Estimating a Model of Strategic Network Choice: The Convenience-Store Industry in Okinawa[*]

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November 5, 2009

Abstract

This paper examines the impacts of the merger of two multi-store firms, using new cross-sectional data from the convenience-store industry in Okinawa, Japan. I propose a general methodology for estimating a game of network choice by two multi-store firms. I use lattice-theoretical results to deal with the huge number of possible network choices. I integrate the entry model with post-entry outcome data, while correcting for the selection of entrants by simulations. Parameter estimates find the acquirer of a hypothetical merger of two chains would increase its number of stores in the city center in Okinawa but would decrease its number in suburbs. The trade-off of cost savings and lost revenues from clustering its own stores plays a central role in explaining this seemingly odd result. I also examine the impacts of eliminating the zoning regulation introduced in 1968, which has been a major urban policy issue.

Keywords: entry; merger; retail location; supermodular game; zoning regulation

JEL-Classification: L13; L40; L81; R52

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1 Introduction

Competition and mergers among multi-store firms are ubiquitous in a wide range of industries. We often observe multi-store firms developing their store networks. Examples include 7-Eleven, Wal-Mart, Target, Walgreens, CVS, Office Depot, Staples, and Whole Foods, just to name a few. Multi-store firms' location decisions depend on two key features. First, firms take the location decision of rival firms into account. Second, firms often internalize the trade-offs of clustering their stores. For example, a retail chain may benefit from clustering its stores in a given market because the chain can save on logistical costs, such as gas for delivery trucks or the costs of advertising in local newspapers (economies of density). On the other hand, a retail chain may want to avoid locating too many of its stores in a single market, because the store-level sales may decrease as the number of stores increases (business stealing). As a result of these two features, understanding the determinants of observed store networks becomes a formidable task. For instance, Figure 1 presents the actual configurations of stores for two convenience-store chains in Okinawa, Japan. Indeed, cluster analysis suggests that the chain-affiliated convenience stores are more geographically clustered than local and non-chain-affiliated convenience stores or whole retail stores in Okinawa, which poses a question of why strikingly dense store-clustering patterns can arise in the industry.

FIGURE 1
STORE CONFIGURATIONS AND 1 KILOMETER SQUARE GRIDS
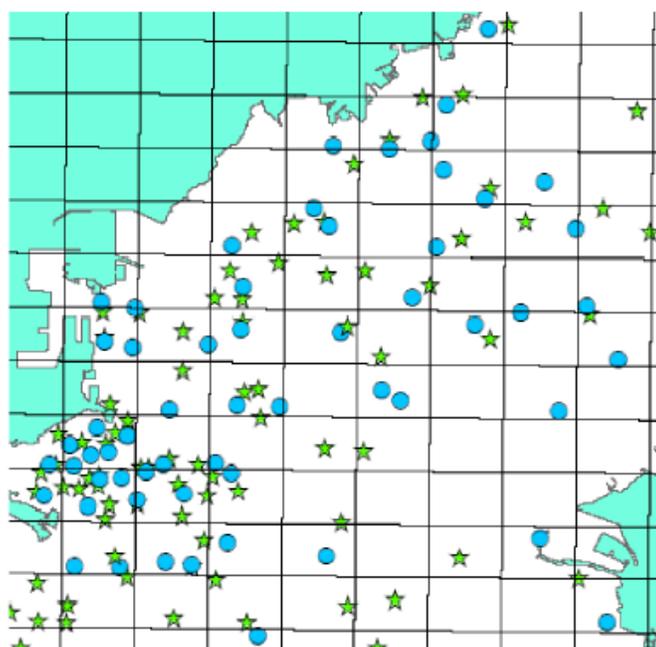
NOTE. - The stars show Family Mart stores and the circles show LAWSON stores.

Given these features that make location decisions highly complex, this paper asks the following questions: How we can explain the observed store-location patterns of multi-store firms, assuming firms act noncooperatively? When do multi-store firms want to cluster their stores and when do they not? Specifically, in the convenience-store industry in Okinawa, why do we observe such surprisingly dense store networks as shown in Figure 1? Can we explain these observed network choices as the outcomes of a game between two chains, Family Mart and LAWSON? If so, what would be the predicted acquirer's store-network choice if the two chains merge? What are the effects of the trade-off from clustering its stores on the resulting store network after a merger or a change in entry regulation? Typically, the U.S. Department of Justice and the Federal Trade Commission evaluate the expected change in price for a proposed merger, but little is known about how the store configurations change.[1] However, as I show later, studying the impact of mergers on store networks is essential in evaluating mergers, because the resulting network can substantially affect total sales, the travel costs of consumers, and profits of the firm. The empirical goal of this paper is thus twofold. The first is to explain striking geographical patterns of store networks in multi-store oligopoly. The second is to simulate new store networks after a merger or a change in entry regulation.

The paper provides a general framework to estimate a model of strategic network choices by two multi-store firms, namely, a chain-entry model. Conceptually, the model departs from earlier work in two major ways. First, the model captures a fundamental force that determines the behavior of multi-store firms, namely, a trade-off from clustering their own stores in a market. This trade-off is between a chain's cost savings and the lost revenues from competition with one's own stores. By focusing on firms' trade-off, one is able to explain the seemingly a puzzle, the strikingly clustered store network patterns observed in the convenience-store industry in Okinawa. It turns out, as I describe later, that the presence of firms' trade-off from clustering has important implications for antitrust and regulatory policy. Second, the empirical model incorporates post-entry outcome equations. By adding revenue information, one is able to decompose profits into costs and revenues and to interpret parameters in monetary units.

The paper addresses two methodological issues that arise when estimating models of entry of multi-store firms. The first and greatest difficulty is the burden of computation of equilibrium

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[1] An example includes a proposed horizontal merger between Staples and Office Depot in 1997. The FTC challenged the merger because "the proposed settlement doesn't resolve the competitive problem that would lead to these higher prices." http://www.ftc.gov/opa/1997/04/stapdep.shtm.

network decisions. For instance, consider a game with two players, 20 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 $5^{20} * 5^{20} = 9.1 * 10^{27}$, which is impossibly large to search for an equilibrium. In order to overcome the computational issue, I use lattice-theoretical results to show that, under some conditions, certain algorithms can substantially reduce the burden of solving for a Nash equilibrium while accommodating either a positive or negative trade-off from clustering. In this respect, my paper nests the chain-entry model of Jia (2008) by expanding the choice set of a chain. The computational algorithms allow us to learn what the equilibrium effects would be in store networks when changes arise in the competitive environment, such as a merger of the two chains or a change in a entry regulation.

The second challenge is that simply adding post-entry outcome data without endogenizing network-choice behavior suffers from a selection bias. For instance, we have revenue data only for the market where a chain decided to open stores. Therefore, in equations explaining revenue, coefficients may be biased since unobservable demand shocks that affect revenue are also likely to affect entry decisions. Another methodological advance I make in this context is that I jointly estimate the system of network choice equations and post-entry revenue equations, while correcting for selection of entrants by simulations.

I use new cross-sectional data from 2001 that I manually collected from the convenience-store industry in Okinawa, Japan. The data are unique and suit the method for several reasons. First, each chain commonly adopts nationwide uniform pricing, allowing us to abstract pricing decisions at the store level. Uniform pricing also means we do not need price data in order to model pricing behavior. Second, the store formats are uniform across stores within a chain and across chains. Combining the first and second features, geographic differentiation in the industry will be a particularly important avenue of product differentiation. Third, the island has two national convenience-store chains, each with a distribution center and a store network, and arguably does not face competition from other chains, which allows us to model the industry as a duopoly.

Estimates of the model show that the trade-off from clustering within a market is, indeed, an important consideration for the convenience-store chains. The most striking finding is that, in a hypothetical merger, the acquirer would increase stores in the city center in Okinawa, whereas it would decrease the number of stores in suburban markets. The implications of this hypothetical merger at first seems to contradict the conventional wisdom that the acquirer would decrease the number of stores in order to avoid the own business-stealing effect (and later to increase the

profits by raising prices). However, the trade-off of clustering explains the reasons for these results. The acquirer increases the number of stores in the city center because it can take advantage of the higher population density and higher positive spillovers from own stores in adjacent markets, offsetting the decrease in revenue due to the business-stealing effect. A key to understanding the store configuration results is that parameter estimates suggest the business-stealing effect is more localized than the cost savings. This finding is consistent with the casual observation that the localized demand and the importance of the distribution network are typical features in Japan's convenience-store industry. Whereas, on average, consumers rarely walk more than 1 kilometer to access stores, delivery trucks generally travel about 40 kilometers for each store per day. I also examine the impacts of eliminating the zoning regulation introduced in 1968, which has been a major urban policy issue. The local government in Okinawa, in accordance with its urban planning, decides on which markets to place zoning restriction. In zoned markets, one needs to obtain development permission from the government in order to open a convenience store. I find that eliminating the existing regulation would increase the total number of stores for each chain by around 40 percent in zoned markets. These findings are robust to plausible alternative specifications on the cost-savings and business-stealing effect. However, one limitation deserves mention: Although my framework allows us to solve the otherwise intractable task of simulating the effect of a merger (or deregulation), the exercise abstracts from changes in price due to merger, in particular, the likely post-merger price increase.

My framework has implications beyond retail industries. For instance, we can use the model to study the strategic location decisions of ATMs in a banking industry since each ATM faces localized demand, and delivery of cash incurs transportation costs. Beyond implications for an entry of multi-store firms, the empirical model applies more broadly to the product-line decisions if we interpret the location as the distance between product characteristics in product space instead of the physical location of stores in geographical space. Furthermore, my framework allows us to study network pricing games among more than two players as in Nishida (2009), where I model strategic fare determinations of U.S. airline carriers.

The paper is organized as follows. In the remainder of this section, I relate my work to earlier literature. In section 2 I describe the dataset. Section 3 specifies the equilibrium network-choice model and provides analytical results. I particularly emphasize my computational algorithms for solving the game and parameter restrictions to use the algorithms. 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 describes the sensitivity analysis. Finally, section 8 provides concluding remarks. The Appendix contains proofs of propositions, computation and estimation details, other robustness checks, a description of the convenience-store industry in Japan, and details of the zoning regulation.

1.1 Related Literature

This paper builds on a vast literature of game-theoretic models of entry, initiated by Bresnahan and Reiss (1990, 1991). Researchers have devoted much effort to adding complexities, such as heterogeneity in fixed costs across players (Berry 1992), endogenizing product-differentiation choice (Mazzeo 2002b), 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 is independent across markets.

This paper is related to recent progress in the entry literature relaxing the isolated markets assumptions by assuming multi-store firms developing their store networks (Holmes 2008; Jia 2008; Ellickson, Houghton, and Timmins 2008). Methodologically, the chain-entry model in this paper generalizes in two ways the one proposed by Jia (2008), who provides a novel approach for dealing with the computational burden of solving for a Nash equilibrium in store networks. First, this paper adds a density dimension to the choice set of a multi-store firm: a firm decides not only where to open stores but also how many stores to open. The practical benefits of the setting are (1) we can allow more rich and flexible patterns of the trade-off of clustering; (2) we can simulate a merger; and (3) we can endogenize all markets, as I discuss in the model section. Second, this paper exploits data on post-entry revenue, which allows us to decompose profits into revenues and costs and to evaluate the estimated model parameters in monetary units. Adding post-entry outcome data can potentially suffer from a selection bias since we only observe such data for the markets in which firms did indeed open stores. This paper corrects for selection of entrants by simulations, thereby distinguishing it from previous studies integrating the data on firms' entry decisions with post-entry information, such as Reiss and Spiller (1989), Berry and Waldfogel (1999), Mazzeo (2002a), and Ellickson and Misra (2008).

This paper complements the growing spatial competition literature by highlighting the importance of choosing retail-store networks strategically. Researchers have studied the geographical

aspect of retail competition 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 eye-glasses (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.[2] However, Seim (2006) has to abstract from the coordinated entry decisions made by national video-rental chains operating multiple outlets.[3]

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

2   Industry and Data

Convenience-Store Industry.   Convenience stores are one of the fastest growing retail for-mats in many countries in the last 20 years.[4] As its name suggests, the industry in Japan 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. The core merchandise of convenience stores is food: about 70 percent of the sales are food, soft drinks, and alcoholic drinks.

