Essays in Empirical Industrial Organization

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Dedication

This dissertation is dedicated to the memory of my grandfather, Tamotsu Yoshida, who passed away while I was working on this study.

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Chapter 1

Overview

This thesis consists of two essays. The first essay "Land Use Regulation as a Barrier to Entry: Evidence from the Texas Lodging Industry" examines the impacts of land use regulation on the intensity of competition among hotels. In the U.S., local governments regulate private land use mainly through zoning. By creating a barrier to entry and lessening competition in local business markets, their regulation has the potential to generate a distortion. This paper assesses the empirical relevance of this hypothesis using microdata on midscale Texas chain hotels and land use regulation data collected from their local municipalities. I construct a dynamic entry-exit model of midscale hotel chains. By endogenizing their entry decisions, the model explicitly considers hotel chains' reactions to the stringency of land use regulation. Reduced form regressions indicate that local markets under stringent regulation tend to undergo fewer entries. To identify the extent to which high entry cost due to stringent land use regulation explains this negative correlation, I estimate structural parameters of the entry model by using a recently developed simulation-based algorithm. To verify the robustness of my results, I also employ a bound estimator that is consistent under weak conditions. Estimation results indicate that imposing stringent regulation increases cost enough to affect hotel chains' entry decisions. Although they are the immediate payers of the increased entry cost, incumbents shift about the half of their cost increase onto consumers by exploiting their increased market power.

The second essay "Does the Threat of Entry Matter?: Case of the Texas Lodging Industry" examines the impacts of the mere threat of entry on entry decisions of hotel chains. Despite large theoretical literature studying at firms' reaction when the threat of entry exists, there has been few empirical studies looking at this topic. In this essay, I attempt to quantify the importance of the threat of entry on firms' behavior in the case of the Texas lodging industry. My approach is to implement counterfactual experiments based on the structural dynamic entry-exit model of hotel chains that are presented and estimated in the previous chapter. To isolate the impacts of the threat of entry from the impacts of real entry, I simulate the entry-exit decisions of hotel chains under the following three distinct environments: (1) pure monopoly, (2) expost monopoly, and (3) pure duopoly. While pure monopoly and pure duopoly consider their decisions under realistic environments, the expost monopoly let hotel chains make entry decisions as if they were in duopoly while real entry never occurs. By comparing these three environments, I attempt to identify the impacts of the threat of the entry separately.

Chapter 2

Land Use Regulation as a Barrier to Entry

2.1 Introduction

In the U.S., local governments regulate private land use within their boundaries mainly through zoning. Zoning regulates private land use from various aspects, including the purpose of land use or the shape of buildings. These regulations impose additional entry costs on new businesses by forcing them, for example, to use expensive materials (e.g., brick) for the exterior of their buildings or to deviate from a prototype building design. Although business owners can request rezonings or exceptions, these requests need to go through processes that could involve city administration, politics and jurisdiction, and often incur considerable expense.

This paper argues that stringent land use regulation generates a distortion in local business markets by increasing the cost of entry and, as a result, lessening competition. Although people in the legal professions have noticed this anticompetitive effect of land use regulation[1], it has attracted little attention from economists and few formal analyses have

[1] People in the legal profession have argued that whether municipalities are immune from antitrust liability arising from their local ordinances. See Sullivan (2000) for a summary of these arguments and several influential cases.

been done.

The goal of this paper is to assess the empirical relevance of this hypothesis using microdata on midscale Texas chain hotels and land use regulation data collected from their local municipalities. Through empirical analysis, I attempt to quantify the size of the distortion and examine who bears its cost. This paper is not intended to be the final word on land use regulation. Instead it focuses on an anticompetitive effect of land use regulation and pays no attention to its other possible benefits and costs. Therefore, the results of this paper are not sufficient per se to make final judgments on land use regulation. If it generates benefits to society through some other channels (e.g., resolves externalities), land use regulation could be beneficial overall, despite the distortion.

Several facts indicate the relevance of this proposed hypothesis to the lodging industry. First, land use regulation appears to be among the major determinants of entry cost, and hence 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 have a significant cost impact. If it were not the case, the change of regulation would rarely affect the degree of competition and my hypothesis would have little quantitative importance. Second, competition in this industry is fairly local. Because of the nature of their product, hotels must locate at the place of consumption. Therefore, 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. If competition were nationwide, entry decisions of local rivals would have little impacts on the intensity of competition, and again, my hypothesis would have little empirical relevance. Third, it appears that people in the lodging industry realize that local land use regulation can act as an entry barrier on their competitors. This is indicated by the following quote:

> There's a short answer to why certain hotel developers choose projects en-

[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.

> cumbered 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 (*Hotel & Motel Management,* 11 August 2003).

My empirical analysis starts with reduced form regressions to assess any correlation between the number of midscale hotels belonging to the seven largest, midscale hotel chains and that market's land use regulations. As a measure of the stringency of land use regulation, I employ the written-survey-based indices developed by Gyourko et al. (2008). Reduced form regression results are consistent with the prediction of my hypothesis. I next construct an entry model for hotel chains and apply it to the revenue data. To make the estimation computationally feasible, I employ the nested pseudo likelihood algorithm recently developed by Aguirregabiria and Mira (2007). The concern of these estimates is their possible inconsistency when regulation is endogenous. To verify the robustness of these estimates, I also employ a bound estimator proposed by Manski (1997), whose consistency does not require exogenous regulation. As a last step, by using the structural parameter estimates, I simulate the entry decisions of the hotel chains under three different policies and observe the changes in surplus.

One of the major obstacles for empirical studies of land use regulation is its quantification. Complicated rules and the prevalence of local discretion in the actual implementation of these regulations indicate that no single index is a definitive measure. 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 obtain a building permit).

Reduced form regressions indicate that markets under stringent land use regulation tend to have fewer hotels. A drawback of these regressions is twofold. First, these regression results do not allow me to conduct welfare analysis by running counterfactual experiments. Second, these results also fail to separately identify the effect of land use regulation on entry cost and local travel demand. Land use regulation could affect local travel demand by, for example, preserving some view that attracts tourists or discouraging constructions of commercial buildings that draw business travelers. When stringent regulation decreases local travel demand overall, this demand-side effect can solely generate the observed negative correlation between the stringency of land use regulation and the number of entries. Therefore, the observed negative correlation does not necessarily imply that land use regulation increases entry cost of hotels. To avoid these drawbacks, I need to pursue structural estimation.

I consider a dynamic entry model of hotel chains in which they maximize their expected profits by choosing the number of hotels they open in a local market every period. The revenue of one hotel in a chain is a function of market-specific revenue shifter, chain-specific revenue shifter 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. The cost of opening one hotel consists of sunk-entry cost and operating cost. While the sunk-entry cost is incurred only at the time of opening, operating cost is incurred at every period until the hotel closes down. I assume a chain's sunk-entry cost is stochastic and only observable to this chain only. Since hotel chains' entry decisions are based on their beliefs about their competitors' entry decisions. In a Markov Perfect equilibrium, these beliefs must be consistent with the actual entry decisions of rival chains.

I estimate this entry model to separately identify structural cost parameters of hotel chains. The wide availability of the hotel-level revenue data and the entry data makes this identification possible. For example, consider two markets (A and B). Without loss of generality, suppose that a chain opens one hotel in market A while it does not open in market B. The mere entry data does not tell whether this observed decision implies higher revenue, lower cost, or both in market A than market B. However, once the revenue data becomes available, it is not the case anymore. From the revenue data, researchers can predict the revenue of a hotel under an imaginary market structure. If the revenue prediction of a hotel in market B is similar to that in market A, this prediction –along with the observed entry decision– imply that the cost of opening a hotel in market B is higher than the cost in market A.

Estimation consists of three stages. I first recover the market-specific revenue shifters from the hotel-level revenue data. Exploiting its longitudinal structure, I can identify market-specific revenue shifters that may be attributable to both observable and unobservable time-invariant factors. Taking these estimates as given, I next recover market-specific cost shifters by finding a set of parameters that rationalizes both the revenue function estimates and the observed entry decisions over time. To take into account the interacting entry decisions of competing hotel chains while maintaining computational burden, I employ the estimation method developed by Bajari et al. (2007). Finally, from the recovered market-specific cost parameter estimates and the land use regulation indices, I draw a statistical inference that stringent land use regulation increases the market-specific cost shifters in the following two methods. I first regress these estimates of the market-specific cost estimates on land use regulation indices as well as other possible cost factors. One potential concern of these regressions is a possible endogeneity of regulation. When regulation indices are correlated with unobservable cost shifters, these regression estimates become inconsistent. To take this possibility into account, I also employ a bound estimator whose consistency only requires that market-specific costs are monotonic in the stringency of land use regulation. Although it only identifies the bound in which the true parameters fall, this bound estimator adds robustness to my results since they are consistent even when the stringency of land use regulation is endogenous.

The main finding of this paper is the quantitative significance of the distortion argued by the proposed hypothesis. First, estimation results indicate that imposing stringent regulation increases entry cost enough to affect a hotel chain's decisions about entering a market. Second, although they are the immediate payers of the increased entry cost, incumbents shift about the half of their cost increase onto consumers by exploiting their market power. Third, a decrease in the total surplus is larger than the cost increase since the lessened competition generates an extra distortion.

This paper makes several contributions to the existing literature. The role of land use regulation is a main concern of urban economics and numerous empirical studies have been conducted in the past.[3] The focus of these studies is considerably broad, including land price (McMillen and McDonald (1991b)), land development (Wu and Cho (2007)), density (McConnell et al. (2006)) and housing markets.[4] Nonetheless, the role of land use regulation in local business markets has not attracted much attention from economists.[5] This paper is intended to fill this existing gap. The main empirical finding of this paper–that land use regulation actually weakens competition of local businesses by discouraging entry–enhances the understanding of the impacts of land use regulation. Another contribution this paper makes to the land use regulation literature is its introduction of a state-of-the-art technique for structural estimation. Most existing empirical studies in this area have relied on reduced form estimates for their statistical inferences. Although reduced form estimates have the advantage of flexibility from restrictive assumptions, they cannot separately identify the effects land use regulation has on cost and travel demand. The structural estimation employed in this paper overcomes this difficulty and is able to calculate the explicit cost entailed by weak competition due to stringent land use regulation. In relation to the literature on empirical industrial organization, this paper belongs to the large literature on firms' entry decisions that originated from classical papers such as Bresnahan and Reiss (1990) and Berry (1992).[6] Among others, this paper is perhaps most closely related to Ryan (2006). In his paper, Ryan estimates a dynamic entry model of cement plants and evaluates the welfare consequences of a change in environmental regulation in the Portland cement industry. Since the change in environmental regulation is uniform

[3] For a survey of empirical studies in this area, see Fischel (1989), Pogodzinski and Sass (1991), Evans (1999) and Quigley (2006). *Regional Science and Urban Economics* published a special issue featuring studies of land use regulation. For the summary of these papers, see Cheshire and Sheppard (2004).

[4] A recent skyrocketing of housing prices in large metropolitan areas prompted studies about the effects of land use regulation in housing markets. For example, a series of empirical studies by Glaeser and his coauthors (Glaeser et al. (2005a), Glaeser et al. (2005b), Glaeser and Ward (2006)) claim that a significant portion of increasing housing prices is attributable to stringent land use regulation.

[5] Ridley et al. (2007) is the only exception I found. In their paper, the authors estimate the effects of zoning on the number of entries by reduced form regressions for five retail industries (restaurants, bars, grocery, gas/convenience and liquor stores).

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

across markets, he relies on the intertemporal difference of the industrial structure for identification. In contrast, this paper attempts to exploit cross-market differences in land use regulation by employing indices that directly measure the stringency of land use regulation in each market.

The rest of the paper proceeds as follows: Section 2 provides an overview of land use regulation for the Texas lodging industry. Section 3 summarizes the data used in the empirical analysis while Section 4 presents the results of the reduced form regressions. Section 5 describes the empirical model used for structural estimation. Section 6 explains the estimation method, and Section 7 presents the estimation results. Section 8 demonstrates the results of counterfactual experiments, and Section 9 concludes.

2.2 Land Use Regulation for the Texas Lodging Industry

The basis of the current zoning ordinances in the U.S. goes back to 1926 when the U.S. Department of Commerce drafted the Standard State Zoning Enabling Act (SZEA), which has become a prototype of state statutes on zoning ordinance.[7] The state of Texas adopted its version of the SZEA in 1927. The Texas statute grants municipalities authority over the legislation and implementation of zoning. According to the Texas statute, the purpose of zoning is "promoting the public health, safety, morals, or general welfare and protecting and preserving places and areas of historical, cultural, or architectural importance and significance."[8]

Implementation of zoning generally involves several departments of a municipal office. Although its process varies from municipality to municipality, its basic structure is similar. Figure 2.1 illustrates an example of the administrative process developers need to undergo to obtain building permits. Developers planning to construct new commercial buildings within the boundaries of a local government (Fredericksburg, Texas) first need to speak with

[7] This section is mainly based on Fischel (1985) for general institutional knowledge of land use regulation and Nance (2006) for information specific to Texas. Other sources I found helpful include O'Flaherty (2005) and O'Sullivan (2000).

[8] Texas Statutes, Local Government Code, Chapter 211.001.

city officials in several departments in order to discuss possible problems with the building plans. If the plans do not violate current zoning restrictions, the process is quite simple. For example, developers submit their applications to the Planning and Zoning Commission, which consists of nine members appointed by the mayor. Unless a disagreement is discovered between the submitted plan and the current zoning ordinance, the commission usually approves the plan. Once approved, developers submit a blueprint of their construction to the building department, which ensures the submitted plan meets building codes. Once it is confirmed that the plans comply with building codes, building permits are issued to the developers.

However, if construction plans do not conform with current zoning laws, developers have three choices. They can (1) request a rezoning, (2) request an exception to current zoning, called a variance or (3) withdraw their plans. The procedure for rezoning is different from that of a variance. If rezoning requires amending the current zoning laws while issuing a variance does not. Developers' requests for rezoning are sent to the Planning and Zoning Commission. After holding a public hearing, the commission sends its recommendation on the requested zoning to the City Council. The City Council makes a final decision after holding the second public hearing. In contrast, requests for variances are sent to the Zoning Board of Adjustment (ZBA), which consists of five regular members and three alternate members appointed by the City Council. The ZBA makes its decision after holding a public hearing. Unlike rezoning, decisions of the ZBA are final and the City Council is not involved in the process.

