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Working Paper #08-27

October 2008

Estimating a Model of Strategic Store-Network Choice

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Estimating a Model of Strategic Store-Network Choice*

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November 15, 2008

Abstract

Competition among multi-store chains is common in retail industries. This paper proposes a method for estimating a model of strategic store-network choices by two chains. In contrast to previous studies, I allow chains to not only choose which markets to enter but also how many stores to open in each of those markets. I use lattice-theoretical results to deal with the huge number of possible network choices. I show that a chain's net trade-off between costs and benefits from clustering their stores in a market can be either positive or negative while still ensuring the existence of an equilibrium. By doing so, the model provides a way to freely estimate this within-market effect from the data. Incorporating revenue data allows us to interpret parameters in monetary units and to decompose the within-market effect into cost savings from clustering stores (economies of density) and lost revenues from competition with one's own stores (own-chain business-stealing effect). I apply the technique to a new data set from the convenience-store industry in Okinawa, Japan. Parameter estimates confirm that own chain business-stealing is an important consideration for a chain. I then use the estimated structural model to perform two counterfactual analyses. First, I consider a hypothetical merger of two chains and find that the merger would decrease the number of stores and total sales, and raise the acquirer's profits, thereby reallocating surplus from consumers to the acquirer. Second, I examine how eliminating the zoning regulation introduced in Japan in 1968, which has been at the forefront of urban policy debates, affects store-network choices.

Keywords: entry; merger; retail location; supermodular game; zoning regulation
JEL-Classification: L13; L40; L81; R52

*I would like to thank my advisors Jeremy Fox, Ali Hortaçsu, Chad Syverson, Jean-Pierre Dubé, and Ting Zhu for their advice and help throughout the project. I have also benefited from discussions with Timothy Conley, Panle Jia, Steve Levitt, Ryo Nakajima, Yukako Ono, Yeşim Orhun, Andy Skrzypacz, Zhu Wang, and seminar participants at Hitotsubashi, IDE-JETRO, Kyoto, Tsukuba, Tokyo, Yokohama National, the Chicago microlunch and IO lunch seminars, the 2008 European Association for Research in Industrial Economics (EARIE) conference, the 2008 Far Eastern Meeting of the Econometric Society, and the 2008 Midwest Economics Association Annual Meeting. I would like to thank Todd Schuble for help with GIS. I would also like to thank Takashi Shinno from Family Mart Co.,Ltd and Yasushi Kinoshita from Tokyo Business Consulting for sharing with me their insights on the convenience store industry. I gratefully acknowledge financial support from the NET Institute (www.netinst.org) and the Kauffman Foundation. I wish to thank the Center of East Asian Studies for funding data acquisition. All remaining errors are my own.

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1 Introduction

Retail markets are a large fraction of total output in developed countries. Multi-store retail chains engage in fierce competition with rival chains by designing their store networks to attract local customers. Having store-location networks enables chains to internalize the benefits and losses from having their own stores nearby. For example, a multi-store chain, such as Wal-Mart or 7-Eleven, may want to cluster its stores in a given market to minimize its distribution costs. Unfortunately, coordinated store-location choice has received less attention, mostly due to practical consideration: modeling a game of entry decisions over many markets poses a formidable methodological challenge for the computation of equilibrium store-network decisions. For instance, consider a game with two players, twenty markets, and five available choices for each player. The number of possible strategy profiles is $5^{20} = 9.5 * 10^{13}$, and the number of feasible outcomes of the game is $5^{20} * 5^{20} = 9.1 * 10^{27}$.

In this paper, I propose an empirical model of spatial competition between two chains choosing their store networks. This paper is the first after Jia (2008) to compute a Nash equilibrium of a chain-entry game in which chains compete by choosing their store networks. I extend the novel results of Jia (2008) to a general class of chain-entry models that allows chains to not only choose which markets to enter but also how many stores to open in each of those markets. Unlike standard models of entry, I incorporate not only data on the number of stores but also post-entry outcome data, such as revenue. My approach has three advantages. First, my method is free from limitations arising from binary choice of entering or not entering a market. One limitation of binary choice is endogeneity bias. Endogeneity bias can arise if store locations are treated as exogenous since store openings are, in fact, endogenous variables of the error terms in each market. Another limitation of binary choice models is the low coverage of data. Dropping large markets from observations will overlook most of the observations from urban markets, forcing us to focus only local markets. The second advantage is that my method introduces a crucial consideration for a chain: the trade-off multiple-store retailers face between the positive benefits of density and lost revenues from competition with its own stores. Traditional entry models with binary choice miss this consideration. For instance, chains can save distribution costs by having shorter routes, but the chains may also suffer a revenue reduction from the presence of their other stores. By using lattice-theoretical results, I show my chain-entry model accommodates either a positive or negative within-market effect, allowing us to freely estimate the within-market parameter from the data. More broadly, my model allows for the richness of real world data sets and should be useful for a broad range of industries in which measuring the relative importance of the economies of density and business stealing is important. Finally, integrating the model with revenue data allows us to interpret the benefits and costs due to merger or policy changes in monetary units, which are, in general, difficult to obtain in standard entry models, which use information on firm entry and demographic characteristics. With revenue data, I also show that we can decompose the within-market effect into cost savings from economies of density, and lost revenues from competition with one's own stores.

I apply the method proposed in this paper to a new data set I collected from the convenience-store industry in Okinawa, Japan. I specify a static game of complete information with two players simultaneously and strategically choosing their store networks over all markets in Okinawa. The technique allows us to conduct "what if" experiments: solving for a pure-strategy Nash equilibrium in the new competitive environment allows us to learn what the equilibrium effects would be in store networks when there are changes in the competitive environment, such as a merger of the two chains or change in a regulation. The convenience-store industry on the island of Okinawa suits the method due to geographic reason: Okinawa has two convenience-store chains, each of which having a distribution center and a store network to serve 1.2 million people in the island.

Turning to the empirical results, I present three findings. First, the estimates confirm that the consideration of the costs and benefits of clustering within a market is, indeed, important for retail chains. I find that lost revenues from competition with one's own stores (own-chain business-stealing effect) is large: having a store of the same chain in the same market reduces the total sales per store by 20 percent, which is approximately the same magnitude as the business-stealing effect from a rival chain store. Second, in a hypothetical merger, I find the acquirer would obtain higher profits than the sum of pre-merger profits of both chains, mainly due to increased cost savings and better store locations by redesigning the locations and the number of stores. For instance, more stores would locate in the city-center in Okinawa after the merger because the acquirer can therefore enjoy higher population density and higher positive spillovers from own stores in adjacent markets. In contrast, in suburban markets, the merged chain would decrease the number of stores, reducing its total sales in those markets. In total, we would expect increased total profits and decreased total sales, resulting in reallocation of surplus from consumers to the merged chain. Finally, due to unattractive demographics in originally zoned markets, I find that eliminating the regulation would increase the total number of stores only by 4 to 5 percent, of which magnitudes are similar across chains. The markets the deregulation would affect are geographically different: chains tend to increase their stores in markets adjacent to their existing store networks. The forgone profits due to the regulation are modest: US$1.2 million, which is 2 percent of total profits of both chains in Okinawa.

The paper proceeds as follows. The remainder of this section discusses the relationship to the existing literature. Section 2 contains information about the dataset I have constructed. Section 3 introduces the entry model and provides analytical results. I particularly emphasize my computational algorithm for solving the game. Section 4 discusses the empirical implementation of the project. Section 5 reports the parameter estimation results. Section 6 performs two counterfactuals: a hypothetical merger and a change in zoning regulation. Section 7 explores the robustness of the results by varying the definition of markets and the equilibrium selection rule. Finally, section 8 provides concluding remarks. Appendix contains a description of the convenience-store industry in Japan, details of the zoning regulation, proofs of proposition 1 and 2, Monte Carlo experiments, and estimation details.

1.1 Relationship to Literature

The paper complements the growing spatial competition literature by highlighting the importance of choosing retail-store networks strategically. The geographic aspect of retail competition has been studied for industries such as fast food (Thomadsen 2005), movie theaters (Davis 2006), and retail gasoline (Manuszak 2000 and Houde 2007), to name a few. Examples of retail competition in the context of retail location choice include video rental (Seim 2006) and eyeglasses (Watson 2005). For instance, Seim (2006) proposes an empirical model of location choice and shows that strategic interactions and geographic differentiation are important when retail outlets are choosing one market from the available markets.[1] However, Seim (2006) has to abstract from the coordinated entry decisions made by national video-rental chains operating multiple outlets.[2] This paper is related to recent progress in quantifying the importance of network effects or positive spillovers between the stores in the same retail-chain industries (Holmes 2008; Jia 2008; Ellickson, Houghton, and Timmins 2008).

This paper builds on a vast literature of game-theoretic models of entry, initiated by Bresnahan and Reiss (1990, 1991). In the last two decades, researchers have been using game theory to investigate the determinants of oligopolistic market structure, which previously had been treated as given. In the game-theoretical framework, agents act strategically and their observed choices are a Nash equilibrium of a game that has been played by these agents. The econometrician then uses

[1] Seim (2006) relaxes the assumption of cross-sectionally independent markets by allowing firms to freely locate within geographically adjacent markets and making entry decisions of a firm dependent on other firms' decisions in surrounding markets.

[2] Progress has been made in this direction: Thomadsen (2007) and Zhu and Singh (2007) explicitly model location choices that can differ across chain brands

the revealed preferences argument: he backs out what was the game that generated the outcomes by observing firms' entry decisions. Since then, static entry games have seen empirical applications in a wide range of industries. Researchers have also devoted much effort to adding complexities to Bresnahan and Reiss (1990,1991), such as introducing heterogeneity in fixed costs across players (Berry 1992), endogenizing product-differentiation choice (Mazzeo 2002), or endogenizing identities of entrants (Ciliberto and Tamer 2007), all under the specification of a game being played in a single market with exogenous sunk costs of entry: an entry decision in a market is independent of entry decisions in other markets. As a consequence, the empirical study has been limited to isolated markets in which one can safely assume a firm's behavior to be independent across markets. In contrast, this paper models a chain as a firm operating many stores and, in a Nash equilibrium, designing an optimal store network given a competitor chain's store network.

Methodologically, the chain-entry model in this paper is closely related to the one in Jia (2008), who provides a novel approach for dealing with the computational burden of solving for a Nash equilibrium in store networks. Only her work and this paper (1) model chains as playing a game and (2) solve for a Nash equilibrium in their store-network choice. One feature of Jia's model is that a chain has a binary choice of entering or not entering a given market, and therefore the model implicitly assumes spillovers between stores of the same chain may only be nonnegative. Unfortunately, assuming only nonnegative spillover is unrealistic in the Japanese convenience-store context due to the dense configurations of stores and the likely trade-off between the positive benefits of density and the negative impact of business-stealing.[3] Unlike Jia, this paper develops the typical binary-choice decision to the more realistic case of multiple store openings in a given market. Although we have to maintain the assumption of nonnegative spillover across markets for the iteration algorithms to work, I find that we can allow for net business stealing or net positive-cost savings within a market. Within-market effect may be harder to assume to be positive or negative ex-ante than the spillovers across markets.

More broadly, the framework this paper proposes can be generalized to the context of product-line design if we interpret the location as a distance between product characteristics instead of the physical location of stores. The model in this paper can be viewed as a static game in which two firms compete against each other by introducing several differentiated products (or brands) in the product space. In the context of this literature, a major feature of my model is that a firm maximizes its profits by choosing the optimal product line, considering not just competition across firms but

[3]Relaxing the sign restriction in a given market is related to Vitorino (2008), who allows for spillovers between rival chain stores in a shopping-mall industry.

also competition within the firm's product line (intra-firm competition or cannibalization), which Moorthy (1984) explores in the setting of a monopolist.

2 Data and Descriptive Analysis

2.1 Data

The data set I use in the study is from Okinawa in 2001, which I have compiled from a variety of sources.

I rely on convenience-store-location data taken from the Convenience Store Almanac in 2002 for chain stores. The almanac contains the store addresses, zip codes, phone numbers, and chain affiliations of outlets. I convert each store's address into a latitude and longitude by using a geographic reference information system from the Ministry of Land, Infrastructure and Transport. Two-hundred-and-seventy-five convenience stores, which are about 80 percent of the total number of 24-hour convenience stores in Okinawa, match at the level of lot addresses. For the remaining 20 percent of stores, I manually acquire individual stores' longitude and latitude information by using mapping software, various online mapping services such as Google Maps or Yahoo!, and corporations' online store locators. I assign each store to the corresponding 1km square grid in which it falls. Figure 1 shows the location of stores for Family Mart and LAWSON in Okinawa Main Island.

I use revenue data as a source of identification for the competitive effects and the across-market effects. The convenience-store-revenue data set is available from the 2002 Census of Commerce from the Ministry of Economy, Trade and Industry. The information on annual revenues is available at the aggregated level of a 1 km^2 uniform grid. Sales are broken into two categories: 24-hour operation stores and non-24-hour stores. Because all chain-stores are 24-hour operation, I treat non-24-hour stores as non-chain stores. The revenue data has an exogenous sample selection rule for each category of stores that, in order to protect privacy, total revenues with less than three stores in a given market will not be disclosed. The data report the total number of stores and total sales at the 1km square level and do not disclose the number of store or sales by chain brands.[4]

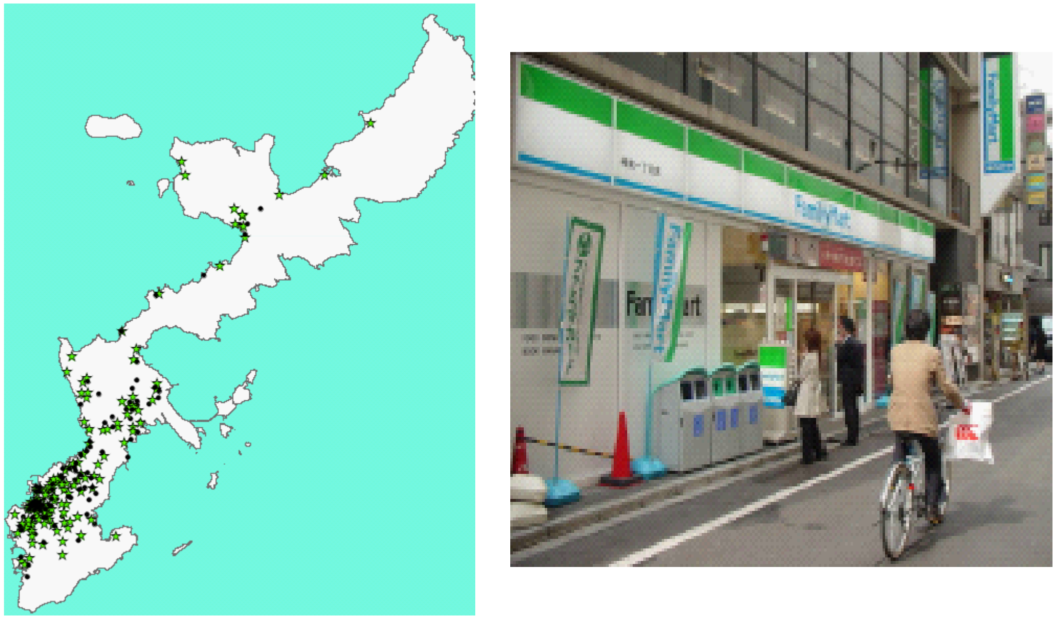
Population is an important predictor of store-location choice. The population data come in two ways: first, the Census of Population at the 1km square grid level from 2000 is available from the Census Bureau that contains the number of people living in the 1km^2 grids. I call this variable "nighttime population." The second source is the 2001 Establishment and Enterprise Census from

[4] For this reason, I compute the number of stores for each chain in a market by matching the store-location data for each chain from the Convenience Store Almanac in 2002 with 1km square grids.

the Bureau of Census. It contains information on the number of business establishments and the number of workers. The number of workers will capture the daytime demand for convenience stores.

FIGURE 1

CONVENIENCE STORES IN OKINAWA

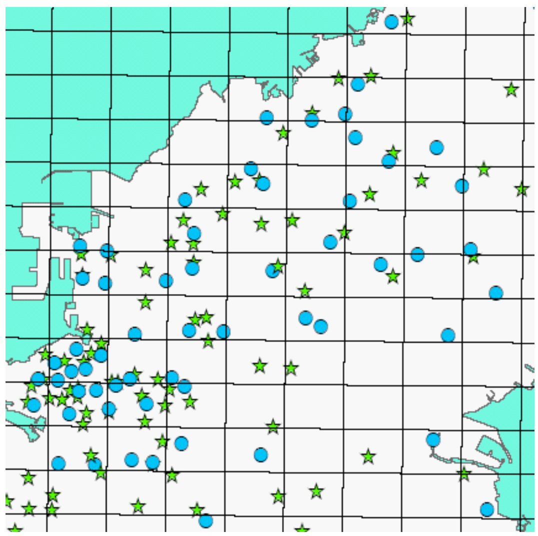


NOTE. - In the left panel, the stars show Family Mart stores and the circles show LAWSON stores.

The sample contains 834 markets. In this study, I define a market as a uniform grid of 1km square following the 2000 Census of Population and the 2001 Establishment and Enterprise Census data, and I use the grids as a unit of analysis. Delineating the geographic market for retail markets is a problem when a natural boundary on the trade area is not available. Bresnahan and Reiss (1991) focus on industries in which markets are small and isolated to avoid the issue of contiguous markets. However, in most industries, finding perfectly isolated markets both in terms of demand and costs, as is the case in this industry, is difficult. I choose a 1 kilometer square as the relevant geographic market for the convenience-store industry because people in Okinawa generally do not travel far to access convenience stores: the average travel time is around 10 minutes by walking. 1 kilometer would be approximately the diameter of the trade area for these people. Convenience-store demand is more localized in Japan than are other types of service industries, such as supermarkets or gas stations: 70 percent of customers visit on foot and 30 percent by cars. To avoid including inhabitable or undevelopable areas such as mountain regions as potential markets for convenience stores, I exclude grids that have no population either during the day or night. This leaves me with a sample of 834 markets that cover 834 km^2 or 322 mile^2, which is 69 percent of the total land area of Okinawa. I define adjacent markets (or neighboring markets) of a market as those 1km square grids that share borders or grid points with the market. So a market has up to eight adjacent markets. Of course, the market definition depends on strong assumptions on how grids and borders are chosen. In the robustness check section, I conduct a sensitivity analysis and examine whether the parameter estimates are robust to reasonable alternative choices of grids. Figure 2 presents the actual 1km square grids and the configurations of stores.

FIGURE 2

TORE CONFIGURATIONS AND 1 KILOMETER SQUARE GRIL



NOTE. - The stars show Family Mart stores and the circles show LAWSON stores.

As Figure 2 shows, we are more likely to see many markets with more than one store for each chain. Table 3 shows that, for Family Mart, only 81 stores out of 142 total stores are single stores within a given market. For LAWSON, 67 stores out of 102 stores in total are single stores within a given market. This observation provides a practical motivation for why we would like to depart from a model that accommodates only one store at maximum for each chain in a given market.

Descriptive Analysis. Here, I provide some descriptive statistics and simple regression results. Table 1 provides a brief summary of all the market level variables. A census 1km grid contains between 0 and $18,977$ people in residence, with $2,588$ people on average. For the number of workers, a grid has between 0 and $1,612$ workers, with 580 people on average. Across zoned and unzoned areas, little difference exists in two of the population variables. Zoned areas, in which one needs to obtain a development permission from the government in order to open a convenience store, represent 15 percent of the total nighttime population and 13 percent of the total daytime population for Okinawa.

The number of stores for the two chains, Family Mart and LAWSON, ranges from 0 to 7 and from 0 to 6, respectively. The aggregate numbers of stores are at 142 and 102 in Okinawa. There are 225 non-chain stores.[5] The combined number of stores of Family Mart and LAWSON comprises 54 percent of the total number of convenience stores in Okinawa. Table 3 displays a matrix of observed market configurations of stores for the two chains. The bottom rows of Table 1 show that the average sales per store are 1.43 million US dollars for Family Mart and $1.45 million for LAWSON. No noticeable difference exists in sales per store among these chains. The average sales per store for non-chain stores are $1.1 million, about 25 percent less than sales per store of the two chains. The combined sales of the two chains, Family Mart and LAWSON, are 60 percent of the total sales of Okinawa's combined convenience-store industry.

