He did not find statistically significant cost impacts of zoning. Ridley et al. (2010) and OECD (2008) also study the impacts of land use regulation on businesses from different perspective. Ridley et al. (2010) studies to what extent the fraction of zoned area affects the intensity of local competition by forcing firms to locate close to each other. OECD (2008), which coincidentally has a title similar to this paper, documents several channels through which land use regulation affects competition and gives several examples taken from OECD member countries.

[5]See Berry and Reiss (2007) for a recent survey in this area.

others, this paper is most closely related to Ryan (2009). In his paper, Ryan estimates a dynamic entry-exit model of cement plants and evaluates the welfare consequences of a change in environmental regulation in the Portland cement industry. While Ryan relies on the intertemporal difference in industrial structure for identification, this paper exploits cross-market differences in land use regulation.

The rest of the paper proceeds as follows: Section 2 summarizes the data used in the empirical analysis while Section 3 presents the results of the reduced-form regressions. Section 4 describes the empirical model used for structural estimation. Section 5 explains the estimation method, and Section 6 presents the estimation results. Section 7 sets out the results of counterfactual experiments, and Section 8 concludes.

2 Data

2.1 Texas Hotel Data

The main data source of this study, *Hotel Occupancy Tax Receipts,* is provided by the Texas Comptroller of Public Accounts.[6] This quarterly data set provides the sale of every single hotel in Texas, as well as other hotel specific information including names, street addresses and numbers of rooms. In addition, I recover each hotel's brand affiliation, if any, by looking for particular brand names (e.g., Best Western) in the name of each hotel.[7] The sample period of this data set is from the first quarter of 1990 through the last quarter of 2005. A notable advantage of this data set is the reliability of its sales data. The original purpose of this data set was to determine the amount of the hotel occupancy tax to be collected by hotel owners and passed on to the state government. Because of this nature, misreporting is unlawful and can be considered tax evasion.

[6] Other studies using this dataset include Chung and Kalnins (2001), Kalnins (2004) and Conlin and Kadiyali (2006).

[7] To increase the accuracy of this process, I rely on other sources, such as *AAA Tourbook*, *Directory of Hotel & Lodging Companies* and various hotel directories provided by the hotel chains themselves.

2.2 Measurement of Land Use Regulation

This study employs the indices developed by Gyourko et al. (2008) to measure the stringency of land use regulation. Based on a written survey collected from 2,649 local governments in the U.S., Gyourko and his coauthors construct eleven subindices that measure stringency of residential land use regulation from various angles as well as one aggregate index (Wharton Residential Land Use Regulatory Index, henceforth WRLURI) that is based on these subindices. This paper uses the aggregate index and the eight subindices that have variation within Texas.[8] Table 1 shows the list of the eight subindices and provides a brief description of each index. See Gyourko et al. (2008) for the precise definitions of these subindices.

One concern of using these indices in my application is the possible discrepancy between residential and commercial land use regulation. When these two types of regulation are different in their relative stringency across markets, estimates based on residential land use regulation indices might bias my empirical results. Ideally I would want to use a set of indices that directly measures the stringency of commercial land use regulation only. However, to the best of my knowledge, that data do not exist. As the best feasible option, this paper instead sticks with the residential land use regulation indices and checks the robustness of results in the following two ways.

The first robustness check is to use only the subindices that have direct relationship with commercial and residential land use regulation. Among the eight subindices shown above, Project Approval and Zoning Approval meet this criterion. My inquiry into several municipality websites indicates that the administrative process to request rezoning or reviewing a new project, which is the target of these subindices, does not depend on the type of building involved in this project.

My second robustness check is to construct new indices based on regulation relevant to multifamily housing using the raw survey data posted at Gyourko's website. The procedure

[8]The subindices that do not have variation within Texas include (1) a measure for state level political pressure, (2) a measure for the influence of state court and (3) the involvement of the local assembly in the implementation of land use regulation.

Table 1: Description of Land Use Regulation Indices

Name	Description
Approval Delay	The average number of months for which developers need to wait to obtain building permits before starting construction.
Density Restrictions	Indicate if local governments have minimum lot size requirements of one acre or more.
Exactions	Indicate if developers have to incur the cost of additional infrastructure attributable to their developments.
Open Space	Indicates if developers have to provide open space for the public.
Political Pressure	Summarizes subjective impressions of the influence of various political groups (council, pressure groups, citizens). Normalized so that its mean and its standard deviation become zero and one, respectively.
Project Approval	The number of local government bodies from which projects that request NO zoning change need to obtain approvals.
Supply Restrictions	Represent the degree of restrictions that limit the number of new buildings
Zoning Approval	The number of local government bodies from which projects that request zoning change need to obtain approvals.

Notes: See Gyourko et al. (2008) for the construction of these indices.

used to make these new indices are almost the same as the original one except the treatment of regulation data that is relevant to either single family housing or multifamily housing but not both.[9] Here the underlying assumption is that relative stringency across markets of land use regulation for multifamily housing (e.g., apartments) is equal to that for commercial buildings (i.e., hotels). This assumption reflects the fact that municipalities often impose the same requirements on multifamily housing and commercial building while they impose different requirements on single-family housing. Based on this idea, I construct the three subindices that correspond to Political Pressure, Approval Delay and Supply Restricitions, respectively. I am unable to construct similar indices for the rest of the five subindices because all the information used to construct these indices is relevant to both single family housing and multifamily housing. See the Supplementary Appendix for the source of other data.

2.3 Market Definition

This study focuses on local competition between mid-scale chain hotels. To determine mid-scale brands, I follow a scale constructed by Smith Travel Research, an independent consulting firm specializing in the lodging industry. Among the hotel chains owning these brands, I consider the six major chains. Table 2 lists the names of these hotel chains and their mid-scale brands in my sample as of the first quarter of 2005. These seven chains account for about 90 percent of the number of mid-scale chain hotels in Texas.

This narrowed focus is beneficial since it makes my empirical analysis considerably neat without losing the essential aspects of local lodging markets. First, as indicated by Mazzeo (2002), the lodging market is highly segmented by service grades, and competition is stronger within segments rather than between segments. Second, among the three segments of hotels (economy, mid-scale and upscale), the mid-scale segment is the largest category in terms

[9] When a subindex is based on regulation for both single-family and multifamily housing, the original procedure always uses their average to construct this subindex. In contrast, my procedure uses only information for multifamily housing. Other than that, my procedure is exactly the same as the original procedure.

Table 2: Midscale Chain Hotels in Texas

Companies	Brands
Best Western	Best Western
Cendant	Amerihost, Howard Johnson, Ramada
Choice Hotels	Clarion, Comfort Inn, Quality Inn, Sleep Inn
Hilton Hotels	Hampton Inn
InterContinental	Candlewood, Holiday Inn, Holiday Inn Express
La Quinta	Baymont Inn, La Quinta Inn

Notes: The number of hotels listed is as of the first quarter of 2005.

of both the number of hotels and the number of rooms. Third, chain hotels have been the primary players in this industry. [10] Independent hotels are generally considered to be in the economy segment, and because services of these other businesses are different from those of the mid-scale hotels, their presence should not be important for the business of mid-scale hotels.

I consider a county as a single local market since more data is available at the county level. In addition, county shape is relatively uniform in Texas and borders have been fixed for a long time. Among the 254 counties in Texas, my sample consists of 40 counties that survive the following three screenings: (1) counties must provide land use regulation indices, (2) counties must have undergone at least four opens/closures of the mid-scale chain hotels during the sample period and (3) counties must not be the flagship counties of the four largest MSAs.[11][12] Figure 1 shows the geographical distribution of these 40 counties.

[10] In 2005, in Texas, chain hotels account for 37 percent of the total number of hotels, 63 percent of the total rooms and 75 percent of total sales. The apparently high ratio of non-chain properties is unlikely to be problematic for my analysis as these non-chain properties consist of independent hotels and various businesses that are not conventionally considered hotels. Texas statutes (Tax Code, Chapter 156.001) define a hotel as "a building in which members of the public obtain sleeping accommodations for consideration". Ranches, cabins and campgrounds all satisfy this definition. Although I remove properties that are obviously not hotels from my sample, there are a significant number of properties whose actual categories are unclear.

[11] These counties are Bexar (San Antonio), Dallas (Dallas-Fort Worth), Harris (Houston), Tarrant (Dallas-Fort Worth) and Travis (Austin).

[12] These criteria could generate a selection problem. Secion 7.3 discusses this issue.

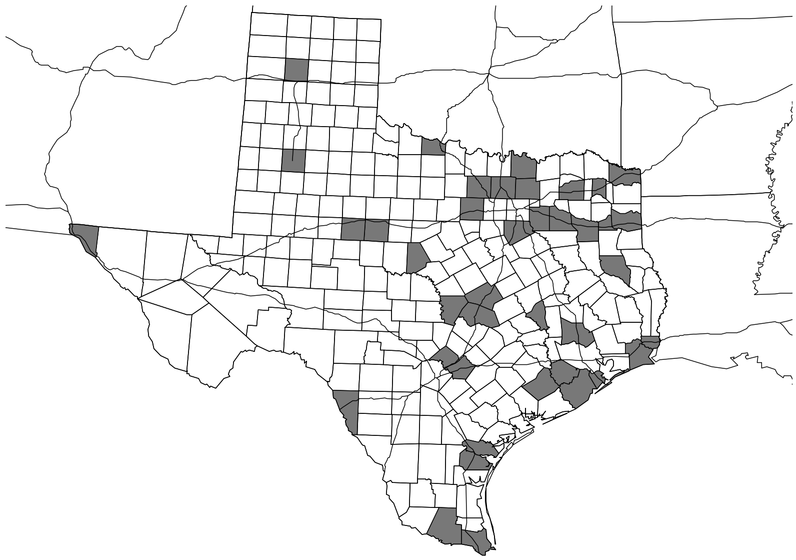

Figure 1: Graphical Representation of Sample Counties (Dark areas)

2.4 Summary Statistics

Table 3 reports the summary statistics of variables that describe the forty markets in my sample. The median market has seven mid-scale chain hotels or 573 rooms, and earns about more than two million dollars for one quarter. Table 3 also shows a considerable variation between the markets in my sample. In terms of population, the market at the sample third quartile is more than four times larger than that of the market at the sample first quartile. About 80 percent of the markets in this sample have access to an Interstate Highway and about one-third of them have access to commercial airports. For all the land use regulation indices, large values imply stringent regulation. The indices that are not binary variables are normalized so that their sample average and standard deviations are equal to zero and one, respectively.[13] Descriptive statistics of the land use regulation indices indicate that some of subindices (e.g., Political Pressure or Project Approval) have more variation than others (e.g., Exactions or Supply Restrictions).

