Better Together? Retail Chain Performance Dynamics in Store Expansion Before and After Mergers*

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Abstract

We study firm performance dynamics in retail growth using a dynamic model of expansion that allow these dynamics to operate through an unobserved serially correlated process that evolves both endogenously and stochastically. The model is estimated with data on convenience-store chain diffusion across Japanese prefectures from 1982 to 2012, whereby an actual merger between two chains takes place in 2001. Given the presence of serial correlation and selection biases in observed revenue, we combine recently developed particle filtering methods for dynamic games with control functions in revenue regressions. The estimated structural model provides us insights about how performance dynamics evolve before and after the merger. Our findings suggest that despite major increases to revenue and profit growth, the underlying unobserved performance dynamics for the merged entity does not improve following the merger.

Keywords: Dynamic discrete choice; Firm size spillovers; Industry dynamics; Learning-by-doing; Market Concentration; Merger analysis; Particle filter; Revenue regression; Serial correlation.

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1 Introduction

Large retail chains, such as 7-Eleven, Wal-Mart, and McDonald's, have expanded rapidly by entering multiple geographical markets and opening many outlets. Motivated by the growing dominance of chains in retail, the study of drivers behind their entry and expansion strategies has received growing interest by researchers (e.g., Beresteanu, Ellickson, and Misra, 2010; Blevins, Khwaja, and Yang, 2014; Hollenbeck, 2013b; Holmes, 2011; Igami and Yang, 2014; Nishida, 2014a; Orhun, 2013; Suzuki, 2013; Toivanen and Waterson, 2005, 2011; Varela, 2013; Vitorino, 2012; and Yang, 2012, 2013). Retail chains shape the landscape of retailing through expansion dynamics, where they may become increasingly profitable over time through performance dynamics such as accumulated customer goodwill (e.g., Pancras, Sriram, and Kumar, 2012) or scale economies (e.g., Aguirregabiria and Ho, 2012; Ellickson, Houghton, and Timmins, 2013; Holmes, 2011; Nishida, 2013b). For instance, we may see such dynamics materialize through persistence in market shares (Bronnenberg, Dhar, and Dubé, 2009). Furthermore, some of these performance advantages may persist over time via firm-specific efficiencies that prevent (or accelerate) organizational retention. However, a challenge that researchers face is that the underlying performance dynamics are inherently unobservable.

Uncovering these performance dynamics is important for firms and policy makers in industries where mergers occur. A retail chain may be interested in understanding whether a merger boost or disrupt these performance dynamics, whereas policy makers may be interested in understanding how market structure and efficiencies evolves after the merger. It seems plausible that mergers will have an impact on performance (Williamson, 1968), as the newly combined firm will have to integrate its corporate culture, logistics, marketing, and overall strategy. In fact, mergers do not necessarily lead to performance gains. Alluding to a well-known failure, retail chains may wish to avoid a scenario like the Wendy's and Arby's merger in 2008. Within a few years of the merger, Wendy's sold Arby's to a private equity firm due to sluggish growth. From a policy perspective, antitrust authorities may block a merger between multistore retailers when the purported efficiencies by the merging firms are hard to verify. For instance, the U.S. Federal Trade Commission blocked a merger between Staples and Office Depot in 1997, two of the three largest nationwide office supply superstores.[1] One of the major debates in the litigation was regarding projected cost savings and to what extent such efficiencies would be passed on to consumers (Baker, 1999). Finally, the fact that many popular (business) media outlets frequently publish stories like "the top 10 best (and worst) mergers" of all time suggests a desire to evaluate mergers, *ex post*.[2]

In this study, we analyze firm performance dynamics in retail growth, before and after a merger. Our research uses a dynamic model of expansion and contraction that allows for these performance dynamics to operate flexibly through a serially correlated and unobserved profitability process, where we contribute to recent literature that incorporates merger events into dynamic oligopoly models (Benkard, Bodoh-Creed, and Lazarev, 2010; Gayle and Le, 2014; Hollenbeck, 2013a; Jeziorski, 2013).[3] We estimate this model using an extensive and manually collected data set on convenience-store chains, including 7-Eleven, LAWSON, Family Mart, circle K, sunkus, and ministop, in all 47 prefectures in Japan from 1982 to 2012. Given the presence of firm-specific and serially correlated unobservables, we make use of an approach akin to Blevins (2014) and Blevins, Khwaja, and Yang (2014) that combine particle filtering methods with two-step estimation of dynamic discrete choice games in a setting that has retail expansion and contraction.[4] Because both revenue and store counts are observed in our data,[5] the estimated model helps us determine the extent to which performance dynamics operate through demand (e.g., customer goodwill), or fixed costs (e.g., scale economies). However, a challenge of incorporating revenue into our analysis is the inherent selection bias (i.e., we only observe non-zero revenues for markets that the firms have at least one store). Given this challenge, we augment the particle filtering method for estimating dynamic games by including the control function approach proposed by Ellickson and Misra (2012) to correct for selection biases when we accurately calibrate revenue.[6]

[1] Please refer to FTC v. Staples Inc. [970 F. Supp. 1066 (D.D.C. 1997)] for more details.

[2] Post-merger evaluation of the validity of claimed cost-efficiencies have been the subject of periodic reports by the OECD; for example, refer to their report *Impact Evaluation of Merger Decisions* (2011). See also Homburg and Bucerius (2005) for research that investigates the effects of post-merger integration.

[3] For analysis of the incentives behind the mergers themselves, we refer readers to Akkus and Hortacsu (2007), Gugler and Siebert (2007), Park (2013), Rhoades and Yeats (1974), Sheen (2014), and Uetake and Watanabe (2013).

[4] Blevins (2011) was the first to incorporate particle filtering in the estimation of dynamic discrete choice games of imperfect information, while Gallant, Hong, and Khwaja (2010) was the first to incorporate particle filtering in dynamic discrete choice games of complete information. Recently, such methods have been also used in dynamic discrete choice models like Fang and Kung (2012). In marketing research, linear and non-linear particle filtering methods have been used in studying dynamic systems (e.g., Bass, Bruce, Majumdar, and Murthi, 2007; Bruce, 2008; Bruce, Foutz, and Kolsarici, 2012; Bruce, Peters, and Naik, 2012; Kolsarici and Vakratsas, 2010).

