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

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**Abstract**

Spatial competition among multi-store firms is ubiquitous in a wide range of retail industries. However, little is known about how those firms optimize their networks of stores after a merger due to the computational burden of solving for an equilibrium in store networks. This paper proposes an empirical framework for estimating a game of network choice by two multi-store firms, which allows us to examine the impact of a hypothetical merger on store configurations, costs, and profits. The model explicitly incorporates a fundamental determinant of location choice for multi-store firms: the trade-off between the business-stealing effect and the cost-saving effect from clustering their own stores. The method integrates the static entry game of complete information with post-entry outcome data while using simulations to correct for the selection of entrants. I use lattice-theoretical results to deal with the huge number of possible network choices. Using unique cross-sectional data on store networks and revenues from the convenience-store industry in the Okinawa Island, Japan, I estimate the firms' revenue and cost functions. Parameter estimates suggest a retailer's trade-off between cost savings and lost revenues from clustering its stores is positive across markets and negative within a market. I find an acquirer of a hypothetical horizontal merger of two multi-store firms would decrease its number of stores in suburbs but increase its number in the city center, affecting consumers in different locations differently. The trade-off from clustering plays a central role in explaining this result.

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# 1 Introduction

How do mergers affect store networks of multi-store firms? Spatial competition among multi-store firms developing their networks of stores, such as 7-Eleven, Wal-Mart, Target, Walgreens, CVS, Office Depot, Staples, Starbucks, McDonald's, and Burger King, has become ubiquitous in a wide range of retail industries.[1,2] The growing presence of multi-store firms has drawn scrutiny from antitrust agencies. A prominent case is *FTC v. Staples Inc.* [970 F. Supp. 1066 (D.D.C. 1997)] in which the U.S. Federal Trade Commission blocked a merger between Staples and Office Depot, two of the three largest nationwide office supply superstores. As the case's hearings and documents have demonstrated, controlling for any likely changes in store repositioning is at the heart of simulating the post-merger prices.[3] In practice, antitrust agencies and merging parties are often forced to rely on ad-hoc assumptions on the post-merger market structure, such as whether the target's stores would be either closed permanently or converted to the acquirer's stores in markets in which both retailers compete head-to-head.[4] Due to multi-firms' trade-offs from clustering their stores, however, the effect of mergers on store networks is theoretically ambiguous.

This paper proposes a framework for estimating a model of strategic network choice by two multi-store firms, which allows us to examine the impact of a hypothetical merger on store configurations, costs, and profits. Despite the growing interest from antitrust agencies, little academic research has been conducted to develop an empirically tractable model of store-network choice, because solving and estimating an equilibrium model of store-network choice poses substantial computational challenges.[5,6] This article addresses these challenges by employing the lattice-theoretical

[1] Retail sales constitute a significant amount of modern economies. In the United States, for instance, estimates suggest sales from retail and food services in 2009 were $4,091 million, which is about 30% of the U.S. GDP in 2009. See the report from the U.S. Bureau of Economic Analysis: http://www2.census.gov/retail/releases/current/arts/sales.pdf.

[2] Multi-store retailers are often marked by their well-designed networks of stores, reflecting product differentiation in location and the economies of scale in distribution and advertising.

[3] The government illustrated the differences in scenarios on the post-merger number and identity of stores, as well as the measurement competition, drive the non-negligible differences in the estimated price change between the government and the merging parties. See Baker (1999) and Ashenfelter, Ashmore, Baker, Gleason, and Hosken (2006) for details.

[4] Another recent case in which the post-merger network of stores is assumed exogenously is the Whole Foods' merger with Wild Oats (*Federal Trade Commission v. Whole Foods Market, Inc.*, 533 F.3d 869 (D.C. Cir. 2008). See Draganska, Mazzeo, and Seim (2009a).

[5] Two notable exceptions are Holmes (2011) and Jia (2008), who provide two complementary methods for studying a multi-store firm's network formation.

[6] For instance, consider a game with 2 players, 20 markets, and 5 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 makes the search for an equilibrium impossibly large. In the empirical application, the number of markets is 834.

approach.

The model explicitly captures two fundamental determinants of multi-store firms' store-network choice, which make location decisions across markets interdependent, unlike a standard entry model in which entry decisions across markets are independent. The first determinant is the trade-off from clustering the firm's stores. On the one hand, a retail chain may want to avoid opening too many of its stores in the neighborhood, because the per-store sales may decrease as the number of own chain stores increases (cannibalization or own-business-stealing effect).[7] On the other hand, a retail chain may benefit from clustering its stores because the firm can save on logistical costs, such as gas for delivery trucks or the costs of advertising in local newspapers (economies of density). Multi-store firms internalize this trade-off from clustering their stores both within a market and across markets. The second determinant is the presence of a rival firm: store-level sales may decrease as the number of rival chain stores increases (business-stealing effect).

This paper makes two methodological contributions. The first contribution is to extend the lattice-theoretical approach by Jia (2008) by introducing a density dimension to the choice of a firm. Namely, firms not only choose whether to enter a given market (the extensive margin) but also the number of stores to open in the market (the intensive margin). This generalization has two advantages. First, the density dimension allows us to evaluate the effects of a merger on the network of stores. The effect of mergers on product choice is theoretically ambiguous even in its simplest form, and several additional factors complicate the chain-entry model, including overlapping markets through demand and cost spillovers and the trade-off from clustering.[8] Practically, unlike a binary-choice model in which one has to either drop observations from urban markets or treat market outcomes in those markets as exogenously given, this framework can conduct a hypothetical merger analysis to answer the empirical question posed above, because it can handle both rural and urban markets. Second, the model enables us to separately identify the gross business-stealing effects from gross cost-saving effects, and the net trade-off from clustering both within a market and across markets. The framework can accommodate either a positive or negative net trade-off from clustering within a market, which has important implications for antitrust and regulatory policies for predicting the store configurations.

The second contribution is to integrate the static entry games of complete information with

[7] In what follows, I use the terms "multi-store firm" and "chain" interchangeably.

[8] For instance, in the class of Hotelling (1929)'s line-segment model of location choice, conclusions vary wildly according to the assumptions on the model primitives, such as fixed costs and transportation costs. For some theoretical examples, see Anderson, De Palma, and Thisse (1992) and Berry and Waldfogel (2001).

post-entry outcome information, such as revenue, to identify cost and revenue functions and to rescale parameters in monetary units. I jointly estimate the system of network choice equations and post-entry revenue equations while correcting for the selection of store openings. I do so by simulations, thereby distinguishing this study from previous ones 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 (2012). The closest paper in this methodological respect is Draganska, Mazzeo, and Seim (2009b), who estimate the model of multi-product firms' product assortment and pricing decisions. A benefit over a standard static entry model is the framework allows us to evaluate in monetary units the efficiency gains in cost savings due to a merger, which are often unavailable.

This paper applies the framework to the data from the convenience-store industry in Okinawa, Japan. Surprisingly little economic research has analyzed the industry, compared to other retail industries, such as supermarkets, discount retailing, and fast food industries, despite its growing presence in many economies.[9][10] The data from Japan provide us a unique opportunity for understanding equilibrium network decisions: each chain adopts nationwide uniform pricing, allowing us to abstract away pricing decisions at the store level (or even Okinawa Island level). Aside from the antitrust standpoint, developing an empirical model of network choice of multi-store firms is of first-order importance for understanding the behavior of multi-store firms. For instance, Figure 1 presents the actual configurations of stores for two convenience-store chains in Okinawa. The figure may prompt a question of why strikingly dense store-clustering patterns can arise in the industry.[11] If we regard the observed networks as the outcomes of a game, what are the underlying structural primitives that yield the observed dense store networks? The article pursues this empirical question.

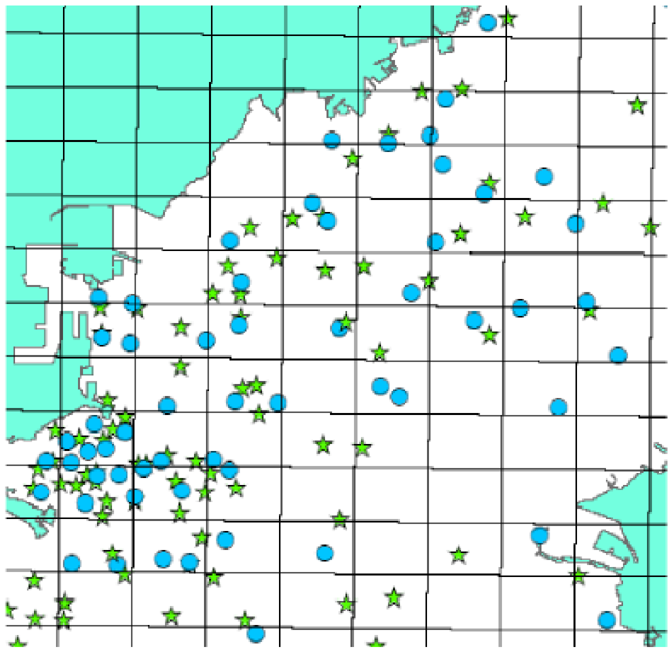
[9] See Wood and Browne (2006) and the references contained therein.

[10] For instance, 7-Eleven, the world's largest convenience chain, operates in more than 16 countries with more than 44,700 stores in 2012. The number of 7-Eleven stores exceeds the number of Wal-Mart stores and McDonald's by approximately 34,000 and 11,000, respectively.

[11] As Section 2 describes, the chain-affiliated convenience stores show geographically different clustering patterns from those of non-chain-affiliated convenience stores or retail stores as a whole in Okinawa.

FIGURE 1

STORE CONFIGURATIONS AND 1 KILOMETER SQUARE GRIDS



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

This paper interprets the data as the noncooperative outcome of a static game of complete information. I use cross-sectional data from 2001 that I manually collected from the convenience-store industry in Okinawa. I estimate the model parameters by minimizing the gap between the data and the model prediction, which I obtain by employing lattice-theoretical results to solve for a Nash equilibrium. Based on the parameter estimates, I simulate the effects of a merger on the acquirer's store network by solving for the profit-maximization problem.

Estimates of the model suggest the net trade-offs from clustering within a market and across markets are negative and positive, and these trade-offs provide, indeed, economically significant impact for the convenience-store chains. The positive (negative) trade-off implies the cost-saving effect dominates (is dominated by) the cannibalization effect. A striking finding from a hypothetical merger is that the acquirer would increase stores in city-center markets in which population density is high, whereas it would decrease the number of stores in suburban and rural markets in which population density is low. In other words, the hypothetical merger affect consumers oppositely in markets with different population density. These findings are robust to plausible alternative specifications. The implications may seem to contradict the conventional wisdom that the acquirer would monotonically decrease the number of stores to avoid cannibalization (business-stealing effect from own stores). However, the trade-offs from clustering, positive across markets and negative within a market, explains the logic behind these results. In a high-population-density market, a merger may increase the total positive net trade-off across markets, because the presence of own stores in adjacent markets may increase due to the merger. The increase in net cost savings across markets may offset the negative trade-off within a market, namely, the net business-stealing effect, resulting in an increase in the total number of store in that market after merger. In contrast, in a market in which own and rival stores exist but no stores can hardly exist in adjacent markets due to low population density, the negative trade-off within a market dominates the total positive net trade-off across markets, resulting in a decrease in the total number of stores in that market after merger.[12]

The second empirical application of the framework is to examine the impact of eliminating the zoning regulation introduced in 1968 that 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 restrictions. In zoned markets, one needs to obtain development permission from the government to open a convenience store. I find that eliminating the existing regulation would increase the total number of stores for each multi-store firm by around $26\% - 28\%$ in zoned markets.

The paper is organized as follows. In the remainder of this section, I relate my work to earlier literature. Section 2 describes the dataset. Section 3 specifies the equilibrium network-choice model and provides analytical results. Section 4 discusses the empirical implementation of the framework. Section 5 reports the parameter estimates. Section 6 performs two counterfactuals: a hypothetical merger and a change in zoning regulation. Section 7 describes the sensitivity analysis. Finally, Section 8 concludes. The Appendix contains proofs of propositions, computation and estimation details, other robustness checks, details of the zoning regulation, and a numerical example.

## 1.1 Related Literature

This paper builds on a vast literature of game-theoretic models of static entry, initiated by Bresnahan and Reiss (1990, 1991). Researchers have added 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 2009), all under the specification of a game being played in a single market: an entry decision in a market is independent of entry decisions in

[12] Section 6 and Appendix E provide detailed explanations for these two cases.

other markets. As a consequence, the empirical study has been limited to isolated markets in which one can safely assume no coordinated entry or demand/cost spillover exists across markets. In contrast, this paper is related to recent progress in the entry literature relaxing the isolated-markets assumptions by assuming firms develop their store networks (Jia 2008; Ellickson, Houghton, and Timmins 2010; Holmes 2011). This paper relates to Davis (2006a) and Jia (2008) in that it applies lattice theory to entry game, and it extends Jia (2008)'s results in two ways. First, this paper allows firms to have a density dimension in the choice set in every market. Second, it integrates the chain-entry game with post-entry outcomes. Both Holmes (2011) and Ellickson, Houghton, and Timmins (2010) employ a revealed preference approach for estimating the model parameters. Compared to those two papers, this paper explicitly solves for the equilibrium to estimate the model. To estimate the trade-off from clustering stores, Holmes (2011) focuses on a single retailer's (i.e., Wal-Mart's) dynamic aspect of store-network formations, whereas Ellickson, Houghton, and Timmins (2010) focus on Wal-Mart, Kmart, and Target's equilibrium location choice using the cross-sectional data. Although Holmes (2011) captures the dynamic aspects of network formations this paper abstracts, this paper accommodates strategic interactions the Holmes's paper abstracts away. The framework by Ellickson, Houghton, and Timmins (2010) has a benefit of not having to restrict the number of multi-store firms up to two. This paper instead (1) accommodates the trade-off across markets, and (2) separately identifies the trade-off components, such as cost-saving and business-stealing effects, and provides interpretations in monetary units.