Several features of the convenience-store industry in Japan promote focusing solely on location decisions of retail outlets. First, each chain commonly adopts nationwide uniform pricing, which can be confirmed by their company websites, where they post each item's price. Second, relative to other retail industries, such as gasoline retailing or supermarkets, convenience stores are densely located because most of the customers visit on foot. Third, for the large nationwide chains, convenience stores offer similar merchandise, services, and shopping experiences across outlets and chains.

Note that, although franchising is widespread in the industry in Japan, chain headquarters

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[2]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.

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

[4]In Japan, the overall industry sales in 2004 were 6.7 trillion yen, which is approximately 5 percent of total retail sales.

make store location decisions. This feature is important for the later empirical work, because the model assumes a chain decides the number of stores for every market.[5]

Market Definition. In this paper, I divide the Okinawa island into 834 1km^2 mutually exclusive grids. Delineating the geographic market for retail markets is a problem when a natural boundary on the trade area is not available. To avoid the issue of contiguous markets, previous studies on entry focus on industries in which markets are small and isolated. However, in most industries, finding perfectly isolated markets both in terms of demand and costs, as is the case in this industry, is difficult. Instead, in order to approximate the multi-store firms' choice, I choose a 1-kilometer (km) square as the relevant geographic unit of analysis for the convenience-store industry. For convenience purpose, I call each grid a "market," allowing for costs and demand spillovers across markets. Evidence shows that treating 1km^2 as a unit is reasonable approximation.[6] 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 exclusion 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) as those 1km^2 grids that share borders or grid points with the market. So a market has up to eight adjacent markets. For the coordinates of grids, I follow the 2000 Census of Population and the 2001 Establishment and Enterprise Census data. Of course, the market definition depends on strong assumptions on how grids and borders are chosen. In the sensitivity analysis section, I examine whether the parameter estimates are robust to reasonable alternative choices of grids.

Data and Summary Statistics. 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

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[5]For more detailed descriptions of the industry, see Appendix D.1.

[6]People in Okinawa generally do not travel far to access convenience stores: the average travel time is around 10 minutes by walking. 1 km 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 % of customers visit on foot and 30 % by cars.

FIGURE 2
CONVENIENCE STORES IN OKINAWA

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

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 $1km^2$ grid in which it falls. Figure 2 shows the location of stores for Family Mart and LAWSON in Okinawa Main Island.

Table 1 provides summary statistics. The number of stores for the two chains, Family Mart and LAWSON, ranges from 0 to 7 and from 0 to 6, respectively. Note that on average there are 0.17 and 0.12 stores per market for Family Mart and LAWSON. The aggregate numbers of stores are at 142 and 102 in Okinawa. There are 133 non-chain stores.[7] Table 3 displays a matrix of observed market configurations of stores for the two chains. The table 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.

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[7]In 2001 in Okininawa, 88 stores of another chain, Hot Spar, existed. 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 coordinated store-location decision are not provided by Hot Spar headquarters.

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. 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 total number of stores and total sales at the 1km^2 level are aggregated and do not disclose the number of store or sales by chain brands.[8] The bottom rows of Table 1 show that the average sales per store are \$1.43 million USD for Family Mart and \$1.45 million for LAWSON, suggesting no noticeable difference exists in sales per store among these chains.

Population is an important predictor of store-location choice. The population data come in two ways: first, the Census of Population at the 1km^2 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 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. Table 1 shows that a census 1kilometer 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.

Evidence on Geographical Clustering Patterns of Stores. The striking density of store networks depicted in Figure 1 and 2 leads us to the question of why we see such clustering patterns of chain-affiliated convenience stores. The answer may simply be that convenience stores tend to operate where population density is high, such as in Okinawa's city areas. If so, we should see similar geographical patterns for chain-affiliated stores and non–chain-affiliated stores.

To evaluate whether chain stores tend to exhibit different geographical patterns of stores than independent stores, I calculate the Moran's I index and the General G index, which are traditional measures of summarizing spatial patterns. Both statistics tell us whether the geographical patterns of stores are dispersed or clustered and measure the degree of such patterns. I use the number of stores in a given market as a unit of analysis. For comparison purposes, I consider geographical

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[8]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^2 grids.

patterns for six store categories: all retail stores including convenience stores; all convenience stores; chain-affiliated convenience stores, namely, Family Mart and LAWSON; independently operated convenience stores; Family Mart stores; and LAWSON stores.

The first and second columns of Table 2 present the Moran's I index and corresponding Z-score for each category. The range of possible values of Moran's I is −1 to 1. If all neighboring markets were to have the same number of stores of a given category, the Moran's I would be near to 1. In other words, the geographical pattern of stores of a given category is clustered. On the other hand, if the number of stores of a given category in neighboring markets were dispersed, that is, if the number of stores were mixed in neighboring markets, the Moran's I would be near to −1. If no apparent geographical pattern of stores were present, the index would be near to 0.[9]

Rows 1 and 2 of Table 2 show the Moran's I index for chain-affiliated convenience stores (0.41) is higher than that for the retail stores as a whole (0.34) or for that of the independently operated (non-chain-affiliated) convenience stores (0.13). The magnitudes suggest convenience stores generally are more clustered than retail stores in Okinawa as a whole. Rows 3 and 4 suggest the clustering of convenience stores is higher for the chain-affiliated stores than for independently operated stores.

To confirm the clustering patterns did not occur by chance, column 2 presents the Z-scores of Moran's I for each category. I find all the Z-scores are above the significant value (1.96 at a confidence level of 95%), indicating that the clustering patterns for all categories are statistically significant. To see the robustness of the ordering of the degree of geographical clustering to the choice of index, I use the General G, another measure of analyzing geographical patterns, to evaluate the degree of concentration. For the General G, the higher the Z-score, the more clustered the geographical pattern. Column 3 gives the results from the General G index. All the Z-scores are above the significant value, and the relative magnitudes of Z-scores among the store categories are similar to those of Moran's I index.

Overall, the results from measures of spatial patterns provide evidence that the chain-affiliated convenience stores are more clustered than non-chain-affiliated stores or retail stores as a whole, suggesting we would need a model of store-network choice incorporating the trade-off from clustering stores.

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[9]See Mitchell (1999) for the details about the definition and the interpretation of Moran's I index.

3   Game of Choosing Store Networks

3.1   Model

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.[10] 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.[11]   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.[12]

Formally, I consider a game in which two players, denoted by player i and player j, $i, j \in \{Family\ Mart, LAWSON\}$, choose their store networks. The model is a simultaneous-move game of complete information.[13] 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

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[10]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.

[11]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 a lack of fresh foods and lunch boxes. So chains need to have an efficient network system that will minimize the costs of delivery.

[12]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, and sandwiches).

[13]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 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 unrealistic 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.

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 $N_j \in \mathbf{N}_j$.

The solution concept is pure-strategy Nash equilibrium, which is a pair of store networks that are best responses. 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 $N_j \in \mathbf{N}_j$

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

where $\pi_{i,m}$ is chain i's profits in market m. I assume firm i's profit function in market m is broken down into revenue and costs, $\pi_{i,m}(N_i, N_j) = r_{i,m}(N_i, N_j) - c_{i,m}(N_i)$, where $i, j \in \{Family\ Mart, LAWSON\}$. Notice that market-level revenue and cost function depend not only on the number of stores in market m but also on the vectors of network choice, N_i and N_j, due to spillover effects of cost savings and business stealing across markets.[14]

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

$$r_{i,m}(N_i, N_j) = N_{i,m} * [\underbrace{-\delta_{own,within} \log(\max(N_{i,m}, 1)) - \delta_{own,adj} \sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}}}_{\text{business-stealing effect, own chain stores}}$$

$$\underbrace{-\delta_{rival,within} \log(N_{j,m} + 1) - \delta_{rival,adj} \sum_{l \neq m} \frac{D_{j,l}}{Z_{m,l}}}_{\text{business-stealing effect, rival chain stores}}$$

$$\underbrace{-\delta_{local,within} \log(N_{local,m} + 1) - \delta_{local,adj} \sum_{l \neq m} \frac{D_{local,l}}{Z_{m,l}}}_{\text{business-stealing effect, local stores}}$$

$$+ \underbrace{X_m \beta}_{\text{demographics}} + \underbrace{\mu_{LAWSON} * 1(i \text{ is LAWSON})}_{\text{brand fixed effect, LAWSON}} + \underbrace{\lambda_1(\sqrt{1 - \rho_1^2} \epsilon_m^r + \rho_1 \eta_{i,m}^r)}_{\text{revenue shocks}}].$$

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[14]Markets are typically isolated both in costs and demand. However, in reality, markets overlap in the sense that people travel across borders to purchase good, and cost complementarity exists across markets. To approximate reality, I consider dividing a certain region, such as Okinawa Island, into mutually exclusive cells, and I call each cell a "market" throughout the paper for the purpose of convenience.

X_m are observable demographic characteristics of the market m that affect the demand for convenience stores. $N_{i,m}$, $N_{j,m}$, and $N_{local,m}$ are the number of own chain, rival chain, and local stores in market m, respectively.[15] 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. $D_{i,m}$ is a dummy variable that equals one if at least one chain i's store is in market m and 0 otherwise. $D_{i,l}, D_{j,l}$, and $D_{local,m}$ are defined similarly. $Z_{m,l}$ measures the distance from market m to the adjacent market l. For instance, $\sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}}$ counts the total number of adjacent markets that contain chain i's stores, weighted by the distance between markets m and l. μ_{LAWSON} measures the LAWSON fixed effect in revenues. ε_m^r is a shock to revenues at the store level that I assume is common to any stores in market m, both local and chain, and i.i.d. across markets. $\eta_{i,m}^r$ is a chain-market-specific shock to revenues i.i.d. across chains and markets.[16] 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 the shocks are independent of the exogenous variables. ρ_1 measures the correlation of combined unobservables across chains in a given market. λ_1 is a parameter that captures the magnitude of the sum of the revenue shocks.

Turning to the notation of parameters, $\delta_{own,within}, \delta_{rival,within}$, and $\delta_{local,within}$ measure the impact of the number of own stores, competitor stores, and rival stores in the same market on store-level sales. Similarly, $\delta_{own,adj}, \delta_{rival,adj}$, and $\delta_{local,adj}$ measure the impact of the presence of own stores, competitor stores, and rival stores in the markets adjacent to market m on store-level sales in market m.

Because I do not observe fixed costs directly, I parameterize fixed costs at market m as a linear

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[15]Throughout the paper, I assume the number of local independent stores is given exogenously.

[16]I assume stores of the same chains in a given grid receive a common revenue shock. Relaxing this assumption does not change the results.

function of observed and unobserved variables:

$$c_{i,m}(N_i) = N_{i,m}[\underbrace{-\alpha_{saving,within}\log(\max(N_{i,m},1)) - \alpha_{saving,adj}\sum_{l\neq m}\frac{D_{i,l}}{Z_{m,l}}}_{\text{cost savings from stores within a market and adjacent markets}}$$

$$+ \underbrace{\mu_{dist}*Distance_{i,m}}_{\text{costs due to distance to distribution center}} + \underbrace{\gamma*1(\text{market } m \text{ is zoned})}_{\text{fixed costs due to regulation}}$$

$$+ \underbrace{\mu_{cost}}_{\text{fixed costs of opening a store}} + \underbrace{\lambda_2(\sqrt{1-\rho_2^2}\epsilon_m^c + \rho_2\eta_{i,m}^c)}_{\text{cost shocks}}],$$

where μ_{cost} are fixed costs of opening a store. $Distance_{i,m}$ 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 can therefore serve as an exclusion restriction for identification.[17] The fixed costs of zoning, parameterized by γ, capture the increase in the fixed costs the store may have to incur for obtaining permission to develop a store in a zoned area. 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. ρ_2 measures the correlation of combined unobservables across chains in a given market. λ_2 is a parameter that captures the magnitude of the sum of the cost shocks. 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. The parameter $\alpha_{saving,adj}$ measures the gross cost savings from the presence of the same chain stores in adjacent markets. $\alpha_{saving,within}$ captures the gross cost savings from from having a store of the same chain in the same market.[18]

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[17]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.