Table 4 shows the sample correlation coefficients between the land use regulation indices

[13]When counties in my sample contain more than one municipality and land use regulation indices are available for both municipalities, I use the weighted average of the original indices of these municipalities for my analysis. City population is used as a weight.

and (logged) population. First, land use regulation tends to be more stringent in markets of larger population size. Both the aggregate index (WRLURI) and four subindices show statistically significant positive correlation with population. Second, as expected, the aggregate index is positively correlated with some but not all of the subindices.[14] Third, four out of the five significant correlations between the subindices are positive, suggesting that local governments implement each individual policy according to certain underlying attitudes such as pro-development or pro-environment. Fourth, the three indices that are based on regulation for multifamily housing show strong correlations (not reported) with the original corresponding indices. Each correlation coefficient is larger than 0.96.

3 Reduced Form Analysis

This section examines the empirical relationship between land use regulation and two endogenous variables—quantity (the number of mid-scale chain hotels) and price (revenue per room)—by running simple reduced-form regressions.[15][16] Regressors consist of the land use regulation indices and various controls that characterize local markets. I use the ordered logit for the number of hotels and the ordinary least squares (OLS) for the revenue per room.

The impact of stringent land use regulation on the equilibrium quantity and the equilibrium price of local lodging markets is not obvious. According to my hypothesis, stringent land use regulation decreases *supply* of lodging services by increasing the cost for hotels. However, its impact on *demand* is ambiguous. On one hand, stringent regulation could decrease local travel demand by discouraging some businesses to come, hence decreasing demand for business travel. On the other hand, it could increase local travel demand by preserving a particular local environment (e.g., nice views or clean water) that is attractive to either

[14] The fact that we observe the forty markets in Texas explains the observed no correlations between the aggregate index and some subindices.

[15] The regression using the total number of rooms as its dependent variable generates similar results.

[16] Increase in revenue-per-room does not necessarily mean increase in prices since not only price, but also occupancy rates (the number of rooms sold over the total number of rooms), affect the revenue-per-room.

Table 3: Summary Statistics of Markets in the Sample

	Mean	Std.Dev.	P25	P50	P75
Midscale Hotels					
# of Hotels	9.00	6.06	1.00	7.00	13.50
# of Rooms	790.28	628.00	255.00	573.00	1,206.00
Quarterly Sales (in millions)	3.13	2.88	.79	2.19	4.93
Indices for Land Use Regulation					
WRLURI (aggregate index)	0.00	1.00	-0.72	-0.27	0.81
Approval Delay	0.00	1.00	-0.85	-0.14	0.45
Density Restrictions	0.27	0.39	0.00	0.01	0.50
Exactions	0.88	0.29	0.92	1.00	1.00
Open Space	0.45	0.45	0.00	0.31	0.97
Political Pressure	0.00	1.00	-0.85	-0.02	0.60
Project Approval	0.00	1.00	-0.62	-0.05	1.05
Supply Restrictions	0.00	1.00	-0.29	-0.29	-0.29
Zoning Approval	0.00	1.00	-0.03	-0.03	0.64
Other County Characteristics					
Population (in thousands)	200.06	190.50	61.96	118.34	278.02
Area (in sq mi)	869.39	255.03	784.22	903.53	945.31
Per Capita Income (in thousands)	27.97	5.49	24.94	27.60	30.89
# of Establishments (in thousands)	3.87	3.38	1.07	2.96	5.81
MSA Dummy	0.75	0.44	0.50	1.00	1.00
Airport Dummy	0.33	0.47	0.00	0.00	1.00
Interstate Highway Dummy	0.78	0.42	1.00	1.00	1.00
Construction Price Index	0.78	0.03	0.76	0.78	0.80

Notes: N=40. All data are as of the first quarter of 2005. WRLURI stands for the Wharton Residential Land Use Regulation Index. Land use regulation index becomes higher as it becomes more stringent. Hotel data are from Hotel Occupancy Tax Receipts. Land use regulation indices are from Gyoruko et al. (2008). All other county data are from County Business Patterns, Regional Economics Information System, PSMeans and road maps. See Section III for details.

Table 4: Correlation Matrix between Market Size and Land Use Regulation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) ln Population	1.00	.	.	.	.	.	.	.	
(2) WRLURI	0.58**	1.00	.	.	.	.	.	.	
(3) Approval Delay	0.50**	0.62**	1.00	.	.	.	.	.	
(4) Density Restrictions	0.10	0.48**	0.14	1.00	.	.	.	.	
(5) Exactions	-0.10	-0.05	0.19	-0.43**	1.00	.	.	.	
(6) Open Space	0.46**	0.66**	0.34**	-0.01	0.18	1.00	.	.	
(7) Political Pressure	0.42**	0.71**	0.23	0.02	0.08	0.50**	1.00	.	
(8) Project Approval	0.37**	0.58**	0.27*	0.21	-0.25	0.35**	0.22	1.00	
(9) Supply Restrictions	0.00	-0.04	-0.06	0.12	0.12	-0.18	–0.06	-0.21	1.00
(10) Zoning Approval	0.07	-0.16	-0.20	-0.14	0.02	0.12	0.10	-0.26	-0.05

Notes: N=40. See Table 1 for the definitions of abbreviations of the land use regulation indices. Correlation coefficients with ** and * are statistically significant at the five and the ten percent level, respectively.

leisure travelers or certain industries. The standard supply-demand framework predicts that when stringent land use regulation *increases* local travel demand overall, the equilibrium *price* increases while the change in equilibrium *quantity* is indeterminate. In contrast, when stringent land use regulation *decreases* local travel demand overall, the equilibrium *quantity* decreases while the change in equilibrium *price* is indeterminate.

Table 5 and Table 6 report the estimates of these reduced-form functions based on the data as of the first quarter of 2005. First, the regression results show that my control variables explain about one-third in the variation of the equilibrium quantity and that adding land use regulation indices to the regressors increases (pseudo) R-squared by 8 percentage points. In contrast, the same control variables explain twenty seven percent of the variation in the equilibrium prices while adding land use regulation indices increases R-squared by 21 percentage points.

Second, the parameter estimates indicate that an increase in Project Approval decreases the equilibrium quantities while increases the equilibrium prices, suggesting the anticompetitive effects of land use regulation. The parameter estimates for Project Approval in both Table 5 and Table 6 are statistically significant at the 5 percent level. What is more, these estimates are quite robust regardless of the specifications employed. In contrast, the parameter estimate for the aggregate index (WRLURI) is statistically significant in the regression of the equilibrium quantities but not the equilibrium prices. The estimated impacts of Project Approval are economically significant as well. Consider an imaginary market whose characteristics are equal to the sample median values. My ordered-logit estimates in the second column of Table 5 indicate that this market is expected to have 4.1 hotels. When the value of Project Approval increases by one standard deviation, the expected number of hotels decreases to 3.4 and the equilibrium prices increases by 13 percent.

Third, the parameter estimates of Open Space suggest the importance of controlling the impacts of land use regulation on the travel demand. The third and the fourth columns of Table 5 and Table 6 indicate that Open Space has statistically significant positive impacts on both the equilibrium quantities and prices. This result would be consistent with the standard supply-demand framework only when stringent regulation increases the travel demand, and this demand side effect dominates the supply-side effect on the equilibrium quantities.

One concern of these regression results is the possible impacts of land use regulation on the size of hotels. When the cost impacts of land use regulation depend on the number of hotels but not the size of hotels, hotel chains might have an incentive to open one large hotel instead of opening two small hotels. If that were the case, even in the absence of the demand effects of land use regulation, negative correlation between the number of hotels and the land use regulation indices may not necessarily imply lessened competition.

To examine this concern, I regress the size of hotels on the land use regulation indices as well as other control variables. The sample of this regression is all the midscale-chain hotels in operation in the first quarter of 2005. Table 7 reports the results of these regressions. First, none of the indices that have direct connections with commercial land use regulation (WRLURI, Project Approval and Zoning Approval) has a statistically significant impact on the size of hotels even at the ten percent level. Second, when you include all the subindices, some subindices (Density Restrictions, Open Space and Political Pressure) present the significant impacts on the size of hotels while the direction of these impacts varies. Considering

Table 5: Ordered Logit Estimates

Dep. Var.	# of Hotels			
	(1)	(2)	(3)	(4)
WRLURI	-0.931**			
	(0.436)			
Project Approval		-1.212**	-1.239**	-1.257**
		(0.468)	(0.527)	(0.521)
Zoning Approval		0.376	0.381	0.345
		(0.358)	(0.394)	(0.399)
Approval Delay			-0.246	-0.230
			(0.557)	(0.540)
Density Restrictions			-0.400	-0.440
			(0.954)	(0.976)
Exactions			-2.399	-2.286
			(1.698)	(1.704)
Open Space			1.987*	1.907*
			(1.119)	(1.120)
Political Pressure			-0.759	-0.559
			(0.467)	(0.450)
Supply Restrictions			0.208	0.292
			(0.375)	(0.378)
Exclude regulation for single-family housing	No	N/A	No	Yes
Log Likelihood	-69.722	-65.856	-63.454	-63.934
Pseudo R-squared	0.353	0.389	0.411	0.406

Notes: N=40. Standard errors are in parentheses. Estimates with ** and * are statistically significant at the five percent and the ten percent level, respectively. See Table 1 for the definitions of land use regulation indices. Estimates and standard errors for control variables and thresholds are suppressed. These control variables include population, the number of establishments, per capita income, area, construction price index and dummy variables for MSA, access to commercial airports and Interstate Highway. Pseudo R-squared of the ordered logit of the number of hotels on control variables only are 0.331.

