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

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This paper investigates a determinant of location choice for multistore retailing firms: the trade-off between the business-stealing effect and the cost-saving effect from clustering their own stores. I present an empirical model of network choice by two multistore firms. I use lattice-theoretical results to address the computational burden of solving for an equilibrium in store networks. The framework integrates the static entry game of complete information with post-entry outcome data while using simulations to correct for the selection of entrants. I present an application of the model to the case of the convenience store industry in Okinawa Island, Japan, using unique cross-sectional data on store networks and revenues. I use parameter estimates to examine the impact of a hypothetical horizontal merger on store configurations, costs, and profits. Results 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 merger of two multistore firms would decrease its number of stores in suburbs but increase its number in the city center.

Keywords: entry; chain; supermodular games; convenience store; merger; retail competition
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1. Introduction

Spatial competition among multistore firms developing their networks of stores, such as 7-Eleven, Walmart, Target, Walgreens, CVS, Office Depot, Staples, Starbucks, McDonald's, and Burger King has become ubiquitous in a wide range of retail industries. The growing presence of multistore 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. 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. Because of multifirms' trade-offs from clustering their stores, however, the effect of mergers on store networks is theoretically ambiguous. This point raises the question of how mergers affect store networks of multistore firms.

This paper aims to answer this question. To this end, I propose a framework for estimating a model of strategic network choice by two multistore firms. This 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. Two notable exceptions are Holmes (2011) and Jia (2008), who provide two complementary methods for studying a multistore firm's network formation.[1] This article addresses these challenges using the lattice-theoretical approach.

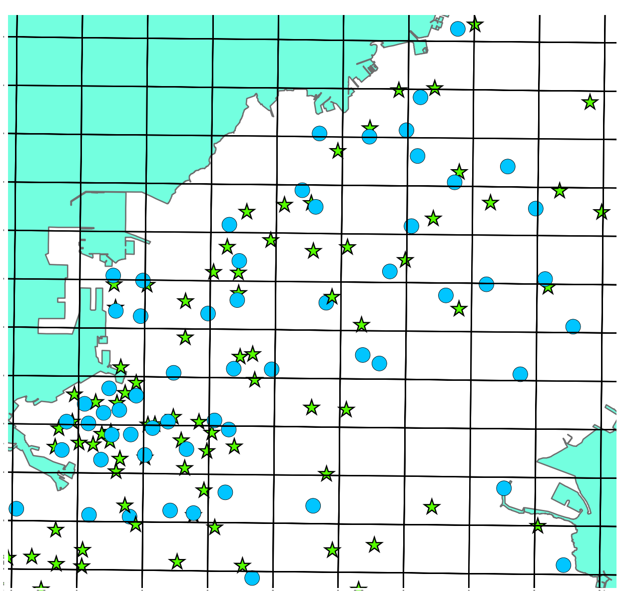
The model explicitly captures two fundamental determinants of multistore firms' (i.e., chains') store-network choice, which make location decisions across markets interdependent, unlike a standard entry model. The first determinant is the trade-off from clustering the firm's stores. On one hand, a retail 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 (i.e., cannibalization or own-business-stealing effect). On the other hand, a retail chain may benefit from clustering its stores because the firm can save on logistical costs, such as

[1] For instance, consider a game with 2 players, 20 markets, and 5 available choices (= 0 store to 4 stores) for each player. The number of possible strategy profiles is $5^{20} = 9.5 \cdot 10^{13}$, and the number of feasible outcomes of the game is $5^{20} \cdot 5^{20} = 9.1 \cdot 10^{27}$, which makes the search for an equilibrium impossibly large. In the empirical application, the number of markets is 834.

gas for delivery trucks or the costs of advertising in local newspapers (i.e., economies of density). Multistore 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 (i.e., business-stealing effect).

This paper applies the framework to the cross-sectional data from 2001 that I manually collected 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. The data from Japan provide a unique opportunity for understanding equilibrium network decisions: Each chain adopts nationwide uniform pricing and almost uniform product assortments. Aside from the antitrust standpoint, developing an empirical model of network choice of multistore firms is of first-order importance for understanding the behavior of multistore 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. Indeed, analysis in Online Appendix 1 §F (available at http://dx.doi.org/10.1287/mksc.2014.0871) suggests that the chain-affiliated convenience stores have different clustering patterns from those of nonchain-affiliated convenience stores or retail stores as a whole in Okinawa. If we regard the observed networks as the outcomes of a game, what are the underlying structural primitives that yield the observed dense

Figure 1 (Color online) Store Configurations and 1 Kilometer Square Grids



Note. The stars show FamilyMart stores and the circles show LAWSON stores.

store networks? This article pursues this empirical question.

This paper interprets the data as the noncooperative outcome of a static game of complete information. I estimate the model parameters by minimizing the gap between the data and the model prediction, which I obtain using 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 that these trade-offs provide economically significant impact for the convenience store chains. The positive (negative) trade-off implies that 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 where population density is low. In other words, the hypothetical merger has an opposite affect on consumers 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, explain 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 stores in that market after merger. In contrast, in a market in which own and rival stores exist but no adjacent market stores can hardly exist 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.

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 other markets. As a consequence, the empirical study has been limited to isolated markets in which one can safely assume that 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 that firms develop their store networks (Jia 2008, Ellickson et al. 2013, Holmes 2011). This paper relates to Davis (2006a) and Jia (2008) in that it applies lattice theory to entry game.[2]

Methodologically, this paper extends the lattice-theoretical approach by Jia (2008) in three dimensions. First, I introduce a density dimension to the choice of a firm. Namely, firms not only choose whether to enter a given market (i.e., the extensive margin) but also the number of stores to open in the market (i.e., 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, unlike a binary-choice model, in which you have to drop observations from urban markets or treat market outcomes in those markets as exogenously given. The effect of mergers on product choice is theoretically ambiguous even in its simplest form. Several additional factors complicate the chain-entry model, including overlapping markets through demand and cost spillovers and the trade-off from clustering. The second advantage is that 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 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. Second, unlike Jia (2008), this model allows the business-stealing effects across markets among multistore firms. This aspect may be advantageous when modeling industries in which consumers often go across markets for purchasing goods or services, such as in this Japanese convenience store industry. Finally, I integrate the static entry games of complete information with 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 this with simulations, thereby distinguishing this study from previous studies that integrate the data on firms' entry decisions with post-entry information, such as Reiss and Spiller (1989), Berry and Waldfogel (1999), Mazzeo (2002a), Draganska et al. (2009b), and Ellickson and Misra (2012).

This paper is related to the literature on strategic marketing-mix decisions. For a broad review of structural approach in strategic marketing, see surveys by Kadiyali et al. (2001) and Dubé et al. (2005). There is a growing strand of literature on structural estimation approach to strategic product (location) positioning decisions. Recent examples include Thomadsen (2007), Draganska et al. (2009b), Sweetings (2010), Fan (2013), and Jeziorski (2013). The list of work provided here is not exhaustive: see, for example, Draganska et al. (2009a) and Crawford (2012), and references therein. Among these works, Draganska et al. (2009b) explore product-location choice using a static firm entry model in an oligopolistic setting and find that incorporating product assortment decisions is critical for evaluating policy simulations. This paper models geographical-location choice of outlets, which is one of the major marketing-mix elements for retail managers, and explores the strategic aspects of outlet-network choice in a duopoly setting. A unique feature of the institutional background in this paper is uniformity of pricing and product assortments across outlets. This aspect allows us to isolate and quantify the importance of the role location plays, controlling other product mixes. Product repositioning after mergers is relevant to other marketing-mix choices, such as pricing, because firms must condition on repositioned products and consumers' responses before making such choices. In this regard, this paper complements Nevo (2000) and Smith (2004), who study how mergers among multiproduct firms affect equilibrium prices.[3] Despite the limitation on the number of players, the methodology in this

[2] Both Holmes (2011) and Ellickson et al. (2013) use a revealed preference approach for estimating the model parameters. To estimate the trade-off from clustering stores, Holmes (2011) focuses on a single retailer's (i.e., Walmart's) dynamic aspect of store-network formations, whereas Ellickson et al. (2013) focus on Walmart, Kmart, and Target's equilibrium location choice using the cross-sectional data. Although Holmes (2011) captures the dynamic aspects of network formations that this paper abstracts, this paper accommodates strategic interactions that the Holmes's paper abstracts away. Whereas this paper does not accommodate the case wherein the number of players exceeds two, the framework by Ellickson et al. (2013) benefits by not having to restrict the number of multistore firms 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. Compared to Holmes (2011) and Ellickson et al. (2013), this paper explicitly solves for the equilibrium to estimate the model.