[5] A growing number of empirical applications of industry dynamics now exploit information about revenues (Dunne et. al., 2013; Hollenbeck, 2013b; Suzuki, 2013).

[6] Note that in a simpler model with fewer choices, one may be able to test for selection biases as in Hollenbeck

To motivate our structural estimation, reduced form analysis reveals that the relationship between past size and expansion/revenue differs across chains. In particular, we find that past size and expansion/revenue are positively correlated for a number of chains. These findings are suggestive of the presence of both accumulated goodwill and scale/scope economies in the industry, and corroborate our structural estimates that reveal the presence of performance dynamics in both sunk cost and revenue channels. This result further stresses the importance of incorporating revenue data into the analysis of expansion dynamics. Furthermore, a comparison of our results across the chains demonstrate substantial heterogeneity in these performance dynamic effects.

With the estimated structural model, we conduct a policy analysis to evaluate the actual merger between circle K and sunkus that takes place in 2001. We make use of this event to explore how performance dynamics are affected by the merger. Evaluating performance dynamics for this merger is particularly relevant, as the well publicized motive for this merger was to pursue "efficiencies of scale by integrating information systems and improving product margins through joint-purchasing negotiations,"[7] while "many argue that it is [still] cost heavy," even after the merger.[8] Should there be performance gains from mergers, it seems plausible that one would see improvements in retail expansion operations; therefore, the Japanese convenience store expansion and revenue dynamics before and after the merger provide us an appropriate setting to evaluate performance improvements (or deterioration). The estimated model allows us to forward simulate the growth trajectories for these two chains in order to evaluate whether or not the merger was successful in improving performance dynamics. Our analysis yields a few main findings. First, the unobserved performance dynamics do not improve for the newly merged firm, as the growth rate for the unobserved profitability actually decreases after the merger. Second, the merger appears to have an increasing effect on revenue growth. Finally, in addition to revenue growth, the profit growth rate increases as well after the merger; such a finding suggests that the decision by sunkus and circle K to merge can be rationalized by the expectation of higher revenue and profit growth. In summary, our collective findings suggest that the circle K and sunkus merger may be viewed unfavorably *ex post* from the perspective of policy makers, but favorably from the perspective of the merged entity

(2013).

[7]Taken from excerpt the holding company's *Investors' Guide 2002* (page 2) available at http://www.circleksunkus.jp/__image__/other/image/company/investor/ir/pdf/ig2002.pdf

[8]Taken from online discussion about the lack of efficiency gains after the merger: http://www.japanconsuming.com/circle-k-sunkus-a-disappointing-merger

itself.

The rest of the paper is organized as follows. Section 2 explains the institutional features of the industry, and provides details about the data. Section 3 lays out the model we use for estimation and simulations. Section 4 goes over our estimation approach. Section 5 summarizes our main results from estimation and subsequent merger analysis. Section 6 concludes.

2 Industry and Data

This section describes the industry we study, and our data from the convenience store chains in Japan (1982-2012). In our description of the industry, we also provide details about the merger between circle K and sunkus, which is one key industry feature that our data captures. Preliminary analysis suggests the presence of intertemporal performance dynamics that affect the firms' future decisions, in that past size and revenue have a noticeable relationship with subsequent expansion efforts.

2.1 Market Definition, Data, and Merger Details

Japan has 47 prefectures, and each is a governmental body with a governor, and this paper treats these prefectures as 47 independent geographic markets. Given this definition of market, the primary source of market structure data is the annual financial statements from the six largest convenience-store chains (7-Eleven, LAWSON, Family Mart, circle K, sunkus, and ministop), which provide the prefecture-level annual sales and the number of stores for each chain. The coverage ranges from 1982 through 2012. The nominal sales across years are deflated by using the annual GDP deflator from the Cabinet Office.

The demographic variables come from multiple sources. Annual population data at the prefecture level come from the Census Bureau at the Ministry of Internal Affairs and Communications. Annual income data at the prefecture level comes from the Cabinet Office. We compute the income per capita by markets by dividing the aggregate income at the prefecture level by the population of that prefecture. Hourly minimum wages at the prefecture level, published as the Annual Handbook of Minimum Wage Decisions, are collected by the Ministry of Health, Labour and Welfare. Annual land price data for multiple points for each of the prefectures are published by the Ministry of

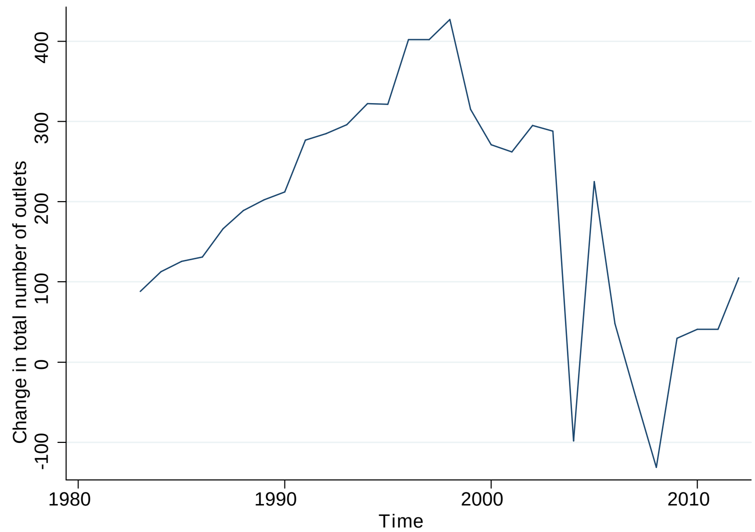
Land, Infrastructure, Transport and Tourism, and we take the average across data points for each of the prefectures to construct the price index for that prefecture that year. Table 1 summarizes the variables we use in this paper.