Table 6: OLS Estimates

Dep. Var.	ln (Revenue Per Room)			
	(1)	(2)	(3)	(4)
WRLURI	0.093			
	(0.066)			
Project Approval		0.129**	0.147**	0.157**
		(0.063)	(0.070)	(0.067)
Zoning Approval		0.035	0.035	0.020
		(0.054)	(0.058)	(0.057)
Approval Delay			-0.004	-0.073
			(0.082)	(0.075)
Density Restrictions			-0.076	-0.061
			(0.151)	(0.059)
Exactions			-0.212	-0.212
			(0.226)	(0.221)
Open Space			0.367**	0.376**
			(0.155)	(0.153)
Political Pressure			-0.055	-0.061
			(0.060)	(0.059)
Supply Restrictions			0.091	0.089
			(0.056)	(0.055)
Exclude regulation for single-family housing	No	N/A	No	Yes
R-squared	0.321	0.369	0.513	0.530

Notes: N=40. Robust standard errors are in parentheses. Estimates with ** and * are statistically significant at the five percent and the ten percent level, respectively. See Table 1 for the definitions of land use regulation indices. Estimates and standard errors for control variables and thresholds are suppressed. These control variables include population, the number of establishments, per capita income, area, construction price index and dummy variables for MSA, access to commercial airports and Interstate Highway. R-squared of the OLS of the revenue per room on control variables only are and revenue-per-room on control variables only are 0.276.

seemingly weak connections between these three subindices and commercial land use regulation, the regulation impacts on the size of hotels do not seem a first-order issue.

The results above suggest some impact of land use regulation on the entry-exit decisions of the chain hotels and its consequence on the equilibrium prices. Nonetheless, these correlations can be the consequence of demand decrease caused by stringent land use regulation and the supply side might have nothing to do with it. To identify these two channels separately from the data, I need to rely on a model and estimate its structural parameters.

4 The Dynamic Entry-Exit Model of Hotel Chains

In this section I construct a dynamic entry-exit model where N hotel chains may operate multiple hotels in a local market $m \in \{1, 2, \cdots, M\}$. I omit subscript m from all variables in this section for simplicity. At the beginning of each period, each chain simultaneously decides whether it opens a new hotel or closes its existing hotels, if any. Both opening a new hotel and closing an existing hotel incur some costs while operating existing hotels incur operating costs. The presence of hotels operated by rival chains affects chain i's entry and exit decision through their impacts on the revenue of hotels belonging to chain i.

4.1 State Space

Denote each chain by $i \in \{1, ..., N\}$ and each period by $t \in \{1, 2, .., \infty\}$. Each chain operates at most H hotels in a market. A *common* state at period t consists of (i) a vector of the number of hotels operated by each chain $\mathbf{h_t} = (h_{1t,} h_{2t}, \ldots, h_{Nt}) \in \{0, 1, \ldots, H\}^N$ and (ii) a vector of exogenous market-specific characteristics (e.g., population) $\mathbf{x_t} \in X \subset \mathbb{R}^L$. This common state is observable to both hotel chains and econometricians. Denote this common state variable by $\mathbf{s_t} = (\mathbf{h_t}, \mathbf{x_t}) \in S \equiv \{0, 1, \ldots, H\}^N \times X$. At the beginning of every period, chain i receives two private shocks, one for entry cost υ_{1it} and one for exit cost υ_{2it}. These shocks are i.i.d. draws from their joint CDF functions $F(\cdot)$. While the shape

Table 7: OLS Estimates of Regulation Impacts on the Size of Hotels Costs

Dep. Var.	ln (Number of Rooms)			
	(1)	(2)	(3)	(4)
WRLURI	-0.037			
	(0.030)			
Project Approval		0.000	-0.018	-0.024
		(0.029)	(0.032)	(0.032)
Zoning Approval		0.006	-0.028	-0.033
		(0.022)	(0.024)	(0.025)
Approval Delay			-0.048	-0.043
			(0.036)	(0.036)
Density Restrictions			-0.098*	-0.083
			(0.053)	(0.054)
Exactions			0.049	0.029
			(0.094)	(0.095)
Open Space			-0.273**	-0.267**
			(0.077)	(0.079)
Political Pressure			0.053*	0.057**
			(0.027)	(0.027)
Supply Restrictions			-0.033	-0.038
			(0.023)	(0.023)
Exclude regulation for single-family housing	No	N/A	No	Yes
R-squared	0.358	0.355	0.391	0.391

Notes: N=325. Robust standard errors are in parentheses. Estimates with ** and * are statistically significant at the five percent and the ten percent level, respectively. Other regressors whose results are suppressed include chain dummies, population, the number of establishments, per capita income, area, construction price index, dummy variables for MSA, access to commercial airports and Interstate Highway. Population, the number of establishments, per capita income and area are in log. R-squared of the regressions of the number of rooms on the control variables only is 0.358.

of the distribution function $F(\cdot)$ is common and known to all players, realized cost shocks $\boldsymbol{\upsilon}_{\mathbf{it}} = (\upsilon_{1it}, \upsilon_{2it})$ are private and only observable to chain i.

4.2 Choice Space

At the beginning of every period, each chain simultaneously chooses the number of hotels it opens or closes. Let a_{it} denote the *change* in the number of hotels chain i operates between period t and $t+1$. Positive a_{it} indicates opening a new hotel while negative a_{it} indicates closing one of its existing hotels. I assume that choices made at period t are realized at $t+1$, hence $h_{it+1} = h_{it} + a_{it}$ holds. I also assume that hotel chains do not open or close more than one hotel in the same period.[17] Since the resulting number of hotels after this change still has to be an element of $\{0, 1, \ldots, H\}$, chain i's choice set is a function of the number of hotels it currently operates, h_{it}, and is written as

$$A_{it}(h_{it}) = \begin{cases} \{ \quad\ \ 0,\ 1\ \}, & \text{if } h_{it} = 0, \\ \{ -1,\ 0,\ 1\ \}, & \text{if } 0 < h_{it} < H, \\ \{ -1,\ 0 \quad\ \}, & \text{if } h_{it} = H. \end{cases} \tag{1}$$

4.3 Period Profit

Chain i's expected period profit comes from any remaining of its expected revenue after subtracting the operating costs of its existing hotels, the entry cost of opening a hotel and the exit cost of a hotel it closes. Given the current state $(\mathbf{s_t}, \boldsymbol{\upsilon}_{\mathbf{it}})$ and its choice $a_{it} \in A_{it}(h_{it})$, chain i's choice-specific expected period profit is written as:

$$\pi_i(a_{it}, \mathbf{s_t}, \boldsymbol{\upsilon}_{\mathbf{it}}) = ER_i(\mathbf{s_t}) - \delta_i h_{it} - 1(a_{it} = 1)(e_i - \rho_1 \upsilon_{1it}) - 1(a_{it} = -1)(-\rho_2 \upsilon_{2it}), \tag{2}$$

[17] This assumption is not restrictive in practice since hotel chains rarely open or close more than one hotel in the same quarter. Out of 15,120 data points in my sample, only 17 data points (0.11 percent) experience this event. In estimation, I treat these data points as if the change were (minus) one rather than (minus) two.

where $ER_i(\mathbf{s}_t)$ represents the expected revenue of chain i from its current operation of h_{it} hotels, δ_i denotes the cost of operating a hotel for one period[18], $(e_i - \rho_1 \upsilon_{1it})$ is the entry cost and $(-\rho_2 \upsilon_{2it})$ is the exit cost. Here the mean exit cost is assumed to be zero, and ρ_1 and ρ_2 represent scale parameters for entry and exit costs, respectively.[19] Exploiting its linearity, I rewrite (2) as the product of two vectors

$$\pi_i(a_{it}, \mathbf{s_t}, \boldsymbol{\upsilon}_{\mathbf{it}}) = \Psi(a_{it}, \mathbf{s_t}, \boldsymbol{\upsilon}_{\mathbf{it}})' \boldsymbol{\theta}_{\mathbf{i}}, \tag{3}$$

where $\Psi(a_{it}, \mathbf{s_t}, \boldsymbol{\upsilon}_{\mathbf{it}}) = [ER_i(\mathbf{s_t}), -h_{it}, -1(a_{it} > 0), 1(a_{it} > 0)\upsilon_{1it}, 1(a_{it} < 0)\upsilon_{2it}]$ and $\boldsymbol{\theta}_{\mathbf{i}} = [1, \delta_i, e_i, \rho_1, \rho_2]$.

4.4 Transition of State Variables

I assume that exogenous market-specific characteristics $\mathbf{x_t}$ follow a Markov process. Let $P(\mathbf{s}'|\mathbf{s}, \mathbf{a}) : S \times S \times A \to [0,1]$ denote the evolution of the common state variables $\mathbf{s}$ conditional on hotel chains' choices $\mathbf{a}$ where $\mathbf{a} \in A = \{-1, 0, 1\}^N$.