[18]Notice that in the empirical specifications I place two assumptions on revenue and costs: (1) the demographics X_m affect revenue but not costs, and (2) zoning affects costs but not revenue. Techinically, I can let the cost function depend also on market-level characteristics, such as rent, if one observes the data.

Comparison of Multiple Choice with the Binary-Choice Setting. One feature of the existing chain-entry model is that a chain has a binary choice of entering or not entering a market. Relative to the model in the earlier literature, the above multi-store framework has the following five features. The first feature is a wider coverage of data. The binary-choice model results in dropping large markets from observations since it would be more likely to observe more than one store in those markets. The multi-store setting, in contrast, allows us to focus not only local markets but urban markets. The second feature is that we can avoid endogeneity bias. Endogeneity bias can arise if store locations are treated as exogenous in large markets with more than one store, because store openings are, in fact, endogenous variables of the error terms in all markets when markets are interdependent on the cost-savings and business-stealing effect. The third feature is that the multi-store framework allows us to simulate a merger, which is infeasible for the binary-choice model since it would not make sense to keep two chains in urban markets while simulating a merger in other markets. The fourth feature is that the multi-store framework does not require a restriction on the model parameters for the trade-off within a market when we use the computational algorithms I describe in the next section. We can imagine splitting existing markets into smaller markets so that we can deal with the industry with the binary-choice model. However, as we see later in the next section, we need to place a restriction on the net spillover of clustering across markets to be always nonnegative. Unfortunately, assuming only net 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. As Figure 1 shows, we are more likely to see many markets with more than one store for each chain. Within-market effect may be harder to assume to be positive or negative ex-ante than the spillovers across markets. In contrast, we don't have to assume anything about the trade-off within a market in the multi-store setting. The fifth feature is that we can have richer patterns of trade-off of clustering stores. Previously, the trade-off of clustering within a market is non existent and the trade-off across markets in binary choice is captured by one parameter representing gross cost savings: costs savings minus the business-stealing effect. In contrast, my empirical model, by having multi-store choice and by separating revenue and costs, has the trade-off both within a market and across markets, and we can decompose the trade-offs into business stealing and cost savings.

3.2 Algorithm to Compute a Nash Equilibrium

I formulate the game as supermodular, thereby ensuring the existence of an equilibrium and providing an algorithm to find a Nash equilibrium. I specify an algorithm to compute a pure-strategy Nash Equilibrium for the supermodular game by iterating myopic best responses. To deal with the computational burden of calculating the best response, 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. I provide below the generalization of Jia (2008)'s arguments from the binary choice of entering or not entering a market to the case of K choices in which chains can open up to K stores in a market.[19]

3.2.1 Supermodularity of Chain-Entry Game

Topkis (1979, 1998) shows that supermodular games have several convenient features. Two such features are the existence of pure strategy Nash equilibria and a so-called round-robin algorithm for computing a Nash equilibrium. In this subsection, I derive the conditions under which 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 define a binary relation on a nonempty set $\mathbf{N}_i$ by $\geq$, such that $N_i \geq N_i'$ if $N_{i,m} \geq N_{i,m}'$ $\forall m = 1, ..., M$.[20] $\mathbf{N}_i$ is a *sublattice* if the meet and join of any two strategy vectors in $\mathbf{N}_i$ is also in $\mathbf{N}_i$.[21] 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 $N_i \in \mathbf{N}_i$.

Now I introduce the definition of supermodularity of a game.[22]

Definition 1 (Supermodularity of a Game) *A supermodular game is one in which, for each $i \in \{Family\ Mart, LAWSON\}$, (1) A strategy space $\mathbf{N}_i$ is a compact sublattice, (2) $\Pi_i(N_i, N_j)$*

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[19]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.

[20]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 "$\geq$".

[21]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 $N_i \vee N_i' \equiv (\max(N_{i,1}, N_{i,1}'), ..., \max(N_{i,M}, N_{i,M}'))$.

[22]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.

has an increasing differences in (N_i, N_j), *and (3)* $\Pi_i(N_i, N_j)$ *is supermodular in* N_i.

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.[23] 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' strategy 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* $\delta_{own,adj} \leq \alpha_{saving,adj}$.

Proof. See Appendix A.1.

The proposition applies to both a non-revenue model and a model with revenue. It asserts that the net spillover effect across markets $\alpha_{saving,adj} - \delta_{own,adj}$ must be nonnegative. Although this assumption seems strong, I find that imposing restrictions on all other parameters, such as $\alpha_{saving,within}$, $\delta_{own,within}$, $\delta_{rival,within}$, or $\delta_{rival,adj}$, is unnecessary for the supermodularity of the game. This finding implies that we can freely estimate these parameters from the data.[24]

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[23]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 $N_j \geq \tilde{N}_j$,

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

[24]One way to motivate the parameter restriction in my analysis is the following: the intuition behind the theoretical result is that the nonnegativity of $\alpha_{saving,adj} - \delta_{own,adj}$ 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 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.

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 $\delta_{own,adj} \leq \alpha_{saving,adj}$, the game has Nash equilibria.

3.2.2 Round-Robin Optimization to Compute A Nash Equilibrium

In a so-called round-robin 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 procedure is as follows:

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

- **Step 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: $N_{FM}^1 = BR_{FM}(N_{LS}^0) \equiv \arg\max_{N_{FM}} \sum_{m=1}^{M} \pi_{FM,m}(N_{FM}, N_{LS}^0)$, where $BR_{FM}(\cdot)$ is a best response function of Family Mart given the store-network choice by LAWSON, N_{LS}.

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

- **Step 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 A.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.

3.2.3 Deriving Lower and Upper Bound of Best Response

The most computationally challenging steps are 2 and 3, where I compute the best response given the competitor chain's entry configuration. 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 nonpositive.

Proposition 4 (Nondecreasing Coordinate-wise Optimality Condition) *$V_i(N_i)$ is nondecreasing in N_i if $\delta_{own,adj} \leq \alpha_{saving,adj}$.*

Proof. See Appendix A.2 and A.3.

Therefore, 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, $V_i : \mathbf{N}_i \rightarrow$ $\mathbf{N}_i$ 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* $\inf E = \inf\{N_i \in \mathbf{N}_i : V(N_i) \leq N_i\}$.

To obtain the least and greatest fixed points of $V_i : \mathbf{N}_i \rightarrow \mathbf{N}_i$, see Appendix A.5. After obtaining the lower and upper bound, 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 $N_i^{LB} \leq N_i \leq N_i^{UB}$.

3.2.4 Dealing with Multiple Equilibria

The pure strategy Nash equilibria may not be unique in the model. The round-robin algorithm allows us to solve for two extremal points of the lattice as the equilibrium outcome of the game: one maximizes profits for Family Mart and one maximizes profits for LAWSON. This paper introduces an equilibrium selection mechanism, which is to pick the most profitable equilibrium for Family Mart. I follow this rule since aggregate profits increase with the number of stores, and the number of stores for Family Mart is 40 percent higher than the total stores for LAWSON.[25]

Of course, the arbitrariness of picking an equilibrium remains a limitation of the study. Although it is computationally infeasible to solve for all equilibria in the model, I try a different selection rule in which I select another external point of the lattice in the sensitivity analysis section. The practical benefit of having a selection rule is that, despite a high dimension of strategy profiles, researchers or regulation authorities can actually obtain equilibrium predictions of the chain-entry game to see the likely equilibrium effects of a merger or a change in an entry regulation on store configurations.

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

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[25]For instance, 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, then the aggregate profits for Family Mart will be approximately 40 % higher.

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.[26]

I construct a moment condition that measures the gap between the observed number of stores and the conditional expectation of a number of stores. 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. 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. θ is a vector of model parameters. Note that the data on the number of stores $N_{i,m}$ are generated at the true θ_0 and predetermined variables (X, ϵ): $N_{i,m} = N_{i,m}(X, \epsilon, \theta_0)$. Using these notation, I obtain a population condition for the number of stores:

$$g_{store}(\theta) \equiv E[(N_{i,m} - E[N_{i,m}(X, \epsilon, \theta|X)]) * f_m(X)|X] = 0 \text{ at } \theta = \theta_0, \tag{1}$$

where $f_m(X)$ is a function of observed predetermined variable X, which will serve as a set of instruments.[27] The sample analogue of the population moment conditions in (1) is given by:

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

where $E[g_{M,store}(\theta)] = 0$ at $\theta = \theta_0$. Since no closed-form expression exists for $E[N_{i,m}(X, \epsilon, \theta)|X]$, I simulate the conditional expectation by averaging $N_{i,m}(X, \epsilon, \theta)$ over a set of simulation draws $\epsilon^{S,all} = (\epsilon^1, \epsilon^2, .., \epsilon^S)$ from the distribution of ϵ:

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

$\epsilon_i^s = (\varepsilon^{s,r}, \varepsilon^{s,c}, \eta_i^{s,r}, \eta_i^{s,c})$, $i \in \{FamilyMart, LAWSON\}$, $s = 1, ..., S$ are drawn from a standard normal distribution. I set $S = 200$ for the study. I also construct the moment conditions on revenue, and I stack up all moment conditions to create a vector of the full sample moment conditions $\hat{g}_M(\theta)$. The method of simulated moments (hereafter MSM) selects the model parameters that minimize

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[26]Monte Carlo evidence on the performance of the estimator for the artificial data I have generated is available upon request.

[27]Taking a conditional expectation of the equation with respect to X multiplied by a function of conditioning variable X yields zero; that is, $E[(N_{i,m} - E[N_{i,m}(X, \epsilon, \theta_0|X)]) * f(X_i)|X_i] = E[(N_{i,m} - E[N_{i,m}]) * f(X_i)|X_i] = 0$.

the following objective function:

$$\hat{\theta}_{MSM} = \arg\min_{\theta} [\hat{g}_M(\theta)]\mathbf{W}[\hat{g}_M(\theta)]', \tag{2}$$

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 $\mathbf{\Lambda}_0 = E[g(X_m, \theta_0)g(X_m, \theta_0)']$. The S^{-1} in the asymptotic variance corresponds to an efficiency loss due to simulations. Appendix B provides further details on (1) the implementation of the full estimation procedure, (2) the construction of 27 moment conditions including moment conditions on revenue, (3) the minimization of the criterion function in Eq.(2), and (4) the generation of the simulation draws.

4.1 Adding Post-Entry Outcome while Correcting for Selection

Adding post-entry outcome is useful for the analysis of entry since it allow us to decompose costs and revenue and to interpret parameters in monetary units. However, simply conducting an analysis of a post-entry outcome itself involves a selectivity problem since we only observe for markets where the multi-store firms actually open stores. To see why selection of entrants becomes problematic, consider the following simple revenue regression

$$(Total\ Revenue)_m = \theta_a X_m + \theta_b N_m + \epsilon_m,$$

where $(Total\ Revenue)_m$ is the aggregate revenue of stores in market m, X_m denotes a vector of demographic characteristics of market m, such as business and night-time population. N_m is the total number of stores in market m. ϵ_m captures factors that affect total revenue in market m that the econometrician does not observe. The revenue equation involves a sample selection problem due to the following two reasons. First, if the unobserved revenue shocks ϵ_m affect the decision of how many stores to open in market m, N_m, which is likely, then the equation violates the zero correlation assumptions needed for consistency. Second, the data on total revenue are available only for the markets where chains indeed open stores. The latter issue appears in other contexts, such as estimating the wage regression in labor economics: we are interested in explaining wage offers as the function of various factors, but we observe wage offers in the data only for the people

who actually decided to work.[28]

To deal with this selectivity issue, the literature on empirical entry has commonly treated market structure ("selection") equations and revenue ("outcome") equations separately to implement the following two-step estimator. Suppose we have post-entry outcome equations and entry (selection) equations. Frequently proposed two-step estimation strategies are designed to avoid the selectivity issue by first estimating the probability of selection or agents' expectations, and then running post-entry outcome regressions by constructing a selectivity-corrected term that is estimated from the first stage results for each outcome of the game or for each strategy of the firm (Mazzeo 2002a and Ellickson and Misra 2008, respectively). However, this two-step estimation procedure would be infeasible in most chain-entry problems since the number of possible outcomes or the number of possible strategies of the game is exponential in the number of markets. Furthermore, estimating the selection equation in the first step is difficult because in the current model specification, the selection equations (chain-entry) involve all parameters in the model, whereas the revenue equation involves some of the parameters, not vice versa.