I now present a reduced-form analysis, which examines how demographics affect store-opening decisions and measures whether the zoning regulation has a large influence on market structure in the retail industry. Table 2 gives the results from the ordinary least-square regressions of the total number of chain stores in a market, both Family Mart and LAWSON brands, on the market's nighttime population and a zoning index that is 1 if the market is zoned and 0 otherwise. In column 2 and 4, I also control for daytime population both in level and in logs. Although differences in statistical significance exist, the results from all four specifications show that the number of convenience-store outlets is negatively associated with the zoning index variable. Turning to the role of local population on entry, population either during the day or night in a market is positively associated with the number of outlets in the market. For example, in log specifications, doubling the nighttime population increases the prediction of the number of stores by 0.3. As columns 2 and 4 suggest, the finding on the role of the zoning regulation is robust to the introduction of daytime population, although the nighttime population coefficient becomes insignificant in the log specification of population in column 4.

3 Game of Choosing Store Networks

This study uses a static model of a simultaneous-move game with complete information. Compared to private information, complete information better describes the outcome of decisions such as entry for two reasons. First, in games of private information, players may possibly have ex-post

[5]In 2001 in Okininawa, there were 88 stores of another chain, Hot Spar. In this study, however, I treat Hot Spar stores as non-chain stores, together with other non-chain stores that are independently operated. I do so because Hot Spar originally started as a voluntary chain in Okinawa and assuming coordinated store-location decision by Hot Spar headquarters is difficult.

regret about their store-network choice in the one-shot game. Treating entry data as the equilibrium outcomes of the game of private information is therefore because in reality players are able to change their actions after information is revealed. Second, we must consider what the econometrician observes versus what the players observe. Games of complete information allow the chains to have more information than the econometrician. Games of private information assume the econometrician has the same uncertainty as each player, which is a strong assumption given that the only market characteristic I observe in the data is population and zoning regulation status.

In the following subsections, I describe how to model the choice of store networks by chains. The model is based on Jia (2008). The main difference is that I generalize the chain-entry model by Jia (2008) from a binary choice to K choices in a market.

3.1 Firm Behavior: Non-revenue Model

In this study, I develop an equilibrium model of entry in which two players strategically compete against each other by choosing a store network. We frequently observe intense rivalry between chain brands with similar characteristics in many retail industries, such as BestBuy vs. Circuit City and Wal-Mart vs. Kmart. In many cases, the market structure is concentrated, and retail stores compete against their rivals in many dimensions, including prices, advertising, and store locations. In the convenience-store industry in Japan, the chains strive to offer similar shopping experiences: the variety of merchandise and other services are as uniform as possible across outlets. A notable feature of the industry is that retailers adopt nationwide pricing across outlets, which allows me 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, in the model, design optimal store networks, each taking into account its competitor's store-network configurations.[6] Therefore, I model the market structure as being determined by the strategic actions of two players choosing a store-network that maximizes each chain's aggregated profits in equilibrium.[7]

[6] 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 that will minimize the costs of delivery.

[7] Ample evidence exists to support the argument that convenience-store chains devote many resources to conducting extensive research on determining the best location before installing new outlets. Conversations with industry participants revealed that a typical chain carefully chooses an outlet location aligned with its own existing store network and the locations of competitors' stores. This finding contrasts with an individual store owner choosing a best location, regardless of chain brands, and a monopoly chain optimally locating outlets over a large choice-set, regardless of rivals' locations. Also, annual company brochures intended for investors spend several pages explaining that chains invest in sophisticated distribution systems to preserve the freshness of foods (e.g., lunchboxes, rice balls,

Formally, I consider a game in which two players, denoted by player i and player j, choose their store networks. The game is a one-shot simultaneous move with strategic interactions by two players. I denote a strategy vector for player i and player j by N_i and N_j. A strategy vector for chain i is an $M*1$ vector: $N_i = (N_{i,1}, ..., N_{i,M})$, where M denotes the total number of markets. A set of mutually exclusive discrete markets exists within a prefecture, and the set of markets is indexed by $m = 1, ..., M$. So $N_{i,m}$ denotes the number of stores chain i opens in market m. In the empirical implementation, each chain can open up to four stores in any market m: $N_{i,m} \in \{0, 1, .., 4\}$. The choice ($K = 4$) covers 832 out of 834 markets in Okinawa. I define chain i's multi-dimensional strategy space by $\mathbf{N}_i$, which is a subset of a finite-dimensional Euclidean space $\mathbf{R}^M$. The number of possible strategy profiles for each player is 5^M when $K = 4$. In the case of two players, $(5^M)^2$ possibilities exist for the equilibrium of the game. Each player maximizes its aggregate profits by choosing its store-network, $N_i = (N_{i,1}, .., N_{i,M})$. I denote the payoff function for chain i and chain j by $\Pi_i(N_i, N_j) : \mathbf{N} \to \mathbf{R}$ and $\Pi_j(N_j, N_i) : \mathbf{N} \to \mathbf{R}$, respectively, for given strategy vectors of chain i and chain j, $N_i \in \mathbf{N}_i$ and $N_j \in \mathbf{N}_j$.

Throughout the paper, I focus on a pure-strategy Nash equilibrium, which is defined as a strategy vector for each chain that maximizes its profit, given a competitor chain's strategy. I do not look at mixed-strategy equilibria in this study. I assume the profit shocks to firm i are public information. In other words, each chain has perfect information on its rival's payoff from entering multiple markets.

Player i maximizes its total profit Π_i by choosing the strategy vector $N_i \in \mathbf{N}_i$ given the competitor's action $N_j \in \mathbf{N}_j$

$$\Pi_i(N_i, N_j) = \Sigma_{m=1}^{M} \pi_{i,m}(N_i, N_{j,m}),$$

where $\pi_{i,m}$ is chain i's profits in market m. I parameterize the payoff function in market m for chain $i \in \{FM, LS\}$ as the number of stores times the profits per store:

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

X_m are observable demographic characteristics of the market m that affect the demand for conve-

and sandwiches).

nience stores. $N_{j,m}$ is the number of competitor stores of chain $j \in \{FM, LS\}$ in the market. Note that in this model, firm profitability at the market level does not only depend on chain i's decision in market m; rather, the profitability is a function of chain i's entire network N_i and the network of its competitor N_j. I assume the revenue declines linearly in the number of competitor stores. $N_{i,l}$ represents the number of stores in market l, which is adjacent to market m. $Z_{m,l}$ measures the distance from market m to the adjacent market l. $\eta_{i,m}$ is a chain-market-specific profit shock, independently and identically distributed (i.i.d.) across chains and markets.[8] ε_m is a market-specific profit shock that affects all the stores of both chains in market m and i.i.d. across markets. I assume both $\eta_{i,m}$ and ε_m are drawn from a standard normal distribution and enter linearly in the profit function. I impose the traditional scale normalization that the variance of a linear combination of unobservables, ε_m and $\eta_{i,m}$, is one. ρ is the correlation parameter: the correlation of combined unobservables across chains in a given market will be ρ^2. I assume both shocks are observed by two chains but are unobserved by the econometrician and are independent of the exogenous variables.

Turning to the notation of parameters, the term δ_{across} measures the net effect of cost savings from having outlets of the same chain in adjacent markets minus the business stealing from those stores. $\delta_{comp,rival}$ measures the impact of the number of competitor stores in the same market on store-level profits. The parameter δ_{within} captures the net effect of two forces that stem from having a store of the same chain in the same market: if the business-stealing effect from the same chain store in the same market ($\delta_{comp,own}$) exceeds the benefits from clustering (δ_{saving}), the parameter is negative: namely, $\delta_{within} = \delta_{comp,own} + \delta_{saving}$.

The fixed costs of zoning, parameterized by γ, capture the effect that the store may have to incur additional costs for opening a store in a zoned area. I treat the profit function of Family Mart and LAWSON symmetrically except for the fixed effect for LAWSON: the chains have the same values for the parameters in the profit function because the model specification needs to be parsimonious due to the number of observations.

3.2 Firm Behavior: Revenue Model

Unlike Jia (2008), I use revenue data, which allows me to decompose profits into revenues and costs. The estimation strategy is similar to the strategy in Reiss and Spiller (1989) and Berry and Waldfogel (1999), who integrate the data on firms' entry decisions with post-entry information such as revenues. Without revenue data, one can only estimate a so-called threshold-crossing condition that is invariant to a positive monotonic transformations. In contrast, by using sales at the 1km grid

[8] I assume stores of same chains in a given grid receive a common shock.

level as a source of identification of revenue related parameters, I am able to evaluate the estimated model parameters in monetary units.[9] Furthermore, with revenue data, we can decompose the net within-market effect $\delta_{within}+\ \delta_{comp\_own}$ and separately identify the gross benefits by clustering δ_{saving} and the gross business stealing by own chain store in the same market $\delta_{comp,own}$.

I assume firm i's profit function in market m is a linear combination of revenue and cost:

$$\pi_{i,m}(N_i, N_{j,m}) = r_{i,m}(N_{i,m}, N_{j,m}) - c_{i,m}(N_i), \tag{1}$$

where $i, j \in \{Family\ Mart, LAWSON\}$. In the following functional specifications, I place a strong assumption on revenue and costs: (1) the demographics X_m affect revenue but not costs, (2) the within-market effect enters in revenues but not costs, (3) the across-market effect enters in costs but not revenue, and (4) zoning affects costs but not revenue.

I use a parametric reduced form for the firm's revenue function at market m:

$$\begin{aligned} r_{i,m}(N_{i,m}, N_{j,m}) \quad = \quad & N_{i,m}[\mu_{revenue} + X_m\beta + \delta_{comp,rival}\ln(N_{j,m}+1) + \delta_{comp,own}\ln(\max\{N_{i,m},1\}) \\ & +\delta_{comp,local}\ln(N_{local,m}+1) + \lambda(\sqrt{1-\rho^2}\varepsilon^r_m + \rho\eta^r_{i,m})]. \end{aligned} \tag{2}$$

Here, ε^r_m is a shock to revenues at the store level that I assume is common to any stores in market m, both local and chain stores and i.i.d. across markets. $\eta^r_{i,m}$ is a chain-market-specific-shock to revenues i.i.d. across chains and markets. I assume both shocks are drawn from a standard normal distribution and are observed by two chains but unobserved by the econometrician. I also assume that the shocks are independent of the exogenous variables. ρ measures the correlation of combined unobservables across chains in a given market. λ is a parameter that captures the magnitude of the sum of the shocks.

Because I do not observe fixed costs, I parameterize the fixed costs using observed and unobserved variables. I parameterize the firm's cost function at market m as

$$\begin{aligned} c_{i,m}(N_i) \quad = \quad & N_{i,m}[\mu_{cost} + \delta_{across}(\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}}) + \delta_{saving}\ln(\max\{N_{i,m},1\}) \\ & +\mu_{dist} * Dist_{i,m} + \gamma * \mathbf{1}(m \text{ is zoned}) + \sqrt{1-\rho^2}\varepsilon^c_m + \rho\eta^c_{i,m}], \end{aligned}$$

where μ_{cost} are fixed costs of entry. $Dist_{i,m}$ measures the (log) distance to chain i's distribution center from market m. This distance variable does not enter the other chain's profit function and

[9] Monetary evaluations of potential benefits and costs due to merger or policy changes will be useful for regulators who assess costs and benefits of potential merger or land-use regulations.

can therefore serve as an exclusion restriction for identification.[10] γ measures the additional fixed costs due to zoning, and ε_m^c is a shock to costs at the store level that I assume is i.i.d. across markets and common to any stores in market m. $\eta_{i,m}^r$ is a chain-market-specific shock to costs i.i.d. across chains and markets. Again, I assume both shocks are drawn from a standard normal distribution and are observed by the two chains but unobserved by the econometrician. I assume that the shocks are independent of the exogenous variables. Notice that δ_{saving} measures the gross cost savings from clustering. Combining with the revenue equation, we have the interpretation $\delta_{within} = \delta_{comp,own} + \delta_{saving}$. In other words, the revenue model permits me to decompose the within-market effect into a business-stealing effect and a costs-saving effect and to estimate these parameters separately.

Because my revenue data comes as the aggregate of the two chains and local stores at the $1km^2$ level, I specify a revenue function for local convenience stores. I use a parametric reduced form for the aggregated revenue equation of local stores in market m:

$$\begin{aligned} r_{local,m} &= \sum_{k=1}^{N_{local,m}} [X_m\beta + \delta_{comp}\ln(N_{i,m} + N_{j,m} + 1) \\ &\quad + \mu_{local} + \delta_{comp,local}\ln(\max\{N_{local,m}, 1\}) + \lambda(\sqrt{1-\rho^2}\varepsilon_m^r + \rho\eta_{local,k,m}^r)] \\ &= N_{local,m}[X_m\beta + \delta_{comp}\ln(N_{i,m} + N_{j,m} + 1) + \mu_{local} \\ &\quad + \delta_{comp,local}\ln(\max\{N_{local,m}, 1\})] + \sum_{k=1}^{N_{local,m}} \lambda(\sqrt{1-\rho^2}\varepsilon_m^r + \rho\eta_{local,k,m}^r). \end{aligned}$$

Here, $N_{local,m}$ is the number of local stores in market m. μ_{local} captures the difference in revenues between local stores and chain stores. $1(\textit{store } k \text{ is 24hrs})$ is an index variable that takes 1 if the local store is open 24 hours a day and 0 if not. The effect from competing stores is proportional to the log of the number of stores, which is a common treatment in the literature. The specification has the property that the business stealing from other stores declines in the number of competing stores. $\delta_{comp,local}$ captures the revenue reduction by having local stores as competitors. I am adding 1 to $N_{i,m} + N_{j,m}$ and taking $\max\{N_{local,m}, 1\}$ to avoid $\log 0$.[11]

[10] To understand the intuition behind identification of parameters by using an exclusion restriction, consider a set of markets that are equally distant from chain i's distribution center. Suppose the locations of distribution centers are different across chains. Therefore, the set of markets has a variation in the distance to chain j's distribution center. The variable that measures the distance to chain j's distribution center shifts the profit function of chain j and thus entry decisions of chain j. The change in chain j's entry decision is independent of the correlated error terms across chain i and j. The shift in chain j's entry behavior would create an exogenous variation in chain i's profit function because the effect of the variation in chain j's distance to the distribution center is excluded from chain i's profit function (exclusion restriction). We should then be able to identify the competitive effect of chain j on chain i by observing how much change in chain j's entry behavior, due to a variation in the distance variable of chain j, causes change in chain i's entry behavior.

[11] In contrast, I am not adding 1 to $N_{local,m}$ because the number of competing local stores is $N_{local,m} - 1$ for the

3.3 Algorithm to Compute a Nash Equilibrium

The underlying difficulties in solving for an equilibrium of a game of store-network choice are two-fold. First, in some models, a pure strategy Nash equilibrium might not exist always. Even if we ensured the existence of an equilibrium, finding all equilibria would be computationally difficult. Second, computation of the best response of a chain, which is an $M * 1$ vector that maximizes the chain's aggregate profit, involves a high-dimensional choice problem because the number of possible network choices becomes enormous quickly as the number of markets increases.

To deal with the first issue, I formulate the game as supermodular, thereby ensuring the existence of an equilibrium and providing an algorithm to find a Nash equilibrium. To deal with the second issue, I derive conditions that are sufficient to use Tarski's fixed-point theorem to obtain a lower bound and an upper bound for the profit maximizing vector. Jia (2008) provides analytical results for the two issues stated above for her model of binary choice in a market, which is entering or not entering. I provide below the generalization of her arguments to the case of K choices in which chains can open up to K stores in a market.[12]

3.3.1 Supermodularity of Chain-Entry Game

Topkis (1979, 1998) shows that supermodular games have several convenient features, such as (1) pure strategy Nash Equilibria exist, and (2) a so-called Round-Robin algorithm is available to compute a Nash equilibrium. In this subsection, I derive the conditions that the chain-entry game I develop in the previous subsections is supermodular.

First, I introduce some terminology on lattice theory. A game is specified by a strategy space for each player, $\mathbf{N}_i$ and $\mathbf{N}_j$, and a payoff function for each player, $\Pi_i(N_i, N_j)$ and $\Pi_j(N_i, N_j)$. Let N_i and N_i' be two outcomes in chain i's strategy space $\mathbf{N}_i$. To compare the $M * 1$ vectors, N_i and N_i', I denote a binary relation on a nonempty set $\mathbf{N}_i$ by $\geq$, such that $N_i \geq N_i'$ if $N_{i,m} \geq N_{i,m}'$ $\forall m = 1, ..., M$.[13] $\mathbf{N}_i$ is a *sublattice* if the meet and join of any two strategy vectors in $\mathbf{N}_i$ is also in $\mathbf{N}_i$.[14] A strategy space $\mathbf{N}_i$ has a *greatest* element $\check{N}_i$ if $N_i \leq \check{N}$ for all $N_i \in \mathbf{N}_i$. Similarly, $\mathbf{N}_i$ has a *least* element $\hat{N}_i$ if $\hat{N} \leq N_i$ for all $N_i \in \mathbf{N}_i$.

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local store.

[12] Topkis initiated the theoretical literature of supermodular games, and Vives (1990) and Milgrom and Roberts (1990) applied the theory to economic problems. For examples of supermodular games and their application to economic problems, and for a more complete discussion of supermodularity, readers should consult the cited works in this section and the references cited therein.

[13] So if a vector N_i dominates N_i' in one component but is dominated in another component, the vectors cannot be compared by the binary relation "$\geq$".

[14] I define the "meet" $N_i \wedge N_i'$ and the "join" $N_i \vee N_i'$ of N_i and N_i' as $N_i \wedge N \equiv (\min(N_{i,1}, N_{i,1}'), ..., \min(N_{i,M}, N_{i,M}'))$ and $N_i \vee N_i' \equiv (\max(N_{i,1}, N_{i,1}'), ..., \max(N_{i,M}, N_{i,M}'))$.

Here, I introduce the definition of supermodularity of a game.

Definition 1 (Supermodularity of a Game) *A supermodular game is such that, for each* $i \in \{Family\ Mart, LAWSON\}$, *(1) A strategy space* $\mathbf{N}_i$ *is a compact sublattice, (2)* $\Pi_i(N_i, N_j)$ *has an increasing differences in* (N_i, N_j), *and (3)* $\Pi_i(N_i, N_j)$ *is supermodular in* N_i.[15]

Increasing differences of a payoff function in (N_i, N_j) (condition 2) imply that chain i's marginal profits of increasing his strategy N_i are increasing in his rival's strategies N_j.[16] Supermodularity of profit function in chain i's strategy (condition 3) implies the following. First, take chain j's strategy as given and consider chain i's aggregate profits from choosing two strategies, N_i' and $N_i'' \in \mathbf{N}_i$, and chain i's aggregate profits from choosing the meet $N_i' \wedge N_i''$ and the join $N_i' \vee N_i''$, which are the two component-wise extremal vectors of N_i' and N_i''. Supermodularity of profit function in chain i' means that having the sum of profits by choosing meet and join of N_i' and N_i'' is more profitable than having the sum of profits by choosing N_i' and N_i''; that is, $\Pi_i(N_i', N_j) + \Pi_i(N_i'', N_j) \leq \Pi_i(N_i' \wedge N_i'', N_j) + \Pi_i(N_i' \vee N_i'', N_j)$ for any $N_i', N_i'' \in \mathbf{N}_i$.

Given the payoff specification in the previous subsections, the following proposition states the restriction on parameters required to formulate the problem as a supermodular game when each chain can open up to $K(> 1)$ stores in a market.

Proposition 2 (Supermodularity of the Chain-Entry Game) *The chain-entry game the previous subsections present is supermodular if* $\delta_{across} \geq 0$.

Proof. See Appendix B.[17] The proposition applies to both a non-revenue model and a model with revenue. It asserts that the spillover effect across markets δ_{across} must be nonnegative. Although this assumption is strong, I find that imposing restrictions on other parameters, such as δ_{within} or $\delta_{savings}$, is unnecessary for the supermodularity of the game. This finding implies that we can freely estimate the parameters δ_{within} or $\delta_{savings}$ from the data, unlike δ_{across}.[18]

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[15] *A sublattice* $\mathbf{N}_i \subset \mathbf{R}^M$, *where* $\mathbf{R}^M$ *is a finite-dimensional Euclidean space, is said to be a compact sublattice in* $\mathbf{R}^M$ *if* $\mathbf{N}_i$ *is a compact set.*

[16] Formally, a payoff function of player i, $\Pi_i(N_i, N_j)$, has an increasing differences in (N_i, N_j) if, for all $(N_i, \tilde{N}_i) \in N_i \times \mathbf{N_i}$ and $(N_j, \tilde{N}_j) \in N_j \times \mathbf{N_j}$ such that $N_i \geq \tilde{N}_i$ and $N_j \geq \tilde{N}_j$,

$$\Pi_i(N_i, N_j) - \Pi_i(\tilde{N}_i, N_j) \geq \Pi_i(N_i, \tilde{N}_j) - \Pi_i(\tilde{N}_i, \tilde{N}_j).$$

[17] Jia (2008) gives a proof for the binary choice case.