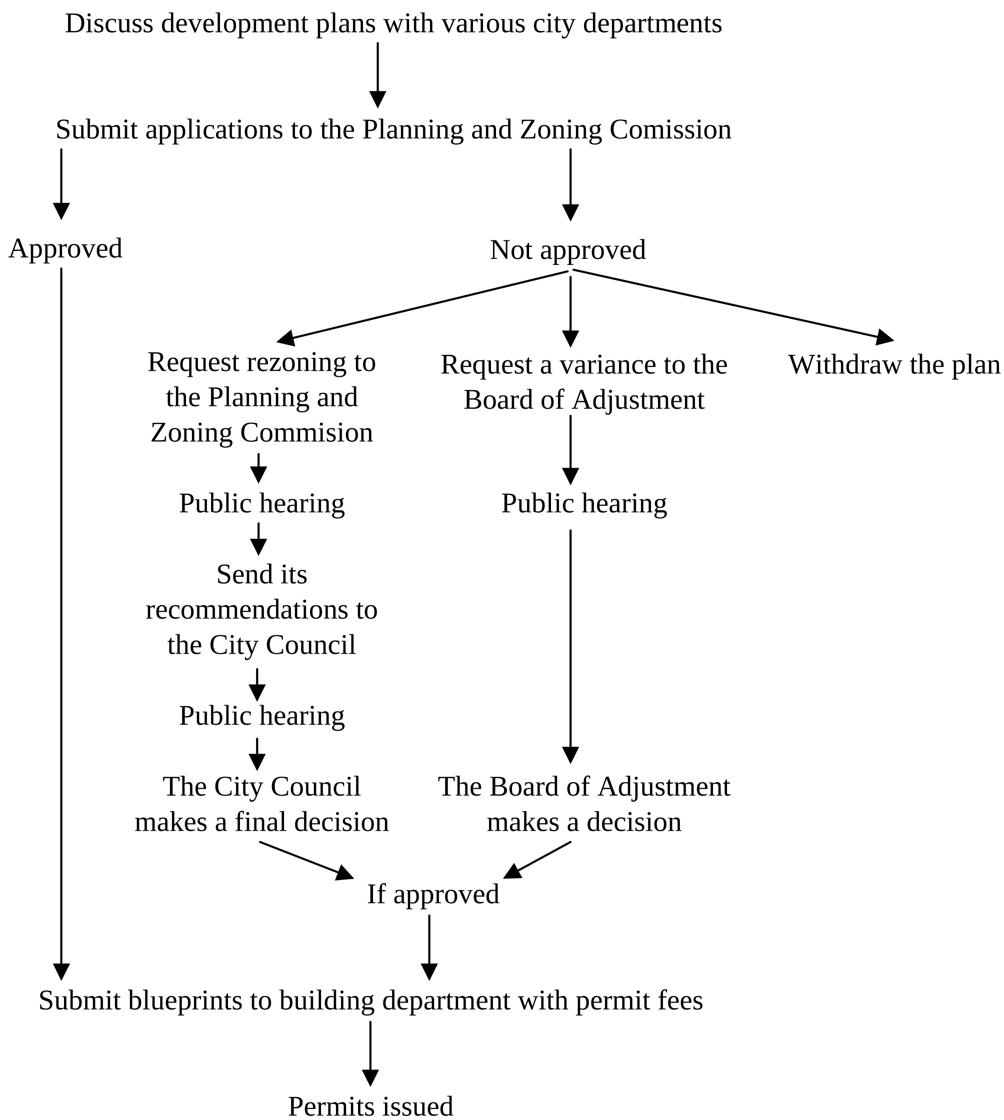

Figure 2.1: Implementation of Zoning Ordinance: Fredericksburg, Tex.

2.3 Related Literature: Empirical Studies of Land Use Regulation

Economic impacts of land use regulation has been one of main concerns among urban economists. Standard undergraduate textbooks of urban economics (O'Flaherty (2005), O'Sullivan (2000)) allot significant spaces to this topic. Moreover, in 2004, *Regional Science and Urban Economics* published a special issue featuring studies of land use regulation[9], indicating that this topic still attracts researchers' attention.

One common approach in this literature is to study quantitative impacts of land use regulation on equilibrium price by running reduced-form regressions. Reflecting the fact that land use regulation potentially affects all sorts of economic activity using land, the focus of these empirical studies has been considerably broad, including land price (McMillen and McDonald (1991b)), land development (Wu and Cho (2007)), density (McConnell et al. (2006)) and housing markets.[10]

2.3.1 Housing Market

Large fraction of studies in this literature focus on the impacts of land use regulation on housing prices. Their main finding is that stringent land use regulation raises housing prices. For example, Gleaser and his coauthors[11] look at to what extent land use regulation is responsible for a recent skyrocketing of housing prices in large metropolitan areas by looking at housing prices. In Glaeser et al. (2005a), the authors employ an indirect approach that does not rely on measures of the stringency of land use regulation. Instead they look at the gap between housing prices and marginal cost of constructing additional apartment in Manhattan and argue that land use regulation is a reasonable explanation for the observed gap. In Glaeser and Ward (2006), the authors instead employ regulation data collected from local governments in the Greater Boston area to find an impact of specific regulations

[9] See Cheshire and Sheppard (2004) for a summary of the papers published in this issue.

[10] For a survey of empirical studies in this area, see Fischel (1989), Pogodzinski and Sass (1991), Evans (1999) and Quigley (2006).

[11] Other studies belonging to this class include Glaeser and Gyourko (2002), Ihlanfeldt (2007) and Quigley (2006).

(e.g., minimum lot size) on housing prices.

There are two obstacles these empirical studies have encountered. First, possible endogeneity of regulation makes it hard to tell the direction of causality and often makes regression estimates inconsistent. For example, suppose that land use regulation has nothing to do with housing prices but quality of local public schools does. When areas with tight land use regulation tend to have good quality of local public schools, observed correlations between the stringency of land use regulation and housing prices are spurious. Standard reaction to this problem is to find instruments that are correlated with regulation but not other factors. While many empirical studies merely assume exogenous regulation, both Glaeser and Ward (2006) and Ihlanfeldt (2007) use demographic variables at the time regulation was imposed as instruments and estimate the model by 2SLS.

Second, quantifying the stringency of land use regulation is a difficult task. Institutional features of land use regulation are hard to compare across local governments. Furthermore, these features might not provide sufficient information when the discretion of local governments plays an important role (and it does) in the actual implementation of regulation.

Reflecting these apparent difficulties, several efforts have been made to measure the stringency of land use regulation.[12] Table 2.1 lists various measures used in previous studies. Roughly speaking, there are two types of measures: (1) deductive measures, and (2) inductive measures. Deductive measures assess the stringency of land use regulation from observables that are expected to affect the stringency of land use regulation. In contrast, inductive measures assess the stringency of land use regulation from observables that reflect the *results* of actual implementation of land use regulation. Some deductive measures rely on the contents of actual statutes regulating private land use. Examples of these indices include the minimum lot size (Glaeser and Ward (2006)), a dummy variable that tells if a local government has a particular regulation (e.g., urban boundary) and the number of type of regulations a local government impose (Ihlanfeldt (2007)). Some other deductive measures do not directly come from actual statutes. Examples of these indices include a dummy vari-

[12] See Quigley (2006) and Saks (2005) for recent surveys of these efforts.

able that tells if the jurisdiction of a local government contains registered historic sites, the number of administration processes needed to go through to get building permits and the subjective impression of political pressure on the actual enforcement of land use regulation (Gyourko et al. (2008)). Examples of inductive measures include the number of building permit granted and the average length of time required to obtain building permits for an approved project. Some measures are more appealing in terms of their direct connections to land use regulation while some other measures might work better when the discretion of local governments is important. In other words, indices in each group work as complements to the other.

2.3.2 Business Market

Impacts of land use regulation on business markets have attracted relatively little attention from researchers. Although research in this area is still premature, empirical evidence shown in past studies implies that stringent land use regulation is costly for local business. For example, Kunce et al. (2002) reports significantly higher drilling cost of federal land and attributes this difference to stricter enforcement of land use regulation there than that in private land. [13] In his recent study, Nishida (2008) finds that zoning regulation has a significant impact on entry of convenience stores in Okinawa, Japan.

While no studies seems to contest the cost impacts of land use regulation, its impacts on the intensity of competition is still unclear. On one hand, stringent land use regulation seems to lead fewer entries by increasing the entry cost. On the other hand, however, Ridley et al. (2007) argues that stringent land use regulation intensifies the degree of competition by restricting retail stores' locations to some limited areas. [14] It should be noted that these two views on land use regulation do not conflict each other. While the former sees land

[13] The authors treated possible endogeneity of ownership by exploiting checkerboard structure of their data set. As a result of allocation process set by the Pacific Railway Acts, each section of privately-owned land in their dataset is surrounded by four sections of federal land, making the whole area looks a checkerboard. By comparing drilling costs of two adjacent lands, the authors managed to control unobserved characteristics specific to some areas.

[14] The authors also recgonized that this intensified competition does not necessarily increase welfare since consumers need to pay higher transportation cost to go to stores.

Table 2.1: Various Measures of Land Use Regulation Found in Literature

Type of Measures	Examples
Deductive Measures	
Presence of particular regulation	Glaeser and Ward (2006)
Subjective impressions of political pressure	Gyourko et al. (2008)
Number of administration processes needed to undergo	Gyourko et al. (2008)
Number of registered historical sites	Ihlanfeldt (2007)
Inductive Measures	
Markup of condominiums in Manhattan	Glaeser et al. (2005a)
Approved ratio of rezoning requests	Gyourko et al. (2008)
Permitted construction volume relative to city size	Kahn (2007)
Average time length to obtain building permits.	Gyourko et al. (2008)

use regulation as an admission uniformly charged to all stores in a market, the latter sees land use regulation (especially zoning) as a forbiddingly high admission charged to stores entering into particular areas.

2.4 Data

2.4.1 Texas Hotel Data

The main data source of this study, *Hotel Occupancy Tax Receipts,* is provided by the Texas Comptroller of Public Accounts.[15] 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. 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. The sample period of this data set is from the first quarter of 1990 through the last quarter of 2005. By exploiting the identification code that is unique and permanent for every hotel,

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

I construct an unbalanced panel data set. 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.

2.4.2 Measurement of Land Use Regulation

This study employs indices developed by Gyourko et al. (2008) as measures for the stringency of land use regulation.[16] Based on a written survey collected from 2,649 local governments in the U.S., Gyourko and his coauthors construct eleven subindices that measure the stringency of residential land use regulation from various angles. Among these indices, I use seven subindices that show considerable variations among the counties in my sample.[17] For all indices, large values imply stringent regulation. Table 2.2 shows the list of these indices and provides a brief description of each index. The precise definitions of these seven indices are found in Gyourko et al. (2008).[18]

2.4.3 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. To do so, I use road maps and websites of commercial airports,

[16] See section three for past efforts to measure the stringency of land use regulation.

[17] The subindices not used here due to their little variation between the counties in my sample are (1) a measure for state level political pressure, (2) a measure for the influence of state court, (3) the involvement of the local assembly in the implementation of land use regulation and (4) the presence of supply restriction.

[18] For some indices, the names used in this paper are slightly different from those used in the original paper for simplicity. These indices are Political Pressure (The Local Political Pressure Index), Zoning Approval (The Local Zoning Approval Index) and Project Approval (Local Project Approval Index). The names in parentheses are those used in Gyourko et al. (forthcoming).

Table 2.2: Description of Land Use Regulation Indices

Name	Description
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.
Zoning Approval	The number of local government bodies from which projects that request zoning change need to obtain approvals.
Project Approval	The number of local government bodies from which projects that request NO zoning change need to obtain approvals.
Density Restriction	Indicates if local governments have minimum lot size requirements of one acre or more.
Open Space	Indicates if developers have to provide open space for the public.
Exactions	Indicates if developers have to incur the cost of additional infrastructure attributable to their developments.
Approval Delay	The average number of months for which developers need to wait to obtain building permits before starting construction.

For the precise definitions of other indices, see Gyourko et.al. (forthcoming).

Table 2.3: Midscale Chain Hotels in Texas

Companies	Brands	# of Hotels
Best Western	Best Western	186
Cendant	Amerihost, Howard Johnson, Ramada	82
Choice Hotels	Clarion, Comfort Inn, Quality Inn, Sleep Inn	214
Hilton Hotels	Hampton Inn	69
InterContinental	Candlewood, Holiday Inn, Holiday Inn Express	174
La Quinta	Baymont Inn, La Quinta Inn	129
Marriott	Fair Field Inn, TownePlace Suites	52

The number of hotels listed is as of the first quarter in 2005. Baymont Inns were aquired by Cedant in 2006.

respectively. Rural land prices come from *Texas Rural Land Prices* and are provided by the Real Estate Center at Texas A&M University. Construction cost data comes from *Means Square Foot Costs* provided by RSMeans.

2.4.4 Market Definition

In the rest of this study, I limit my focus to local competition between midscale chain hotels. To determine midscale 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 seven major chains. Table 2.3 lists the names of these hotel chains, their midscale brands, and the number of midscale hotels in my sample as of the first quarter of 2005. These seven chains account for about 90 percent of the number of midscale 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.[19] For example, Expedia.com, an on-line travel agency, hits 103 options for a one night stay in Austin, Texas. These choices range from a room in a budget motel for $45 a night to a room in a luxury hotel

[19] Mazzeo (2002) finds that hotels tend to choose a category different from other hotels in the same market, indicating high substitution within segments.

for \$259. High grade hotels often provide restaurants, room service and fitness centers in addition to nicely decorated rooms. In contrast, low grade hotels, often called “no frill” hotels, merely provide clean and safe rooms for a low price. These two types of hotels belong to different segments and do not appear to compete against each other. Second, among the three segments of hotels (economy, midscale and upscale), the midscale segment is the largest category in terms of both the number of hotels and the number of rooms. Third, chain hotels have been the primary players in this industry. 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.[20] Independent hotels are generally considered to be in the economy segment, and because services of these other businesses are different from those of the midscale hotels, their presence should not be important for the business of midscale hotels.