Instead, this paper proposes an alternative strategy. I call this strategy as a one-step estimation procedure since I use joint MSM estimation of the entire model parameters by stacking up the moment conditions regarding selection and outcome.[29] The intuition on how simulation method allows us to avoid the selectivity issue can be summarized by a remark by McFadden (1996): "If one finds Nature's data generating process, then data generated (by simulation) from this process should leave a trail that in all aspects resembles the real data." In the context of the chain-entry problem, if I figured out a correctly specified model and true parameters, then I should be replicating the model outcome variables, such as number of stores or revenue at each market, in a such way that we don't see any systematic deviations from the observed data sets. The key variable to constructing the selection model is to have a selection indicator for the total number in market m in s th simulation. Appendix B covers the details on the construction and the implementation of the method.

The major advantage of the one-step approach with simulation is simplicity: the one-step procedure is easy to implement because, unlike the two-step approach, the method does not require integration of the errors over complex regions to calculate the selectivity-corrected term nor involve

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[28] See Heckman (1979) for a classical treatment of this sample selection issue.

[29] For more detailed and general discussion of one-step and two-step estimators in the context of selectivity, see Prokhorov and Schmidt (2009).

sequential steps including estimating agents' expectation and control function.

5 Empirical Results

Table 4 presents the MSM estimates of the model parameters. All of these estimates have highly intuitive signs. As expected, the daytime population has a positive and statistically significant effect on store profitability. The magnitude is 68 percent of the one of the nighttime population. The coefficient on the nighttime population implies that sales in a market having one thousand more people than other markets will be higher by $69,100 annually (or about 7 million yen).

The estimates in rows 3 - 8 of column 1 in Table 4 measure the business-stealing effect due to the presence of three types of stores. The parameters that measure the business-stealing effect within a market by own chain stores ($\delta_{own,within}$) and by rival chain stores ($\delta_{rival,within}$) are precisely estimated and positive, 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 $194,000 ($= \ln 2 * \$280,000$) annually, which is 14 percent of total annual sales for an average chain store. Similarly, the presence of a rival chain store dampens the sales by 18 percent of total annual sales. The presence of a non-chain store reduces the revenue less than an own or rival chain store does, but the magnitude is not statistically significant. All the three parameters that measure the business-stealing effect across markets by own chain stores ($\delta_{own,adj}$), by rival chain stores ($\delta_{rival,adj}$), and by local stores ($\delta_{local,adj}$) are imprecisely estimated. The magnitude of these parameters suggests that the business-stealing effect across markets does not seem to be playing a big role in the industry.

Next, I turn to the interactions among own chain stores. Row 14 of Table 4 displays the estimate of $\alpha_{saving,adj}$, the coefficient on the gross cost savings from the presence of stores from the same chain in adjacent markets. The point estimate is $37,600 per year and per market and is insignificant at the 5 percent level. The magnitude of the parameter is of the same order of magnitude as annual salary of the average truck driver in Japan, which is around $41,200.

Row 13 contains the estimate of $\alpha_{saving,within}$, 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 $125,300, and the fraction of the cost savings to the total costs is 12 percent. The sign is positive as expected. However, clear evidence of economies of density or the positive spillovers among own stores on the costs side does not exist in either within a market case or across markets case.

Of interest is the coefficient on the zoning status index in row 16, which is positive and not precisely estimated. The sign 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, and the monetary value of the annual costs translates into $41,400 per year.

I estimate the constant in the revenue equation to be $512,500. The estimated constant on the cost equation implies that the average costs of installing and operating a convenience store is about $1,038,000 annually. I find no evidence that stores benefit from locating close to the distribution center: the parameter estimate $\mu_{distance}$ enters the costs equation neither statistically nor economically significantly. The parameter coefficient predicts that the farthest store from the distribution center incurs $16,000 as distribution costs, which is less than 15 percent of the annual fixed costs of the store (μ_{cost}).

The correlation parameter for revenue equation, ρ_1, is 0.89, which means the correlation of the revenue shocks across chains in a given market is 0.79. On the other hand, the correlation parameter for cost equation, ρ_2, is 0.02. Rows 12 and 19 show that λ_1 and λ_2, the standard deviation of revenue and costs, are estimated at around $220,000, which is about 15 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 total stores each chain opens with the actual store counts. Rows 20 and 21 of column 1 in Table 4 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 139.9 on average across 200 simulations with a standard deviation of 8.7 stores. The model predicts the total number of LAWSON stores, which is 100 in the data, to be 97.1 stores on average across 200 simulations with a standard deviation of 9.8 stores. The model predicts the aggregate sales, which is $169,334,000 in the data, to be $173,992,313.

6   Policy Simulations

In this section, I use the parameter estimates of the model to perform "what-if" experiments, namely, evaluating the impacts of a hypothetical merger and changes in the zoning regulation on the market structure. In all simulations, the demographics, including population, are taken as exogenous and unchanging before and after the policy change. The model solves for each simulation

using the same revenue and cost shocks that are used for estimating the model parameters.

6.1 Effects of a Merger on Store Networks

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 result 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 between two chains, which will be of interest for a regulator who decides whether to approve the merger that will yield a monopolist chain.

Because there are two chains, a proposed merger would create a monopoly of one chain. One can use the best response iteration algorithm to obtain the profit maximizing, post-merger configurations of stores for the monopolist. I set the maximum number of stores the merged chain can open to eight within a market, which is doubled from the duopoly in the pre-merger regime.

The second column of Table 5 presents the results in which Family Mart takes over as a monopolist. The fourth column presents the results of the scenario in which LAWSON takes over. Given the small magnitude of the LAWSON fixed effect in Table 4, 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 stores in Okinawa decreases by 11 to 12 percent from 237 stores, which is the combined number of Family Mart and LAWSON stores before the merger. The total sales also decline by 10 percent, a proportion similar to the reduction in the total number of stores. However, the combined profits increase by 12 to 14 percent. The third and fourth rows from the bottom in columns 2 and 4 show that profits per store have increased significantly: a 34 percent increase for Family Mart and a 20 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 3 percent.

We can confirm from Figure 4 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 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

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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 stores in the most populated markets, the acquirer has fewer stores in less-populated markets. Fewer stores are in the suburbs after the merger due to the reduction in random entry events: the chain-market specific profit shocks occurs only for Family Mart and not for LAWSON after a merger.

The third panel from the top in Table 5 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 are the same as the one before merger. The profits for the merged chain increase by \$21.5 million due to an increase in cost savings, both across market and within a market. (On the other hand, the loss from business stealing among the two chain stores increases by around \$17 million. Although the loss from business stealing among its stores outweighs the cost-savings benefits from clustering, the profits increase from having no rival stores will compensate for the loss from the competition net of the cost savings.

6.2 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 the sample, 140 markets out of 834 markets are categorized as zoned areas. In zoned areas, the regulation does not place an upper bound for the number of stores firms can develop; rather, the act permits developing stores in zoned areas, provided stores comply with strict construction requirements.[30] As Figure 7 shows, the zoned area is more likely to be suburban in highly populated area and surrounds the city center of Okinawa.

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 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

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[30]This exception is detailed in Article 34-1. Potential store developers have to file and show that the store serves the needs of local residents. Local ordinances give other detailed conditions.

the regulation for commercial outlets in zoned areas by constructing ordinances that specify the conditions entering stores must meet.[31] 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 firms' 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).

Simulation Design. The simulation eliminates the zoning regulation completely from the 140 currently zoned markets. Two chains re-optimize their store-network choices given the new policy environment. The new equilibrium is computed by running the best response iteration algorithm described in the previous model section. Note that calculating the economic welfare would be infeasible in the study due to data restrictions; I don't have information on price and quantity separately, which we would need to compute consumer surplus.

Several limitations exist in the counterfactual 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 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 taking the local stores' entry behavior as exogenous will make the analysis simpler, it may not be ideal when calculating the new equilibrium in chains' store networks. Nonetheless, the results, when interpreted carefully, have implications regarding the likely impacts of the change in policy regimes on store configurations, sales, and profits in the industry.

Results. Table 6 summarizes the key findings of these counterfactual experiments. Column 2 displays the predictions about current equilibrium in the number of stores, which will serve as a baseline for a comparison of the outcomes of two hypothetical policy regimes.

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[31] 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.

Column 3 in Table 6 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 2.3 and 2.2 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 26 percent for both chains. The model also predicts aggregate sales and profits will increase by 2 percent. Regarding the aggregate costs due to the regulation, I calculate the magnitude by multiplying the 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: $2,000,000$, which is 0.6 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, 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.

Figure 5 presents 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 predicted to have stores after the deregulation are different across Family Mart and LAWSON because their market-chain specific revenue and cost shocks and their store networks are different. In particular, the figure shows that the previously zoned markets in which the number of stores increases due to removing the regulation tend to be 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 6 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 8 to 12 percent.

7 Sensitivity Analysis

This section provides a set of alternative specifications on the empirical model to explore the robustness of the results.

Choices of Grids. This robustness check examines whether the original market definition is driving the parameter estimates Table 4 reports. To this end, I construct a second sample of markets with store counts and demographics by using the original grid-level data. In particular, as Figure 3 shows, I consider a different set of 1 km² grids of which borders are located at the midpoint of the original borders.

FIGURE 3
SHIFTED 1 KILOMETER SQUARE GRIDS
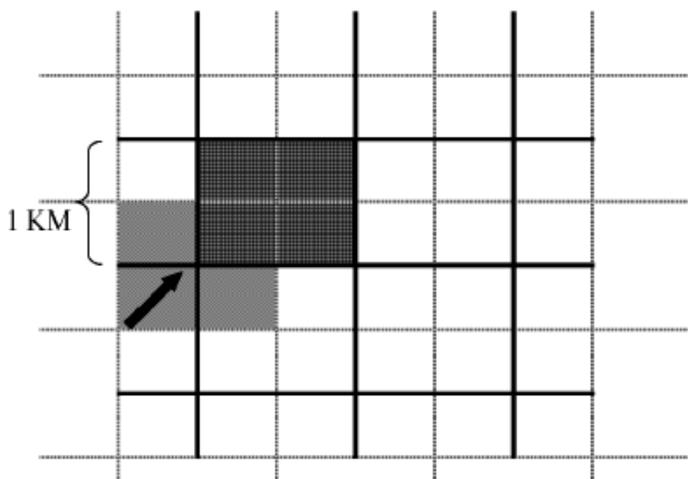
NOTE. - Dashed and bold lines show original and newly defined borders for markets, respectively.

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 $1km^2$ grid level are resampled into the new $1km^2$ 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. 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 7 present the estimates for the original market definition, and columns 3 and 4 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.

Alternative Equilibrium Selection Rule. In this robustness check, I examine whether the results are sensitive to the choice of the equilibrium selection rule. Although it is natural to assume the observed outcome is the equilibrium that is most profitable to the larger chain, which is Family Mart, I re-estimate the model with the assumption that the equilibrium market participants choose is the one that favors LAWSON.

Column 5 in Table 7 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 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.

Fixed Costs of Closing and Remodeling a Target's Store in Merger Simulation. In the main specification of the merger simulation, I assume no costs of closing existing stores or remodeling the target chain's stores to match 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. A more realistic setting would be to 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 tenants can move in. The second parameter is the cost of converting a store from a target chain into the monopolist chain store. An acquirer has to pay the costs of remodeling, such as changing name boards or the interior design. 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. Consistent with the chains' financial statements in 2001 and 2002, I assume in this simulation that a chain incurs $100,000$ 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 target chain store over opening a new one.