4.5 Markov Perfect Equilibrium

I assume that chain i's decision is characterized by a pure Markov strategy $\sigma_i(\mathbf{s}, \boldsymbol{\upsilon}_{\mathbf{i}}) : S \times \mathbb{R} \to A$. Let $\sigma(\mathbf{s}, \boldsymbol{\upsilon}) = \{\sigma_1(\mathbf{s}, \boldsymbol{\upsilon}), \ldots, \sigma_N(\mathbf{s}, \boldsymbol{\upsilon})\}$ be a vector of each chain's Markov strategy while $\sigma_{-i}(\mathbf{s}, \boldsymbol{\upsilon}) = \sigma(\mathbf{s}, \boldsymbol{\upsilon}) \backslash \{\sigma_i(\mathbf{s}, \boldsymbol{\upsilon})\}$ be a vector of all but chain i's Markov strategies. Let $\beta \in (0,1)$ denote a discount factor common to all chains. Chain i's discounted sum of expected profits at time t under σ is

$$V_i(\mathbf{s_t}; \sigma) = E\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \Psi_i(\sigma_i(\mathbf{s}_{\boldsymbol{\tau}}, \boldsymbol{\upsilon}_{\mathbf{i}\boldsymbol{\tau}}), \mathbf{s}_{\boldsymbol{\tau}}, \boldsymbol{\upsilon}_{\mathbf{i}\boldsymbol{\tau}}) \boldsymbol{\theta}_{\mathbf{i}} \middle| \sigma_{-i}, \mathbf{s_t}\right] = W_i(\mathbf{s}; \boldsymbol{\sigma}) \boldsymbol{\theta}_i, \tag{4}$$

[18] I assume that operation costs are constant returns to the number of hotels to maintain the linearity of the period profit function while maintaining the number of parameters to be small.

[19] I put minus signs before ρs for notational convenience.

where the expectations of the above formula is defined by the distributions of $\upsilon_{i\tau}$ and $\mathbf{s}_{\boldsymbol{\tau}}$, and $W_i(\mathbf{s};\sigma) = E\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \Psi_i\left(\sigma_i\left(\mathbf{s}_{\boldsymbol{\tau}}, \boldsymbol{\upsilon}_{\mathbf{i}\boldsymbol{\tau}}\right), \mathbf{s}_\tau, \boldsymbol{\upsilon}_{\mathbf{i}\boldsymbol{\tau}}\right) \middle| \sigma_{-i}\right]$.

In a Markov perfect equilibrium, every chain's equilibrium strategy must be the best response to its rivals' equilibrium strategies. Formally speaking, a Markov perfect equilibrium of this dynamic entry-exit model consists of a vector of Markov strategies σ^* such that

$$V_i\left(\mathbf{s};\sigma_i^*,\sigma_{-i}^*\right) \geq V_i\left(\mathbf{s},\sigma_i',\sigma_{-i}^*\right) \text{ for all } i,\, \mathbf{s} \in S \text{ and } \sigma_i'. \tag{5}$$

Exploiting the linearity of the period profit function, this equilibrium condition is rewritten as

$$\left\{W_i\left(\mathbf{s};\sigma_i^*,\sigma_{-i}^*\right) - W_i\left(\mathbf{s};\sigma_i',\sigma_{-i}^*\right)\right\}\boldsymbol{\theta}_i \geq 0 \text{ for all } i,\, \mathbf{s} \in S \text{ and } \sigma_i'. \tag{6}$$

5 Estimation

I estimate the structural parameters of the model presented in the previous section by applying the estimation method proposed by Bajari et al. (2007) to the data of M local markets. Estimation consists of three stages. In the first stage, I separately estimate hotel-level revenue functions, hotel chains' policy functions and transition functions. In the second stage, I find the set of structural cost parameters that make the observed policy the most profitable choice compared to possible alternatives given the environment specified by the transition functions and the hotel-level revenue function. In the third stage, I infer the relationship between the recovered market-specific cost parameters and the stringency of land use regulation by running regressions.

5.1 First Stage

Consider a local market $m \in \{1, 2, \cdots, M\}$. Let r_{ikmt} denote the revenue of chain i's kth hotel at period t in market m. This revenue is given by

$$\ln r_{ikmt}(\mathbf{s}_{mt}) = \gamma_i + \eta_{1m} + \mathbf{x}'_{1m\mathbf{t}}\boldsymbol{\eta}_{\mathbf{2}} - \eta_3 \ln(\Sigma_j h_{jmt}) - \eta_4 \ln h_{imt} + \epsilon_{ikmt}, \tag{7}$$

where γ_i is a chain dummy, η_{1m} is a market fixed effect and ϵ_{ikmt} is an error term. Exogenous market-specific characteristics $\mathbf{x}_{1m\mathbf{t}}$ consist of (i) population, (ii) the number of establishments and (iii) state-level sales of mid-scale hotels. The last one is put to capture the state-wide time trend.[20] I also include the quarter-specific dummies, which I omit from (7) for the sake of the simplicity. The fourth and fifth regressors, $\Sigma_j h_{jt}$ and h_{it}, represent the revenue impacts of the presence of other hotels in the same market. While the fourth term represents the intensity of local competition, the fifth term captures the possible higher substitution between hotels belonging to the same chain (cannibal effects).

I estimate this function by OLS. The consistency of these OLS estimates rely on the assumption that ϵ_{ikmt} satisfies strong exogeneity. In particular, I assume that ϵ_{ikmt} is an i.i.d. draw from a normal distribution.[21] To justify these assumptions, I control the following three factors that can be a source of serial correlation: (i) time-invariant market-specific characteristics, (ii) time-invariant chain-specific characteristics and (iii) quarterly shocks. The dummy variables inserted in (7) deal with the first three factors. Time trend does not appear here since state-wide sales in $\mathbf{x}_{1m\mathbf{t}}$ capture the time trend.

I represent hotel chains' policy functions by a variant of the multinomial logit model. I impose three assumptions. First, the private cost shocks, υ_{1imt} and υ_{2imt}, have the same scale parameter, namely $\rho = \rho_1 = \rho_2$. Second, these private cost shocks are an i.i.d. draw from the Type I extreme value distribution whose mean is zero and whose variance is $\frac{\pi^2}{6}$.

[20] I do not employ time dummy variables here. The model with them does not allow me to simulate hotel chains' revenue out of the sample period while such simulations are necessary in the second stage.

[21] Imposing the normality here allows me to calculate $E(r_{ikmt}(s_{mt}))$ in an analytical form. Consistency does not require this assumption though.

Third, the maximum number of hotels a chain can operate in a market is seven $H = 7$.[22] Let $\Pi(a_{imt}, \mathbf{s}_{imt})$ be the deterministic part of chain i's choice-specific value function normalized by ρ. Then

$$\Pi_i(a_{imt}, \mathbf{s}_{mt}) = \begin{cases} \frac{1}{\rho}\begin{bmatrix} ER_i(\mathbf{s}_{mt}) - \delta_{im}h_{imt} - 1(a_{imt}=1)\,e_{im} \\ +\beta EV_i\left(\mathbf{s}_{mt+1}; \sigma_i^*, \sigma_{-i}^* | \mathbf{s}_{mt}, a_{imt}\right) \end{bmatrix} & \text{if } a_{imt} \in A_i(\mathbf{s}_{mt}) \\ -\infty & \text{otherwise} \end{cases}. \quad (8)$$

Under this notation, chain i's decision problem is written as

$$\max\left(\Pi_i(1, \mathbf{s}_{mt}) + v_{1imt},\ \Pi_i(0, \mathbf{s}_{mt}),\ \Pi_i(-1, \mathbf{s}_{mt}) + v_{2imt}\right). \quad (9)$$

Although v_{1imt} and v_{2imt} are assumed to be the Type I extreme value distribution, the choice probability of the conventional multinomial logit model is not applicable here since hotel chains' payoffs are not subject to any cost shock when they neither open nor close a hotel (i.e., $a_{imt} = 0$). Therefore I derive the choice probabilities that directly capture this particular feature.[23][24] To estimate these policy functions, I need to specify both $\Pi(1, \mathbf{s}_{mt}) - \Pi(-1, \mathbf{s}_{mt})$ and $\Pi(0, \mathbf{s}_{mt}) - \Pi(-1, \mathbf{s}_{mt})$ as a function of observable characteristics. I approximate them as a linear function of state variables $\mathbf{s}_{mt}$, chain-fixed effects and market fixed effects.[25] The land use regulation indices do not appear here as they have perfect collinearity with market fixed effects. I use maximum likelihood for this estimation. I estimate the transition functions of $\mathbf{x}_t$ by running AR1 regressions.

[22] This upper limit is hardly restrictive. During the sample period, only one hotel chain hits this limit.

[23] See Supplementary Appendix for the derivations of these choice probabilities.

[24] Taking into account this nature of the model is important to make forward simulations explained later consistent with the model.

[25] Ideally, one might want to employ a more flexible form by inserting, for example, a dummy variable for each chain-market pair or estimating a policy function for each market. However, data limitation does not allow me to take this approach. For example, suppose a hotel chain has not operated any single hotel during the sample period in a market (i.e.,$h_{imt} = 0$ for all t). If I employ one of the flexible forms mentioned above, the predicted probability of entry becomes zero even when the actual entry probability is strictly positive. Under the current specification, the predicted probability of each choice is always strictly positive as long as there is at least one entry and exit for every chain and for every market during the sample period.