The seminal article by Hotelling (1929) introduced the model of competition with spatial differentiation. Researchers have studied the geographical aspect of competition for industries such as fast food (Thomadsen 2005; Toivanen and Waterson 2005; Yang 2012), movie theaters (Davis 2006b), discount retailers (Zhu and Singh 2009), retail gasoline (Manuszak 2000 and Houde 2011), wholesale gasoline (Pinkse, Slade, and Brett 2002), video rental (Seim 2006), and eyeglasses (Watson 2005). This paper complements the subsequent spatial-competition literature by highlighting the importance of strategically choosing networks of stores.

Lastly, by interpreting the location as the distance between product characteristics, this paper is linked to the literature on the effect of mergers on product choice and pricing of multi-product firms. Recent examples include Draganska, Mazzeo, and Seim (2009b), Sweetings (2010), Fan (2011), and Jeziorski (2011).[13] The closest paper in focusing on the post-merger store-location choice of multi-

[13] The list of work provided here is not exhaustive: see, for instance, Draganska, Mazzeo, and Seim (2009a) and Crawford (2012), and references therein.

store firms is Gandhi, Froeb, Tschantz, and Werden (2008), who provide a numerical analysis on the post-merger pricing and store-location choice in a single market with a fixed number of stores. Compared to those approaches above, this paper makes progress by focusing on product positioning, thereby providing an empirical model of multi-product duopoly in which the number of product markets is quite high and interdependent due to demand and cost spillovers across markets. This paper complements Nevo (2000) and Smith (2004), who study how mergers among multi-product firms affect equilibrium prices.

## 2 Industry and Data

**Convenience-Store Industry in Japan.** The convenience-store industry is a rapidly growing retail format in many countries in the last several decades.[14] The convenience-store industry in Japan is concentrated in that a handful of nationwide large players with many outlets dominate the industry: the six national chains account for 71% of total number of convenience-store outlets in Japan in 2002 ($41,770$ stores) and 82% of the total sales. Nationwide, a large number of stores achieves the economies of scale in distribution, advertising, product developments, and purchasing power, just as in the case of discount retailers or supermarket chains.

As its name suggests, the industry focuses on consumer convenience in store accessibility and the variety of items available relative to floor space. 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 or bicycle and 30% by car. Each chain strives to offer similar shopping experiences: the variety of merchandise and other services are as uniform as possible across outlets. Due to nationwide uniform pricing and the homogeneity of store formats across stores, such as the number of items, the variety of services, and floor size, geographic differentiation is the most important avenue of product differentiation.

The industry invests heavily in sophisticated distribution networks for two reasons. First, each store does not have much space for inventory, because a typical store has about $3,000$ items on about 110 square meters ($1,184$ square feet) of floor space. Second, 70% of the sales are perishables: stores need to preserve the freshness of foods, such as lunchboxes, rice balls, and sandwiches, which

[14] In Japan, most stores do not have fuel pumps. The overall industry sales in Japan in 2004 were 6.7 trillion yen, or about US$60 billion, which is approximately 5% of total retail sales. In the United States, the corresponding industry sales in 2007, namely, the sales of stores excluding stores with fuel pumps, were about US$21 billion. Industry sales of gasoline stations with convenience stores were US$331 billion.

delivery trucks need to replace two to three times a day.

Given the importance of location, unsurprisingly, 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 network of stores and the locations of its competitors' stores. Although franchising is widespread in the industry in Japan, chain headquarters make store-location and pricing decisions.

Okinawa has an area of $1,201$ square kilometers (463.7 square miles), and in 2002, a population of 1.4 million. The island has only two nationwide convenience-store chains, Family Mart and LAWSON, each with a distribution center and a network of stores. Family Mart is the third-largest convenience-store chain in Japan with approximately $5,800$ retail stores nationwide, in 36 prefectures in 2001. LAWSON is the second-largest convenience-store chain (after 7-Eleven, which had $8,600$ stores in Japan in 2001), with $7,600$ retail stores in all prefectures in Japan in 2001. Family Mart opened its first store in 1988, 10 years earlier than LAWSON. In the Okinawa prefecture, the numbers of stores for Family Mart and LAWSON were 142 and 102, respectively, in 2001.

**Market Definition.** Most entry models treats markets as isolated in costs and demand. However, retail markets often overlap in both dimensions: people travel across borders to purchase goods, and cost complementarity exists across markets. To avoid treating contiguous markets, previous studies on entry focus on industries in which markets are small and isolated. This paper takes an opposite stance: I divide Okinawa into $1,201$ mutually exclusive grids with an identical shape and area (1km$^2$), treating a grid as the smallest unit of analysis. For the purpose of convenience, I call each cell or grid a "market" throughout the paper, although I allow for costs and demand spillovers across adjacent markets. To avoid including uninhabitable or undevelopable areas, such as mountain regions, as potential markets for convenience stores, I exclude 367 grids that have no population either during the day or night. This exclusion leaves me with a sample of 834 markets that cover 834km$^2$ or 322mi$^2$, which is 69% 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 each 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.

**Data and Summary Statistics.** I have manually compiled the cross-sectional data sets I use in the study from a variety of sources. For the convenience-store-location data, I rely on the Convenience Store Almanac in 2002 (TBC 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% of the total number of 24-hour convenience stores in Okinawa, match at the level of lot addresses. For the remaining 20%, 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. The left panel of Figure 2 shows the location of stores for Family Mart and LAWSON in Okinawa.

FIGURE 2
CONVENIENCE STORES IN OKINAWA

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

Table 1 provides summary statistics. 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, which 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 Census Bureau. It contains information on the number of workers, which captures the daytime demand for convenience stores. Table 1 shows a $1\text{km}^2$ 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.

The number of stores in a given $1\text{km}^2$ market for these two chains ranges from 0 to 7 and 0 to 6, respectively. Note that on average there are 0.17 and 0.12 stores per market for Family Mart and LAWSON, respectively. There are 80 non-chain local stores.[15] For Family Mart, only 81 stores out of 142 total stores are single stores within a given market. For LAWSON, 67 stores out of total 102 stores are single stores within a given market.

Each chain has its own distribution center. Rows 9 and 10 show the distance from the centroid of each market to the distribution center for each chain is about 30 kilometers on average.

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 $1\text{km}^2$ uniform grid. The revenue data have an exogenous sample selection rule for each category of stores that, to protect the privacy of each individual store, total revenues with less than three stores in a given market will not be disclosed. The total sales at the $1\text{km}^2$ level do not disclose the sales by multi-store firm brands. The bottom rows of Table 1 show the average sales per store are US$1.43 million for Family Mart and US$1.45 million for LAWSON, suggesting no noticeable difference in sales per store between these chains.

**Evidence on Geographical Clustering Patterns of Stores.** The strikingly dense store networks depicted in Figures 1 and 2 lead 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 (Cliff and Ord 1981) and the General G index, both of which are traditional measures for 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 patterns for three store-type categories: all retail stores including

[15] In 2001 in Okinawa, another chain, Hot Spar, existed. In this study, however, I treat the Hot Spar stores as non-chain local stores for which locations store owners choose. I do so because the Hot Spar company originally started as a voluntary chain in Okinawa, and the company did not make coordinated store-location decisions.

convenience stores; chain-affiliated convenience stores, namely, Family Mart and LAWSON; and independently operated convenience 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.[16] Rows 1 through 3 of Table 2 show the Moran's I index for chain-affiliated convenience stores (0.41) is higher than for the retail stores as a whole (0.34) or for the independently operated (non–chain-affiliated) convenience stores (0.13). 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 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 to evaluate the degree of concentration.[17] Column 3 gives the results from the General G index. All Z-scores are above the significant value, and the ranking of Z-scores among the store categories are similar to those of Moran's I index.

Overall, the results that different store categories yield different degrees of geographical clustering motivate a further analysis of multi-store firms' store-network choice.

# 3 Game of Choosing Store Networks

## 3.1 Model

The convenience-store industry in Okinawa has two players, Family Mart and LAWSON, who, in the model, design optimal store networks, each taking into account its competitor's store-network configurations. I model the market structure as being determined by the strategic actions of two players choosing a player's store network in equilibrium.

Formally, I consider an entry game in which two players, player $i$ and player $j$, $i, j \in \{Family\ Mart, LAWSON\}$, choose their store networks in the first stage and compete either in prices or quantities in the second stage. The first stage is a simultaneous-move game of complete information.[18] I denote a strategy vector for player $i$ and player $j$ by $N_i$ and $N_j$. A set of mutually exclusive

[16] If all neighboring markets were to have the same number of stores of a given category, the Moran's I would be near 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 $-1$. If no apparent geographical pattern of stores were present, the index would be near 0.

[17] The higher the Z-score, the more clustered the geographical pattern.

[18] Complete information has two advantages over private information in the context of static entry games. First, in games of private information, players may have ex-post regret about their store-network choice. This feature makes

discrete markets exists within the Island, and the set of markets is indexed by $m = 1, ..., M$. A strategy vector for multi-store firm $i$, or firm $i$'s store network, is an $M * 1$ vector: $N_i = (N_{i,1}, ..., N_{i,M})$. So the $m$th element of $N_i$, $N_{i,m}$, denotes the number of stores player $i$ opens in market $m$. $N_{i,m} = 0$ implies firm $i$ does not enter market $m$. I define player $i$'s multi-dimensional strategy space by $\mathbf{N}_i$, which is a subset of a finite-dimensional Euclidean space $\mathbf{R}^M$.[19] Each firm chooses its store network, $N_i = (N_{i,1}, .., N_{i,M})$, to maximize its profits.

I start by specifying the per-store profit function for player $i$ in market $m$ as $\pi_{i,m}(N_i, N_j)$. This per-store firm profitability at market $m$ does not depend only on player $i$'s decision regarding the number of stores in market $m$, $N_{i,m}$; rather, the profitability is a function of player $i$'s entire network $N_i$ and the competitor's network $N_j$ due to the trade-off between cost savings and business stealing across markets, in addition to the demographics in market $m$.

I decompose this firm $i$'s per-store profit function into per-store revenue and costs as $\pi_{i,m}(N_i, N_j) = r_{i,m}(N_i, N_j) - c_{i,m}(N_i)$, where $r_{i,m}(N_i, N_j)$ is the per-store revenues and $c_{i,m}(N_i)$ is the per-store costs for firm $i$ stores in market $m$. Because I do not have information on prices and quantities, I follow the tradition in the static entry literature by modeling the revenue and cost functions in a reduced-form fashion.[20] The firm $i$'s per-store revenues at market $m$ are modeled as a function of the number of stores, market characteristics, and unobservable revenue shocks:

$$
\begin{aligned}
r_{i,m}(N_i, N_j) \quad = \quad & \underbrace{X_m \beta}_{\text{demographics}} + \underbrace{\delta_{own,within} \log(\max(N_{i,m}, 1)) + \delta_{own,across} \sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}}}_{\text{cannibalization, or business-stealing effect from own chain stores}} \\
& \underbrace{\delta_{rival,within} \log(N_{j,m} + 1) + \delta_{rival,across} \sum_{l \neq m} \frac{D_{j,l}}{Z_{m,l}}}_{\text{business-stealing effect from rival chain stores}} \\
& \underbrace{\delta_{local,within} \log(N_{local,m} + 1) + \delta_{local,across} \sum_{l \neq m} \frac{D_{local,l}}{Z_{m,l}}}_{\text{business-stealing effect from local stores}} \\
& + \underbrace{\mu_{LAWSON} * 1(i \text{ is LAWSON})}_{\text{brand fixed effect, LAWSON}} + \underbrace{\lambda_1 (\sqrt{1 - \rho_1^2} \epsilon_m^r + \rho_1 \eta_{i,m}^r)}_{\text{revenue shocks}}.
\end{aligned}
$$

treating the observed data as the equilibrium outcomes of the static game more difficult. Second, games of private information assume the econometrician has the same uncertainty as each player about a rival player's payoff, which is unlikely to hold, particularly when we do not observe detailed market characteristics.

[19] 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. 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.

[20] See, for example, Berry (1992), Mazzeo (2002), and Seim (2006).

In the above per-store revenue function, $N_{i,m}$, $N_{j,m}$, and $N_{local,m}$ are the number of stores of own firm, rival firm, and local stores in market $m$, respectively. The within-market competition-effect 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 in market $m$. If these within-market business-stealing effects indeed exist due to other stores in the same market, we would expect $\delta_{own,within} \leq 0, \delta_{rival,within} \leq 0$, and $\delta_{local,within} \leq 0$. Similarly, the across-market competition-effect parameters, $\delta_{own,across}, \delta_{rival,across}$, and $\delta_{local,across}$, measure the impact of the presence of own stores, competitor stores, and rival stores in markets other than market $m$ on store-level sales in market $m$.[21] $D_{i,l}$ is a dummy variable that equals one if at least one firm $i$'s store is in market $l$ and 0 otherwise. $D_{j,l}$ and $D_{local,l}$ are defined similarly. $\sum_{l \neq m} \frac{D_{i,l}}{Z_{m,l}}$ counts the total number of adjacent markets that contain firm $i$'s stores, weighted by the distance between markets $m$ and $l$, $Z_{m,l}$. I follow the conventional treatment in the entry literature that the revenue at the store level is declining in the log number of stores in the same market, implying the marginal loss in revenues by adding a store is declining in the number of stores in a given market. For the revenue decrease due to the stores outside of the market, I assume the presence of stores in adjacent markets can matter.[22] $X_m$ are observable demographic characteristics of market $m$ that affect the demand for convenience stores. $\mu_{LAWSON}$ measures the LAWSON fixed effect in revenues. $\varepsilon^r_m$ is a shock to revenues at the store level that I assume is common to any stores in market $m$, both local and multi-store firm, and i.i.d. across markets. $\eta^r_{i,m}$ is a firm-market-specific shock to revenues i.i.d. across firms and markets.[23] I assume both shocks are drawn from a standard normal distribution and are observed by two multi-store firms but unobserved by the econometrician. I also assume the shocks are independent of the exogenous variables. $\rho_1$ measures the correlation of combined unobservables across multi-store firms in a given market. $\lambda_1$ is a parameter that captures the magnitude of the sum of the revenue shocks.