For this study, I consider a county a single local market since more data is available at the county level and its shape is relatively uniform in Texas. From the 254 counties in Texas, I remove those that do not provide a land use regulation index and the flagship counties of the four largest MSAs.[21] I throw away the flagship counties in the four largest MSAs since each of these counties has too many hotels to believe that it forms a single market. After this screening, 60 counties remain. Figure 2.2 shows the geographical distribution of these 60 counties. In terms of population, these 60 counties are larger than those removed for lack of the indices[22] and smaller than the flagship counties of the four largest MSAs.

[20] 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 significant number of properties whose actual categories are unclear.

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

[22] The median population of counties in this sample is 77,100 and 65 percent of them belong to some MSAs while the median population of counties that fail to provide land use regulation indices is 10,970 and only 17 percent of them belong to some MSAs.

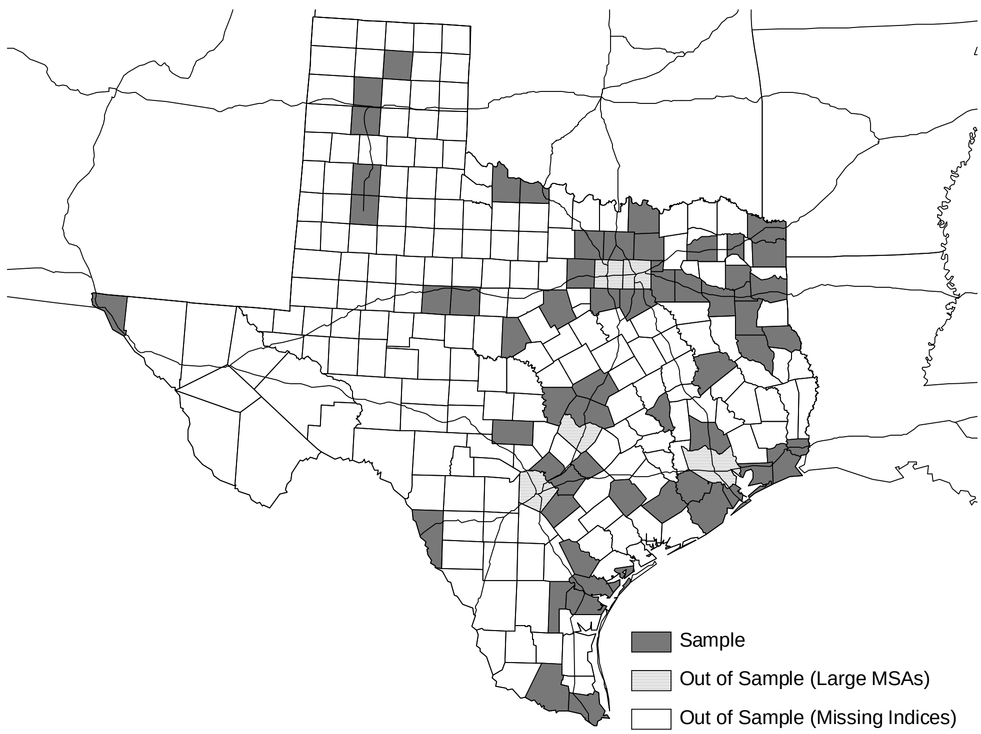

Figure 2.2: Geographical Representation of the Sample Coverage

2.4.5 Summary Statistics

Table 2.4 reports the summary statistics of variables that describe the 60 markets in my sample. The median market has four midscale chain hotels or 264 rooms, and earns about one million dollars for one quarter. These numbers imply that each hotel has 69 rooms and each of these rooms earns $39 for a night. Table 2.4 also shows a considerable size variation between the markets in my sample. In terms of population, the size of the market at the sample first quartile is more than four times larger than that of the market at the sample third quartile. More than half of the markets in this sample have access to an Interstate Highway and about one fifth of them have access to commercial airports.

Descriptive statistics of the land use regulation indices are not straightforward because of their lack of units. Instead, I observe the relationship between market size and these indices by constructing a correlation matrix shown in Table 2.5.[23] First, land use regulation tends to be more stringent in large markets. Out of the seven indices this paper uses, five of them show statistically significant positive correlation with population. Second, all three significant correlations between these seven subindices are positive, suggesting that local governments implement each individual policy according to certain underlying attitudes such as pro-development or pro-environment.

2.5 Reduced Form Analysis

This section examines an empirical relationship between the stringency of land use regulation and the entry decisions of the midscale hotel chains by estimating several reduced-form equilibrium quantity functions. Each regression differs in its dependent variable, which serves as a proxy for the equilibrium quantity. These proxies are the number of hotels, the total number of rooms, and total sales. The regressors consist of the land use regulation indices and various controls that characterize local markets. I use ordered logit for the number of hotels and ordinary least squares (OLS) for the total number of rooms and total

[23] 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 weights.

Table 2.4: Summary Statistics of Markets in the Sample

	Mean	Std.Dev.	P25	P50	P75
Midscale Hotels					
# of Hotels	6.62	6.02	2.00	4.00	11.00
# of Rooms	561.67	606.91	121.50	263.50	869.00
Quarterly Sales (in million)	2.23	2.68	.46	.94	3.15
Indices for Land Use Regulation					
Political Pressure	-.02	1.00	-.79	-.32	.56
Exactions	.83	.35	.91	1.00	1.00
Open Space	.44	.46	.00	.20	1.00
Approval Delay	3.11	1.86	1.67	2.68	3.90
Zoning Approval	2.11	.81	2.00	2.00	2.80
Project Approval	1.10	.77	.44	1.00	1.90
Density Restriction	.18	.35	.00	.00	.13
Other County Characteristics					
Population (in thousand)	147.28	173.16	36.38	77.10	173.45
Area (in sq mi)	849.18	260.10	755.91	901.50	958.33
Per Capita Income (in thousand)	27.41	5.15	24.76	26.54	30.12
# of Establishments (in thousand)	2.84	3.14	.73	1.35	4.05
Employments (in thousand)	41.15	49.17	8.08	17.90	63.50
MSA Dummy	.65	.48	.00	1.00	1.00
Airport Dummy	.22	.42	.00	.00	.00
Interstate Highway Dummy	.63	.49	.00	1.00	1.00
Construction Price Index	.78	.03	.76	.78	.80
Land Price (in thousand per acre)	2.52	1.48	1.50	2.11	3.49

N=60. All data are as of the first quarter of 2005. 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. (forthcoming). All other county data are from County Business Patterns, Regional Economics Information System, PSMeans and road maps. See Section 4 for details.

Table 2.5: Correlation Matrix between Market Size and Land Use Regulation Indices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) ln Population	1.000	.	.	.	.	.	.	.
(2) Political Pressure	.44**	1.00	.	.	.	.	.	.
(3) Exactions	.09	-.03	1.00	.	.	.	.	.
(4) Open Space	.36**	.35**	.21	1.00	.	.	.	.
(5) Approval Delay	.39**	.12	.10	.31**	1.00	.	.	.
(6) Zoning Approval	-.04	.03	-.06	.07	-.10	1.00	.	.
(7) Project Approval	.26**	.14	-.00	.30**	.16	-.11	1.00	.
(8) Density Restriction	.29**	.09	-.20	-.00	.13	-.15	.19	1.00

N=60. See Table 2 for the definitions of abbreviations of land use regulation indices. Correlation coefficients with ** and * are statistically significant at the five and ten percent level, respectively.

sales. For OLS estimation, I employ the robust standard errors to take into account the possible heteroskedasticity in error terms.

The effect of stringent land use regulation on the equilibrium quantity of local lodging markets is not obvious. According to my hypothesis, stringent land use regulation decreases *supply* of lodging services by increasing the entry 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, stringent land use regulation could increase local travel demand if it helps to maintain a particular local environment (e.g., nice views or clean water) that is attractive to either leisure travelers or certain industries. Therefore, under the standard supply-demand framework, stringent land use regulation decreases the equilibrium quantity when it decreases local travel demand. However, the effects of stringent regulation on the equilibrium quantity are indeterminate when it increases local travel demand.

Tables 2.6 and 2.7 report the estimates of these reduced-form equilibrium-quantity functions based on the data as of the first quarter of 2005. I estimate these regressions under various specifications to observe the change of estimates as more indices are added to the regressors. First, these reduced form functions fit the data quite well. The regression results show that the R^2 of the regressions are no less than .80 regardless of the specification.[24] Comparison between these results and the (suppressed) regression results using only control variables but no regulation indices imply that adding land use regulation indices to the regressors increases R^2 by one to four percent points. Second, the parameter estimates for most of these seven regulation indices are not statistically significant. One exception is the parameter estimates for the Project Approval index. The parameter estimates for this index are negative and statistically significant when the number of hotels or the number of rooms is used as the dependent variable. These regression results imply that an imaginary market whose characteristics are equal to the sample median values is expected to have 4.6 hotels or 324 rooms. When its Project Approval exogenously shifts to the sample first quartile level, the expected number of hotels and rooms in this market increases to 5.2 hotels and 362 rooms, respectively, due to lenient regulation. In contrast, if its Project Approval exogenously shifts to the sample third quartile level, these numbers decrease to 3.6 hotels and 272 rooms, respectively.

The results above suggest some impact of land use regulation on the entry decisions of the chain hotels. Nonetheless, these results do not suffice to verify my hypothesis that stringent land use regulation lessens local competition in local lodging markets by erecting a barrier to entry. Reduced form estimates do not tell if these observed correlations between the equilibrium quantity and the stringency of land use regulation come from either the demand side or the supply side. As discussed above, this negative correlation can be the consequence of demand decrease caused by stringent land use regulation and the supply side might have nothing to do with it. If this is the case, stringent land use regulation does not change the degree of local competition and no additional distortion is generated. However, if this observed negative correlation comes from the supply side, stringent land use regulation could be a source of distortion. To identify these two channels separately from the data, I need to rely on a model and estimate its structural parameters.

[24] For the ordered logit model, I use the generalized coefficient of determination proposed by Cox and Snell (1989).

Table 2.6: Ordered Logit Estimates

	Dep. Var. = Number of Midscale Hotels						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Political Pressure	-.177	-.218	-.221	-.328	-.322	-.306	-.316
	(.291)	(.292)	(.302)	(.320)	(.321)	(.329)	(.330)
Exactions	.	-.688	-.692	-.681	-.685	-1.306	-1.431
	.	(.887)	(.897)	(.928)	(.928)	(.949)	(.998)
Open Space	.	.	.024	.273	.227	.932	.930
	.	.	(.652)	(.680)	(.695)	(.743)	(.749)
Approval Delay	.	.	.	-.232	-.220	-.033	-.029
	.	.	.	(.205)	(.207)	(.203)	(.202)
Zoning Approval	.	.	.	.	.136	-.080	-.102
	.	.	.	.	(.363)	(.391)	(.395)
Project Approval	.	.	.	.	.	-1.562	-1.580
	.	.	.	.	.	(.466)	(.467)
Density Restriction	.	.	.	.	.	.	-.293
	.	.	.	.	.	.	(.842)
R-squared	.868	.869	.869	.872	.872	.892	.892

N=60. See Table 2 for the meaning of abbreviations for land use regulation indices. Standard errors are in parentheses. Estimates and standard errors for control variables are suppressed. Control variables include population, per capita income, the number of establishments, area, construction price index, rural land prices and dummy variables for MSA, access to commercial airports and Interstate Highway.

Table 2.7: OLS Estimates

	Dep. Var. = Logarithm of the Number of Rooms						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Political Pressure	-.013	-.017	.013	-.009	-.008	.014	.015
	(.052)	(.053)	(.058)	(.057)	(.057)	(.054)	(.054)
Exactions	.	-.092	-.050	-.071	-.074	-.079	-.066
	.	(.193)	(.189)	(.195)	(.188)	(.178)	(.184)
Open Space	.	.	-.301	-.269	-.265	-.209	-.204
	.	.	(.139)	(.151)	(.144)	(.144)	(.145)
Approval Delay	.	.	.	-.042	-.043	-.026	-.025
	.	.	.	(.051)	(.050)	(.056)	(.056)
Zoning Approval	.	.	.	.	-.024	-.044	-.042
	.	.	.	.	(.090)	(.079)	(.081)
Project Approval	.	.	.	.	.	-.193	-.195
	.	.	.	.	.	(.110)	(.109)
Density Restriction	.	.	.	.	.	.	.044
	.	.	.	.	.	.	(.146)
R-squared	.862	.863	.872	.874	.874	.884	.884

	Dep. Var. = Logarithm of Quarterly Sales						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Political Pressure	-.010	-.003	.026	.040	.041	.047	.048
	(.065)	(.069)	(.083)	(.089)	(.089)	(.087)	(.088)
Exactions	.	.179	.218	.232	.227	.226	.254
	.	(.337)	(.340)	(.342)	(.331)	(.331)	(.355)
Open Space	.	.	-.284	-.306	-.299	-.284	-.274
	.	.	(.274)	(.290)	(.281)	(.284)	(.277)
Approval Delay	.	.	.	.028	.027	.031	.032
	.	.	.	(.068)	(.067)	(.072)	(.072)
Zoning Approval	.	.	.	.	-.038	-.043	-.039
	.	.	.	.	(.096)	(.093)	(.093)
Project Approval	.	.	.	.	.	-.051	-.054
	.	.	.	.	.	(.127)	(.126)
Density Restriction	.	.	.	.	.	.	.095
	.	.	.	.	.	.	(.235)
R-squared	.802	.803	.810	.810	.811	.811	.812

N=60. See Table 2 for the meaning of abbreviations for land use regulation indices. Robust standard errors are in parentheses. Estimates and standard errors for control variables are suppressed. See Table 4 for the list of control variables.

2.6 The Dynamic Entry Model of Hotel Chains

In this section I construct an entry model where N hotel chains make their entry decisions to an isolated local market every period. At the beginning of every period, each chain simultaneously decides if it opens additional new hotels or closes its existing hotels, if any. While the closure of existing hotels does not incur any cost, opening new hotels does incur sunk cost. Rival chains' past and current entry decisions affect chain i's entry decision through their impacts on the revenue of hotels belonging to chain i.