5.2 Second Stage

In the second stage, I estimate the set of chain i's structural cost parameters in market, m $\{\delta_{im}, e_{im}\}$, and a scale parameter ρ. I assume ρ is common to every local market. I first estimate $W_{im}\left(\mathbf{s};\sigma_{im},\sigma_{-im}\right)$ defined in the previous section by forward simulations. I consider the following two situations: (1) when all chains follow the observed policy; and (2) when all hotel chains except chain i follow the observed policies while chain i follows a policy that is slightly different from its observed policy. I consider N_I such alternative policies $\left\{\sigma_{im}^k\right\}_{k=1}^{N_I}$. For notational convenience, let σ_{im}^0 denote chain i's observed policy. The goal is to estimate $W_i\left(\mathbf{s};\sigma_{im}^k,\sigma_{-im}^0\right)$ for every $k\in\{0,1,\cdots,N_I\}$. For kth estimation, I simulate each chain's decisions over T periods for N_S times by using the policy functions and transition functions obtained in the first stage. I also record chain i's expected revenue $\left\{\widetilde{ER}_{im\tau}^{k,n}\right\}_{\tau=0}^{T}$, the number of hotels it operates $\left\{\tilde{h}_{im\tau}^{k,n}\right\}_{\tau=0}^{T}$, its entry and exit decisions $\left\{\tilde{a}_{im\tau}^{k,n}\right\}_{\tau=0}^{T}$ and its private cost shocks $\{\tilde{v}_{1im\tau}^n,\tilde{v}_{2im\tau}^n\}_{\tau=0}^T$.[26] I use the revenue function estimated in the first stage to calculate $\widetilde{ER}_{im\tau}^{k,n}$. The resulting estimate is

$$\tilde{W}_{im}\left(\sigma_{im}^k,\sigma_{-im}^0\right)=\frac{1}{N_S}\sum_{n=1}^{N_S}\sum_{\tau=0}^{T}\beta^t\left[\begin{array}{l}\widetilde{ER}_{im\tau}^{k,n},-\tilde{h}_{im\tau}^{k,n},-1\left(\tilde{a}_{im\tau}^{k,n}=1\right),1\left(\tilde{a}_{im\tau}^{k,n}=1\right)\tilde{v}_{1im\tau}^n,\\-1\left(\tilde{a}_{im\tau}^{k,n}=-1\right),1\left(\tilde{a}_{im\tau}^{k,n}=-1\right)\tilde{v}_{2im\tau}^n\end{array}\right]. \tag{10}$$

See Supplementary Appendix for the algorithm of these forward simulations, including the way to choose inequalities. In the actual estimations, I employ the following setting: $N_I=800$, $N_S=10,000$, $T=80$ and $\beta=0.974$.[27]

I next estimate structural cost parameters by using the simulation results obtained by eq (10). Let $g_{imk}\left(\boldsymbol{\theta}_{im}\right)$ denote a function that calculates to what extent the observed policy σ_{im}^0 brings more profit to chain i compared to the kth alternative policy σ_{im}^k when its rivals

[26] These two shocks do not have a superscript k since I use the same set of draws for every policy $k\in\{0,\cdots,N_I\}$.

[27] Note that the unit of the time period is quarter rather than year. Hence $T=80$ is equivalent to 20 years and $\beta=0.974$ is equivalent to 0.9 annual discount rate.

follow the observed policies σ^0_{-im}. Then

$$g_{imk}\left(\boldsymbol{\theta}_{im}\right)=\left\{\tilde{W}_{im}\left(\sigma^0_{im},\sigma^0_{-im}\right)-\tilde{W}_{im}\left(\sigma^k_{im},\sigma^0_{-im}\right)\right\}\boldsymbol{\theta}_{im}. \tag{11}$$

I evaluate a set of parameters $\boldsymbol{\theta}_{im}$ by employing the following loss function

$$\left(\min\left\{g_{imk}\left(\boldsymbol{\theta}_{im}\right),0\right\}\right)^2. \tag{12}$$

This loss function gives zero when the observed policy σ^0_{im} brings more profit than the kth alternative policy σ^k_{im}. When the opposite is true, this function gives the squared expected difference in the resulting profits between these two policies. Finally I estimate a set of structural cost parameters $\Theta^*=\{\boldsymbol{\theta}^*_{im}\}_{i,m}$ by finding the one that minimizes the sum of this loss function across chains, markets and alternative policies subject to nonnegative constraints[28]

$$\min_{\boldsymbol{\Theta}\geq\mathbf{0}}\frac{1}{N\cdot M\cdot N_I}\sum_{i=1}^{N}\sum_{m=1}^{M}\sum_{k=1}^{N_I}\left(\min\left\{g_{imk}\left(\boldsymbol{\theta}_{im}\right),0\right\}\right)^2. \tag{13}$$

5.3 Third Stage

The last step infers the impacts of the stringency of land use regulation on structural cost parameters (δ_{im},e_{im}) by running regressions. I assume that the logarithms of these costs are linear functions of the land use regulation indices, hotel chain dummy and other observable market characteristics.

[28]What distinguishes (δ_{im},e_{im}) from $(\delta_{i'm'},e_{i'm'})$ in this estimation is the variation in the parameter estimates of market dummies and chain dummies in both the revenue function and the policy function. These dummies are either chain-specific or market-specific but not chain-market specific. Therefore estimation in the second stage is the mapping from both chain-specific variables and market-specific variables to chain-market specific variables. Due to nonlinearity of this mapping, resulting structural parameters do not have additivity such as $\delta_{im}=\delta_i+\delta_m$ for all i and m.

Table 8: Estimates of Policy Functions

	Policy Functions			
	(1)		(2)	
	$\Pi(1) - \Pi(-1)$	$\Pi(0) - \Pi(-1)$	$\Pi(1) - \Pi(-1)$	$\Pi(0) - \Pi(-1)$
# of Hotels	0.007	0.022	-0.061	-0.178
	(0.036)	(0.041)	(0.052)	(0.062)
# of Hotels under the Same Chain	-0.714	-0.998	-0.787	-1.060
	(0.089)	(0.110)	(0.105)	(0.123)
Log Likelihood	-2324.542		-2280.459	
Market Dummy	No		Yes	

Notes: N=15,120. Standard errors are in parentheses. Estimates and standard errors of control variables (population, the number of establishments, market dummies and chain dummies are suppressed. Likelihood functions take into account the constraint that no closure is possible when hotel chains operate no hotels.

6 Results

6.1 First Stage

Table 8 shows the estimation results of the policy function. To see the empirical importance of unobservable market-specific characteristics, I estimate this function under two different specifications: one with market dummy variables and one without them. The estimation results indicate that including market dummy variables into regressors are crucial to properly characterize the policy functions. As shown in Table 8, these two specifications provide quite different conclusions on the extent to which the presence of incumbents affect hotel chains' entry decisions. These results suggest that observable characteristics (i.e., population and establishments) are not sufficient to characterize the demand size of local markets. Hereafter I use the estimation results of the model using market dummy variables.

To provide some idea about what these estimates imply, I calculate the change in Best Western's predicted entry (i.e., $a_{imt} = 1$) and exit (i.e., $a_{imt} = -1$) probabilities in a market[29] as the number of hotels in this market increases. I consider the following two cases. In case

[29] This figure uses the data of Potter county, a part of the Amarillo MSA, in the first quarter of 2005. The population of this market is close to the sample median in this period.

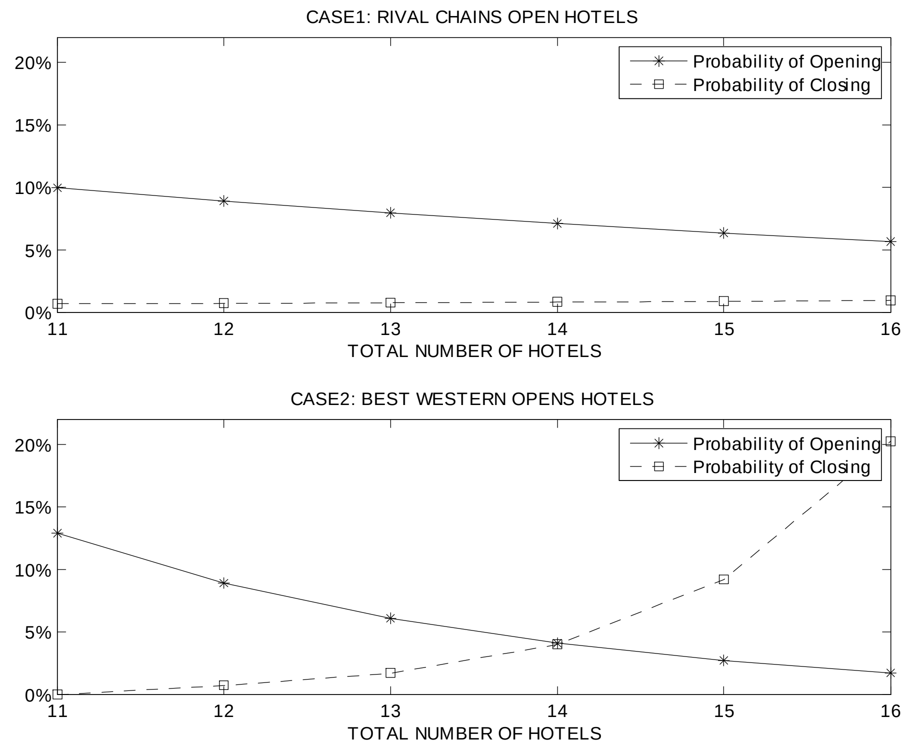

Figure 2: Impacts of the number of incumbents on Best Western's entry decisions

one, the number of hotels belonging to the other hotel chains increases from ten to fifteen while Best Western operates only one hotel. In case two, the number of hotels operated by Best Western increases from zero to five while the number of hotels operated by the other chains is fixed at eleven. In both cases, the total number of hotels increases from eleven to sixteen. Figure 2 shows the result of this exercise. In case one, Best Western's entry probability decreases from about 10 percent to 6 percent as its rival chains open new hotels while its exit probability slightly increases from 0.7 percent to 1 percent. In contrast, reflecting high substitution between hotels under the same chain, its entry probability decreases from 13 percent to 1.7 percent and its exit probability increases from 0 percent to 20 percent.