[3] This paper is also related to the literature on competition with spatial differentiation. Researchers in economics and marketing have extensively studied the geographical aspect of competition for industries such as fast food (Thomadsen 2005, Toivanen and Waterson 2005, Yang 2013), grocery (Datta and Sudhir 2013), movie theaters (Davis 2006b), discount retailers (Zhu and Singh 2009), lodging (Suzuki 2013), retail gasoline (Manuszak 2000 and Houde 2012), supermarket (Griffith and Harmgart 2008, Orhun 2013), wholesale gasoline (Pinkse et al. 2002), video rental (Seim 2006), shopping centers (Vitorino 2012), and eyeglasses (Watson 2005). This paper complements the subsequent spatial-competition literature by highlighting the importance of strategically choosing networks of stores.

paper would be useful for merger analyses in two ways. First, from the standpoint of market participants, namely, firms, consumers, and antitrust agencies, one of the largest changes in market structure is from duopoly to monopoly (or the opposite). Second, even when more than two multistore firms compete at the national level, local markets often have one or two stores.[4] This framework may serve as an approximation in these geographical markets.

The paper is organized as follows. Section 2 specifies the equilibrium network-choice model and the empirical implementation. Section 3 describes the data sets. Section 4 reports the parameter estimates. Section 5 simulates a hypothetical merger. Section 6 presents final comments and suggestions for future research.

2. Model

Empirical Model. I model the market structure as being determined by the strategic actions of two players, chain A and chain B, choosing a player's store network in equilibrium. This is a simultaneous-move game of complete information. I denote a strategy vector for player i and player j by N_i and N_j. A set of mutually exclusive discrete markets is indexed by $m = 1, \ldots, M$. A strategy vector for multistore firm i, or firm i's store network is an $M \times 1$ vector: $N_i = (N_{i,1}, \ldots, N_{i,M})$. So the mth element of N_i, $N_{i,m}$, denotes the number of stores player i opens in market m, and $N_{i,m} = 0$ implies firm i does not enter market m. I define player i's multidimensional strategy space by $\mathbf{N}_i$, which is a subset of a finite-dimensional Euclidean space $\mathbf{R}^M$. Each firm chooses its store network, $N_i = (N_{i,1}, \ldots, N_{i,M})$, to maximize its profits.

The per-store profit function for player i in market m, $\pi_{i,m}(N_i, N_j)$, does not depend only on player i's decision about 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. See, for example, Berry (1992), Mazzeo (2002b), and Seim (2006). 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

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

where $N_{i,m}$, $N_{j,m}$, and $N_{\text{local},m}$ are the number of stores of own firm, rival firm, and local stores in market m, respectively. The within-market competition-effect parameters, $\delta_{\text{own, within}}$, $\delta_{\text{rival, within}}$, and $\delta_{\text{local, within}}$, 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 $\delta_{\text{own, within}} \leq 0$, $\delta_{\text{rival, within}} \leq 0$, and $\delta_{\text{local, within}} \leq 0$. Similarly, the across-market competition-effect parameters, $\delta_{\text{own, across}}$, $\delta_{\text{rival, across}}$, and $\delta_{\text{local, across}}$, 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. $D_{i,l}$ 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 $D_{\text{local},l}$ are similarly defined. $\sum_{l \neq m}(D_{i,l}/Z_{m,l})$ 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. This implies that the marginal loss in revenues by adding a store is declining in the number of stores in a given market.[5] X_m^r are

[4] For instance, when challenging the proposed merger between Staples and Office Depot in 1996, the FTC investigated the possible impact on prices in local markets served by Office Depot and Staples.

[5] 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, the game is supermodular by slightly modifying the original proof in §A.1 of Online Appendix 2. The proofs are available on request. Section C.1 in Online Appendix 2 contains the empirical results based on this alternative cost specification.

observable demographic characteristics of market m and the markets adjacent to m that affect the demand for convenience stores. μ_{chainB} measures the chain B fixed effect in revenues. ε_m^r is a shock to revenues at the store level that I assume is common to any stores in market m, both local and multistore firms, and i.i.d. across markets. $\eta_{i,m}^r$ is a firm-market-specific shock to revenues i.i.d. across firms and markets. I assume both shocks are drawn from a standard normal distribution and are observed by two multistore firms but unobserved by the econometrician. I also assume the shocks are independent of the exogenous variables. ρ_1 measures the correlation of combined unobservables across multistore firms in a given market. λ_1 is a parameter that captures the magnitude of the sum of the revenue shocks. The specification assumes that stores that are not in markets adjacent to market m do not impact sales and the cost of stores in market m and that stores of the same chains in a given grid receive a common revenue shock. Relaxing these assumptions does not change the following analytical results (Online Appendix 2 §A.1).

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 shocks

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

The parameter α_{within} captures the gross cost increases from having a store of the same firm in the same market, and α_{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 $\alpha_{\text{within}} \leq 0$ ($\alpha_{\text{across}} \leq 0$). In other words, the cost savings effect within a market and across markets are $-\alpha_{\text{within}}$ and $-\alpha_{\text{across}}$, respectively. The parameter μ_{cost} is the component of per-store fixed costs common across firms and markets. The parameter $d_{i,m}$ measures the (log) distance to firm i's distribution center from market m. The fixed costs of zoning, parameterized by γ, capture the increase in the fixed costs the store may incur in obtaining permission to develop a store if market m is a zoned area. X_m^c captures other observable market characteristics of market m that affect the costs. I follow Bresnahan and Reiss (1991) for which demographic variables are included or excluded in revenue and cost equations. ε_m^c is a shock to costs at the store level that I assume is i.i.d. across markets and common to any stores in market m. $\eta_{i,m}^r$ is a firm-market-specific shock to costs i.i.d. across firms and markets. ρ_2 measures the correlation of combined unobservables across firms in a given market. λ_2 is a parameter that captures the magnitude of the sum of the cost shocks. Again, I assume that 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.

Ideally, we would like to allow for asymmetry across chains in those parameters in the empirical model. Indeed, the proofs in the Online Appendices 1 and 2 show that the assumption that business-stealing and cost-saving effects are identical across both chains is not necessary for the supermodularity of the game to hold. The empirical application is, however, based on the parsimonious model presented above. Accordingly, all the asymmetries across chains are collapsed into the chain-brand dummy parameter (μ_{chainB}), which represents the mixture of asymmetric effects of business-stealing and cost-saving effects both within and across markets.

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 $m = 1, \ldots, M$. 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, $N_{i,m}$, as in Davis (2006a) and Ellickson et al. (2013). Namely, $\Pi_i(N_i, N_j) = \sum_{m=1}^{M}[N_{i,m} \cdot \pi_{i,m}(N_i, N_j)]$. 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, $N_i = (N_{i,1}, \ldots, N_{i,M})$. The solution concept is pure-strategy Nash equilibrium, which is a pair of store networks that are best responses.

2.1. Computing a Nash Equilibrium

To address the computational burden of computing an equilibrium, I formulate the game as supermodular.

In the empirical implementation, each chain can open up to four stores in any market m: $N_{i,m} \in \{0, 1, \ldots, 4\}$. This choice ($K = 4$) covers 832 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. Topkis (1979, 1998) shows that supermodular games have several convenient features. Two such features are the existence of pure-strategy Nash equilibria and a round-robin algorithm for computing a Nash equilibrium via iterations of myopic best responses. The most computationally challenging step is to calculate the myopic best response given the competitor chain's entry configuration. Online Appendix 1 §C derives an algorithm that yields the upper and lower bounds of the best response for each chain based on the fixed point theorem by Tarski (1955).

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

Proposition 1, which Online Appendix 1 §A proves, asserts the net trade-off across markets, κ_{across} $(=\delta_{\text{own, across}} - \alpha_{\text{across}})$, must be nonnegative. 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 ($\delta_{\text{own, across}}$) dominates the cost-savings effect ($-\alpha_{\text{across}}$) is difficult and imposing parameter restrictions on the trade-off would be thus problematic.[6] This theoretical result highlights the crucial departure from the binary-choice model: I may split existing markets into smaller new markets so that the binary-choice model can address 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, $\kappa_{\text{across}} \geq 0$, which may be hard to justify for an industry with dense configurations of stores. On the other hand, in the multistore setting, we do not have to restrict the sign of the trade-off within a market, both in gross and net. As a result, the model accommodates richer patterns of trade-offs from clustering stores. Online Appendix 1 §§A and B discuss the technical details of supermodularity of the game and computational algorithms.[7, 8]

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. Among all equilibria, the round-robin algorithm allows us to compute two extremal equilibria, the most profitable equilibrium for FamilyMart and the most profitable for LAWSON. If we start the algorithm from FamilyMart (LAWSON), the algorithm reaches the equilibrium that maximizes the aggregate profits $\Pi_i(N_i, N_j)$ for FamilyMart (LAWSON).