The firm $i$'s per-store costs at market $m$ are modeled as a function of the number of firm $i$'s stores, distance to each firm's distribution center, market characteristics, and unobserved cost

[21] In the empirical specification, I restrict my attention to the case in which stores that are not in markets adjacent to market $m$ do not impact the sales and the cost of stores in market $m$. However, Appendix A.1 provides a general proof that applies to the case in which this restriction is not necessary for the analytical results in the following subsection to hold.

[22] An alternative specification of the demand spillover would be to assume the per-store sales decline in the total number of stores in adjacent markets. Under this specification, we can prove the game will be supermodular by slightly modifying the original proof in Appendix A.1. The proofs are available upon request. Appendix C.1. contains the empirical results based on this alternative cost specification.

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

shocks:

$$\begin{aligned} c_{i,m}(N_i) = \quad & \underbrace{\alpha_{within}\log(\max(N_{i,m},1)) + \alpha_{across}\sum_{l\neq m}\frac{D_{i,l}}{Z_{m,l}}}_{\text{cost increases from stores within a market and adjacent markets}} \\ & + \underbrace{\mu_{dist} * d_{i,m}}_{\text{costs due to distance to distribution center}} + \underbrace{\gamma * 1(\text{market } m \text{ is zoned})}_{\text{fixed costs due to regulation}} \\ & + \underbrace{\mu_{cost}}_{\text{common fixed costs}} + \underbrace{\lambda_2(\sqrt{1-\rho_2^2}\epsilon_m^c + \rho_2\eta_{i,m}^c)}_{\text{cost shocks}}. \end{aligned} \quad (1)$$

The parameter $\alpha_{within}$ captures the gross cost increases from having a store of the same firm in the same market. $\alpha_{across}$ measures the gross cost increases from the presence of the same chain stores in adjacent markets. Note the positive signs in front of these parameters in the cost function: if the presence of own chain stores in the same market (adjacent markets) indeed reduces the per-store costs due to several factors, including cost savings in distribution or advertising, we would expect $\alpha_{within} \leq 0$ ($\alpha_{across} \leq 0$).[24] I define the net across-market trade-off from the presence of the same chain stores in adjacent markets as $\kappa_{across} \equiv \delta_{own,across} - \alpha_{across}$. If this trade-off parameter $\kappa_{across}$ is positive, the trade-off positively impacts the profits. Similarly, I define the net within-market trade-off from clustering as $\kappa_{within} \equiv \delta_{own,within} - \alpha_{within}$. The parameter $\mu_{cost}$ is the component of per-store fixed costs common across firms and markets. $d_{i,m}$ measures the (log) distance to firm $i$'s distribution center from market $m$. The fixed costs of zoning, parameterized by $\gamma$, capture the increase in the fixed costs the store may incur in obtaining permission to develop a store in a zoned area. $\varepsilon_m^c$ 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 firm-market-specific shock to costs i.i.d. across firms and markets. $\rho_2$ measures the correlation of combined unobservables across firms in a given market. $\lambda_2$ 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 firms but unobserved by the econometrician. I assume the shocks are independent of the exogenous variables. I take the location choice of a distribution center for each firm as given due to analytical tractability.

I denote the payoff function for player $i$ and player $j$ 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 player $i$ and player $j$, $N_i \in \mathbf{N}_i$ and $N_j \in \mathbf{N}_j$. Firm $i$'s total profits, $\Pi_i(N_i, N_j)$, are the sum of the market-level profits across all markets

[24] In other words, the cost saving effect within a market and across markets are $-\alpha_{within}$ and $-\alpha_{across}$, respectively.

$m = 1, .., M$. The market-level profits in market $m$ are simply the per-store profits at market $m, \pi_{i,m}$, multiplied by the number of stores in market $m$, $N_{i,m}$.[25] Namely,

$$\Pi_i(N_i, N_j) = \Sigma_{m=1}^{M}[N_{i,m} * \pi_{i,m}(N_i, N_j)].$$

This specification includes a normalization that if firm $i$ does not open a store in $m$, profit contribution from that market is zero. Player $i$ maximizes this objective function, $\Pi_i(N_i, N_j)$, by choosing its store network, $N_i = (N_{i,1}, ..., N_{i,M})$. The solution concept is pure-strategy Nash equilibrium, which is a pair of store networks that are best responses.

## 3.2 Algorithm One: Computing a Nash Equilibrium

### 3.2.1 Supermodularity of Chain-Entry Game

This subsection provides conditions under which the chain-entry game I develop in the previous subsections is supermodular. Topkis (1979, 1998) shows supermodular games have several convenient features.[26] Two such features are the existence of pure-strategy Nash equilibria and a round-robin algorithm for computing a Nash equilibrium.

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 firm $i$'s strategy space $\mathbf{N}_i$. To compare two $M * 1$ 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 $N_{i,m} \geq N_{i,m}'$ $\forall m = 1, ..., M$.[27] $\mathbf{N}_i$ is a *sublattice* if the meet and join of any two strategy vectors in $\mathbf{N}_i$ is also in $\mathbf{N}_i$.[28] 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 $N_i \in \mathbf{N}_i$.[29]

Now I introduce the definition of supermodularity of a game and the proposition that provides sufficient conditions for the game to be supermodular.

[25] Davis (2006a) and Ellickson, Houghton, and Timmins (2010) adopt the same approach to construct the market-level profits for a multi-store firm.

[26] 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.

[27] 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 "$\geq$".

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

[29] 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.

**Definition (Supermodularity of a Game)** *A supermodular game is one in which, for each* $i \in \{Family\ Mart, LAWSON\}$*, (1) a strategy space* $N_i$ *is a compact sublattice, (2)* $\Pi_i(N_i, N_j)$ *has increasing differences in* $(N_i, N_j)$*, and (3)* $\Pi_i(N_i, N_j)$ *is supermodular in* $N_i$*.*

**Proposition 1 (Supermodularity of the Chain-Entry Game)** *The chain-entry game the previous subsections present is supermodular if* $\kappa_{across}(= \delta_{own,across} - \alpha_{across}) \geq 0$*,* $\delta_{rival,within} \leq 0$*, and* $\delta_{rival,across} \leq 0$*.*

**Proof**. See Appendix A.1.

Increasing differences of a payoff function in $(N_i, N_j)$ (condition 2) in Definition imply firm $i$'s marginal profits of increasing his strategy $N_i$ are increasing in his rival's strategies $N_j$.[30] Supermodularity of profit function in firm $i$'s strategy (condition 3) in Definition implies that for a given firm $j$'s strategy, firm $i$'s sum of profits by choosing the meet $N_i' \wedge N_i''$ and the join $N_i' \vee N_i''$ 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 $N_i', N_i'' \in \mathbf{N}_i$.

Proposition 1 asserts the net trade-off across markets, $\kappa_{across}$, must be nonnegative; in other words, the presence of own stores in adjacent markets is cost reducing, that is, profit increasing, and the presence of a rival store always reduces the revenue.[31] Namely, aside from the parameter restrictions in the proposition, we can use the data to freely estimate the levels of these trade-off parameters within a market and across markets. This result is useful when knowing ex-ante whether the cannibalization effect ($\delta_{own,across}$) dominates the cost-savings effect ($-\alpha_{across}$) is difficult and

[30] The non-positive signs of $\delta_{rival,within}$ and $\delta_{rival,across}$ in Proposition 1 indicates the number of rival stores needs to be strategic substitutes. Although this condition is natural in the context of entry games in which an entry of rival firms often makes entering the market less attractive, the condition may seem contradictory to the increasing differences property in Definition of supermodularity of a game. Indeed, Appendix A-1 reveals these non-positive parameters will lead to decreasing differences in $(N_i, N_j)$ for the profit function $\Pi_i$. As I discuss in the appendix, a transformation technique in Vives (1990), which defines new strategies for two players, $\hat{N}_i = N_i$ and $\hat{N}_j = -N_j$, together with the non-positive signs of $\delta_{rival,within}$ and $\delta_{rival,across}$, will yield increasing differences in $(\hat{N}_i, \hat{N}_j)$ for the profit function $\Pi_i(\hat{N}_i, \hat{N}_j)$. This transformation defines a new equivalent game that is supermodular. For expositional convenience, notation throughout this paper continues with the original strategies and profit function, $(N_i, N_j)$ and $\Pi_i(N_i, N_j)$, because the transformation will not affect the analytical results.

[31] The first parameter restriction implies the cost reduction from economies of density ($-\alpha_{across}$, gross cost savings) across markets dominate the gross cannibalization ($\delta_{own,across}$, business-stealing effect) across markets. The second and third restrictions imply stores are substitutes. Imposing those restrictions can be problematic if people could gain from shopping multiple convenience stores by having more variety of goods and services, such as a shopping center industry, and therefore gross positive demand spillovers could result from clustering. In the convenience-store industry in Japan, because the store format is pretty homogeneous across stores within a firm and across firms, people usually do not visit multiple stores at a time.

imposing parameter restrictions on the trade-off would be thus problematic.[32] This theoretical result highlights the crucial departure from the binary-choice model: we may split existing markets into smaller new markets so the binary-choice model can deal with every market. However, we would always need to have the cost savings from the presence of stores in newly-created adjacent markets to be always profit increasing; that is, $\kappa_{across} \geq 0$, which may be hard to justify for an industry with dense configurations of stores. On the other hand, in the multi-store setting, we do not have to restrict the sign of the trade-off within a market, both in gross and in net. As a result, the model accommodates richer patterns of trade-offs from clustering stores.

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

**Theorem 1 (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 $i$.*

### 3.2.2 Round-Robin Optimization to Compute a Nash Equilibrium

I specify a round-robin algorithm, in which each player proceeds sequentially to update his own strategy by choosing a myopic best response, whereas the strategy of the other player is held fixed.[33] 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, $N_{LS}^0 = \inf(\mathbf{N}_{LS}) = (0, 0, .., 0)$.

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

[32] The analytical result does not rely on specific functional forms of the within-market cannibalization effect (own-business-stealing effect) and the within-market cost-savings effect. The underlying insight of the proof in Appendix A-1 is that changing the order of summation does not change the sum for the within-market tradeoff term when checking condition 3 of supermodularity.

[33] This iterated best-response approach is essentially the same as the one Davis (2006a) explores, although he refers to it as Cournot tattonnement.

- **Step 3**. Compute the best response of LAWSON given Family Mart's best response $N^1_{FM}$: $N^1_{LS} = \underset{N_{LS}}{\arg\max} \Pi_{LS}(N_{LS}, N^1_{FM})$.
- **Step 4**. Iterate the above steps (b)-(c) $T$ times until we obtain convergence: $N^T_{FM} = N^{T+1}_{FM}$ and $N^T_{LS} = N^{T+1}_{LS}$. Converged vectors of strategy profiles for Family Mart and LAWSON, $(N^T_{FM}, N^T_{LS})$, are a Nash equilibrium. The number of iterations, $T$, is bounded by the number of markets, $M$: $T \leq 4M$.

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

### 3.3 Algorithm Two: Deriving Lower and Upper Bounds of Best Response

Of the above steps, the most computationally challenging are steps 2 and 3, in which I compute the best response given the competitor firm's entry configuration. This subsection derives an algorithm that yields the upper and lower bounds of the best response for each multi-store firm based on the Tarski (1955)'s fixed-point theorem. By doing so, one need only evaluate the strategy vectors that are above the lower bound and below the upper bound instead of all possible strategy vectors, substantially reducing the burden of searching for the profit-maximizing vector.

The starting point of the algorithm is to construct a function that maps from firm $i$'s strategy space choice to itself. In particular, I introduce a coordinate-wise updating function $V_{i,m}$, 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 firm $i$. Because $N^*_i$ is the profit-maximizing vector for firm $i$ given rival's decision $N_j$, it follows $N^*_{i,m} = V_{i,m}(N^*_i, N_j)$. 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 the optimality condition $V_i$ is nondecreasing in its argument as long as the across-market trade-off is nonnegative.

**Proposition 2 (Nondecreasing Coordinate-wise Optimality Condition)**$V_i(N_i)$ *is nonde-*

*creasing in* $N_i$ *if* $\delta_{own,across} - \alpha_{across} \geq 0$ *(or, equivalently,* $\kappa_{across} \geq 0$*).*

**Proof**. See Appendices 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 $V(N_i) \geq V(\tilde{N}_i)$. By using the property of $V_i(N_i)$ being nondecreasing in $N_i$, I 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 2 (Fixed-Point Theorem [Tarski 1955])** *Let* $\mathbf{N}_i$ *be a complete lattice,* $V_i : \mathbf{N}_i \to \mathbf{N}_i$ *a nondecreasing function, and* $E$ *the set of the fixed points of* $V_i$*. Then* $E$ *is nonempty and is a complete lattice. In particular, because* $E$ *is a complete lattice, a greatest and least fixed point exist in* $E$*; that is,* $\sup E = \sup\{N_i \in \mathbf{N}_i : V(N_i) \geq N_i\}$ *and* $\inf E = \inf\{N_i \in \mathbf{N}_i : V(N_i) \leq N_i\}$*.*

To obtain the least and greatest fixed points of $V_i : \mathbf{N}_i \to \mathbf{N}_i$, see Appendix A.5. After obtaining the lower and upper bounds, $N_i^{LB}$ and $N_i^{UB}$, I find the best-response vector $N_i^* = \underset{N_i \in \{0,1,..,K\}^M}{\arg\max} \Pi_i(N_i, N_j)$ by evaluating every vector $N_i$ such that $N_i^{LB} \leq N_i \leq N_i^{UB}$.