[18] One way to motivate the parameter restriction in my analysis is the following: the intuition behind the theoretical result is that the nonnegativity of δ_{across} will be more reasonably defended in a situation in which cost savings from clustering dominates the business-stealing effect across markets. Normally, we would expect two effects in opposite directions from the stores in a given market on the profits of the store of the same chain in the same market. On the

Topkis (1979) shows that the set of equilibrium points for a supermodular game is a nonempty complete lattice and a greatest and a least equilibrium point exist.

Theorem 3 (Existence of Equilibria in Supermodular Game (Topkis 1979)) *In a supermodular game the equilibrium set E is nonempty and has a greatest,* $\sup\{N_i \in \mathbf{N}_i : BR_i(N_i) \geq N_i\}$ *, and a least,* $\inf E = \inf\{N_i \in \mathbf{N}_i : BR_i(N_i) \leq N_i\}$*, element, where BR_i is the best-response function of player i.*

Because the chain-entry game I consider is supermodular when $\delta_{across} \geq 0$, the game has Nash equilibria.

3.3.2 Round-Robin Optimization to Compute A Nash Equilibrium

In this subsection, I specify an iteration algorithm to compute a pure-strategy Nash Equilibrium for the supermodular game. The second benefit of using supermodular games is that a so-called Round-Robin algorithm is available to solve for a Nash equilibrium. In this algorithm, each player proceeds sequentially to update his own strategy by choosing a best response, whereas the strategy of the other player is held fixed. Topkis (1998) provides a proof that in supermodular games, the iteration algorithm converges to a pure-strategy Nash equilibrium point. The iteration steps are as follows:

1. Start from the smallest strategy vector in LAWSON's strategy space, $N_{LS}^0 = \inf(\mathbf{N}_{LS}) = (0, 0, \ldots .0)$.

2. Compute the best response of Family Mart N_{FM}^1 given parameter θ, simulation draw ϵ^s, and LAWSON's strategy N_{LS}^0: $N_{FM}^1 = BR_{FM}(N_{LS}^0) \equiv \underset{N_{FM}}{\arg\max} \sum_{m=1}^{M} \pi_{FM,m}(N_{FM}, N_{LS}^0)$, where $BR_{FM}(\cdot)$ is a best response function of Family Mart given the store-network choice by LAWSON, N_{LS}.

3. Compute the best response of LAWSON given Family Mart's best response N_{FM}^1: $N_{LS}^1 = \underset{N_{LS}}{\arg\max} \sum_{m=1}^{M} \pi_{LS,m}(N_{LS}, N_{FM}^1)$.

one hand, having many stores of the same chain in the market will save on delivery costs. 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 configurations of stores because consumer demand is more localized than the cost of delivery. The localized demand and the importance of distribution network are typical features in the convenience-store industry in Japan. Whereas, on average, consumers rarely walk more than 1km to access stores, delivery trucks for stores generally travel about 40 kilometers for each store per day.

4. Iterate the above steps (b)-(c) T times until we obtain convergence: $N_{FM}^{T} = N_{FM}^{T+1}$ and $N_{LS}^{T} = N_{LS}^{T+1}$. Converged vectors of strategy profiles for Family Mart and LAWSON, (N_{FM}^{T}, N_{LS}^{T}), are a Nash equilibrium. The number of iterations, T, is bounded by the number of markets, M: $T \leq 4M$.

In Appendix B.4, I provide a proof that the Round-Robin iteration algorithm, starting from zero stores in every market for LAWSON ($N_{LS}^{0} = \inf(\mathbf{N}_{LS})$), leads to the equilibrium that delivers the highest profits for Family Mart among all equilibria of the game.

3.3.3 Deriving Lower and Upper Bound of Best Response

This subsection deals with the second issue of computing the best response given the competitor chain's entry configuration, which is step 2 and step 3 in the above iteration algorithm. Finding the best response is computationally demanding because solving for the profit maximizing vector by simply searching all possible strategy profiles is practically infeasible. To circumvent the daunting task of searching over every possible strategy profile in a strategy space, I derive the upper and lower bounds of the best response for each chain, avoiding evaluating the strategy vectors that are below the lower bound or above the upper bound when searching for the profit maximizing vector.

The idea is to consider the chain i's best response regarding the number of stores in every market, N_i^*, a fixed point to a function that maps from chain i's strategy space choice to itself. In particular, I introduce a coordinate-wise necessary condition for profit maximization $V_{i,m}$ that updates the current number of stores in market m, holding the competitor's decision in all markets and the player's decisions in other markets $l \neq m$ fixed. Namely,

$$V_{i,m}(N_i, N_j) = \underset{N_{i,m} \in \{0,1,..,K\}}{\arg\max}\ \Pi_i(N_i, N_j).$$

Let N_i^* be the best response strategy vector for chain i. Because N_i^* is the profit maximizing vector for chain i given rival's decision N_j, it follows that $N_{i,m}^* = V_{i,m}(N_i^*, N_j)$. Stacking up $V_{i,m}$ for every market $m = 1, .., M$ yields

$$N_i^* = V_i(N_i^*, N_j),$$

where $V_i : \mathbf{N}_i \to \mathbf{N}_i$ is an $M * 1$ vector of optimality condition in all markets from market 1 to M : $V_i = (V_{i,1}, ..., V_{i,M})'$. Here, N_i^* is a fixed point of the function V_i.

The following proposition states that the optimality condition V_i in the specification of the chain-entry model presented in previous subsections is nondecreasing in its argument as long as the across-market effect is nonnegative.

Proposition 4 (Nondecreasing Coordinatewise Optimality Condition) *$V_i(N_i)$ is nondecreasing in N_i if $\delta_{across} \geq 0$.*

Proof. See Appendix B. So for any $N_i, \tilde{N}_i \in \mathbf{N}_i$ with $N_i \geq \tilde{N}_i$, it follows that $V(N_i) \geq V(\tilde{N}_i)$.

By using the property of $V_i(N_i)$ being nondecreasing in N_i, I am able to employ the following lattice theoretical fixed point theorem by Tarski (1955), which shows the existence of a fixed point for a nondecreasing function defined on lattices.

Theorem 5 (Fixed Point Theorem (Tarski 1955)) *Let $\mathbf{N}_i$ be a complete lattice, $V_i : \mathbf{N}_i \to \mathbf{N}_i$ a nondecreasing function, and E the set of the fixed points of V_i. Then, E is nonempty and is a complete lattice. In particular, because E is a complete lattice, a greatest and least fixed point exist in E, that is;* $\sup E = \sup\{N_i \in \mathbf{N}_i : V(N_i) \geq N_i\}$ *and* $\inf E = \inf\{N_i \in \mathbf{N}_i : V(N_i) \leq N_i\}$.

The benefit of applying Tarski's fixed point theorem to the optimality condition is two-fold when finding the best response of chain i over chain i's strategy space: First, by Tarski's fixed point theorem, the set of the fixed points of V_i is complete lattice and a greatest and least fixed point exist. Therefore, if I obtain the least and greatest fixed points, the number of strategy vectors need to evaluate in order to find the best response strategy vector substantially decreases. This decrease is because the set of fixed points is ordered and the profit maximizing vector locates between the greatest and least fixed points. Second, I am, in fact, able to compute for the greatest and least fixed points by applying the optimality condition to the two extreme points in the strategy space. To obtain the least fixed points of $V_i : \mathbf{N}_i \to \mathbf{N}_i$, I define a sequence $\{N_i\}$ that is derived by applying the optimality condition V_i multiple times. i.e., $\{N_i^t\}$ such that $N_i^1 = V_i(N_i^0)$, $N_i^2 = V_i(N_i^1), ..., N_i^{t+1} = V_i(N_i^t)$, where $N_i^0 \in \mathbf{N}_i$ is the starting vector for the sequence. Suppose I set $N_i^0 = \inf(\mathbf{N}_i) = (0, .., 0)$. Because $V_i(N_i)$ is nondecreasing in N_i, we have $N_i^1 = V_i(N_i^0) \geq N_i^0$ and $N_i^2 = V_i(N_i^1) \geq N_i^1$. By iterating this T times over the optimality condition, I will have a convergent vector $N_i^T = N_i^{LB}$ such that $N_i^{LB} = V_i(N_i^{LB})$. This N_i^{LB} is the least fixed point. In order to show this result by contradiction, suppose N_i^{LB} is not the least point. Then the least fixed point exists N_i^{least} such that $N_i^{least} \leq N_i^{LB}$. Applying the optimality condition to both sides of inequality T times yields $V^T(N_i^{least}) \leq V^T(N_i^{LB}) = (0, .., 0)$, which contradicts $\mathbf{N}_i = \{0, 1, 2, .., 4\}^M$. Similarly, if I start from $N_i^0 = \sup(\mathbf{N}_i) = (4, .., 4)$, I obtain the greatest fixed point N_i^{UB}.

After obtaining N_i^{LB} and N_i^{UB}, I find the best response vector $N_i^* = \underset{N_i \in \{0,1,..,K\}^M}{\arg\max} \sum_{m=1}^{M} \pi_{i,m}(N_i, N_j)$ by evaluating every vector N_i, such that $N_i^{LB} \leq N_i \leq N_i^{UB}$.

3.3.4 Dealing with Multiple Equilibria

The possibility of multiple equilibria complicates estimating static discrete games. The pure strategy Nash equilibria may not be unique in the model of the paper. In fact, multiple equilibria may occur more frequently than in Jia (2008)'s model because the number of possible outcomes of the game has increased greatly (from $(2^M)^2$ to $(5^M)^2$) as we increase the maximum number of stores in a given market from 1 to 4.

In this paper, I introduce an equilibrium selection mechanism, which is to pick the most profitable equilibrium for Family Mart. The reason I am using the extremal points of the lattice as the equilibrium outcome of the game is that I can compute the equilibrium by using the round-robin algorithm and the optimality condition that satisfies nonnegativity in its argument. I select the equilibrium that favors Family Mart because the data tell us that the number of stores for Family Mart is 40 percent higher than the total stores of LAWSON. Note that the aggregate profits increase with the number of stores. For instance, the aggregate profits will be approximately 40 percent higher if the profits per store are the same across chains on average, which is not unrealistic given the fact that the sales per store are similar across chains, as the bottom rows in Table 1 in the original paper show.

The benefit of this approach is that one can obtain equilibrium predictions of the chain entry game even with a high dimension of strategy profiles. Since the applied questions of the paper involve counterfactuals, the ability to simulate the model to obtain the likely equilibrium effect of a merger or a change in an entry regulation on store-network choice is crucial to researchers. Of course, the arbitrariness of picking an equilibrium remains a limitation of the study. The concern is that this selection rule is too strong to assume, and we would like to see the outcomes when we change the equilibrium selection rule. Although an informal solution, I tried another external point of the lattice and to determine whether the parameters are robust. From the parameter results I obtain in Table 5, the parameter estimates appear robust to the selection rule.

4 Estimation via Method of Simulated Moments

I estimate the model by choosing model parameters so that the objective function, which depends on the difference between observed data and outcomes the model predicts, such as entry configurations and revenues, is minimized. Unfortunately, the supermodular game does not yield a closed-form solution for the equilibrium number of stores and revenues, making exactly computing moment conditions regarding the outcomes variables difficult. Instead, the mapping from the parameters to moments, which include model predictions of equilibrium entry patterns and sales, is approximated by simulation methods.

4.1 Constructing Moment Conditions: A set-up

Remember that for the revenue data at the 1km square grid level, we have an exogenous sample selection rule that in order to protect privacy, revenues with less than three stores in a given market will not be disclosed. To simply denote this rule, I define a selection indicator I_m for each market m:

$$I_m \equiv \begin{cases} 1 \text{ if } N_m \geq 3 \\ 0 \text{ if } N_m < 3 \end{cases},$$

where N_m is the total number of two chains' stores in a given market m: $N_m = N_{i,m} + N_{j,m}$, $i, j \in \{FamilyMart, LAWSON\}, i \neq j$. Similarly, I construct a simulation counterpart of the selection indicator for the total number in market m in s th simulation

$$I_m^s \equiv \begin{cases} 1 \text{ if } N_m^s \geq 3 \\ 0 \text{ if } N_m^s < 3 \end{cases},$$

where $N_m^s = N_{i,m}^s + N_{j,m}^s$ is the number of total stores in market m predicted by the model parameters and s th simulation draws.

I denote aggregate revenue at market m by $R_m^* = r_{i,m} + r_{j,m}$, where $r_{i,m}$ is the total revenue of chain i in market m that is classified to the econometrician. Let us define aggregate revenue that the econometrician observes by

$$R_m \equiv \begin{cases} r_{i,m} + r_{j,m} \text{ if } N_m \geq 3 \\ 0 \;\text{ if } N_m < 3 \end{cases} = I_m R_m^*.$$

Similarly, I denote aggregate revenue at market m in sth simulation by $R_m^{*,s} = r_{i,m}^s + r_{j,m}^s$, where $r_{i,m}$ is the total revenue of chain i in market m in s th simulation. I construct a simulation counterpart of the total revenue

$$R_m^s \equiv \begin{cases} r_{i,m}^s + r_{j,m}^s \text{ if } N_m^s \geq 3 \\ 0 \;\text{ if } N_m^s < 3 \end{cases} = I_m^s R_m^{*,s}.$$

4.2 Construction of Population Moment Conditions

I define a function $R_m(X, \epsilon, \theta)$, a revenue-data generating process for market m, where X and ϵ are $M * 1$ vectors of predetermined variables, observed and unobserved to the econometrician. X

contains exogenous market characteristics, such as population and the zoning regulation status. Note that the revenue data R_m are generated at the true θ_0 and predetermined variables (X_i, ϵ_i): $R_m = R_m(X, \epsilon, \theta_0)$.

I construct a moment condition that measures the gap between the observed total revenue and the conditional expectation of the revenue function $R_m(X, \epsilon, \theta)$:

$$\begin{aligned} R_m - E[R_m(X,\epsilon,\theta)|X] &= I_m R_m^* - E[I_m R_m^*(X,\epsilon,\theta)|X] \quad (3)\\ \text{where } \theta &= (\beta, \delta_{across}, \delta_{within}, \delta_{comp,own}, \delta_{comp,rival}, \delta_{local}, \mu_{revenue}, \mu_{cost}, \mu_{local}, \mu_{dist}, \rho, \gamma)\\ \epsilon_i &= (\varepsilon^r, \varepsilon^c, \eta_i^r, \eta_i^c). \end{aligned}$$

This moment condition in Eq.(3) will be zero when $\theta = \theta_0$ because

$$\begin{aligned} & E[I_m R_m^* - E[I_m R_m^*(X,\epsilon,\theta_0|X)]|X] \\ = \ & E[R_m - E[R_m]|X] = 0. \quad (4) \end{aligned}$$

Now consider interacting the original moment condition in Eq.(3) with a m th element in a function of observed predetermined variable X, $f_m(X)$, obtaining a population moment condition for revenue:

$$g_{rev}(\theta) \equiv E[(I_m R_m^* - E[I_m R_m^*(X,\epsilon,\theta|X)]) * f_m(X)|X] \ = 0 \text{ at } \theta = \theta_0.\text{[19]} \quad (5)$$

Similarly, I define $N_{i,m}(X, \epsilon, \theta)$, which specifies the data-generating process for the number of stores of chain i in market m. Note that the data on the number of stores $N_{i,m}$ are generated at the true θ_0 and predetermined variables (X, ϵ): $N_{i,m} = N_{i,m}(X, \epsilon, \theta_0)$. I obtain a population condition for the number of stores:

$$g_{store}(\theta) \equiv E[(N_{i,m} - E[N_{i,m}(X,\epsilon,\theta|X)]) * f_m(X)|X] \ = 0 \text{ at } \theta = \theta_0. \quad (6)$$

[19] Taking a conditional expectation with respect to X of Eq. (3) multiplied by a function of conditioning variable X yields zero; that is, $E[(I_m R_m^* - E[I_m R_m^*(X,\epsilon,\theta_0|X)]) * f(X_i)|X_i] = E[(I_m R_m^* - E[I_m R_m^*]) * f(X_i)|X_i] = 0$.

4.3 Construction of Sample Moment Conditions

The sample analogues of the population moment conditions in (5) and (6) are

$$
\begin{aligned}
g_{rev,M}(\theta) &\equiv \frac{1}{M}\sum_{m=1}^{M}(I_m R_m^* - E[I_m R_m^*(X,\epsilon,\theta)|X]) * f_m(X) \\
g_{store,M}(\theta) &\equiv \frac{1}{M}\sum_{m=1}^{M}(N_{i,m} - E[N_{i,m}(X,\epsilon,\theta)|X]) * f_m(X),
\end{aligned}
$$

where $E[g_{M,rev}(\theta)] = 0$ and $E[g_{M,store}(\theta)] = 0$ at $\theta = \theta_0$ by using the same reasoning described in the footnote.

Now the issue is that no closed-form expression exists for $E[I_m R_m^*(X,\epsilon,\theta)|X]$ or $E[N_{i,m}(X,\epsilon,\theta)|X]$, making implementing the usual GMM or Method of Moments infeasible. Instead, we consider simulating the conditional expectation by averaging $I_m R_m^*(X,\epsilon,\theta)$ over a set of simulation draws $\epsilon^{S,all} = (\epsilon^1, \epsilon^2, .., \epsilon^S)$ from the distribution of ϵ:

$$
\hat{g}_{rev,M}(\theta) \equiv \frac{1}{M}\sum_{m=1}^{M}(I_m R_m^* - \frac{1}{S}\sum_{s=1}^{S} I_m^s R_m^{*,s}(X,\epsilon^s,\theta)) * f_m(X).
$$

Similarly, I construct sample moment conditions regarding the number of stores for each chain

$$
\hat{g}_{store,M}(\theta) = \begin{bmatrix} \frac{1}{M}\sum_{m=1}^{M}(N_{i,m} - \frac{1}{S}\sum_{s=1}^{S} N_{i,m}^s(X,\epsilon^s,\theta)) * f_m(X) \\ \frac{1}{M}\sum_{m=1}^{M}(N_{j,m} - \frac{1}{S}\sum_{s=1}^{S} N_{j,m}^s(X,\epsilon^s,\theta)) * f_m(X) \end{bmatrix}.
$$

I stack up all moment conditions to create a vector of the full sample moment conditions:

$$
\hat{g}_M(\theta) = \begin{bmatrix} \hat{g}_{rev,M}(\theta) \\ \hat{g}_{store,M}(\theta) \end{bmatrix}.
$$

Appendix D provides details on how I construct 22 sample moment conditions in the study.

4.4 Method of Simulated Moments

The method of moments (hereafter MSM) estimator is

$$
\hat{\theta}_{MSM} = \arg\min_{\theta}\, [\hat{g}_M(\theta)]\mathbf{W}[\hat{g}_M(\theta)]', \tag{7}
$$

where $\mathbf{W}$ is a weighting matrix. Following McFadden (1989), the limit distribution of the MSM estimator is

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

where $\mathbf{G}_0 \equiv E[\boldsymbol{\nabla}_\theta g(X_m, \theta_0)]$ and $\boldsymbol{\Lambda}_0 = E[g(X_m, \theta_0)g(X_m, \theta_0)']$. The S^{-1} in the asymptotic variance corresponds to an efficiency loss due to simulations. We can estimate the derivative matrix $\hat{\mathbf{G}}$ by taking a sample mean of Jacobian of the simulated moments.[20] To account for the geographic interdependence of close-by markets, I use Conley (1999)'s nonparametric covariance matrix estimator. So the covariance matrix $\boldsymbol{\Lambda}$ is estimated by

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

where B^m is the set of markets adjacent to market m.

I use a two-step efficient approach. In the first step, I use an identity matrix for the weighting matrix $\mathbf{W}$ to consistently estimate the parameter, $\hat{\theta}^{first}_{MSM}$, and plug this estimate into the covariance matrix $\hat{\boldsymbol{\Lambda}}$. In the second step, I choose the weighting matrix $\mathbf{W} = \hat{\boldsymbol{\Lambda}}^{-1}$ and minimize the objective function again to obtain the final efficient parameter estimates, $\hat{\theta}_{MSM}$.

$\epsilon_i^s = (\varepsilon^{s,r}, \varepsilon^{s,c}, \eta_i^{s,r}, \eta_i^{s,c})$, $i \in \{FamilyMart, LAWSON\}$, $s = 1, ..., S$ are drawn from a standard normal distribution. I set $S = 200$ for the study.

Appendix D provides further details on (1) the implementation of the estimation procedure, (2) the construction of moment conditions, (3) the minimization of the criterion function in Eq.(7), and (4) the generation of the simulation draws.