2.6.1 State Space

Denote each chain by $i \in \{1, ..., N\}$ and each period by $t \in \{1, 2, .., \infty\}$. Each chain operates at most K hotels in a market. A *common* state at period t consists of (i) a vector of the number of hotels operated by each chain $h_t = (h_{1t,} h_{2t}, \ldots, h_{Nt}) \in \{0, 1, \ldots, K\}^N$ and (ii) a vector of market-specific characteristics (e.g., population) $x_t \in X \subset \mathbb{R}^L$. This common state is observable to both hotel chains and econometricians. Denote this common state variable by $s_t = (h_t, x_t) \in S \equiv \{0, 1, \ldots, K\}^N \times X$. In addition to these common state variables, chain i receives an i.i.d. cost shock v_{it} from its standard normal distribution function $\Phi(\cdot)$ at the beginning of every period. While the shape of the distribution function $\Phi(\cdot)$ is common and known to all players, realized cost shocks v_{it} is private and only observable to chain i.

2.6.2 Choice Space

At the beginning of every period, each chain simultaneously chooses the number of hotels it *additionally* 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 additional opening while negative a_{it} indicates the closure of existing hotels. I assume that entry/exit decisions made at period t are realized in the next period, hence $h_{it+1} = h_{it} + a_{it}$ holds. I also assume that hotel chains do not open or close more than two hotels in the same period.[25] Since the resulting number of hotels after this change still has to be an element of $\{0, 1, \ldots, K\}$, chain i's choice set is a function of the number of hotels it currently operates, h_{it}, and is written as,

$$A_{it}(h_t) = \begin{cases} \{ \quad\quad\quad\quad 0, \; 1, \; 2 \; \} & \text{if } h_{it} = 0 \\ \{ \quad\quad -1, \; 0, \; 1, \; 2 \; \} & \text{if } h_{it} = 1 \\ \{ \; -2, \; -1, \; 0, \; 1, \; 2 \; \} & \text{if } h_{it} \in \{2, 3, .., K-2\} \\ \{ \; -2, \; -1, \; 0, \; 1 \quad \} & \text{if } h_{it} = K-1 \\ \{ \; -2, \; -1, \; 0 \quad\quad \} & \text{if } h_{it} = K. \end{cases}$$

2.6.3 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 and the sunk entry cost of opening additional hotels. Let δ_i denote the cost of operating a hotel for one period while the sunk entry cost of opening additional one hotel is equal to $e_i + \rho_i \upsilon_{it}$. Since υ_{it} is an i.i.d. draw from the standard normal distribution, chain i's sunk entry cost is a random variable drawn from the normal distribution $N(e_i, \rho_i)$.

Given the current state (s_t, υ_{it}) and its entry/exit decision $a_{it} \in A_{it}(h_t)$, chain i's choice-specific period profit is written as:

$$\pi_i(a_{it}, s_t, \upsilon_{it}) = ER_i(s_t) - \delta_i h_{it} - (e_i + \rho_i \upsilon_{it}) 1(a_{it} > 0) a_{it}. \tag{2.1}$$

where $ER_i(s_t)$, represents the expected revenue of chain i from its current operation of h_{it} hotels. Since this period profit function is linear with respect to the structural cost parameters, we can rewrite this function as the product of two vectors,

$$\pi_i(a_{it}, s_t, \upsilon_{it}) = \Psi(a_{it}, s_t, \upsilon_{it})' \theta_i,$$

where

[25] This assumption is not restrictive. In my data set, no hotel chain opens/closes more than two hotels in one quarter, a unit of a period used in my estimation part.

$$
\begin{aligned}
\Psi\left(a_{it}, s_t, \upsilon_{it}\right) &= \left[R_i\left(s_t\right), -h_{it}, -1\left(a_{it}>0\right) a_{it}, -1\left(a_{it}>0\right) a_{it}\upsilon_{it}\right] \\
\theta_i &= \left[1, \delta_i, e_i, \rho_i\right].
\end{aligned}
$$

As shown in the estimation part, this linearity significantly reduces the computational burden of my estimation.

2.6.4 Transition of State Variables

I assume that the evolution of market-specific characteristics x_t is a Markov process. I assume that x_t is weakly exogenous. Namely, x_t is independent of $\{h_\tau\}_{\tau=0}^{\infty}$ while the opposite is not necessarily true. Let $P\left(s'|s,a\right): S \times S \times A \to [0,1]$ denote the evolution of the common state variables s where $A = \{-2,-1,0,1,2\}$. Note that $P\left(s'|s,a\right) = 0$ for $a \notin A\left(s\right)$.

2.6.5 Markov Perfect Equilibrium

I assume that chains' entry decisions are characterized by a Markov strategy $\sigma_i\left(s, \upsilon_i\right): S \times \mathbb{R} \to A$. When all chains follow their own Markov strategies, chain i's discounted sum of expected profits at time t is:

$$
\begin{aligned}
V_i\left(s_t;\sigma\right) &= E_\upsilon\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t}\Psi_i\left(\sigma_i\left(s_\tau, \upsilon_{i\tau}\right), s_\tau, \upsilon_{i\tau}\right)\theta_i\right] \\
&= W_i\left(s;\sigma\right)\theta_i
\end{aligned}
$$

where $\beta \in (0,1)$ is a discount factor common to all chains, $\sigma\left(s,\upsilon\right) = \{\sigma_1\left(s,\upsilon\right), \ldots, \sigma_N\left(s,\upsilon\right)\}$ and $W_i\left(s;\sigma\right) = E_\upsilon\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Psi_i\left(\sigma_i\left(s_\tau,\upsilon_{i\tau}\right), s_\tau, \upsilon_{i\tau}\right)\right]$.

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

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

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

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

2.7 Estimation

I estimate the model proposed in the previous section by employing the estimation method proposed by Bajari et al. (2007). In the first stage, I separately estimate hotel chains' reduced-form policy functions, transition functions and hotel-level revenue functions. In the second stage, I attempt to find the structural cost parameters that most rationalizes the observed policy 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.

2.7.1 First Stage

Hotel-level Revenue Function

I assume that the revenue function of the kth hotel belonging to chain i at period t takes the following form:

$$\ln r_{ikt}\left(s_t\right) = \gamma_i + \eta_1 + x_t'\eta_2 - \eta_3 \ln\left(\Sigma_j h_{jt}\right) - \eta_4 \ln h_{it} + \epsilon_{ikt}, \tag{2.2}$$

where r_{ikt} is a hotel-level revenue, γ_i is a chain dummy, η_1 is a market dummy and ϵ_{ikt} is an i.i.d. draw from the normal distribution. The revenue impacts of the presence of other hotels in the same market appear in the fourth and the fifth term of this revenue function. While the fourth term uses the total number of hotels regardless of their brands as a proxy of the intensity of competition, the fifth term use the number of hotels belonging to the same chain. I include this additional term to explicitly take into account the possible higher substitution between hotels belonging to the same chain. I estimate this function by using OLS.

One obvious concern here is the endogeneity of the number of hotels h_{jt}. When h_{jt} is correlated with an error term ϵ_{ikt}, OLS provides inconsistent estimates. This could happen, for example, when hotel chains make their entry decisions after observing the current ϵ_{ikt}

or when the current ϵ_{ikt} is correlated with ϵ_{ikt-1} and ϵ_{ikt-1} affected hotel chains' entry decisions h_{jt}. Here the consistency of my OLS estimates depends on the following two assumptions. First, I assume that hotel chains determine h_{it} before they observe current shocks ϵ_{ikt}. This assumption is consistent with the timing of entry decisions specified by the entry model. Second, I also assume that all unobservable market-specific characteristics are time-invariant. Under this assumption, the error term ϵ_{ikt} does not reflect any shock in the past since market-specific dummy variable takes care of the impacts of time-invariant unobservable factors.

Policy Function

I estimate the following ordered logit model to characterize hotel chains' entry/exit policies:

$$a_{it} = \begin{cases} -2 & \text{if } y^*_{it} \in (-\infty, \bar{a}_{-2}] \text{ \& } h_{it} \geq 2 \\ -1 & \text{if } y^*_{it} \in (\bar{a}_{-2}, \bar{a}_{-1}] \text{ \& } h_{it} \geq 1 \text{ or } y^* \in (-\infty, \bar{a}_{-2}] \text{ \& } h_{it} \in \{0,1\} \\ 0 & \begin{array}{l} \text{if } y^*_{it} \in (\bar{a}_{-1}, \bar{a}_1] \text{ or } a^* \in (\bar{a}_1, \infty] \text{ \&} \\ h_{it} = K or y^* \in (-\infty, \bar{a}_{-1}] \& h_{it} = 0 \end{array} \\ 1 & \text{if } y^*_{it} \in (\bar{a}_1, \bar{a}_2] \text{ \& } h_{it} \leq K-1 \text{ or } y^* \in (\bar{a}_2, \infty) \text{ \& } h_{it} = K-1 \\ 2 & \text{if } y^*_{it} \in (\bar{a}_2, \infty] \text{ \& } h_{it} + 2 \leq K \end{cases} \tag{2.3}$$

$$y^*_{it} = \alpha_1 + \alpha_2 x_t - \alpha_3 h_{it} - \alpha_4 \left(\Sigma_{j \neq i} h_{jt}\right) + \omega_{it}, \tag{2.4}$$

where y^*_{it} is a latent variable, $\{\bar{\alpha}_l\}_{l \in \{-2,-1,1,2\}}$ is threshold parameters, ω_{it} is an i.i.d. draw from the Type I extreme-value distribution.

One interpretation of this reduced-form policy function is to consider y^*_{it} as an index of "residual demand" new hotels would face had they opened. Large value of this index implies markets can accommodate more hotels while its small value implies markets cannot even accommodate existing hotels.

Transition Function

I include the following three variables: (1) population, (2) the number of establishments and (3) state-level sales of midscale hotels into x. I estimate their transition functions by running AR1 regressions.

2.7.2 Second Stage

In the second stage, I attempt to find values of chain i's cost parameters $\{\delta_i, e_i, \rho_i\}$ that makes the observed policy the most profitable choice among other possible policies.

Forward Simulations

I first generate many alternative policies that slightly deviates from chain i's observed policy. Next, by forward simulation, I approximate chain i's discounted sum of expected profits in the following two situations: (1) when all chains follow the observed policy; and (2) when chain i follows one of the alternative policies while its rival chains follow the observed ones. To be specific, I follow the steps below to implement this idea:

1. Fix a market and a hotel chain i.

2. Generate a set of chain i's alternative policies by slightly perturbing the observed policy function specified in eq (2.3) and (2.4). I implement this idea by adding a normal random variable to each parameter estimate of the policy function obtained in the first stage[26]. Let $\{\sigma_i^m\}_{m=1}^{NI}$ denote a set of such alternative policies for chain i. For notational convenience, let σ_i^0 denote chain i's *observed* policy.

3. Let n denote an index of the forward simulation. At the beginning of nth simulation, generate a simulated series of market-specific time-varying variables x_t for T periods by using the estimates obtained in the first stage. Denote this series as $\{\tilde{x}_\tau^n\}_{\tau=0}^T$. For $\tilde{x}_0^n$, use the corresponding value in the raw data at the initial period.

[26] When this perturbation changes the order of the thresholds $\{\bar{a}_{-2}, \bar{a}_{-1}, \bar{a}_1, \bar{a}_2\}$, I interchange these values so that the order of these thresholds are maintained.

4. Simulate the entry decisions of all hotel chains for T periods when chain i follows σ_i^m while its rivals follow the observed policy σ_{-i}^0.

   (a) Calculate chain i's revenue, $\tilde{R}_{it}^{m,n}$, by using the first stage estimates and a vector of simulated state variables $\tilde{s}_t^n = \left(\tilde{h}_t^n, \tilde{x}_t^n\right)$. For $\tilde{h}_0^n$, use the corresponding value in the raw data at the initial period.

   (b) For each chain, generate a uniform random draw from $[0, 1]$ and pin down its resulting entry decision, $\tilde{a}_{it}^{m,n}$, according to its corresponding policy.

   (c) Backout $\tilde{v}_{it}^{m,n}$ by imposing the generated uniform draw to the inverse CDF of the standard normal distribution.

   (d) Iterate this process for all $m \in \{0, 1 \ldots, NI\}$. Note that chain i follows the observed policy when $m = 0$.

5. Iterate step 3 and 4 for NS times and calculate

$$\tilde{W}_i\left(\sigma_i^m, \sigma_{-i}^0\right) = \frac{1}{NS}\sum_{n=1}^{NS}\sum_{t=0}^{T}\beta^t \begin{bmatrix} \tilde{R}_{it}^{m,n}, -\tilde{h}_{it}^{m,n}, -1\left(\tilde{a}_{it}^{m,n} > 0\right)\tilde{a}_{it}^{m,n}, \\ -1\left(\tilde{a}_{it}^{m,n} > 0\right)\tilde{a}_{it}^{m,n}\tilde{v}_{it}^{m,n} \end{bmatrix}.$$

Recovering Cost Parameters

Based on the outcome of the forward simulations, I evaluate the superiority of the observed policy to the alternative policies for a set of parameters θ, based on the following loss function:

$$\frac{1}{NI}\sum_{m=1}^{NI}\left(\min\left\{g_m(\theta), 0\right\}\right)^2$$
$$\text{where } g_m(\theta) = \left\{\tilde{W}_i\left(\sigma_i^0, \sigma_{-i}^0\right) - \tilde{W}_i\left(\sigma_i^m, \sigma_{-i}^0\right)\right\}\theta.$$

This loss function evaluates to what extent an alternative policy brings more profit to chain i than the observed policy when its rivals follow their own observed policies. If the observed policy σ_i^0 brings more profit than an alternative one σ_i^m for a given θ, we have

$\min\{g_m(\theta), 0\} = 0$. In contrast, when the opposite is true, we have $\min\{g_m(\theta), 0\} = g_m(\theta)$.

Finally I define cost parameter estimates as the one that minimizes this loss function subject to nonnegative constraints:

$$\theta^* = \arg\min_{\theta \in R^3_+} \frac{1}{NI} \sum_{m=1}^{NI} \left(\min\{g_m(\theta), 0\}\right)^2.$$

One thing worth mentioning here is that the linearity of the period profit function significantly reduces the computational burden of the estimation of this model. Without this linearity assumption, I have to conduct forward simulations to evaluate the loss function for each possible θ, which is computationally infeasible.