### 3.4 Multiple Equilibria

As is often the case for static simultaneous-move games of complete information, the pure-strategy Nash equilibria may not be unique in the model. Note 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.

There are three approaches to deal with the issue. First, one may focus on the uniquely predicted quantity from the model, such as the total number of firms in a market in the framework of Bresnahan and Reiss (1991). Davis (2006a) finds the market output is uniquely determined within the set of Nash equilibrium in the differentiated product quantity games of multi-store firms. Unfortunately, numerically computing the model predictions from these two extreme equilibria reveals the model does not uniquely predict the aggregate number of stores across equilibria. Second, one may be agnostic about the equilibrium selection via the partial identification as in Ciliberto and Tamer (2009). I do not choose this route, however, because a goal of this paper is to simulate the post-merger store network. This paper choose the third approach, which is to introduce an equilibrium selection mechanism. The algorithm allows us to compute two equilibria, the most profitable equilibrium for Family Mart and the most profitable one for LAWSON. I choose the former equilibrium because Family Mart's aggregate profits are likely to be higher than the ones of LAWSON, because Family Mart, the first mover in Okinawa, has about 40% more stores than LAWSON. Section 7 discusses the robustness check on the equilibrium selection.

## 4 Estimation via Method of Simulated Moments

I estimate the model by choosing model parameters that minimize the difference between observed data and outcomes the model predicts. Because the supermodular game does not yield a closed-form solution for the equilibrium number of stores and revenues for a given parameter $\theta$, I employ simulation methods to generate moment conditions that measure the gap between the observed revenues and number of stores and the conditional expectation of revenues and number of stores.

Formally, I define $N_{i,m}(X,\epsilon,\theta)$, which specifies the data-generating process for the number of stores of firm $i$ in market $m$. $\epsilon$ is a vector of predetermined shocks unobserved to the econometrician. Matrix $X = [X_{i,1}, d_{i,1}, d_{j,1}; ...; X_{i,m}, d_{i,m}, d_{j,m}; ...; X_{i,M}, d_{i,M}, d_{j,M}]$ consists of $X_{i,m}$, which contains exogenous market characteristics for firm $i$, such as daytime and nighttime population, the zoning regulation status, other retail sales, and $d_i$ and $d_j$, which measure the distance from market $m$ to the firm $i's$ and $j'$s distribution center, respectively. $\theta$ is a vector of model parameters. Note the data on the number of stores $N_{i,m}$ are generated at the true $\theta_0$ and predetermined variables $(X,\epsilon)$: $N_{i,m} = N_{i,m}(X,\epsilon,\theta_0)$. Using these notations, I obtain a population condition for the number of stores:

$$g_{store}(\theta) \equiv E[(N_{i,m} - E[N_{i,m}(X,\epsilon,\theta|X)]) * f_m(X)|X] \ = 0 \text{ at } \theta = \theta_0, \tag{2}$$

where $f_m(X)$ is a function of observed predetermined variable $X$, which will serve as a set of instruments. The sample analogue of the population moment conditions in Eq.(2) is given by

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

where $E[g_{M,store}(\theta)] = 0$ at $\theta = \theta_0$. I simulate the conditional expectation $E[N_{i,m}(X_i,\epsilon,\theta)|X]$ 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 $\epsilon$:

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

I assume $\epsilon^s_i = (\varepsilon^{s,r}, \varepsilon^{s,c}, \eta^{s,r}_i, \eta^{s,c}_i)$, $i \in \{FamilyMart, LAWSON\}$, $s = 1, ..., S$ are drawn from a standard normal distribution. The number of simulations is set at $S = 200$ for the study.

I also construct the moment conditions on revenue in a similar manner. I stack up all these 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 the following objective function:

$$\hat{\theta}_{MSM} = \arg\min_{\theta} [\hat{g}_M(\theta)]\mathbf{W}[\hat{g}_M(\theta)]', \tag{3}$$

where $\mathbf{W}$ is a weighting matrix. Note that decisions firms make in each market is not independent across markets due to the cannibalization and cost savings across markets. To account for this geographic interdependence of nearby markets, I use Conley (1999)'s nonparametric covariance matrix estimator. Appendix B provides further details on (1) the implementation of the full estimation procedure, (2) the construction of 39 moment conditions including moment conditions on revenue, (3) the minimization of the criterion function in Eq.(3), (4) the nonparametric estimation of the covariance matrix under spatial dependence across markets, and (5) the generation of Halton draws.

### 4.1 Exclusion Restriction

The parameters measuring across-market cost savings and cannibalization are identified by the observed geographical clustering patterns of stores and the cross-sectional variations in revenues. Incorporating the revenue information allows us to identify the cannibalization parameter separately from the cost-savings parameter. The distance variable to distribution center in Eq.(1) serves as an exclusion restriction for identification of the competitive effect, because this variable does not enter the other firm's profit function. To understand the intuition, consider a set of markets that are equally distant from firm $i$'s distribution center. Suppose the locations of distribution centers are different across firms. The set of markets has a variation in the distance to firm $j$'s distribution center. The variable that measures the distance to firm $j$'s distribution center shifts the profit function of firm $j$ and thus entry decisions of firm $j$. The change in firm $j$'s entry decision due to the distance to its distribution center is independent of the correlated error terms across firm $i$ and $j$. The shift in firm $j$'s entry behavior would therefore create an exogenous variation in firm $i$'s profit function because the effect of the variation in firm $j$'s distance to the distribution center is excluded from firm $i$'s profit function (exclusion restriction). We then identify the competitive effect of firm $j$ on firm $i$ by observing how much change in firm $j$'s entry behavior, due to a variation in the distance variable of firm $j$, causes change in firm $i$'s entry behavior.

## 4.2 Adding Post-Entry Outcome while Correcting for Selection

Adding post-entry outcome allows us to separately identify cost and revenue functions and to rescale parameters in monetary units. Simply estimating revenue equations separately from entry models and feeding parameters to entry models without endogenizing network-choice behavior, however, suffers from a selection issue. The problem is we only observe revenues for markets in which the multi-store firms actually open stores, and, therefore, unobservable demand shocks that affect revenue are also likely to affect decisions regarding whether to enter a market and how many stores to open. For example, 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 observed aggregate revenue of stores in market $m$ and $X_m$ 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 $m$. $\epsilon_m$ captures factors that affect total revenue in market $m$ that the econometrician does not observe. The revenue equation involves a sample selection problem for the following two reasons. First, if the unobserved revenue shocks $\epsilon_m$ affect the decision of how many stores to open in market $m$, $N_m$, the equation violates the zero-correlation assumptions needed for consistency. Second, the data on total revenue are available only for the markets in which multi-store firms 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.[34]

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 first estimate the probability of selection or agents' expectations, and then run 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 2012, respectively). However, this two-step estimation procedure would be infeasible in most chain-entry problems because the number of possible outcomes or the number of possible strategies of the game is exponential in the

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

number of markets. Furthermore, estimating the selection equation in the first step is difficult for the chain-entry model because 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 considers an alternative strategy in which I use joint MSM estimation of the entire model parameters by stacking up the moment conditions regarding selection and outcome.[35] McFadden (1996) summarizes the intuition on how the simulation method allows us to avoid the selectivity issue: "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 model, if I figured out a correctly specified model and true parameters, I should be replicating the model outcome variables, such as number of stores or revenue at each market, in such a way that we do not see any systematic deviations from the observed data. The key variable in constructing the selection model is to have a selection indicator for the total number in market $m$ in $s$th simulation.[36]

An advantage of the one-step approach with simulation is its simplicity: unlike the two-step approaches, the method does not require integration of the errors over complex regions to calculate the selectivity-corrected term nor involve sequential steps including estimating the control function.

## 5 Empirical Results

Table 4 presents the parameter estimates from the two specifications of the model. I first discuss the results from the baseline specification, which are in the first column of the table. I later return in Section 7 to the results from the sensitivity-check specification, which are in the second column.

All of the demographic parameters have a positive and statistically significant effect on store sales. For instance, the coefficient on the nighttime population implies per-store sales in a market having $1,000$ more people than other markets will be higher by US$$52,850$ annually, which is about 4% of total annual sales for an average store.

The presence of stores in the same market, regardless of its chain affiliation, has a negative impact on the store-level revenues as expected. The estimates in rows 4 - 9 of column 1 in Table 4 measure the business-stealing effect due to the presence of three types of stores. These parameters that measure the cannibalization effect (own-business-stealing effect) within a market by own firm

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

[36] See Appendix B for details.

stores ($\delta_{own,within}$) and the business-stealing effect by rival firm stores ($\delta_{rival,within}$) are negative and precisely estimated at the 1% confidence level, suggesting the existence of other stores in the same market pushes down the revenue significantly. For example, when a firm has only one store in a market, adding another store from the same firm in the same market decreases the revenue of a store by US$186,297 ($= \log 2 * \$268,770$) annually, which is about 13% of total annual sales for an average store. Similarly, adding a rival store in the same market dampens the per-store sales by 16% of total annual sales. The presence of a non-chain store reduces the revenue much less than an own or rival store does, and the magnitude is not statistically significant. Meanwhile, the business-stealing effects seem to decline quickly with distance: all three parameters that measure the business-stealing effect across markets, $\delta_{own,across}$, $\delta_{rival,across}$, and $\delta_{local,across}$, are smaller than the corresponding within-market business-stealing effects and imprecisely estimated. This finding suggests the business-stealing effects across markets (or gross demand spillovers across 1km$^2$ grids) do not seem to be playing a big role in the industry, which is consistent with various surveys that suggest the consumer's average travel time to a convenience store is around 10 to 20 minutes by walking, and a trade area for a typical convenience store has a radius of about 500 to 700 meters.[37]

The presence of own chain stores has a positive effect on profits. Row 1 in the second panel from the top in Table 4 presents the estimate of $-\alpha_{within}$, the coefficient on the gross cost savings from the presence of stores from the same firm in the same market. The estimated magnitude of the parameter is US$97,796 ($= \log 2 * \$141,090$). The positive sign of $-\alpha_{within}$ implies the presence of the same chain store within a market lowers the costs. Row 2 of the second panel in Table 4 displays the estimate of $\kappa_{across}$, the net trade-off from the presence of stores from the same chain in adjacent markets. The point estimate is positive and $8,500 per year and per market and is statistically significant at the 5% confidence level. In contrast to the positive net trade-off from clustering across markets, $\kappa_{across}$, the net trade-off from clustering within a market, $\kappa_{within}$, implied by the business-stealing and cost-saving parameters within a market, will be negative and US$127,680 ($\kappa_{within} = \delta_{own,within} - \alpha_{within} = -\$268,770 - (-\$141,090)$). The implied gross cost savings from the stores in adjacent markets, $-\alpha_{across} = -(\delta_{own,across} - \kappa_{across})$, will be US$32,330($= -(-\$23,830 - \$8,500)$). The magnitude of the gross cost savings is of the same order of magnitude as the annual salary of the average truck driver in Japan, which is

[37] Although not shown in the tables due to space constraints, I also estimate the model without these three types of business-stealing effect across markets. Not too surprisingly, the quantitative results are similar to the ones described in this section.

US\$41,200. Overall, the results confirm the presence of net economies of density (or cost savings) across markets. One implication of positive trade-off across markets, $\kappa_{across}$, and negative trade-off within a market, $\kappa_{within}$, would be that even though both the cannibalization effect and the cost-saving effect decline in distance, the cannibalization effect is more localized in the sense that the cost cost savings decrease less with distance than the cannibalization effect does.[38]

Of further interest is the coefficient on the zoning status index in row 4 in the second panel in Table 4, which is positive and precisely estimated. The sign implies being in the zoned area increases the store's fixed costs of operation, including the combined costs of going through all the application and screenings. The monetary value of the annual costs translates to US\$42,410 per year.

As anticipated, I find that stores benefit from locating close to the distribution center: the parameter estimate $\mu_{distance}$ enters the costs equation statistically significantly. The parameter coefficient predicts a typical store incurs US\$55,000$(= \log(30) * 16.2)$ in distribution costs, which is about 6% of the annual fixed costs of a store ($\mu_{cost}$).

One way to measure the overall fit of the model is to compare the model predictions of how many total stores each multi-store firm opens with the actual store counts. Rows 1 and 2 in Table 3 present the observed data, implied aggregate number of stores, and the standard deviation of its prediction for each firm across simulations. In general, the estimated model fits the patterns of the data reasonably well. The mean of the simulated number of stores from the model with estimated parameters matches closely the actual number of stores: the model predicts the total number of Family Mart stores, which is 139 in the data, to be 140.83 on average across 200 simulations, with a standard deviation of 11.63. The model predicts the total number of LAWSON stores, which is 100 in the data, to be 99.02 stores on average across 200 simulations, with a standard deviation of 10.62 stores. The model predicts the aggregate sales, which is US\$169,334,000 in the data, to be US\$167,379,590, with a standard deviation of US\$13,331.81.

## 6 Policy Simulations

This section uses the parameter estimates of the model to perform "what-if" experiments, namely, evaluating the impact of a hypothetical merger and changes in the zoning regulation on the mar-

[38] This finding is consistent with casual observations 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.

ket structure. In all simulations, the demographics and the number of local stores are taken as exogenous and unchanging before and after the policy change.