5 Empirical Results

5.1 Parameter Estimates from the Non-Revenue Model

Before examining the model with revenue, I provide parameter estimates from a simpler static entry model that only uses the number of stores and demographics. The goal of estimating the non-revenue model is to provide a basis for comparison to the model that integrates revenue data because the non-revenue model is commonly used in the literature. As is the case with the usual discrete-choice model, I estimate parameters up to a constant because the parameter estimates are normalized so that the aggregate variance of profits shock will be one. To understand the economic implication of the parameters, the relative magnitudes of the effects on entry need to be gauged by running counterfactual simulations, which I discuss in section 6.

[20] Newey and McFadden (1994) discuss a set of conditions to obtain the asymptotic normality for simulated moment estimators, allowing the sample moment to be discontinuous (Theorem 7.2). Condition 2 states that the population moment condition is differentiable at the true theta with derivative matrix G. I estimate the G by taking a finite-difference of sample moments for a given simulation draw and take average of G over simulations. The derived estimate $\hat{G}$ will be consistent under the conditions of Theorem 7.2.

Column 1 in Table 5 presents the MSM estimates of the parameters in the non-revenue baseline specification. Each parameter has the anticipated sign. First, the nighttime and daytime population coefficients, β_{pop} and β_{bus} in Table 5, are positive and statistically significant at the 1 percent level. Whereas the across-market effect δ_{across} is not statistically significant, the net within-market effect δ_{within} and the competitive effects from a rival chain store δ_{comp_rival} are estimated precisely. The magnitude of the former is -0.701 and the latter is -0.945. As one might expect, revenue decreases when a competitor is in the same grid, and the effect of the competitor is large: the effect amounts to a decrease of about $6,000$ people in the nighttime population in terms of contribution to reduction in sales. The parameter for the zoning regulation γ is estimated to be -0.103 and statistically significant at the 5 percent level. Consistent with the reduced-form regression results, the zoning regulation has a negative impact on store-level profits, implying that one must incur positive costs when applying for permission to open a store. The magnitude of the coefficient tells us that to make up the reduction in profits due to zoning, the market has to have nearly 600 additional people in the nighttime population, holding other factors constant. Policy experiments in the subsequent section illustrate the relative magnitude of zoning-index coefficients in terms of how many store openings zoning policy would affect.

The last two rows in columns 1 and 2 in Table 5 compare the data and the prediction of the estimated model for the number of markets with one or more stores from a chain. The model predicts the number of Family Mart stores to be 131.3 on average across 200 simulations with a standard deviation of 98.9 stores. The model predicts the number of LAWSON stores to be 96.2 stores on average across 200 simulations with a standard deviation of 138.7 stores. The actual numbers of stores are 127 and 95, respectively.

5.2 Parameter Estimates from the Revenue Model

Turning to the full revenue model, Table 6 presents the estimated parameters of the revenue and cost equations at the market level.

All of these estimates have highly intuitive signs and most of them are significantly different from zero at the 5 percent level. The signs of the estimated parameters closely resemble the ones of the non-revenue model in the previous subsection. Unlike the non-revenue model, however, I measure the parameters in monetary units (thousands of US dollars) except for ρ, which measures the magnitudes of the variance of profit shocks. For example, the coefficient on the nighttime population implies that sales in a market having one thousand more people than other markets will be higher by $\$71,000$ annually (or about 7.1 million yen). As expected, the daytime population has a positive and statistically significant effect on store profitability. The magnitude is 66 percent of the one of the nighttime population.

The estimates in rows 3 - 5 of column 1 in Table 6 measure the business-stealing effect due to the presence of three types of stores. The parameters that measure the business-stealing effect by own chain stores ($\delta_{competitive,own}$) and the business-stealing effect by rival chain stores ($\delta_{competitive,rival}$) are precisely estimated and all three parameters are estimated to be negative, showing that the competition among stores pushes down the revenue. For example, having another store from the same chain decreases the revenue of a store by $\$377,765$ ($= \ln 2 * \$545,000$) annually, which is 26 percent of total annual sales for an average chain store. Similarly, the presence of a rival chain store dampens the sales by 18 percent of total annual sales. The presence of a non-chain store reduces the revenue less than an own or rival chain store does, but the magnitude is not statistically significant: a $\$75,483$ decrease from the first entrant. The difference in magnitude is consistent with the fact that local stores are open fewer hours than chain stores and therefore have less chance of stealing business from other stores at night.[21]

Next, I turn to the interactions among own chain stores. Row 9 of Table 6 displays the estimate of δ_{across}, the coefficient on the net cost savings from the presence stores from the same chain in adjacent markets. The parameter is estimated at $\$59,500$ per year and is insignificant at the 5 percent level. The magnitude of the parameter is higher than an annual salary of an average truck driver in Japan, which is around $\$41,200$. Recalling that δ_{across} measures positive-spillover effect minus business-stealing effect, the gross business-stealing effect by stores from the same chain in across markets likely cancels out the gross positive cost savings.

Row 10 contains the estimate of δ_{within}, the coefficient on the gross cost savings from the presence of stores from the same chain in the same market. The estimated magnitude of the parameter is $\$125,800$ and the fraction of the cost savings to the total costs is 11 percent. Although the parameter is not statistically significant, the sign is negative as expected: unlike δ_{across}, the parameter measures the *gross* benefits by clustering stores in a given market. Clear evidence of economies of density or the positive spillovers among own stores on the costs side does not exist in either case.

Of interest is the coefficient on the zoning status index in row 11, which is negative and not precisely estimated. This finding implies that being at the zoned area increases the store's fixed costs of operation, including the combined costs of going through all the application and screenings,

[21] More than 30 percent of local stores are not 24-hour operations in Okinawa, whereas all the stores from Family Mart and LAWSON are open 24 hours a day.

and the monetary value of the annual costs translates into $50,300 per year.

Although insignificant, the parameter estimate μ_{local} suggests being a local store decreases the store's sales by $31,200 annually. I estimate the constant in the revenue equation to be $820,700 or 85 million Japanese yen. The estimated constant on the cost equation implies that the average costs of installing and operating a convenience store is about $1,129,000 annually. I find no evidence that stores benefit from locating close to the distribution center: the parameter estimate μ_{dist} enters the costs equation neither statistically nor economically significantly. The parameter coefficient predicts that the most distant store from the distribution center incurs $53,000 as distribution costs, which is less than 5 percent of the annual fixed costs of the store (μ_{cost}).

The correlation parameter ρ is equal to 0.93, which means the correlation of the combined profit shocks across chains in a given market is 0.86. The last row shows that the λ parameter, the standard deviation of profits, is estimated at $121,000, which is about 8 percent of mean sales per store.

We can measure the overall fit of the model in many ways. One is to compare the model predictions of how many stores each chain opens in total with the actual store counts. Rows 15 and 16 of column 1 in Table 7 present the implied aggregate number of stores for each chain. The mean of the simulated number of stores from the model with estimated parameters matches closely the actual number of stores: the model predicts the total number of Family Mart stores, which is 139 in the data, to be 140.3 on average across 200 simulations with a standard deviation of 7.7 stores. The model predicts the total number of LAWSON stores, which is 100 in the data, to be 98.7 stores on average across 200 simulations with a standard deviation of 8.2 stores. The actual numbers of stores are 127 and 95, respectively. Tables 3 and 4 provide actual and simulated market configurations. These tables show that the model replicates well the distribution of stores for Family Mart and LAWSON.

6 Policy Simulations

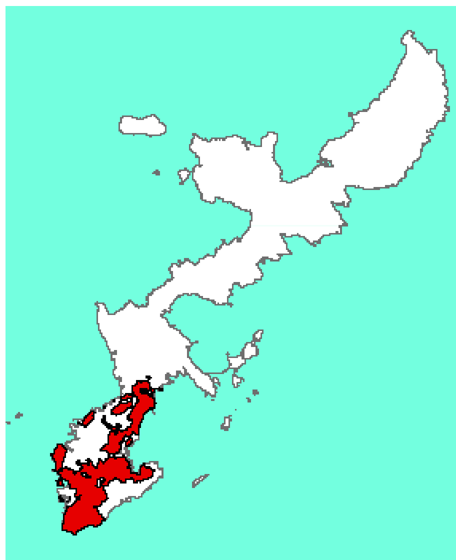
Making an assumption that the observed choices are a Nash equilibrium allow me to predict the equilibrium market structure under alternative policy environments. In this section, I use the parameter estimates of the non-revenue model and model with revenue to perform "what-if" experiments. First, I evaluate the impact of hypothetical changes in the zoning regulation on the market structure, the total sales, and the profits of the two chains. Next, I provide merger simulation analysis. The model with revenue data also allows me to evaluate the changes in consumer and producer surplus.

6.1 The 1968 Urban Planning Law

The current Urban Planning Law, enacted in 1968 to prevent urban sprawl, defines zoned areas and, in principle, prohibits firms and residents from locating freely. In zoned areas, the act permits developing stores in zoned areas, provided stores comply with strict requirements for constructions.[22] As Figure 3 shows, the zoned area is more likely to be suburban in highly populated area and surrounds the city center of Okinawa.

FIGURE 3

ZONED AREAS (RED)



Measuring the impact of zoning regulation on entry is important for two reasons. First, the deregulation of zoning restrictions in urban areas in Japan has been at the forefront of urban policy debates in recent years. Although the zoning regulation has provided neighborhood amenities such as open space and promoted city planning, mounting public opinion has been calling for deregulating the current zoning laws on the basis that the requirements are restrictive for retail outlets to be opened in zoned areas. The land-use restrictions are a big concern, especially for potential local grocery stores or convenience stores, because the choice of a good location is a key to success in a retail business. In responding to these concerns, some local governments have recently relaxed the regulation for commercial outlets in zoned areas by constructing ordinances that specify the

[22] 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. Local ordinances give other detailed conditions.

conditions entering stores must meet.[23] The exceptions, however, are limited still to specific types of store formats, such as stores attached to gas stations, local highways, or rest areas. Second, the regulation directly affects firm's decisions regarding where to open their stores. In contrast to the increasing attention zoning restrictions are receiving in the press, we know surprisingly little about the effect zoning regulation has on entry. 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. This paper aims to fill that gap in the literature by incorporating the zoning information into the structural model of entry as in Ridley, Sloan, and Song (2008) and Suzuki (2007).

Why Do We Need a Structural Model to Examine the Impact of Zoning on Entry? In the simple OLS regressions in Table 2, we confirm that zoning is decreasing the number of stores. Although reduced-form regressions are suggestive about the likely direction and strength of the effect of zoning on entry, I employ structural modeling for the purpose of the project for several reasons.[24] First, suppose a regulator would like to obtain precise estimates of costs due to zoning because he wants to evaluate whether the costs are of an economically meaningful magnitude. However, we are not sure if we are obtaining reliable estimates of costs due to zoning from a reduced form because, in reality, "Nature" does not randomly give the number of outlets in the right-hand side of the regressions; rather, firms maximizing their profits determine the number of stores. Moreover, reduced-form regressions are inadequate approaches for modeling many characteristics of the industry. Examples include strategic interactions between Family Mart and LAWSON, headquarters' decision of the store networks, and markets that are contiguous to one another. All of these are important features that characterize the firms and the market, and failure to properly account for these crucial features of industry can lead to biased estimates.

Second, an advantage 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 in geographic patterns of market configurations by two chains due to change in regulations, we can look at distribution consequences of policy interventions, such as who benefits from a change in zoning and who does not. Or we can ask practical questions a regulator may find relevant, such as in which markets we would find the impact of deregulation to be most effective on entry behavior. These are questions I cannot answer with reduced-form

[23] According to the survey I conducted in 2007, 28 out of 97 cities deregulated the zoning law under Article 34-8. Okinawa is not included in those 28 cities.

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

analysis.

Finally, a structural model allows us to recover unobserved economic parameters that could not otherwise be inferred from reduced-form analysis. Examples in this paper include positive spillovers across markets, strategic effect across chain brands, and sunk costs of entry.

Design. In the sample, 140 markets are categorized as zoned areas. I consider two different zoning policy scenarios. The first eliminates the zoning regulation completely from the 140 currently zoned markets. The possible deregulation of zoning restrictions has been at the heart of urban policy debates. However, little research has been conducted regarding the economic consequences of such deregulation. The second policy experiment of interest places the current regulation in all 834 markets.[25] In both scenarios, the same model parameters and the same demographics, including population, are held fixed when solving for the new equilibrium number of stores for each chain. The only thing I change is that in the first (second) scenario, the zoning regulation status variable is exogenously set to zero (one) in every market. For each scenario, chains re-optimize their store-network choices given the new policy environment. The new equilibrium prediction about the number of stores for each chain is computed by running the best response iteration algorithm described in the previous section for the estimated model.

Calculating the economic welfare requires measurement of both consumer surplus and producer surplus. Given the lack of data on price and quantity, I use the change in store sales as an approximation of the change in consumer surplus instead of focusing on the equivalent variation (EV).[26] To calculate producer surplus, I measure the aggregate profits of the two chains. I define the total surplus as the sum of consumer surplus and producer's profits. I measure the welfare numbers in units of thousands of US dollars.

Several limitations exist in the welfare analysis and one should interpret the numbers with some caution. First, zoning regulation serves a variety of purposes, and the paper does not take into account benefits consumers may receive from the regulation, such as neighborhood quality or open space. Second, in the model, I abstract from the substitution of consumers between convenience

[25] Here, I implicitly assume the shape of reduced-form revenue function is invariant to the change in regulations.

[26] Deaton and Muellbauer (1980) provide a justification of this approach. From the first-order conditions for utility maximization, we have $\frac{\vartheta v(q)}{\vartheta q_i} = \lambda p_i$,where v is an indirect utility function, q_i is the quantity of good i, λ is the marginal utility of income, and p_i is the price of good i. By taking the total differential of utility, I obtain the change in utility due to change in quantity:

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

which turns out to be the area under the Marshallian (uncompensated) demand curve. This way of measuring consumer surplus will be particularly relevant for this industry as it maintains uniform pricing across every market in Okinawa.

stores and other types of businesses such as grocery stores. Third, the analysis has held the number of local stores fixed before and after the policy change. Although assuming the exogenously of local stores' entry behavior will make the analysis simpler, it may not be ideal when calculating the new equilibrium in chains' store networks. Due to these reasons, I take into account only the welfare of the two chains and their customers. Nonetheless, the results, when interpreted carefully, are suggestive of likely impacts of the change in policy regimes on economy.

Results. Table 7 summarizes the key findings of these counterfactual experiments. Column 2 displays the predictions about current equilibrium in the number of stores. I compute sales and profits given the estimated parameters of the model with revenue in Table 6, observed demographics, and the existing regulation regime. The predictions serve as a baseline for a comparison of the outcomes of two hypothetical policy regimes.

Column 3 in Table 7 presents the results under the no-zoning-permission-system regime. As would be expected from the negative sign and the magnitude of parameter γ, I find that eliminating the current zoning regulation would moderately increase the number of stores: rows 1 and 3 of column 3 show that for Family Mart and LAWSON, we would expect a 4.6 and 3.6 percent increase in the total store counts, respectively. Rows 2 and 4 focus on the change in the originally zoned 140 markets, and I find that most of these increases in store counts are largely due to an increase in the number of stores in these 140 markets in which there has been a deregulation in the zoning policy. In fact, in those 140 markets, the percentage increase in the total number of stores is large: around 40 percent for both chains. The model also predicts aggregate sales and profits will increase by 4 percent and 2.6 percent for Family Mart and 3 percent and 2 percent for LAWSON, respectively. Regarding the aggregate costs due to the regulation, I calculate the magnitude by multiplying the zoning costs parameter γ by the number of stores in zoned markets. I find the reduction of costs associated with the regulation for Family Mart and LAWSON is small: $\$1,100,000$, which is 0.3 percent of total sales of Family Mart and LAWSON. Two reasons exist for the small costs that the zoning regulation introduces. First, the effect of eliminating the zoning regulation is small because the number of markets the change in the zoning policy affects is small. For instance, in 694 markets, which is 86 percent of all markets in Okinawa, obtaining development permission is unnecessary and we should see no costs due to the zoning regulation. Second, as the first six rows in Table 1 show, zoned markets tend to have less daytime and nighttime population than unzoned markets, making zoned markets unattractive places to enter regardless of their zoning status. The bottom row of column 3 in Table 7 presents the sum of aggregate sales and aggregate profits for Family Mart and

LAWSON. The increase in the sum from the baseline is 3.4 percent. So the percentage gain from the deregulation is almost the same as the percentage increase in the number of stores. The gain in total surplus is not coming directly from the reduction in costs of the zoning regulation; rather, the gain is largely due to the increase in the number of stores (therefore, the increase in sales) that the reduction in costs associated with the zoning regulation induces.

Figures 5 and 6 present the configurations of stores before and after eliminating the current zoning policy. As the figures show, we can confirm from the map that in no zoning-regimes, the increase in the number of stores is subtle compared to the baseline case, and this finding is true for both chains. However, markets that are predicted to have stores after the deregulation are different across Family Mart and LAWSON because their market-chain specific profit shocks and their store networks are different. In particular, two figures show that the previously zoned markets in which the number of stores increases due to removing the regulation are adjacent to the markets in which each chain has its existing stores.

Also of note is how much the opposite policy regime affects the results. Column 5 in Table 7 provides the market outcomes under the policy regime in which the zoning regulation is in place in all 834 markets in Okinawa. I find the installation of the zoning regulation in all markets would substantially decrease the number of stores, sales, and profits: the magnitude of these decreases is 16 to 17 percent. Not too surprisingly, the sum of total sales and total profits is predicted to decline by about \$40 million, which is about 12 percent of the sum in the baseline case. The decrease in total surplus is largely due to a decrease in the aggregate sales, which is caused by a decrease in the number of stores. In this second policy regime that places zoning restriction in all markets, the magnitude of the changes in sales, profits, and total surplus is almost five times the magnitude of the changes in the first policy regime.

Although the simple non-revenue model does not predict sales or profits, we can see how the conclusions from the full-revenue model regarding the number of stores hold up in the non-revenue model. Columns 1 and 2 in Table 5 provide the results of these counterfactual simulations. First, from rows 13 and 14 of column 1 in which I predict the first scenario of eliminating the zoning regulations, we would expect roughly a 1.4 to 1.5 percent increase in the number of entering markets 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, the last two rows in column 1 show the number of outlets in the second scenario, in which the zoning restrictions are placed all over in Okinawa. The model predicts that the number of markets in which convenience stores are present decreases by roughly 7 percent. Note that the full and non-revenue models are consistent in the directions of the predictions of the policy experiments, but qualitatively the non-revenue models predict more modest changes in magnitude.

6.2 Effects of a Merger on Store Networks

In this section, I evaluate the impacts of a horizontal merger among two chains on product variety measured by the number of stores and economic welfare. A classic question in antitrust policy is whether a merger that leads to a decrease in the number of players is welfare reducing. The answer typically hinges on the trade-off between changes in costs efficiency and changes in consumer surplus due to changes in the store network. Although the horizontal merger can increase costs efficiency, the merger can results in underprovision of stores, which will harm the consumers. The purpose of the exercise is therefore to simulate and examine the likely welfare effects of a merger among two chains, which will be of interest for a regulator who decides whether to approve the merger that will yield a monopolist chain.[27]

Given the estimated model and pre-merger empirical data, one can use the iteration algorithm to obtain the profit maximizing, post-merger configurations of stores for the monopolist. Because there are two chains, a proposed merger would create a monopoly of one chain. I assume the hypothetical "one-time" merger happens exogenously and unexpectedly. I set the maximum number of stores the merged chain can open to 8 within a market, which is doubled from the duopoly in the pre-merger regime. For the merger simulation, I consider the following two scenarios.

1. "De Novo" Entry, No Costs of Closing and Remodeling a Store. In the first scenario, I assume no costs of closing existing stores or remodeling the target chain's stores into those of one's own chain. So the post-merger situation is more like a "de novo" entry, in which a monopolist chain enters into Okinawa, given the configurations of local stores and demographics. The second (fourth) column of Table 8 presents the results of the first scenario in which Family Mart (LAWSON) takes over as a monopolist. Given the small magnitude of the LAWSON fixed effect in Table 6, it is not surprising that columns 2 and 4 provide similar quantitative conclusions. In both cases, the monopolist chain increases its stores from its duopoly store counts, but the total number of the stores in Okinawa decreases by 5 percent from 239 stores, which is the combined number of stores of Family Mart and LAWSON before the merger. The total sales also decline by 7 to 8 percent, a proportion similar to the reduction in the total number of stores. However,

[27] One limitation of this merger analysis is that this exercise abstracts from changes in price due to merger, in particular the likely post-merger price increase.

the combined profits increase by 37 to 38 percent. The third and fourth rows from the bottom in columns 2 and 4 show that profits per store have increased significantly: a 51 percent increase for Family Mart and a 36 percent increase for LAWSON, respectively. Rows 14 and 15 in columns 2 and 4 show that there is a decrease in sales per store after the merger, which is 6 to 7 percent.

