The Effect of Zoning Regulations on Entry in the Retail Industry*

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PRELIMINARY and INCOMPLETE

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Abstract

Zoning regulations restrict location decisions of firms in retail markets. This paper investigates how significantly the zoning regulations affect firms' coordinated entry decisions using land use regulation introduced in Japan in 1968. I specify a static game of two retail chains that engage in multilocational competition. Both chains strategically choose their store network, taking into account the role of geography. Using data on outlet locations and local demographics, I estimate the model parameters by method of simulated moments (MSM). I use the estimated model to conduct counterfactual experiments demonstrating the impact of change in zoning policy environments on the number of convenience stores in Okinawa, Japan. The preliminary results suggest that removing the current zoning restriction increases entry of stores by around 4 percent.

Keywords: Convenience stores; Zoning regulation; Multimarket competition; Entry

JEL-Classification: L13; L81; R52

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1 Introduction

Deregulation of zoning restrictions in urban areas in Japan has been at the forefront of urban policy debates in recent years. The current Urban Planning Law, enacted in 1968 in order to prevent urban sprawl, defines zoned areas and in principle prohibits firms and residents from locating freely. While developing stores in zoned areas are permitted under strict requirements that they need to comply with for any constructions[1], there has been mounting public opinion calling for deregulating the current zoning laws, expressing that the requirements are too restrictive for retail outlets to be opened in zoned areas. The land use restrictions are big concerns especially for potential local grocery stores or convenience stores, because the choice of good location is a key to success in retail business. In responding to these concerns, some local governments have recently relaxed the regulation for commercial outlets in zoned areas by constructing ordinances which specifies the conditions that entering stores must meet[2]. Still, however, the exceptions are limited to very specific types of store formats, such as stores attached to gas station, local highways, or rest areas.

In contrast to the increasing attention to zoning restrictions, surprisingly little is known about the roles that zoning plays on entry. The purpose of this paper is to examine how zoning affects market structure of concentrated markets by focusing on (1) what would be the equilibrium effect of a change in zoning on entry configurations; and (2) how large is the magnitude of the costs of zoning in monetary units. In order to answer these questions, I use a unique dataset that I collected on land use regulation in Japan, and demographic information for 834 contiguous locations in the Okinawa prefecture. I specify a static game of two players that strategically choose a store network for contiguous locations. In order to capture the well-designed outlet networks, I extend a method recently proposed by Jia (2008), which studies entry of multistore retailers. I write down a framework that endogenizes each chain's coordinated location decisions of entry into adjacent locations. Modeling the additional costs of entry due to zoning structurally will allow me to predict the equilibrium market structure under alternative policy environments. Also, based on the predictions of geographical entry patterns as a result of changes in policy, I consider the distributional consequences due to changes in zoning policy. With parameter estimates, I conduct a simple exercise on whether zoning is welfare enhancing in terms of economic efficiency.

Two features of the industry are suitable for the analysis of zoning and entry. First, convenience stores are one of major types of commercial store formats that are allowed to apply for an exception

[1] This exception is detailed in Article 34-1. Potential store developers have to file and show that the store serves the need of local residents. Other detailed conditions are given by local ordinances.

[2] According to my survey conducted in 2007, 28 out of 97 cities have deregulated the zoning law under Article 34-8.

of zoning regulation under Article 34-1. Second, zoning may be more relevant for retail industries, because demand for retail stores is localized due to travel costs on the consumer side. Furthermore, we would expect that zoning is a more relevant consideration for the industries that exhibit network externalities, such as ATM or retailers. This feature of industry makes the location choice of firms particularly interesting because zoned areas are usually geographically contiguous rather than discrete, which would shape the strategy of spatial entry across locations.

As a theoretical framework, I develop an equilibrium model of entry in which two national players strategically compete by choosing a store location network. Modeling multiple players making discrete choices over many locations poses a formidable methodological challenge for computation of optimal behavior, because the number of possible location choices gets astronomically large even when the number of locations and agents are relatively small. This paper extends the work of Jia (2008) who provides a novel approach to deal with the issue. She demonstrates that by formulating the model as a supermodular game of two players we can implement the seemingly infeasible task of finding equilibria out of vast number of possible combinations of outcomes. This approach is attractive in my setting because a convenience store chain headquarter in Okinawa can choose over 834 available locations. I extend her methodology in two dimensions. First, I allow chains to have more than one outlet in a given location, whereas in her model the choice is binary. This is a relevant extension for my study because it is quite common that we observe more than one outlet in a given grid, as locations are connected to each other and grid borders are not natural borders. A proof for supermodularity of this game needs to be modified and is provided in the appendix. Second, I use annual sales data at a uniform grid level to back out the revenue and costs function. The parameters of these functions will allow me to calculate sunk entry costs and the costs due to zoning in monetary units.

Turning to the results, the simulation exercises suggest that the supermodular game framework offers a tractable way to analyze entry games with large numbers of interdependent locations. In the empirical results, I find negative and sizable effects of zoning laws on firm entry behavior both in the reduced form and structural model. I use estimated parameters to run counterfactual policy experiments to demonstrate the magnitude of the effects. The estimated model predicts that the number of convenience store outlets will increase by 4 % in Okinawa, if the current zoning policy is abolished. If zoning regulations are placed in every location, on the other hand, then we would expect roughly a 20 % decrease in the number of outlets. Extensions, which are currently in progress, will determine the increased costs due to zoning in monetary term, examining if zoning regulations are the significant determinants for entry decisions. This result will reveal to what extent failure to account for the zoning restrictions can bias the parameter estimates.

This paper builds on the vast literature of entry and market structure[3]. By modeling entry behavior as a discrete choice and regarding observed choices as a Nash equilibrium to the static game, Bresnahan and Reiss (1991) pioneered the literature on market size and number of firms. Since then, much effort has been devoted to add complexities to the original model, such as asymmetry of players in costs (Berry 1992), endogenizing product differentiation choice (Mazzeo 2002), or endogenizing identities of entrants (Ciliberto and Tamer 2007), under the specification of a game being played in a single market with exogenous sunk costs of entry. However, existing empirical analyses on entry have not dealt with zoning directly, treating it as an unobserved profit shock to the econometrician. Such analysis will miss the contribution from the effect of zoning on entry, and may lead to omitted variable bias. In this paper, I aim to fill that gap in the literature by incorporating the zoning information into the structural model of entry.

My paper complements the growing spatial competition literature by highlighting the role of geographical store network in strategic entry decisions. While the common framework of entry into geographically isolated markets makes the analysis a lot simpler and tractable, it is not applicable when we turn to contiguous locations. Progress has been made in the direction of spatial competition by Seim (2006) and subsequent work by Watson (2005) and others[4], showing that strategic interactions and geographical differentiation is important when retail firms are choosing location among available areas. Meanwhile, they maintain the assumption that every player is symmetric, and each firm makes independent location decision. As a consequence, there is no consideration for coordinated entry decisions by national chains operating multiple outlets. As described above, I instead model chains as operating many stores, and design an optimal network of stores. In addition to the literature on spatial competition, this paper is related to recent progress in quantifying the importance of network effects or positive spillovers between the same chain stores in retail industry (Holmes 2008, Jia 2008, Ellickson, Houghton, and Timmins 2008).

More broadly, this paper has implications beyond the specific impact of zoning on entry: the fully estimated equilibrium model will allow us to quantify economic inefficiency arising from zoning

[3] Traditionally, Industrial Organization (IO) economists care about entry and market structure, which are long-run decisions made by firms. In the entry literature of the last twenty years, they have been using a game theory to analyze the determinant of oligopolistic market structure, which had been treated as given. Usually, the purpose of the studies is to learn the relationship between market demographics (e.g., population) and the number of entrants or pricing behavior resulting from the market structure.

[4] They relax the assumption of cross-sectionally independent markets by allowing firms to freely locate within geographically adjacent locations and making entry decisions of a firm dependent of other firms' decisions in surrounding locations. In doing so, they formulate the market configuration as being generated by the equilibrium probability of choosing any one of location that is consistent across all locations in a given market.

regulation, which is of central importance from the social welfare standpoint. There is a large theoretical literature on free entry and social efficiency, and theoretical implications are ambiguous on whether free entry is pro-competitive. Salop (1979) shows in his circular city model that free entry generates too many firms compared to the socially optimal number of firms under linear or quadratic costs of traveling. On the other hand, Mankiw and Whinston (1986) demonstrate that free entry can lead to socially excessive, insufficient, or even optimal entry, once we allow consumers to benefit from product variety. Ridley, Sloan, and Song (2008) show that zoning can increase competition by forcing sellers to cluster, which can drive prices to decrease and some sellers to exit. These theoretical results suggest that the question on social efficiency hinges on the relative magnitude of the business stealing effect, set-up costs, which are socially wasteful expenses, and consumer utility from product diversity. With no clear theoretical prediction, the impact of zoning on entry and welfare is therefore an open empirical question. While land use controls have not been subject to benefit-cost analysis due to its nature[5], the costs associated with the social regulation can large enough to offsets the social benefits from zoning[6].

The rest of the paper proceeds as follows. Section 2 gives a description of the zoning regulation. Section 3 contains information about the industry and dataset I have constructed. Some descriptive regressions are performed. Section 4 introduces an entry model and provides simulation results. Section 5 discusses the empirical implementation of the project. Section 6 reports the estimation results and provides counterfactual analyses of the equilibrium effect of zoning on market structure. Section 7 discusses the expected output and the timeline for the summer. Section 8 concludes.

2 The 1968 Urban Planning Law

2.1 Description of Zoning Regulations

In this subsection, I describe zoning laws for urban areas in Japan. In 1968, the government of Japan introduced the Urban Planning Law (UPL), which is a comprehensive zoning regulation at the national level. This law is designed to prevent urban sprawl and disorganized urbanization, in accordance with preservation of farm land or natural environment. To this end, the law creates three types of zones in an urban area, and places different restrictions on land-use for each type, depending

[5] Zoning is traditionally perceived as a social regulation: to preserve farmland, scenery, and environment, or to prevent sprawl of cities.

[6] For example, if private costs include direct costs associated with compliance with the regulations or foregone profits that retail outlet could have earned, or disutility from increased travel distance on the consumer side, then such social regulations may not defendable.

on whether to promote urbanization in that area or not. The three types are: (1) Urbanization area; (2) Urbanization control area; and (3) Undelineated area. Urbanization area is defined as the urbanized area or the area where the government put high priority for urbanization by constructing public facilities such as water, gas, and electricity. In this area, there is no restriction to develop or construct facilities whose areas are less than $1,000m^2$, such as a convenience store outlet. On the other hand, the aim of urbanization control area is the opposite to one of urbanization area, in which most development actions are suppressed. Therefore, public infrastructure is less adequately provided in this area compared to an urbanization area. The law requires one to apply for permission from the governor of the prefecture or the city to build a new residential home or a commercial facility such as convenience store, demanding that the applicant must show that the establishment will not go against the urban planning in that area. For the undelineated area, getting permission is not required when installing an outlet under $3,000m^2$, which is easily met for convenience stores, as the average floor size is $110m^2$.