### 6.1 Effects of a Merger on Store Networks

Predicting the post-merger network of stores is one of the backbones of antitrust analysis in which the impact of a merger on welfare is assessed. With the estimated model, we can simulate the likely impact of a hypothetical merger on the acquirer's store network. Because this chain-entry model is static, I treat the hypothetical merger as an exogenous one-time event and evaluate the changes in the network of stores and profits.[39] I reoptimize the acquirer's store network by solving the monopolist's profit-maximization problem. Given the pre-merger duopoly networks of stores, the acquirer decides whether to open new stores, close own or rival stores, or convert rival stores to own stores in a given market. To solve for the profit-maximizing configurations of stores, I use the algorithm on deriving lower and upper bounds of best response in Section 3. The model solves for each simulation using the same draw of the revenue and cost shocks that are used for estimating the model parameters. I set the maximum number of stores the merged chain can open to eight within a market, which is doubled from the pre-merger regime.

Often an acquiring firm bears one-time sunk costs associated with making changes in the pre-merger store networks. There are three types: costs of opening, closing, and converting a store. The costs of opening a store include the fraction of the initial setup costs of a store that cannot be recovered when the store exits the market. Similarly, the costs of closing a store include unavoidable costs associated with cleaning up the site so other types of tenants can move in. The costs of converting a store from a target chain into own chain include the costs of changing name boards, IT systems, or interior decorations. I rely on information sources about the costs of changing the networks of store. In particular, I assume a firm incurs costs of US$350,000, US$150,000, and US$100,000 for opening, converting, and closing a store.[40] For the costs of opening and closing a

[39] A nationwide merger that is exogenous to the markets in Okinawa prefecture would be an example.

[40] I rely on external sources regarding these cost estimates because without panel data, the estimated fixed cost parameters in Table 4 cannot separately identify operating fixed costs from sunk costs. See Bresnahan and Reiss (1994) for a method of identifying sunk costs using an extended model of Bresnahan and Reiss (1991) with panel data of entry and exit. More ideally, one may prefer to recover from structural models the sunk costs of opening and closing a store. The literature of estimating sunk costs of entry and exit in dynamic games has been growing recently, after the development of two-step methods to estimate the distribution of entry and exit costs of dynamic entry games. Examples include Aguirregabiria and Mira (2007), Bajari, Benkard, and Levin (2007), Pakes, Ostrovsky, and Berry (2007), Pesendorfer and Schmidt-Dengler (2008), and Arcidiacono and Miller (2011). I do not choose this route because estimating a dynamic game of store-network choice would require the panel data on timing of entry and exit, which unfortunately I do not have. Also, adding the dynamic aspect to this chain-entry model is analytically

store, I use the direct cost estimates from these chains' Annual Securities Report in 2001 (Family Mart 2001). For the cost of converting a rival chain store into own chain store, I use the cost estimates from the 2010 acquisition of a nationwide chain (ampm) by Family Mart. Because the costs of converting a store are less than the sum of the costs of closing and opening a store, an acquiring chain that considers expanding the number of stores in a market would convert rival establishments into own stores rather than scrap existing rival stores and build new stores. This assumption is consistent with the industry practice, which is probably not very surprising given the store formats are similar across chains.[41] Because the model parameters measure per-period flow (i.e., annual), I set the discount factor to 10% per year to rescale those one-shot lump-sum costs into the costs incurred annually.[42] Later, I employ an alternative assumption of 5% discount factor as a robustness check.

Table 5 displays the simulation results. The second column presents the results in which Family Mart takes over as a post-merger monopolist. The total number of stores in Okinawa decreases by 0.7% from 239.8 stores, which is the combined number of Family Mart and LAWSON stores before the merger. Although the total number of stores does not change significantly, rows 4 through 8 suggest the acquirer goes through a massive reoptimization of its store configurations. Family Mart, for instance, converts 45 out of a total 99 rival stores, and the remaining 54 rival stores closed permanently. The 53 stores the acquirer newly opens are in different markets than those in which the 54 rival stores were originally located. The forth column of Table 5 presents the results in which LAWSON takes over as a post-merger monopolist. 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.

Figure 4 presents the increase (left panel) and decrease (right panel) in the total number of stores for each market after merger. The figure reveals that, although the total number of stores does not change significantly, the store network after the merger exhibits quite different geographical patterns compared to the pre-merger geographical store networks. With the geographical distribution of population density shown in Figure 8 in mind, a striking pattern is that the acquirer tends to increase the number of stores in city centers to fully exploit the cost-savings benefits from adjacent markets, whereas the acquirer reduces the number of stores in non-city centers or rural markets.

intractable because of the dimensionality of the strategy space.

[41] I also tried other specifications in which the costs of coverting a store exceed the combined costs of opening and closing a store. The simulation results are similar to the ones described in this section.

[42] We back out the per-year costs of opening a store, $c_{open}$, by $\frac{c_{open}}{0.1} = \$350,000$.

The post-merger store-network of LAWSON as the acquirer exhibits quite similar geographical patterns: more clustering in the city centers and less in the rural markets.

The trade-off from clustering provides the intuition behind this post-merger patterns of stores.[43] For a given firm, a market is "active" when it has at least one store from the firm. The positive net trade-off across markets, $\kappa_{across}$, implies the more active markets a firm has in adjacent markets, the more positive net trade-off across markets the firm would receive from these adjacent markets overall. For instance, consider a market in which a chain does not have rival chain's store. If the chain has three active adjacent markets before merger, the store(s) in that market would enjoy $3 * \kappa_{across}$, if we abstract from the difference in the distance from the market to each of these adjacent markets. If, after the merger between Family Mart and LAWSON, the acquirer has six active markets in adjacent locations for a given market, the acquirer would enjoy $6 * \kappa_{across}$ from these adjacent markets. The acquirer, therefore, have more incentive to open an additional store for that market, because the increased total trade-off across markets from adjacent markets may offset the negative within-market trade-off from clustering, $\kappa_{within}$. In contrast, the acquirer might have fewer stores in less populated markets, because the negative within-market trade-off, caused by the cannibalization effect dominating the cost-saving effect within a given market, is more likely to outweigh the total positive trade-off across markets from active adjacent markets. If the merger makes no change in the number of active markets in adjacent markets due to low population, the acquirer might decrease the total number of stores in that market to internalize and avoid the business stealing within a market.[44]

Both Figure 6 and the right panel of Table 5 explore the robustness of the simulation results to the alternative 5% discount factor assumption. By using this value, I am essentially halving the annual costs of opening, converting, and closing a store. In theory, I should observe more rival stores to be converted and fewer stores to be closed, because the absolute difference in costs between converting and closing a store becomes narrower. I should expect more stores to open, because the threshold of opening a store becomes lower. Columns 6 through 9 in Table 5 confirm the results are consistent with these predictions. In general, I find no significant difference from the baseline specification. Figure 6 exhibits the geographical post-merger pattern of stores is similar to the one in Figure 4: more stores in the city-center markets and fewer in the rural markets.

[43] Appendix E contains numerical examples of two cases: the total number of stores in a given market (1) increases after merger, and (2) decreases after merger.

[44] On the consumer side, the increase in the number of stores in urban markets will have a positive effect in terms of decreased travel costs, whereas the decrease in the number of stores in rural markets will have a negative impact.

The second panel from the top in Table 5 shows the total sales decline by about 3% to 4%, following the reduction in the total number of stores. The per-store sales also decline by about 3%, a proportion similar to the reduction in the total number of stores. The aggregate profits, on the other hand, increase by 25%, suggesting the merger is highly profitable without the change in prices. The third and fourth rows from the bottom in columns 2 and 4 reveal the per-store profitability has increased proportionally: a 24.9% increase for Family Mart and a 25.1% increase for LAWSON. Column 4 in the third panel from the top in Table 5 provides a breakdown of the changes in the total profits. The number shows the contribution to the change in total profits that comes from the increased cost efficiencies due to clustering, combining both within and across markets, is economically significant: US$27 million. The magnitude of this gross cost savings is large enough to offset the the increase in the total business-stealing effects from clustering, combining both within and across markets, which is US$15 million.

Overall, the simulation results provide evidence that the cost-savings and the business-stealing parameters are indeed key variables in predicting the resulting store network, cost savings, and profits after a merger.

### 6.2 The 1968 Urban Planning Law

The current Urban Planning Law, enacted in 1968 to prevent urban sprawl, defines zoned areas and requires firms and residents to obtain permission from local authorities before constructing a building in zoned areas. The regulation does not place an upper bound on the number of stores firms can develop; rather, the act permits developing stores in zoned areas, provided the submitted store development plan complies with strict construction requirements.[45] As Figures 7 and 8 show, zoned areas are more likely to be suburban areas surrounding Okinawa's city center. In the sample, 140 out of 834 markets are categorized as zoned areas.

Measuring the impact of zoning regulation on entry is important for two reasons. First, the deregulation of zoning restrictions in urban areas 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 claim that the requirements are excessively restrictive for retail outlets wanting to open in zoned areas. Second, the regulation directly affects firms' decisions regarding where to

[45] See Appendix D.1. for the institutional details of the regulation.

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 or land-use regulation 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 model of entry as in Griffith and Harmgart (2008), Ridley, Sloan, and Song (2008), Suzuki (2010), and Datta and Sudhir (2011).

To conduct the deregulation policy experiment, I set the index function in Eq.(1), $1(m \text{ is zoned})$, to zero in every market in the data. To conduct the opposite policy experiment in which a firm needs to apply for zoning approval in all 834 markets, I set this index function to one in every market. In each scenario, the model solves for the equilibrium that favors Family Mart using the same draw of the revenue and cost shocks that are used for estimating the model parameters. The prediction from the model is given by the equilibrium store network averaged across 200 simulations.

Table 7 summarizes the key findings of these counterfactual experiments. Columns 2 and 3 present the results under the no-zoning-permission-system regime. As would be expected from the positive sign and the magnitude of the zoning parameter $\gamma$, I find that eliminating the current zoning regulation would moderately increase the number of stores because it is now less costly to open a store: rows 1 and 3 of column 3 show that for Family Mart and LAWSON, we would expect about a 2.2% increase in total stores. Rows 2 and 4 focus on the change in the originally zoned 140 markets, and I find most of these increases in store counts are largely due to an increase in the number of stores in the previously zoned markets. In fact, in those 140 zoned markets, the percentage increase in the total number of stores is large: around 26.1% and 27.6% for Family Mart and LAWSON, respectively. The model also predicts aggregate sales and profits will increase by 1.3% to 1.4%, almost proportional to the increase in the number of stores. Regarding the costs due to the permission system, I define the magnitude of the cost by multiplying the zoning parameter $\gamma$ by the number of stores in zoned markets. I find the reduction of costs associated with the deregulation for Family Mart and LAWSON is US$0.83 million, which is 1.2% of aggregate profits of Family Mart and LAWSON.[46] The impact of zoning deregulation on costs is nontrivial considering the number of stores currently located in zoned markets is small: 11.4 stores for Family Mart and 8.2 stores for LAWSON. Illustrating this point, columns 4 and 5 in Table 7 show how

[46] Note the costs' calculation does not take into account benefits consumers may receive from the regulation, such as neighborhood quality or open space, due to the data limitation.

much the opposite policy regime affects the results. 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. For instance, the increase in the cost associated with regulatory compliance would be US$8.11 million, which constitutes 14.9% of the combined profits of Family Mart and LAWSON. The number of stores drop significantly, too: around a 12% decrease for both firms.

Figure 5 presents the configurations of stores before and after eliminating the current zoning policy. These figures confirm that in no-zoning regimes, the increase in the number of stores occurs primarily at the border that divides zoned and unzoned markets. Markets predicted to have stores after the deregulation are different across Family Mart and LAWSON because their store networks before the deregulation and cost shocks are different. In particular, the figure shows 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 firm has its existing stores.

# 7 Sensitivity Analysis

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

**Full Model with A Smaller Set of Variables.** One might be concerned some of the parameters from the baseline model in Table 4 that are not precisely estimated, including the business-stealing effects across markets and the LAWSON dummy, may drive the policy exercise results in Tables 5 and 7 and Figures 4 and 6. To address this concern, I re-estimate the model by removing all variables from the baseline model that are not statistically significant at the 5% confidence level. The second column in Table 4 shows the signs and the magnitude of the estimates are reasonably similar to those of the baseline model.

Table 6 presents the merger counterfactual results. Probably not too surprisingly given estimates are close across specifications, both specifications 1 and 2 yield the results quantitatively and qualitatively similar to the ones we have in Table 5, indicating imprecisely estimated parameters do not drive the counterfactual results. Although not shown due to space limitations, the findings from the zoning policy experiments these estimates imply do not change either qualitatively or quantitatively. Figure 9 shows the merger counterfactual using the parameter estimates in the second column in Table 4. The degree of store clustering is smaller than the ones in Figures 4 and 6, which is reasonable given the smaller magnitude of the estimated net cost savings across markets. However, similar geographical patterns of network of stores that we observe in Figures 4 and 6 remain: the acquirer increases the number of stores in the city-center markets and decreases the number in non-city markets.