2.2. Estimation via Method of Simulated Moments

I estimate the model by choosing model parameters that minimize the difference between observed data and the 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 θ, I use simulations to approximate the moment conditions.

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. ϵ is a vector of predetermined shocks unobserved to the econometrician. Matrix $X = [X_{i,1}, d_{i,1}, d_{j,1}; \ldots; X_{i,m}, d_{i,m}, d_{j,m}; \ldots; X_{i,M}, d_{i,M}, d_{j,M}]$ 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. θ is a vector of model parameters. The data on the number of stores $N_{i,m}$ are generated at the true θ_0 and predetermined variables (X, ϵ): $N_{i,m} = N_{i,m}(X, \epsilon, \theta_0)$. The population condition for the number of stores is given by

[6] The analytical result does not rely on specific functional forms of the within-market cannibalization effect (i.e., own-business-stealing effect) and the within-market cost-savings effect. The underlying insight of the proof in §A.1 of Online Appendix 2 is that changing the order of summation does not change the sum for the within-market trade-off term when checking condition 3 of supermodularity.

[7] The first parameter restriction implies that the cost reduction from economies of density ($-\alpha_{\text{across}}$, gross cost savings) across markets dominate the gross cannibalization ($\delta_{\text{own, across}}$, business-stealing effect) across markets. The second and third restrictions imply that 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 fairly homogeneous across stores within a firm and across firms, people usually do not visit multiple stores at a time.

[8] A consequence of this assumption on the positive trade-off across markets within a chain is that we need to have a market definition consistent with the assumption. However, it may not be obvious before estimating the empirical model whether making such an assumption is innocuous. Therefore, the framework would benefit from some prior or external knowledge about the reasonable grid size or geographical/administrative boundaries such that for that market definition we can maintain that assumption. This aspect remains a practical limitation of this methodology when applying it to a specific empirical application. Note that the framework does not require any assumptions on the signs of revenues or costs.

$g_{\text{store}}(\theta) \equiv E[(N_{i,m} - E[N_{i,m}(X, \epsilon, \theta \mid X)]) \cdot f_m(X) \mid X] = 0$ at $\theta = \theta_0$, 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 is given by

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

where $E[g_{M,\text{store}}(\theta)] = 0$ at $\theta = \theta_0$. I simulate the conditional expectation $E[N_{i,m}(X_i, \epsilon, \theta) \mid X]$ by averaging $N_{i,m}(X, \epsilon, \theta)$ over a set of simulation draws $\epsilon^{S,\text{all}} = (\epsilon^1, \epsilon^2, \ldots, \epsilon^S)$ from the distribution of ϵ:

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

I assume $\epsilon_i^s = (\varepsilon^{s,r}, \varepsilon^{s,c}, \eta_i^{s,r}, \eta_i^{s,c})$, $i \in \{\textit{FamilyMart}, \textit{LAWSON}\}$, $s = 1, \ldots, S$ are drawn from a standard normal distribution. The number of simulations is set at $S = 200$ for the study. I construct the moment conditions on revenue in a similar manner as

$$\hat{g}_{\text{revenue},M}(\theta) \equiv \left[\frac{1}{M} \sum_{m=1}^{M} \left(R_m - \frac{1}{S} \sum_{s=1}^{S} R_m^s(X, \epsilon^s, \theta)\right) \cdot f_m(X)\right],$$

where R_m and R_m^s are the revenue data and simulated revenue, respectively, at the market level.

The current set of 39 moments that match the model prediction and the data is the following: (1) number of FamilyMart stores; (2) number of LAWSON stores; (3) number of FamilyMart stores in adjacent markets; (4) number of LAWSON stores in adjacent markets; (5) interaction between moments (1) and (3); (6) interaction between moments (2) and (4); (7) total sales; (8)–(14): interaction between moments (1)–(7) and daytime population; (15)–(21): interaction between moments (1)–(7) and nighttime population; (22)–(27): interaction between moments (1)–(6) and zoning status index; (28)–(33): interaction between moments (1)–(6) and retail sales; and (34)–(39): interaction between moments (1), (2), (7), and the (log) distance to each of the distribution centers. I stack 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:

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

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

Identification. Model parameters in static entry games are identified from cross-sectional variations in covariates and outcomes. In this application, the data on revenues and market characteristics on demand, such as population, identify the parameters in the revenue equation on how demographics affect revenues. The parameters in the cost equations are identified from both the market characteristics on costs, such as land prices, and the residual variations in choices of chains, namely, variations in the number of outlets across markets. For instance, the positive cost spillover parameters are identified from the geographical clustering patterns of outlets across markets within a chain after observing revenues. For the strategic interaction parameters, the model needs an exclusion restriction where the choice of one firm is being shifted independently of the choices of other firms as Bajari et al. (2010) discuss. In this application, the distance variable to a distribution center in Equation (1) serves as an exclusion restriction for identification of the competitive effect because this variable does not enter the other firm's profit function.[9]

The model has multiple equilibria, which poses a challenge for identification of payoff parameters because multiple equilibria often lead to non-one-to-one mapping between the model and outcomes. Computing all Nash equilibria is infeasible given the size of the strategy space. Instead, this work approaches the issue by focusing on the two extremal equilibria that the round-robin algorithm finds, which maximize the aggregate profits Π_i for FamilyMart and LAWSON, respectively. The baseline specification chooses the former equilibrium because the number of outlets for FamilyMart (140) is approximately 40% higher than the

[9] 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 the 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 firms 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). I 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.

Table 1 Descriptive Statistics Across Markets

	834 sample markets				
Variable	Mean	Std. dev.	Min	Max	Total
Number of stores					
FamilyMart	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					
FamilyMart	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)					
FamilyMart	29.73	20.77	0.35	84.86	—
LAWSON	30.80	20.98	0.55	86.18	—
1 km^2 *square grid-level aggregate revenues* (thousand U.S. dollars) ($)	339	1,518	0	17,867	173,588
Number of residents (units: people)	1,434	2,588	0	18,977	1,195,787
Number of workers (units: people)	580	1,612	0	32,776	484,097
Land price per square meters (U.S. dollars) ($)	672	863	20	9,280	—

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

number of outlets for LAWSON (100).[10] The intuition behind this choice is that the aggregate profits Π_i increase as the number of outlets increases. Table 1 shows that the average store-level sales are almost identical across chains. In a case wherein the store-level profitability is also at the same level across chains, FamilyMart would have 40% more profits than LAWSON because $\Pi_i = (\textit{Average Store-level Profits}) \cdot (\textit{Number of Outlets})$. Online Appendix 1 §G discusses as a robustness check the estimation results when I choose the equilibrium that maximizes the aggregate profits for LAWSON.

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, introduces a selection issue. The problem is that we only observe revenues for markets in which the multistore firms actually open stores. Therefore, unobservable demand shocks that affect revenue are also likely to affect decisions about whether to enter a market and how many stores to open. Online Appendix 1 §D discusses the issue in detail with an example.

[10] Two other approaches exist to address 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). Unfortunately, numerically computing the model predictions from these two extreme equilibria shows that 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 impose the equilibrium selection rule because a goal of the paper is to simulate the post-merger store network.

To address this endogeneity issue due to selection, 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 that 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 estimated from the first-stage results for each outcome of the game or for each strategy of the firm (Mazzeo 2002a, 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 game strategies is exponential in the 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. Alternatively, in the labor economics literature, this form of endogeneity due to selection is handled through incidental truncation methods, such as censored Tobit (Wooldridge 1998). Unfortunately, we cannot use a Tobit for this empirical setup because the selection mechanisms, i.e., the number of stores that each chain chooses, are not linear in endogenous variables, such as revenue. Rather, the selection can be described only indirectly by an equilibrium of a game in which two multistores compete against each other to maximize their profits.