The third panel from the top in Table 8 provides a breakdown of the changes in total profits. Columns 1 and 2 of this panel suggest that the increase in total profits comes from a variety of sources. First, profits contribution from demographics increases by \$18.3 million because the monopolist chain can pick better markets in which to open stores than the pre-merger markets by re-designing its store networks. The profits for the merged chain also increase by \$36.5 million due to an increase in cost savings, both across-market and within-market. (On the other hand, the loss from business-stealing among the two chain stores increases by around \$45 million (from $-\$36.1-\$37.0$ to $-\$118$ million), which leads to a decrease in per-store sales. The results support a story in which the monopolist chain clusters its stores in profitable markets. Although the loss from business-stealing among its stores outweighs the cost-saving benefits from clustering, the profits increase from improved demographics, such as higher population, will compensate for the loss from the competition net of the cost savings.

Because the reduction in sales dominates the increase in profits, the sum of total profits and total sales decreases by 4 percent, implying that there is a transfer of surplus from consumer to the merged chain.

2. Fixed Costs of Closing and Remodeling a Target's Store. To be more realistic about merger simulation, the second scenario considers the effect of pre-merger store networks on the post-merger choice of a store network. In particular, I introduce two new parameters. First, closing a store incurs exit costs. If a chain decides to close a store that existed in the pre-merger state, whether the store of its own chain or a rival chain, the chain has to pay a positive cost of closing a store. Such costs could include cleaning up the site so that other types of tenant can move in. The second parameter is a cost of converting a store from a target chain into the monopolist chain store. An acquirer has to pay costs of remodeling, such as changing name boards or the interior design to make the store look like the acquiring chain's brand. I allow the acquiring chain to choose whether to convert an existing rival store (if any) when increasing the number of stores in the market, depending on the relative magnitude of exit and remodeling costs. As approximations of these costs, I use average numbers obtained from chains' financial statements in 2001 and 2002. From the documents, these two costs appear non-negligible in the magnitudes:

approximately $\$100,000$ for closing a store and $\$50,000$ for remodeling a store of the rival chain. Because the costs of remodeling a store are less than the costs of closing a store, an acquiring chain that considers expanding its network in a given market would prefer to remodel a store of a target's chain over opening a new one. To see the robustness of the results, I estimate two alternative costs specifications.

The sixth and eighth columns of Table 8 present the results of the second scenario. Although there is no significant difference in the number of total stores between the pre-merger and the post-merger store configurations, total sales decrease by 7 to 8 percent. This decrease is mainly due to an increased business-stealing effect among chain stores as is the case with the first scenario: the third panel in Table 8 shows that the reduction in total sales due to increased competition among chain stores is $80 million. The decrease in the number of stores is more modest than in the first "de novo" scenario: an 8 percent decrease if Family Mart is the acquirer and a 7 percent decrease if LAWSON takes over. Rows 4 through 8 in the sixth and eighth columns present the breakdown of how the merged chain uses the existing store networks of both chains. Although no difference exists in the number of closing rival stores (row 7), asymmetry in the number of remodeled stores arises between two chains due to the difference in the number of stores in pre-merger regime: 138.5 for Family Mart and 102.8 for LAWSON.[28] As a consequence of this asymmetry in the number of stores to be remodeled, the total cost of remodeling is larger for LAWSON than Family Mart by $2.2 million. The reduction in sales is also smaller than the one of the "de novo" entry case. Due to the burden of closing and remodeling stores, which is $7.0 million for Family Mart and $9.2 million for LAWSON, the profits for both chains are smaller than the corresponding profits in the first scenario in Table 8, and the profits are less by $7.3 million for Family Mart (from $67.7 million to $60.4 million, a 11 percent decrease) and by $9.5 million dollars for LAWSON (from $68.3 million to $58.8 million, a 14 percent decrease). The difference across chains exists largely because of the asymmetry in the number of remodeled stores. Overall, the decrease in the sum of total profits and total sales is 3 percent, and no noticeable difference exists between the second scenario and the "de novo" entry scenario.

Figures 7 and 8 present the predictions of geographic store-network patterns as a result of the merger and the increase in the total number of stores in a given market before and after the merger. We can confirm that the acquirer, either Family Mart or LAWSON, tends to cluster more at the city center and less at suburbs than the sum of the two chains' stores in pre-merger status. We know that

[28] The number of total stores for Family Mart and LAWSON is an average of the model predictions over 200 simulations.

although opening an additional store will steal business from stores of the same market, opening a store benefits not only the stores of the same market but also the stores of adjacent markets. The degree of clustering in the centers increases because in city centers, the number of stores in adjacent markets is higher than markets in non-city centers. Thus, cost savings are greater in city centers than in non-city centers. Although the number of stores a merged chain has is more than the combined number of Family Mart and LAWSON in the most-populated markets, the acquirer has less number of stores in less-populated markets. The reason why fewer stores are in suburbs for the acquirer than for Family Mart and LAWSON is the reduction in random entry events: the chain-market specific profit shocks occurs only for Family Mart and not for LAWSON after merger.

To check the sensitivity of results to the costs assumption, Table 9 presents some robustness checks. I use two alternative assumptions for the magnitudes of the costs of closing a store and the costs of remodeling a store. The first and third column of Table 9 give the results in which the costs of closing a store has been increased by $\$50,000$, holding the costs of remodeling a store fixed at $\$50,000$, as in the second specification in Table 8.

Both specifications deliver similar quantitative results on the total profits. For instance, rows 7 and 8 of column 2 show that an increase in the costs of closing a store makes remodeling a store cheaper than closing a store relative to the second scenario in Table 8, leading to an increase in the number of stores through a decrease in the stores to be closed (from 41.9 to 33.8) and an increase in the stores to be remodeled (from 56.8 to 64.9). Because the number of stores to be remodeled increases and the number of stores to be closed decreases, the total number of stores increase relative to the second scenario. The sixth and eighth columns of Table 9 provide the results in which the costs of remodeling a store have been increased by $\$50,000$, holding the costs of remodeling a store at $\$100,000$ as in the second specification in Table 8. The opposite force is at work: the magnitude of a decrease in combined number of stores from the pre-merger case is less than the second cost specification in Table 8 because remodeling a rival chain's store is more costly than the previous cost specification. This change in relative costs of remodeling and closing a store leads to a decrease in the number of stores to be remodeled and an increase in the number of rival chain stores to be closed. Regardless of the cost specifications, the merger between Family Mart and LAWSON would decrease the sum of total sales and chain profits mainly due to a decrease in total sales, and the magnitude ranges from 1 to 8 percent depending on the size of the costs of closing and remodeling a store.

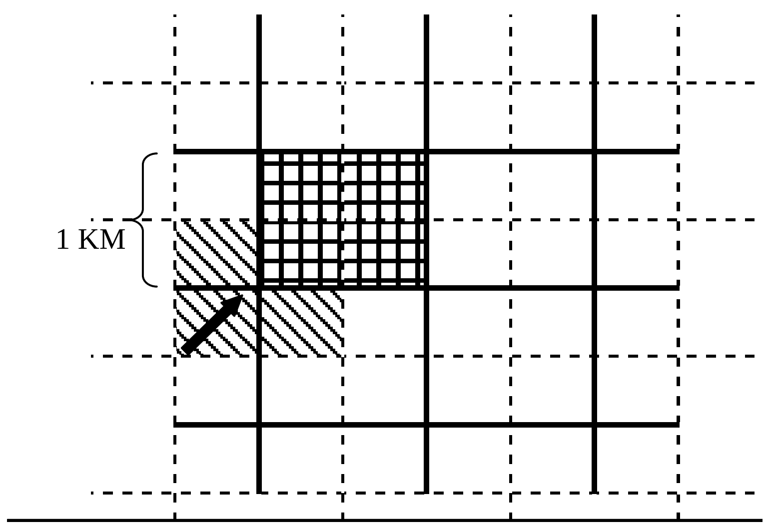
7 Robustness Checks

This section provides a set of alternative specifications on the empirical model to explore the robustness of the results. Two major concerns are the robustness of the parameter estimates to the choices of grids and the imposed equilibrium selection rule.

Choices of Grids. This robustness check examines whether the original market definition is driving the results Table 5 reports, which we can investigate in a number of ways. One way to verify this result is to construct a second sample of markets with store counts and demographics by using the original grid-level data. In particular, as Figure 4 shows, I consider a different set of 1 km square grids of which borders are located at the midpoint of the original borders.

FIGURE 4

SHIFTED 1 KILOMETER SQUARE GRIDS



NOTE. - Dashed and bold lines show original and newly defined borders for markets, respectively.

Each cell of these newly defined grids contains the same set of information as the original grids: store counts of convenience stores of three types (Family Mart, LAWSON, local), demographics such as population, and zoning index variable. The original data at the 1km square grid level are resampled into the newly 1km square mesh level data. To create the store counts variable, I use location data of the convenience stores. To generate demographic variables for a given market, I focus on the four markets with original borders overlapping with the market with new borders: I add up one-fourth of the population and the number of workers of the four markets, assuming the population density and number of workers density are uniform within the four original grids. I call this procedure resampling. As in the original sample, I exclude from our sample markets that have no population either in daytime or nighttime, leaving a sample of $1,138$ markets.

I use the non-revenue model for comparison because revenue information is available only when a market has more than two stores, and resampling substantially reduces the number of observations for the revenue variable. We will not have well-defined revenue data for a newly defined market unless there are four adjacent markets with more than two stores, which is rare in the sample.

Columns 1 and 2 in Table 5 present the estimates for the original market definition and column 3 and 4 in Table 5 provide the results for the newly created sample. Results from both specifications exhibit the same signs and statistical significance for all parameter estimates. Also, the relative magnitudes among the coefficients on all variables appear similar across both specifications. Overall, the shifted grid specification yields similar results to the baseline specification, providing evidence that the assumption about the location of the grid has not played a big role in driving the results.

Equilibrium Selection Rule. In this robustness check, I examine whether the results are sensitive to the choice of the equilibrium selection rule. I re-estimate the model with the assumption that the equilibrium market participants choose is the one that favors LAWSON the most. The motivation is the following: the baseline specification assumes the observed outcome is the equilibrium that is most profitable to Family Mart. This assumption is intuitive because the aggregate profits increase with the number of stores. For instance, given that the number of Family Mart stores is 40 percent higher than the number of LAWSON stores, the aggregate profits will also be 40 percent higher if the profits per store are the same across chains on average. Although the assumption makes sense in this industry, the concern is that this selection rule is too strong to assume, and we would like to see the outcomes when we change the equilibrium selection rule.

Column 5 in Table 5 displays the estimation results with the alternative equilibrium selection rule. Although the parameter estimate regarding competitive effects across chains loses its significance, no significant difference exists in the demographics and zoning parameter across specifications. Furthermore, the model with the alternative selection rule predicts a similar number of stores for each chain as the one by the baseline model does. The largest difference is that now we have a negative and significant coefficient on the LAWSON dummy variable, implying that we need to have a large and negative fixed effect for LAWSON in order to justify the current market configurations.

8 Concluding Remarks

This paper proposes and estimates an empirical model of strategic store-network choices by two chains. By formulating the model as a supermodular game of two players, I implement the seemingly infeasible task of finding equilibria out of a vast number of possible combinations of outcomes. In contrast to previous studies, the model allows chains to choose which markets to enter as well as how many stores to open in each of those markets. Generalizing the model to a larger number of stores is beneficial to the convenience-store industry in Okinawa due to dense configurations of stores. The specification of the industry as a game by two chains formulating store networks enables me to investigate policy questions. In particular, I consider two counterfactual simulations: whether a merger or regulations have economically significant impacts on entry behavior of retail chains and profits and total sales.

I report three findings. First, I show that, by introducing multiple-store choice in chain-entry model, the model accommodates both positive and negative effects among own stores in the same market ("within-market effect"). This framework would be particularly useful in studying retail industries with dense configurations of stores. The within-market effect is estimated to be negative and as large as the business-stealing effect, the reduction in revenues due to the presence of a rival chain store. Second, merger simulations confirm that a hypothetical merger between Family Mart and LAWSON would likely result in a smaller number of total stores, although the post-merger density of stores in the city center would be greater than the pre-merger density. Total sales decrease due to a decline in the total number of stores, suggesting that the merger would not benefit consumers. Finally, an experiment of eliminating the current zoning regulation shows that, in the new equilibrium, chains would increase their number of stores and sales, but the magnitude of the increase is modest.

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Appendix

A.1 Japanese Convenience-Store Industry: Background

Convenience stores are one of the fastest growing retail formats in the last twenty years.[29] The industry is concentrated in that a handful of nationwide large players with many outlets dominate the industry: the six national chains account for 71 percent of the total number of convenience-store outlets in Japan in 2002 and 82 percent of the total sales. Among franchise chains, 7-Eleven is the largest convenience chain in the world, operating in more than 20 countries.[30]

As its name suggests, the industry focuses on consumer convenience in order to increase customer satisfaction in terms of store accessibility and the variety of items available relative to floor space. Convenience-store chains pursue this goal by (1) access: minimizing the travel costs by opening many stores that are on average 110 square meters or $1,184$ square feet, which is smaller on average than local supermarkets, groceries, and other food retail stores; (2) variety: increasing the number of items per store floor area so consumers can find what they are looking for without having to travel to grocery stores or general stores. Convenience-store chains aim for 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 is typical in the supermarket industry. The core merchandise of convenience stores is food: about 70 percent of the sales are food, soft drinks, and alcoholic drinks. According to the 2004 Census of Commerce, average annual sales per store are 1.6 million US dollars or 161 million yen, and 1.8 million dollars for 24-hour outlets.

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

In retail markets, 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 finding is especially true when outlets offer similar quality of services and

[29] The overall industry sales in 2004 were 6.7 trillion yen, which is approximately 5 percent of total retail sales.

[30] 7-Eleven Japan, which is the biggest company of all national 7-Elevens, owns companies in the United States and China that yielded 23 billion dollars annually in 2005.

a variety of products through franchising, which is the case in Japan's convenience-store industry. Several features of the convenience-store industry in Japan promote focusing solely on location decisions of retail outlets. First, the industry for nationwide chain companies commonly adopts uniform pricing, allowing me to abstract pricing decisions from each store. This ability to abstract means we do not need price data in order to model pricing behavior. Emphasis on geographic differentiation in the industry is a natural consequence of lack of a differentiation in product or price. 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 nationwide chains, convenience stores offer similar merchandise, services, and shopping experiences across outlets and chains. Of course, the quality of shopping experiences matters as well. In fact, we see noticeable differences across chains in brand images and quality of goods and services provided, two fronts in which chains invest to improve. These quality differences consumers perceive will eventually show up in the differences in sales across chain companies.

Two ownership types exist: franchised stores and corporate stores. For example, more than 80 percent of the total number of 7-Eleven stores in Japan are franchises. As is common in many industries, obtaining the franchise status of stores is difficult because chains treat this information as proprietary. In the analysis, I do not distinguish between franchised stores and corporate stores. I believe this decision is not problematic for this study because chain headquarters, not individual franchise owners, decide how many outlets to install each year and where to put those new outlets.

A.2 The 1968 Urban Planning Law

Description of Zoning Regulations. 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 prioritize infrastructure investment and prevent urban sprawl and disorganized urbanization in accordance with the government's urban planning, such as preservation of farm land, scenery, 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 on whether the government wants to promote urbanization in that area. The three types are: (1) Urbanization area, (2) Urbanization control area, and (3) Undelineated area. I define the Urbanization area as the urbanized area or the area the government established as high priority for urbanization by constructing public facilities such as water, gas, and electricity. In this area, no restriction prevents the development or construction of facilities whose areas are less than $1,000m^2$, such as a convenience-store outlet. On the other hand, the aim of an Urbanization control area, in which most development actions are suppressed, is opposite that of the Urbanization area. Therefore, this area provides less adequate public infrastructure than an Urbanization area does. 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 a convenience store, demanding that the applicant must prove the establishment will not go against the urban planning in that area. For the Undelineated area, permission is not required to install 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 rule that prohibits the development of commercial stores or residential houses without government permission. Although in principle you cannot build convenience-store outlets in any Urbanization control area under the regulation above, a building permit system allows exceptions: under Article 34-1 of UPL, 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.[31] Another requirement of complying with the law is the need to show that the establishment one wants to build meets restrictions the cities set, such as proximity to residential areas or maximum floor space.

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

Endogeneity Concern. An ideal empirical model for measuring the impacts of zoning on entry would involve randomly assigning zoning restrictions to markets and comparing the outcomes across zoned and unzoned markets. 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 were made based on some unobserved (to the econometrician) market-specific factors, arising either from the demand or the cost sides, which affect profitability of convenience-store outlets. Then one may be mistakenly attributing observed outcomes, such as variations in the number of outlets across markets, to costs of zoning and not to systematic differences in profitability across markets. As a result, the parameter

[31] 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 facilities, then under some conditions the development is permitted. However, in Okinawa, this type of convenience store is not allowed; therefore, I am not going to attend to this exception.

estimates can suffer from an omitted variable bias.

To alleviate the omitted variable bias, I include in the empirical model demographics at the market level, such as population and the number of workers, to what otherwise would be a key omitted variable. One suggestive feature of the industry favors this argument: consumers in city areas travel smaller distances to visit convenience-store outlets, compared to other types of retail formats such as large discount retailers or department stores. Furthermore, one piece of anecdotal evidence mitigates the concern. A conversation with a local regulator's staff 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 activity is not considered because it involves the hard task of predicting the size of commercial sales in the near future.

B.1 Proof of Proposition 1: Supermodularity for Multiple Stores within a Market

A game is (strict) supermodular if (1) $\mathbf{N}_i$ is nonempty compact sublattice $\mathbf{N}_i$ into $\mathbf{N}_i$, (2) the payoff $\Pi_i(N_i, N_j)$ is supermodular in its own strategy N_i for each N_j, and (3) the player i's payoff Π_i has increasing differences in (N_i, N_j) for all $N_i \in \mathbf{N}_i$ and $N_j \in \mathbf{N}_j$. In the first subsection, I provide a proof of supermodularity of the game when the across-market effect occurs at the store level: the positive spillovers across markets depends on not only the mere presence of outlets in neighborhood markets but also on the number of outlets in these markets. In the next subsection, I provide a proof of a case in which an across-market effect occurs at the market level: the magnitude of positive spillover across markets depends on the presence of chain i in the neighborhood markets. So I assume the effect does not depend on the number of outlets but rather the number of markets in which chain i's outlets are present.

Case (1): Across-Market 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 market m for chain $i \in \{FM, LS\}$. In our analysis, I allow that chains have up to four stores in a market. So $N_{i,m} = \{0, 1, .., 4\}^M$. The following proof is made in general, in the sense that it will also contain the binary-choice case or more-than-five-choices case: if I allow only one store in each market, we will replace $N_{i,m}$ by $D_{i,m}$, and the profit function will look like Jia (2008)'s model.

Assuming symmetry across outlets within a given grid, the profit function for chain i is given by

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

I introduce a new term above, $h_{i,m}(N_{i,m})$, that measures how much net of spillovers (cost savings minus business stealing) you would obtain from having more than one store of the same chain i in market m. The reason for having this term is that we may not observe a simple linear relationship between the number of outlets and revenue in a given market. For example, if chain i has two outlets in market m, the revenue from market m may not be just two times the revenue of having a store in market m, holding other conditions equal. I introduce this term because positive spillovers from having the same chain's store(s) in the same market may dominate the business stealing among those own stores or the other way around. 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 markets, can take negative or positive values, and can be linear or nonlinear in the number of outlets in the market m.