Table 1: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Market Characteristics					
Population	2666.614	2481.959	582	13230	10528
Income per capita	2590.847	538.132	1347.643	5232.25	9541
Minimum wage	572.532	99.094	400.709	910.064	10199
Land price	172256.776	211004.075	31860.813	2480561.209	9870
Sales					
7-Eleven	56757.888	59292.341	31.045	364726.344	559
LAWSON	28733.695	32692.574	3346.591	261521.594	564
Family Mart	25832.317	35733.175	2.098	250225.5	668
sunkus	13943.18	15857.824	11.643	104912.438	327
circle K	18666.55	27488.137	119.161	174104.75	287
ministop	12246.53	12506.798	2.86	57916.926	329
CK+SKS	28680.531	38290.167	320.888	199770.516	259
Number of outlets					
7-Eleven	277.139	274.59	1	1864	799
LAWSON	179.301	201.035	8	1549	795
Family Mart	144.308	189.698	1	1616	884
sunkus	76.605	77.528	1	506	509
circle K	116.309	163.987	1	902	417
ministop	77.382	73.744	1	308	380
CK+SKS	165.004	194.11	5	1007	259

We now describe a brief chronology of how sunkus and circle K, the fourth and fifth largest convenience-store chains in Japan, came to a financial integration in July 2001. Initially, they started their business separately. In 1980, Nagasakiya Co., Ltd, a large retailer in Japan focusing on clothes, established sunkus Co.,Ltd. as a subsidiary company and opened its first outlet. Similarly, in the same year, UNY Co., Ltd, a licensee of circle K Stores, Inc. in the U.S., established circle K Japan Co., Ltd. and opened its first outlet. Since then, circle K Japan Co., Ltd became a subsidiary of UNY Co., Ltd until 2014. Meanwhile, sunkus experienced two ownership turnovers. In 1994, Nagasakiya Co., Ltd sold its shares of sunkus to Ono group. In 1998, UNY Co., Ltd. and circle K Japan Co., Ltd. started to form an alliance with sunkus by acquiring sunkus' share. Afterwards, circle K and sunkus formed a holding company called C&S in 2001, under which both circle K and sunkus became subsidiaries. Both sunkus and circle K are kept as separate chain brands, but they

Figure 1: Total Annual Change in Number of circle K and sunkus



increased the joint operations and management decisions. C&S, sunkus, and circle K conducted the three-way merger in 2004, forming a company Circle K Sunkus Co., Ltd. that is responsible for both chain brands. The complete integration at the operation level took longer than this capital integration– in 2007 circle K and sunkus fully integrated their vendor and logistics networks.

2.2 Expansion Dynamics for Merging Chains

We now direct our attention onto the expansion dynamics for circle K and sunkus, the two chains that merged in 2001. A simple plot of the expansion/contraction patterns for circle K and sunkus (Figure 1) reveals an apparent change in expansion/contraction trends after 2001; we see similar changes before and after the merger for sales dynamics (Figure 2). Prior to the merger, the total number of circle K and sunkus does not change, or increases. It is not until after the merger do we see contraction in the total number of circle K and sunkus outlets. To further investigate the possibility of a structural break in the expansion dynamics, we conduct a Chow test and see whether the relationship between size and expansion (or change in sales) changes after the merger. Our test reveals that the null hypothesis of "no structural break" is rejected at 1% significance (Table 2).

Although such a test result is suggestive of the idea that mergers have an impact on performance dynamics, we are cautious to jump to that conclusion based on this reduced form evidence alone. To gain more robust insights about performance dynamics and the impact of mergers, we turn to

Figure 2: Total Annual Change in Sales of circle K and sunkus

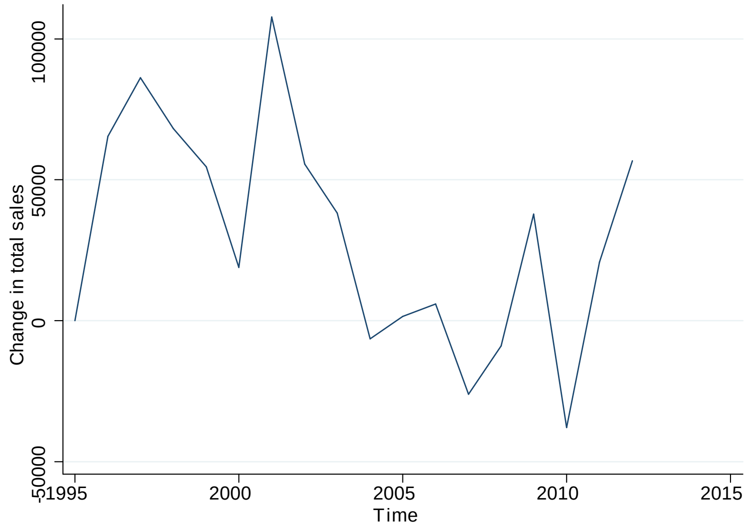


Table 2: Results from Chow Test for Structural Break in Relationship with Firm Size

	Expansion	Change in sales
F statistic	201.81***	104.76***
Controls	Yes	Yes
Market fixed effects	Yes	Yes
Time trend	Yes	Yes

our estimable model that allows for strategic and forward looking expansion/contraction decisions, selection in revenue, and unobservable performance dynamics.

3 Model

We consider a model with I forward looking firms in a retail industry that make decisions about operating in market m at time t. At the beginning of time period t and for each given market m, each firm decides how many new stores to add or subtract, denoted as $n_{imt} \in \mathcal{N}_i = \{-K_i, ..., -1, 0, 1, ..., K_i\}$. Based on this decision, the total number of stores that a firm has in market m and time t evolves according to:

$$N_{imt} = N_{imt-1} + n_{imt}.$$

A current period's market structure can then be summarized as $N_{mt} = \{N_{imt}\}_i$.