The Urban Planning Law establishes a building permit system that prohibits development of commercial stores or residential houses under the rule of reason, not per-se illegal. While in principle you cannot build convenience store outlets in any urbanization control area under the regulation above, there is a building permit system, allowing exceptions: under Article 34-1 of UPL, in order to acquire a permit for building and operating an outlet in an urbanization control area, the owner of the outlet needs to document two things: 1) the outlet serves local people, and 2) the outlet provides daily necessities for the people living in that urbanization control area[7]. Another cost of complying with the law is to show that the establishment one tries to build meets restrictions that are set by the cities, such as proximity to residential areas or maximum floor space.

Urbanization area, Urbanization control area and Undelineated area account for 15 %, 37 %, and 48 % of urban areas in Japan. The extent of coverage of population by the urban planning area is substantial: These areas account for roughly 90% of the population in Japan. In Okinawa, 7% of total population lives in urbanization control area, and 85 percent lives in other city-areas. The rest of 8% live in non-city area.

2.2 Endogeneity Concern

In this subsection, I discuss the set of assumptions regarding zoning regulations.

[7] In practice, there can be another exception for some cities under Article 34-8 of UPL: if the store serves traffic drivers on major roads at roadside rest facility, then under some conditions the development is permitted. However, in Okinawa, this type of convenience store is not allowed, and I am not going to focus on this.

An ideal empirical model for the study of measuring impacts of zoning on entry would involve randomly assigning zoning restrictions to locations and comparing the outcomes across zoned and unzoned locations. In reality, however, such social experiments are usually difficult to conduct. Instead, I treat the zoning regulation as exogenous in this study. The exogeneity of zoning assumption would be especially problematic if zoning decisions by were made based on some unobserved (to the econometrician) location specific factors, arising either from the demand or the cost sides, that affect profitability of convenience store outlets. If that is the case, I may be mistakenly attributing observed outcomes, such as variations in number of outlets across locations, to costs of zoning and not to systematic differences in profitability across locations. As a result, the parameter estimates would likely to suffer from an omitted variable bias.

In order to alleviate the problem arising from omitted variable bias, I include in the empirical model demographics at the location level, such as population, to make them otherwise (not perfectly but close to) identical locations. There is one suggestive feature of the industry in favor of this argument: consumers in city areas travel smaller distances to visit convenience store outlets, compared to other type of retail formats such as large discount retailers or department stores. Furthermore, one piece of anecdotal evidence will mitigate the concern. Conversation with local regulator staffs has revealed that in practice the decisions on where to assign zoned/unzoned area are made solely on conditions regarding population, and the degree of commercial activities are not considered because it involves hard task of predicting the size of commercial sales in near future.

3 Industry, Data, and Descriptive Analyses

This section describes the industry, dataset used in the estimation, and reduced form analysis. In this version of the paper, I focus on the store networks in Okinawa, Japan for two reasons. First, Okinawa is an island with approximately one million people, so I can treat them as an isolated market as a whole. Second, the Okinawa market fits the model framework because there are two nation-wide convenience store chains, Family Mart and LAWSON, opening stores in Okinawa[8].

3.1 Convenience Store Industry

Convenience stores are one of the fastest growing retail formats in the last twenty years[9]. The industry is dominated by a handful of nation-wide large players with many outlets: the six national

[8] On-going work uses other prefectures in Japan as well to check the robustness of the analysis.

[9] The overall industry sales in 2004 was 6.7 trillion yen, which is approximately 5.0 percent of total retail sales.

chains account for 71 % of the total number of convenience store outlets in Japan in 2002 and 82 % of the total sales. Among franchise chains, 7-Eleven is the largest convenience chain in the world, operating in more than 20 countries[10].

As its name suggests, the industry focus on consumer convenience, which is to increase customer satisfaction in term of store accessibility and variety of items relative to its floor space. They pursue this goal by 1) access: minimizing the travel costs by opening many stores that are on average 110 square feet, smaller on average than local supermarkets, grocery, and other food retail stores; 2) variety: increasing the number of items per store floor area, so that consumers can find what they are looking for without having to travel to groceries or stationery stores. They aim at one-stop service as much as possible. As for price, the industry adopts low-volume and high-margin strategy, rather than high-volume low-margin as typical in the supermarket industry. The core merchandise of convenience stores is food: about 70 % of sales is foods, soft drinks, and alcoholic drinks. According to the Census of Commerce 2004, the average annual sales per outlet is 161 million yen and 176 million yen for 24 hours outlet.

Two features of the industry are suitable for the analysis of zoning and entry. First, convenience stores are one of major types of commercial store formats that are allowed to apply for an exception of zoning regulation under Article 34-1. Second, zoning may be more relevant for retail industries, because demand for retail stores is localized due to travel costs on the consumer side. Furthermore, we would expect that zoning is a more relevant consideration for the industries that exhibit network externalities, such as ATM or retailers. This feature of industry makes the location choice of firms particularly interesting because zoned areas are usually geographically contiguous rather than discrete, which would shape the strategy of spatial entry across locations.

In retail locations, the success of outlets greatly depends on price and location due to localized demand. In choosing among similar stores, consumers' major considerations are based on prices and store locations. This is especially true when outlets offer similar quality of services and a variety of products through franchising, which is the case in the convenience store industry in Japan. There are several features of the convenience store industry in Japan make it attractive to focus solely on location decisions of retail outlets. First, there is a common practice for the industry that the nationwide chain companies adopt uniform pricing, allowing us to abstract from pricing decisions by each outlet. This means that we do not have to have price data to model pricing behavior. Emphasis on location in the industry is a natural consequence of lack of differentiation in product,

[10] 7-Eleven Japan, which is the biggest company of all national 7-Elevens, owns companies in the United States and China, yielding 23 billion dollars annually in 2005.

service, or price: rather, they strive to find key location. Relative to other retail industries such as gasoline retailing or supermarkets, convenience stores are densely located because most of the customers visit on foot.

Second, for the large nation-wide chains, convenience stores offer quite similar merchandise, services, and shopping experiences across outlets and chains. Of course the quality of shopping experiences will matter as well. In fact there are noticeable differences across chains in chain brand images and quality of goods and services provided, upon which fronts chain companies are investing and advertising every year in order to improve. These quality differences, perceived by consumers, will eventually show up in the differences in sales across chain companies.

Lastly, due to the nature of the business, demand is more localized than in other types of service industries, such as supermarkets or gas stations: 70% of customers visit on foot, and 30% by cars. People do not travel far to go to convenience stores: the average travel time is around 10 minutes.

There are two ownership types: franchised stores and corporate stores. For example, more than 80 % of total 7-Eleven stores in Japan are franchised stores. As is common in many industries, it is often difficult to obtain the types of stores, because chain companies keep this data as proprietary information. In the following analysis, I do not distinguish between franchised stores and corporate stores. I believe this is not problematic for my study, because the decisions of how many outlets to install each year and where to put those new outlets are primarily made by chain headquarters, not by individual franchised owners. In this study, I condition on chains' choice on which prefectures to enter. There are two reasons for this. First, the main issue of the paper is to quantify the impact of zoning on entry of outlets, and I focus on chain's behavior locally. Second, modeling both entry into prefectures and location choice as a simultaneous decision will complicate the analysis, making the analysis infeasible. Of course, this is an interesting issue and it will be an useful topic for future study.

3.2 Data Source

I have collected a single cross-sectional dataset on convenience store outlets and demographics come from a variety of sources.

2002 Convenience Store Almanac. I collect data on the convenience store industry, the end of year annual sales in 2001, using a number of different sources. The location data of the convenience stores in 2002 are taken from the Convenience Store Almanac 2002. The almanac contains the store addresses, zip-codes, phone numbers, and chain affiliations for 40,016 and outlets.

I geocode and assign each store location a latitude and longitude by using geographical reference information system provided by the Ministry of Land, Infrastructure and Transport[11]. 275 stores, which is about 80% of convenience stores, match at the level of lot addresses. For the rest of 20% of stores, I manually acquire individual stores' longitude and latitude information by using mapping software, various online mapping services such as Google Map or Yahoo!, and corporations' online store locators. Each store is assigned to the corresponding 1km square grid it falls into. For the unsatisfactory I calculate the distance from the centroid of each census block to the five closest outlets, and distances are measured as straight lines.

In addition to the location data, I obtain the annual sales of the six biggest chains[12] from annual financial statements of chain store companies[13]. The retail sales are available at the prefecture level, and all figures are adjusted to 2000 constant yens. I also obtain the location of each chain brand's headquarter and distribution centers from the websites of the chains or the distribution companies or both.

2000 Population Census. The population census from 2000 is available from the Census Bureau, Ministry of Internal Affairs and Communications[14]. A census block contains between zero and 18,722 people, with an average size of 247 people. I place all of the population at the centroid of the corresponding census block, which is a common simplification in the literature[15]. I then aggregate the population at the corresponding 1km square grid. For the boundary census blocks that intersect with border of grids, I assign the population proportional to the area of intersection, assuming that population density is uniform within that census block.

2001 Establishment and Enterprise Census. I use census of the establishment and enterprise from 2001, and it is available from the Census Bureau. It contains information on the number of business establishments and the number of workers. The data are resampled into the 1km square mesh level data that I am going to use as a unit of analysis. The main idea is that the number of workers will capture some of the daytime demand for convenience stores.

[11] The following website is available for geocoding: http://pc035.tkl.iis.u-tokyo.ac.jp/~sagara/geocode/index.php

[12] They are: 7-Eleven, Family Mart, LAWSON, circleK, sunkus, and ministop. The top five chains of largest sales in Japan, including both listed and unlisted companies, are 7-Eleven, Family Mart, LAWSON, circleK, and sunkus.

[13] In Japan, reporting financial statements is a mandatory for publicly traded companies.

[14] It is available from their website: http://e-stat.go.jp/

[15] See Thomadsen (2005) for example.

3.2.1 Location Definition

The appropriate definition of a location is a difficult task if there is no clear boundary on trade area. Bresnahan and Reiss (1989) focus on industries where markets are small and isolated in order to avoid the issue of handling contiguous markets. However, in most industries, it is hard to find perfectly isolated markets both in terms of demand and costs, and this is exactly the case in this industry. Moreover, we will ignore a large portion of the economy if we do not study this. To deal with this issue, I adopt a definition similar to Seim (2005) that allow me to model the interdependent location decisions for a given market.

Definition of Location. Following the 2002 Census of Commerce data, I define a location as a uniform grid of 1km square. I define the neighborhood locations as grids of which centroids are within 1.6 kilometers from the centroid of the location.

Sample Locations. In order to make the model work, I have to restrict my locations to the subset where the number of the nation-level firms is at most two. This is because in theory I can transform a game where the best response is decreasing in opponents' strategy into a supermodular game only when the number of players is two or less. However, I believe that it will not pose a serious problem in terms of dataset. I have a large amount of data for urban areas where the number of national chains are two. The selected markets have big cities, such as Okinawa. It is an island with 1.4 million people and has nearly twice of population of San Francisco. In total, I have 7,463,000 people, covering up seven large cities, which account for six percent of population in Japan.

3.3 Descriptive Analyses

In this subsection, I provide some descriptive statistics and simple regression results. The motivation for this kind of reduced form analysis is that we want to see whether the zoning has a large influence on the market structure in the retail industry.

3.3.1 Reduced Form Regressions

Table 5 gives the result from ordinary least square regressions of the total number of outlets in the location, both Family Mart and LAWSON brands, on the log-population and zoning. In column 4, I also control for log number of workers in the location.