First, I verify the second condition of supermodularity of the game. The profit function for chain i is supermodular in its own strategy if and only if $\Pi_i(N_i')+ \Pi_i(N_i'') \leq \Pi_i(N_i' \wedge N_i'') + \Pi_i(N_i' \vee N_i'')$ for any N_i' ,$N_i'' \in \mathbf{N}_i$. For convenience, I define $N_{i,m}^1 \equiv N_{i,m}' - \min(N_{i,m}', N_{i,m}'')$, $N_{i,m}^2 \equiv N_{i,m}'' - \min(N_{i,m}', N_{i,m}'')$, and $N_{i,m}^3 \equiv \min(N_{i,m}', N_{i,m}'')$. The combined profits from choosing N_i' and N_i'' are given by

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

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

$$\begin{aligned}
& \Pi_i(N_i' \wedge N_i'') + \Pi_i(N_i' \vee N_i'') \\
= & \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'') * (\mathbf{Y}_{i,m} + \delta_{across}\Sigma_{l\neq m}\frac{(N_{i,l}' \wedge N_{i,l}'')}{Z_{m,l}} + h_{i,m}(N_{i,m}' \wedge N_{i,m}'')] \\
& +\Sigma_{m=1}^{M}[(N_{i,m}' \vee N_{i,m}'') * (\mathbf{Y}_{i,m} + \delta_{across}\Sigma_{l\neq m}\frac{(N_{i,l}' \vee N_{i,l}'')}{Z_{m,l}} + h_{i,m}(N_{i,m}' \vee N_{i,m}'')] \\
= & \Sigma_{m=1}^{M}(N_{i,m}^1 + N_{i,m}^2 + N_{i,m}^3)(\mathbf{Y}_{i,m} + \delta_{across}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}(N_{i,l}^1 + N_{i,l}^2 + N_{i,l}^3) \\
& +\Sigma_{m=1}^{M}N_{i,m}^3(\mathbf{Y}_{i,m} + \delta_{across}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}N_{i,l}^3) \\
& +\Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'')] \\
= & B + \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') && \text{(A-2)} \\
& +(N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'')], && \text{(A-3)} \\
\text{where } B \equiv & \Sigma_{m=1}^{M}[(N_{i,m}^1 + N_{i,m}^2 + N_{i,m}^3)(\mathbf{Y}_{i,m} + \delta_{across}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}(N_{i,l}^1 + N_{i,l}^2 + N_{i,l}^3) \\
& +N_{i,m}^3(\mathbf{Y}_{i,m} + \delta_{across}\Sigma_{l\neq m}\frac{1}{Z_{m,l}}N_{i,l}^3)].
\end{aligned}$$

Now, subtracting Eq.(A-1) from Eq.(A-2) provides

$$\begin{aligned}
& \Pi_i(N_i' \wedge N_i'') + \Pi_i(N_i' \vee N_i'') - (\Pi_i(N_i') + \Pi_i(N_i'')) \\
= & B + \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'')] \\
& -[A + \Sigma_{m=1}^{M}[N_{i,m}'h_{i,m}(N_{i,m}') + N_{i,m}''h_{i,m}(N_{i,m}'')] \\
= & B - A + \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'') \\
& -(N_{i,m}'h_{i,m}(N_{i,m}') + N_{i,m}''h_{i,m}(N_{i,m}''))] \\
= & \delta_{across}\Sigma_{m=1}^{M}\Sigma_{l\neq m}\frac{N_m^2N_l^1 + N_m^1N_l^2}{Z_{m,l}} \\
& +\Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'') \\
& -(N_{i,m}'h_{i,m}(N_{i,m}') + N_{i,m}''h_{i,m}(N_{i,m}''))]. && \text{(A-4)}
\end{aligned}$$

The first term is the same as the binary-choice case (entry or exit) if we replace numerator $N_m^2N_l^1 + N_m^1N_l^2$ by corresponding index functions, $D_m^2D_l^1 + D_m^1D_l^2$, 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 the second term market by market. Among a given set of the 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 market

m, $N'_{i,m} \wedge N''_{i,m} = \min(N'_{i,m}, N''_{i,m}) = N''_{i,m}$, 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.(A-4) becomes

$$\begin{aligned}
& (N'_{i,m} \wedge N''_{i,m})h_{i,m}(N'_{i,m} \wedge N''_{i,m}) + (N'_{i,m} \vee N''_{i,m})h_{i,m}(N'_{i,m} \vee N''_{i,m}) \\
& -(N'_{i,m}h_{i,m}(N'_{i,m}) + N''_{i,m}h_{i,m}(N''_{i,m})) \\
= \;& N''_{i,m}h_{i,m}(N''_{i,m}) + N'_{i,m}h_{i,m}(N'_{i,m}) - (N'_{i,m}h_{i,m}(N'_{i,m}) + N''_{i,m}h_{i,m}(N''_{i,m})) \\
= \;& 0. \qquad \text{(A-5)}
\end{aligned}$$

Combining Eq.(A-4) and Eq. (A-5) yields

$$\begin{aligned}
& \Pi_i(N'_i \wedge N''_i) + \Pi_i(N'_i \vee N''_i) - (\Pi_i(N'_i) + \Pi_i(N''_i)) \\
= \;& \delta_{across}\Sigma_{m=1}^{M}\Sigma_{l \neq m}\frac{N^2_{i,m}N^1_{i,l} + N^1_{i,m}N^2_{i,l}}{Z_{m,l}}. \qquad \text{(A-6)}
\end{aligned}$$

Noting that the numerator of the first term, $N^2_{i,m}N^1_{i,l} + N^1_{i,m}N^2_{i,l}$, is always nonnegative because 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 $\delta_{across} \geq 0$, regardless of the specification of $h_{i,m}(N_{i,m})$.

Eq.(A-6) implies that, within a given market, whether the positive spillover across outlets of the same chain i dominates revenue reduction due to the presence of own store in the same market (cannibalization or business stealing) does not affect whether the game is supermodular in its own strategy.

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

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

If δ_{comp} is positive, meaning that the profits increase when you have a competitor chain in the same grid, the profit function Π_i has increasing differences in $N_{i,m}$. If δ_{comp} is negative, the profit function Π_i has decreasing differences in $N_{i,m}$ because $N_j \geq \tilde{N}_j$. However, by using a simple transformation trick in Vives (1990) in order to define a new strategy for competitor, $\hat{N}_j = -N_j$, the profit function Π_i will have increasing differences.

Case (2): Across-Market Effect at the Market 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 market m, $D_{i,m}$, which equals 1 if chain i enters in market m, 0 otherwise. So $D_{i,m} = 1$ if and only if $N_{i,m} \geq 1$, $D_{i,m} = 0$ otherwise.

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

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

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

$$\begin{aligned} & \Pi_i(N'_i \wedge N''_i) + \Pi_i(N'_i \vee N''_i) - (\Pi_i(N'_i) + \Pi_i(N''_i)) \\ = \; & \delta_{across}\Sigma_{m=1}^{M}\Sigma_{l \neq m}\frac{N_{i,m}^2 D_{i,l}^1 + N_{i,m}^1 D_{i,l}^2}{Z_{m,l}}. \end{aligned} \quad \text{(A-7)}$$

Noting that

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

is nonnegative because 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 $\delta_{across} \geq 0$.

Eq.(A-7) implies that, within a given market, whether there is positive spillover across outlets of the same chain i or revenue reduction due to the presence of own store in the same market (cannibalization) does not affect whether the game is supermodular in its own strategy.

Now 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:

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

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

B.2 Proof of Proposition 2: Derivation of Necessary Condition: V(N)

In this section, I derive a necessary condition $V(N)$ and provide a proof of increasing in N in general. Player i maximizes the profits from every market:

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

Notice I represent the within-market effect by a functional form $h(N_{i,m})$ instead of $\delta_{within}\mathbf{1}(N_{i,m} = 2)$ in the empirical specification of the paper. I assume $h(1) = h(0) = 0$ as no other store is in market m.

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 market m, $N_{i,m} \in \{0, 1, .., K\}$, so that the updated entry decision $N^{updated}_{i,m} = V_m(N_i)$ maximizes the profit contribution from market m. By definition, the profit maximizing vector $N^*_i = \arg\max_{N_i} \Pi_i(N_i, N_j)$ is a fixed point of the function $V(N^*_i) = N^*_i$.

Consider updating $N_{i,m}$, which maximizes the profits from market m to aggregated profits, holding the choice of the number of stores in other markets fixed. To find a maximizer componentwise $N^*_{i,m} = \arg\max_{N_{i,m}} \Pi_i(N_i, N_j)$, I adopt the following algorithm, which sequentially compares and updates the choice in the number of stores in market m, $N_{i,m}$.

In the first step, I compare the profits Π_i when choosing $N_{i,m} = 0$ and $N_{i,m} = 1$, holding the choice of the number of stores in other markets fixed. Let us denote the decision rule in this step by an index function D_m^1, defined as

$$D_m^1 = \begin{cases} 1 \text{ if } \Pi_i(N_{i,1}..., 1, .., N_{i,M}) \geq \Pi_i(N_{i,1}..., 0, .., N_{i,M}) \\ 0 \text{ otherwise.} \end{cases}$$

I define $N''_{i,m} = \arg\max_{N_{i,m}=\{0,1\}} \Pi_i(N_{i,1}..., N_{i,m}, .., N_{i,M})$. In the second step, I compare the profits Π_i when choosing $N_{i,m} = N''_{i,m}$ and $N_{i,m} = 2$, holding the choice of the number of stores in other markets $N_{i,l\neq m}$ fixed. I define the decision rule D_m^2 in the similar way as in the previous step:

$$D_m^2 = \begin{cases} 1 \text{ if } \Pi_i(N_{i,1}..., 2, .., N_{i,M}) \geq \Pi_i(N_{i,1}..., N''_{i,m}, .., N_{i,M}) \\ 0 \text{ otherwise.} \end{cases}$$

In general, I iterate this $K + 1$ times by increasing $N_{i,m}$ by one each time I go to the next step, starting from $N_{i,m} = 0$. When I reach the final candidate $N_{i,m} = K$, the algorithm stops and I should have the maximizer $N''_{i,m} = \arg\max_{N_{i,m}} \Pi_i(N_i, N_j) = N^*_{i,m}$. The maximizer $N^*_{i,m}$ can be explicitly represented in the linear combination of the decision rules, $(D_m^1, .., D_m^K)$:

$$\begin{aligned} N^*_{i,m} &= V_m^K(N_i) = D_m^K * K + (1 - D_m^K) * [D_m^{K-1} * (K-1) + (1 - D_m^{K-1}) * [D_m^{K-2} * (K-2) + (1 - D_m^{K-2})[.. \\ &\quad .. * [D_m^1 * 1 + (1 - D_m^1) * 0]]..]]]. \end{aligned}$$

This necessary condition V_m^K can be written in a recursive form as

$$\begin{aligned} V_m^K &= D_m^K * K + (1 - D_m^K) * V_m^{K-1} \\ \text{where } V_m^K &= \begin{cases} K \text{ if } D_m^K = 1 \\ V_m^{K-1} \text{ otherwise} \end{cases}, \end{aligned} \tag{A-8}$$

and D_m^K compares the profits by choosing $N_{i,m} = K$ and $N_{i,m} = V_m^{K-1}$ and takes 1 if $\Pi_i(N_{i,m} = K) \geq \Pi_i(N_{i,m} = V_m^{K-1})$, 0 otherwise. In the nonrevenue model in the paper, K is set 2 and the necessary condition will be

$$\begin{aligned} V_m^2(N_i) &= D_m^2 * 2 + (1 - D_m^2)[D_m^1 * 1 + (1 - D_m^1) * 0] \\ &= D_m^2 * 2 + (1 - D_m^2) D_m^1, \end{aligned}$$

where the exact form of decision rule D_m^K is given in the next subsection.

B.3 Proof of Proposition 3: $V(N_i)$ is Nondecreasing in N_i

Here, I derive the exact formula for D_m^K. In general, the index function describing the decision rule regarding whether to choose $N'_{i,m}$ over $N''_{i,m}(\neq N'_{i,m})$ is given as

$$D_m(N'_{i,m}, N''_{i,m}) = \begin{cases} 1 \text{ if } \Pi_i(N_{i,1}..., N'_{i,m}, ,.., N_{i,M}) \geq \Pi_i(N_{i,1}..., N''_{i,m}, .., N_{i,M}) \\ 0 \text{ otherwise.} \end{cases} \tag{A-9}$$

Without loss of generality, I set $N'_{i,m} > N''_{i,m}$. The decision rule D_m will be

$$\begin{aligned} D_m &= \mathbf{1}[(N'_{i,m} - N''_{i,m})[\mathbf{Y}_{i,m} + 2(N'_{i,m} - N''_{i,m})\delta_{across}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}}] + N'_{i,m}h(N'_{i,m}) - N''_{i,m}h(N''_{i,m}) \geq 0] \\ &= \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{across}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + \frac{N'_{i,m}h(N'_{i,m}) - N''_{i,m}h(N''_{i,m})}{N'_{i,m} - N''_{i,m}} \geq 0]. \end{aligned} \tag{A-10}$$

So the D_m^K will be represented by

$$D_m^K(N'_{i,m}= K, N''_{i,m}= V_m^{K-1}) = 1[Y_{i,m}+2\delta_{across}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}}+\frac{K * h(K) - V_m^{K-1} * h(V_m^{K-1})}{K - V_m^{K-1}}\geq 0].^{32} \tag{A-10}$$

To show that $V(N_i)$ is nondecreasing in N_i, I first show that V_m^K is nondecreasing in $N_{i,m}$. In the case of $K = 1$, V_m^1 will be

$$\begin{aligned} V_m^1 &= D_m^1 * 1 + (1 - D_m^1) * 0 = D_m^1, \\ \text{where } D_m^1 &= \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{across}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} \geq 0]. \end{aligned} \tag{A-11}$$

V_m^1 is nondecreasing in $N_{i,m}$ because $V_m^1 = D_m^1$ does not depend on the current choice in the market

[32] If we assume the functional form for profit interactions among own stores in the same market is linear in the number of stores,

$$\begin{aligned} h(N_{i,m}) &= \begin{cases} \delta_{within}(N_{i,m} - 1) \text{ if } N_m \geq 2 \\ 0 \text{ if } N_m < 2 \end{cases} \\ &= \delta_{within}(\max\{N_{i,m}, 1\} - 1) \end{aligned}$$

then D_m^K will be

$$D_m^K(N'_{i,m} = K, N''_{i,m} = V_m^{K-1}) = \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{across}\sum_{l\neq m}\frac{N_{i,l}}{Z_{m,l}} + \delta_{within}(K + V_m^{K-1} - 1) \geq 0].$$

m, as is clear from Eq.(A-11). Next, in the case of $K = 2$, V_m^2 will be

$$V_m^2(N_i) = D_m^2 * 2 + (1 - D_m^2) D_m^1, \tag{A-12}$$

$$\text{where } D_m^2 = \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{across} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \frac{2 * h(2) - V_m^1 * h(V_m^1)}{2 - V_m^1} \geq 0] \tag{A-13}$$

$$= \begin{cases} \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{across} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + 2h(2) - h(1) \geq 0] \text{ if } V_m^1 = 1 \\ \mathbf{1}[\mathbf{Y}_{i,m} + 2\delta_{across} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + h(2) \geq 0] \text{ if } V_m^1 = 0. \end{cases}$$

Substituting Eq.(A-11) and Eq.(A-13) into Eq.(A-12) yields $V_m^2(N_i)$, which does not depend on $N_{i,m}$ because neither Eq.(A-11) nor Eq.(A-13) contains $N_{i,m}$. Therefore, V_m^2 is nondecreasing in $N_{i,m}$. By using an induction argument starting from $K = 1$, V_m^K is nondecreasing in $N_{i,m}$.

Second, I show that V_m^K is nondecreasing in $N_{i,l}$ for any market $l \neq m$. In the case of $K = 1$, V_m^1 is nondecreasing in $N_{i,l}$ as long as δ_{across} is nonnegative, as one can examine from Eq.(A-11). In general, consider two vectors N_i and $\tilde{N}_i$ with $N_{i,l} \geq \tilde{N}_{i,l}$ and $N_{i,m} = \tilde{N}_{i,m}$ for market $m \neq l$.

I prove by contradiction. Suppose there exist vectors N_i and $\tilde{N}_i$ with $N_{i,l} \geq \tilde{N}_{i,l}$ and $N_{i,m} = \tilde{N}_{i,m}$ for market $m \neq l$ such that $V_m^K(N_i) < V_m^K(\tilde{N}_i)$. Let us define

$$\begin{aligned} V_m^K(N_i) &= N_{i,m}^* \\ V_m^K(\tilde{N}_i) &= N_{i,m}^{**} \end{aligned}$$

and we have $N_{i,m}^* < N_{i,m}^{**}$. By using Eq.(A-10), the above equations implies that

$$\begin{aligned} D_m(N_{i,m}^*, N_{i,m}^{**}, N_{i,l}) &= 1 \\ D_m(N_{i,m}^*, N_{i,m}^{**}, \tilde{N}_{i,l}) &= 0, \end{aligned}$$

or

$$D_m(N_{i,m}^*, N_{i,m}^{**}, N_{i,l}) = 1[Y_{i,m} + 2\delta_{across} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \frac{N_{i,m}^* h(N_{i,m}^*) - N_{i,m}^{**} h(N_{i,m}^{**})}{N_{i,m}^* - N_{i,m}^{**}} \geq 0] = 1 \tag{A-14}$$

$$D_m(N_{i,m}^*, N_{i,m}^{**}, \tilde{N}_{i,l}) = 1[Y_{i,m} + 2\delta_{across} \sum_{l \neq m} \frac{\tilde{N}_{i,l}}{Z_{m,l}} + \frac{N_{i,m}^* h(N_{i,m}^*) - N_{i,m}^{**} h(N_{i,m}^{**})}{N_{i,m}^* - N_{i,m}^{**}} \geq 0] = 0 \tag{A-15}$$

However, both Eq.(A-14) and Eq.(A-15) cannot hold at the same time as long as δ_{across} is nonnegative and $N_{i,l} \geq \tilde{N}_{i,l}$ because $D_m(N_{i,m}^*, N_{i,m}^{**}, N_{i,l})$ is a nondecreasing function in $N_{i,l}$.

B.4

In this section, I provide a proof that the Round-Robin iteration algorithm, starting from zero stores in every market for LAWSON, leads to the equilibrium that delivers the highest profits among all equilibria of the game. As in section 3, I denote the equilibrium by (N_{FM}^T, N_{LS}^T). By construction, $(N_{FM}^T, N_{LS}^T) = (N_{FM}^{T+1}, N_{LS}^{T+1})$.

First, I show that $N_{LS}^T \leq N_{LS}^*$ for any N_{LS}^* that belongs to the set of all Nash equilibria of the game, $\mathbf{N}^*$. Because the iteration starts from zero entry in every market, $N_{LS}^0 = \inf(\mathbf{N}_{LS})$, we have $N_{LS}^0 \leq N_{LS}^*$ and $N_{LS}^0 \leq N_{LS}^1$. Topkis (1979) shows that in a supermodular game, the best response function of player i is nonincreasing in player $-i$'s strategy for each i.[33] It follows that

$$\begin{aligned} N_{FM} &= BR_{FM}(N_{LS}) \text{ is nonincreasing in } N_{LS} \text{ and } N_{LS}^0 \leq N_{LS}^1 \\ &\Rightarrow N_{FM}^1 = BR_{FM}(N_{LS}^0) \geq N_{FM}^2 = BR_{FM}(N_{LS}^1). \end{aligned} \tag{A-16}$$

Similarly, for LAWSON,

$$\begin{aligned} N_{LS} &= BR_{LS}(N_{FM}) \text{ is nonincreasing in } N_{FM} \text{ and } N_{FM}^1 \geq N_{FM}^2 \\ &\Rightarrow N_{LS}^1 = BR_{LS}(N_{FM}^1) \leq N_{LS}^2 = BR_{LS}(N_{FM}^2). \end{aligned} \tag{A-17}$$

By iterating the operations in Eq.(A-16) and (A-17) sequentially for Family Mart and LAWSON until the best response algorithm converges, I have the following sequence:

$$\begin{aligned} N_{LS}^0 &\leq N_{LS}^1 \leq ... \leq N_{LS}^T = N_{LS}^{T+1} \\ N_{FM}^1 &\geq N_{FM}^1 \geq ... \geq N_{FM}^T. \end{aligned}$$

It holds that $N_{LS}^T \leq N_{LS}^*$ for any N_{LS}^* that belongs to the set of all Nash equilibria of the game because if $N_{LS}^T > N_{LS}^*$, the iteration process in Eq.(A-16) and (A-17) should have converged earlier than at Tth iterations. This conclusion contradicts the initial assumption that the iteration process converges at Tth iteration. Because the profit function for Family Mart, $\Pi_{FM}(N_{FM}, N_{LS})$, is nonincreasing in the rival chain's strategy N_{LS}, provided that the competitive effect from rival

[33] In the original statement of Topkis (1979, 1998 Lemma 4.2.2.), in a supermodular game, the best response function of player i is nonincreasing in player $-i$'s strategy for each i. The transformation trick in Vives (1990) in order to define a new strategy for competitor, $\hat{N}_j = -N_j$, will recover the stated results above.

chain is nonpositive ($\delta_{comp,rival} \leq 0$) it follows that

$$\Pi_{FM}(N_{FM}^{*}, N_{LS}^{T}) \geq \Pi_{FM}(N_{FM}^{*}, N_{LS}^{*}) \tag{A-18}$$

for any (N_{FM}^{*}, N_{LS}^{*}) that belongs to the set of all Nash equilibria of the game. Also,

$$\Pi_{FM}(N_{FM}^{T}, N_{LS}^{T}) \geq \Pi_{FM}(N_{FM}^{*}, N_{LS}^{T}) \tag{A-19}$$

holds because N_{FM}^{T} is the best response to N_{LS}^{T}. Combining Eq.(A-18) and (A-19), we have

$$\Pi_{FM}(N_{FM}^{T}, N_{LS}^{T}) \geq \Pi_{FM}(N_{FM}^{*}, N_{LS}^{*}) \ \forall \{N_{FM}^{*}, N_{LS}^{*}\} \in \mathbf{N}^{*},$$

where $\mathbf{N}^{*}$ is the set of all Nash equilibria of the game.