The sixth and eighth columns of Table 5 present the results of this scenario. Overall, the decrease in the sum of total profits and total sales is 7 to 9 percent, and no noticeable difference exists between the scenario and the "de novo" entry scenario.

As for 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, the acquirer, either Family Mart or LAWSON, clusters more at the city center and less at suburbs than the sum of the two chains' stores in pre-merger status as in the main specification.

Table 8 presents additional robustness checks by using 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 8 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 5. Both specifications deliver similar quantitative results on store configurations and total profits.

Alternative Cost-Savings Specification. The most striking result from the merger simulation in Section 6 is that the acquirer tends to increase the number of stores in city centers to fully exploit the cost-savings benefits from adjacent markets. Such an increase leads to a denser store network in these markets than the combined network of Family Mart and LAWSON stores before the merger. A potential criticism would be that the particular specification of the spillover in the cost function may drive the geographical store-network pattern after the merger. To check the robustness of the results to the choice of cost-savings specification, I use an alternative cost function. A natural alternative is that the cost-savings effect across markets increases linearly with the absolute number of stores in adjacent markets.

To run the counterfactual merger simulation, I re-estimate the parameters of the revenue model as before, the sole exception being that the cost function is given differently.[32] Parameter estimates of the model have no significant differences in magnitude from the estimates of the main specification model, although the table does not show this result. Table 9 presents results of the merger simulation by using parameter estimates from the alternative specification of costs. Overall, the new specification delivers similar qualitative predictions on many dimensions. As shown in Figure 6, the acquirer tends to increase the number of stores in city centers and decrease the number of stores in suburbs, which supports the simulation result of the main specification.

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. Two features of the framework distinguish it from previous work. First, 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 allows us (1) to endogenize all markets; (2) to model the trade-off of clustering, which is a fundamental force that governs multi-store firms' behavior; and (3) to simulate a merger. Second, I integrate the entry model with post-entry outcome data, while correcting for the selection of entrants by simulations. The specification of the industry as a game between two chains formulating store networks enables me to investigate policy questions, such as whether a merger or deregulation have economically significant impacts on network configurations of multi-store firms.

The paper shows how the existence of the trade-off from clustering its stores, the cost-savings and business-stealing effect, drastically affects how a merger impacts a store's location decisions. Surprisingly, the simulations confirm that after a hypothetical merger between Family Mart and LAWSON, the post-merger density of stores of the monopolist chain in the city center would be greater than the combined density of Family Mart and LAWSON stores before the merger. The reason is that the net spillover across markets within a chain, which is defined as the cost-savings effect minus the business-stealing effect, would be higher for the city center markets due to a higher

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[32] A proof that the supermodularity of the game holds under this alternative cost specification is available from the author upon request.

density of stores. This significantly large spillover will make having one additional store more profitable after a merger, offsetting the negative business-stealing effect from having additional store.

Two limitations in the model deserve mention. First, the framework abstracts from change in price before and after a merger or deregulation. Although the abstraction is not a concern for the convenience-store industry in Japan since it employs nationwide uniform pricing, in general, the model's inability to incorporate how prices are determined could be problematic. Nonetheless, in future work, I hope to combine pricing decisions and entry decisions that will enable researchers to incorporate the policy effect on price. Second, the model is static and therefore ignores dynamic aspects of the industry, such as preemption of the first mover. Although data limitation and dimensionality of choice set make modeling dynamics of the industry impossible, relaxing the static assumption and incorporating the sequential-move feature of the multi-store firms to the model framework would be beneficial.

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FIGURE 4

INCREASE (LEFT) AND DECREASE (RIGHT) IN NUMBER OF STORES, AFTER MERGER
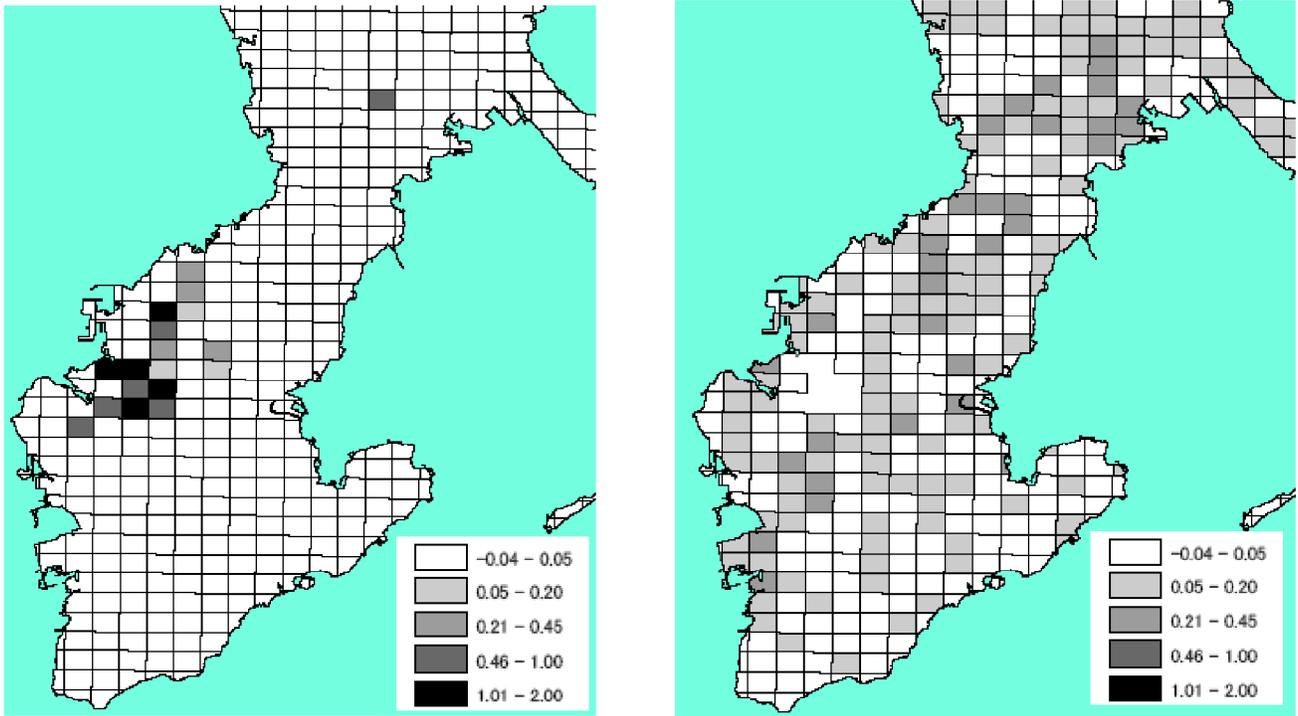
NOTE. - Family Mart as the acquirer. I construct the difference by comparing the number of Family Mart and LAWSON stores and the number of the acquirer's stores. I assume the costs of closing and remodeling a store are zero.
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FIGURE 5

INCREASE IN NUMBER OF STORES AFTER DEREGULATION: FAMILY MART(LEFT) AND LAWSON (RIGHT)
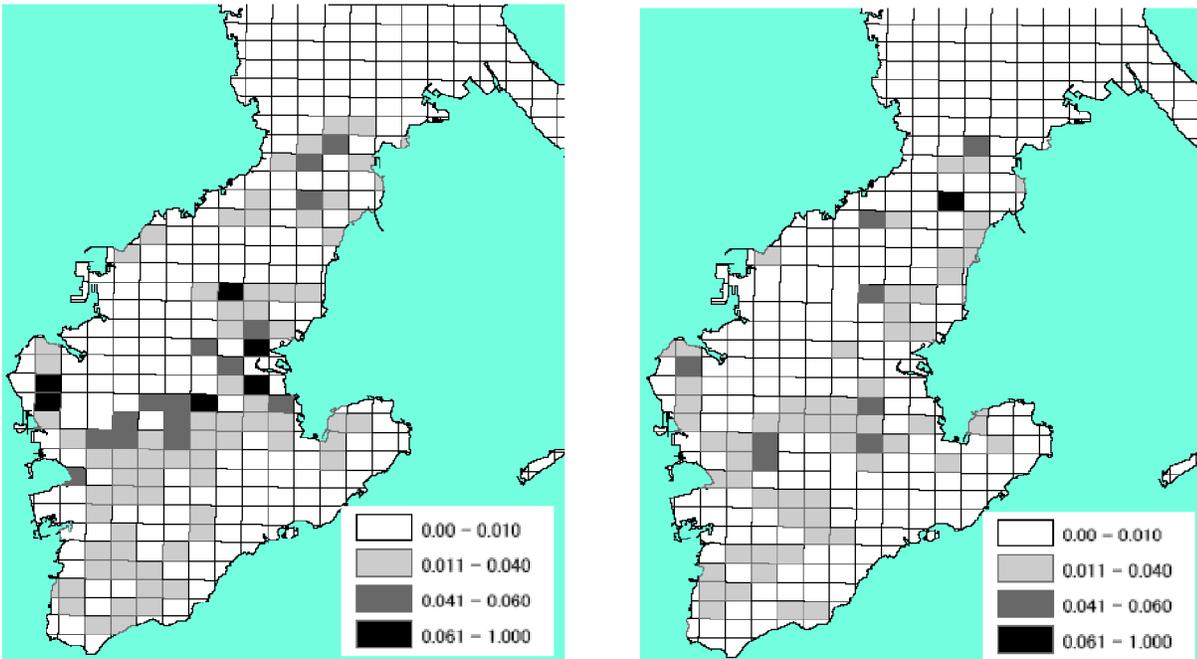
FIGURE 6
INCREASE (LEFT) AND DECREASE (RIGHT) IN NUMBER OF STORES, AFTER MERGER
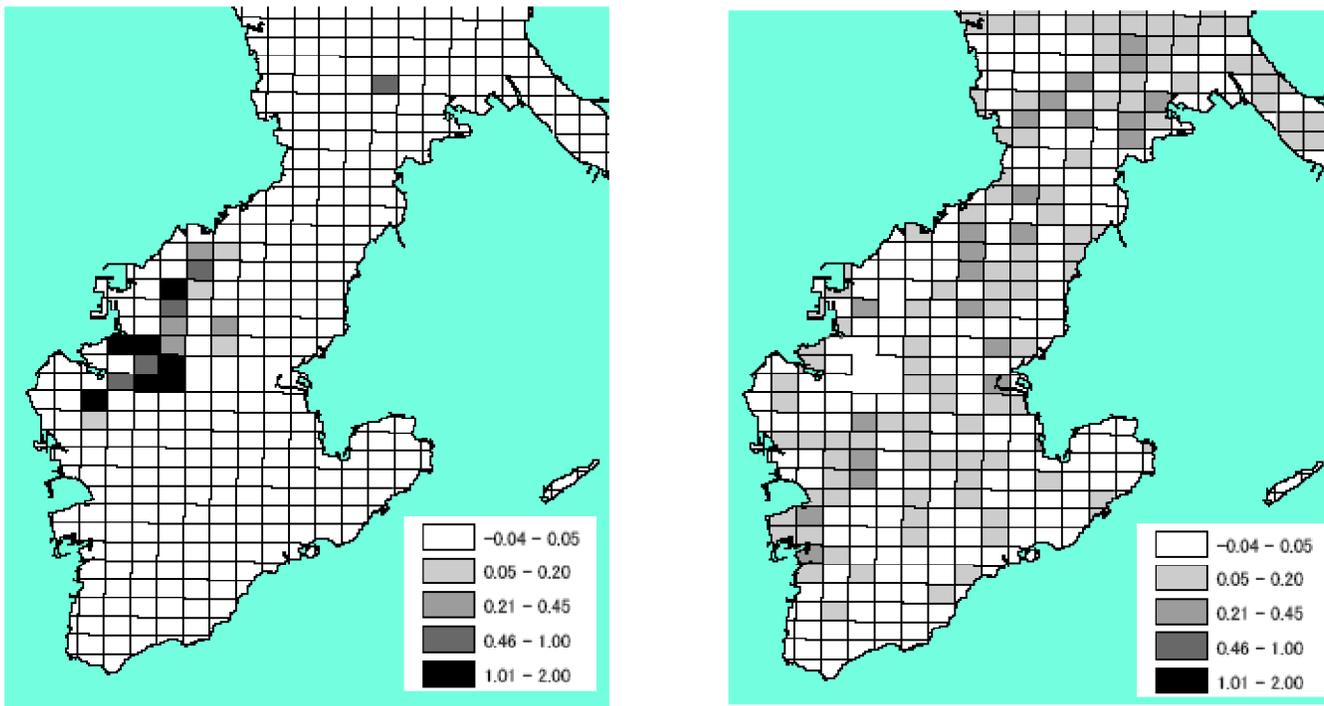
NOTE. - Family Mart as the acquirer. I construct the difference by comparing the number of Family Mart and LAWSON stores and the number of the acquirer's stores. I assume the costs of closing and remodeling a store are US $100,000 and US $50,000, respectively. —