The number of convenience store outlets is negatively and strongly associated with the zoning variable: the sign of zoning coefficients is negative and statistically significant at the 5 percent level. With information on magnitude, column 2 and 3 of Table 5 implies that a zoned location has on average 0.3 to 0.4 fewer stores than unzoned location, everything else equal. Considering that the average number of outlets in a given location in which at least one outlet is present is 1.85, the effect of zoning on entry is sizable. Turning to the role of location population on entry, the population in a given location is positively associated with the number of outlets in the location. Locations with doubled population have 0.3[16] more number of stores than location with original population(column 1 and 2). As suggested by column 3, the finding on the role of zoning is robust to the introduction of number or workers, although the population coefficient gets insignificant.

3.3.2 Need for Structural Model

In the simple OLS regression, we have seen that zoning seems to be playing a significant role in entry of outlets. While reduced form regressions may be suggestive about the likely direction and strength of the effect of zoning on entry, there are at least three reasons why I employ structural modeling for the purpose of the project[17]. First, suppose that a regulator would like to get precise estimates of the costs due to zoning because he wants to evaluate if the costs are of an economically meaningful magnitude. However, we are not sure if we are getting reliable estimates of costs due to zoning from reduced form, because in reality the number of outlets in the right hand side of the regressions is not randomly given by the nature; rather it is endogenously determined by firms maximizing their profits. Moreover, reduced form regressions are inadequate approaches for modeling many characteristics of the industry, and examples include: strategic interactions between Family Mart and LAWSON, decisions of the store network by the headquarter, and locations that are contiguous to one another. All of these are important features that characterize the firms and the location and failing to properly account for these crucial features of industry often leads to severely biased estimates.

Second, and perhaps most importantly, a structural model permits counterfactual policy experiments. One of the main interests of my paper is to assess the equilibrium consequences of market structure in response to zoning policy changes. One of the advantages of structural modeling is that it allows us to conduct realistic out-of-sample predictions about changes in market structure due to zoning policy changes, once we uncover basic model parameters. By predicting the change

[16] ln2 times (coefficient on log population)

[17] Reiss and Wolak (2007) provide useful discussions on structural modeling in industrial organization.

in geographical patterns of location configurations by two players due to change in regulations, we can look at distributional consequences of policy interventions, such as who benefits from change in zoning and who does not, or we can ask practical questions that a regulator may find relevant, such as in which locations we would find the impact of deregulation to be most effective on entry behavior. These are the questions that I cannot answer with reduced form analysis.

Lastly, a structural model allows us to recover unobserved economic parameters that could not otherwise be inferred from data. Examples in this paper include: positive spillovers across locations; strategic effect across chain brands; and sunk costs of entry. For example, quantifying the magnitude of positive spillovers is important, because it measures the departure of the model from the common assumption that the most of entry studies has relied on: firms enter into a location if and only if it is profitable to do so. In the structural model in this paper, I allow for a more complicated situation: For example, it may still be profitable for a chain to install a store in a location where the store alone receive negative profits, because there are other stores in adjacent locations, thereby offsetting the loss by positive spillover across locations. Also, these sunk costs parameters will be needed to conduct welfare calculations under different policy schemes.

4 Entry Model

In this section, I discuss model setup. This study uses a static model of simultaneous-move game with complete information. In the following subsections, I first discuss the empirical modeling choice and then describe how to model the behavior of chains.

4.1 Empirical Model Selection

The empirical model selection is made based on the goals of my project. Since the purpose of the paper is to conduct what would happen under counterfactual zoning regulations, I need to adopt a conceptually more straightforward way of modeling that will allow me to solve the store location network decisions by firms. The biggest obstacle in terms of computation is to solve the optimal network decision for a chain. In general, it is a daunting task because it involves computing all the possible combinations of store location decisions, and it is astronomically large even when the number of locations and agents are relatively small. For games with six players, three strategies, and twenty locations, the vector of each player's strategies has $20 * 6 = 120$ dimensions, and there are 3 available choices for each element of the vector. The number of possible elements in the choice set is $3^{20} = 3.4 * 10^9$, and the number of the possible combinations for all players is

$(3^{20})^6 = 3^{120} = 1.8 * 10^{57}$. Furthermore, even after solving the problem one usually will be left with a large number of equilibria and will find it difficult to establish a unique mapping from variables in the model to observed outcomes. This will pose econometric issues especially when one would like to form a likelihood function.

A natural way of dealing with the multiplicity of equilibria and the astronomical numbers of the strategy profile is to use a bounds approach, such as Pakes, Porter, Ho, and Ishii (2006). This approach does not rely on assumptions regarding the equilibrium selection. Therefore, it would be a more appropriate choice, if my main goal was to accurately estimate the network effect of the industry and the sunk costs of entry in zoned areas. At the same time, it introduces a new difficulty for the researcher who wishes to analyze policy counterfactuals because we have no information on which equilibrium has been played in the dataset, and there is no guarantee that the same equilibrium will be played in the simulation. The bounds approach is unclear about equilibrium selection rules when estimating the parameters. Without taking a stance on selection, however, it would be impossible to simulate the behavior from the model and parameters. In light of this, I extend Jia (2008)'s novel work that implements the seemingly infeasible task of finding all equilibria out of a vast number of possible combinations of outcomes. While her method is still computationally demanding, it is feasible because it exploits the supermodularity of the game. Moreover, there are four reasons why I prefer this model in my application.

First, by using this framework, I can model the multimarket entry behavior more realistically than assuming independent decisions by outlets owner, which is the tradition in the entry literature, as in Bresnahan and Reiss (1991). Second, while some people may find selecting an equilibrium uncomfortable, this model will allow me to predict the equilibrium market structure if there is a change in zoning policy. Third, this model can be a defense of why I use static model. Estimating a dynamic model of location choice of multistore players would be computationally intractable, because static model of location choice by multi players is already complex enough. Fourth, I do not have to make a strong assumption regarding the number of "potential entrants" as Seim (2006) does. There are some drawbacks, however: first, it may be problematic to assume that the (net) "chain effect" between adjacent location (=grid) is always positive, since the chain effect is (gross) chain spillover minus competition business stealing effect. Second, Jia's framework does not works for more than two players, limiting our scope of analysis to locations with monopoly or duopoly.

4.2 Allowing Multiple Outlets in a Location

In this subsection, I describe one feature of my empirical model: multiple outlets up to two establishments in a given grid. In her original model, Jia (2008) assumes that the players of the model to have a binary choice regarding entry decision and does not allow for more than one store in a given location. In the appendix, I show the derivation of optimality conditions and proofs of supermodularity in the modified game.

There are two motivations for extending the model to have multiple outlets within a grid. First, multiple outlets setting provides more accurate description of the industry; this is practically useful because we often see more than one outlet in a given grid, as grid borders are arbitrarily for consumers and firms if we use the grid-type definition of locations. While the binary outcome setting simplifies the model analysis and reduces computational burden, it may not accurately capture the characteristics of industry that I focus on. In fact, for Family Mart and LAWSON in the Okinawa prefecture, the grids with single outlets are 78 % and 86 % of total grids. If I allow for two outlets at maximum, the fractions go up significantly: 95 % and 98 %. Second, and perhaps more importantly, the extension addresses one of the resulting limitations of Jia's original model in that it does allow either cannibalization (or business stealing effects) or positive spillovers across stores in a given location. In other words, the signs of the net effect of the store of the same chain within a location are flexible contrary to the chain effect across locations, which needs to be positive for the supermodularity to hold.

The intuition behind the theoretical result in the appendix is that the positive network effect across locations δ_{chain}, which I need to maintain for the iteration algorithm to work, will be more reasonably defended in the empirical project, if you choose a grid wisely enough so that the business stealing effects δ_{within} die away rather quickly than the benefits in delivery distribution. Normally, we would expect that there are two effects in opposite directions from the stores of same chain brand in the same market on the profits of my store. On the one hand, having many stores of the same chain in the market will save the costs of delivery. On the other hand, stores are more likely to compete against each other as the number of stores increases. The benefits from clustering can be cost savings in delivery. The implication of the result is that my model would be particularly useful for retail industries with dense store network with delivery, because consumer demand is more localized than the cost of delivery. This is typically the case in the convenience store industry in Japan: while consumers walk rarely more than 1km to access stores, a delivery trucks for stores on average travels about 40 kilometers for each store per day in total.

4.3 Firm Behavior

In this subsection, I develop an equilibrium model of entry in which two players strategically compete against each other by choosing a store location network. We frequently observe intense rivalry between chain brands of similar characteristics in many retail industries, such as BestBuy vs. Circuitcity, WalMart vs. Kmart, Staples vs. OfficeDepot, to name just a few. In many cases, the market structure is concentrated, and they compete against their rivals in many dimensions including prices, advertisement, and store locations. In the convenience store industry in Japan, they strive to offer quite similar shopping experiences: they variety of merchandise and other services as uniform as possible across outlets. A notable feature of the industry is that they adopt nation-wide uniform pricing across outlets, which allows us to focus on their main avenue of horizontal product differentiation- spatial differentiation. The convenience store industry in Okinawa has two national players, Family Mart and LAWSON, who design optimal store network, taking into account their competitor's store network configuration[18]. It is thus natural to model the market structure as being determined by strategic actions of two players choosing an outlet network that maximizes each chain's aggregated profits[19].

Formally, I start with a model of multimarket duopoly. I consider a static simultaneous move game with strategic interactions by two players. There are a set of mutually exclusive discrete locations within a prefecture-level market, and the set of locations is indexed by $m = 1, ..., M$. In the game, two firms i, j simultaneously choose a discrete action from a finite set of trinary choice $N_{i,m} \in \{0, 1, 2\}$ for each location m. So each player chooses a $M \times 1$ strategy vector, $N_i = (N_{i,1}, .., N_{i,M})$.

In this paper, I focus on a pure strategy Nash equilibrium, which is defined as a strategy vector for each chain that maximizes its profit, given competitor chain's strategy profile. I do not look at mixed strategy equilibria in this study.

I assume that the profit shocks to firm i are public information. In other words, each chain has perfect information on their rival's payoff from entering multiple locations.

[18] The industry has a developed distribution system and well planned store networks. As Lee (2004) argues, building an efficient logistic network is the key competitive feature of the convenience store industry. For example, delivery trucks need to visit the same outlet every eight hours to avoid lack of stock of fresh foods and lunch boxes. So chains need to have an efficient network system which will minimize the costs of delivery.

[19] There is ample evidence that the convenience store chains devote lots of resources to conduct extensive research on a best location before installing a new outlet. Conversations with industry participants revealed that a typical chain carefully chooses an outlet location aligned with his own existing store network and locations of competitors' stores, rather than an individual store owner choosing a best location for him regardless of chain brands, or a monopoly chain optimally locating outlets over a large choice set regardless of rivals' presence. Also, company annual brochures intended for investors spend several pages to explain that they invest in sophisticated distributional systems to preserve the freshness of foods (lunchboxes, rice-balls, and sandwiches).

In what follows, I focus on the chains' problem of where to locate and how many store outlets to open, which is the main issue of this paper. While which prefecture (state) to enter is an interesting issue by itself and is closely related to my project, I will take those decisions by chains as exogenous when considering the chains' behavior of installing and building store networks.