**Model without Revenue Equation and Alternative Choices of Grids.** This robustness check examines whether incorporating revenue data or using the original grid definition is driving the parameter estimates Table 4 reports. The simplified profit function at the store level for firm $i$ in the non-revenue model is specified similar to the full model as

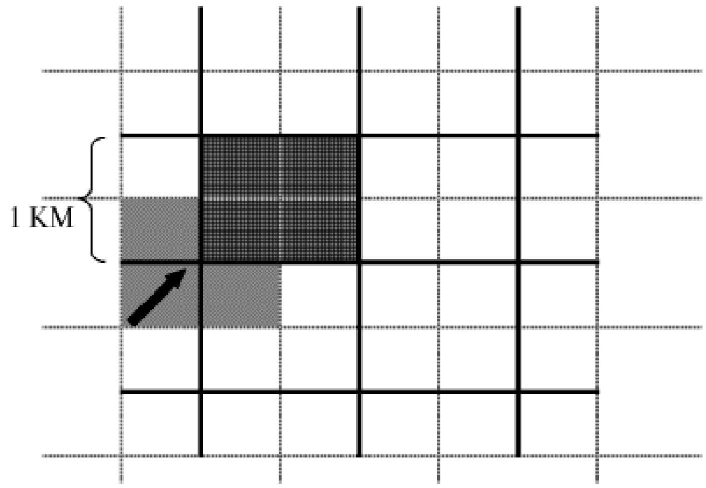
$$\begin{aligned}\pi_{i,m}(N_i, N_{j,m}) &= X_m\beta + \delta_{rival,within} \ln N_{j,m} + \kappa_{across} \sum_{l \neq m} \frac{N_{i,l}}{Z_{m,l}} + \kappa_{within} \ln(\max\{N_{i,m}, 1\}) \\ &\quad + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{i,m} + \gamma \mathbf{1}(m \text{ is zoned}).\end{aligned}$$

I assume both $\varepsilon_m$ and $\eta_{i,m}$ are normally distributed. The variance of the error term is normalized to one because it cannot be separately identified from the scale of the model parameters. No signs are assumed ex-ante except for the restriction $\kappa_{across}$ being nonnegative. I use this non-revenue model for the robustness check of the grid definition because the Census Bureau holds back revenue information from the public when a market has less than three stores, and we will not have well-defined revenue data for most of the newly defined markets unless there are four adjacent markets with more than two stores, which is rare in the sample.

I construct a second sample of markets with store counts and demographics by using the original grid-level data. Figure 3 presents a different set of 1km$^2$ 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 store), demographics, such as population, and a zoning index. 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 the point 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 worker density are uniform within the four original grids. As in the original sample, I exclude from the sample markets that have no population either during the day or at night, leaving a sample of $1,138$ markets.

Columns 1 and 2 in Table 8 display the estimates for the original market definition, and columns 3 and 4 provide the results for the newly created sample. In both specifications, most parameters have the anticipated sign. For instance, the net trade-off within a market, $\kappa_{within}$, is negative, implying the own-business-stealing effect dominates the cost-saving effect within a market, which is consistent with the full model. The relative magnitudes among the coefficients on variables are similar across both specifications, although the statistical significance differs somewhat. Appendix D.3. shows the non-revenue model yields impact of the zoning policy on store configurations that are quantitatively similar to the full model with revenue. The last two rows in columns 1 and 3 in Table 8 compare the data and the estimated model's prediction. Both the baseline and shifted grids specifications fit the data in a similar way. Overall, the shifted-grid specification yields similar results to the baseline specification, providing evidence that neither the post-entry data nor the assumption about the location of the grid has played a big role in driving the results in Section 6.

**Alternative Equilibrium Selection Rule.** This robustness check examines whether the results are sensitive to the choice of the equilibrium selection rule. To implement this robustness check, I re-estimate the model with the assumption that the equilibrium is the one most profitable for LAWSON. Column 5 in Table 8 displays the estimation results with this alternative equilibrium selection rule. Again, the net trade-off within a market, $\kappa_{within}$, is negative. The model with the alternative selection rule predicts a number of stores for each chain similar to the number the baseline model predicts. The difference between the baseline and the alternative selection-rule specification is the presence of a negative coefficient on the LAWSON dummy variable. This negative fixed effect for LAWSON shows the estimated parameters need to reconcile the fact that the observed number of stores is about 40% fewer than Family Mart with LAWSON being the first mover in the myopic best-response iterations in the round-robin algorithm. Aside from this fixed effect, no significant difference exists in the signs of parameter across specifications.

## 8 Concluding Remarks

Assumptions on the post-merger network of stores are crucial for evaluating multi-store firms' merger cases. This paper proposes an empirical model of strategic store-network choices by two multi-store firms, which allows us to examine the impact of a hypothetical merger on store configurations, cost savings, and profits. This paper extends the existing lattice-theoretical approach by introducing a density dimension to the choice of a firm: firms not only choose whether to enter a given market (the extensive margin) but also the number of stores to open in the market (the intensive margin). In doing so, the model explicitly incorporates two fundamental determinants of multi-store firms' store-network choice, which make location decisions across markets interdependent: the trade-off from clustering its stores and the presence of rival firms. The method integrates the static entry games of complete information with post-entry outcome data while correcting for the selection of entrants by simulations. I employ lattice-theoretical results to deal with the huge number of possible network choices. I use the cross-sectional data from 2001 that I manually collected from the convenience-store industry in Okinawa. Based on the parameter estimates, I simulate the effects of a merger on a retailer's store network by solving for the acquirer's profit-maximizing problem. Estimates of the model suggest the net trade-offs from clustering are, indeed, an important consideration for the convenience-store chains. The simulation results confirm that after a hypothetical merger between Family Mart and LAWSON, the post-merger density of stores of the monopolist firm in the city center would be greater than the combined density of Family Mart and LAWSON stores before the merger. I find that eliminating the existing zoning regulation would increase the total number of stores for each multi-store firm by around $26\% - 28\%$ in zoned markets.

Three limitations in the model deserve mention. First, the framework abstracts from change in price before and after a merger or deregulation. An important extension would incorporate models of differentiated product demand, such as Berry (1994) and Berry, Levinsohn, and Pakes (1995), if a researcher has information on prices and quantities. This integration would also allow us to explore the welfare consequences of mergers through the price elasticities. Second, the current framework does not accommodate the case in which the number of players exceeds two. In reality, many industries have more than two multi-store firms. Last, the model is static and therefore ignores dynamic aspects of the industry, such as merger decisions or preemption of the first mover. Although the dimensionality of choice set poses a formidable challenge for incorporating dynamics, relaxing the static assumption would prove useful.

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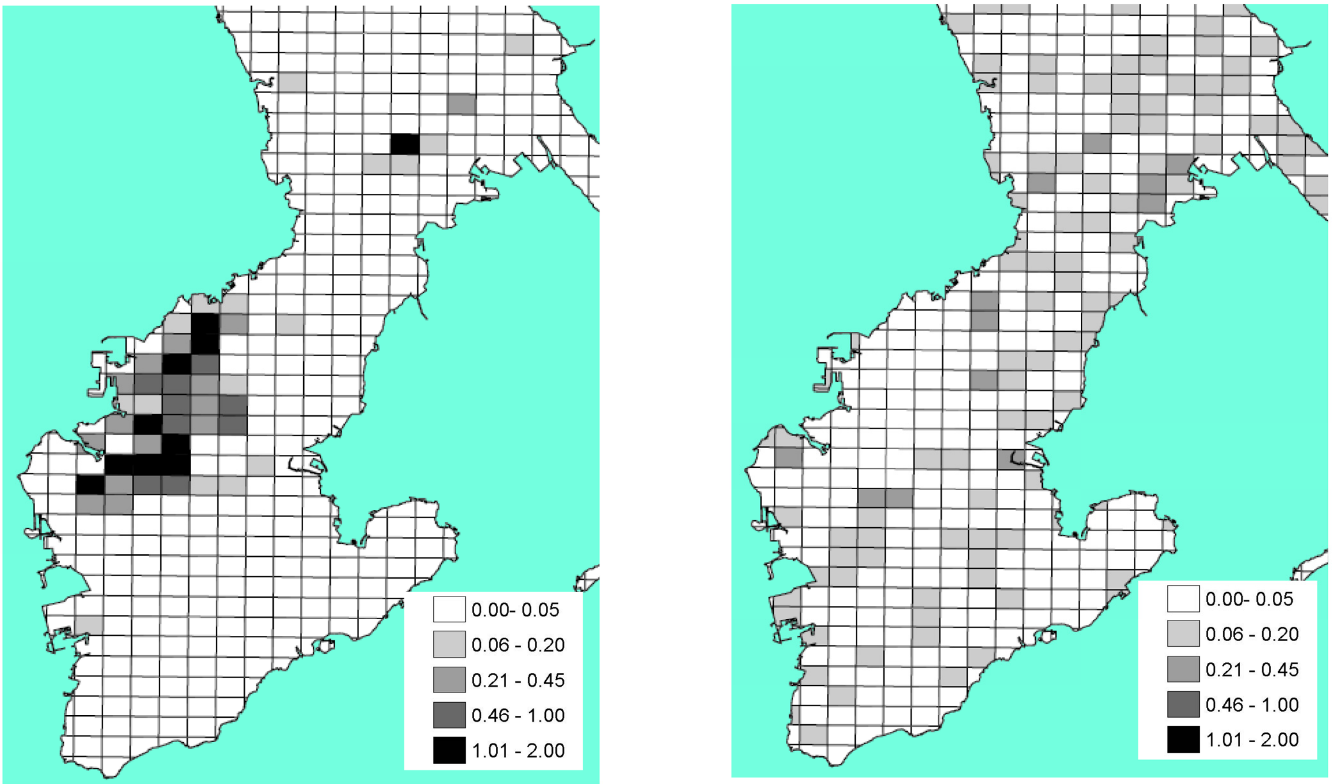
FIGURE 4

INCREASE (LEFT) AND DECREASE (RIGHT) IN TOTAL 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. The counterfactual exercise employs the parameter estimates from the first column in Table 4 (the baseline specification). I assume the costs of opening, converting, and closing a store are US$35,000, US$15,000, and US$10,000. The discount factor is set at 0.90.

FIGURE 5

INCREASE IN NUMBER OF STORES AFTER DEREGULATION: FAMILY MART(LEFT) AND LAWSON (RIGHT)

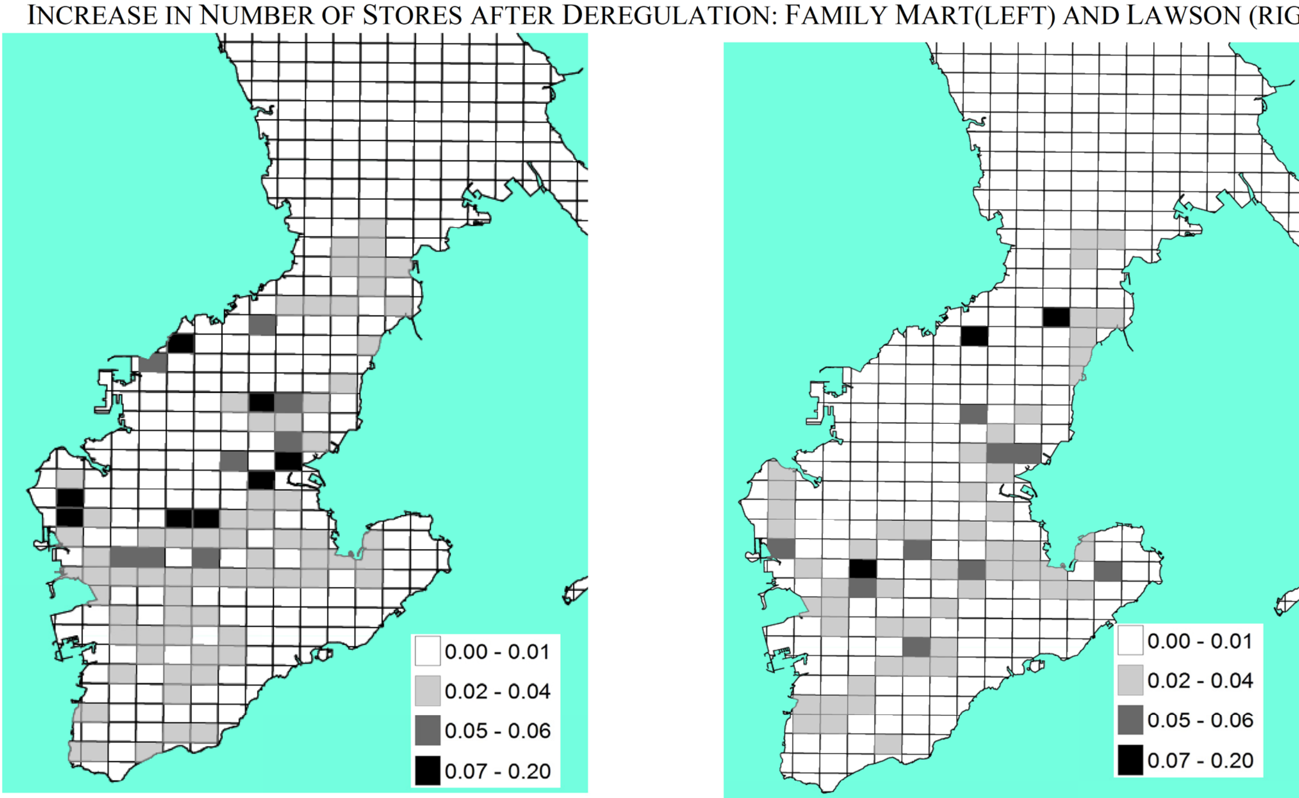
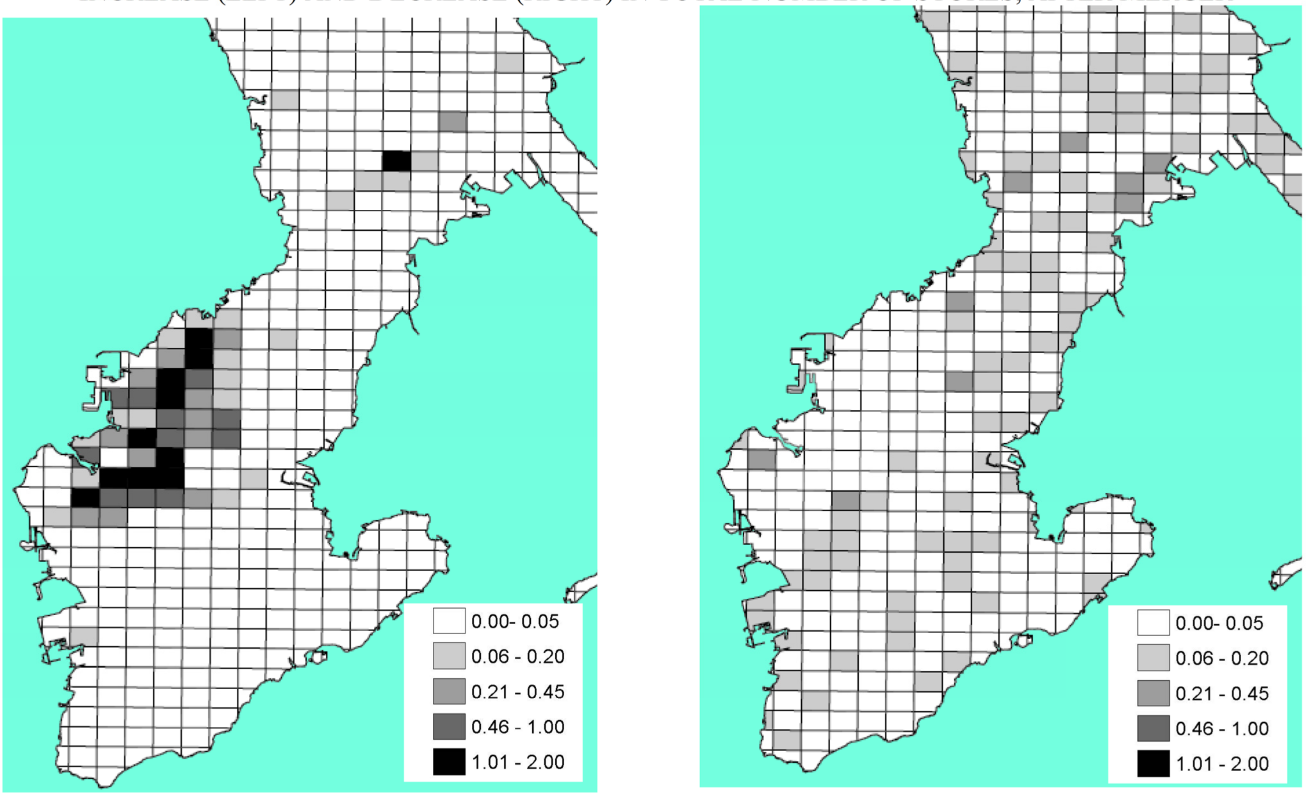