FIGURE 7
ZONED AREAS (RED)
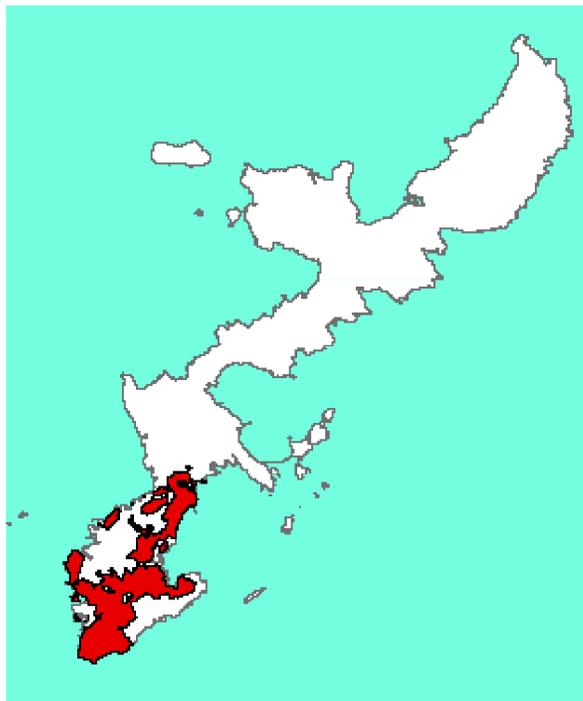
TABLE 1
DESCRIPTIVE STATISTICS ACROSS MARKETS

Variable	834 Sample Markets				
	Mean	SD	Min	Max	Total
Number of Residents (Units: people)	1,434	2,588	0	18,977	1,195,787
Number of Workers (Units: people)	580	1,612	0	32,776	484,097
Number of Stores					
Family Mart	0.170	0.550	0	7	142
LAWSON	0.122	0.434	0	6	102
Local Store	0.096	0.499	0	5	80
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
Local Store	1.179	1.895	0	14	983
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)	5,462	3,288	2,662	16,687	169,334

Sales (thousand US dollars)	Total	Per Store (=Total Sales / # of Stores)
Family Mart	203,040	1,430
LAWSON	148,540	1,456

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

TABLE 2
DEGREE OF GEOGRAPHICAL CLUSTERING

Store category	Moran's I		General G
	Index	Z-score	Z-score
All retail stores	0.34	27.72	26.96
All convenience stores	0.44	29.76	28.82
Convenience stores, chain-affiliated	0.41	27.97	27.17
Convenience stores, local	0.13	8.97	8.90
Family Mart Stores	0.43	28.83	28.26
LAWSON Stores	0.32	22.01	21.69

NOTE. - I calculate the Moran's I and the General G, using the number of stores of each category in a 1km square grid as a unit of observation.

TABLE 3
OBSERVED MARKET CONFIGURATIONS FOR FAMILY MART AND LAWSON

Number of Stores, Family Mart	Number of Stores, LAWSON					Number of Markets
	0	1	2	3	6	
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
PARAMETER ESTIMATES FROM MODEL

Variable	Estimate	Standard Error
Revenue Equation		
Nighttime Population ($\beta\ pop$)	69.1	26.3
Daytime Population ($\beta\ bus$)	46.7	14.4
Business-Stealing Effect by Own Chain Store, within a Market ($\delta\ own\ within$)	280.1	133.4
Business-Stealing Effect by Own Chain Store, Adjacent Markets ($\delta\ own\ adj$)	33.0	111.0
Business-Stealing Effect by Rival Chain Store, within a Market ($\delta\ rival\ within$)	364.2	180.0
Business-Stealing Effect by Rival Chain Store, Adjacent Markets ($\delta\ rival\ adj$)	1.1	11.9
Business-Stealing Effect by Local Store, within a Market ($\delta\ local\ within$)	24.4	81.8
Business-Stealing Effect by Local Store, Adjacent Markets ($\delta\ local\ adj$)	0.1	1.41
LAWSON Store ($\mu\ LAWSON$)	4.7	38.5
Constant in Revenue Equation ($\mu\ revenue$)	512.5	475.9
Correlation Parameter in Revenue Shocks (ρ_1)	0.89	0.31
Standard Deviation of the Unobserved Revenues (λ_1)	215.3	76.5
Cost Equation		
Cost-Savings Effect by Own Chain Store, within a Market ($\alpha\ saving\ within$)	125.3	127.5
Cost-Savings Effect by Own Chain Store, Adjacent Markets ($\alpha\ saving\ adj$)	37.6	122.8
Distance from the Distribution Center ($\mu\ distance$)	16.2	42.3
Zoned Area (γ)	41.4	45.4
Constant in Cost Equation ($\mu\ cost$)	1,038.7	255.0
Correlation Parameter in Cost Shocks (ρ_2)	0.02	0.25
Standard Deviation of the Unobserved Costs (λ_2)	229.6	118.6

Model Prediction	Data	Prediction	Std.Dev
Aggregate Number of Stores			
Family Mart	139	139.9	8.7
LAWSON	100	97.1	9.8
Aggregate Number of Stores in Adjacent Markets			
Family Mart	1041	1023.4	67.4
LAWSON	725	705.6	80.0
Aggregate Sales (thousand US dollars)	169,334	173,992	11,506

NOTE. - Parameters 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 5
IMPACT OF MERGER ON ENTRY, SALES, AND COSTS

	Current	Merger Scenario							
		"De Novo" Entry: No Costs of Closing No Costs of Remodeling				Robustness Check (1) 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	237.0	207.9	-12.3%	209.9	-11.4%	215.4	-9.1%	218.8	-7.7%
Family Mart	139.9	207.9	48.6%			215.4	54.0%		
LAWSON	97.1			209.9	116.2%			218.8	125.4%
Aggregate Number of Stores to:									
Maintain (Own Chain)						139.9		97.1	
Open (Own Chain)						25.3		30.7	
Close (Own Chain)						0.0		0.0	
Close (Rival Chain)						46.9		48.9	
Remodel Rival Stores						50.2		91.0	
Aggregate Sales									
Family Mart and LAWSON	$234.6	$209.9	-10.5%	$211.6	-9.8%	$214.6	-8.5%	$217.2	-7.4%
Family Mart	$135.6	$209.9	54.8%			$214.6	58.3%		
LAWSON	$99.0			$211.6	113.8%			$217.2	119.4%
Local Stores	$109.0	$111.6	2.4%	$111.4	2.2%	$110.9	1.7%	$110.6	1.5%
Sales per Store									
Family Mart	$0.97	$1.01	4.2%			$1.00	2.8%		
LAWSON	$1.02			$1.01	-1.1%			$0.99	-2.7%
Aggregate Profits									
Family Mart and LAWSON	$58.7	$65.9	12.3%	$66.6	13.6%	$58.5	-0.2%	$57.0	-2.9%
Family Mart	$33.1	$65.9	99.3%			$58.5	77.0%		
LAWSON	$25.6			$66.6	160.2%			$57.0	122.5%
Breakdown of Profits			Δprofits		Δprofits		Δprofits		Δprofits
Profits from Demographics	$113.1	$112.2	-$0.9	$112.8	-$0.3	$112.8	-$0.3	$113.7	$0.6
Costs Savings, Across-Market	$2.6	$3.5	$0.9	$3.7	$1.0	$3.7	$1.1	$3.9	$1.2
Costs Savings, Within-Market	$23.0	$21.6	-$1.4	$21.8	-$1.2	$22.1	-$0.8	$22.6	-$0.3
Business Stealing, Own Chain	-$52.1	-$69.1	-$17.1	-$69.4	-$17.3	-$70.6	-$18.5	-$71.4	-$19.4
Business Stealing, Rival Chain	-$25.7	$0.0	$25.7	$0.0	$25.7	$0.0	$25.7	$0.0	$25.7
Business Stealing, Local Stores	-$14.1	-$2.3	$11.8	-$2.3	$11.8	-$2.3	$11.7	-$2.3	$11.7
Costs of Closing & Remodeling	$0.0	$0.0	$0.0	$0.0	$0.0	-$7.2	-$7.2	-$9.4	-$9.4
Profits per Store									
Family Mart	$0.24	$0.32	34.1%			$0.27	15.0%		
LAWSON	$0.26			$0.32	20.3%			$0.26	-1.3%
Total Sales plus Total Profits									
All Stores	$372.4	$360.2	-3.3%	$362.2	-2.7%	$356.1	-4.4%	$356.5	-4.3%
Family Mart and LAWSON	$293.2	$275.8	-5.9%	$278.3	-5.1%	$273.2	-6.8%	$274.2	-6.5%

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 4. The number of local stores and demographics for each market are held fixed throughout this counterfactual analysis.

TABLE 6

IMPACT OF THE ZONING REGULATION ON ENTRY, SALES, AND COSTS

	Current: 140 Zoned Markets		Case 1: No Market		Case 2: All 834 Markets	
				Zoning Regulation Policy Regime		
Variable	Data	Prediction	Prediction	%Δ	Prediction	%Δ
Aggregate Number of Stores						
Family Mart	139	139.9	143.2	2.3%	123.2	-11.9%
(in originally zoned 140 markets)	14	11.9	15.0	26.9%	11.8	-0.5%
LAWSON	100	97.1	99.2	2.2%	86.0	-11.4%
(in originally zoned 140 markets)	11	8.3	10.4	26.2%	8.2	-0.3%
Aggregate Number of Own Stores in Adjacent Markets						
Family Mart	1041	1023.4	1047.7	2.4%	911.4	-10.9%
LAWSON	725	705.6	721.4	2.2%	631.5	-10.5%
Aggregate Sales (million US dollars)						
Family Mart	$203.0	$135.6	$137.9	1.7%	$124.0	-8.6%
(in originally zoned 140 markets)	n/a	$10.1	$12.5	23.1%	$10.1	-0.3%
LAWSON	$148.5	$99.0	$100.6	1.7%	$90.9	-8.2%
(in originally zoned 140 markets)	n/a	$7.5	$9.1	22.6%	$7.4	-0.2%
Aggregate Sales in Markets with More than 2 Stores (million US dollars)						
All Stores	$169.3	$174.0	$175.3	0.8%	$163.3	-6.1%
Aggregate Profits (million US dollars)						
Family Mart	n/a	$33.1	$33.6	1.6%	$29.1	-11.9%
LAWSON	n/a	$25.6	$26.0	1.5%	$22.7	-11.5%
Aggregate Costs of Zoning Regulation (million US dollars)						
All Stores	n/a	-$2.1	$0.0	-100.0%	-$17.5	742.6%
Family Mart and LAWSON	n/a	-$0.8	$0.0	-100.0%	-$8.7	940.5%

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 4. The number of local stores and demographics for each market is held fixed throughout this counterfactual analysis.

TABLE 7

PARAMETER ESTIMATES FROM NON-REVENUE MODEL

Variable	Baseline		50 % Shifted Grids		Equilibrium favors LAWSON	
	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 (δ $rival$)	-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	
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.