Table 9 shows the estimation results of the hotel-level revenue function specified in eq (7). I use the OLS for this estimation. To take into account possible correlations between error terms of hotels that operate in the same market at the same time, I employ the standard errors robust to clustering. I estimate this function under two specifications, with and without using market dummy variables.

First, the estimation results show that imposing market-specific dummy variables significantly changes some of the estimates. In particular, the parameter estimate for the number of rival hotels (the first row) changes from -0.047 to -0.380. These results imply that ignoring market-specific unobservable factors lead to inconsistent parameter estimates. For further analysis, I use the parameter estimates in Column (2). Second, the presence of other hotels significantly reduces the revenue of a hotel. In particular, its revenue impact becomes more severe when the hotel and its rival hotels belong to the same chain, reflecting possible cannibalization. Figure 3 visibly illustrates the implication of these results by showing how the revenue of a hotel, rather than a chain, decreases as other hotels open. To highlight the distinct revenue impacts from hotels belonging to the same chain and those belonging to its rival chains, the figure considers two situations: (1) when all of its rival hotels belong to other hotel chains and (2) when the hotel and all of its rival hotels belong to the same chain. My estimation results imply that a hotel's revenue under duopoly is about 23 percent lower than the one under monopoly when its rival belongs to a different chain. However, when its rival hotel belongs to the same chain, its revenue decreases by 34 percent.[30]

To check the quantitative importance of controlling the stringency of land use regulation on the demand side, I regress the estimated market fixed effects of the revenue function on the land use regulation indices as well as the other control variables used in the reduced form analysis. Omitted regression results suggest the importance of controlling the impacts of land use regulation on the demand side to isolate the cost impacts of land use regulation. First, although none of the estimates on land use regulation indices are individually significant when all the indices are included, these estimates are jointly significant at the the 1 percent level according to the F test. Second, land use regulation indices are quantitatively important.

[30] One might wonder why more intense competition due to the change from monopoly to duopoly does not decrease the revenue of a hotel more than fifty percent. This conjecture is not necessarily true in my setting, which abstracts hotel chains' within-market location decisions. The location of the second hotel is generally different from that of the first one and as a result the first hotel needs to compete with the second hotel for only a fraction of its potential customers.

Table 9: Revenue Function Estimates

	(1)	(2)
# of Hotels	-0.047	-0.380
	(0.023)	(0.025)
# of Hotels under the Same Chain	-0.198	-0.230
	(0.019)	(0.018)
Market Dummy	No	Yes
R-squared	0.998	0.998

Notes: N=13,626. Cluster standard errors are in parentheses. Each cluster is market and time period specific. Other control variables include population, the number of establishments and sales. All of these variables are in log. Estimates and standard errors for these control variables, market dummies, chain dummies and quarter dummies are suppressed.

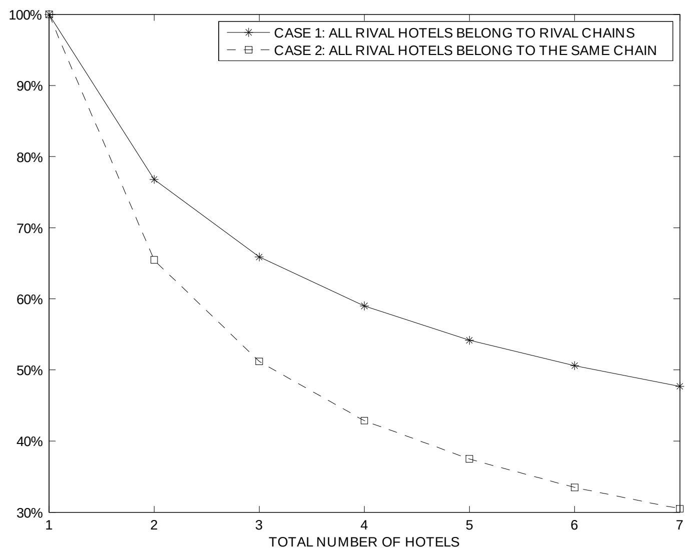

Figure 3: Revenue Impacts of Having Rival Hotels

For example, the change in the values of these indices from the first sample quartile to the third sample quartile decreases the revenue by 2 percent.

The estimation results of the transition functions for state-level sales, market-level establishments and population are in Supplementary Appendix.

6.2 Second Stage

The second stage estimation provides the scale parameter ρ and a pair of operating cost and entry cost (δ_{mi}, e_{mi}) for each combination of market-chain. Table 10 reports the descriptive

Table 10: Summary Statistics of the Cost Parameter Estimates

	Operating Cost (δ)	Entry Cost (e)
All Samples		
Mean	232.5	3,714.0
Std. Dev.	153.6	1,030.2
Mean by Chains		
Best Western	163.8	3,709.3
Cendant	114.3	3,973.7
Choice Hotels	114.0	3,839.9
Hilton	223.3	4,274.4
Inter-Continental	385.5	3,505.4
La Quinta	416.1	2,909.7

Notes: N=40. All statistics are in thousands of dollars. Operating cost expresses the amount of cost a hotel incurs for its three-month operation.

statistics of these cost parameter estimates.

Under the assumption that the mean exit cost is zero, the average hotel chain incurs \$233 thousand each quarter to operate a hotel and about \$3.7 million to open a new hotel in the average market. Their standard deviations indicate that these cost parameter estimates significantly vary across the markets. Furthermore, the last six rows of this table indicate significant cost difference across chains. The difference can be explained by difference in capacity and difference in quality such as the availability of free breakfast or business centers.

6.3 Third Stage: Cost Function Regression

Table 11 and 12 report the regression estimates for the operating costs (δ_{mi}) and the entry costs (e_{mi}).[31] To avoid omitted variable problems, all the regressions here include the control variables used in the reduced form regressions.

The first two columns of Table 11 show that an increase in either WRLURI or Project Approval by one standard deviation increases the operating costs by 8 percent.[32] However,

[31] I exclude the six chain-market pairs whose entry cost estimates are zeros from these regressions.

[32] There are several situations that land use regulation may affect the operating costs of hotels. First, obeying regulation may require frequent maintenance of buildings. Second, in markets with tight regulation on signs, hotels need to advertise their presence by more expensive ways such as advertisements in travel guides.

as shown in the last two columns of the same table, the statistical significance of Project Approval goes away once I include the other subindices. Excluding the data of regulation aimed for single-family housing makes little difference.

The parameter estimates in the last two regressions are difficult to interpret. First, while all the parameter estimates except the one for Project Approval are statistically significant, five out of the seven estimates have negative signs, indicating stringent regulation decreases the operating costs. Second, evaluating the total impacts of these estimates is tricky. Suppose I calculate the total impacts by increasing all of the indices by one standard deviation. This change is hardly comparable to an increase by one standard deviation in either the aggregate index or Project Approval because the correlations between these indices are weak (See Table 4).

To provide some idea of these estimates despite this difficulty, I compare the impacts of these subindices between two markets whose aggregate indices is about one standard deviation away.[33] The results are somewhat mixed. Among three pairs of such markets,[34] the only one pair finds that the order of their aggregate indices matches with that of the predicted impacts. These results along with the negative signs of the estimates may suggest weak correlations between the stringency of commercial land use regulation and the subindices that have no direct relationship with commercial buildings.

As for the entry costs, Table 12 shows that an increase in Project Approval by one standard deviation increases the entry cost by 10 percent. Remarkably, this result is quite robust to all the three specifications that involve this index. These estimates are statistically significant at the five percent level for the first two specifications while its significance level goes down to the ten percent level for the last specification. Unlike the regressions of operating

[33]To be precise, I first calculate the products of each subindex and its corresponding estimate and sum them up. I next calculate the value of the exponential function using this total value as its argument. I compare the markets within in the same pair by using this value. I do not use the predicted value of the operating costs as it reflects other characteristics of each market.

[34]I consider the following three pairs: (1) San Patricio and Lubbok, (2) Wise and Nagogdoches and (3) Orange and Wise. For every pair, the market that comes first has more stringent regulation in terms of the aggregate index.

costs, neither the parameter estimates of the aggregate index (WRLURI) nor those of the other subindices are statistically significant.

There are two possible limitations in these estimates. First, market-specific costs and the stringency of land use regulation may be determined simultaneously. Consider a local market whose cost of doing business is high for some reason other than land use regulation. To stimulate its economy, the local government of this market might not impose tight regulations to attract businesses. If this is the case, these regression estimates are possibly inconsistent. The standard solution of this problem is to find valid instruments that exogenously shift the stringency of land use regulation. However, there is little hope of finding such valid instruments,[35] let alone the fact that I would have to find seven different such instruments. Second, the criteria that are used to select sample markets may cause a sample selection problem. In particular, my sample excludes the markets that underwent very few entries and exits during the sample period. Excluding these markets does not seem to affect policy function estimates since their slight variations result in a very large (or very small) market fixed effects and do not have an effect on other estimates. However, regressions in the third stage can be problematic. For example, suppose that markets with high entry costs tend to undergo fewer entries and hence are less likely to be in my sample. If this is the case, my regressions in the third stage are subject to a selection bias.

7 Counterfactual Experiments

This section reports the results of counterfactual experiments, using the parameter estimates obtained in the previous section. The goal of this exercise is to quantitatively evaluate the cost impacts of land use regulation on the decisions of hotel chains and hence the intensity of competition. To isolate this particular effect, I construct an imaginary environment where a

[35] McMillen and McDonald (1991a) examines the possible selection bias in land value function estimation when zoning decisions are endogenous. For instruments, they use an indicator variable that tells whether a parcel is incorporated or not by municipals. This instrument is not applicable in my study since my study focuses on the effects of land use regulation on a county as a whole rather than each single parcel within a county.