2.7.3 Third Stage

The last step aims to infer the impacts of the stringency of land use regulation on the market average of structural cost parameters $\tilde{\theta}_j = \frac{1}{7}\Sigma_i \tilde{\theta}_{ij}$. I assume that these market-specific cost are exponential functions of land use regulation indices (w_{1j}), other observable market-specific cost factors (w_{2j}) and an unobservable market-specific cost factor (ξ_j):

$$\ln \theta_j = w'_{1j}\alpha^C_1 + w'_{2j}\alpha^C_2 + \xi_j. \tag{2.5}$$

Note that θ_j is a vector, and hence α^C_1 and α^C_2 are matrices.

Although this regression approach is straightforward, its obvious caveat is possible inconsistent estimates due to endogeneity of land use regulation w_{1m}.[27] On one hand, land use regulation might increase market-specific cost. Yet on the other hand, local authorities in markets with a high market-specific cost might have some incentive to loosen land use regulation to attract more business. This is the classic simultaneity problem causing OLS

[27] McMillen and McDonald (1991a) and McMillen and McDonald (1991b) examine 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.

estimates to be inconsistent. A conventional reaction to this problem is the use of instruments. However, it is unlikely to find reasonable instruments that exogenously shift the stringency of land use regulation but not market-specific cost.

For that reason, this paper instead examines whether the OLS estimates are consistent with the results of other estimators that do not presume exogenous regulation. I employ the bound estimator developed by Manski (1997) for this purpose. One notable feature of this estimator is that its consistency only requires the market-specific cost function to be an increasing function of the stringency of regulation. Therefore, its consistency is maintained even when regulation is endogenous.

Consider a population of markets that choose certain stringency of regulation, $\tilde{w}_1$, but differ in their market-specific cost factors other than regulation. For given cost level $\bar{\theta}$, Manski's bound estimator provides an estimate of an upper bound $\bar{p}\left(\tilde{w}, \bar{\theta}\right)$ and a lower bound $\underline{p}\left(\tilde{w}, \bar{\theta}\right)$ in which $\Pr(\theta < \bar{\theta}|\tilde{w}_1)$ falls. Namely, these two functions satisfy,

$$\underline{p}\left(\tilde{w}_1, \bar{\theta}\right) < \Pr(\theta < \bar{\theta}|\tilde{w}_1) < \bar{p}\left(\tilde{w}_1, \bar{\theta}\right). \tag{2.6}$$

On the other hand, the OLS estimates also provide a point estimate of $\Pr(\theta < \bar{\theta}|\tilde{w}_1)$ by assuming the distribution of ξ_m is normal. When the OLS estimates are immune from the simultaneous problem, an estimate of $\Pr(\theta < \bar{\theta}|\tilde{w}_1)$ should fall in the bound defined in (2.6), ignoring the sampling error. Although it is not a formal statistical hypothesis test, this comparison at least helps to examine the robustness of the OLS estimates.

Intuition of Manski's bound estimator is straightforward. Let $\tilde{w}_1$ and $\bar{\theta}$ as given. The monotonicity assumption implies that when the target regulation $\tilde{w}_1$ becomes more (less) stringent than the observed level w_{1m}, we can at least infer that its market-specific cost under $\tilde{w}_1$ would be no less (more) than the observed level θ_m,

$$\begin{cases} \theta_m > \bar{\theta} \\ w_{1m} \leq \tilde{w}_1 \end{cases} \implies g\left(\tilde{w}_1, w_{2m}, \xi_m\right) > \bar{\theta}, \tag{2.7}$$

$$\begin{cases} \theta_m \leq \bar{\theta} \\ w_{1m} > \tilde{w}_1 \end{cases} \implies g\left(\tilde{w}_1, w_{2m}, \xi_m\right) \leq \bar{\theta}. \tag{2.8}$$

Using this inference, we can estimate $\widehat{\overline{p}}\left(\bar{\theta}|\tilde{w}_1\right)$ and $\widehat{\underline{p}}\left(\bar{\theta}|\tilde{w}_1\right)$ from the fractions of samples satisfying (2.7) and (2.8) as shown below:

$$\begin{aligned} \widehat{\overline{p}}\left(\bar{\theta}|\tilde{w}_1\right) &= 1 - \frac{1}{M}\sum_m 1(\theta_m > \bar{\theta}, w_{1m} \leq \tilde{w}_1), \\ \widehat{\underline{p}}\left(\bar{\theta}|\tilde{w}_1\right) &= \frac{1}{M}\sum_m 1(\theta_m \leq \bar{\theta}, w_{1m} > \tilde{w}_1). \end{aligned}$$

2.8 Results

2.8.1 First Stage

Policy Function

Table 2.8 shows estimation results of the policy function specified in eq (2.3) and (2.4). I employ the ordered logit to estimate this 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. Table 2.8 reports the estimation results of this policy function under the two different specifications.

First, the estimation results indicate the clear tendency that hotel chains are less likely to open additional hotels in which they have already operated some. Second, including market dummy variables into regressors are vital to properly characterize the policy functions. As shown in the first and second rows of Table 2.8, 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

Table 2.8: Policy Function Estimates

	(1)	(2)
# of Hotels	.092	-.242
	(.042)	(.093)
(# of Hotels)^2	-.003	.007
	(.002)	(.004)
# of Hotels under the Same Chain	-.426	-.399
	(.124)	(.118)
(# of Hotels under the Same Chain)^2	-.046	-.053
	(.025)	(.024)
Population	-.126	.961
	(.239)	(1.448)
Establishments	.814	1.038
	(.294)	(1.601)
Sales	.948	1.789
	(.306)	(.284)
Log Likelihood	-2882.314	-2843.782
Market Dummy	No	Yes

N=26,460. Standard erros are in parentheses. Population, establishments and sales are in log. Estimates and standard errors for market dummies, chain dummies and thresholds are suppressed. Likelihood fucnctions explicitly take into account the constraint that no closure is possible when hotel chains operate no hotels.

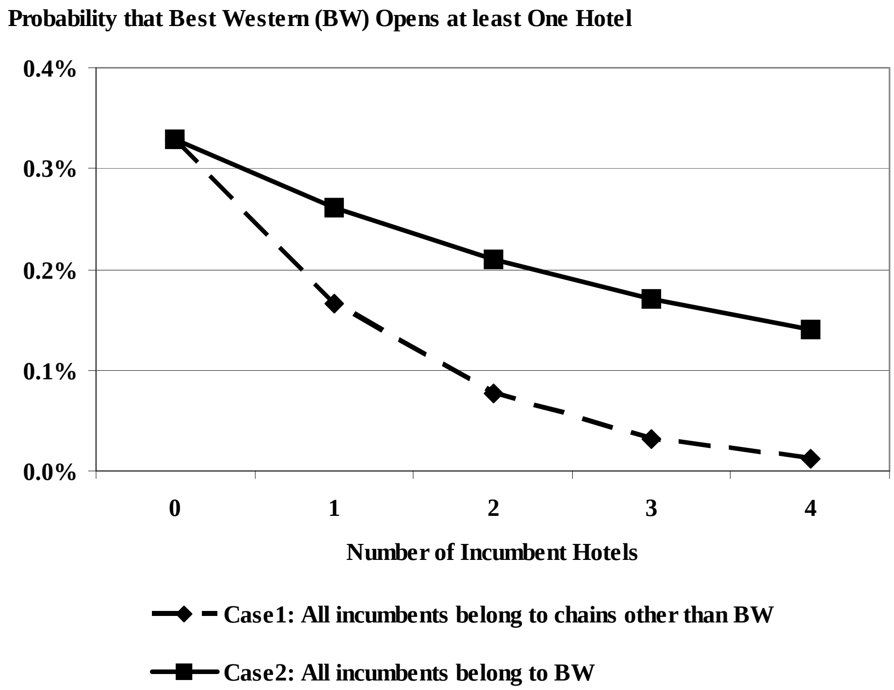

Figure 2.3: Impacts of the Number of Incumbent Hotels on Best Western's Entry Decision

establishments) are not sufficient to characterize the demand size of local markets.

Figure 2.3 shows the change in the predicted probability that a particular chain (Best Western) opens additional hotels in reaction to an increase in the number of incumbents in a market.[28] I construct this figure to provide more intuition of policy function estimates since the parameter estimates in the table merely represent marginal impacts on the latent variable. The figure considers two extreme cases: (i) when all incumbents belong to some chains other than Best Western and (ii) when all incumbents belong to Best Western. When there are no incumbents in this market, my estimates indicate that the probability that Best Western opens new hotel(s) in a quarter are 0.33 percent. As the number of incumbents increases to four, this probability decreases to 0.14 percent in the former case and 0.01 percent in the latter case.

To check the relevance of the specification of the error term, I also estimate the function

[28] This figure uses the data of Denton county, located in the suburb of Dalls-Fort Worth MSA, in the first quarter of 2000. The population of this market is equal to the sample median in this period.

by the ordered probit. Comparison between these two specifications show little quantitative difference in terms of their predicted probability. For my main results, I use the estimation results of the ordered logit using market dummy variables.

Revenue Function

Table 2.9 shows estimation results of the revenue function specified in eq (2.2). 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 to see the empirical relevance of imposing market-specific dummy variables.

First, my estimation results shows that imposing market-specific dummy variables significantly changes some of my parameter estimates. In particular, the parameter estimate for the number of rival hotels (the first row) changes from -.076 to -.386. These results imply that ignoring market-specific unobservable factors lead to inconsistent parameter estimates. For further analysis, I use the parameter estimates based on the specification using market dummy variables. Second, my estimation results indicate that the presence of rival 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. Figure 2.4 visibly illustrates the implication of these results by showing how the revenue of a hotel decreases as it faces more rival hotels. 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 hotel chains and (2) when the hotel and all of its rival hotels belong to the same chain. My estimation results imply that when a hotel competes with one hotel (i.e., duopoly), its revenue is 24 percent lower than its revenue under the monopoly when its rival hotel belongs to different chains. However, when its rival hotel belongs to the same chain, its revenue decreases by 35 percent.[29]

[29] Some might wonder why more intense competition due to the change from monopoly to duopoly does not decrease the revenue of a hotel more than 50 percent. This conjecture is not necessarily true in my

Table 2.9: Revenue Function Estimates

	(1)	(2)
# of Hotels	-.076	-.386
	(.023)	(.025)
# of Hotels under the Same Chain	-.217	-.228
	(.019)	(.018)
Population	-.496	-.061
	(.041)	(.148)
Establishments	.856	.271
	(.045)	(.121)
Sales	-.052	.452
	(.040)	(.039)
Market Dummy	No	Yes
R-squared	.997	.998

N=15,482. Cluster standard erros are in parentheses. Each cluster is market and time period specific. Population, establishments and sales are in log. Estimates and standard errors for market dummies, chain dummies and quarter dummies are suppressed.

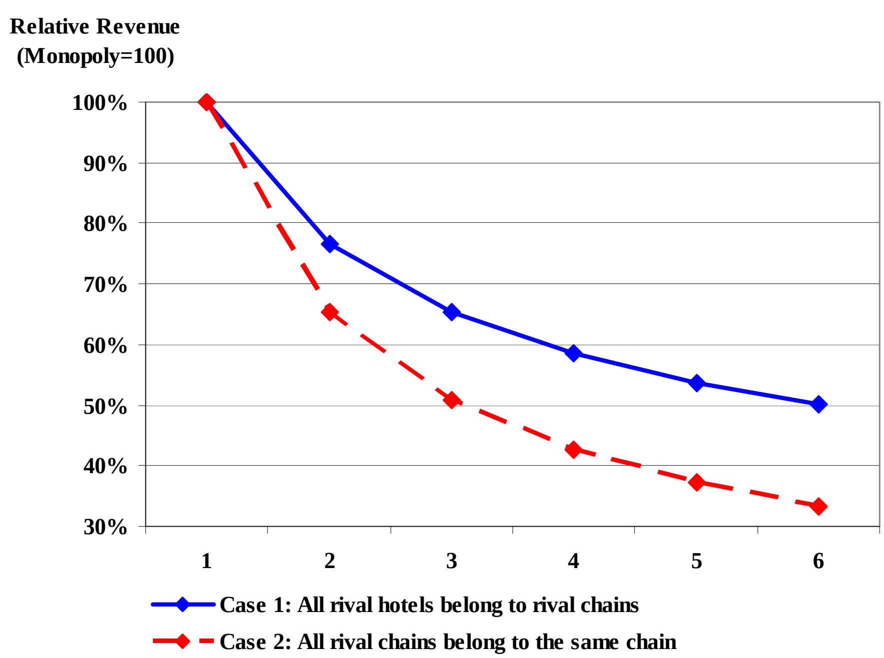

Figure 2.4: Revenue Impacts of Rival Hotels

Table 2.10: Transition Function Estimates

	Dependent Variables		
	Sales	Establishments	Population
Lagged Dep. Var.	.992	1.005	1.002
	(.020)	(.001)	(.002)
Constant	.	.013	.022
	.	(.001)	(.005)
Quarter Dummy			
Q1	.076		
	(.114)		
Q2	.170		
	(.114)		
Q3	.045		
	(.117)		
Q4	-.052		
	(.117)		

N=64 for sales and 1020 for establishments and population. Standard erros are in parentheses. All dependent variables are in log.

Transition Function

Table 2.10 reports estimation results of the transition functions for state-level sales, market-level establishments and population. Quarterly data are available for state sales while it is not the case for the other two. Estimates of quarterly dummy variables verify that strong seasonal demand in summer (second quarter) and weak seasonal demand in winter (fourth quarter).

2.8.2 Second Stage

The second stage estimation provides a vector of structural cost parameter estimates for each chain-market pair; $\theta_{ij} = \left(\delta_{ij}, e_{ij}, \rho_{ij}\right)$ where j is an index for market $j \in \{1, 2, \ldots, J\}$.

setting that 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.

I describe these estimates from two different angles: its market average $\tilde{\theta}_j = \frac{1}{7}\Sigma_j \tilde{\theta}_{ij}$ and its chain-specific average $\tilde{\theta}_i = \frac{1}{J}\Sigma_j \tilde{\theta}_{ij}$.

Table 2.11 reports descriptive statistics for the distribution of market average cost, $\tilde{\theta}_j$. In a hypothetical market whose cost parameters are equal to the sample average, a hotel chain incurs 177 thousand dollars for every quarter to operate a hotel and incur more than three milliion dollars to open a new hotel. My estimates also indicate that the values of cost parameters significantly vary across markets. Comparison between the market at the first quartile and the one at the third quartile implies that hotel chains need to pay about 50 percent more in the former to operate a hotel for one quarter. Parameter estimates for the distribution of sunk entry costs show similar significant difference across markets.