FIGURE 6

INCREASE (LEFT) AND DECREASE (RIGHT) IN TOTAL 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. The counterfactual exercise employs the parameter estimates from the first column in Table 4 (the baseline specification). I assume the costs of opening, converting, and closing a store are US$35,000, US$15,000, and US$10,000. The discount factor is set at 0.95.

FIGURE 7

ZONED AREAS (SHADED AREA)

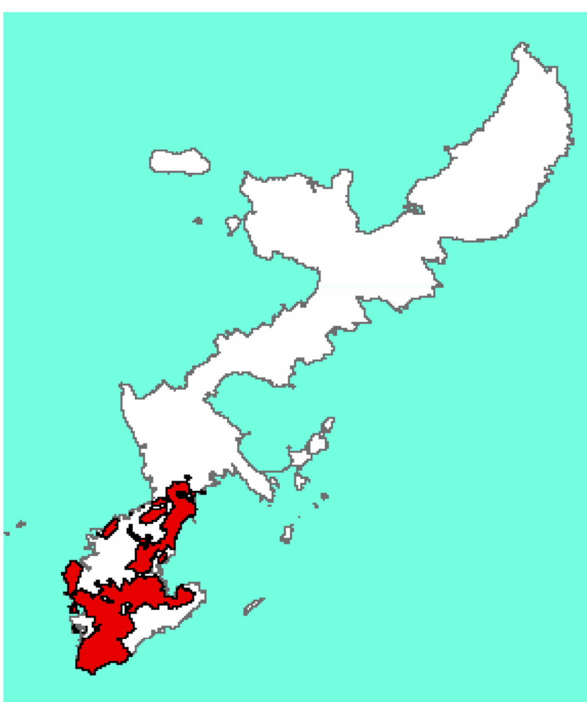


FIGURE 8

POPULATION (NIGHTTIME)

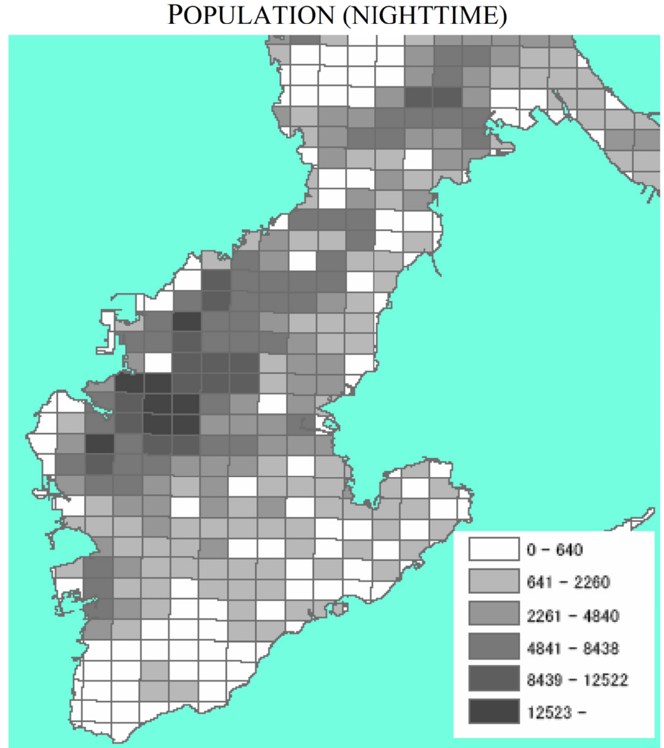
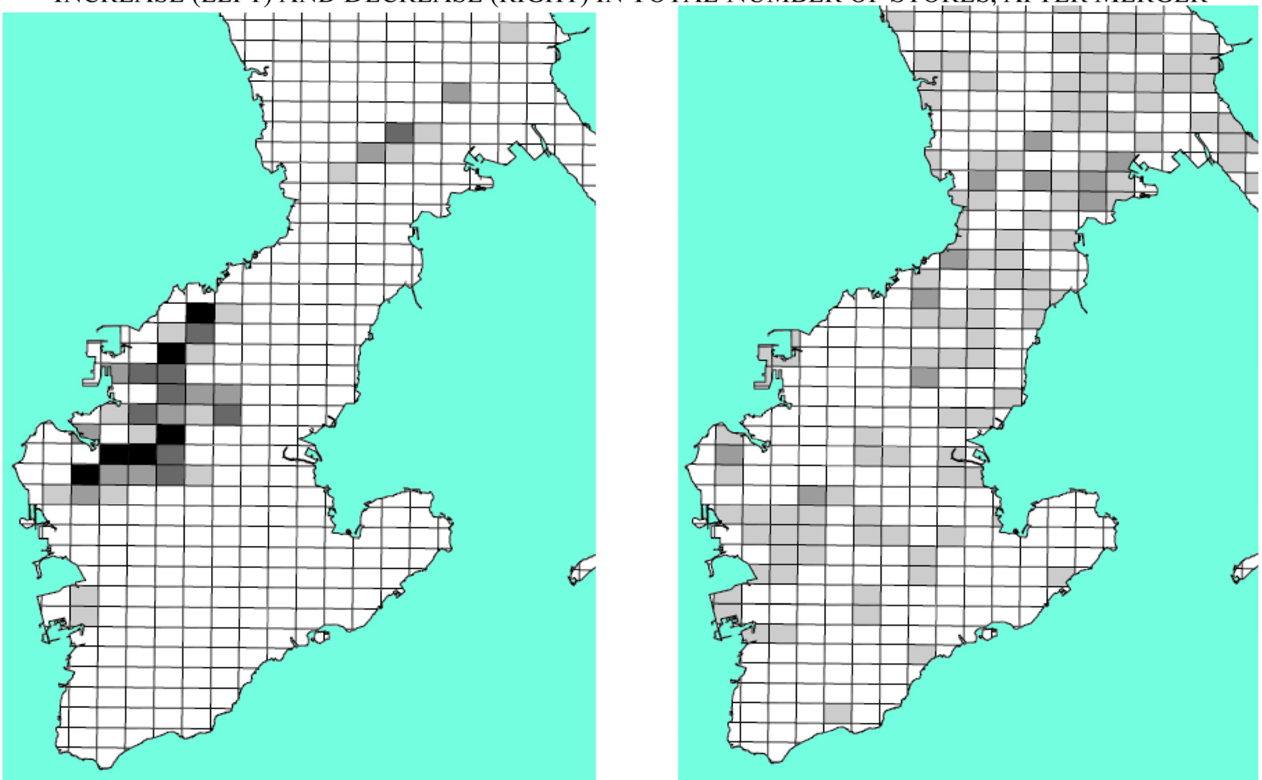


FIGURE 9

INCREASE (LEFT) AND DECREASE (RIGHT) IN TOTAL 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. The counterfactual exercise employs the parameter estimates from the second column in Table 4 (the sensitivity check specification). I assume the costs of opening, converting, and closing a store are US$35,000, US$15,000, and US$10,000. The discount factor is set at 0.90.

TABLE 1

DESCRIPTIVE STATISTICS ACROSS MARKETS

| | 834 Sample Markets | | | | |
|---|---|---|---|---|---|
| Variable | 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 | 0.17 | 0.55 | 0 | 7 | 142 |
| LAWSON | 0.12 | 0.43 | 0 | 6 | 102 |
| Local Store | 0.10 | 0.50 | 0 | 5 | 80 |
| Number of Own Chain Stores in Adjacent Markets | | | | | |
| Family Mart | 1.25 | 2.67 | 0 | 19 | 1,041 |
| LAWSON | 0.87 | 1.92 | 0 | 15 | 725 |
| Local Store | 1.18 | 1.90 | 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 | - |
| Per-Store Sales (thousand US dollars) | | | | | |
| Family Mart | $1,429.86 | | | | |
| LAWSON | $1,456.27 | | | | |

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

TABLE 2

DEGREE OF GEOGRAPHICAL CLUSTERING

| | Moran's I | | General G |
|---|---|---|---|
| Store category | Index | Z-score | Z-score |
| All retail stores | 0.34 | 27.72 | 26.96 |
| Family Mart and LAWSON | 0.41 | 27.97 | 27.17 |
| Convenience stores, local | 0.13 | 8.97 | 8.90 |

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

THE GOODNESS OF FIT OF THE BASELINE SPECIFICATION

| Model Prediction | Data | Prediction | Std.Dev |
|---|---|---|---|
| Aggregate Number of Stores | | | |
| Family Mart | 139 | 140.83 | 11.63 |
| LAWSON | 100 | 99.02 | 10.62 |
| Aggregate Number of Stores in Adjacent Markets | | | |
| Family Mart | 1041 | 1029.35 | 90.49 |
| LAWSON | 725 | 717.40 | 86.22 |
| Aggregate Sales (thousand US dollars) | $169,334 | $167,379.59 | $13,331.81 |

TABLE 4

PARAMETER ESTIMATES OF THE MODEL

| Variable in Revenue Equation | Specifications: Baseline | Specifications: Sensitivity Check |
|---|---|---|
| **Demographics** | | |
| Nighttime Population | 52.85 | 56.91 |
| | (2.60) | (2.66) |
| Daytime Population | 62.38 | 57.49 |
| | (7.00) | (5.63) |
| Retail Sales | 1.10 | 1.31 |
| | (0.28) | (0.18) |
| **Competition Effects** | | |
| "Cannibalization" (Business-Stealing Effect by Own Chain Store), within a Market ($\delta$ *own within*) | -268.77 | -293.40 |
| | (17.79) | (18.07) |
| "Cannibalization" (Business-Stealing Effect by Own Chain Store), across Markets ($\delta$ *own across*) | -23.83 | |
| | (87.02) | |
| Business-Stealing Effect by Rival Chain Store, within a Market ($\delta$ *rival within*) | -330.41 | -286.34 |
| | (22.58) | (18.13) |
| Business-Stealing Effect by Rival Chain Store, across Markets ($\delta$ *rival across*) | -1.07 | |
| | (0.60) | |
| Business-Stealing Effect by Local Store, within a Market ($\delta$ *local within*) | -26.70 | |
| | (476.87) | |
| Business-Stealing Effect by Local Store, across Markets ($\delta$ *local across*) | -3.15 | |
| | (56.07) | |
| **Other Parameteres in Revenue Equation** | | |
| LAWSON Store Dummy ($\mu$ *LAWSON*) | 4.12 | |
| | (3.53) | |
| Constant in Revenue Equation | 305.22 | 291.77 |
| | (24.33) | (48.20) |
| Correlation Parameter in Revenue Shocks ($\rho_1$) | 0.85 | 0.06 |
| | (0.01) | (0.00) |
| Standard Deviation of the Unobserved Revenues ($\lambda_1$) | 228.60 | 232.81 |
| | (28.10) | (19.29) |
| **Variable in Cost Equation** | **Baseline** | **Sensitivity Check** |
| **Cost-Savings Effects** | | |
| Gross Cost-Savings Effect by Own Chain Store, within a Market ($-\alpha$ *_within*) | 141.09 | 140.30 |
| | (19.76) | (24.01) |
| Net Trade-off from Clustering Stores in across Markets ($\kappa$*_across*) | 8.50 | 3.66 |
| | (4.27) | (0.97) |
| **Other Parameteres in Cost Equation** | | |
| Distance from the Distribution Center ($\mu$ *distance*) | 16.20 | 13.41 |
| | (3.07) | (2.37) |
| Zoned Area ($\gamma$) | 42.41 | 49.01 |
| | (15.32) | (14.37) |
| Constant in Cost Equation ($\mu$ *cost*) | 907.65 | 850.23 |
| | (27.75) | (17.50) |
| Correlation Parameter in Cost Shocks ($\rho_2$) | 0.15 | 0.04 |
| | (0.01) | (0.00) |
| Standard Deviation of the Unobserved Costs ($\lambda_2$) | 261.05 | 223.10 |
| | (27.90) | (14.02) |