I specify the payoff function at location m for firm $i \in \{FM, LS\}$ as:

$$
\begin{aligned}
\pi_{i,m} &= N_{i,m}[X_m\beta + \delta_{comp}N_{j,m} + \delta_{chain}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + \delta_{within}\mathbf{1}(N_{i,m}=2) \\
&\quad + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{i,m} + \gamma\mathbf{1}(m \text{ is zoned})] \\
&= N_{i,m} * [\mathbf{Y}_{i,m} + \delta_{chain}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + \delta_{within}\mathbf{1}(N_{i,m}=2)] \\
\text{where } \mathbf{Y}_{i,m} &\equiv X_m\beta + \delta_{comp}N_{j,m} + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{i,m} + \gamma\mathbf{1}(m \text{ is zoned})
\end{aligned}
$$

where X_m are demographic characteristics of the location m that affect the demand for convenience stores. $N_{j,m}$ is the number of competitor stores of chain $j \in \{FM, LS\}$ in the location. I assume that the revenue declines linearly in the number of competitor stores. $N_{i,l}$ represents number of stores in location l, which is adjacent to location m. $Z_{m,l}$ measures distance from location m to adjacent location l. $\eta_{i,m}$ is a chain-location specific profit shock[20], *i.i.d.* across chains and locations, ε_m is the location level profit shock that affects all the firms existing in the location m. Both $\eta_{i,m}$ and ε_m are assumed to enter linearly in the profit function. Turning to the notation of parameters, δ_{chain} represents the costs savings by having outlets of the same chain nearby locations, which presumably include benefits from efficient delivery network. δ_{comp} measures the impact of the number of competitor stores in the same location on store-level profits. The parameter δ_{within} captures changes in profits from having a store of the same chain brand in the same location. If the business stealing effect from the same chain brand store in the same location exceeds the benefits, then the parameter is negative. I impose a traditional restriction that the variance of a linear combination of unobservables, ε_m and $\eta_{i,m}$, is one, and ρ measures the weight between the two shocks. The fixed costs of zoning, parameterized by γ, capture the effect that the store may have to incur additional costs for opening an outlet in urbanization control area. The profit function of Family Mart and LAWSON are treated symmetrically: they have the same values for the parameters in the profit function, because the model specification needs be parsimonious due to the number of observations.

[20] I assume that stores of same chains in a given grid recieve a common shock.

4.4 Solution Algorithm

In this subsection, I briefly discuss the solution algorithm of the model.

The goal of the algorithm is to obtain the equilibrium most profitable to Family Mart, and the following Round-Robin steps will attain the equilibrium. First, start off by having the smallest vector in LAWSON's strategy space. i.e. $N^0_{LS} = \inf(N) = \{0, ..., 0\}$. Second, given LAWSON's strategy, N^0_{LS}, derive Family Mart's best response, $N^1_{FM} \equiv \arg\max_{N_{FM}} \sum_{m=1}^{M} \pi_{FM,m}(N_{FM,m}, N^0_{LS,m})$. Third, given Family Mart's best response N^1_{FM}, I derive the LAWSON's best response as$N^1_{LS} \equiv \arg\max_{N_{LS}} \sum_{m=1}^{M} \pi_{LS,m}(N_{LS,m}, N^1_{FM,m})$. By iterating the best responses by Family Mart and LAWSON, it is guaranteed that the iterations converge to the equilibrium that is most profitable for the first mover (Family Mart). The nice thing about the iterations is that the number of iterations, T, is bounded by the number of locations, M: $T \leq M$. In this application, I use Family Mart as the most profitable chain, since it entered Okinawa in 1988, about 10 years before LAWSON entered. As we see in Table 1, Family Mart was still the leading chain in Okinawa in 2002 in terms of number of outlets.

While the above approach will guarantee the existence of an equilibrium, the most computationally demanding part involved in the above procedure is to compute the best response given the competitor chain's entry configuration. This is because it is infeasible to solve for the profit maximizing vector by simply searching all possible strategy profile, especially when the number of locations is large. In our application, since the number of locations is 834, the number of possible strategy profiles in the choice set is 3^{834}.To circumvent the daunting task of searching over possible element in the choice set, I narrow the range of the search region by getting the lower and upper bound for my strategy profile. Given the competitor's decision, the problem reduces to a single agent maximization problem. In order to find the upper and lower bound for Family Mart, N^U_{FM} and N^L_{FM}, I first define the following nondecreasing function $V : N_i \rightarrow N_i$ whose mth element is given by

$$\begin{aligned}
V_m(N_i) &\equiv [1 - \frac{V_m^{(0,2)}}{2}]V_m^{(0,1)} + \frac{V_m^{(0,2)}}{2} V_m^{(1,2)} \\
\text{where } V_m^{(0,2)} &= 2 * \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \geq 0] \\
V_m^{(0,1)} &= \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} \geq 0] \\
V_m^{(1,2)} &= \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + 2\delta_{within} \geq 0] + 1
\end{aligned}$$

The derivation of $V_m(N_i)$ by using the optimality conditions, and the proof of the function $V(N_i)$ is nondecreasing in N_i, are provided in the appendix. Second, start with $N^0_{FM} = \sup(N) = (2, .., 2)$ and define a sequence $\{N^t\}$. So $N^1 = V(N), N^{t+1} = V(N^t)$. Then the sequence is not increasing and converging to a vector $N^u \equiv N^T, V(N^U) \equiv N^U$. Likewise, I derive the lower bound by starting from $N^0_{FM} = (0, 0, ..0)$ and the number iterations are less than $2M$ times. Now we have the set of convergent vector, N^L and N^U, and it will reduce the computational burden because we have tighter bounds between N^L and N^U, so that we do not have to try on every possible strategy profiles.

4.5 Monte Carlo Experiments for Robustness Checks

Here I illustrate the performance of the simulated method of moments (hereafter MSM) estimator for the model. The purpose of this exercise is to see whether the MSM estimator recovers the true parameter values.

4.5.1 Setups

I run two sets of simulations. First, I estimate the structural parameters $\hat{\theta}_{MSM}$ by using twenty simulation draws of shock terms. To do this, I first create a "true" dataset, which consists of observables: demographics and entry configurations $(X_m, N_{FM,m}, N_{LS,m})$ for each location $m = 16, 36, 144, 1,600$ Actual entry configurations of Family Mart and LAWSON are derived by computing the Nash equilibrium most favorable to Family Mart, given a set of true parameter values $\theta = (\beta, \delta_o, \delta_c, \rho)$ and population data X_m. X_m are generated from a standard normal distribution. Then I formulate a frequency simulator by drawing twenty sets of i.i.d. pseudo-random variables $u^s_m = (\varepsilon^s_m, \eta^s_{FM,k}, \eta^s_{LS,k}), s = 1, ..20$, from a trivariate standard normal distribution, and for each simulation s I solve the equilibrium entry configurations N^s_{FM}, N^s_{LS}. Second, I repeat the previous estimation 50 times to obtain 50 MSM estimates, $\hat{\theta}^r_{MSM}, r = 1, ..50$, which I call as replications. The standard errors are calculated to allow for the spatial interdependence of locations arising from chains network decision.

4.5.2 Monte Carlo Experiments

Table 2 presents a Monte Carlo study. I report the mean of the estimated parameters $\hat{\theta}_{MSM} = (\beta, \delta_{chain}, \delta_{comp}, \rho)$ that are averaged across 50 artificial datasets (replications). The mean of the estimated parameters are close to the true values, and are within a single standard error from the truth values. β and ρ are more precisely estimated compared to two other parameters $\delta_{chain}, \delta_{comp}$.

While the standard errors are not so small to make the parameters statistically significant, the mean of our MSM estimator performs well on average in terms of recovering the true values, and the estimates are robust results across the number of hypothetical locations, ranging from 16 to 1,600. Overall, simulation results suggest that the supermodular game framework offers a feasible way to analyze network entry in large number of interdependent locations.

5 Estimation via Method of Simulated Moments

In this subsection, I describe the details of estimation approach used to estimate the model.

I estimate the model by choosing model parameters, so that the objective function, which depends on difference between predicted entry configurations and observed data, is minimized.

The supermodular game does not yield a closed form solution for the moment conditions nor allow for numerically computing these conditions. In stead, I use simulation-based methods: the mapping from the parameters to moments, which includes model predictions of equilibrium entry patterns, is approximated by simulation methods.

A simple frequency simulator for entry configurations, $g(N_{FM,m}, N_{LS,m}|X_m, \theta)$, is given by a Monte Carlo estimate

$$\hat{g}(\hat{N}_{FM,m}, \hat{N}_{LS,m}|X_m, \theta, u_i^S) = \frac{1}{S}\sum_{s=1}^{S} g(N_{FM,m}, N_{LS,m}|X_m, \theta, u_m^s)$$

where $u_m^s = (\eta_{FM,m}^s, \eta_{LS,m}^s, \varepsilon_m^s)$, $s = 1, ..., S$ are drawn from a certain distribution. I use Halton sequence for u_m^s instead of pseudo-random numbers, as a variance reduction technique. I set $S = 60$ for the study. As Train (2003) argues, many studies have confirmed that, two properties of Halton draws, negative correlation over observations and better coverage than random draws, make simulation errors much smaller than random draws of the same size.

The MSM estimator is derived by

$$\hat{\theta}_{MSM} = \arg\min_{\theta} [\frac{1}{M}\sum_{i=1}^{M} \hat{q}(X_m, \theta)]\mathbf{W}[\frac{1}{M}\sum_{i=1}^{M} \hat{q}(X_m, \theta)]' \quad (1)$$

where $\hat{q}(X_m, \theta)$ are the moment conditions constructed by using the dataset and a frequency simulator for the moment. I give a brief description of moment conditions later in the subsection. I need to introduce a weighting matrix $\mathbf{W}$ in the right hand side in case the number of moments exceeds the number of parameters (overidentified), and the estimation of parameters will be in the similar way as we do in GMM.

Since the objective function is not differentiable in the argument $\theta = (\beta, \delta_{chain}, \delta_{within}, \delta_{comp}, \rho, \gamma, intercept)$, I use nonderivative optimization methods. To ensure the reliability of the estimates, I employ simulated annealing method, which uses the nonlocal information, in addition to Nelder-Meade simplex search. I tried several different starting values for each parameter not to fall into local minimum.

Following McFadden (1989), the limit distribution of the MSM estimator that uses a frequency simulator is given by

$$\sqrt{M}(\hat{\theta}_{MSM} - \theta_0) \xrightarrow{d} N(0, (1 + S^{-1})(\mathbf{G}_0' \mathbf{\Lambda}_0^{-1} \mathbf{G}_0)^{-1})$$

where $\mathbf{G}_0 \equiv E[\nabla_\theta q(X_m, \theta_0)]$ and $\mathbf{\Lambda}_0 = E[q(X_m, \theta_0) q(X_m, \theta_0)']$. The estimated asymptotic variance is $\widehat{Avar(\theta_{MSM})} = (1 + \frac{1}{S}) \frac{1}{M} (\hat{\mathbf{G}}' \hat{\mathbf{\Lambda}}^{-1} \hat{\mathbf{G}})^{-1}$, where S^{-1} in the first term corresponds an efficiency loss caused by simulation. The derivative matrix $\hat{\mathbf{G}}$ can be estimated by taking a sample mean of Jacobian of the simulated moments[21]. To account for the geographical interdependence of close-by locations, I follow Conley (1999)'s nonparametric covariance matrix estimator. So the covariance matrix $\mathbf{\Lambda}$ is estimated by

$$\hat{\mathbf{\Lambda}} = \frac{1}{M} \sum_{m=1}^{M} \sum_{l \in B^m} [\hat{q}(X_m, \theta) \hat{q}(X_l, \theta)']$$

where B^m is the set of locations adjacent to location m.