Table 2.12 reports the chain-specific average of cost parameter estimates, $\tilde{\theta}_i$ and the median of the number of rooms. These results clearly indicate that the cost structure of each hotel chain is significantly different. For example, the operation cost Inter-Continental incurs is 86 percent higher than that of Best Western. Capacity difference explains a part of this difference. The median number of rooms of a hotel is 80 for Inter-Continental while the corresponding number is 61 for Best Western. The difference not explained by this capacity difference may reflect possible quality difference between chains such as the availability of free breakfast or business centers.

I next examine the relevance of these estimates by comparing with cost data provided by industrial source. In particular, I am looking at the estimate for Best Western and La Quinta since their company websites provide detailed information about their construction guidelines. According to my calculation, construction cost of a new Best Western hotel is about 2.4 million dollars while my point estimate for its sunk entry cost is 2.9 million dollars. For La Quinta, its construction cost is 4.5 million dollars while my point estimate is 4.8 million dollars. See an appendix for the details of how I calculate these numbers.

Table 2.11: Summary Statistics of the Market-Average Cost Parameter Estimates

	Operating Cost (δ)	Sunk Entry Cost Mean (e)	Sunk Entry Cost Std. Dev. (ρ)
Mean	176.6	3041.8	1298.0
Std. Dev.	56.7	1084.0	472.8
P25	145.5	2286.3	964.5
P50	172.9	2939.6	1296.3
P75	214.1	3825.8	1618.4

N=56. All statistics are in thousand dollars.

Table 2.12: Average Cost Parameter Estimates: By Chain

	Operating Cost (δ)	Sunk Entry Cost Mean (e)	Sunk Entry Cost Std. Dev. (ρ)	Median Number of Rooms
Best Western	141.1	2,890.7	1,304.9	61
Cendant	110.8	1,912.5	746.7	85
Choice Hotels	112.3	2,305.4	1,009.5	60
Hilton	177.6	2,628.9	981.9	69
Inter-Continental	260.7	5,025.8	2,285.4	80
La Quinta	300.7	4,788.6	2,133.4	114
Marriott	132.9	1,740.8	624.0	72

Operating cost and sunk entry cost are in thousand dollars. Operating cost expresses the amount of cost a hotel incurs for its three-month operation.

2.8.3 Third Stage: Cost Function Regression

OLS Estimates

Table 2.13 and Table 2.14 report the OLS estimates[30] of the market-specific cost function (2.5) under various specifications. While Table 2.13 shows the impact of land use regulation on the market-specific operation cost δ_j, Table 2.14 shows its impact on the shape of the sunk-entry-cost distribution, e_j and ρ_j.

These regression results indicate that stringent regulation increases operation cost and the mean of the sunk entry cost. Moreover, Table 2.14 indicates that the stringent regulation also increases the volatility of sunk entry cost. Among the seven indices that attempt to capture the stringency of land use regulation, my regression results indicate that Local Political Pressure Index is the most important index for its statistically significance and its quantitative impacts on the cost. First, my OLS estimates for the coefficients of this index are statistically significant at five percent level regardless of the choice of dependent variables and regressors and their signs are consistent with the claim that stringent regulation increases the cost. Second, the parameter estimates for this index imply that the increase of this index from its sample first quartile level to its sample median level increases the level of the market-specific operating cost, the mean of the sunk entry cost and the standard deviation of the sunk entry cost (normalized by the mean sunk-entry cost) by 21 percent, 19 percent and 36 percent, respectively. Other indices worth mentioning include Exactions Index and Density Restriction Index. While coefficients for Exactions Index are statistically significant for shaping the distribution of the sunk entry cost (but not operating cost), its quantitative impact is much smaller than that of the Political Pressure Index. Increase in this index from the first quartile to the third quartile increases the mean of the distribution of the sunk entry cost by three percent and its standard deviation by five percent. In contrast, coefficients for Density Index is statistically significant for the level of operation cost.

[30] One might suggest to estimate these regressions at once by employing seemingly unrelated regressions (SUR) instead of OLS. In this case, however, SUR and OLS provide the same parameter estimates since all equations share the same regressors. See Ruud (2000) for more details.

Table 2.13: OLS Estimates of Regulation Impacts on Operation Cost

	Dep. Var. = Log of Operation Cost							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const. Cost	1.172	.560	-.010	.130	.193	.220	.003	-.023
	(.905)	(1.000)	(1.052)	(1.033)	(1.071)	(1.048)	(1.055)	(1.037)
Political Press	.	.145	.137	.140	.142	.143	.138	.135
	.	(.052)	(.049)	(.048)	(.048)	(.049)	(.046)	(.045)
Density Rest	.	.	.285	.329	.333	.320	.287	.289
	.	.	(.131)	(.148)	(.153)	(.162)	(.143)	(.141)
Exactions	.	.	.	.261	.268	.261	.258	.252
	.	.	.	(.167)	(.176)	(.181)	(.166)	(.167)
Aprvl Delay	.	.	.	.	-.008	-.009	-.013	-.014
	.	.	.	.	(.027)	(.027)	(.026)	(.028)
Zoning Aprvl	.	.	.	.	.	-.034	-.028	-.029
	.	.	.	.	.	(.058)	(.058)	(.059)
Project Aprvl	.	.	.	.	.	.	.098	.093
	.	.	.	.	.	.	(.061)	(.061)
Open Space	.	.	.	.	.	.	.	.026
	.	.	.	.	.	.	.	(.098)
R-squared	.019	.143	.206	.266	.267	.273	.307	.308

N=56. Robust standard errors are in parentheses.

Table 2.14: OLS Estimates of Regulation Impacts on the Distribution of Sunk Entry Cost

	Dep. Var. = Log of the Mean of Sunk Entry Cost							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const. Cost	1.002	.538	.503	.667	1.070	1.118	1.108	1.127
	(1.222)	(1.236)	(1.260)	(1.225)	(1.163)	(1.147)	(1.156)	(1.193)
Political Press	.	.102	.102	.105	.117	.120	.119	.121
	.	(.051)	(.050)	(.050)	(.047)	(.047)	(.047)	(.048)
Density Rest	.	.	.017	.069	.090	.067	.066	.064
	.	.	(.111)	(.128)	(.129)	(.127)	(.128)	(.130)
Exactions	.	.	.	.303	.346	.335	.335	.339
	.	.	.	(.144)	(.132)	(.137)	(.136)	(.136)
Aprvl Delay	.	.	.	.	-.050	-.052	-.053	-.051
	.	.	.	.	(.026)	(.027)	(.027)	(.028)
Zoning Aprvl	.	.	.	.	.	-.061	-.061	-.059
	.	.	.	.	.	(.054)	(.055)	(.056)
Project Aprvl	.	.	.	.	.	.	.004	.007
	.	.	.	.	.	.	(.067)	(.067)
Open Space	.	.	.	.	.	.	.	-.019
	.	.	.	.	.	.	.	(.115)
R-squared	.012	.078	.078	.151	.204	.220	.220	.220

	Dep. Var. = Log of the Standard Deviation of Sunk Entry Cost							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const. Cost	.939	.367	.167	.360	.735	.793	.839	.857
	(1.278)	(1.280)	(1.318)	(1.276)	(1.265)	(1.242)	(1.263)	(1.288)
Political Press	.	.117	.115	.118	.128	.132	.133	.134
	.	(.048)	(.046)	(.045)	(.043)	(.042)	(.043)	(.044)
Density Rest	.	.	.100	.161	.181	.153	.160	.158
	.	.	(.104)	(.120)	(.125)	(.122)	(.127)	(.129)
Exactions	.	.	.	.359	.399	.385	.386	.390
	.	.	.	(.136)	(.127)	(.130)	(.130)	(.131)
Aprvl Delay	.	.	.	.	-.047	-.049	-.049	-.047
	.	.	.	.	(.028)	(.028)	(.028)	(.029)
Zoning Aprvl	.	.	.	.	.	-.074	-.075	-.074
	.	.	.	.	.	(.053)	(.053)	(.055)
Project Aprvl	.	.	.	.	.	.	-.020	-.017
	.	.	.	.	.	.	(.074)	(.075)
Open Space	.	.	.	.	.	.	.	-.019
	.	.	.	.	.	.	.	(.120)
R-squared	.010	.098	.104	.196	.237	.257	.258	.258

N=56. Robust standard errors are in parentheses.

Robustness Check by Manski's Bound Estimator

Figure 2.5 presents predicted change in the probability that each cost parameter is below its sample median value as regulation becomes more stringent. I use the Political Pressure Index as a measure of the stringency of regulation since the previous regression results indicate that the change in this index brings the most significant impacts on the three cost parameters. To see the robustness of my OLS estimates to endogeneity, I present both point estimates provided by my OLS results (solid line) and Manski's bound estimates (dotted lines). I implement this idea to the three cost parameters: operation cost, and the mean and the standard deviation of the sunk cost distribution.

The main finding here is that the predicted probabilities based on the OLS estimates are consistent with the bound Manski's estimator provides. If the simultaneity problem makes the OLS estimate inconsistent, there is no guarantee that the estimate based on the OLS estimate falls in the bound of Manski's estimator. Although they do not necessarily imply that my OLS estimates are immune from the endogeneity problem, these results at least add some robustness to my OLS estimates.

2.9 Counterfactual Experiments

This section shows the results of policy experiments, using the parameter estimates obtained in the previous section. The goal of this exercise is to quantitatively evaluate the supply side effect of regulation change on entry decisions of hotel chains and the size of the resulting distortion. To isolate this particular effect, I construct an imaginary environment where land use regulation affects the market-specific cost only. In other words, this imaginary environment shuts down all other possible functions of land use regulation, including its effects on local travel demand and the property values of privately owned land. I can replicate this imaginary environment only because I have the structural parameter estimates in hand. Reduced form estimates might predict, for example, the change of the equilibrium number of hotels as a response to the change of land use regulation; however, they do not

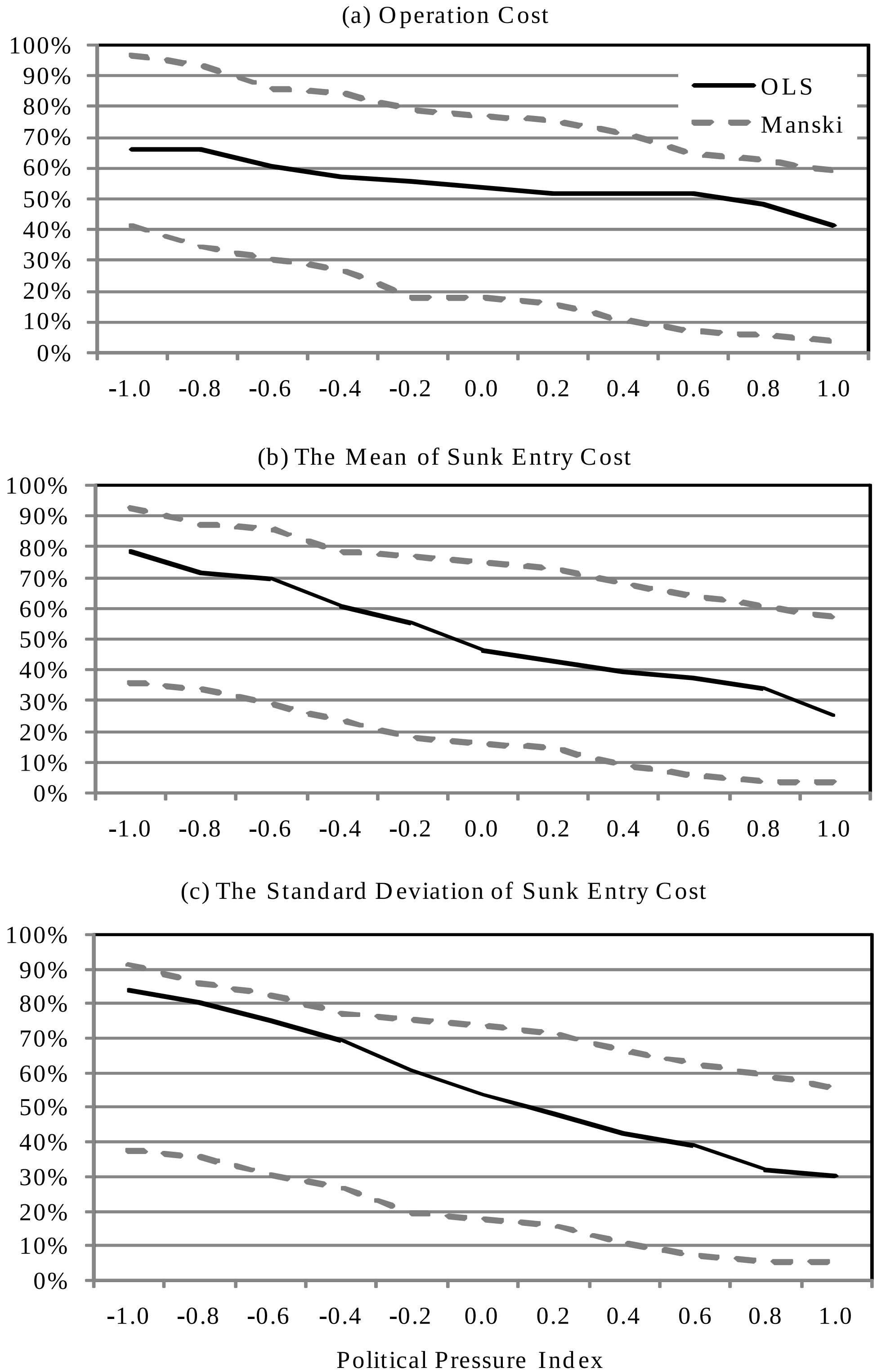

Figure 2.5: Comparison between the OLS estimates and Manski's Bound Estimates

tell how much of these changes come through the demand side or the supply side.

Through these experiments, I first examine whether imposing stringent regulation increases the market-specific cost enough to influence entry decisions of hotel chains. If their entry decisions are rarely affected by changes in regulation, cost increase due to stringent regulation does not generate additional distortion. I next quantify the size of the distortion, if any, and examine who bears it by calculating the changes in both consumer surplus and producer surplus under two different policies.