NOTE. - Standard errors are in parentheses. Parameters are measured in thousand $US with the exception of $\rho$. 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

| | Pre-Merger Duopoly | Merger: specification 1 ($\beta$ = 0.90) | | | | Merger: specification 2 ($\beta$ = 0.95) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Family Mart takes over | | LAWSON takes over | | Family Mart takes over | | LAWSON takes over | |
| Variable | Prediction | Prediction | % Δ | Prediction | % Δ | Prediction | % Δ | Prediction | % Δ |
| Number of Stores | | | | | | | | | |
| Family Mart and LAWSON | 239.85 | 238.28 | -0.7% | 239.34 | -0.2% | 243.79 | 1.6% | 246.63 | 2.8% |
| Family Mart | 140.83 | | | | | | | | |
| LAWSON | 99.02 | | | | | | | | |
| Number of Stores to: | | | | | | | | | |
| Maintain (Own Chain) | | 140.83 | | 99.02 | | 140.83 | | 99.02 | |
| Open (Own Chain) | | 52.70 | | 57.27 | | 57.84 | | 63.93 | |
| Close (Own Chain) | | 0.00 | | 0.00 | | 0.00 | | 0.00 | |
| Close (Rival Chain) | | 54.26 | | 57.77 | | 53.89 | | 57.14 | |
| Convert Rival Stores into Own Stores | | 44.76 | | 83.05 | | 45.13 | | 83.69 | |
| Aggregate Sales | | | | | | | | | |
| Family Mart and LAWSON | $195.45 | $188.02 | -3.8% | $189.30 | -3.1% | $189.67 | -3.0% | $191.72 | -1.9% |
| Family Mart | $111.21 | | | | | | | | |
| LAWSON | $84.24 | | | | | | | | |
| Sales per Store | | | | | | | | | |
| Family Mart and LAWSON | $0.81 | $0.79 | -3.2% | $0.79 | -2.9% | $0.78 | -4.5% | $0.78 | -4.6% |
| Family Mart | $0.79 | | | | | | | | |
| LAWSON | $0.85 | | | | | | | | |
| Aggregate Profits | | | | | | | | | |
| Family Mart and LAWSON | $67.14 | $83.86 | $0.25 | $83.96 | $0.25 | $85.43 | $0.27 | $85.93 | $0.28 |
| Family Mart | $37.01 | | | | | | | | |
| LAWSON | $30.13 | | | | | | | | |
| Breakdown of Profits | | | Δprofits | | Δprofits | | Δprofits | | Δprofits |
| Profits from Demographics | $122.59 | $130.60 | $8.01 | $131.45 | $8.87 | $132.13 | $9.54 | $133.29 | $10.70 |
| Cost Savings, Across-Market | $18.63 | $27.60 | $8.97 | $28.73 | $10.10 | $28.63 | $9.99 | $30.04 | $11.41 |
| Cost Savings, Within-Market | $32.96 | $50.88 | $17.92 | $51.13 | $18.17 | $52.61 | $19.65 | $53.22 | $20.26 |
| Business Stealing, Own Chain | -$76.52 | -$117.26 | -$40.74 | -$118.58 | -$42.05 | -$121.32 | -$44.80 | -$123.52 | -$47.00 |
| Business Stealing, Rival Chain | -$25.97 | $0.00 | $25.97 | $0.00 | $25.97 | $0.00 | $25.97 | $0.00 | $25.97 |
| Business Stealing, Local Stores | -$4.55 | -$4.90 | -$0.35 | -$4.95 | -$0.40 | -$4.99 | -$0.44 | -$5.07 | -$0.52 |
| Costs of Closing & Remodeling & Converting Stores | $0.00 | -$3.06 | -$3.06 | -$3.83 | -$3.83 | -$1.62 | -$1.62 | -$2.03 | -$2.03 |
| Profits per Store | | | | | | | | | |
| Family Mart and LAWSON | $0.28 | $0.35 | 25.7% | $0.35 | 25.3% | $0.35 | 25.2% | $0.35 | 24.5% |
| Family Mart | $0.26 | | | | | | | | |
| LAWSON | $0.30 | | | | | | | | |

NOTE. - Sales and profits are in million US$. Variables are aggregated to the level of Okinawa unless otherwise stated. For each simulation, I solve for the profit-maximizing network of stores for each chain, using the parameter estimates from the first column in Table 4 (the baseline specification). The number of local stores and demographics for each market are held fixed throughout this counterfactual analysis. I assume the costs of opening, converting, and closing a store are US$35,000, US$15,000, and US$10,000. Specifications 1 and 2 assume the discount factor as 0.90 and 0.95, respectively. The cost-saving and business-stealing effects are in gross terms. %Δ denotes the percentage change. Δprofits denotes the absolute change in profits.

TABLE 6
IMPACT OF MERGER ON ENTRY, SALES, AND COSTS (SENSITIVITY CHECK)

| Variable | Pre-Merger Duopoly | Merger: specification 1 ($\beta$ = 0.90) | | | | Merger: specification 2 ($\beta$ = 0.95) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Family Mart takes over | | LAWSON takes over | | Family Mart takes over | | LAWSON takes over | |
| | Prediction | Prediction | % Δ | Prediction | % Δ | Prediction | % Δ | Prediction | % Δ |
| Number of Stores | | | | | | | | | |
| Family Mart and LAWSON | 252.18 | 244.10 | -3.2% | 241.96 | -4.1% | 248.79 | -1.3% | 247.48 | -1.9% |
| Family Mart | 145.56 | | | | | | | | |
| LAWSON | 106.62 | | | | | | | | |
| Number of Stores to: | | | | | | | | | |
| Maintain (Own Chain) | | 145.56 | | 106.62 | | 145.56 | | 106.62 | |
| Open (Own Chain) | | 40.27 | | 42.83 | | 44.65 | | 47.77 | |
| Close (Own Chain) | | 0.00 | | 0.00 | | 0.00 | | 0.00 | |
| Close (Rival Chain) | | 48.35 | | 53.05 | | 48.04 | | 52.47 | |
| Convert Rival Stores into Own Stores | | 58.28 | | 92.51 | | 58.59 | | 93.09 | |
| Aggregate Sales | | | | | | | | | |
| Family Mart and LAWSON | $223.82 | $222.17 | -0.7% | $221.19 | -1.2% | $224.14 | 0.1% | $223.64 | -0.1% |
| Family Mart | $126.62 | | | | | | | | |
| LAWSON | $97.20 | | | | | | | | |
| Sales per Store | | | | | | | | | |
| Family Mart and LAWSON | $0.89 | $0.91 | 2.6% | $0.91 | 3.0% | $0.90 | 1.5% | $0.90 | 1.8% |
| Family Mart | $0.87 | | | | | | | | |
| LAWSON | $0.91 | | | | | | | | |
| Aggregate Profits | | | | | | | | | |
| Family Mart and LAWSON | $72.43 | $89.81 | 24.0% | $89.05 | 22.9% | $91.23 | 26.0% | $90.80 | 25.4% |
| Family Mart | $39.12 | | | | | | | | |
| LAWSON | $33.31 | | | | | | | | |
| Breakdown of Profits | | | Δprofits | | Δprofits | | Δprofits | | Δprofits |
| Profits from Demographics | $137.42 | $143.72 | $6.29 | $143.13 | $5.71 | $145.49 | $8.07 | $145.04 | $7.62 |
| Cost Savings, Across-Market | $2.41 | $3.22 | $0.81 | $3.25 | $0.84 | $3.30 | $0.89 | $3.36 | $0.95 |
| Cost Savings, Within-Market | $32.01 | $49.81 | $17.80 | $49.41 | $17.40 | $51.41 | $19.41 | $51.14 | $19.13 |
| Business Stealing, Own Chain | -$66.93 | -$104.16 | -$37.23 | -$103.32 | -$36.39 | -$107.51 | -$40.58 | -$106.93 | -$40.00 |
| Business Stealing, Rival Chain | -$32.47 | $0.00 | $32.47 | $0.00 | $32.47 | $0.00 | $32.47 | $0.00 | $32.47 |
| Business Stealing, Local Stores | $0.00 | $0.00 | $0.00 | $0.00 | $0.00 | $0.00 | $0.00 | $0.00 | $0.00 |
| Costs of Opening, Closing, & Converting Stores | $0.00 | -$2.77 | -$2.77 | -$3.42 | -$3.42 | -$1.46 | -$1.46 | -$1.80 | -$1.80 |
| Profits per Store | | | | | | | | | |
| Family Mart and LAWSON | $0.29 | $0.37 | 28.1% | $0.37 | 28.1% | $0.37 | 27.7% | $0.37 | 27.7% |
| Family Mart | $0.27 | | | | | | | | |
| LAWSON | $0.31 | | | | | | | | |

NOTE. - Sales and profits are in million US$. Variables are aggregated to the level of Okinawa unless otherwise stated. For each simulation, I solve for the profit-maximizing network of stores for each chain, using the parameter estimates from the second column in Table 4 (the sensitivity check specification). The number of local stores and demographics for each market are held fixed throughout this counterfactual analysis. I assume the costs of opening, converting, and closing a store are US$35,000, US$15,000, and US$10,000. Specifications 1 and 2 assume the discount factor as 0.90 and 0.95, respectively. The cost-saving and business-stealing effects are in gross terms. %Δ denotes the percentage change. Δprofits denotes the absolute change in profits.

## TABLE 7
### IMPACT OF THE ZONING REGULATION ON ENTRY, SALES, AND COSTS

| | Zoning Regulation Policy Regime | | | | |
|---|---|---|---|---|---|
| | Current: 140 Markets Are Zoned | Case 1: No Market Is Zoned | | Case 2: All 834 Markets Are Zoned | |
| Variable | Prediction | Prediction | % Δ | Prediction | % Δ |
| Aggregate Number of Stores | | | | | |
| Family Mart | 140.83 | 143.95 | 2.2% | 123.73 | -12.1% |
| (in originally zoned 140 markets) | 11.40 | 14.37 | 26.1% | 11.30 | -0.9% |
| LAWSON | 99.02 | 101.19 | 2.2% | 87.12 | -12.0% |
| (in originally zoned 140 markets) | 8.17 | 10.42 | 27.6% | 8.12 | -0.6% |
| Aggregate Sales (million US dollars) | | | | | |
| Family Mart | $111.21 | $112.77 | 1.4% | $102.86 | -7.5% |
| (in originally zoned 140 markets) | $7.04 | $8.55 | 21.4% | $7.00 | -0.5% |
| LAWSON | $84.24 | $85.36 | 1.3% | $77.95 | -7.5% |
| (in originally zoned 140 markets) | $5.47 | $6.67 | 22.0% | $5.44 | -0.6% |
| Aggregate Profits (million US dollars) | | | | | |
| Family Mart | $37.01 | $37.52 | 1.4% | $32.93 | -11.0% |
| LAWSON | $30.13 | $30.51 | 1.3% | $27.01 | -10.4% |
| Aggregate Costs of Zoning Regulation (million US dollars) | | | Δcosts | | Δcosts |
| Family Mart and LAWSON | -$0.83 | $0.00 | $0.83 | -$8.94 | -$8.11 |

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 the first column in Table 4. The number of local stores and demographics for each market is held fixed throughout this counterfactual analysis.

## TABLE 8
### PARAMETER ESTIMATES FROM NON-REVENUE MODEL

| | Baseline | | 50 % Shifted Grids | | Equilibrium favors LAWSON | |
|---|---|---|---|---|---|---|
| Variable | Estimate | Standard Error | Estimate | Standard Error | Estimate | Standard Error |
| Nighttime Population | 0.15 | 0.05 | 0.12 | 0.21 | 0.16 | 0.03 |
| Daytime Population | 0.65 | 0.10 | 1.13 | 0.70 | 0.58 | 0.27 |
| Zoned Area ($\gamma$) | -0.10 | 0.05 | 0.02 | 0.23 | -0.11 | 0.11 |
| Across-market Net Cost Savings ($\kappa\_across$) | 0.05 | 0.04 | 0.03 | 1.21 | 0.05 | 0.13 |
| Within-market Net Cost Savings ($\kappa\_within$) | -0.70 | 0.34 | -1.49 | 1.83 | -0.90 | 0.95 |
| Business Stealing by Rival Chain Store ($\delta\_rival\_within$) | -0.95 | 0.18 | -1.21 | 0.77 | -0.47 | 0.69 |
| Constant in Profit Function | -1.93 | 0.10 | -2.20 | 0.36 | -1.82 | 0.15 |
| LAWSON Store Dummy | 0.03 | 0.13 | 0.02 | 0.40 | -0.32 | 0.15 |
| Model Prediction | Level | Std.Dev | Level | Std.Dev | Level | Std.Dev |
| Number of Stores, Family Mart (Data:127) | 131.30 | 98.90 | 127.72 | 75.06 | 130.10 | 30.90 |
| Number of Stores, LAWSON (Data: 95) | 96.20 | 138.70 | 99.26 | 127.00 | 97.16 | 128.10 |

NOTE. - The number of simulations used in the MSM estimation is 200. The number of markets are 834, 1,138, and 834, respectively.