Instead, this paper deals with this nonlinearity by setting the problem as a large generalized method of moments (GMM) system of simultaneous equations, and I stack moment conditions about selection and outcome $g_M(\theta)$ in Equation (2). Because we have no closed-form expression in the parameters of the model for the objective function, I use simulations (MSM).[11] McFadden (1996, p. 7) 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 identified 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 sth simulation. (See Online Appendix 2 §B for details.) 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 does it involve sequential steps including estimating the control function.

3. Data Description

The Japanese Convenience-Store Industry. Over the past several decades, the convenience-store industry has become a rapidly growing retail format in many countries. Nationwide, a large number of stores achieves the economies of scale in distribution, advertising, product developments, and purchasing power, as is the case with discount retailers or supermarket chains. 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, FamilyMart and LAWSON. In 2001 there were 142 FamilyMart stores and 102 LAWSON stores in Okinawa. The average sales per store in Okinawa, computed from each company's financial statements in 2002, were US$1.43 million for FamilyMart and US$1.45 million for LAWSON. This suggests no noticeable difference in sales per store between these 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. Because of nationwide uniform pricing and the homogeneity of store formats across stores, such as product assortments, variety of services, and floor size, geographic differentiation is the most important avenue of product differentiation.

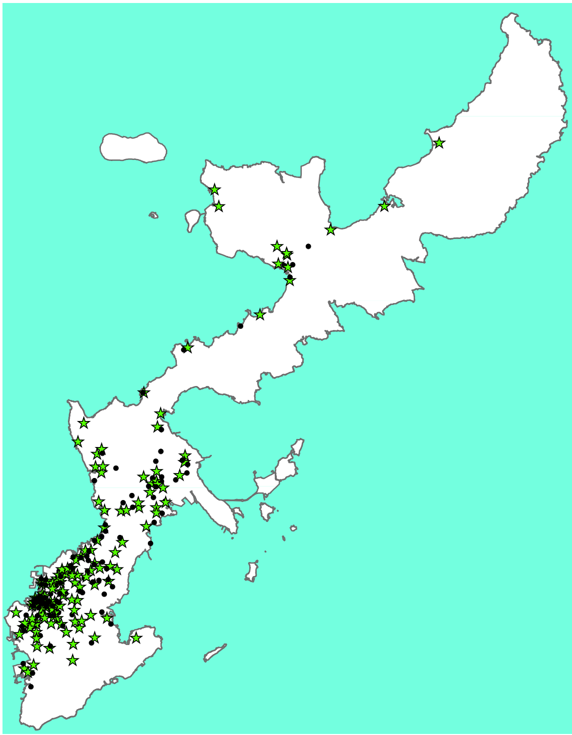
The industry invests heavily in sophisticated distribution networks for two reasons. First, each store has limited inventory space; a typical store has about 3,000 items on about 110 square meters (1,184 square feet) of floor space. Second, 70% of the sales are perishables: Stores need to preserve the freshness of foods, such as lunchboxes, rice balls, and sandwiches, which delivery trucks need to replace two to three times a day.

Market Definition. Most entry models treat 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 (1 km^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 (e.g., mountain regions) as potential markets for convenience stores, I exclude 367 grids that have no population during the day or night. This exclusion leaves me with a sample of 834 markets that cover 834 km^2 or 322 mi^2, which is 69% of the total land area of Okinawa. I define adjacent markets (or neighboring markets) as those 1 km^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 Sources and Summary Statistics. I have manually compiled the cross-sectional data sets from a variety of sources. For the convenience-store-location data, I rely on the 2002 Convenience Store Almanac (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 using a geographic reference information system from the Ministry of Land, Infrastructure, and Transport, mapping software, various online mapping services, such as Google Maps or Yahoo!, and corporations' online store locators. I assign each store to the corresponding 1 km^2 grid in which it falls. The left panel of Figure 2 shows the location of stores for FamilyMart and LAWSON in Okinawa.

[11] 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).

Figure 2 (Color online) Convenience Stores in Okinawa



Notes. In the left panel, the stars indicate FamilyMart stores and the circles denote LAWSON stores. Photograph courtesy of the author.

Each chain has its own distribution center. Using the geographical location information of the distribution centers, I compute the distance from a distribution center to a given market for each chain.

The convenience-store-revenue information at the 1 km^2 grid level is available from the 2002 Census of Commerce from the Ministry of Economy, Trade, and Industry. The government imposes two restrictions on the revenue data to protect the privacy and identity of each store. First, this sales information is available not at the store level, but at the aggregated level of a 1 km^2 uniform grid. The government publishes the sales at the grid level as an aggregate of total sales from all stores in a given grid, and therefore does not have breakdowns by categories, such as chain brands. Second, the government sets an exogenous sample selection rule for this revenue data: Total revenues with fewer than three stores in a given market will be treated as missing data regardless of chain brands of stores in a given grid. Therefore, a researcher would only observe the total sales at the grid level if there are more than two outlets in that grid.

The demographic variables come from several sources. Population data, which are an important predictor of store-location choice, come in two ways. First, the 2000 Census of Population at the 1 km^2 grid level is available from the Census Bureau; this provides the number of people living in the 1 km^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. The data on land prices come from the Ministry of Land, Infrastructure, Transport, and Tourism. The data contain locations and land prices of 215 geographically distinct points; I treat the closest point from the centroid of a square grid (= market) as the market's land price. The data on the zoning regulations status at the market level is available from the Ministry of Land, Infrastructure, Transport, and Tourism. A chain needs to obtain permission when developing an outlet in a zoned market. In Okinawa, 140 out of 834 markets are zoned. See Nishida (2014) for institutional details about the regulation.

Table 1 provides summary statistics. The number of stores in a given 1 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 FamilyMart and LAWSON, respectively. There are 80 nonchain local stores. For FamilyMart, only 81 stores of 142 total stores are single stores within a given market. For LAWSON, 67 stores of 102 total stores are single stores within a given market. Each chain has its own distribution center. Rows 9 and 10 show that the distance from the centroid of each market to the distribution center for each chain is about 30 kilometers on average. The revenue at the market level is US$339,000 on average annually and varies significantly. As explained above, the revenue data are available from markets with more than two outlets. If I summarize the mean and standard deviation from the markets with nonmissing revenue data only (54 of 834 markets), the mean and standard deviation of annual revenue at the market level is $5,235,700 and $3,173,944, respectively. For major demographic variables, Table 1 shows a 1 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, with 580 people on average.

The strikingly dense store networks in Figures 1 and 2 may simply indicate 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 nonchain-affiliated stores. For this purpose, I calculate the Moran's I index and the Getis-Ord General G statistic, both of which are traditional measures for summarizing spatial patterns. The results in Online Appendix 1 §F confirm that the clustering patterns did not occur by chance, motivating a further analysis of multistore firms' store-network choice.

4. Results

Table 2 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 §5 to the results from the sensitivity-check specification, which are in the second column.

All of the demographic parameters except daytime population in adjacent markets have a positive and statistically significant effect on store sales at the 5% confidence level. For instance, the coefficient on the nighttime population in the same market implies that per-store sales in a market with 1,000 more people than other markets will be higher by US$46,290 annually, which is about 3% of total annual sales for an average store. As expected, the presence of stores in the same market, regardless of its chain affiliation, has a negative impact on the store-level revenues. The estimates in rows 6–11 of column 1 in Table 2 measure the business-stealing effect due to the presence of three types of stores. The parameters that measure the cannibalization effect (own-business-stealing effect) within a market by own firm stores ($\delta_{\text{own, within}}$) and the business-stealing effect by rival firm stores ($\delta_{\text{rival, within}}$) are negative and precisely estimated at the 1% confidence level. This suggests that the existence of other stores in the same market pushes the revenue down 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$166,639 ($= \log 2 \cdot \$240{,}410$) annually, which is about 12% of total annual sales for an average store. Similarly, adding a rival store in the same market dampens the per-store sales by 15% of total annual sales. The presence of a nonchain store reduces the revenue much less than an own or rival store, and the coefficient for the same market 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, $\delta_{\text{own, across}}$, $\delta_{\text{rival, across}}$, and $\delta_{\text{local, across}}$, are smaller than the corresponding within-market business-stealing effects and imprecisely estimated except the parameter for nonchain stores. This finding suggests that the business-stealing effects across markets (or gross demand spillovers across 1 km^2 grids) do not seem to play a big role in the industry. This is consistent with various surveys that suggest that the consumer's average travel time to a convenience store is around 10 to 20 minutes on foot, and that a trade area for a typical convenience store has a radius of about 500 to 700 meters. Although not shown in the tables due to space constraints, I also estimate the model without these three types of business-stealing effects across markets. Not too surprisingly, the quantitative results are similar to those described in this section.