2.9.1 Environments

My counterfactual experiments consider two local markets (Bee County and Bell County) where two heterogeneous hotel chains (Best Western and Cendant) consider their entry decisions every period. These two markets are chosen as a representative of small markets and large markets, respectively. Table 2.15 shows the demographics of these two markets and the corresponding sample median. Ideal experiments might allow all seven heterogeneous hotel chains to make entry decisions in each of 58 markets considered in the previous chapter. However, the limitation of computational resources prevents this approach. For that reason, the results of counterfactual experiments shown here should be considered as a mean that helps us to understand what the structural estimates convey rather than the actual welfare impacts of land use regulation in this local market. Each simulation is different in hotel chains' cost structure. Benchmark simulations consider various cost structure arisen from the different value of land use regulation indices. Note that change in regulation affects not only the mean of sunk entry cost but also affect both operation cost and the variance of sunk entry cost. To calculate cost parameters under imaginary regulations, I rely on the OLS estimates in the ninth column of Table 2.13 and Table 2.14. In bench mark simulations, I consider three imaginary policies: $Q1$, $Q2$ and $Q3$. Each of these three policies is different each other in its value of the Political Pressure index. The value of this index is equal to the sample first quartile ($Q1$), the sample median ($Q2$) and the sample third quartile ($Q3$), respectively. I focus on this particular index in benchmark simulations since its OLS

Table 2.15: **Characteristics of the Sample Markets**

	Small Market (Bee County)	Large Market (Bell County)	Sample Median
Population (in thousand)	25.07	191.65	77.10
Area (in sq mi)	880.14	1059.72	901.50
Per Capita Income (in thousand)	12.4	15.61	26.54
# of Establishments (in thousand)	0.49	3.33	1.35
Employments (in thousand)	4.33	50.1	17.90
MSA Dummy	0	1	1.00
Airport Dummy	0	1	.00
Interstate Highway Dummy	0	1	1.00

estimate is statistically significant and its sample variation is large enough to choose several points.

2.9.2 Procedure

To implement these experiments, I first 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 policy functions, I next simulate the model. I employ the algorithm originally suggested by Pakes and McGuire (1994) and extended by Doraszelski and Satterthwaite (2007) to games of incomplete information. I approximate the value functions by using Chebyshev polynomials. Since the model contains both discrete and continuous state variables, one Chebyshev polynomial is unable to provide a good approximation of the value function. Instead, I approximate the value function by employing a Chebyshev polynomial for each mutually exclusive combination of discrete state variables. Since the model has three discrete state variables (the number of hotels, the number of rival hotels and quarter dummy), I employ 256 Chebyshev polynomials with their monomials equal to 4. That implies each chain's value function is characterized by 1,280 coefficients.

As the starting values of coefficients, I use the ones that solve a monopoly model.[31] All benchmark simulations converge after about 800 iterations. [32]

2.9.3 Simulation Results

Table 2.16 reports the mean of the equilibrium variables of the two sample markets under the three different policies. The simulation results support the empirical relevance of my hypothesis that stringent regulation leads to less entry. Under the most lenient policy ($Q1$), the average number of hotels in the small market is 2.3. As the policy becomes more stringent, this number decreases to 2.1 ($Q2$) and 1.9 ($Q3$). In terms of the number of rooms, these decreases are equivalent to a four percent decrease ($Q1 \rightarrow Q2$) and a fifteen percent decrease ($Q1 \rightarrow Q3$). Combining the change of the total number of rooms and the change of the total sales, my results imply that imposing stringent regulation *increases* the revenue per room by two percent ($Q1 \rightarrow Q2$) and five percent ($Q2 \rightarrow Q3$). These increases are suggestive of higher prices in the market imposing more stringent regulation. Simulation in the large market presents similar results. [33]

Table 2.17 reports the change of the consumer surplus and the producer surplus brought about by the stringent regulation. The change from the most lenient policy ($Q1$) to the modest one ($Q2$) in the small market decreases producer surplus and consumer surplus by 0.6 million dollars and 0.3 million dollars, respectively.[34] The effects of stringent regulation are more serious for the change from the lenient policy ($Q1$) to the harsh one ($Q3$). This policy change decreases both producer surplus and consumer surplus by 1.5 million dollars and more than one million dollars, respectively. Again, the results based on the large market also indicates significant welfare loss.

[31] I put zeros to all coefficients that do not exist in a value function of a monopoly model.

[32] Here I added a small pertubation term to the sunk entry cost to ensure that the model converges.

[33] 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.

[34] I calculate the lower bound of the change in consumer surplus between the two different regulations by the difference in consumers' expenditures under the two different prices. I evaluate this difference at the equilibrium quantity after the policy change. Since my model only predicts the product of the equilibrium prices and quantity but does not predict these two variables separately, I use the total number of rooms as a proxy for the equilibrium quantity.

Table 2.16: Counterfactual Experiments

	Small Market			Large Market		
	Political Pressure Index			Political Pressure Index		
	Q1	Q2	Q3	Q1	Q2	Q3
# of Hotels						
Total	2.28	2.16	1.91	11.39	10.97	9.72
Best Western	1.34	1.24	1.05	6.72	6.67	6.00
Cendant	0.94	0.93	0.86	4.66	4.30	3.73
# of Rooms						
Total	160.97	154.07	136.63	802.66	769.04	680.05
Best Western	81.07	75.02	63.53	406.56	403.54	363.00
Cendant	79.90	79.05	73.10	396.10	365.50	317.05
Daily Revenue per Room						
Total	27.09	27.45	28.47	18.63	19.25	20.78
Best Western	34.77	35.27	36.45	23.81	24.47	26.18
Cendant	20.70	21.12	21.92	13.09	13.46	14.58

Daily revenue per room is obtained by dividing quarter revenue by 92 days.

Table 2.17: Counterfactual Experiments

	Small Market		Large Market	
	Political Pressure Index		Political Pressure Index	
	Q1=>Q2	Q1=>Q3	Q1=>Q2	Q1=>Q3
Change in the Producer Surplus				
Total	-616.6	-1472.1	-2043.7	-4255.8
Best Western	-439.9	-956.1	-691.9	-1453.5
Cendant	-176.7	-516.0	-1351.8	-2802.3
Change in the Consumer Surplus	-321.7	-1030.9	-1377.1	-4471.9

All the change in surplus is in thousand dollars

2.10 Conclusion

This paper studies the role of land use regulation as a barrier to entry in the case of the midscale Texas lodging industry. I argue that stringent land use regulation lessens local competition by increasing entry costs for potential entrants. This lessened competition generates a distortion by providing hotels that enter with additional market power. The structural estimates obtained in this paper are informative to assess the empirical relevance of this hypothesis. According to my estimates, the change in the stringency of land use regulation, measured by the Political Pressure Index, from the sample first quartile level to the sample third quartile level increases the level of the market-specific operating cost and the mean of the sunk entry cost by 21 percent and 19 percent, respectively.

This paper is among the first to empirically examine the anticompetitive effect of land use regulation on local business markets. Although people in the lodging business and legal professions have noticed this effect, there has been no formal analysis that identifies it. This paper also contributes an introduction of structural estimation to the literature. Most of previous studies have relied on reduced form regressions for their statistical inference. Although reduced form estimates might be more flexible from restrictive assumptions, they do not tell whether these results come through the supply side or the demand side. The structural estimation employed in this paper has the advantage of separately identifying these two effects.

Chapter 3

Does the Threat of Entry Matter?: Case of the Texas Lodging Industry

3.1 Introduction

Understanding the impacts of the threat of entry on firms' investment decisions is one of classical questions in industrial organization. In the past, many theoretical studies have attempted to explain when and why the threat of entry matters to the behavior of incumbents[1]. A next natural question is to what extent. However, efforts to examine the empirical relevance of this theoretical literature have been limited. This paper attempts to fill in this gap.

The goal of this paper is to evaluate the quantitative importance of the threat of entry on firms' behavior in the case of the Texas lodging industry. This paper attempts to answer these quantitative questions by implementing counterfactual experiments. For this purpose, I employ the structural dynamic entry-exit model of hotel chains that are presented and estimated in the previous chapter. In this model, each hotel chain decides the number of hotels it operates every period by taking into account its rivals' current and future decisions.

These counterfactual experiments consider three distinct imaginary situations. First

[1] See Tirole (1988), Gilbert (1989) and Wilson (1992) for the survery of theoretical studies.

case is pure monopoly, where one hotel chain makes its entry-exit decision every period as a pure monopolist. Since no rival chains exist, the entry decision of this chain reflects neither the impacts of the threat of entry nor that of real entry. Second case considers, what I call, ex-post monopoly. In this imaginary environment, a hotel chain makes its entry decisions as if the market were duopoly while real entry never occurs. The behavior of a hotel chain in this environment only reflects the impacts of the threat of entry. Note that only structural models can replicate firms' decisions in this imaginary environment. In the real world, one rarely observes firms making their investment decisions based on false assessment of the presence of rival firms, making difficult to isolate the impacts of the threat of entry from those of real entry. Third case is pure duopoly, where two hotel chains make their entry-exit decisions every period by competing each other. Since this environment allows real entry to occur, the behavior of each chain should reflect both the impacts of the threat of entry and real entry. This paper argues that comparing hotel chains' behaviors under these three environments allows econometricians to isolate the impacts of the threat of the entry from the impacts of real entry. While the comparison between the pure monopoly and the ex-post monopoly extracts the impacts of the mere threat of entry, the comparison between the ex-post monopoly and the pure duopoly extracts the impacts of real entry.

This paper exploits the difference between these three distinct cases to isolate the impacts of the threat of entry from the impacts of actual entry. Comparison between the first two experiments helps to isolate the impacts of the threat of entry while comparison between the latter two experiments helps to isolate the impacts of real entry.

Lodging industry is one of the industries where the threat of future entry seems to affects firms' current entry decisions. Since its high sunk cost makes frequent entry and exit impractical, hotel chains' current entry decisions should be affected by their prospects of their rivals' entry decisions in the future. If hotel chains incurred little sunk cost, its rivals' future entry decisions should not affect its own current entry decisions since it can costlessly change its entry decisions after observing the real entry of its rivals.

The main finding of this paper is that hotel chains are unlikely to change their entry decisions to deter their rivals' entry while they sometimes change the one to accommodate their rivals' entry. Moreover, I also find that the impacts of the threat of entry are asymmetric and depend on the size of local markets. High substitution between hotels under the same chain and no scale economy in its cost structure seem to indicate that accommodation is more profitable than implementing expensive entry deterrence strategy.

This paper makes contributions to the empirical literature of entry deterrence behaviors by providing predictions based on counterfactual experiments. Most existing empirical studies looking at entry deterrence rely on reduced form models for their empirical finding. For example, Goolsbee and Syverson (2009) document how airline carriers change their pricing strategy as future entry of South West in a particular route becomes more likely. To measure the likelihood of future entry of South West in a particular route, the authors look whether South West is in operation in its two end points. In another example, Conlin and Kadiyali (2006) examines whether observed idle capacity in the Texas lodging industry is the result of entry deterrence behaviors. To dismiss other possible explanations such as predicted future demand growth, they relies on predictions of a theoretical model and examine if the data show a correlation predicted by this theoretical model.

Unlike the papers mentioned above, this paper attempts to isolate firms' entry deterrence behaviors, if any, by comparing the results of counterfactual experiments. The advantage of this approach is that one does not have to rely on the nature of data to find an exogenous change in the threat of entry or a particular theoretical model for identification.

The rest of the paper proceeds as follows: Section 2 documents the details of counterfactual experiments. Section 3 reports the counterfactual experiments and section 4 discusses the implication of my finding and its limitation. Section 4 concludes.

3.2 Design of Experiments

This section describes the details of the counterfactual experiments. These experiments mimic a simple environment where only either one or two hotel chains consider to open hotels every period. This simplification significantly facilitates the implementation of counterfactual experiments by maintaining the size of computational burden to a feasible level.

The implementation of counterfactual experiments consists of two main steps. First, I numerically solve each player's dynamic programming problem by finding a numerical approximation of their Bellman equations that are consistent with my structural cost estimates obtained in the previous chapter. Here I consider two situations: (1) pure monopoly and (2) pure duopoly. For these approximations, I have employed Chebyshev polynomials with their monomials equal to 4. Second, I simulate two hotel chains' entry decisions under three different situations: (1) pure monopoly, (2) expost monopoly and (3) pure duopoly. In each simulation, I simulate their entry decisions for 260 quarters or 65 years and iterate this process for 10,000 times. In the end, I calculate the average number of hotels they operate during the simulation and the resulting revenue per rooms as its proxy for prices[2]. All simulation rely on the same random draws. Therefore, all differences realized among the three experiments are due to the difference in its policy function rather than the results of using different random seeds.

What is different among these three simulations is the type of value function used to simulate entry decisions and the entry decisions of its opponent. Table 3.1 summarizes the situation considered in each simulation. In the case of pure monopoly, a hotel chain plays in a real monopoly market. Hence it's entry decision is a that of a monopolist and it never faces rival hotels. In the case of expost monopoly, a hotel chain makes its entry decision as if it were playing in a duopoly market so its policy function is derived from its approximated Bellman equation in the duopoly market. However, this imaginary environment completely shuts down the entry of its opponent. Hence, this hotel chain never observes real entry from its rival chain while this hotel chain's decision reflect the threat of entry. Finally, in the case of pure duopoly, a hotel chain's entry decision is that of a duopolist and its opponent also makes actual entry decision based on its policy function derived from its own approximated Bellman equation. As the last step, I compare the results of simulations

[2] Unlike limit pricing models, my model does not allow incumbents to use prices as a way to deter entry of rival firms. Entry-exit decisions are merely based on the current market structure and shocks on entry-exit costs.

Table 3.1: Three Types of Simulations

	Pure Monopoly	Expost Monopoly	Pure Duopoly
Bellman Equation Used	Monopoly	Duopoly	Duopoly
Real Entry of Cendant	No	No	Yes

under three different environments to isolate the impacts of the threat of entry on each chain's entry decisions from those of real entry.

Note that these experiments cannot be replaced by simple reduced-form regressions such as logits. Aside from specification errors on functional forms and the distribution of error terms, in principle, these reduced form models can predict firms' probability of entry conditional on state variables. However, these predicted probabilities might not properly reflect the impacts of the threat of entry or that of real entry. For example, when markets are expected to grow in the future, hotel chains are more likely to open hotels and reduced form estimates implicitly include these impacts. In contrast, my counterfactual experiments allow me to prevent these unwanted noise from affecting firms' behavior by hypothetically shutting down the growth of this market.