In our model firms are forward-looking, they seek to maximize the discounted profit stream $\sum_s \rho^s \Pi_{imt+s}$, where Π_{imt} is the one-shot payoff as defined by:

$$\begin{aligned} \Pi_{imt}(n_{imt}, N_{mt-1}, X_{mt}, Z_{imt}, \zeta_{imt}, \xi_{imt}, \theta) \quad &= \quad R_i(n_{imt}, N_{mt-1}, X_{mt}, Z_{imt}, \zeta_{imt}, \xi_{imt}, \theta^R) \\ &\quad -C_i(n_{imt}, N_{mt-1}, X_{mt}, Z_{imt}, \zeta_{imt}, \xi_{imt}, \theta^C). \end{aligned}$$

The one-shot payoff consists of two main components, the revenue, and the fixed cost. Here, revenue is denoted by $R_i(\cdot)$. Revenue is a function of the number of active outlets the chain has in the market (N_{imt}), market characteristics (X_{mt}), and the competitive landscape (N_{-imt}). We assume here that firms play a game of incomplete information, as in Seim (2006), so $\zeta_{imt} = (\zeta^R_{imt}, \zeta^C_{imt})$ can be interpreted as private information that is i.i.d. (across markets and time) with Type I Extreme Value distribution. Similar to Ellickson and Misra (2012), we also include optimization error, $\xi_{imt} = (\xi^R_{imt}, \xi^C_{imt})$. Unlike ζ_{imt}, the optimization error will not have an impact on firm behavior, such that they are ignored when we construct best response functions. For example, we can think of such optimization errors as idiosyncratic miscalculations in forecasted revenue or costs during *pro forma* real estate analysis prior to expansion. Similar to Blevins, Khwaja, and Yang (2014), we allow for firm-specific unobserved profitability across markets and time in revenue, as denoted by Z_{imt}.

$$\begin{aligned} R_i(n_{imt}, N_{mt-1}, X_{mt}, Z_{imt}, \zeta_{imt}^R, \xi_{imt}^R, \theta^R) &= N_{imt}(\theta_1^R + \theta_2^R X_{mt} + \theta_3^R N_{imt} + \theta_4^R N_{-imt}) \\ &\quad + \gamma^R Z_{imt} + \zeta_{imt}^R + \xi_{imt}^R \end{aligned}$$

Cost is denoted by $C_i(\cdot)$, and is affected by market characteristics, entry costs, expansion costs, and contraction costs. Furthermore, we allow there to be a private information shock and optimization error, as in the revenue specification. Furthermore, unobserved profitability may affect the fixed cost component of profits. Because the unobserved profitability enter into both revenue and cost, comparisons between γ^R and γ^C would be helpful in determining the extent to which unobserved profitability matters for revenue and cost respectively.

$$\begin{aligned} C_i(n_{imt}, N_{mt-1}, X_{mt}, Z_{imt}, \zeta_{imt}^C, \xi_{imt}^C, \theta^C) &= \theta_1^C X_{mt} + \theta_2^C \cdot 1\{N_{imt-1} = 0, n_{imt} > 0\} \\ &\quad + \theta_3^C \cdot 1\{n_{imt} > 0\} \cdot n_{imt} + \theta_4^C \cdot 1\{n_{imt} < 0\} \cdot n_{imt} + \gamma^C Z_{imt} + \zeta_{imt}^C + \xi_{imt}^C. \end{aligned}$$

A key difference between our model, and typical dynamic oligopoly models of entry is the inclusion of a serially correlated and unobserved profitability term. We assume that this unobserved profitability follows a simple autoregressive process, which is captured by the following transition equation,

$$Z_{imt} = \mu_i + \delta_i Z_{imt-1} + \beta_i N_{imt-1} + \eta_m + \epsilon_{imt},$$

where $\epsilon_{imt} \sim \mathrm{N}(0, \psi_\epsilon^2)$ are i.i.d. There are two main components to this unobserved profitability measure. The first component, δ_i, is the persistence of profitability (i.e., retention). The second component, β_i, is related to movements along the learning curve as the chain's size in a given market that changes over time (i.e., size spillover).[9] Finally, ϵ_{imt} are normally distributed i.i.d. innovations to unobserved profitability with standard deviation ψ_ϵ. Heterogeneity across firms is captured by different parameters across firms. Ultimately, this specification allows for firm-market-specific unobserved heterogeneity that is potentially serially correlated. We make the assumption that Z_{imt} is observed by all firms, but unobserved to the econometrician. However, the model

[9] Refer to Benkard (2000, 2004) for a similar econometric specification for learning-by-doing in production. Alternatively, one may interpret this specification as capturing network effects or scale economies.

allows for some elements of a firm's profitability to be private information incorporated in ζ_{imt}.

The model's structural parameters can therefore be represented as $\alpha = \{\alpha_i\}_{i=1}^{I}$, where

$$\alpha_i = (\theta_1^R, \theta_2^R, \theta_3^R, \theta_4^R, \theta_1^C, \theta_2^C, \theta_3^C, \gamma^R, \gamma^C, \delta_i, \beta_i, \psi_\epsilon, \eta_m).$$

Given the current pay-off relevant state $s_{imt} = (N_{mt-1}, X_{mt}, Z_{imt}) \in S$, which is known to all players, the firm's expected total discounted profit at time t prior to the private shock ζ_{imt} being realized is given by,

$$\mathbb{E}\left[\sum_{\tau=t}^{\infty} \rho^{\tau-t}\{\Pi_{im\tau}(s_{im\tau}, \zeta_{im\tau}; \alpha_i)\}\right],$$

where ρ is the discount factor, $\rho \in (0,1)$. The firm's objective is to maximize the present discounted value of its profit at each time period t taking as given the equilibrium action profiles of other firms. The expectations is over the rivals' actions in the current period, the future evolution of the state variables and the private information shock to the firm in the current period.