I use two-step efficient approach as is the case with traditional method of moments estimators. In the first step, I use an identity matrix for the weighting matrix $\mathbf{W}$ to consistently estimate parameter $\hat{\theta}_{MSM}^{first}$ and plug this into the covariance matrix $\hat{\mathbf{\Lambda}}$, In the second step, I choose the weighting matrix $\mathbf{W} = \hat{\mathbf{\Lambda}}^{-1}$, and perform the minimization of objective function again to obtain the final efficient parameter estimates $\hat{\theta}_{MSM}$.

Construct Moment Conditions. In theory, any functions of exogenous variables can be used to construct moment conditions. As noted in Draganska et al. (2008), however, there seems to be no clear agreement on which moment conditions to choose for the implementation of method of moments estimation. In the spirit of Berry (1992) and Jia (2008), I interact the estimated residual

[21] To approximate the gradient, I use numerical derivatives instead of analytical ones. Notice that in general $\mathbf{G}$ is nonsmooth in parameters θ due to the discrete nature of the outcome variables: the gradients of moment conditions are initially flat (zero) for small change in parameters and then jumps. I use the following two-sided formula as given by

$$\hat{\mathbf{G}} = \frac{1}{M} \sum_{m=1}^{M} \nabla_\theta [\hat{q}(X_m, \hat{\theta}_{MSM})] \doteq \frac{1}{M} \sum_{m=1}^{M} \frac{\hat{q}(X_m, \hat{\theta}_{MSM} + \triangle\theta) - \hat{q}(X_m, \hat{\theta}_{MSM} - \triangle\theta)}{2\triangle\theta}$$

from the model and functions of the exogenous data $k(X_m)$, to get moment conditions $\hat{q}(X_m, \theta)$.

$$\hat{q}(N_{FM,m}, N_{LS,m}|X_m, \theta) = \frac{1}{M}\sum_{m=1}^{M} \hat{v}_m(X_m, \theta) \otimes k(X_m)$$

where $\hat{v}(X_m, \theta) = g_m - \frac{1}{S}\sum_{s=1}^{S} g(X_m, u_m^s, \theta)$ is the estimated residual, g_m is a vector of observed outcomes for location m, and $\frac{1}{S}\sum_{s=1}^{S} g(X_m, u_m^s, \theta)$ is a simple frequency simulator for entry configurations. In the current application, g_m contains four elements: the number of outlets in location m for each chain ($N_{FM,m}$ and $N_{LS,m}$), the number of outlets in locations adjacent to location m for each chain.

6 Results

In this section, I provide estimation results for 834 locations in Okinawa, Japan.

6.1 Parameter Estimates

This subsection presents the parameters from the method of simulated moments estimator.

Table 3 provides the main results. Each of the parameters has the anticipated sign. First, the population and number of workers coefficients, β and β_{bus} in Table 3, are positive and statistically significant at the 1% level. This means that both nighttime population and daytime population positively impacts the profits of stores, and 10% increase in population amounts to 23% increase in number of workers in terms of magnitude of impact. While the chain effect δ_{chain} and the cannibalization effect δ_{within} are not statistically significant, the competitive effects δ_{comp} are estimated to be -0.39 and are statistically significant at the 1 percent level. As one might expect, revenue decreases when you have a competitor in the same grid, and its effect is large: it amounts to nearly 100% increase in the number of population in terms of contribution to reduction in sales. The weight on the error term ρ is insignificant at the 5 % level.

Turning to the parameter of interest, the zoning parameter γ is estimated to be -0.26 and statistically significant at the 1% level. Consistent with the reduced form regression results, it has a negative impact on outlet profits, implying that in a zoned area you have to incur positive costs. The magnitude of the coefficient tells that in order to make up the reduction in revenue due to zoning, you have to have nearly doubled population in the location, holding other factors constant.

Columns 1 and 2 in Table 4 compare the data and the fit of the estimation in terms of the number of entering locations. The model predicts the number of Family Mart stores as 125.2 where actual number is 127, and the number of LAWSON as 91.6 stores where actual number of stores is 95.

In the current specification, parameters are estimated up to a constant because I treat profit to be the latent variable. Therefore, the relative size of the effects on entry needs to be gauged by running counterfactual simulations, which I will discuss in the following subsection.

6.2 Counterfactual Simulations

In this subsection, I perform counterfactual analyses, using the estimates of the model, to demonstrate the economic significance of zoning policy change on entry of convenience store outlets. Specifically, I consider two extreme policy scenarios and study how entry of convenience store outlets changes. The two scenarios are: (1) zoning regulations are completely removed from the Okinawa market, (2) zoning regulations are in place for all locations in Okinawa.[22] As in any prediction analysis, I make it clear what I am conditioning on in this exercise: I fix the number of population constant before and after the change in zoning policy environment.

Columns 3 and 4 in Table 4 provide the results of counterfactual simulations. First, from column 3 in which I predict the first scenario of abolishing the zoning regulations, I would expect roughly a 4 to 5 percent increase in the number of entering grids for both chains. The direction of change in the number of stores is reasonable if zoning is interpreted as an increase in sunk entry costs. On the other hand, column 4 of Table 4 shows the number of outlets in Okinawa in the second scenario in which zoning restrictions are placed all over in Okinawa. The model predicts that the number of location where convenience stores are present decreases by roughly 20 percent in Okinawa, which is sizable impact. The difference in magnitudes for each extreme scenarios may partially attributed to the fact that the fraction of zoned locations is currently 10 % of all Okinawa locations: the number of locations subject to change due to a policy change in the second simulation is 9 times as large as the number of locations subject to change in the first policy experiment.

7 Extensions [In-progress]

In this section, I discuss three extensions that are currently works-in-progress. The first extension is to estimate parameters of revenue, sunk costs, and costs due to zoning. The second extension is to prove the solution algorithm for more than 3 choice case. The third extension is to run a

[22]Here I am implicitly assuming that the shape of reduced form revenue function is invariant to the change in regulations.

counterfactual exercise that analyzes the welfare consequences of changes in zoning laws.

7.1 Use Revenue to Estimate Demand and Cost

The first extension is to use revenue data as a source of identification for the competitive effect and chain effect parameters. I have acquired recently available convenience store revenue data from the 2002 Census of Commerce, which are aggregated at a uniform 1km square grid level. My estimation strategy will be similar to the one considered in Berry and Waldfogel (1999), in which they estimate costs from entry data after estimating demand from revenue data. Incorporating revenue data into the current framework will be beneficial for my study for two reasons. First, by using revenue data at the 1km grid level as a source of identification of revenue related parameters, I will be able to quantify the actual monetary costs of zoning. This information will be useful for regulators who assess costs and benefits of land use regulations. Second, we will be able to measure the consequences for economic welfare due to policy interventions. The costs of traveling in monetary terms, the cost estimates will allow us to investigate whether the industry has seen too many outlets or not enough outlets. This will lead to another intriguing question which is whether zoning regulation works in favor of enhancing economic efficiency.

The 2002 Census of Commercial revenue data on total retail sales, total convenience store sales, which include nonaffiliated stores, and other types of retail sales, all at the prefecture level, are available from the Ministry of Economy, Trade and Industry. The information on annual sales, floor space, and the number of outlets is available at the aggregated level of 1 km^2 uniform grid, each for two store types (24 hours operation stores and non 24 hours stores). Unfortunately, the sales and floor space data are hidden when the grid has less than three outlets in order to protect the identity of each outlet.

In the following subsections, I briefly describe my setups for this extension.

Parameterize Revenue and Costs. In this subsection, I discuss the parameterization on revenue and costs, which is the final aspect of the model.

I model firm i's profit function in location m as linear combination of revenue, cost, and profit shocks.

$$\pi_{i,m} = r_{i,m} - c_{i,m} + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{i,m}$$

where ε_m is the location level profit shocks that affect all the firms in the location m, and $\eta_{i,m}$ are the firm specific profit shocks which are public information and *i.i.d.* across players and locations.

I use the parametric reduced form for the firm's revenue function as

$$r_{i,m} = N_{i,m}[X_m\beta + \delta_{comp}N_{j,m} + \delta_{within}N_{i,m}]$$

Since I do not observe fixed costs directly, I therefore parameterize the fixed costs using observed variables and unobserved variables. The per store costs consist of four parts: marginal costs, fixed costs of production that the store pays per period, fixed costs of entry, and additional costs from complying with zoning.

$$c_{i,m} = \delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + FC_i + \gamma * \mathbf{1}(m \text{ is zoned})$$

where FC_i are fixed costs including setup costs for installing an outlet and this must be paid regardless of the level of output. The fixed costs of zoning capture the idea that the store may have to incur additional costs for opening an outlet in an urbanization control area which is zoned.

I use the same empirical model I used to derive the preliminary results.

Welfare Consequences of Zoning. In order to calculate the economic welfare, I need to measure both producer surplus and consumer surplus. Measuring producer surplus will be rather straightforward: it is approximated by $\Pi_i = \sum_{m=1}^{M} \pi_{i,m}$. Meanwhile, the exact calculation of consumer surplus, either equivalent variation or compensating variation, is difficult because I don't have price and quantity data separately. Instead, what I can do with my revenue data is to bound the area of consumer surplus by focusing on the revenue change due to a change in policy, using the argument in Deaton and Muellbauer (1980).

From the first order conditions for utility maximization, $\frac{\vartheta v(q)}{\vartheta q_i} = \lambda p_i$,where v is indirect utility function, q_i is the quantity of good i, λ is the marginal utility of income, and p_i is the quantity of good i. By taking the total differential of utility, I get the change in utility due to change in quantity

$$du = \sum \lambda p_i dq_i,$$

which turns to be the area under the Marshallian (uncompensated) demand curve.

Placing a bound on the consumer surplus due to change in quantity will be relevant for this application, especially because the industry adopts uniform pricing and we would expect no price change before and after the policy change.

7.2 Generalize Model to $N_{i,m} \in \{0, .., K\}$ Case

The second extension is to generalize the current theoretical results to $K > 3$ choice in a given location. As of now, all the proof of my theoretical model is based on the trinary choice of players, $N_{i,m} \in \{0, 1, 2\}$. While the trinary choice covers approximately 95 % of all locations in the convenience store industry the Okinawa market, the generalized result will greatly enhance the applicability of the model to other industries with denser branch network.

7.3 Sensitivity Analysis of Spatial Correlation

The third extension is to investigate whether the empirical results are sensitive to the introduction of correlated location level shocks ε_m. The presence of spatial dependence of the error term may be potentially problematic because it is highly likely that the shocks correlate across locations with no clear natural boundary.