C Monte Carlo Experiments

I provide Monte Carlo evidence on the performance of the method of simulated moments estimator for a simplified version of the model of chain-store network decisions. The central purpose of this exercise is to perform robustness checks: to examine the extent to which the MSM estimator recovers the true parameter values from data I have artificially generated.

I construct fake data sets by choosing the "true" parameters of the model θ_0, the profit shocks $u_m = (\eta_{FM,m}, \eta_{LS,m}, \varepsilon_m)$ that are drawn from a standard normal distribution, and the exogenous data on demographics X_m that are artificially created from a standard normal distribution. With the true parameters θ_0, profit shocks u_m, and demographics X_m, I compute the data on the entry configurations $(N_{FM,m}, N_{LS,m})$ for each data set by solving for the pure-strategy Nash equilibrium most favorable to Family Mart. I repeat this data-generating process 50 times with the same parameters θ_0 and the same demographics X_m but different profit shocks u_m across 50 repetitions to obtain 50 independent data sets. Second, for each of the 50 different data sets, I estimate the structural parameters $\hat{\theta}_{MSM}$ by using the data on demographics X_m and entry configurations $(N_{FM,m}, N_{LS,m})$, pretending I observe neither the true parameter θ_0 nor the particular realization of profit shocks u_m. By doing so, I obtain 50 sets of parameter estimates $\hat{\theta}_{MSM}$. The simulation draws I use for the estimation are different from the ones used for generating fake data sets. Finally, to implement the experiments, I use four different numbers of total markets $M = 16, 36, 144$,and 1600. So I generate 50 data sets for these four different settings on the number of markets.

Columns 2 through 4 in Table 10 summarize the results of Monte Carlo experiments for the number of markets $M = 16, 36, 144$, and 1600 case. I find that in all four cases, the estimator performs similarly. To show the precision of the estimator, I report the mean and the standard deviation of the estimated parameters $\hat{\theta}_{MSM} = (\beta, \delta_{across}, \delta_{comp}, \rho)$. The mean of the estimated parameters is a simple average of 50 parameter estimates for 50 different data sets, and it falls within a single standard error from the truth values. Parameters β and ρ are more precisely estimated than the other parameters $\delta_{across}, \delta_{comp}$. The mean of our MSM estimator performs well on average in terms of recovering the true values, and the estimates are robust across different settings on the number of markets, ranging from 16 to $1,600$.

D Estimation Details

D.1 Implementations of Estimation

I take the following steps to estimate θ.

1. Prepare a set of simulation draws $\epsilon^{S,all} = (\epsilon^1, \epsilon^2, .., \epsilon^S)$, where $\epsilon^s = (\varepsilon^{s,r}, \varepsilon^{s,c}, \eta^{s,r}_{FM}, \eta^{s,r}_{LS}, \eta^{s,c}_{FM}, \eta^{s,c}_{LS})$ are profit shocks and S is the number of simulations.
2. For a given value of model parameter θ and a given simulation draw ϵ^s, solve for equilibrium predictions regarding the number of stores by the Round-Robin algorithm. It involves the following four steps.
   (a) Start from the smallest strategy vector in LAWSON's strategy space, $N^0_{LS} = (0, 0, \ldots .0)$.
   (b) Compute the best response of Family Mart N^1_{FM}, given parameter θ, simulation draw ϵ^s, and LAWSON's strategy N^0_{LS}. The computation process involves the following three steps.
      i. Starting from $N_{FM} = (0, .., 0)$, I update the choice of $N_{FM,m}$ by applying a component-wise optimality condition V until convergence, obtaining the lower bound vector of Family Mart's best response.
      ii. Starting from $N_{FM} = (4, .., 4)$, I update the choice of $N_{FM,m}$ by applying a component-wise optimality condition V until convergence, obtaining the upper bound vector of Family Mart's best response.
      iii. Evaluate all the vectors between the upper and the lower bound vector of my best response to find the vector that maximizes the total profits.

(c) Compute the best response of LAWSON, given Family Mart's best response N^1_{FM}: .

(d) Iterate the above steps (b)-(c) T times until we obtain convergence: $N^T_{FM} = N^{T+1}_{FM}$ and $N^T_{LS} = N^{T+1}_{LS}$. Converged vectors are a Nash equilibrium.

3. Repeat the previous step S times by using S different simulation draws.

4. Formulate a simulator by taking an average of the simulated outcomes over S times.

5. Construct and compute the value of the objective function.

6. Search for the value of θ that minimizes the objective function by repeating the steps (2) – (5), obtaining $\hat{\theta}_{MSM}$.

D.2 Moment Conditions

The current set of 22 moments that match the model prediction and the data is the following: (1) Number of Family Mart stores, (2) Number of LAWSON stores, (3) Number of Family Mart stores in adjacent markets, (4) Number of LAWSON stores in adjacent markets, (5) Total Sales, (6) Total Sales, 24-hour stores, (7) - (12): Interaction between moments (1) - (6) and daytime population, (13) - (18): Interaction between moments (1) - (6) and nighttime population, and (19) - (22): Interaction between moments (1) - (4) and zoning status index.

In population representation, moments (1) - (6) have an expected mean of zero at the true parameter as Eq.(4) in Section 4 shows. Moments (7) -(22) are based on Eq.(5) and (6) in Section 4; namely, multiplying the moment conditions (1) - (6) by any function of conditioning variables (i.e., market characteristics X_m, containing three variables: daytime population, nighttime population, zoning status) should also have expected mean zero at the true parameter. This multiplication creates $6 * 3 = 18$ moments additionally. I didn't include interaction between (5) - (6) and zoning status index because, in the data, interactions are zero in virtually all markets, meaning that sales data are not available in most of zoned markets. The zero interaction is because the number of total stores in those zoned markets rarely exceeds two.

D.3 Minimization

Because the objective function in Eq.(7) is not differentiable in the argument θ, I use nonderivative optimization methods. To ensure the reliability of the estimates, I employ a simulated annealing algorithm in addition to the Nelder-Meade simplex search. The non-smoothness of the objective function stems from the fact that the simulated outcomes are often not smooth. For instance, consider constructing a simple simulator for choice probability $P(\theta)$ for fixed number of simulations S. The simulated probabilities, $\tilde{P}(\theta)$, will be in the set $\{0, 1/S, 2/S, ..., S/S\}$. We can see that as θ varies, $\tilde{P}(\theta)$ will jump between fraction of S. As a consequence, $\tilde{P}(\theta)$ is discontinuous in θ and so is the sample moment and the criterion function for minimization. The non-smoothness of $\tilde{P}(\theta)$ is the reason gradient-based optimization routines will not work. I use simulated annealing or simplex methods, which do not rely on differentiability of the function in θ. I tried several different starting values for each parameter so as not to fall into a local minimum. For evidence that being careful with the sources of numerical inaccuracy matters, see Dube, Fox, and Su (2008).

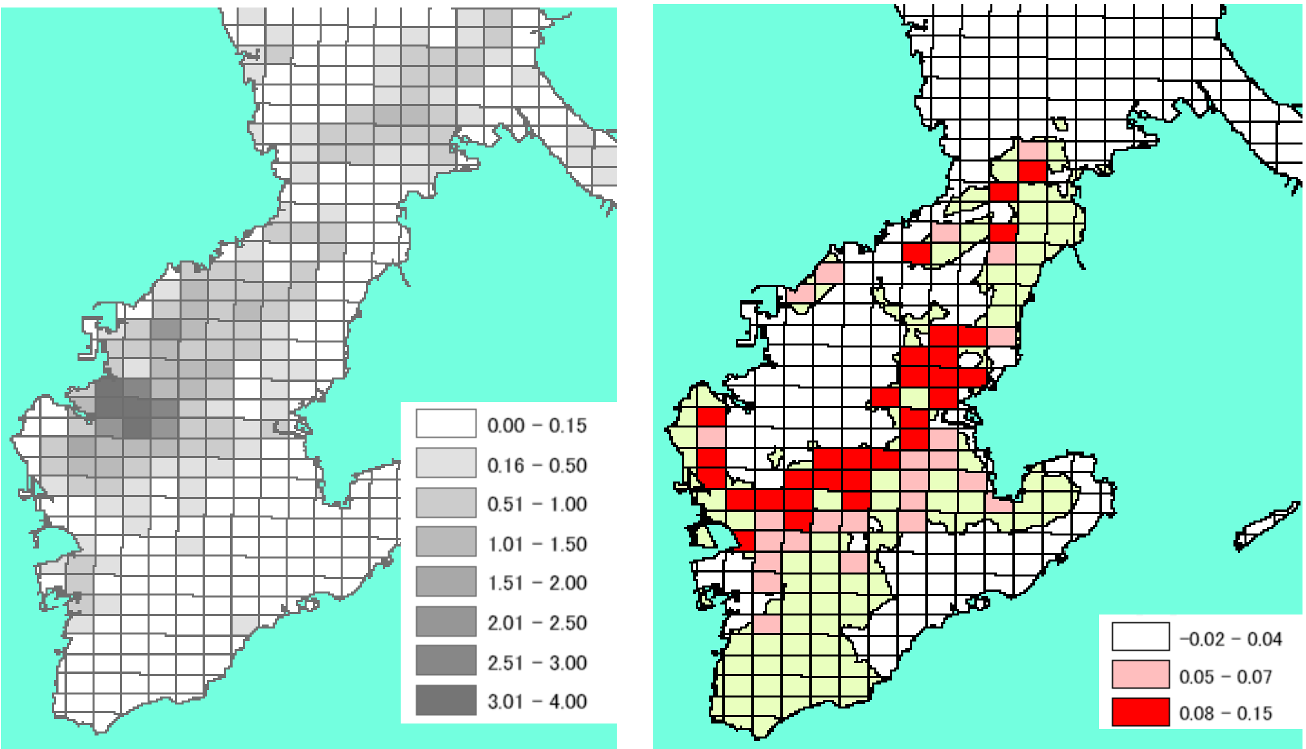
D.4 Simulation Draws

I use Halton draws from a standard distribution for each element in $\epsilon^s = (\varepsilon^{s,r}, \varepsilon^{s,c}, \eta_{FM}^{s,r}, \eta_{LS}^{s,r}, \eta_{FM}^{s,c}, \eta_{LS}^{s,c})$ instead of drawing from pseudo-random numbers as a variance reduction technique. As Train (2000) argues, many studies confirm 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. Two steps exist to obtain simulation draws for each element in ϵ^s. First, I generate a Halton sequence of numbers, such as $1/3, 2/3, 1/9, 4/9, 7/9, ...$, all of which are between 0 and 1. Second, I obtain simulation draws from a standard normal distribution by plugging Halton sequence numbers into the inverse of the standard normal cumulative distribution function. If we are running 200 simulations, the number of simulation draws I generate for each element in ϵ^s is 834 (# of markets)$*$200 (# of simulations).

FIGURE 5

NUMBER OF STORES

BASELINE (LEFT) AND INCREASE DUE TO ELIMINATION OF REGULATION (RIGHT), FAMILY MART

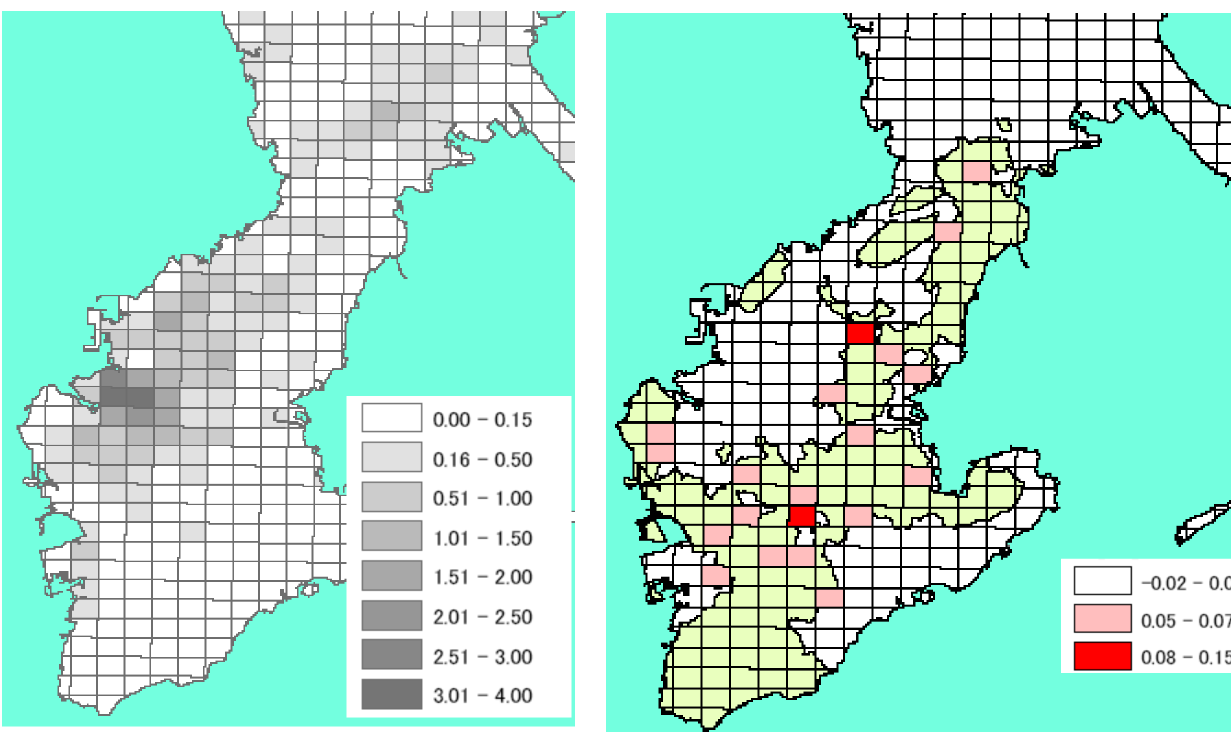


NOTE. - Green areas in the right panel shows zoned areas.

FIGURE 6

NUMBER OF STORES

BASELINE (LEFT) AND INCREASE DUE TO ELIMINATION OF REGULATION (RIGHT), LAWSON



NOTE. - Green areas in the right panel shows zoned areas.

FIGURE 7

NUMBER OF STORES, BOTH CHAINS (BEFORE MERGER, LEFT) AND FAMILY MART (ACQUIRER)

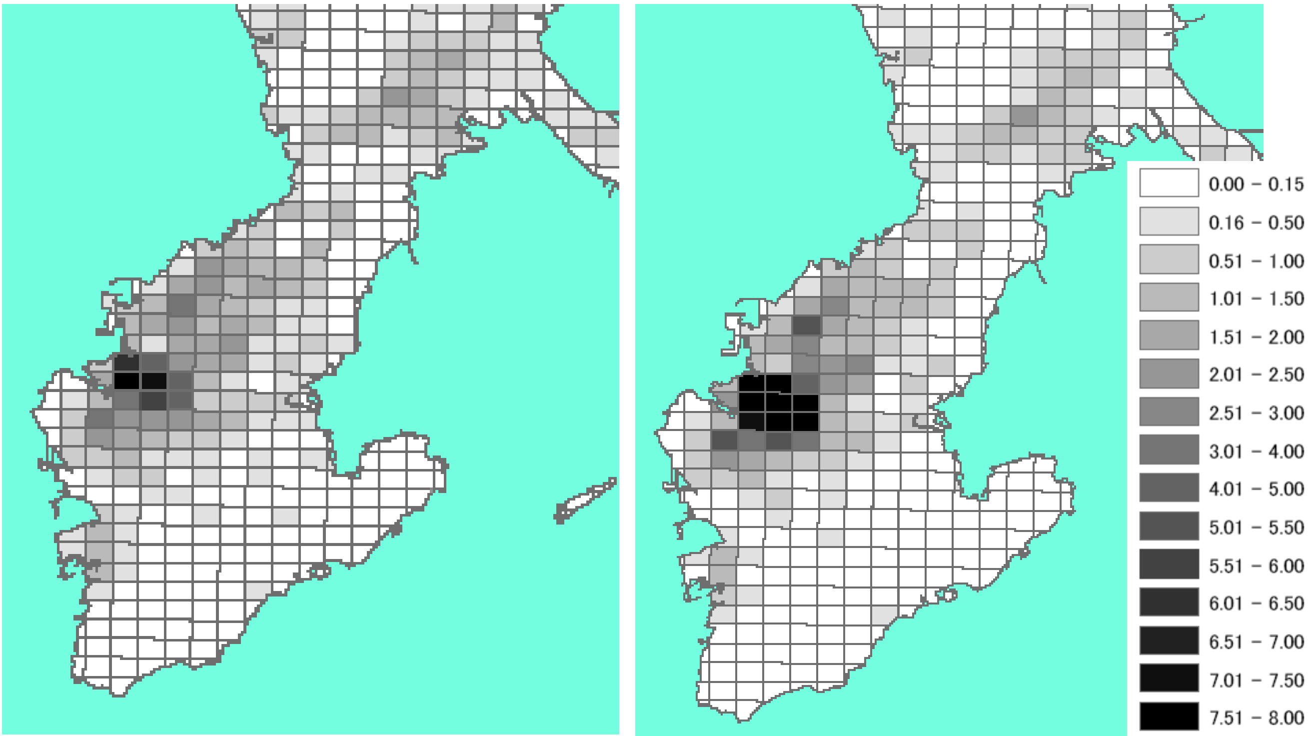
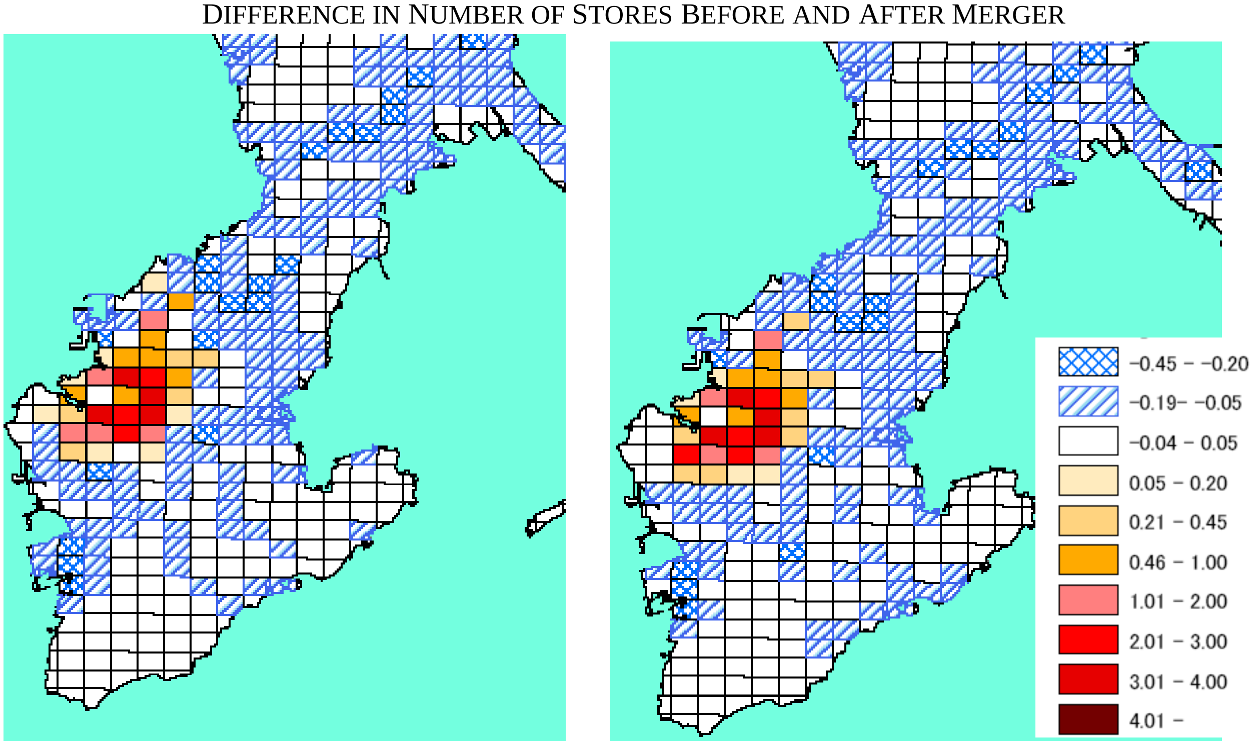


FIGURE 8

DIFFERENCE IN NUMBER OF STORES BEFORE AND AFTER MERGER



NOTE. - Family Mart as the acquirer (left) and LAWSON as the acquirer (right). I construct the difference by subtracting the number of Family Mart and LAWSON stores from the number of the acquirer's stores. I assume the costs of closing and remodeling a store are US $100,000 and US $50,000, respectively.