Table 11: OLS Estimates of Regulation Impacts on the Operating Costs

Dep. Var.	ln (Operating Costs)			
	(1)	(2)	(3)	(4)
WRLURI	0.085**			
	(0.028)			
Project Approval		0.081**	0.028	0.032
		(0.037)	(0.037)	(0.036)
Zoning Approval		0.011	-0.058*	-0.072**
		(0.026)	(0.031)	(0.031)
Approval Delay			-0.094**	-0.133**
			(0.035)	(0.035)
Density Restrictions			-0.221**	-0.181**
			(0.079)	(0.077)
Exactions			-0.375**	-0.379**
			(0.105)	(0.101)
Open Space			0.122*	0.104*
			(0.065)	(0.060)
Political Pressure			0.077**	0.087**
			(0.025)	(0.026)
Supply Restrictions			-0.092**	-0.107**
			(0.040)	(0.040)
Exclude regulation for single-family housing	No	N/A	No	Yes
R-squared	0.769	0.770	0.819	0.828

Notes: N=234. Robust standard errors are in parentheses. Estimates with ** and * are statistically significant at the five percent and the ten percent level, respectively. Other regressors whose results are suppressed include chain dummies, population, the number of establishments, per capita income, area, construction price index, dummy variables for MSA, access to commercial airports and Interstate Highway. Population, the number of establishments, per capita income and area are in log. R-squared of the regressions of operating cost on the control variables only is 0.763.

Table 12: OLS Estimates of Regulation Impacts on the Entry Costs

Dep. Var.	ln (Entry Costs)			
	(1)	(2)	(3)	(4)
WRLURI	0.059			
	(0.044)			
Project Approval		0.103**	0.108**	0.100*
		(0.047)	(0.544)	(0.055)
Zoning Approval		0.042	0.032	0.035
		(0.033)	(0.038)	(0.035)
Approval Delay			-0.050	-0.026
			(0.034)	(0.033)
Density Restrictions			0.051	0.052
			(0.087)	(0.088)
Exactions			-0.037	-0.047
			(0.129)	(0.132)
Open Space			0.058	0.052
			(0.093)	(0.093)
Political Pressure			-0.010	-0.009
			(0.031)	(0.031)
Supply Restrictions			-0.004	-0.006
			(0.046)	(0.045)
Exclude regulation for single-family housing	No	N/A	No	Yes
R-squared	0.194	0.213	0.219	0.217

Notes: N=234. Robust standard errors are in parentheses. Estimates with ** and * are statistically significant at the five percent and the ten percent level, respectively. Other regressors whose results are suppressed include chain dummies, population, the number of establishments, per capita income, area, construction price index, dummy variables for MSA, access to commercial airports and Interstate Highway. Population, the number of establishments, per capita income and area are in log. R-squared of the regressions of entry cost on the control variables only is 0.187.

change in land use regulation affects only costs but not demand. Ideally, one wants to simulate the entry-exit decisions of the six hotel chains. However, solving even a Markov perfect equilibrium of six heterogeneous players is numerically demanding. For that reason, I instead simulate the model in an environment in which solving an equilibrium is computationally feasible.

Counterfactual experiments consider Grayson County, in which two hotel chains (Best Western and Cendant) choose their entry decisions every period. In 2005, the population of this market is equal to the sample median. I simulate the entry-exit decisions of these two hotel chains under three different policies: Lenient, Observed and Stringent. Each policy is different in the value of Project Approval. While Observed uses the actual value of this market, the value of this index is smaller for Lenient and larger for Stringent by one standard deviation compared to the observed value. To calculate the operating costs and the entry costs under each policy, I use the parameter estimates in the second column of Table 11 and Table 12. See Supplementary Appendix for the actual procedure of these experiments.

Table 13 reports the results of the counterfactual experiments. All variables except producer surplus are based on the sample average of the simulated periods while the producer surplus comes from the value of the value function under the initial state.[36] These results indicate that cost increase due to stringent land use regulation has a sizable effect on chains' entry decisions. Under the most lenient policy (Lenient), the average number of hotels in this market is 2.3. As the policy becomes more stringent, this number decreases to 2.0 (Observed) and 1.7 (Stringent). Assuming the number of rooms in each hotel is equal to the chain-average, these results imply that imposing stringent regulation increases the revenue per room by 3 percent (Lenient→Observed) and 12 percent (Observed→Stringent). These increases are suggestive of higher prices in the market imposing more stringent regulation. Despite of their higher market power, the hotel chains do not necessarily make higher profits. According to the results, the total producer surplus decreases by \$3.2 million (Lenient→Observed) and

[36] I am unable to calculate the consumer surplus since the model abstracts the demand side by using the revenue function.

Table 13: Counterfactual Experiments

	Land Use Regulation		
	Lenient	Observed	Stringent
Operating Costs (in thousand dollars)			
Best Western	89.43	99.14	109.89
Cendant	73.74	81.74	90.61
Entry Costs (in million dollars)			
Best Western	4.47	4.84	5.25
Cendant	3.76	4.08	4.42
# of Hotels			
Total	2.3	2.0	1.7
Best Western	1.1	0.9	0.8
Cendant	1.2	1.1	0.9
Daily Revenue per Room (in dollars)			
Best Western	28.1	29.9	31.5
Cendant	14.6	15.4	16.4
Producer Surplus (in million dollars)			
Total	14.95	11.79	9.01
Best Western	6.32	4.88	3.64
Cendant	8.63	6.91	5.37

Notes: Daily revenue per room is obtained by dividing quarter revenue by ninety-two days.

$2.8 million (Observed→Stringent).

8 Conclusion

This paper studies the role of land use regulation as a barrier to entry in the case of the Texas lodging industry. The estimation results indicate that stringent land use regulation lessens local competition by increasing the costs of hotels. According to my estimates, its change b y one standard deviation increases the operating cost by 8 percent and the entry costs by 10 percent, respectively. This cost increase discourages hotel chains' entry, decreasing the equilibrium number of hotels by 15 percent. As a result, the revenue-per-room, a proxy for the price, increases by 5 to 6 percent.

To the best of my knowledge, this paper is the first that empirically examines the anti-competitive effect of land use regulation on local business markets by taking into account its impacts on the demand. Although people in the lodging business and legal scholars have noticed it, there has been no formal analysis that quantifies this effect. This paper also contributes an introduction of structural estimation to the literature on the empirical studies of land use regulation. The structural estimation employed in this paper has the advantage of separately identifying the impacts of land use regulation on costs from those on demand.

Note that this paper is not intended to be the final word on land use regulation. It focuses on the anticompetitive effect of land use regulation and ignores its other possible benefits and costs. Therefore, the results of this paper are not sufficient per se to make final judgments about its efficacy. When it generates benefits to society through some other channels (e.g., resolves externalities), land use regulation could be beneficial overall, despite the potential distortion that is the focus of this paper.

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A Appendix: Other Data

Demographic data is from the decennial census and *the Regional Economics Information System* provided by the Bureau of Economic Analysis. This demographic data includes population, per capita personal income and area. Local business activity data is obtained from *County Business Patterns* provided by the Census Bureau. This business data includes the number of employees and the number of establishments. I also construct dummy variables for each county's access to the Interstate Highway System along with their access to commercial airports from road maps and the Internet. Construction cost data comes from *Means Square Foot Costs* provided by RSMeans.

B Appendix: Derivation of the Choice Probability

This appendix derives the choice probabilities when a hotel chain's decision problem is written as

$$\max\left(\Pi\left(1,\mathbf{s}\right)+\upsilon_1,\ \Pi\left(0,\mathbf{s}\right),\ \Pi\left(-1,\mathbf{s}\right)+\upsilon_2\right).$$

I omit all subscripts for simplicity. While this model is quite similar to the standard multinomial logit model, the lack of stochastic shock in a particular choice (i.e., $a=0$) brings different forms of the choice probabilities. The derivation is quite similar to that of the standard multinomial logit model shown in, for example, Train (2003). For notational purpose, I first rewrite this problem as

$$\max\left(g_1+\upsilon_1,\ g_0,\ \upsilon_{i2}\right)$$

where

$$\begin{aligned}
g_1 &= \Pi(1, \mathbf{s}) - \Pi(-1, \mathbf{s}) \\
g_0 &= \Pi(0, \mathbf{s}) - \Pi(-1, \mathbf{s}).
\end{aligned}$$

The probability that hotel chains choose no change is

$$\begin{aligned}
\Pr(a = 0) &= \Pr(g_0 > \upsilon_2 \text{ and } g_0 > g_1 + \upsilon_1) \\
&= F(g_0) \cdot F(g_0 - g_1) \\
&= \exp\left(-e^{-g_0}\right) \cdot \exp\left(-e^{-(g_0 - g_1)}\right) \\
&= \exp\left(-e^{-g_0}\left(1 + e^{g_1}\right)\right).
\end{aligned}$$

The probability that hotel chains choose closing a hotel is

$$\begin{aligned}
\Pr(a = -1) &= \Pr(\upsilon_2 > g_0 \text{ and } \upsilon_2 > g_1 + \upsilon_1) \\
&= \int_{-\infty}^{\infty} 1(\upsilon_2 > g_0) \cdot F(\upsilon_2 - g_1)\, dF(\upsilon_2) \\
&= \int_{-\infty}^{\infty} 1(\upsilon_2 > g_0) \exp\left(-e^{-(\upsilon_2 - g_1)}\right) \exp(-\upsilon_2) \exp\left(-e^{-\upsilon_2}\right) d\upsilon_2 \\
&= \int_{g_0}^{\infty} \exp\left(-e^{-\upsilon_2}\left(e^{g_1} + 1\right)\right) e^{-\upsilon_2} d\upsilon_2.
\end{aligned}$$