Simply estimating the autocovariance consistent covariance matrix nonparametrically as in Conley (1999) would not be going to work in this application, because if we do that we may not identify the model parameters such as δ_{chain}. Instead, I plan to conduct sensitivity analysis in the same spirit of Conley, Hansen, McCulloch, and Rossi (2007). I assume different level of spatial independence of the market level shocks, and see how the estimation results will be affected by the degree of correlation.

8 Conclusion

This paper estimates the effect of zoning regulations on entry of convenience store outlets in Okinawa, Japan. Empirical results find negative effects of zoning laws on firm entry behavior. Counterfactual policy experiments demonstrate that the number of convenience store outlets will increase by 4 % in Okinawa, Japan, if the current zoning policy is abolished. I discuss the plan for the summer, in order to achieve the model estimates to conduct counterfactual analysis.

Two major extensions are in progress. First, I am incorporating revenue data at the grid level and use this to identify the costs of zoning in monetary units. Second, I am investigating whether the empirical results are sensitive to the introduction of correlated location level shocks ε_m.

There are several avenues for future extensions. First, the current approach abstracts from dynamic considerations. Obviously, this is a very strong restriction because I do not consider dynamic issues such as (spatial) preemption or timing decisions by firms of when to install outlets. As a consequence, the parameter estimates can be misleading if these dynamic effects are important determinants of firm behavior in this industry. While the dynamic model is theoretically appealing, however, it might be intractable to estimate a model with location choice in the dynamic settings, given the large dimensionality of the strategy space of firms. Moreover, the static game assumption, which essentially implies that I regard the outlet configuration of the industry in the dataset being generated by a long run equilibrium of a static game, would be a realistic picture of the industry in 2002, as number of stores get stabilized after 2000. Second, my model is based on the strong assumption regarding a positive network effect, and we would like to develop a way to relax this.

Eventually, my plan is to use the model parameters as a building block to analyze the welfare consequences of changes in zoning laws. It requires me to have structural models that incorporate sales data, and will lead to the investigation of the optimal policy to maximize the economic efficiency.

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9 Appendix

9.1 Derivation of Necessary Condition: $V(N)$

In my model, players maximize the profits from every locations:

$$\Pi_i(N_i, N_j) = \sum_{m=1}^{M} \pi_{i,m} = \sum_{m=1}^{M} [N_{i,m}[\mathbf{Y}_{i,m}(N_j) + \delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \mathbf{1}(N_{i,m} = 2)]]$$

Let's define a function $V(N_i) = (V_1(N_i), ..V_m(N_i), ..V_M(N_i))$, which maps from the current strategy vector $N_i \in \mathbf{N}_i$ to itself $V(N_i) \in \mathbf{N}_i$. The purpose of the function $V_m(N_i)$ is to update the current entry decision in location m, $N_{i,m} \in \{0, 1, 2\}$ to maximize the profit contribution from location m. By definition, a profit maximizing vector $N_i^* = \arg\max_{N_i} \Pi_i(N_i, N_j)$ is a fixed point of the function: $V(N_i^*) = N_i^*$.

To choose the optimal entry decision in location m, I assume that the player i performs a pairwise profit comparison in the following two steps. First, the chain i compares profits from choosing entry decision $N_{i,m} = 0$ and $N_{i,m} = 2$, holding its entry decisions in other locations $N_{i,l \neq m}$ constant, and it picks the one which delivers higher contribution to the total profit Π_i. Call it $N'_{i,m}$. Second, the chain compares profit between $N_{i,m} = 1$ and $N'_{i,m}$, and pick the one which delivers higher profits to aggregated profit.

First, I explore the decision rule for the first step explicitly. Subtracting profits $\Pi_i(N_{i,1}, ..., 2, .., N_{i,M}) - \Pi_i(N_{i,1}, ..., 0, .., N_{i,M})$ gives

$$\begin{aligned}
&2[\mathbf{Y}_{i,m} + \delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \underbrace{\mathbf{1}(N_{i,m} = 2)}_{1}] - 0[\mathbf{Y}_{i,m} + \delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \underbrace{\mathbf{1}(N_{i,m} = 2)}_{0}] \\
&+\delta_{chain} \sum_{l \neq m} N_{i,l} \frac{N_{i,m}}{Z_{l,m}} - \delta_{chain} \sum_{l \neq m} N_{i,l} \frac{N_{i,m}}{Z_{l,m}} = 2[\mathbf{Y}_{i,m} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within}] \qquad (2)
\end{aligned}$$

Eq. (2) tells us that if $\mathbf{Y}_{i,m} + \delta_{within} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}}$ is positive, then it is relatively more profitable for the chain i to choose $N_{i,m} = 2$, rather than choosing $N_{i,m} = 0$.I summarize the decision rule in the following function:

$$V_m^{(0,2)} \equiv 2 * \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \geq 0] \qquad (3)$$

The superscript $(0, 2)$ denotes that this is the function V_m describes the optimal decision rule when we are given a choice between $N_{i,m} = 0$ and 2

In the second step, first consider the case in which Eq. (2) is positive: we have $N'_{i,m} = 2$.

Consider comparing profits with strategy vector with $N_{i,m} = 1$, holding entry choice in other locations fixed. Choosing $N_{i,m} = 2$ would be more profitable for the player if the following holds.

$$\Pi_i(N_{i,1}..., 2, .., N_{i,M}) \geq \Pi_i(N_{i,1}..., 1, .., N_{i,M}) \tag{4}$$

Eq. (4) implies that $\Pi_i(N_{i,1}..., 2, .., N_{i,M}) - \Pi_i(N_{i,1}..., 1, .., N_{i,M}) \geq 0$, or

$$\begin{aligned}
& 2[\mathbf{Y}_{i,m} + \delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \overbrace{\mathbf{1}(N'_{i,m} = 2)}^{1}] - [\mathbf{Y}_{i,m} + \delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \overbrace{\mathbf{1}(N_{i,m} = 2)}^{0}] \\
& + \delta_{chain} \sum_{l \neq m} N_{i,l} \frac{\overbrace{N'_{i,m}}^{2}}{Z_{l,m}} - \delta_{chain} \sum_{l \neq m} N_{i,l} \frac{\overbrace{N_{i,m}}^{1}}{Z_{l,m}} \\
= \quad & \mathbf{Y}_{i,m} + 2\delta_{within} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} \geq 0
\end{aligned}$$

I define a function $V_m^{(1,2)}$ which describes optimal decision rule when we are given choices $N_{i,m} = 1$ and 2.

$$V_m^{(1,2)} \equiv \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + 2\delta_{within} \geq 0] + 1 \tag{5}$$

Next, consider the case in which Eq. (2) is negative: we have $N'_{i,m} = 0$.Consider comparing profits from strategy vector $N'_{i,m} = 0$ with $N_{i,m} = 1$, holding entry choice in other locations fixed.Choosing $N_{i,m} = 1$ would be more profitable for the player if

$$\begin{aligned}
& 1[\mathbf{Y}_{i,m} + \delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \overbrace{\mathbf{1}(N_{i,m} = 2)}_{0}] - 0[\mathbf{Y}_{i,m} + \delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \overbrace{\mathbf{1}(N'_{i,m} = 2)}_{0}] \\
& + \delta_{chain} \sum_{l \neq m} N_{i,l} \frac{\overbrace{N_{i,m}}^{1}}{Z_{l,m}} - \delta_{chain} \sum_{l \neq m} N_{i,l} \frac{\overbrace{N'_{i,m}}^{0}}{Z_{l,m}} \\
= \quad & [\mathbf{Y}_{i,m} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}}] \geq 0
\end{aligned}$$

I define a function $V_m^{(0,1)}$ which corresponds to the optimal decision rule when we are given choices $N_{i,m} = 0$ and 1.

$$V_m^{(0,1)} \equiv \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} \geq 0] \tag{6}$$

Combining conditions from Eq. (3), (5), and (6) gives the final form of $V(N_i)$.

$$
\begin{aligned}
V_m(N_i) &\equiv [1 - \frac{V_m^{(0,2)}}{2}]V_m^{(0,1)} + \frac{V_m^{(0,2)}}{2}V_m^{(1,2)} && (7)\\
\text{where } V_m^{(0,2)} &= 2 * \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + \delta_{within} \geq 0] && (8)\\
V_m^{(0,1)} &= \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} \geq 0]\\
V_m^{(1,2)} &= \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{chain}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + 2\delta_{within} \geq 0] + 1
\end{aligned}
$$

9.2 Proof of $V(N_i)$ is Nondecreasing in N_i

Consider two strategy profiles for player i, N_i and N_i', with vector ordering $N_i \geq N_i'$. I use the usual componentwise ordering: $N_i \geq N_i'$ if and only if $N_{i,m} \geq N_{i,m}'$ for any element m of the vectors. The function $V(N_i)$ is nondecreasing in N_i if $N_i \geq N_i'$ implies $V(N_i) \geq V(N_i')$.

To show this nondecreasing property, it suffices to show that for any given location m, $V_m(N_i)$ is increasing in entry decisions in other locations $N_{i,l\neq m}$. This is because the function $V_m(N_i)$ does not depend on its current entry choice $N_{i,m}$, as shown in Eq.(7). Eq. (8) tells us that, as we increase the number of stores in other locations $N_{i,l\neq m}$, we are more likely to see the event $V_m^{(0,2)} = 2$ to be happening. This is due to the assumption that the chain effect δ_{chain} is positive. The intuition is that having more stores will make it easier for you to increase stores in location m because of increased chain effects. As $V_m^{(0,2)}$ increases in $N_{i,l\neq m}$, this will never decrease the value of $V_m(N_i)$, because it always holds that $V_m^{(0,1)} \leq V_m^{(1,2)}$ since $V_m^{(0,1)} \in \{0,1\}$ and $V_m^{(1,2)} \in \{1,2\}$. Therefore $V_m(N_i)$ is increasing in entry decisions in location choice N_i.■

9.3 Proof of Supermodularity for Multistore within a Location

A game is said to be (strict) supermodular if 1) $\mathbf{D}_i$ is nonempty compact sublattice $\mathbf{D}_i$ into $\mathbf{D}_i$; 2) the payoff $\Pi_i(D_i, D_{-i})$ is supermodular in its own strategy D_i for each D_{-i}, and; 3) the player i's payoff Π_i has increasing differences in (D_i, D_j) for all $D_i \in \mathbf{D}_i$ and $D_{-i} \in \mathbf{D}_{-i}$. In the first subsection, I provide a proof of supermodularity of the game when the chain effect occurs at the outlet level: the positive spillovers across locations depends not only mere presence of outlets in neighborhood locations, but also on the number of outlets in these locations, not merely on if there is chain i's presence in adjacent locations. In the next subsection, I provide a proof of a case in which chain effect occurs at the location level: the magnitude of positive spillover across locations depends on the presence of chain i in the neighborhood locations. So I assume that the effect does not depend on the number of outlets, but the number of locations in which chain i's outlets are present.