The presence of own chain stores reduces costs, thereby having a positive effect on profits. Row 1 in the second panel from the top in Table 2 presents the estimate of $-\alpha_{\text{within}}$, 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$92,112 ($= \log 2 \cdot \$132{,}890$). The positive sign of $-\alpha_{\text{within}}$ implies that the presence of the same chain store within a market lowers the costs. Row 2 of the second panel in Table 2 displays the estimate of κ_{across}, the net trade-off from the presence of stores from the same chain in adjacent markets. The point estimate is positive and $5,840 per year and per market and is statistically significant at the 1% confidence level. In contrast to the positive net trade-off from clustering across markets, $\kappa_{\text{across}} (= \delta_{\text{own, across}} - \alpha_{\text{across}})$, the net trade-off from clustering within a market, κ_{within}, implied by the business-stealing and cost-saving parameters within a market, will be negative and US$107,520 ($\kappa_{\text{within}} = \delta_{\text{own, within}} - \alpha_{\text{within}} = -\$240{,}410 - (-\$132{,}890)$). The implied gross cost savings from the stores in adjacent markets, $-\alpha_{\text{across}} = -(\delta_{\text{own, across}} - \kappa_{\text{across}})$, will be US$34,040 ($= -(-\$28{,}240 - \$5{,}800)$). 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 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, κ_{across}, and negative trade-off within a market, κ_{within}, would be that even

Table 2 Parameter Estimates of the Model

	Specifications	
	Baseline	Sensitivity check
Variable in revenue equation		
Demographics for revenues		
Nighttime population	46.29 (2.27)	44.56 (4.26)
Nighttime population in adjacent markets	0.97 (0.44)	1.03 (0.13)
Daytime population	55.51 (5.67)	58.01 (7.59)
Daytime population in adjacent markets	0.98 (0.84)	
Retail sales	1.05 (0.12)	1.09 (0.27)
Competition effects		
"Cannibalization" (business-stealing effect by own chain store), within a market ($\delta_{\text{own, within}}$)	−240.41 (19.08)	−233.92 (16.78)
"Cannibalization" (business-stealing effect by own chain store), across markets ($\delta_{\text{own, across}}$)	−28.24 (133.64)	
Business-stealing effect by rival chain store, within a market ($\delta_{\text{rival, within}}$)	−315.01 (21.18)	−336.11 (16.00)
Business-stealing effect by rival chain store, across markets ($\delta_{\text{rival, across}}$)	−1.12 (19.69)	
Business-stealing effect by local store, within a market ($\delta_{\text{local, within}}$)	−26.18 (461.82)	
Business-stealing effect by local store, across markets ($\delta_{\text{local, across}}$)	−2.83 (0.93)	−3.23 (0.89)
Other parameters in revenue equation		
LAWSON store dummy (μ_{Lawson})	4.67 (3.94)	
Constant in revenue equation	281.55 (35.34)	226.65 (41.50)
Correlation parameter in revenue shocks (ρ_1)	0.85 (0.00)	0.09 (0.00)
Standard deviation of the unobserved revenues (λ_1)	225.71 (19.93)	235.38 (21.68)
Variable in cost equation		
Cost-savings effects		
Gross cost-savings effect by own chain store, within a market ($-\alpha_{\text{within}}$)	132.89 (9.45)	122.65 (12.56)
Net trade-off from clustering stores across markets (κ_{across})	5.84 (0.75)	3.44 (1.53)
Demographics for costs		
Distance from the distribution center (μ_{distance})	15.66 (2.77)	15.06 (2.10)
Zoned area (γ)	46.44 (17.56)	46.72 (22.16)
Land price	−1.01 (0.62)	
Other parameters in cost equation		
Constant in cost equation (μ_{cost})	874.86 (26.79)	824.24 (22.48)
Correlation parameter in cost shocks (ρ_2)	0.28 (0.01)	0.04 (0.01)
Standard deviation of the unobserved costs (λ_2)	246.65 (13.09)	236.56 (21.54)

Notes. Standard errors are in parentheses. Parameters are measured in thousand \$US except parameter ρ. Observations are 834 markets. The number of simulations used in the MSM estimation is 200.

Table 3 The Goodness of Fit of the Baseline and Sensitivity Specifications

		Baseline		Sensitivity check	
Model prediction	Data	Prediction	Std. dev.	Prediction	Std. dev.
Aggregate number of stores					
FamilyMart	139	140.24	12.12	138.61	12.65
LAWSON	100	100.27	11.92	99.27	12.67
Aggregate number of stores in adjacent markets					
FamilyMart	1,041	1,027.02	93.43	1,013.42	97.65
LAWSON	725	728.32	91.50	720.87	96.16
Aggregate sales (thousand U.S. dollars) ($)	169,334	167,866	13,009	169,454	13,236

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 savings decrease less with distance than the cannibalization effect.[12] As anticipated, I find that stores benefit from being close to the distribution center: μ_{distance} is positive and statistically significantly. The parameter coefficient predicts that a typical store incurs US$53,262 ($=\log(30)\cdot$ $\$15,660$) in distribution costs, which is about 6% of the annual fixed costs of a store (μ_{cost}).

One way to measure the overall fit of the model is to compare the model predictions of how many total stores each multistore firm opens with the actual store counts. Columns 1 through 3 in Table 3 present the observed data, the prediction from the model, 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. For instance, the model predicts the total number of FamilyMart stores, which is 139 in the data, to be 140.24 on average across 200 simulations, with a standard deviation of 12.12.

5. Effects of a Merger on Store Networks

This section uses the parameter estimates of the model to perform "what-if" experiments, i.e., evaluating the impact of a hypothetical horizontal merger on the market structure. Because this chain-entry model is static, I treat the hypothetical merger as an exogenous one-time event, such as a nationwide merger that is exogenous to the markets in Okinawa. I reoptimize the acquirer's store network by solving the monopolist's profit-maximization problem. Given the premerger 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. 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 premerger regime. The demographics and the number of local stores are taken as exogenous and unchanging before and after the merger. I assume a firm incurs costs of US$350,000, US$150,000, and US$100,000 for opening, converting, and closing a store.[13]

The left panel of Table 4 displays the simulation results where I use a 10% discount factor assumption ($\beta=0.90$) to rescale those one-shot lump-sum costs into the costs incurred annually. The second column presents the results in which FamilyMart takes over as a post-merger monopolist. The total number of stores in Okinawa decreases by 0.6% from 240.5 stores, which is the combined number of FamilyMart and LAWSON stores before the merger. Although the total number of stores does not change significantly, rows 4 through 8 suggest that the acquirer goes through a massive reoptimization of its store configurations. FamilyMart, for instance, converts 42 of a total of 100 rival stores; the remaining 58 rival stores closed permanently. The acquirer's 57 newly opened stores are in different markets than those in which the 58 rival stores were originally located. The fourth column of Table 4 presents the results in which LAWSON takes over as a post-merger monopolist. Given the small magnitude of the LAWSON fixed effect in Table 2, 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

[12] 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.

[13] I rely on annual financial statements of these cost estimates because without panel data, the estimated fixed cost parameters in Table 2 cannot separately identify operating fixed costs from sunk costs. See Online Appendix 1 §E for detailed discussion on this issue.