We follow Bajari, Benkard and Levin (2008) and analyze the dynamic game of incomplete information using the solution concept of pure strategy Markov perfect equilibria (MPE).[10] We use the following notation to set up the MPE. A Markov strategy for firm is a map from its payoff relevant state variables and private information to its set of actions, i.e., $\sigma_{imt} : S \times \mathbb{R} \rightarrow \mathcal{N}_i$. Furthermore, a profile of Markov strategies is the vector, $\sigma_{mt} = (\sigma_{1mt}, \ldots, \sigma_{Imt})$, where $\sigma : S \times \mathbb{R}^I \rightarrow \mathcal{N}$. A MPE is defined as a Markov strategy profile σ_{mt} such that no firm has an incentive to deviate from its strategy. Thus, there is no firm i, with an alternative Markov strategy σ'_{imt}, that it prefers to the strategy σ_{imt} with its rivals using the strategy profile $\sigma_{-i,mt}$. More formally, σ_{mt} is defined to be a MPE if for all firms i, in all stages s_{imt}, and for all alternative Markov strategies, σ'_{imt} the following condition holds,

$$V_i(s_{imt}, \zeta_{imt}|\sigma_{imt}, \sigma_{-i,mt}) \geq V_i(s_{imt}, \zeta_{imt}|\sigma'_{imt}, \sigma_{-i,mt}) \quad \forall\, i, m, t.$$

Given a Markov strategy profile σ_{imt}, the ex-ante value function and the associated Bellman

[10] Refer to Ericson and Pakes (1995) for the general MPE framework.

equation for the present discounted value of the stream of profits for firm i can be written as,

$$V_i(s_{imt}, \zeta_{imt}|\sigma_{mt}) = \mathbb{E}_{\zeta_{-i,mt}}\Big[\Pi_{imt}(\sigma_{mt}(s_{mt}, \zeta_{mt}), s_{imt}, \zeta_{imt}) + \rho\, \mathbb{E}_{t+1}\big[V_i(s_{im,t+1}, \zeta_{im,t+1}|\sigma_{mt})\big]\Big],$$

where $s_{mt} = (s_{1mt}, \ldots, s_{Imt})$ and $\zeta_{mt} = (\zeta_{1mt}, \ldots, \zeta_{Imt})$. The expectations $\mathbb{E}_{\zeta_{-i,mt}}$ are with respect to current values of the private shocks and hence current actions of rivals, and the expectations $\mathbb{E}_{t+1}$ are with respect to future values of all state variables, future values of private shocks for the firm and its rivals, and future actions of rivals.

4 Estimation

To estimate the model of retail dynamics, we pair the methods proposed by Blevins, Khwaja, and Yang (2014) and Ellickson and Misra (2012). These methods help us address two key issues. First, Blevins, Khwaja, and Yang (2014) combine flexible particle filtering techniques with the Bajari, Benkard, and Levin (2007) two-step method to allow for serially correlated and firm-specific unobservables in a dynamic model of retail expansion.[11] The incorporation of particle filtering helps integrate out the serially correlated unobservables via sequential Monte Carlo re-sampling procedures, whereby the posterior distribution for the sequence of serially correlated unobservables is successively updated with each simulation draw. Second, Ellickson and Misra (2012) employ propensity-score based methods to address potential selection biases in revenues. As our analysis makes use of revenue data, controlling for such selection biases is important.

Our estimation approach follows three main steps. First, we estimate each firm's beliefs via pre-merger and post-merger policy function approximation, at the same time, employing particle filtering to obtain the posterior distribution of the serially correlated unobservable. Second, we use the approximated policies to estimate selectivity-corrected revenue equations via regression; note that because we are using pre-merger and post-merger policy functions, we run the revenue regressions separately before and after the merger. In the final step, using the calibrated revenue equations, we construct trajectories of profits using forward simulations and estimate remaining cost parameters via Bajari, Benkard, and Levin (2008).

[11] Similar to Blevins (2011), we use a bootstrap particle filter (Gordon, Salmond and Smith, 1993).

4.1 Policy Function Approximation and Particle Filtering

The objective of our first stage estimation is to estimate jointly the posterior distributions for the serially correlated unobservables Z_{imt}, as well as the reduced form policy functions for each of the retail chains. These reduced form policy functions are meant to model each chain's decision regarding its expansion or contraction decision, n_{imt}.

As before, we denote X_{mt} to be the vector of exogenous state variables (i.e., population, income, etc...), while $Z_{mt} = \{Z_{imt}\}_{\forall i}$ are vectors for the serially correlated unobservable state variables. For brevity, let us collect all reduced form parameters pertaining to the first stage into ϕ,[12] which include the coefficients for the reduced form policy, market fixed effects, and the parameters in the transition of X_{mt} and Z_{mt}. Given the data $\{n_{mt}, X_{mt}\}$, we maximize the following likelihood function:

$$L(\phi) = \prod_m \prod_t \int l_m(n_{mt}|X_{mt}, Z_{mt}, N_{mt-1}, \phi) p(X_{mt}|X_{mt-1}, \phi) p(Z_{mt}|N_{mt-1}, X_{mt-1}, \phi) dZ_{mt}.$$

The likelihood consists of four main components. First, we have the firm-specific choice probabilities l_m, which are estimated via an ordered probit specification (see Appendix). Second, we have the transition probabilities for the exogenous characteristics, $p(X_{mt}|X_{mt-1}, \phi)$; these transition probabilities are estimated using a seemingly unrelated regression (SUR), which is described in more detail in the Appendix. The final component is $p(Z_{mt}|N_{mt-1}, X_{mt-1}, \phi)$, which are the posterior distributions for the serially correlated unobservables. Given an initial distribution for the unobserved state and the recursive relation, we can simulate entire sequences for these posterior distributions.

We can then perform the filtering step using the following:

$$p(Z_{mt}|N_{mt-1}, X_{mt-1}, \phi) = \frac{l_m(n_{mt-1}, X_{mt-1}|X_{mt-2}, N_{mt-2}, Z_{mt-1}, \phi) p(Z_{mt-1}|N_{mt-2}, X_{mt-2}, \phi)}{\int l_m(n_{mt-1}, X_{mt-1}|X_{mt-2}, N_{mt-2}, Z_{mt-1}, \phi) p(Z_{mt-1}|N_{mt-2}, X_{mt-2}, \phi) dZ_{mt-1}}.$$

Here, we update the posterior distribution for Z_{mt} using the joint probability distribution for (n_{mt-1}, X_{mt-1}). More specifically, our first stage policy estimation implements the particle filtering (i.e., sequential Monte Carlo) using the following steps:

[12] Note that these parameters are not the same as the structural parameters, α. The parameters ϕ are reduced form in the sense that they help us approximate the true policy functions, which must be inferred using data.

1. *Initialization*: Draw Z^r_{mt} from some distribution for each simulation draw $r = 1, ..., R$.

2. *Recursion*: Repeat the following steps for each $t = 1, ..., T$.