9.3.1 Case (1): Chain Effect at the Outlet-level

I define chain i's strategy space as $N_i = \{N_{i,1}, .., N_{i,M}\}$, where $N_{i,m}$ is the number of outlets in location m for chain $i \in \{FM, LS\}$. In the current application, I will allow that chains have up to two outlets. So $N_{i,m} = \{0, 1, 2\}^M$. The following profit function is general, in the sense that it will also contain the binary choice case: If I allow only one outlet in each location, then we will replace $N_{i,m}$ by $D_{i,m}$,and the profit function would look like exactly the same as the Jia (2008)'s framework. Assuming symmetry across outlets within a given grid, the profit function for chain i is given by:

$$\begin{aligned}
\Pi_i(N_i, N_j) &= \Sigma_{m=1}^{M}[N_{i,m} * (X_m\beta + \delta_{chain}\Sigma_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + \delta_{ij}N_{j,m} \\
&\quad + h_{i,m}(N_{i,m}) + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{i,m} + \gamma\mathbf{1}(m \text{ is zoned})] \\
&= \Sigma_{m=1}^{M}[N_{i,m} * (\mathbf{X}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + \delta_{ij}N_{j,m} + h_{i,m}(N_{i,m})] \\
&= \Sigma_{m=1}^{M}[N_{i,m} * (\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + h_{i,m}(N_{i,m})] \\
\text{where } j &: \text{ chain } i\text{'s competitor} \\
\mathbf{X}_{i,m} &\equiv X_m\beta + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{i,m} + \gamma\mathbf{1}(m \text{ is zoned}) \\
\mathbf{Y}_{i,m} &\equiv X_m\beta + \delta_{ij}N_{j,m} + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{i,m} + \gamma\mathbf{1}(m \text{ is zoned})
\end{aligned}$$

As it is clear from the equation above, I have introduced a new term $h_{i,m}(N_{i,m})$ that measures how much spillovers or business stealing you would get from having more than one outlet of the same chain i in location m. The idea of having this term is that we may not observe simple linear relationship between the number of outlets and revenue in a given location. For example, if chain i has two outlets in location m, then the revenue from location m may not just two times revenue of having one outlet in location m, holding other conditions equal. This is because there may be positive spillovers from the same chain's outlet(s) in the same location, or business stealing if they are competing against each other. Notice that I place no restrictions on the functional form of $h_{i,m}(N_{i,m})$: The function can be different across chains and locations, can take negative or positive values, can be linear or nonlinear in the number of outlets in the location m.

First, I verify the second condition of supermodularity of the game. The profit function for chain i is supermodular in its own strategy iff $\Pi_i(N_i')+ \Pi_i(N_i'') \leq \Pi_i(N_i' \wedge N_i'') + \Pi_i(N_i' \vee N_i'')$, for any N_i'

,$N''_i \in \mathbf{N}_i$. For convenience, I define $N^1_{i,m} \equiv N'_{i,m} - \min(N'_{i,m}, N''_{i,m})$, $N^2_{i,m} \equiv N''_{i,m} - \min(N'_{i,m}, N''_{i,m})$, and $N^3_{i,m} \equiv \min(N'_{i,m}, N''_{i,m})$. The combined profits from choosing N'_i and N''_i are given by

$$
\begin{aligned}
\Pi_i(N'_i) + \Pi_i(N''_i) &= \Sigma_{m=1}^{M}[N'_{i,m} * (\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{D'_{i,l}}{Z_{m,l}} + h_{i,m}(N'_{i,m})] \\
&\quad + \Sigma_{m=1}^{M}[N''_{i,m} * (\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{D''_{i,l}}{Z_{m,l}} + h_{i,m}(N''_{i,m})] \\
&= A + \Sigma_{m=1}^{M}[N'_{i,m}h_{i,m}(N'_{i,m}) + N''_{i,m}h_{i,m}(N''_{i,m})] \qquad (9) \\
\text{where } A &\equiv \Sigma_{m=1}^{M}(N^1_{i,m} + N^3_{i,m}) * (\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}(N^1_{i,l} + N^3_{i,l})) \\
&\quad + \Sigma_{m=1}^{M}(N^2_{i,m} + N^3_{i,m}) * (\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}(N^2_{i,l} + N^3_{i,l}))
\end{aligned}
$$

Likewise, the combined profits from choosing $N'_i \wedge N''_i$ and $N'_i \vee N''_i$ will be

$$
\begin{aligned}
&\Pi_i(N'_i \wedge N''_i) + \Pi_i(N'_i \vee N''_i) \\
&= \Sigma_{m=1}^{M}[(N'_{i,m} \wedge N''_{i,m}) * (\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{(N'_{i,l} \wedge N''_{i,l})}{Z_{m,l}} + h_{i,m}(N'_{i,m} \wedge N''_{i,m})] \\
&\quad + \Sigma_{m=1}^{M}[(N'_{i,m} \vee N''_{i,m}) * (\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{(N'_{i,l} \vee N''_{i,l})}{Z_{m,l}} + h_{i,m}(N'_{i,m} \vee N''_{i,m})] \\
&= \Sigma_{m=1}^{M}(N^1_{i,m} + N^2_{i,m} + N^3_{i,m})(\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}(N^1_{i,l} + N^2_{i,l} + N^3_{i,l}) \\
&\quad + \Sigma_{m=1}^{M}N^3_{i,m}(\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}N^3_{i,l}) \\
&\quad + \Sigma_{m=1}^{M}[(N'_{i,m} \wedge N''_{i,m})h_{i,m}(N'_{i,m} \wedge N''_{i,m}) + (N'_{i,m} \vee N''_{i,m})h_{i,m}(N'_{i,m} \vee N''_{i,m})] \\
&= B + \Sigma_{m=1}^{M}[(N'_{i,m} \wedge N''_{i,m})h_{i,m}(N'_{i,m} \wedge N''_{i,m}) + (N'_{i,m} \vee N''_{i,m})h_{i,m}(N'_{i,m} \vee N''_{i,m})] \qquad (10) \\
\text{where } B &\equiv \Sigma_{m=1}^{M}[(N^1_{i,m} + N^2_{i,m} + N^3_{i,m})(\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}(N^1_{i,l} + N^2_{i,l} + N^3_{i,l}) \\
&\quad + N^3_{i,m}(\mathbf{Y}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}N^3_{i,l})]
\end{aligned}
$$

Now, subtracting Eq. (9) from Eq. (10) provides

$$
\begin{aligned}
& \Pi_i(N_i' \wedge N_i'') + \Pi_i(N_i' \vee N_i'') - (\Pi_i(N_i') + \Pi_i(N_i'')) \\
= \; & B + \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'')] \\
& -[A + \Sigma_{m=1}^{M}[N_{i,m}' h_{i,m}(N_{i,m}') + N_{i,m}'' h_{i,m}(N_{i,m}'')] \\
= \; & B - A + \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'') \\
& -(N_{i,m}' h_{i,m}(N_{i,m}') + N_{i,m}'' h_{i,m}(N_{i,m}''))] \\
= \; & \delta_{chain} \Sigma_{m=1}^{M} \Sigma_{l \neq m} \frac{N_m^2 N_l^1 + N_m^1 N_l^2}{Z_{m,l}} \\
& + \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'') \\
& -(N_{i,m}' h_{i,m}(N_{i,m}') + N_{i,m}'' h_{i,m}(N_{i,m}''))] \qquad (11)
\end{aligned}
$$

The first term is exactly the same as binary choice case (entry or exit) if we replace numerator $N_m^2 N_l^1 + N_m^1 N_l^2$ by corresponding index functions, $D_m^2 D_l^1 + D_m^1 D_l^2$, where $D_m^1 \equiv D_{i,m}' - \min(D_{i,m}', D_{i,m}'')$ and $D_m^2 \equiv D_{i,m}'' - \min(D_{i,m}', D_{i,m}'')$.

Now I examine the value of second term location by location. Among a given set of number of outlets $\{N_{i,m}', N_{i,m}''\}$, I can set $N_{i,m}' = \max(N_{i,m}', N_{i,m}'')$, without loss of generality. Then it follows from above that $N_{i,m}'' = \min(N_{i,m}', N_{i,m}'')$. Also, from the definition of meet and join, for each location m,it holds that $N_{i,m}' \wedge N_{i,m}'' = \min(N_{i,m}', N_{i,m}'') = N_{i,m}''$, and $N_{i,m}' \vee N_{i,m}'' = \max(N_{i,m}', N_{i,m}'') = N_{i,m}'$. The inside of summation in the second term in Eq. (11) becomes

$$
\begin{aligned}
& (N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'') \\
& -(N_{i,m}' h_{i,m}(N_{i,m}') + N_{i,m}'' h_{i,m}(N_{i,m}'')) \\
= \; & N_{i,m}'' h_{i,m}(N_{i,m}'') + N_{i,m}' h_{i,m}(N_{i,m}') - (N_{i,m}' h_{i,m}(N_{i,m}') + N_{i,m}'' h_{i,m}(N_{i,m}'')) \\
= \; & 0 \qquad (12)
\end{aligned}
$$

Combining Eq.(11) and Eq. (12) yields

$$
\begin{aligned}
& \Pi_i(N_i' \wedge N_i'') + \Pi_i(N_i' \vee N_i'') - (\Pi_i(N_i') + \Pi_i(N_i'')) \\
= \; & \delta_{chain} \Sigma_{m=1}^{M} \Sigma_{l \neq m} \frac{N_{i,m}^2 N_{i,l}^1 + N_{i,m}^1 N_{i,l}^2}{Z_{m,l}} \qquad (13)
\end{aligned}
$$

Noting that the numerator of the first term, $N_{i,m}^2 N_{i,l}^1 + N_{i,m}^1 N_{i,l}^2$, is always nonnegative since each component is nonnegative by construction, and the denominator, distance variable $Z_{m,l}$, is always positive, I can conclude that the necessary and sufficient condition for supermodularity in its own strategy to hold is $\delta_{chain} > 0$, regardless of the specification of $h_{i,m}(N_{i,m})$. ■

Eq. (13) implies that, within a given location, whether there is positive spillover across outlets of the same chain i or revenue reduction due to presence of own outlet in the same location (cannibalization or business stealing), does not affect whether the game is supermodular in its own strategy or not.

Now I verify the third condition of supermodularity of the game. The third condition holds if, for all $(N_i, \tilde{N}_i) \in N_i$ and $(N_j, \tilde{N}_j) \in N_j$ such that $N_i \geq \tilde{N}_i$ and $N_j \geq \tilde{N}_j$,

$$\begin{aligned} \Pi_i(N_i, N_j) - \Pi_i(\tilde{N}_i, N_j) &\geq \Pi_i(N_i, \tilde{N}_j) - \Pi_i(\tilde{N}_i, \tilde{N}_j) \\ \text{or equivalently, } \Pi_i(N_i, N_j) - \Pi_i(N_i, \tilde{N}_j) &\geq \Pi_i(\tilde{N}_i, N_j) - \Pi_i(\tilde{N}_i, \tilde{N}_j) \end{aligned}$$

In other words, "increasing difference says that an increase in the strategies of player i's rivals raise the desirability of playing a high strategy for player i."(Fudenberg and Tirole 1991 p.492) So it reduces to show that $\Pi_i(N_i, N_j) - \Pi_i(N_i, \tilde{N}_j)$ is increasing in N_i.

$$\begin{aligned} & \Pi_i(N_i, N_j) - \Pi_i(N_i, \tilde{N}_j) \\ = \;& \Sigma_{m=1}^{M}[N_{i,m} * (\mathbf{X}_{i,m} + \delta_{chain}\Sigma_{l \neq m}\frac{N_{i,l}}{Z_{m,l}} + \delta_{ij}N_{j,m} + h_{i,m}(N_{i,m})] \\ & -\Sigma_{m=1}^{M}[N_{i,m} * (\mathbf{X}_{i,m} + \delta_{chain}\Sigma_{l \neq m}\frac{N_{i,l}}{Z_{m,l}} + \delta_{ij}\tilde{N}_{j,m} + h_{i,m}(N_{i,m})] \\ = \;& \delta_{ij} * \Sigma_{m=1}^{M}N_{i,m}(N_{j,m} - \tilde{N}_{j,m}) \end{aligned}$$

Provided that δ_{ij} is negative, this implies the profit function Π_i has decreasing differences in $N_{i,m}$, since $N_j \geq \tilde{N}_j$. By using a simple transformation trick in Vives (1990), that is to define a new strategy for competitor, $\hat{N}_j = -N_j$, the profit function Π_i will have increasing differences. ■

9.3.2 Case (2): Chain Effect at the Location-level

For the variables $N_i, N_{i,m}^1, N_{i,m}^2, N_{i,m}^3, \mathbf{X}_{i,m}, \mathbf{Y}_{i,m}$, and $h_{i,m}(N_{i,m})$,I use the same definition as in the previous subsection. I also define an indicator function for chain i's presence in location m, $D_{i,m}$, which equals 1 if chain i enters in location m, zero otherwise. So $D_{i,m} = 1$ iff $N_{i,m} \geq 1$, $D_{i,m} = 0$ otherwise.