TABLE 1
DESCRIPTIVE STATISTICS ACROSS MARKETS
OKINAWA, 2002

Variable	Mean	Std. Dev.	Minimum	Maximum	Total
	834 Sample Markets				
Population (Units: people)					
All Markets (834 Markets)	1,434	2,588	0	18,977	1,195,787
Zoned Markets (140 Markets)	1,298	1,299	0	6,119	181,669
Unzoned Markets (694 Markets)	1,461	2,777	0	18,977	1,014,118
Number of Workers (Units: people)					
All Markets (834 Markets)	580	1,612	0	32,776	484,097
Zoned Markets (140 Markets)	457	634	0	4,008	64,014
Unzoned Markets (694 Markets)	605	1,743	0	32,776	419,870
Number of Stores					
All Stores	0.542	1.295	0	13	452
Family Mart	0.170	0.550	0	7	142
LAWSON	0.122	0.434	0	6	102
Local Store	0.255	0.694	0	7	213
Local Store, 24 hours	0.160	0.499	0	5	133
Number of Own Chain Stores in Adjacent Markets					
Family Mart	1.248	2.675	0	19	1,041
LAWSON	0.869	1.923	0	15	725
Geographical Distance to Its Distribution Center (kilometer)					
Family Mart	29.73	20.77	0.35	84.86	-
LAWSON	30.80	20.98	0.55	86.18	-
Total Sales at the Market Level (thousand US dollars)					
Markets with more than two stores (50 Markets)	5,340	3,250	1,946	17,867	266,988
Markets with more than two 24-hour stores (31 Markets)	5,462	3,288	2,662	16,687	169,334

Sales (thousand US dollars)	Total	Per Store (=Total Sales / # of Stores)
All Stores	587,120	1,299
Family Mart	203,040	1,430
LAWSON	148,540	1,456
Local Store	235,540	1,106

NOTE. - A market is defined as a 1km square grid of which borders are defined by the Bureau of Census.

TABLE 2

DESCRIPTIVE REGRESSIONS, OLS

Variable	(1)	(2)	(3)	(4)
Nighttime Population (thousand people)	0.240	0.109		
	(0.008)***	(0.008)***		
Log Nighttime Population (thousand people)			0.339	0.017
			(0.018)***	(0.03)
Daytime Population (thousand people)		0.320		
		(0.014)***		
Log Daytime Population (thousand people)				0.491
				(0.038)***
Zoned Area	-0.098	-0.072	-0.332	-0.264
	(0.057)*	(0.044)	(0.069)***	(0.063)***
R-squared	0.51	0.70	0.30	0.42

NOTE. - * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in parentheses. Observations are 834 markets. The dependent variable is the aggregate of Family Mart and LAWSON stores in a given market.

TABLE 3

OBSERVED MARKET CONFIGURATIONS FOR FAMILY MART AND LAWSON

	Number of Stores, LAWSON					
Number of Stores, Family Mart	0	1	2	3	6	Number of Markets
0	**693**	**35**	**2**	**0**	0	730
1	**53**	**25**	**3**	**0**	0	81
2	**5**	**5**	**5**	**1**	0	16
3	**2**	**0**	**0**	**0**	0	2
4	**0**	**2**	**0**	**1**	1	4
7	0	0	0	1	0	1
Number of Markets	753	67	10	3	1	834

NOTE. - Each element in the matrix shows the number of markets in the sample that corresponds to the market configuration of the vertical (Family Mart) and the horizontal (LAWSON) axis. Shaded market configurations are the ones endogenized by the model.

TABLE 4

PREDICTED MARKET CONFIGURATIONS FOR FAMILY MART AND LAWSON

	Number of Stores, LAWSON					
Number of Stores, Family Mart	0	1	2	3	4	Number of Markets
0	669.1	47.8	0.5	0.1	0.1	718
1	77.6	23.4	1.5	0.5	0.6	104
2	2.7	2.1	0.5	0.2	0.4	6
3	0.6	1.1	0.3	0.1	0.3	2
4	0.3	1.4	0.8	0.3	1.6	4
Number of Markets	750	76	3	1	3	834

NOTE. -Each element in the matrix shows the simulated number of markets in the sample that corresponds to the market configuration of the vertical (Family Mart) and the horizontal (LAWSON) axis. The reported number in each cell is averaged over 200 simulations. I treat the market configurations (FM,LS) = (7,3) and (4,6) as (4,3) and (4,4), respectively.

TABLE 5

PARAMETER ESTIMATES FROM NON-REVENUE MODEL

	Baseline		50 % Shifted Grids		Equilibrium favors LAWSON	
Variable	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Nighttime Population (β_pop) (Units: 1,000 people)	0.154	0.052	0.296	0.077	0.157	0.027
Daytime Population (β_bus) (Units: 1,000 people)	0.646	0.096	0.286	0.080	0.578	0.266
Zoned Area (γ)	-0.103	0.052	-0.282	0.148	-0.110	0.113
Across-market Effect (δ_across)	0.046	0.038	0.003	0.179	0.046	0.134
Within-market Effect (δ_within)	-0.701	0.336	-0.453	0.769	-0.895	0.947
Business-Stealing Effect by Rival Chain Store ($\delta\_competitive\_rival$	-0.945	0.184	-0.816	0.337	-0.472	0.691
Constant in Latent Profit Function (μ)	-1.927	0.098	-2.063	0.226	-1.819	0.153
LAWSON Store (μ_LAWSON)	0.026	0.135			-0.322	0.148
Number of Markets	834		1138		834	
Value of the Objective Function	3.2		42.3		13.4	
Model Prediction	Level	Std.Dev	Level	Std.Dev	Level	Std.Dev
Number of Stores, Family Mart (Data:127)	131.3	98.9			130.1	30.9
Number of Stores, LAWSON (Data: 95)	96.2	138.7			97.2	128.1
Policy 1: No Zoning	Level	% Δ	Level	% Δ	Level	% Δ
Number of Stores, Family Mart	133.2	1.4%			137.9	6.0%
Number of Stores, LAWSON	97.6	1.5%			92.9	-4.4%
Poilcy 2: Zoning Everywhere						
Number of Stores, Family Mart	122.0	-7.1%			125.1	-3.8%
Number of Stores, LAWSON	89.5	-7.0%			83.9	-13.7%

NOTE. - The number of simulations used in the MSM estimation is 200.

TABLE 6

PARAMETER ESTIMATES FROM MODEL WITH REVENUE

Variable		Estimate	Standard Error
Revenue Equation			
Nighttime Population (*β_pop*) (Units: 1,000 people)		71.3	23.2
Daytime Population (*β_bus*) (Units: 1,000 people)		47.6	5.4
Business-Stealing Effect by Own Chain Store (*δ_competitive_own*)		-545.0	84.8
Business-Stealing Effect by Rival Chain Store (*δ_competitive_rival*)		-378.4	170.5
Business-Stealing Effect by Local Store (*δ_competitive,local*)		-108.9	112.7
LAWSON Store (*μ_LAWSON*)		2.5	9.7
Local Store (*μ_local*)		-31.2	590.7
Constant in Revenue Equation (*μ_revenue*)		820.7	168.6
Cost Equation			
Across-market Effect (*δ_across*)		-59.5	59.9
Cost-Savings Effect by Own Chain Store (*δ_saving*)		-125.8	208.6
Distance from the Distribution Center (*μ_dist*)		8.0	19.7
Zoned Area (γ)		50.3	47.6
Constant in Cost Equation (*μ_cost*)		1,129.2	113.0
Correlation Parameter in Profit Shocks (ρ)		0.93	0.13
Standard Deviation of the Unobserved Profits (λ)		121.2	44.4
Model Prediction	Data	Level	Std.Dev
Number of Stores			
Family Mart	139	140.3	7.7
LAWSON	100	98.7	8.2
Number of Stores in Adjacent Markets			
Family Mart	1041	1038.2	57.6
LAWSON	725	722.8	61.6
Aggregate Sales			
All Stores (thousand US dollars)	266,988	225,882	11,621
24-hour Stores (thousand US dollars)	169,334	157,884	9,311

NOTE. - Parameters below the second row are measured in thousand US dollars with the exception of ρ. Observations are 834 markets. The number of simulations used in the MSM estimation is 200.

TABLE 7
IMPACT OF THE ZONING REGULATION ON ENTRY, SALES AND COSTS
PREDICTIONS FROM MODEL WITH REVENUE
OKINAWA, 2002

	Zoning Regulation Policy Regime					
	Current: 140 Zoned Markets		Case 1: No Market		Case 2: All 834 Markets	
Variable	Data	Prediction	Prediction	% Δ	Prediction	% Δ
Aggregate Number of Stores						
Family Mart	139	140.3	146.8	4.6%	118.4	-15.6%
(in originally zoned 140 markets)	14	13.6	19.8	45.8%	13.3	-1.6%
LAWSON	100	98.7	102.2	3.6%	81.9	-17.0%
(in originally zoned 140 markets)	11	8.6	12.2	41.8%	8.5	-1.5%
Aggregate Number of Own Stores in Adjacent Markets						
Family Mart	1041	1038.2	1087.0	4.7%	892.0	-14.1%
LAWSON	725	722.8	749.1	3.6%	613.4	-15.1%
Aggregate Sales (million US dollars)						
All Stores	$587.1	$514.3	$524.0	1.9%	$481.0	-6.5%
Family Mart	$203.0	$169.6	$176.4	4.0%	$148.9	-12.2%
(in originally zoned 140 markets)	n/a	$15.9	$22.4	41.1%	$15.6	-1.5%
LAWSON	$148.5	$121.4	$125.1	3.0%	$104.9	-13.6%
(in originally zoned 140 markets)	n/a	$10.0	$13.8	37.4%	$9.9	-1.4%
Local Stores	$235.5	$223.3	$222.6	-0.3%	$227.2	1.7%
Aggregate Sales in Markets with More than 2 Stores (million US dollars)						
All Stores	$267.0	$225.9	$228.3	1.1%	$212.1	-6.1%
24-hour Stores	$169.3	$157.9	$158.9	0.6%	$144.8	-8.3%
Aggregate Profits (million US dollars)						
Family Mart	n/a	$27.7	$28.4	2.6%	$23.6	-14.8%
LAWSON	n/a	$21.7	$22.1	1.9%	$18.4	-15.2%
Aggregate Costs of Zoning Regulation (million US dollars)						
All Stores	n/a	-$2.6	$0.0	-100.0%	-$20.8	692.9%
Family Mart and LAWSON	n/a	-$1.1	$0.0	-100.0%	-$10.1	805.4%
Total Sales plus Total Profits (million US dollars)						
All Stores	n/a	$544.9	$556.6	2.1%	$499.0	-8.4%
Family Mart and LAWSON	n/a	$340.3	$352.0	3.4%	$295.8	-13.1%

NOTE. - Variables are aggregated to the level of Okinawa unless otherwise stated. For each simulation, I solve for an equilibrium number of stores for each chain, using the parameters from Table 6. The number of local stores and demographics for each market is held fixed throughout this counterfactual analysis.

TABLE 8
IMPACT OF MERGER ON ENTRY, SALES AND COSTS
PREDICTIONS FROM MODEL WITH REVENUE

	Current	Merger Scenario							
		"De Novo" Entry: No Costs of Closing No Costs of Remodeling				Costs of Closing: US $-100 thousand per store Costs of Remodeling: US $ -50 thousand per store			
	Family Mart and LAWSON	Family Mart takes over		LAWSON takes over		Family Mart takes over		LAWSON takes over	
Variable	Prediction	Prediction	% Δ	Prediction	% Δ	Prediction	% Δ	Prediction	% Δ
Aggregate Number of Stores									
Family Mart and LAWSON	238.9	226.5	-5.2%	228.1	-4.6%	237.2	-0.7%	239.6	0.3%
Family Mart	140.3	226.5	61.5%			237.2	69.1%		
LAWSON	98.7			228.1	131.1%			239.6	142.8%
Number of Stores: Pre-merger -> Post-Merger									
Maintain (Own Chain)						140.3		98.7	
Open (Own Chain)						40.2		44.0	
Close (Own Chain)						0.0		0.0	
Close (Rival Chain)						41.9		43.4	
Remodel (Rival -> Own) and Maintain						56.8		96.9	
Aggregate Sales (million US dollars)									
All Stores	$514.3	$483.8	-5.9%	$485.6	-5.6%	$492.1	-4.3%	$494.5	-3.8%
Family Mart and LAWSON	$291.0	$258.3	-11.2%	$260.2	-10.6%	$268.3	-7.8%	$270.8	-6.9%
Family Mart	$169.6	$258.3	52.3%			$268.3	58.2%		
LAWSON	$121.4			$260.2	114.3%			$270.8	123.0%
Local Stores	$223.3	$225.4	1.0%	$225.4	0.9%	$223.9	0.3%	$223.7	0.2%
Sales per Store (million US dollars)									
Family Mart	$1.21	$1.14	-5.6%			$1.13	-6.4%		
LAWSON	$1.23			$1.14	-7.3%			$1.13	-8.1%
Aggregate Profits (million US dollars)									
Family Mart and LAWSON	$49.4	$67.7	37.1%	$68.3	38.3%	$60.4	22.4%	$58.8	19.2%
Family Mart	$27.7	$67.7	144.7%			$60.4	118.5%		
LAWSON	$21.7			$68.3	214.6%			$58.8	171.2%
Breakdown of Profits			Δprofits		Δprofits		Δprofits		Δprofits
Profits from Demographics	$116.4	$131.9	$15.5	$132.8	$16.4	$133.7	$17.3	$134.8	$18.4
Costs Savings, Across-market	$12.4	$37.5	$25.1	$38.1	$25.7	$38.9	$26.4	$39.7	$27.2
Costs Savings, Within-market	$8.3	$25.8	$17.5	$26.1	$17.8	$26.7	$18.3	$27.1	$18.7
Business Stealing, Own Chain	-$36.1	-$111.8	-$75.7	-$113.1	-$76.9	-$115.5	-$79.4	-$117.3	-$81.1
Business Stealing, Rival Chain	-$37.0	$0.0	$37.0	$0.0	$37.0	$0.0	$37.0	$0.0	$37.0
Business Stealing, Local Stores	-$26.6	-$15.7	$10.9	-$15.8	$10.9	-$16.2	$10.4	-$16.3	$10.3
Costs of Closing & Remodeling	$0.0	$0.0	$0.0	$0.0	$0.0	-$7.0	-$7.0	-$9.2	-$9.2
Profits per Store (million US dollars)									
Family Mart	$0.20	$0.30	51.5%			$0.25	29.2%		
LAWSON	$0.22			$0.30	36.1%			$0.25	11.7%
Total Sales plus Total Profits (million US dollars)									
All Stores	$544.9	$534.9	-1.8%	$537.2	-1.4%	$534.4	-1.9%	$535.0	-1.8%
Family Mart and LAWSON	$340.3	$326.0	-4.2%	$328.4	-3.5%	$328.7	-3.4%	$329.6	-3.1%

NOTE. - Variables are aggregated to the level of Okinawa unless otherwise stated. For each simulation, I solve for an equilibrium number of stores for each chain, using the parameters from Table 6. The number of local stores and demographics for each market are held fixed throughout this counterfactual analysis.

TABLE 9
IMPACT OF MERGER ON ENTRY, SALES AND COSTS
PREDICTIONS FROM MODEL WITH REVENUE
CASE 2: FIXED COSTS OF CLOSING AND REMODELING A STORE, ROBUSTNESS CHECK

	Baseline	Robustness Check (1)				Robustness Check (2)			
		Costs of Closing: US $-150 thousand Costs of Remodeling: US $ -50 thousand				Costs of Closing: US $-100 thousand Costs of Remodeling: US $ -100 thousand			
	FM and LAWSON	Family Mart takes over		LAWSON takes over		Family Mart takes over		LAWSON takes over	
Variable	Prediction	Prediction	% Δ	Prediction	% Δ	Prediction	% Δ	Prediction	% Δ
Aggregate Number of Stores									
Family Mart and LAWSON	238.9	246.9	3.3%	250.0	4.6%	226.5	-5.2%	228.1	-4.6%
Family Mart	140.3	246.9	76.0%			226.5	61.5%		
LAWSON	98.7			250.0	153.4%			228.1	131.1%
Number of Stores: Pre-merger -> Post-Merger									
Maintain (Own Chain)		140.3		98.7		140.3		98.7	
Open (Own Chain)		41.7		45.5		38.4		42.1	
Close (Own Chain)		0.0		0.0		0.0		0.0	
Close (Rival Chain)		33.8		34.5		50.9		53.0	
Remodel (Rival -> Own) and Maintain		64.9		105.8		47.8		87.3	
Aggregate Sales (million US dollars)									
All Stores	$514.3	$499.6	-2.9%	$502.6	-2.3%	$483.8	-5.9%	$485.6	-5.6%
Family Mart and LAWSON	$291.0	$277.0	-4.8%	$280.3	-3.7%	$258.3	-11.2%	$260.2	-10.6%
Family Mart	$169.6	$277.0	63.4%			$258.3	52.3%		
LAWSON	$121.4			$280.3	130.9%			$260.2	114.3%
Local Stores	$223.3	$222.6	-0.3%	$222.3	-0.5%	$225.4	1.0%	$225.4	0.9%
Sales per Store (million US dollars)									
Family Mart	$1.21	$1.12	-7.2%			$1.14	-5.6%		
LAWSON	$1.23			$1.12	-8.9%			$1.14	-7.3%
Aggregate Profits (million US dollars)									
Family Mart and LAWSON	$49.4	$58.5	18.6%	$56.9	15.3%	$57.8	17.1%	$54.2	9.9%
Family Mart	$27.7	$58.5	111.6%			$57.8	109.0%		
LAWSON	$21.7			$56.9	162.2%			$54.2	150.0%
Breakdown of Profits			Δprofits		Δprofits		Δprofits		Δprofits
Profits from Demographics	$116.4	$134.7	$18.3	$136.0	$19.6	$131.9	$15.5	$132.8	$16.4
Costs Savings, Across-market	$12.4	$39.9	$27.5	$40.9	$28.4	$37.5	$25.1	$38.1	$25.7
Costs Savings, Within-market	$8.3	$27.4	$19.0	$27.9	$19.5	$25.8	$17.5	$26.1	$17.8
Business Stealing, Own Chain	-$36.1	-$118.6	-$82.4	-$120.6	-$84.5	-$111.8	-$75.7	-$113.1	-$76.9
Business Stealing, Rival Chain	-$37.0	$0.0	$37.0	$0.0	$37.0	$0.0	$37.0	$0.0	$37.0
Business Stealing, Local Stores	-$14.6	-$16.6	-$2.0	-$16.7	-$2.1	-$15.7	-$1.1	-$15.8	-$1.1
Costs of Closing & Remodeling	$0.0	-$8.3	-$8.3	-$10.5	-$10.5	-$9.9	-$9.9	-$14.0	-$14.0
Profits per Store (million US dollars)									
Family Mart	$0.20	$0.24	20.2%			$0.26	29.4%		
LAWSON	$0.22			$0.23	3.5%			$0.24	8.1%
Total Sales plus Total Profits (million US dollars)									
All Stores	$544.9	$538.6	-1.1%	$539.7	-1.0%	$525.0	-3.7%	$523.2	-4.0%
Family Mart and LAWSON	$340.3	$335.6	-1.4%	$337.2	-0.9%	$316.1	-7.1%	$314.4	-7.6%

NOTE. - Variables are aggregated to the level of Okinawa unless otherwise stated. For each simulation, I solve for an equilibrium number of stores for each chain, using the parameters from Table 6. The number of local stores and demographics for each market are held fixed throughout this counterfactual analysis.

TABLE 10

SIMULATION ESTIMATES FOR 50 REPLICATED DATASETS

Variable	"truth"	MSM point estimates (standard error)			
Population (β)	1.00	1.30	1.03	1.00	1.45
		(0.65)	(0.29)	(0.40)	(1.01)
Across-market Effect (δ_*across*)	0.20	0.20	0.24	0.27	0.25
		(0.18)	(0.09)	(0.09)	(0.14)
Competitive Effect (δ_*competitive*)	-0.50	-0.27	-0.74	-0.73	-0.50
		(0.84)	(0.35)	(0.46)	(0.29)
Correlation Parameter (ρ)	0.50	0.65	0.68	0.65	0.55
		(0.34)	(0.15)	(0.16)	(0.41)
Number of Markets		16	36	144	1,600

NOTE. - The number of simulations per replication is 20, except for the last column, where s is set to 7. I assume 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.