Table 4 Impact of Merger on Entry, Sales, and Costs

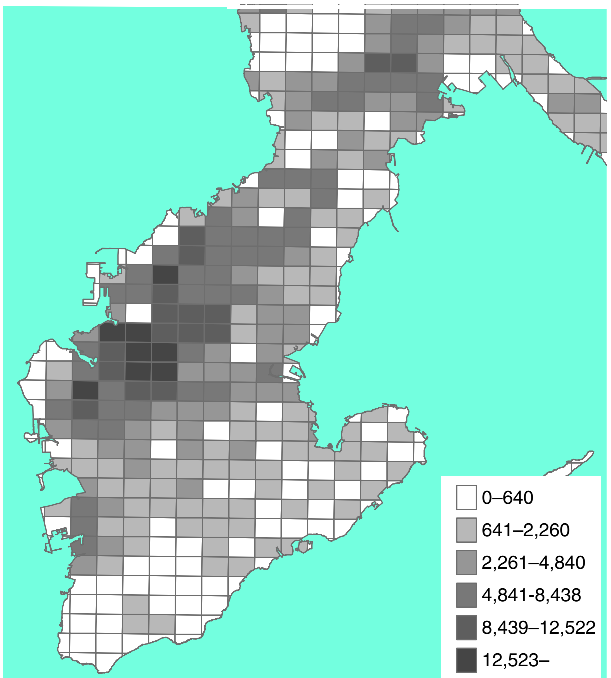
	Pre-merger duopoly	Merger: specification 1 ($\beta = 0.90$)				Merger: specification 2 ($\beta = 0.95$)			
		FamilyMart takes over		LAWSON takes over		FamilyMart takes over		LAWSON takes over	
Variable	Prediction	Prediction	%Δ	Prediction	%Δ	Prediction	%Δ	Prediction	%Δ
Number of Stores									
FamilyMart and LAWSON	240.51	239.11	−0.6%	240.40	0.0%	244.60	1.7%	247.78	3.0%
FamilyMart	140.24								
LAWSON	100.27								
Number of Stores to:									
Maintain (Own Chain)		140.24		100.27		140.24		100.27	
Open (Own Chain)		57.06		61.37		62.32		68.19	
Close (Own Chain)		0.00		0.00		0.00		0.00	
Close (Rival Chain)		58.45		61.48		58.23		60.92	
Convert Rival Stores into Own Stores		41.82		78.76		42.05		79.32	
Aggregate Sales									
FamilyMart and LAWSON	$191.31	$184.34	−3.6%	$185.48	−3.0%	$185.92	−2.8%	$187.81	−1.8%
FamilyMart	$108.32								
LAWSON	$82.99								
Sales per Store									
FamilyMart and LAWSON	$0.80	$0.77	−3.1%	$0.77	−3.0%	$0.76	−4.4%	$0.76	−4.7%
FamilyMart	$0.77								
LAWSON	$0.83								
Aggregate Profits									
FamilyMart and LAWSON	$64.57	$80.02	23.9%	$80.34	24.4%	$81.67	26.5%	$82.37	27.6%
FamilyMart	$35.42								
LAWSON	$29.15								
Breakdown of Profits			Δ profits		Δ profits		Δ profits		Δ profits
Profits from Demographics ($)	115.96	123.90	7.95	125.08	9.12	125.39	9.43	126.88	10.93
Cost Savings, Across-Market ($)	18.85	27.82	8.96	29.06	10.20	28.74	9.88	30.30	11.45
Cost Savings, Within-Market ($)	33.06	50.42	17.37	50.77	17.72	52.18	19.12	52.91	19.85
Business Stealing, Own Chain ($)	−75.43	−114.27	−38.85	−115.93	−40.51	−118.21	−42.79	−120.82	−45.40
Business Stealing, Rival Chain ($)	−23.56	0.00	23.56	0.00	23.56	0.00	23.56	0.00	23.56
Business Stealing, Local Stores ($)	−4.31	−4.64	−0.33	−4.69	−0.38	−4.73	−0.42	−4.80	−0.49
Costs of Closing & Remodeling ($) *and Converting Stores*	0.00	−3.21	−3.21	−3.94	−3.94	−1.70	−1.70	−2.09	−2.09
Profits per Store									
FamilyMart and LAWSON	$0.27	$0.33	24.7%	$0.33	24.5%	$0.33	24.4%	$0.33	23.8%
FamilyMart	$0.25								
LAWSON	$0.29								

Notes. 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 2 (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, respectively. 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. Δ profits denotes the absolute change in profits.

quite different geographical patterns compared to the premerger geographical store networks. With the geographical distribution of population density shown in Figure 3 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 noncity centers or rural markets. As the acquirer, LAWSON's post-merger store network exhibits similar geographical patterns, i.e., more clustering in the city centers and less in the rural markets.

The trade-off from clustering provides the intuition behind these post-merger patterns of stores. 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, κ_{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 the merger, the store(s) in that market would enjoy $3 \cdot \kappa_{\text{across}}$, if we abstract from the difference in the distance from the market to each of these adjacent markets. If, after the merger between FamilyMart and LAWSON, the acquirer has six active markets in adjacent locations for a given market, the acquirer

Figure 3 (Color online) Population (Nighttime)



would enjoy $6 \cdot \kappa_{\text{across}}$ from these adjacent markets. The acquirer, therefore, has 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, κ_{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.[14] In Online Appendix 2, §D provides numerical examples of two cases: The total number of stores in a given market (1) increases after merger, and (2) decreases after merger.

The second panel from the top in Table 4 shows that 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 that the merger is highly profitable without the change in prices. The third and fourth rows from the bottom in columns 2 and 4 show that the per-store profitability has increased proportionally, i.e., a 23.9% increase for FamilyMart and a 24.4% increase for LAWSON. Column 4 in the third panel from the top in Table 4 provides a breakdown of the changes in the total profits. The number shows that the contribution to the change in total profits from the increased cost efficiencies due to clustering, combining both within and across markets, is economically significant, i.e., US$26 million (= $8.96 M + $17.37 M). The magnitude of this gross cost savings is large enough to offset the increase in the total business-stealing effects from clustering, combining both within and across markets, which is US$15 million.

Both Figure 5 and the right panel of Table 4 explore the robustness of the simulation results to the alternative 5% discount factor assumption ($\beta = 0.95$). 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 converted and fewer stores closed because the absolute difference in costs between converting and closing a store narrows. I should expect more stores to open because the threshold of opening a store lowers. Columns 6 through 9 in Table 4 confirm that the results are consistent with these predictions. In general, I find no significant difference from the baseline specification. Figure 5 shows that the geographical post-merger pattern of stores is similar to the one in Figure 4, i.e., more stores in the city-center markets and fewer in the rural markets.

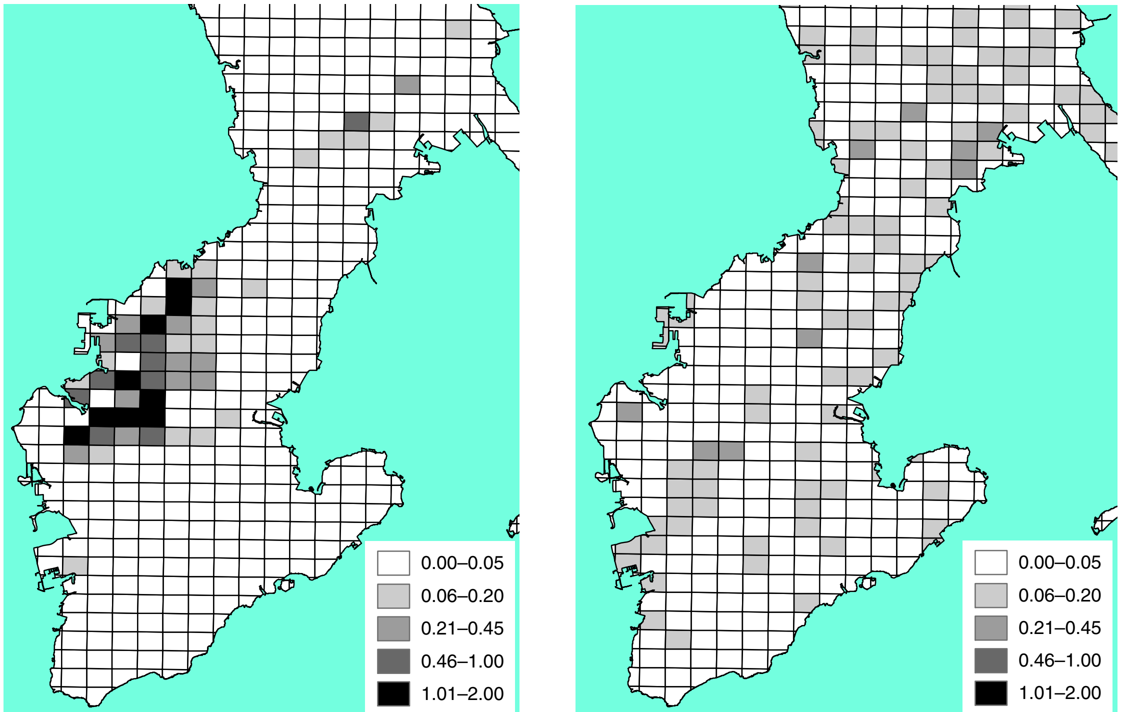
Overall, the simulation results provide evidence that the cost-savings and the business-stealing parameters are, indeed, key variables in predicting the resulting store network, cost savings, and profits after a merger.