First, I verify the second condition of supermodularity of the game. The profit function will be this form

$$\Pi_i(N_i, N_j) = \Sigma_{m=1}^{M}[N_{i,m} * (Y_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{D_{i,l}}{Z_{m,l}} + h_{i,m}(N_{i,m})]$$

The only difference from the previous subsection is the second term: we now have $\delta_{chain}\Sigma_{l\neq m}\frac{D_{i,l}}{Z_{m,l}}$ instead of $\delta_{chain}\Sigma_{l\neq m}\frac{N_{i,l}}{Z_{m,l}}$.I define $D^1_{i,l} \equiv D'_{i,l} - \min(D'_{i,l}, D''_{i,l})$, $D^2_{i,l} \equiv D''_{i,l} - \min(D'_{i,l}, D''_{i,l})$, and $D^3_{i,l} \equiv \min(D'_{i,l}, D''_{i,l})$. By following a similar algebra as before, I get the second condition as

$$\begin{aligned} & \Pi_i(N'_i \wedge N''_i) + \Pi_i(N'_i \vee N''_i) - (\Pi_i(N'_i) + \Pi_i(N''_i)) \\ = \ & \delta_{chain}\Sigma_{m=1}^{M}\Sigma_{l\neq m}\frac{N^2_{i,m}D^1_{i,l} + N^1_{i,m}D^2_{i,l}}{Z_{m,l}} \end{aligned} \quad (14)$$

Noting that

$$\begin{aligned} N^2_{i,m}D^1_{i,l} + N^1_{i,m}D^2_{i,l} \ = \ & [N''_{i,m} - \min(N'_{i,m}, N''_{i,m})][D'_{i,l} - \min(D'_{i,l}, D''_{i,l})] \\ & +[N_{i,m} - \min(N'_{i,m}, N''_{i,m})][D''_{i,l} - \min(D'_{i,l}, D''_{i,l})] \end{aligned}$$

is nonnegative since either $N^2_{i,m}, D^1_{i,l}, N^1_{i,m}$,or $D^2_{i,l}$ is nonnegative, we can conclude that the necessary and sufficient condition for supermodularity in its own strategy to hold is $\delta_{chain} > 0$. ■

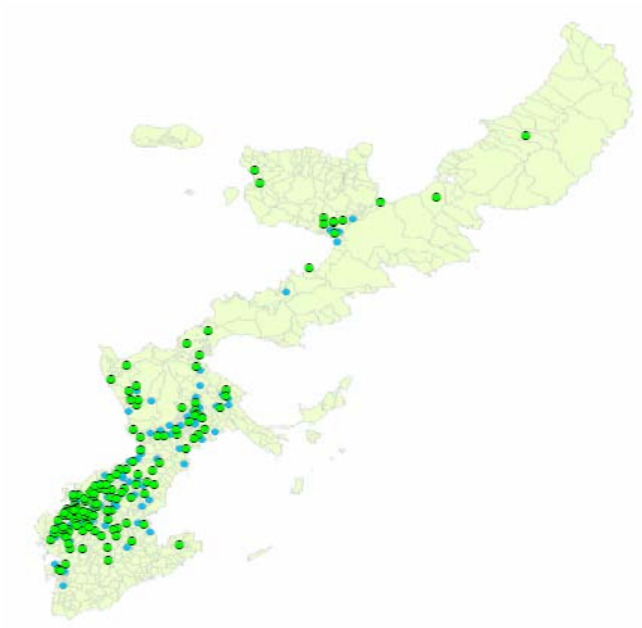
Eq. (14) implies that, within a given location, whether there is positive spillover across outlets of the same chain i or revenue reduction due to presence of own outlet in the same location (cannibalization), does not affect whether the game is supermodular in its own strategy or not.

Now in order to verify the third condition of supermodularity of the game, I show that $\Pi_i(N_i, N_j) - \Pi_i(N_i, \tilde{N}_j)$ is increasing in N_i.

$$\begin{aligned} & \Pi_i(N_i, N_j) - \Pi_i(N_i, \tilde{N}_j) \\ = \ & \Sigma_{m=1}^{M}[N_{i,m} * (\mathbf{X}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{D_{i,l}}{Z_{m,l}} + \delta_{ij}N_{j,m} + h_{i,m}(N_{i,m})] \\ & -\Sigma_{m=1}^{M}[N_{i,m} * (\mathbf{X}_{i,m} + \delta_{chain}\Sigma_{l\neq m}\frac{D_{i,l}}{Z_{m,l}} + \delta_{ij}\tilde{N}_{j,m} + h_{i,m}(N_{i,m})] \\ = \ & \delta_{ij} * \Sigma_{m=1}^{M}N_{i,m}(N_{j,m} - \tilde{N}_{j,m}) \end{aligned}$$

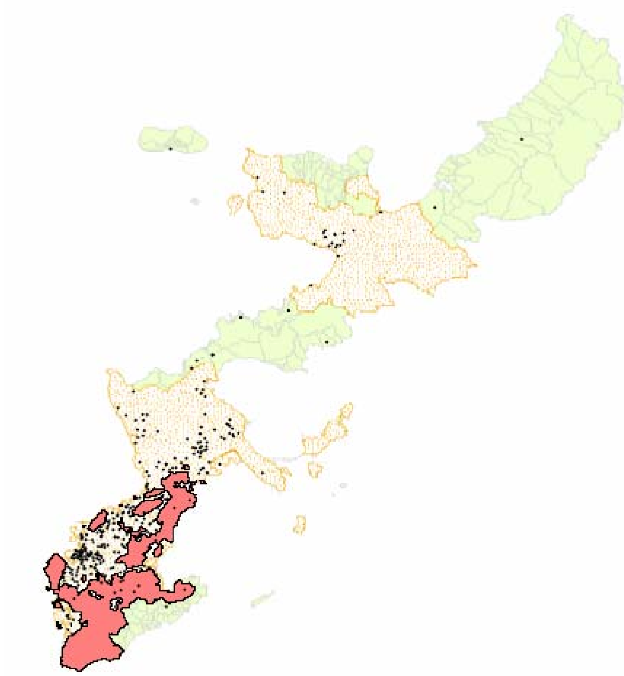
, which is exactly the same as case 1. Therefore, by using the same argument, the profit function Π_i will have increasing differences. ■

Figure 1: Convenience Stores in Okinawa



Notes: Green points are Family Mart, and blue points are LAWSON outlets.

Figure 2: Zoning Map



Notes: Brown region is unzoned area, and red region is zoned area (=urbanization control area). Small dots represent location of convenience stores.

Table 1: Summary Statistics at the Location Level

Variable	Mean	Std. Dev.	Min	Max
	834 Sample Locations			
Population: All Locations	1,434	2,588	0	18,977
Population: Zoned Area (140 Locations)	1,298	1,299	1	6,119
Population: Unzoned Area (694 Locations)	1,461	2,777	0	18,977
Number of Workers: All Locations	580	1,612	0	32,776
Workers: Zoned Area (140 Locations)	457	634	0	4,008
Workers: Unzoned Area (694 Locations)	605	1,743	0	32,776
Number of Outlets, Family Mart	0.170	0.539	0	5
Number of Outlets, LAWSON	0.122	0.438	0	5

Notes: Location is 1km square grid, which border is defined in census of bureau. Population variable is aggregagted at the 1km square grid level

Table 2: Simulation Estimates for 50 Replicated Datasets

parameter		"truth"	MSM point estimates (mean)			
Population	β	1.00	1.30 (0.65)	1.03 (0.29)	1.00 (0.40)	1.45 (1.01)
Chain Effect	δ_{own}	0.20	0.20 (0.18)	0.24 (0.09)	0.27 (0.09)	0.25 (0.14)
Competitive Effect	$\delta_{competitive}$	-0.50	-0.27 (0.84)	-0.74 (0.35)	-0.73 (0.46)	-0.50 (0.29)
Rho	ρ	0.50	0.65 (0.34)	0.68 (0.15)	0.65 (0.16)	0.55 (0.41)
Number of Locations			16	36	144	1,600

Notes: The number of simulations per replication is 20, except for the last column where s is set to 7. I assumed symmetry of both players. To account for the spatial interdependence of markets, I follow Conley (1999)'s nonparametric covariance matrix estimator. Standard errors are in parentheses.

Table 3: MSM Parameter Estimates, Okinawa

parameter		point estimates
ln Population	β	0.3083 (0.0520)**
ln Number of Workers	βbus	0.7159 (0.0741)**
Chain Effect	$\delta chain$	0.0036 (0.1325)
Cannibalisation Effect	$\delta within$	-0.4054 (0.2966)
Competitive Effect	$\delta competitive$	-0.3906 (0.1363)**
Rho	ρ	0.1163 (0.0865)
Zoning Dummy	γ	-0.2584 (0.1099)**
Constant		-3.1895 (0.0993)**
Number of Locations		834

Notes: Standard errors are in the parenthesis. I set the number of simulations to 60. I assume symmetry of both players. I use Conley (1999)'s nonparametric covariance matrix estimator for the standard errors. * significant at 5%; ** significant at 1%.

Table 4: Counterfactual Simulations

	Data	Model Fit	No Zoning	All Zoning
Family Mart	127	125.2	130.7	100.7
LAWSON	95	91.6	95.7	72.3

Notes: The number in Fit column shows the number of outlets predicted by the estimated model. No Zoning refers there is no zoning restriction placed on markets in Okinawa. All zoning means that zoning restrictions are placed on all markets in Okinawa.

Table 5: Descriptive Regressions in Okinawa, OLS

Regressor	(1)	(2)	(3)
log population	0.425	0.441	0.043
	(0.022)**	(0.022)**	(0.036)
log workers			0.609
			(0.045)**
zoning dummy		-0.407	-0.322
		(0.083)**	(0.075)**
R-squared	0.310	0.330	0.450

Notes: The dependent variable is the total number of convenience store outlets in the market. The number of observations is 834. Standard errors in parentheses. * significant at 5%; ** significant at 1%.