In what follows, I consider the situation where Best Western and Cendant make their entry decisions into two local markets of different demand size. These three local markets consists of (1) Bee County in 1990 and (2) San Patricio County in 1998. I consider these different periods so that local demand size reflects the change in the observed macro trend. To prevent that the possibility of future growth affects hotel chains' entry decisions, I do not allow each local market to change its market-specific characteristic overtime. Table 3.2 shows the market characteristics of each market in the period considered here.

3.3 Results

This section reports the results of the counterfactual experiments.

Table 3.2: Characteristics of the Target Market

	Small	Medium
County Name	Bee	San Patricio
Population (in thousand)	25.1	66.9
Area (in sq mi)	880.1	901.5
Per Capita Income (in thousand)	12.4	
# of Establishments (in thousand)	0.5	1.0
Employments (in thousand)	4.3	
MSA Dummy	0	1
Airport Dummy	0	0
Interstate Highway Dummy	0	1

Case 1: Small Market

Table 3.3 and Table 3.4 report the simulation results in the case of the small market (Bee County in 1990). These results indicate that the impacts of threat of entry are asymmetric among players. I first compare the probability that a hotel chain opens a new hotel when there are no hotels in this market. I consider two situations: (1) pure monopoly and (2) pure duopoly. Since there exist no rival hotels in this environment, the difference in the entry probability between these two environments should reflect the impacts of the threat of entry on each hotel chain's entry decision.

Table 3.3 reports these calculated probabilities in the case of the small market. In short, the shift from the pure monopoly to the pure duopoly have little impacts on Best Western's entry probability while this shift does affect Cendant's entry probability. According to my structural estimates, Best Western's chance of opening new hotels is 9.0 percent under the pure monopoly when there is no hotel in this market. When the market is under pure duopoly, the corresponding probability is decreased to 8.8 percent, or 0.2 percent decrease from the pure monopoly. In contrast, Cendant's entry decisions significantly change when the market becomes more competitive. Under the pure monopoly, Cendant's chance of opening at least one new hotel is 6.2 percent while the corresponding number under the

Table 3.3: Entry Probability: Small Market

	Pure Monopoly	Pure Duopoly
$\Pr(a > 0 \| h = 0)$		
Best Western	9.0%	8.8%
Cendant	6.2%	4.8%

pure duopoly is 4.8 percent, about 1.4 percent decrease.

Table 3.4 reports the long run impacts of the threat of entry on market structure. First-two rows report the average number of hotels operated by each chain during first 260 periods. In the case of pure monopoly, Best Western operates 1.0 hotels on average. The mere threat of entry seems to have little impact. When Best Western behaves as if they were in the pure duopoly despite no real entry, this hotel chain operates .97 hotels on average, slightly lower than the case of the pure monopoly. While Best Western operates fewer hotels in the case of duopoly (.93), the quantitative impacts on its entry decision seems somewhat limited. In contrast, this table confirms once more the significant impact of both threat of entry and real entry on Cendant's entry decisions. In the case of the pure monopoly, Cendant operates .71 hotels on average. However, once the threat of the entry is present, it operates only .49 hotels on average, 31 percent decrease compared to the case of the pure monopoly. This tendency is further intensified when real entry occurs. Under the pure duopoly, Cendant operates only .26 hotels, 63 percent decrease from the pure monopoly and 47 percent decrease from the expost monopoly. Note that I use the same random draw for each simulation. Hence, the observed difference among these three solely comes from the difference in their policy functions.

Case 2: Medium-Size Market

Table 3.5 and Table 3.6 shows the simulation results in the medium-size market. (San Patricio County, 1998). Main finding in this case is that both the threat of entry and pure duopoly do not seem significant impacts in the long run. Table 3.5 reports each chain's

Table 3.4: Results of Counterfactual Experiments: Small Market

	Pure Monopoly	Expost Monopoly	Pure Duopoly
# of Hotels			
Best Western	1.00	.97	.93
Cendant	.71	.49	.26
Revenue per room			
Best Western	$34.2	$34.2	$32.7
Cendant	$17.3	$17.2	$14.2
Total Profit (in thousands)			
Best Western	$2.7	$2.7	$2.5
Cendant	$.7	$.7	$.4

The market considered here is Bee county in the first quarter of 1990.

probability of opening new hotels when there are no hotels in operation in this market. For Best Western, the shift from the pure monopoly to the pure duopoly seems to have little impacts on its probability of opening first hotel in this market. According to my structural estimates, the chance that Best Western opens its first hotel in the market is 21.3 percent under the pure duopoly and 20.2 percent under pure duopoly. In contrast, again the shift from the pure monopoly to the pure duopoly seems to have some impacts on Cendant's entry decision. Under the pure monopoly, its chance of opening its first hotel is 21.3 percent while this probability is decreased to 15.8 percent under the pure duopoly. While Cendant's entry probability seems to be affected by the threat of entry, its long-run impact is ambiguous. As shown in Table 3.6, the average numbers of hotels each chain operates under three different environments are roughly same. Best Western operates about 1.1 hotels on average while Cendant operates 1 to 1.1 hotels.

Table 3.5: Entry Probability: Medium-Size Market

	Pure Monopoly	Pure Duopoly
$\Pr(a > 0 \mid h = 0)$		
Best Western	21.3%	20.2%
Cendant	21.3%	15.8%

Table 3.6: Results of Counterfactual Experiments: Medium-Size Market

	Pure Monopoly	Expost Monopoly	Pure Duopoly
# of Hotels			
Best Western	1.12	1.15	1.17
Cendant	1.12	1.11	1.03
Revenue per room			
Best Western	\$65.3	\$64.6	\$50.2
Cendant	\$32.4	\$32.3	\$24.3
Total Profit (in thousands)			
Best Western	\$8.2	\$8.2	\$5.7
Cendant	\$5.1	\$5.0	\$3.0

The market considered here is San Patricio county in 1998. Total profit is the sum of discounted profits.

3.4 Discussion

Why Do They Accommodate?

Theoretical studies provide ambiguous predictions on this issue. According to Tirole (1988), firms' optimal investment decisions depend on two factors. First factor is whether their additional investment (i.e., opening a new hotel) decreases their rivals' profits. Second factor is if firms' choice variables after investment are strategic complements or strategic substitutes. Based on these two types of information, Tirole (1988) classifies situations into four categories: (1) Top Dog, (2) Puppy Dog, (3) Lean and Hungry, and (4) Fat Cat. The lodging industry definitely satisfies the first factor since opening a new hotel lures a fraction of customers from other hotels and leads a decrease in profits of rival hotel chains. Also, hotel chain's choice variables after investment seems to be strategic complements since only factors hotel chains can change after investment decisions are prices. In this case, hotel chains' optimal decisions depend on the situations. Ultimately, they need to see whether deterrence is actually more profitable than accommodation.

The results of my experiments indicate that accommodation seems the best possible strategy for both Best Western and Cendant. At least no hotel chains' investment decisions become aggressive due to the threat of its rivals' entry. However, its quantitative impacts are asymmetric between these two chains. Best Western hardly changes its entry decision under the threat of entry regardless of market size. In contrast, Cendant significantly changes its entry behavior under the small market while it does not when it is in the large market.

The results that these two chains prefer to accommodate their rival chains rather than deterring indicate that accommodation is relatively more profitable than deterrence. The following two factors seem to matter this result. First, the huge sunk-cost indicates that the cost of choosing deterrence is significant. Second, higher substitution between hotels in the same chain makes the benefit of choosing deterrence relatively small. A chain's second hotel cannot capture the whole demand its rival chain's first hotel would capture.

The impacts of these factors seem more serious in larger markets. Our results indicate that in large markets, even Cendant hardly changes its entry decision just because of the threat of entry. In the case of small markets, hotel chains can deter their rivals' entry by opening one hotel. However, as market size becomes larger, operating one hotel is not sufficient to deter its rivals' entry. To deter rival chains' entry, hotel chains must open additional hotels. When market size reaches a certain point, choosing entry deterrence becomes too costly and will switch to accommodate rival chains. For example, consider a market where Best Western has already operated one hotel while Cendant operates none. When a market is large enough, Cendant has an incentive to open its own first hotel. To deter its entry, Best Western needs to open its second hotels so that it can makes this market less attractive to Cendant. However, choosing this strategy is not always in the best interest of Best Western. By blocking entry, Best Western can prevent Cendant from taking its customers. However, Best Western might have to pay a steep price to block its rival's entry. On one hand, Best Western has to pay the sunk cost of opening hotels. However, doing this does not secure all the revenue Cendant would make when it opened its first hotel. This occurs since two Best Western hotels are very close substitutes compared to one Best Western hotel and one Cendant hotel. Therefore in some circumstances, it is more profitable for Best Western to accommodate its rival hotel rather than blocking them by opening additional hotels.

Multiple Equilibria

Multiple equilibria is a potential concern of these experiments. Since the unique equilibrium is unlikely, all analysis done here implicitly expect that all equilibria of the model are quantitatively quite similar and comparing one of them under one environment to the one under another environment still provides a good picture of equilibrium outcome under several different environments. However, it is possible that my expectation turns out to be incorrect. For example, suppose that both chains' entry decisions become aggressive when there is no threat of entry in one equilibrium (Type A) while their decisions are less aggressive (Type B) in another equilibrium. If I happen to pick a Type-A equilibrium in one experiment while picking Type-B equilibrium in another experiment, the comparison between these two equilibria might provide little insights. One possible direction is to try to find all possible equilibria systematically so that I can capture the nature of multiple equilibria more precisely. One way to implement this idea is to use the homotopy method as recently suggested by Borkovsky et al. (2008).

3.5 Conclusion

This paper examines the quantitative importance of firms' reaction when its market is subject to the threat of entry of rival firms. Unlike previous studies that rely on the special nature of data or correlations predicted by theory, this paper attempts to isolate it by conducting counterfactual experiments under three distinctive environments: (1) pure monopoly, (2) expost monopoly and (3) pure duopoly. The advantage of this approach is that we can directly check the impact of the threat of entry without relying on the special nature of data or particular theory.

My simulation results indicate that in some situations the mere threat of entry affect significant impacts on firms' entry decisions. However, these impacts can be asymmetric among firms and also depend on market size. First, my simulation results do not suggest any entry deterrence activity. No hotel chains' entry decisions become significantly aggressive when there is the threat of entry. Rather, they tend to be more defensive by operating fewer hotels. Second, the impacts of the threat of entry become weak in a larger market. No hotel chains do not block their rivals' entry by filling larger markets with its own hotels since higher substitution between hotels in the same chain makes this strategy very costly.

One direction of the future research is to examine the quantitative relevance of theoretical models about entry deterrence. For example, several existing studies (e.g., Gilbert and Vives (1986)) concerned if entry deterrence is considered as a public good. Examining the empirical relevance of these theories is a promising direction for future research.

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Appendix A: Recovering the Construction Cost of a Midscale Chain Hotel

This appendix describes the procedure I follow to calculate the construction cost of a mid-scale chain hotel in Texas from industry source. I limit my focus on Best Western and La Quinta since their websites provide detailed information (but not construction cost) about their prototype models. Calculation consists of three steps. I first estimate the total building square footage of their prototype hotels. I next estimate the square foot cost for hotel construction in Texas. Finally, I obtain a construction cost estimate from the product of these two numbers.

My calculation for the total building square footage of a Best Western hotel and La Quinta hotel relies on the brochures they put on their websites. Among several prototypes proposed by these two chains, I look at Classic Mid-Scale Prototype for Best Western[3] and Design B Prototype for La Quinta[4].

Best Western's floor plan shows the amount of area allocated to each function of a hotel (e.g, guest rooms and administrative). Although I am able to obtain the total building square footage of this prototype by summing up these numbers, I do not use this sum directly since this prototype seems to reflect higher standards imposed to newly constructed hotels only and hotels in my sample do not necessarily follow this higher standards. First, its prototype has more rooms than those in my sample (80 rooms vs 60 rooms). Second, this prototype reflects its minimum room size requirement imposed to only new hotels (312 square foot) than that imposed to existing hotels (200 square foot). Considering these facts, I consider a hotel that has 60 guest rooms of 280 square foot. Assuming the amount of areas used for other functions are not different between this prototype and existing hotels, I conclude that a total building square footage of a Best Western hotel during my sample period is 29,600 foot. Table 3.7 provides a breakdown of this calculation. For La Quinta, I use the total building square footage shown in the brochure since the capacity difference

[3] http://www.bestwesterndevelopers.com/resources/classic/AS1.00.pdf
[4] http://www.lq.com/lq/about/franchise/PrototypeGuide-B.pdf

Table 3.7: **Total Building Square Footage for a Best Western hotel**

Functions		Area (Sq. Foot)
Sixty Guest Rooms		16,800
Guest Room Support	Corridors, Stairs, Guest Laundry	4,741
Administrative	Offices	545
Public Areas	Lobby, Business Center, Fitness Center	4,415
Back of House Areas	Employee Lounge, Linen, Storage	3,099
Total		29,600

The average guest rooms size is assumed to be 280 squares foot.

between this prototype and the sample median is relatively small (114 rooms vs 105 rooms) and the brochure does not provide the breakdown of this total building square footage anyway. As a result, I use 55,041 square foot for the total building square footage for a La Quinta hotel.

I next calculate the square foot construction cost for a motel. RS-Means provides a square foot construction cost for various types of commercial buildings. Among them, I employ the one for a two to three story motel. To reflect locational difference of construction costs, I also employ Location Factors, a price index provided by RS-Means. Finally, I normalize this square foot cost to 2000 dollars by employing Turner Building Cost Index provided by Turner Construction. Following these steps, I obtain 81.3 dollar for square foot cost.[5]

Finally, I multiply the obtained square foot cost with the total building square footage. As a result, I obtain $2,407 thousand dollars ($= 81.3 \times 29,600$) as an estimate for the total

[5] The breakdown of this calculation is 147.75 dollar as a square footage construction cost, .790 as a location factor and .697 as Turner Building Cost Index. Rouding brings a slight difference between the product of these three numbers and the number shown in the text.

construction cost of a Best Western hotel and \$4,505 thousand dollars for that of a La Quinta hotel.