Sensitivity Analysis: Full Model with a Smaller Set of Variables. One might be concerned that some of the parameters from the baseline model in Table 2 that are not precisely estimated, including the business-stealing effects across markets and the LAWSON dummy, may drive the simulation exercise results in Table 4 and Figures 4 and 5. 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 2 shows that the signs and the magnitude of the estimates are reasonably similar to those of the baseline model.

Table A3 in Online Appendix 1 §A presents the merger counterfactual results. Probably not too surprisingly, given that estimates are close across specifications, both specifications 1 and 2 yield results that are quantitatively and qualitatively similar to those in Table 4. This indicates that imprecisely estimated parameters do not drive the counterfactual results. Figure 6 shows the merger counterfactual results using the parameter estimates in the second column in Table 2.

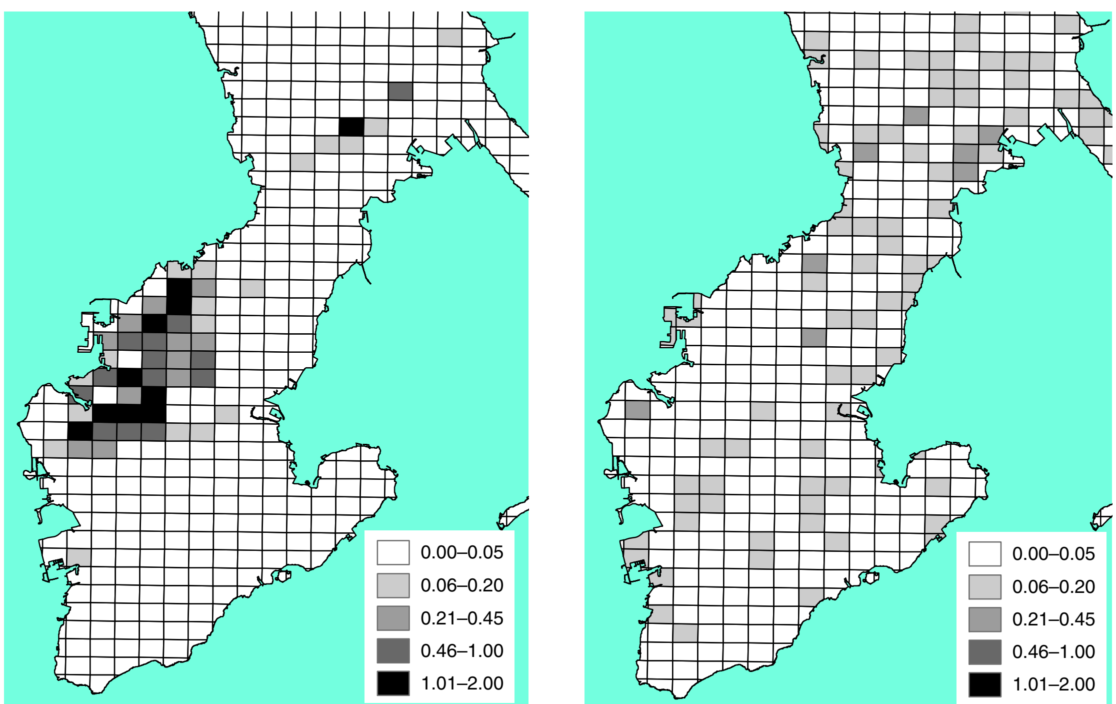
[14] On the consumer side, the increase in the number of stores in urban markets will have a positive effect in terms of decreased travel costs, whereas the decrease in the number of stores in rural markets will have a negative impact.

Figure 4 (Color online) Increase (Left) and Decrease (Right) in Total Number of Stores, After Merger: Full Model



Notes. FamilyMart is the acquirer. I construct the difference by comparing the number of FamilyMart and LAWSON stores and the number of the acquirer's stores. The counterfactual exercise uses the parameter estimates from the first column in Table 2 (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, respectively. The discount factor is set at 0.90.

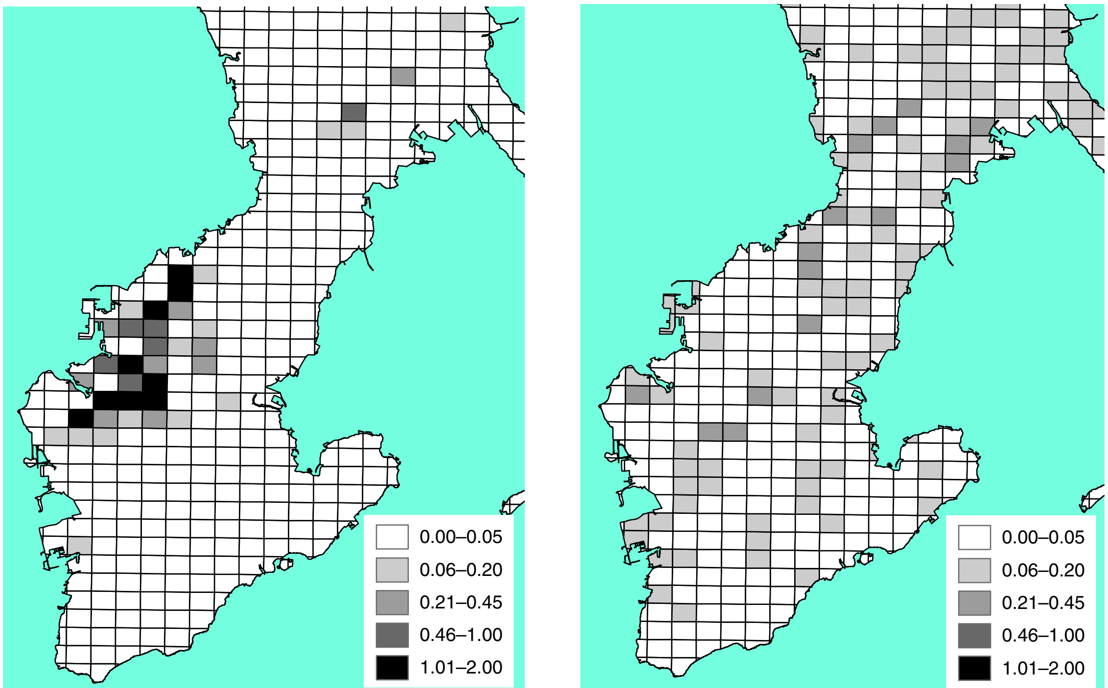
Figure 5 (Color online) Increase (Left) and Decrease (Right) in Total Number of Stores, After Merger: Full Model with an Alternate Discount Factor



Notes. The discount factor is set at 0.95. For other details, see notes to Figure 4.

The degree of store clustering is smaller than that in Figures 4 and 5. This is reasonable given the smaller magnitude of the estimated net cost savings across markets. However, similar geographical patterns of networks of stores that we observe in Figures 4 and 5 remain: The acquirer increases the number of stores in

Figure 6 (Color online) Increase (Left) and Decrease (Right) in Total Number of Stores, After Merger: Full Model with a Smaller Set of Variables



Notes. The counterfactual exercise uses the parameter estimates from the second column in Table 2 (the sensitivity check specification). The discount factor is set at 0.90. For other details, see notes to Figure 4.

the city-center markets and decreases the number in noncity markets.

Online Appendix 1 §G provides additional robustness checks on (1) model without revenue equation, (2) alternative choices of grids, and (3) the alternative equilibrium selection rule. Overall, the nonrevenue specification and shifted-grid specification yield similar results to the baseline specification. This provides evidence that neither the post-entry revenue data nor the assumption about the location of the grid has played a big role in driving the results.

6. Conclusion

The post-merger network of stores is crucial for evaluating multistore firms' merger cases. This paper proposes an empirical model of strategic store-network choices by two multistore firms, which allows us to examine the impact of a hypothetical merger on store configurations, cost savings, and profits. I extend 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 multistore firms' store-network choice, which make location decisions across markets interdependent, i.e., 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 use lattice-theoretical results to address the huge number of possible network choices. I use the 2001 cross-sectional data 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 that 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 FamilyMart and LAWSON, the post-merger density of stores of the monopolist firm in the city center would be greater than the combined density of FamilyMart and LAWSON stores before the merger.