   - *Importance sampling*: Draw Z^r_{mt} based on the transition equation for the Z process, and set weights according to $w^r_t = l_m(n_{mt-1}|X_{mt-1}, N_{mt-2}, Z^r_{mt-1}, \phi)$ for each simulation draw $r = 1, ..., R$. Note that $l_m(n_{mt}|X_{mt-1}, N_{mt-2}, Z^r_{mt}, \phi)$ is the probability of observing n_{mt} given the state X_{mt-1}, and drawn values of Z^r_{mt}.
   - *Re-sampling*: For each simulation draw $r = 1, ..., R$, draw posterior values $\tilde{Z}^r_{mt}$ from collection of Z^r_{mt}, in proportion to the weights, w^r_t, computed in the previous step.

An alternative way to integrate out the unobserved states is the expectation-maximization method by Arcidiacono and Miller (2011).[13] We choose to deviate from popular convention for the following reasons. First, it is practically easier to incorporate continuous unobserved states using particle filtering, as opposed to Arcidiacono and Miller's (2011) method that works particularly well for discrete persistent or time-varying unobserved Markovian states. However, the incorporation of discrete unobserved states will require an *a priori* assumption about the number of unobserved types.[14] Second, and most importantly, we are interested in an unobserved state that evolves both endogenously (through past size N_{mt-1}), and stochastically (through draws of ϵ_{imt}).

4.2 Estimating the Revenue Function

Our analysis makes use of the fact that we observe firm-specific revenues. However, the realized revenues will suffer from selection bias that is induced by the underlying dynamic game of expansion, as revenues are only observed for the strategies that are played in equilibrium. Strategies are chosen that maximize discounted profits, and are a function of the same unobserved private shocks that affect revenues, ζ^R_{imt}. Denoting the composite shock as $\omega^R_{imt} = \zeta^R_{imt} + \xi^R_{imt}$, it becomes clear that given this selection bias, $\mathbb{E}(\omega^R_{imt}|n_{imt} = k) \neq 0$.

To address the selection bias described above, we follow Ellickson and Misra (2012), and adopt a propensity-based based method. This procedure amounts to running revenue regressions, with the

[13] Recent applications of their method under the context of retail chain location/expansion include Hollenbeck (2013b), Igami and Yang (2014), and Yang (2013).

[14] Igami and Yang (2014) address such issues by implementing Kasahara and Shimotsu's (2009) identification results to find the number of unobserved market types before using Arcidiacono and Miller (2011).

inclusion of a control function $\Lambda(\hat{n}_{imt})$. Here, $\hat{n}_{imt}$ is the predicted number of opened/closed outlets as determined using the first stage policy approximation. For the control function, we make it a flexible function of $\hat{n}_{imt}$, which is approximated using high order polynomials. The main revenue regression is defined as:

$$R_{imt} = N_{imt}(\theta_1^R + \theta_2^R X_{mt}^R + \theta_3^R N_{imt} + \theta_4^R N_{-imt}) + \Lambda(\hat{n}_{imt}) + \ \gamma^R \hat{Z}_{imt} + \tilde{\omega}_{imt}^R.$$

To obtain $\hat{Z}_{imt}$, we first simulate many trajectories for each market-time. We then obtain the average value of the simulated posteriors to obtain $\hat{Z}_{imt}$. Similarly, $\hat{n}_{imt}$ is the average number of outlets across simulations for a given market and time. With the estimated parameters, we proceed to the final step. Ellickson and Misra (2012) point out that the private information assumption regarding ζ_{imt} helps us simplify the problem greatly, as this assumption allows us to decompose the joint selectivity problem into a collection of individual (firm-specific) selectivity problems.

Note that in our application, we do not run revenue regressions for each possible alternative of n_{imt}, but instead use the predicted number $\hat{n}_{imt}$ via forward simulations as a sufficient statistic. The main reason we make this simplification is the avoid the curse of dimensionality associated with many multinomial choice problems. For example, if there are 8 expansion/contraction options a firm can make as to how many stores to subtract or add, and if we used a second order polynomial approximation for the control function, we would have to estimate 32 parameters alone for the selectivity correction component alone.

4.3 Estimating the Profit Function

The final stage of our estimation proceeds using Bajari, Benkard, and Levin's (2007) forward simulation approach, which allows us to recover the structural parameters given the estimated first stage parameters ϕ. The estimated first stage parameters allow us to forward simulate the policies, exogenous state variables, and serially correlated unobserved states.

For any given initial state $S_1 = (N_0, X_1, Z_1)$, we can then forward simulate the following:

$$\begin{aligned}\bar{V}_i(S_1; \sigma, \alpha) &= \mathbb{E}\left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} \Pi_i(\sigma(S_\tau, \nu_\tau), S_\tau, \nu_{i\tau}; \alpha) \,|\, S_1, \sigma\right] \\ &\simeq \frac{1}{\bar{S}} \sum_{s=1}^{\bar{S}} \sum_{\tau=1}^{T} \rho^{\tau-1} \Pi_i(\sigma(S_\tau^s, \nu_\tau^s), S_\tau^s, \nu_{i\tau}^s; \alpha).\end{aligned}$$

Subscript s represents each simulation, where $\bar{S}$ paths of length T are simulated in the second stage. The term $\sigma(S_\tau^s, \nu_\tau^s)$ denotes a vector of simulated actions based on the policy profile σ. With this construction of forward simulated actions and payoffs, we can then consider perturbations of the policy function to generate B alternative policies. With each alternative policy, we can obtain the forward simulated profit stream using the previous two steps. We let b index the individual inequalities, with each inequality consisting of an initial market structure and state $S_1^b = (N_0^b, X_1^b, Z_1^b)$, an index for the deviating firm i, and an alternative policy $\tilde{\sigma}_i$ for firm i. The difference in valuations for firm i using inequality b is denoted by

$$g_b(\hat{\sigma}, \alpha) = \bar{V}_i(S_1^b; \hat{\sigma}, \alpha) - \bar{V}_i(S_1^b; \tilde{\sigma}_i, \hat{\sigma}_{-i}, \alpha).$$

This difference should be positive in equilibrium. Therefore, this criterion listed below identifies a $\hat{\alpha}$ to minimize the violations of the equilibrium requirement:

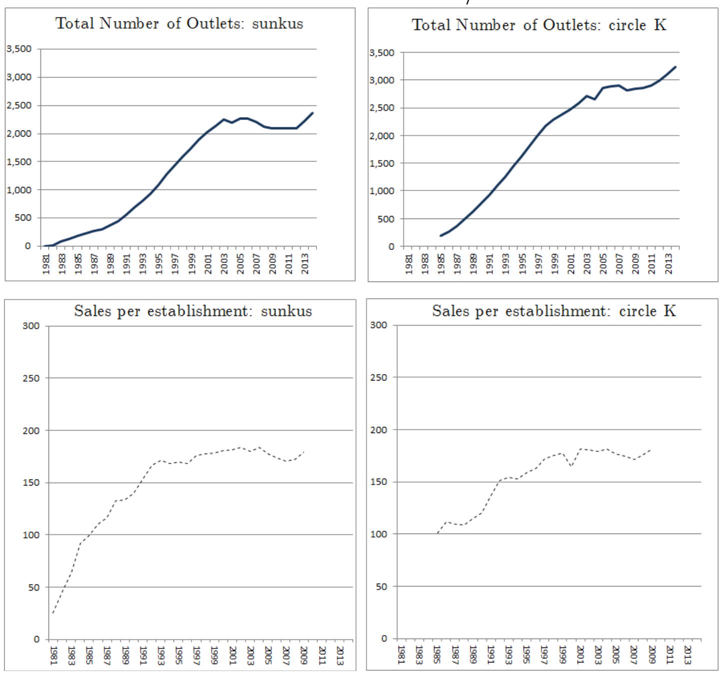
$$Q(\alpha) = \frac{1}{B} \sum_{b=1}^{B} (\min\{g_b(\hat{\sigma}, \alpha), 0\})^2.$$

4.4 Incorporating the Merger Event

One of the interesting features of our setting is that in 2001, sunkus and circle K merged into one entity.[15] This means that our sample of observations may be split into pre- and post-merger time periods. To accommodate the merger event, we allow the equilibrium played to be different, depending on whether or not the merged has occurred. This empirical strategy departs from Benkard, Bodoh-Creed, and Lazarev (2010), who assume that the equilibrium being played does

[15] For our analysis, we interpret all years from 2002 onward as being post-merger years.

Figure 3: The Evolution of Store Counts/Revenue Before Merger



not change after the merger.[16] Given these pre-merger and post-merger policy functions, we can then forward simulate the industry outcomes before and after the merger.

Furthermore, our estimation will make use of the following states. Before the merger, we make use of the actual N_{imt} in the first stage policy function estimation for sunkus and circle K. After the merger, we set $N_{imt} = 0$ for sunkus and circle K, and make use of the actual N_{imt} for the merged entity called C&S in the first stage policy function estimation. In the forward simulation stage, we take into account the merger by computing the discounted profit streams based on whether or not sunkus and circle K has merged. Note that unlike Benkard, Bodoh-Creed, and Lazarev (2010), the merger between sunkus and circle K is factual, and not merely a proposed merger. If instead the C&S merger did not actually occur yet, we would use the pre-merger factual data to obtain first stage policy function approximations, which would then be used to forward simulate market structure dynamics in light of a hypothetical merger at some date.

Our analysis relies on the assumption that when the firms are employing a pre-merger equilibrium strategy, they are not anticipating a merger event well in advance. For example, one or both of the companies may have an incentive to adjust their expansion/sales strategies as a means to

[16] Note that we also tried a specification whereby the policy functions are the same before and after the merger. These results are available upon request.

make themselves more attractive as merger targets. To check that pre-merger equilibrium behavior is not erratic leading up to the merger, we plot the trajectory of store counts and revenue in Figure 3. From the graphs, we see that the expansion and sales growth in the 10 years prior to 2001 do not appear to be volatile; that is, they follow a fairly linear growth rate leading up to the merger. After the merger in 2001, we do see a change in the growth rate for store counts and sales, but this change can be rationalized by a sudden change in the state as per Benkard, Bodoh-Creed, and Lazarev's (2010) merger analysis framework; moreover, the fact that we are estimating policy functions separately before and after the merger will capture some of these sudden change in growth rates.

4.5 Identification

Our identification arguments follow closely those of Ellickson and Misra (2012) and Blevins, Khwaja, and Yang (2014). In particular, we will now discuss the identification of strategic effects, revenue regression parameters, and the unobserved profitability process.

Identification conditions for models with strategic interactions is well known. A common strategy is to make use of exclusion restrictions, which affect one firm's payoffs directly, but not the payoffs of other firms. For our analysis, we make use of the lagged size of the firm, as it affects the firm directly through the unobserved profitability process and sunk costs, while having no direct effect on its rivals' payoffs. It will, however, have an indirect impact on rivals through their beliefs about the firm's expansion or contraction strategies.

To identify the underlying parameters in revenue, we make use of another exclusion restriction. More specifically, we have variables (e.g., wages, property value) that should have an impact on cost, but not revenue. These cost-side variables have an impact on the strategies, but can be excluded from the regression specification. As suggested by Ellickson and Misra (2012), property value is likely the better candidate as an exclusion restriction, as we can better interpret it as a market characteristic that affects sunk costs.

Finally, the unobserved profitability process is identified by the exclusion restriction involving the states that enter revenue and cost directly, but not unobserved profitability. For example, beliefs about a rival's current size is relevant for revenue, but does not have an impact on the unobserved profitability process. Furthermore, revenue and cost shifters, such as population, income, minimum wage, and property enter the payoffs, but not the unobserved profitability. Finally, intertemporal volatility of these exogenous states also ensure that they do not mirror the market fixed effect found in the evolution of unobserved profits. With these exclusion restrictions, the posterior distribution for the unobserved profitability can be identified, which can then be used to obtain the underlying parameters in unobserved profitability. In the absence of such exclusion restrictions, the identification strategy presented by Hu, Shum and Tan (2010) suggest that a necessary (but not sufficient) requirement for identification of dynamic games with serial correlation include a long panel, and rich transitions in the observed states, both of which our data easily satisfies.