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TABLE 8
IMPACT OF MERGER ON ENTRY, SALES, AND COSTS
FIXED COSTS OF CLOSING AND REMODELING A STORE, ROBUSTNESS CHECK

	Baseline	Robustness Check (2)				Robustness Check (3)			
		Costs of Closing: US $150 thousand Costs of Remodeling: US $50 thousand				Costs of Closing: US $100 thousand Costs of Remodeling: US $100 thousand			
	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	237.0	222.3	-6.2%	227.2	-4.1%	207.9	-12.3%	209.9	-11.4%
Family Mart	139.9	222.3	58.9%			207.9	48.6%		
LAWSON	97.1			227.2	134.0%			209.9	116.2%
Aggregate Number of Stores to:									
Maintain (Own Chain)						139.9		97.1	
Open (Own Chain)						25.0		30.4	
Close (Own Chain)						0.0		0.0	
Close (Rival Chain)						54.1		57.5	
Remodel Rival Stores						43.0		82.4	
Aggregate Sales									
All Stores	$343.6	$328.8	-4.3%	$331.9	-3.4%	$321.5	-6.4%	$323.0	-6.0%
Family Mart and LAWSON	$234.6	$218.7	-6.8%	$222.0	-5.3%	$209.9	-10.5%	$211.6	-9.8%
Family Mart	$135.6	$218.7	61.3%			$209.9	54.8%		
LAWSON	$99.0			$222.0	124.3%			$211.6	113.8%
Local Stores	$109.0	$110.2	1.1%	$109.9	0.8%	$111.6	2.4%	$111.4	2.2%
Sales per Store									
Family Mart	$0.97	$0.98	1.5%			$1.01	4.2%		
LAWSON	$1.02			$0.98	-4.1%			$1.01	-1.1%
Aggregate Profits									
Family Mart and LAWSON	$58.7	$56.4	-3.9%	$54.7	-6.7%	$56.2	-4.2%	$52.6	-10.3%
Family Mart	$33.1	$56.4	70.5%			$56.2	70.0%		
LAWSON	$25.6			$54.7	113.8%			$52.6	105.6%
Breakdown of Profits			Δprofits		Δprofits		Δprofits		Δprofits
Profits from Demographics	$113.1	$112.9	-$0.2	$114.1	$1.0	$112.2	-$0.9	$112.8	-$0.3
Costs Savings, Across-Market	$2.6	$3.9	$1.2	$4.0	$1.4	$3.5	$0.9	$3.7	$1.0
Costs Savings, Within-Market	$23.0	$22.6	-$0.3	$23.4	$0.5	$21.6	-$1.4	$21.8	-$1.2
Business Stealing, Own Chain	-$52.1	-$71.8	-$19.8	-$73.4	-$21.3	-$69.1	-$17.1	-$69.4	-$17.3
Business Stealing, Rival Chain	-$25.7	$0.0	$25.7	$0.0	$25.7	$0.0	$25.7	$0.0	$25.7
Business Stealing, Local Stores	-$14.1	-$2.4	$11.7	-$2.4	$11.7	-$2.3	$11.8	-$2.3	$11.8
Costs of Closing & Remodeling	$0.0	$0.0	$0.0	$0.0	$0.0	-$7.6	-$7.6	-$9.9	-$9.9
Profits per Store									
Family Mart	$0.24	$0.25	7.3%			$0.27	14.4%		
LAWSON	$0.26			$0.24	-8.6%			$0.25	-4.9%
Total Sales plus Total Profits									
All Stores	$372.4	$356.6	-4.2%	$357.7	-3.9%	$350.5	-5.9%	$348.2	-6.5%
Family Mart and LAWSON	$293.2	$275.0	-6.2%	$276.8	-5.6%	$266.1	-9.3%	$264.3	-9.9%

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 4. The number of local stores and demographics for each market are held fixed throughout this counterfactual analysis.

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TABLE 9
IMPACT OF MERGER ON ENTRY, SALES, AND COSTS (second specification)

	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%
Aggregate Number of Stores to:									
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 Stores						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. The number of local stores and demographics for each market are held fixed throughout this counterfactual analysis.

Not for Publication: Appendix for Estimating a Model of Strategic Network Choice: The Convenience-Store Industry in Okinawa

November 5, 2009

A. Proofs

A.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 $N_j \in \mathbf{N}_j$. I provide a proof of a case in which across-market cost-savings and business-stealing effects occur at the market level: the magnitude of positive and negative spillover across markets depends on the presence of chain i in the neighborhood markets.[1]

I introduce a new term $h_{i,m}(N_{i,m})$ 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. In general, 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. Note here that the proof below places 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

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[1] Instead, we can think that an across-market cost-savings 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. A proof of supermodularity for this setting is available upon request.

values, and can be linear or nonlinear in the number of outlets in the market m. In the empirical specification in the main text, $h_{i,m}(N_{i,m})$ will be defined as:

$$h_{i,m}(N_{i,m}) = -\delta_{own,within} \ln(\max\{N_{i,m}, 1\}) + \alpha_{saving,within} \ln(\max\{N_{i,m}, 1\}).$$

For convenience, I define $\mathbf{X}_{i,m}$ and $\mathbf{Y}_{i,m}$ as

$$
\begin{aligned}
\mathbf{X}_{i,m} &\equiv X_m \beta + \mu_{LAWSON} * \mathbf{1}(i \text{ is LAWSON}) \\
&\quad -\delta_{local,within} \ln(N_{local,m} + 1) - \delta_{local,adj} \Sigma_{l \neq m} \frac{D_{local,l}}{Z_{m,l}} \\
&\quad -\mu_{cost} - \mu_{dist} * Distance_{i,m} - \gamma * \mathbf{1}(m \text{ is zoned}) \\
&\quad +\lambda_1 (\sqrt{1 - \rho_1^2} \varepsilon_m^r + \rho_1 \eta_{i,m}^r) - \lambda_2 (\sqrt{1 - \rho_2^2} \varepsilon_m^c + \rho_2 \eta_{i,m}^c) \\
\mathbf{Y}_{i,m} &\equiv \mathbf{X}_{i,m} - \delta_{rival,within} \ln(N_{j,m} + 1) - \delta_{rival,adj} \Sigma_{l \neq m} \frac{D_{j,l}}{Z_{m,l}}.
\end{aligned}
$$

The aggregate profit function for chain i is given by

$$
\begin{aligned}
\Pi_i(N_i, N_j) &= \Sigma_{m=1}^{M} \pi_{i,m}(N_i, N_j) \\
&= \Sigma_{m=1}^{M} [N_{i,m} * (\mathbf{X}_{i,m} + h_{i,m}(N_{i,m}) \\
&\quad -(\delta_{own,adj} + \alpha_{saving,adj}) \Sigma_{l \neq m} \frac{D_{i,l}}{Z_{m,l}} \\
&\quad -\delta_{rival,within} \ln(N_{j,m} + 1) - \delta_{rival,adj} \Sigma_{l \neq m} \frac{D_{j,l}}{Z_{m,l}}] \\
&= \Sigma_{m=1}^{M} [N_{i,m} * (\mathbf{Y}_{i,m} + (-\delta_{own,adj} + \alpha_{saving,adj}) \Sigma_{l \neq m} \frac{D_{i,l}}{Z_{m,l}} + h_{i,m}(N_{i,m})].
\end{aligned}
$$

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 $N_{i,m}^1 \equiv N_{i,m}' - \min(N_{i,m}', N_{i,m}'')$, $N_{i,m}^2 \equiv N_{i,m}'' - \min(N_{i,m}', N_{i,m}'')$, $N_{i,m}^3 \equiv \min(N_{i,m}', N_{i,m}'')$, $D_{i,l}^1 \equiv D_{i,l}' - \min(D_{i,l}', D_{i,l}'')$, $D_{i,l}^2 \equiv D_{i,l}'' - \min(D_{i,l}', D_{i,l}'')$,

and $D_{i,l}^3 \equiv \min(D_{i,l}', D_{i,l}'')$. The combined profits from choosing N_i' and N_i'' are given by

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

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

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

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

$$
\Pi_i(N_i' \wedge N_i'') + \Pi_i(N_i' \vee N_i'') - (\Pi_i(N_i') + \Pi_i(N_i''))
$$

$$
= \; B + \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'')]
$$

$$
- [A + \Sigma_{m=1}^{M}[N_{i,m}'h_{i,m}(N_{i,m}') + N_{i,m}''h_{i,m}(N_{i,m}'')]
$$

$$
= \; B - A + \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'')
$$

$$
- (N_{i,m}'h_{i,m}(N_{i,m}') + N_{i,m}''h_{i,m}(N_{i,m}''))]
$$

$$
= \; (-\delta_{own,adj} + \alpha_{saving,adj})\Sigma_{m=1}^{M}\Sigma_{l \neq m}\frac{N_m^2 D_l^1 + N_m^1 D_l^2}{Z_{m,l}}
$$

$$
+ \Sigma_{m=1}^{M}[(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'')
$$

$$
- (N_{i,m}'h_{i,m}(N_{i,m}') + N_{i,m}''h_{i,m}(N_{i,m}''))]. \tag{A-3}
$$

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-3) becomes

$$
(N_{i,m}' \wedge N_{i,m}'')h_{i,m}(N_{i,m}' \wedge N_{i,m}'') + (N_{i,m}' \vee N_{i,m}'')h_{i,m}(N_{i,m}' \vee N_{i,m}'')
$$

$$
- (N_{i,m}'h_{i,m}(N_{i,m}') + N_{i,m}''h_{i,m}(N_{i,m}''))
$$

$$
= \; N_{i,m}''h_{i,m}(N_{i,m}'') + N_{i,m}'h_{i,m}(N_{i,m}') - (N_{i,m}'h_{i,m}(N_{i,m}') + N_{i,m}''h_{i,m}(N_{i,m}''))
$$

$$
= \; 0.
$$

Combining with Eq.(A-3) yields

$$
\Pi_i(N_i' \wedge N_i'') + \Pi_i(N_i' \vee N_i'') - (\Pi_i(N_i') + \Pi_i(N_i''))
$$

$$
= \; (-\delta_{own,adj} + \alpha_{saving,adj})\Sigma_{m=1}^{M}\Sigma_{l \neq m}\frac{N_{i,m}^2 D_{i,l}^1 + N_{i,m}^1 D_{i,l}^2}{Z_{m,l}}. \tag{A-4}
$$

Note that

$$
N_{i,m}^2 D_{i,l}^1 + N_{i,m}^1 D_{i,l}^2 = \; [N_{i,m}'' - \min(N_{i,m}', N_{i,m}'')][D_{i,l}' - \min(D_{i,l}', D_{i,l}'')]
$$

$$
+ [N_{i,m} - \min(N_{i,m}', N_{i,m}'')][D_{i,l}'' - \min(D_{i,l}', D_{i,l}'')]
$$

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is nonnegative because either $N_{i,m}^2, D_{i,l}^1, N_{i,m}^1$, or $D_{i,l}^2$ is nonnegative. Therefore, we can conclude that the sufficient condition for supermodularity in its own strategy to hold is $(-\delta_{own,adj} + \alpha_{saving,adj}) \geq 0$ or $\delta_{own,adj} \leq \alpha_{saving,adj}$.

Eq.(A-4) 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 $N_j \geq \tilde{N}_j$ (so $D_{j,l} \geq \tilde{D}_{j,l}$)

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

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

So the proof reduces to show that $\Pi_i(N_i, N_j) - \Pi_i(N_i, \tilde{N}_j)$ is increasing in N_i:

$$
\begin{aligned}
&\Pi_i(N_i, N_j) - \Pi_i(N_i, \tilde{N}_j) \\
=\ & \Sigma_{m=1}^M [N_{i,m} * (\mathbf{X}_{i,m} + h_{i,m}(N_{i,m}) \\
& + (-\delta_{own,adj} + \alpha_{saving,adj}) \Sigma_{l \neq m} \frac{D_{i,l}}{Z_{m,l}} \\
& - \delta_{rival,within} \ln(N_{j,m} + 1) - \delta_{rival,adj} \Sigma_{l \neq m} \frac{D_{j,l}}{Z_{m,l}})] \\
& - \Sigma_{m=1}^M [N_{i,m} * (\mathbf{X}_{i,m} + h_{i,m}(N_{i,m}) \\
& + (-\delta_{own,adj} + \alpha_{saving,adj}) \Sigma_{l \neq m} \frac{D_{i,l}}{Z_{m,l}} \\
& - \delta_{rival,within} \ln(\tilde{N}_{j,m} + 1) - \delta_{rival,adj} \Sigma_{l \neq m} \frac{\tilde{D}_{j,l}}{Z_{m,l}})] \\
=\ & -\delta_{rival,within} * \Sigma_{m=1}^M N_{i,m}(\ln N_{j,m} - \ln \tilde{N}_{j,m}) \\
& - \delta_{rival,adj} * \Sigma_{m=1}^M N_{i,m}[\Sigma_{l \neq m}(\frac{D_{i,l} - \tilde{D}_{j,l}}{Z_{m,l}})].
\end{aligned}
$$

If both $\delta_{rival,within}$ and $\delta_{rival,adj}$ are negative, 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 both $\delta_{rival,within}$ and $\delta_{rival,adj}$ are negative, the profit function Π_i has decreasing differences in $N_{i,m}$ because $N_j \geq \tilde{N}_j$ and $D_{j,l} \geq \tilde{D}_{j,l}$. 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.