Beyond its contributions to the literature, this paper offers two implications for decision making in marketing. First, the framework provides a tool with which a manager can design a complex network of outlets that maximizes profits, which is often a daunting task. Second, and more important, the conventional wisdom is that a firm should decrease the store counts in local markets after a merger to decrease cannibalization (own business-stealing effect) and increase market power. By contrast, the empirical model implies that for markets with high demand, such as city centers, a manager may be able to increase profits by increasing the number of outlets after a merger. Whether a manager should increase the outlets depends on the trade-off by clustering at the market level, i.e., cost savings and cannibalization within a chain.

A main limitation of the paper is that it does not explicitly address change in price before and after a merger. In the specific application to the case of the Japanese convenience store industry, the lack of pricing is unlikely to affect the main conclusion due to uniform pricing at the national level. In other markets, however, consideration of pricing behavior will be essential. Incorporating models of differentiated product demand, such as Berry (1994) and Berry et al. (1995), would prove useful in this context, if a researcher has information on prices and quantities. This integration would also allow us to explore the welfare consequences of mergers due to changes in both pricing and store network choice.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2014.0871.

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References

Bajari P, Hong H, Krainer J, Nekipelov D (2010) Estimating static models of strategic interactions. *J. Bus. Econom. Statist.* 28(4):469–482.

Berry S, Levinsohn J, Pakes A (1995) Automobile prices in market equilibrium. *Econometrica* 63(4):841–890.

Berry ST (1992) Estimation of a model of entry in the airline industry. *Econometrica* 60(4):889–917.

Berry ST (1994) Estimating discrete-choice models of product differentiation. *RAND J. Econom.* 25(2):242–262.

Berry ST, Waldfogel J (1999) Free entry and social inefficiency in radio broadcasting. *RAND J. Econom.* 30(3):397–420.

Bresnahan TF, Reiss PC (1990) Entry in monopoly markets. *Rev. Econom. Stud.* 57(4):531–553.

Bresnahan TF, Reiss PC (1991) Entry and competition in concentrated markets. *J. Political Econom.* 99(5):977–1009.

Ciliberto F, Tamer E (2009) Market structure and multiple equilibria in airline markets. *Econometrica* 77(6):1791–1828.

Conley TG (1999) GMM estimation with cross sectional dependence. *J. Econometrics* 92(1):1–45.

Crawford GS (2012) Endogenous product choice: A progress report. *Internat. J. Indust. Organ.* 30(3):315–320.

Datta S, Sudhir K (2013) Does reducing spatial differentiation increase product differentiation? Effects of zoning on retail entry and format variety. *Quant. Marketing Econom.* 11(1):83–116.

Davis P (2006a) Estimation of quantity games in the presence of indivisibilities and heterogeneous firms. *J. Econometrics* 134(1):187–214.

Davis P (2006b) Spatial competition in retail markets: Movie theaters. *RAND J. Econom.* 37(4):964–982.

Draganska M, Mazzeo M, Seim K (2009a) Beyond plain vanilla: Modeling joint product assortment and pricing decisions. *Quant. Marketing Econom.* 7(2):105–146.

Draganska M, Mazzeo M, Seim K (2009b) Addressing endogenous product choice in an empirical analysis of merger effects. Technical report, Northwestern University, Evanston, IL.

Dubé J-P, Sudhir K, Ching A, Crawford GS, Draganska M, Fox JT, Hartmann W, Hitsch GJ, Viard VB, Villas-Boas M, et al. (2005) Recent advances in structural econometric modeling: Dynamics, product positioning and entry. *Marketing Lett.* 16(3–4):209–224.

Ellickson PB, Misra S (2012) Enriching interactions: Incorporating outcome data into static discrete games. *Quant. Marketing Econom.* 10(1):1–26.

Ellickson PB, Houghton S, Timmins C (2013) Estimating network economies in retail chains: A revealed preference approach. *RAND J. Econom.* 44(2):169–193.

FamilyMart (2001) 2000–2001 Annual Securities Report. FamilyMart Co., Ltd., Tokyo.

Fan Y (2013) Ownership consolidation and product characteristics: A study of the U.S. daily newspaper market. *Amer. Econom. Rev.* 103(5):1598–1628.

Griffith R, Harmgart H (2008) Supermarkets and planning regulation. Technical report No. 6713, CEPR Discussion Papers, London.

Holmes TJ (2011) The diffusion of Wal-mart and economies of density. *Econometrica* 79(1):253–302.

Houde JF (2012) Spatial differentiation and vertical mergers in retail markets for gasoline. *Amer. Econom. Rev.* 102(5):2147–2182.

Jeziorski P (2013) Estimation of cost synergies from mergers without cost data: Application to U.S. radio. *RAND J. Econom.* Forthcoming.

Jia P (2008) What happens when Wal-mart comes to town: An empirical analysis of the discount retailing industry. *Econometrica* 76(6):1263–1316.

Kadiyali V, Sudhir K, Rao VR (2001) Structural analysis of competitive behavior: New empirical industrial organization methods in marketing. *Internat. J. Res. Marketing* 18(1):161–186.

Manuszak MD (2000) Firm conduct and product differentiation in the Hawaiian retail gasoline industry. Technical report, Carnegie Mellon University, Pittsburgh.

Mazzeo MJ (2002a) Competitive outcomes in product-differentiated oligopoly. *Rev. Econom. Statist.* 84(4):716–728.

Mazzeo MJ (2002b) Product choice and oligopoly market structure. *RAND J. Econom.* 33(2):1–22.

McFadden D (1996) Lectures on Simulation-Assisted Statistical Inference. Technical report, presented at the EC-squared Conference, Florence, Italy.

Nevo A (2000) Mergers with differentiated products: The case of the ready-to-eat cereal industry. *RAND J. Econom.* 31(3):395–421.

Nishida M (2014) The costs of zoning regulations in retail chains: The case of the city planning act of 1968 in Japan. *J. Regulatory Econom.* 45(3):305–328.

Orhun AY (2013) Spatial differentiation in the supermarket industry: The role of common information. *Quant. Marketing Econom.* 11(1):3–37.

Pinkse J, Slade ME, Brett C (2002) Spatial price competition: A semiparametric approach. *Econometrica* 70(3):1111–1153.

Prokhorov A, Schmidt P (2009) GMM redundancy results for general missing data problems. *J. Econometrics* 151(1):47–55.

Reiss PC, Spiller PT (1989) Competition and entry in small airline markets. *J. Law Econom.* 32(2):S179–S202.

Seim K (2006) An empirical model of firm entry with endogenous product-type choices. *RAND J. Econom.* 37(3):619–640.

Smith H (2004) Supermarket choice and supermarket competition in market equilibrium. *Rev. Econom. Stud.* 71(1):235–263.

Suzuki J (2013) Land use regulation as a barrier to entry: Evidence from the Texas lodging industry. *Internat. Econom. Rev.* 54(2): 495–523.

Sweeting A (2010) The effects of mergers on product positioning: Evidence from the music radio industry. *RAND J. Econom.* 41(2):372–397.

Tarski A (1955) A lattice-theoretical fixpoint theorem and its applications. *Pacific J. Math.* 5(2):285–309.

TBC (2002) Japan's Convenience Store Almanac, TBC, Tokyo.

Thomadsen R (2005) The effect of ownership structure on prices in geographically differentiated industries. *RAND J. Econom.* 36(4):908–929.

Thomadsen R (2007) Product positioning and competition: The role of location in the fast food industry. *Marketing Sci.* 26(6):792–804.

Toivanen O, Waterson M (2005) Market structure and entry: Where's the beef? *RAND J. Econom.* 36(3):680–699.

Topkis DM (1979) Equilibrium points in nonzero-sum n-person submodular games. *SIAM J. Control Optim.* 17(6):773–787.

Topkis DM (1998) *Supermodularity and Complementarity* (Princeton University Press, Princeton, NJ).

Vitorino MA (2012) Empirical entry games with complementarities: An application to the shopping center industry. *J. Marketing Res.* 49(2):175–191.

Watson RB (2005) Entry and location choice in eyewear retailing. Technical report, University of Texas at Austin.

Wooldridge JM (1998) Selection corrections with a censored selection variable. Technical report, Department of Economics, Michigan State University, East Lansing.

Yang N (2013) March of the chains: Herding in restaurant locations. Technical report, Yale School of Management, Yale University, New Haven, CT.

Zhu T, Singh V (2009) Spatial competition with endogenous location choices: An application to discount retailing. *Quant. Marketing Econom.* 7(1):1–35.