Denoting $t = e^{-\upsilon_2}$, I have $d\upsilon_2 = -\frac{dt}{e^{-\upsilon_2}} = -\frac{dt}{t}$.

$$\begin{aligned}
\Pr(a = -1) &= \int_{g_0}^{0} \exp\left(-t\left(e^{g_1} + 1\right)\right) t \left(-\frac{dt}{t}\right) \\
&= \int_{0}^{e^{-g_0}} \exp\left(-t\left(e^{g_1} + 1\right)\right) dt \\
&= \left[\frac{e^{-t\left(e^{g_1}+1\right)}}{-\left(e^{g_1} + 1\right)}\right]_0^{e^{-g_0}} \\
&= \left(1 - e^{-e^{-g_0}\left(e^{g_1}+1\right)}\right) \cdot \frac{1}{e^{g_1} + 1} \\
&= (1 - \Pr(a = 0)) \cdot \frac{1}{e^{g_1} + 1}.
\end{aligned}$$

Finally, the probability that hotel chains choose opening a new hotel (i.e., $a=1$) is

$$
\begin{aligned}
\Pr(a=1) &= 1-\Pr(a=-1)-\Pr(a=0) \\
&= 1-(1-\Pr(a=0))\frac{1}{e^{g_1}+1}-\Pr(a=0) \\
&= (1-\Pr(a=0))\cdot\frac{e^{g_1}}{e^{g_1}+1}.
\end{aligned}
$$

Summarizing the result, if $h\in\{1,\cdots,6\}$,

$$
\begin{cases}
\Pr(a=-1)=\left(1-\exp\left(-e^{-g_0}\left(1+e^{g_1}\right)\right)\right)\cdot\frac{1}{e^{g_1}+1} \\
\Pr(a=0)=\exp\left(-e^{-g_0}\left(1+e^{g_1}\right)\right) \\
\Pr(a=1)=\left(1-\exp\left(-e^{-g_0}\left(1+e^{g_1}\right)\right)\right)\cdot\frac{e^{g_1}}{e^{g_1}+1}
\end{cases}
$$

or

$$
\begin{cases}
\Pr(a=-1)=(1-U(s))\cdot\frac{1}{1+\exp(\Pi(1,\mathbf{s})-\Pi(-1,\mathbf{s}))} \\
\Pr(a=0)=\exp\left(-e^{-(\Pi(0,\mathbf{s})-\Pi(-1,\mathbf{s}))}\left(1+e^{\Pi(1,\mathbf{s})-\Pi(-1,\mathbf{s})}\right)\right) \\
\Pr(a=1)=(1-U(s))\cdot\frac{\exp(\Pi(1,\mathbf{s})-\Pi(-1,\mathbf{s}))}{1+\exp(\Pi(1,\mathbf{s})-\Pi(-1,\mathbf{s}))}.
\end{cases}
$$

where

$$
U(s)=\exp\left(-e^{-\Pi(0,\mathbf{s})}\left(e^{\Pi(-1,\mathbf{s})}+e^{\Pi(1,\mathbf{s})}\right)\right)
$$

If $\Pi(-1,\mathbf{s})\to-\infty$ (i.e., $h=0$),

$$
\begin{cases}
\Pr(a=-1)=0 \\
\Pr(a=0)=\exp\left(-e^{\Pi(1,\mathbf{s})-\Pi(0,\mathbf{s})}\right) \\
\Pr(a=1)=1-\exp\left(-e^{\Pi(1,\mathbf{s})-\Pi(0,\mathbf{s})}\right).
\end{cases}
$$

If $\Pi(1, \mathbf{s}) \to -\infty$ (i.e., $h = 7$),

$$\begin{cases} \Pr(a = -1) = 1 - \exp\left(-e^{-(\Pi(0,\mathbf{s}) - \Pi(-1,\mathbf{s}))}\right) \\ \Pr(a = 0) = \exp\left(-e^{-(\Pi(0,\mathbf{s}) - \Pi(-1,\mathbf{s}))}\right) \\ \Pr(a = 1) = 0. \end{cases}$$

C Appendix: Implementing Forward Simulations

The steps below explain how to implement the simulation to calculate eq (10).

1. Fix a market m and a hotel chain i.

2. Simulate a series of exogenous time-variant market specific variables over T periods for N_S times by using the AR1 models obtained in the first stage. Let $\{\widetilde{\mathbf{x}}^n_{m\tau}\}_{\tau=1}^T$ denote its nth series. For the initial value $\widetilde{\mathbf{x}}^n_{m1}$, use the corresponding value in the raw data at the initial sample period in market m.

3. Simulate chain i's cost shocks $(\tilde{\upsilon}^n_{1im\tau}, \tilde{\upsilon}^n_{2im\tau})$ over T periods for N_S times by generating random draws from Type I extreme value distribution whose mean is normalized to be zero and whose variance is equal to $\frac{\pi^2}{6}$.

4. Generate chain i's N_I alternative policies by perturbing the observed policy function obtained in the first stage. I implement this perturbation as follows. I first generate N_I vectors, $\left(\gamma^1, \cdots, \gamma^{N_I}\right)$ of i.i.d. random draws from the standard normal. The length of γ^k is equal to the number of the parameters of the policy functions. Second, I perturb the estimates of the observed policy function by multiplying $\left(1 + .005\gamma^k\right)$ to their parameter estimates.

5. For every $k \in \{1, 2, \cdots, N_I\}$, simulate chain i's expected revenue $\left\{\widetilde{ER}^{k,n}_{im\tau}\right\}_{\tau=0}^T$, the number of hotels it operates $\left\{\tilde{h}^{k,n}_{im\tau}\right\}_{\tau=0}^T$, its entry and exit decisions $\left\{\tilde{a}^{k,n}_{im\tau}\right\}_{\tau=0}^T$ and its private cost shocks $\{\tilde{\upsilon}^n_{1im\tau}, \tilde{\upsilon}^n_{2im\tau}\}_{\tau=0}^T$ for N_S times when σ^k_{im} decides its choice while its rivals' decisions are based on the observed policies $\left\{\sigma^0_{-im}\right\}$.

   (a) At the beginning of nth simulation, set the initial state $\widetilde{\mathbf{s}}^{k,n}_{m1} = \left(\widetilde{\mathbf{h}}^{k,n}_{m1}, \widetilde{\mathbf{x}}^n_{m1}\right)$. For the initial value $\widetilde{\mathbf{h}}^{k,n}_{m1}$, uses the corresponding value in the raw data at the initial sample period in market m.

Table 14: Transition Function Estimates

	Dependent Variables		
	Sales	Population	Establishments
Lagged Dep. Var.	0.992	1.007	1.001
	(0.020)	(0.004)	(0.005)
Constant		0.006	0.035
		(0.021)	(0.005)
R-squared	0.999	0.999	0.999

Notes: N=63 for sales and 1,020 for establishments and population. Standard errors are in parentheses. All dependent variables are in log. Estimates and standard errors for quarter dummies suppressed.

(b) Simulate the choice of all hotel chains at period one $\widetilde{\mathbf{a}}_{im1}^{k,n}$ by using σ_{im}^{k} and $\{\tilde{\upsilon}_{1im1}^{n}, \tilde{\upsilon}_{2im1}^{n}\}$ for chain i's choice, and σ_{-im}^{0} for the choices of the other chains. Update the state variables $\widetilde{\mathbf{s}}_{m2}^{k,n} = \left(\widetilde{\mathbf{h}}_{m2}^{n}, \widetilde{\mathbf{x}}_{m2}^{n}\right) = \left(\widetilde{\mathbf{h}}_{m1}^{k,n} + \widetilde{\mathbf{a}}_{m1}^{k,n}, \widetilde{\mathbf{x}}_{m2}^{n}\right)$. I need to simulate chain i's choice by using $\{\tilde{\upsilon}_{1m1}^{n}, \tilde{\upsilon}_{2m1}^{n}\}$ so that I can calculate the entry and exit costs chain i actually incurs. In contrast, I can simulate the other chains' choices by directly using the choice probability based on σ_{-im}^{0} since further steps do not require the entry and exit costs these chains incur.

(c) Simulate a series of state variables over T periods $\left\{\widetilde{\mathbf{s}}_{m\tau}^{k,n}\right\}_{\tau=1}^{T}$ by iterating the process shown in (b) for T times.

(d) Calculate chain i's expected revenue $\widetilde{ER}_{imt}^{k,n}$ by using the revenue function estimates and $\widetilde{\mathbf{s}}_{mt}^{k,n} = \left(\widetilde{\mathbf{h}}_{mt}^{k,n}, \widetilde{\mathbf{x}}_{mt}^{n}\right)$.

(e) Calculate eq (10).

D Appendix: Transition Function Estimates

E Appendix: Procedure of Counterfactual Experiments

I first calculate the predicted values of the operating costs and the entry costs of these two chains under each policy by using the OLS estimates in the second column of Table 11 and Table 12. I put zeros to the parameters of Zoning Approval since these estimates are not statistically significant in both regressions. I next numerically solve the Bellman equation under a particular set of structural parameters to obtain the approximated value function and the resulting policy functions. Using these equilibrium policy functions, I simulate the model. I employ the algorithm originally suggested by Pakes and McGuire (1994) and extended by Doraszelski and Satterthwaite (2010) to games of incomplete information. In all the experiments, I fix all market-specific values, such as population, to their value in the first quarter of 2005 to reduce the state space. Hence the state space consists of the number of hotels belonging to one chain, the number of hotels belonging to the rival chain and which quarter is the current period. The number of possible states is 256 ($= 8 \cdot 8 \cdot 4$). All the experiments converge after around 600 iterations.