A.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:

$$
\begin{aligned}
\Pi_i(N_i, N_j) &= \sum_{m=1}^{M} \pi_{i,m} \\
&= \Sigma_{m=1}^{M}[N_{i,m} * (\mathbf{Y}_{i,m} + (-\delta_{own,adj} + \alpha_{saving,adj})\Sigma_{l \neq m}\frac{D_{i,l}}{Z_{m,l}} + h_{i,m}(N_{i,m})].
\end{aligned}
$$

.I 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 $N_{i,m}^{updated} = V_m(N_i)$ 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 component-wise $N_{i,m}^* = \arg\max_{N_{i,m}} \Pi_i(N_i, N_j)$, 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

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

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:

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

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

$$
V_m^K = D_m^K * K + (1 - D_m^K) * V_m^{K-1} \tag{A-5}
$$

$$
\text{where } V_m^K = \begin{cases} K \text{ if } D_m^K = 1 \\ V_m^{K-1} \text{ otherwise} \end{cases},
$$

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

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

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

$$
D_m(N_{i,m}', N_{i,m}'') = \begin{cases} 1 \text{ if } \Pi_i(N_{i,1}..., N_{i,m}', .., N_{i,M}) \geq \Pi_i(N_{i,1}..., N_{i,m}'', .., N_{i,M}) \\ 0 \text{ otherwise.} \end{cases} \tag{A-6}
$$

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

$$
D_m = 1[(N_{i,m}' - N_{i,m}'')[Y_{i,m} - 2(N_{i,m}' - N_{i,m}'')(-\delta_{own,adj} + \alpha_{saving,adj}) \sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}}]
$$

$$
+ N_{i,m}' h(N_{i,m}') - N_{i,m}'' h(N_{i,m}'') \geq 0]
$$

$$
= 1[Y_{i,m} - 2(-\delta_{own,adj} + \alpha_{saving,adj}) \sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}}
$$

$$
+ \frac{N_{i,m}' h(N_{i,m}') - N_{i,m}'' h(N_{i,m}'')}{N_{i,m}' - N_{i,m}''} \geq 0]. \tag{A-7}
$$

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So the D_m^K will be represented by

$$D_m^K(N'_{i,m} = K, N''_{i,m} = V_m^{K-1}) = \mathbf{1}[Y_{i,m} - 2(-\delta_{own,adj} + \alpha_{saving,adj}) \sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}} + \frac{K * h(K) - V_m^{K-1} * h(V_m^{K-1})}{K - V_m^{K-1}} \geq 0].^2$$

(A-7)

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

$$V_m^1 = D_m^1 * 1 + (1 - D_m^1) * 0 = D_m^1,$$

$$\text{where } D_m^1 = \mathbf{1}[\mathbf{Y}_{i,m} - 2(-\delta_{own,adj} + \alpha_{saving,adj}) \sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}} \geq 0]. \qquad \text{(A-8)}$$

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 m, as is clear from Eq.(A-8). Next, in the case of $K = 2$, V_m^2 will be

$$V_m^2(N_i) = D_m^2 * 2 + (1 - D_m^2)D_m^1, \qquad \text{(A-9)}$$

$$\text{where } D_m^2 = \mathbf{1}[\mathbf{Y}_{i,m} - 2(-\delta_{own,adj} + \alpha_{saving,adj}) \sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}} + \frac{2 * h(2) - V_m^1 * h(V_m^1)}{2 - V_m^1} \geq 0] \qquad \text{(A-10)}$$

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

Substituting Eq.(A-8) and Eq.(A-10) into Eq.(A-9) yields $V_m^2(N_i)$, which does not depend on $N_{i,m}$ because neither Eq.(A-8) nor Eq.(A-10) 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 nonpositive, as one can examine from Eq.(A-8). 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 $N_{i,m} = \tilde{N}_{i,m}$

---

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

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

$$= \delta_{within}(\max\{N_{i,m}, 1\} - 1)$$

then D_m^K will be

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

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-7), 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

$$
D_m(N_{i,m}^*, N_{i,m}^{**}, N_{i,l}) = 1[Y_{i,m} - 2(-\delta_{own,adj} + \alpha_{saving,adj}) \sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}}
$$
$$
+ \frac{N_{i,m}^* h(N_{i,m}^*) - N_{i,m}^{**} h(N_{i,m}^{**})}{N_{i,m}^* - N_{i,m}^{**}} \geq 0] = 1 \tag{A-11}
$$

$$
D_m(N_{i,m}^*, N_{i,m}^{**}, \tilde{N}_{i,l}) = 1[Y_{i,m} - 2(-\delta_{own,adj} + \alpha_{saving,adj}) \sum_{l \neq m} \frac{\tilde{D}_{i,l}}{Z_{m,l}}
$$
$$
+ \frac{N_{i,m}^* h(N_{i,m}^*) - N_{i,m}^{**} h(N_{i,m}^{**})}{N_{i,m}^* - N_{i,m}^{**}} \geq 0] = 0. \tag{A-12}
$$

However, both Eq.(A-11) and Eq.(A-12) cannot hold at the same time as long as δ_{across} is nonpositive 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 $N_{i,l}$.

A.4 Proof of Equilibrium Selection-Highest for Family Mart

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.[3] It follows that

$$
\begin{aligned}
N_{FM} &= BR_{FM}(N_{LS}) \text{ is nonincreasing in } N_{LS} \text{ and } N_{LS}^0 \le N_{LS}^1 \\
&\Rightarrow N_{FM}^1 = BR_{FM}(N_{LS}^0) \ge N_{FM}^2 = BR_{FM}(N_{LS}^1).
\end{aligned} \tag{A-13}
$$

Similarly, for LAWSON,

$$
\begin{aligned}
N_{LS} &= BR_{LS}(N_{FM}) \text{ is nonincreasing in } N_{FM} \text{ and } N_{FM}^1 \ge N_{FM}^2 \\
&\Rightarrow N_{LS}^1 = BR_{LS}(N_{FM}^1) \le N_{LS}^2 = BR_{LS}(N_{FM}^2).
\end{aligned} \tag{A-14}
$$

By iterating the operations in Eq.(A-13) and (A-14) sequentially for Family Mart and LAWSON until the best response algorithm converges, I have the following sequence:

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

It holds that $N_{LS}^T \le N_{LS}^*$ 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-13) and (A-14) 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 chain is nonpositive ($\delta_{comp,rival} \le 0$), it follows that

$$
\Pi_{FM}(N_{FM}^*, N_{LS}^T) \ge \Pi_{FM}(N_{FM}^*, N_{LS}^*) \tag{A-15}
$$

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

$$
\Pi_{FM}(N_{FM}^T, N_{LS}^T) \ge \Pi_{FM}(N_{FM}^*, N_{LS}^T) \tag{A-16}
$$

---

[3]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 above results.

holds because N_{FM}^T is the best response to N_{LS}^T. Combining Eq.(A-15) and Eq.(A-16), 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.

A.5 Finding Lower and Upper Bounds

I define a sequence $\{N_i\}$ that is derived by applying the optimality condition V_i multiple times, that is, $\{N_i^t\}$ 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}.

B. Estimation

B.1 Construction of Moment Conditions on Revenue

Remember that for the revenue data at the 1km^2 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

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

I define a function $R_m(X, \epsilon, \theta)$, a revenue-data generating process for market m. 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 $R_m(X, \epsilon, \theta)$:

$$R_m - E[R_m(X, \epsilon, \theta)|X] \quad = \quad I_m R_m^* - E[I_m R_m^*(X, \epsilon, \theta)|X], \tag{A-17}$$

$$\text{where } \epsilon_i \quad = \quad (\varepsilon^r, \varepsilon^c, \eta_i^r, \eta_i^c).$$

This moment condition in Eq.(A-17) will be zero when $\theta = \theta_0$ because

$$E[I_m R_m^* - E[I_m R_m^*(X, \epsilon, \theta_0|X)]|X]$$

$$= \quad E[R_m - E[R_m]|X] = 0. \tag{A-18}$$

Now consider interacting the original moment condition in Eq.(A-17) with a m-th element in $f_m(X)$,

obtaining a population moment condition for revenue:

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

The sample analogues of the population moment conditions in (A-19) is

$$g_{revenue,M}(\theta) \equiv \frac{1}{M} \sum_{m=1}^{M} (I_m R_m^* - E[I_m R_m^*(X, \epsilon, \theta)|X]) * f_m(X),$$

where $E[g_{M,revenue}(\theta)] = 0$ at $\theta = \theta_0$.

I simulate 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:

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

B.2 Moment Conditions Used in the Estimation

The current set of 27 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) interaction between (1) and (3), (6) interaction between (2) and (4), (7) Total Sales, (8)-(14): Interaction between moments (1)-(7) and daytime population, (15)-(21): Interaction between moments (1)-(7) and nighttime population, and (22)-(27): Interaction between moments (1)-(6) and zoning status index.

In population representation, moments (1)-(7) have an expected mean of zero at the true parameter as Eq.(A-18) shows. Moments (8)-(27) are based on population moment conditions. Multiplying the moment conditions (1)-(7) 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. I didn't include interaction between (7) 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.

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B.3 Method of Simulated Moments

We can estimate the derivative matrix $\hat{\mathbf{G}}$ by taking a sample mean of Jacobian of the simulated moments. 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 the average of G over simulations. The derived estimate $\hat{G}$ will be consistent under the conditions of Theorem 7.2. To account for the geographic interdependence of close-by markets, I use Conley (1999)'s nonparametric covariance matrix estimator. So the covariance matrix $\mathbf{\Lambda}$ is estimated by

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

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

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

B.4 Implementation 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 $\epsilon^s = (\varepsilon^{s,r}, \varepsilon^{s,c}, \eta_{FM}^{s,r}, \eta_{LS}^{s,r}, \eta_{FM}^{s,c}, \eta_{LS}^{s,c})$ 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, $N_{LS}^0 = (0, 0, \ldots .0)$.

    (b) Compute the best response of Family Mart N_{FM}^1, given parameter θ, simulation draw ϵ^s, and LAWSON's strategy N_{LS}^0. The computation process involves the following three steps.

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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_{FM}^1: .

(d) 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 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 $\hat{\theta}_{MSM}$.

B.5 Minimization of Objective Function

Because the objective function of MSM 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 and a pattern-search 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).

B.6 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).

C. Robustness Checks

C.1 Parameter Estimates from the Non-Revenue Model

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.

Column 1 in Table 6 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 6, 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

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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 6 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.

D. Japanese Convenience-Store Industry

D.1 Industry Background

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.[4]

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

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[4]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.

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. According to the 2004 Census of Commerce, average annual sales per store are $1.6 million USD or 161 million yen, and $1.8 million USD 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 from 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 a variety of products through franchising, which is the case in Japan's convenience-store industry.

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.

E. The 1968 Urban Planning Law

E.1 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 a requirement 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.[5] 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.

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[5] 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.

E.2 Descriptive Analysis on Zoning

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 A1 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.

Zoned areas represent 15 percent of the total nighttime population and 13 percent of the total daytime population for Okinawa.

E.3 Effects of Eliminating Zoning: Non-Revenue Model

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 7 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.

E.4 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 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 shorter 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 concerning 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.

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TABLE A1
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.