5 Main Results

For all of the specifications we estimate, we report bootstrap standard errors. The first stage order probit is estimated using sieve maximum likelihood that includes all exogenous variables and relevant interactions; this first stage policy approximation is paired with particle filtering that uses $R = 1,000$ simulation draws (i.e., particle "swarms") so as to integrate out the unobserved profitability. With the first stage estimates, we then run our revenue regressions that incorporate control functions. In the second stage, we use $B = 1,000$ simulated inequalities. Each inequality contains an alternative policy function that we generated by perturbing the coefficients in the first stage policy function. Finally, we obtain standard errors using block bootstrapping.

5.1 Summary of Estimates

We now report the estimates from the first stage. The first stage estimates we focus our discussion around are those pertaining to the unobserved profitability process (Tables 3 and 4).[17] In general, we see some heterogeneity in these estimates across the chains. For instance, before the merger, the firm fixed effect (μ) is largest for sunkus. The retention effect (δ) is largest for circle K. Finally, we see that the size spillover (β) is largest for ministop prior to the merger. After the merger, the merged firm has the largest firm fixed effect, while Family Mart and 7-Eleven have the largest retention and size spillover estimates respectively.

Focusing our attention on the merged firms, sunkus and circle K, we see that the parameters

[17] Note that the full set of estimates for the parametrized first stage are available upon request.

Table 3: Estimates for the Unobserved Profitability Process Before Merger

	7-Eleven	LAWSON	Family Mart	sunkus	circle K	ministop
Firm FE (μ)	0.0120	0.3390	0.1630	0.7511	0.3124	0.5243
	(0.0000)	(0.0009)	(0.0002)	(0.0023)	(0.0018)	(0.0005)
Retention (δ)	0.6016	0.2619	0.6465	0.6892	0.7539	0.4467
	(0.0011)	(0.0006)	(0.0039)	(0.0173)	(0.0070)	(0.0005)
Size spillover (β)	0.2265	0.9038	0.1508	0.8163	0.5319	0.9858
	(0.0002)	(0.0008)	(0.0001)	(0.0006)	(0.0005)	(0.0010)

Table 4: Estimates for the Unobserved Profitability Process After Merger

	7-Eleven	LAWSON	Family Mart	ministop	CK+SKS
Firm FE (μ)	0.7022	0.1994	0.0307	0.4832	0.9120
	(0.0005)	(0.0001)	(0.0000)	(0.0004)	(0.0006)
Retention (δ)	0.6144	0.6223	0.8641	0.1849	0.2418
	(0.0008)	(0.0005)	(0.0007)	(0.0002)	(0.0003)
Size spillover (β)	0.8940	0.0289	0.4950	0.7202	0.5063
	(0.0008)	(0.0000)	(0.0006)	(0.0002)	(0.0002)

related to unobserved profitability change after the merger. Comparing these tables, we see that the Z process for the chains change after the merger. For example, the retention and size spillover effects improve for some of the chains after the merger. We conjecture that competitors of circle K and sunkus, such as 7-Eleven and Family Mart, may have improved their organizational efficiency in response to a potentially larger threat in the form of a merged firm. In contrast, the merger appears to have led to lower retention and size spillover effects for the merged firm, while raising the firm fixed effect. Therefore, the estimates from the Z process provide us no evidence that the merger improved the underlying performance dynamics for sunkus and circle K.

Tables 5 and 6 display the main results from our revenue regressions. For the control function specification, we choose a simple third-order polynomial, which is a flexible non-linear function of the predicted number of added or subtracted outlets $\hat{n}_{imt}$:

$$\Lambda(\hat{n}_{imt}) = \varphi_1 \hat{n}_{imt} + \varphi_1 \hat{n}_{imt}^2 + \varphi_3 \hat{n}_{imt}^3.$$

With this specification for the control function, we see that for all of the chains, $\hat{n}_{imt}$ appears to have a positive (albeit non-monotonic) effect on revenue through $\Lambda(\hat{n}_{imt})$.[18] Note that we run

[18] The estimates for the third-order polynomial are not listed in the table, but are available upon request.

Table 5: Estimates from the Revenue Regressions Before Merger

	7-Eleven	LAWSON	Family Mart	sunkus	circle K	ministop
Constant (θ_1^R)	143.6119	255.8917	141.6601	354.5573	128.3249	291.6507
	(0.7648)	(2.6290)	(2.9564)	(6.5136)	(5.3707)	(4.4546)
Population ($\theta_{2,population}^R$)	-0.0068	-0.0195	-0.0059	-0.0370	-0.0475	-0.0229
	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0004)	(0.0002)
Income ($\theta_{2,income}^R$)	0.0300	-0.0651	0.0045	-0.0777	0.0017	-0.0496
	(0.0003)	(0.0009)	(0.0008)	(0.0019)	(0.0017)	(0.0014)
N_i (θ_3^R)	0.0653	0.1431	0.1354	-0.0372	0.2763	0.3025
	(0.0009)	(0.0057)	(0.0026)	(0.0261)	(0.0080)	(0.0064)
N_{-i} (θ_4^R)	0.0016	0.0971	-0.0053	0.2147	0.1986	0.0954
	(0.0002)	(0.0012)	(0.0010)	(0.0039)	(0.0020)	(0.0010)
Unobserved profitability (γ^R)	3.7070	1.4062	-2.5088	0.4559	-0.1176	0.2223
	(0.0653)	(0.0656)	(0.0940)	(0.0074)	(0.0186)	(0.0053)

Table 6: Estimates from the Revenue Regressions After Merger

	7-Eleven	LAWSON	Family Mart	ministop	CK+SKS
Constant (θ_1^R)	10.1989	67.4064	62.1962	108.8947	149.3767
	(1.3633)	(0.9226)	(0.9635)	(0.8274)	(0.3135)
Population ($\theta_{2,population}^R$)	0.0268	-0.0109	-0.0021	-0.0079	0.0033
	(0.0007)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Income ($\theta_{2,income}^R$)	0.0173	0.0488	0.0410	0.0262	0.0015
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0000)
N_i (θ_3^R)	-0.0720	0.0501	-0.0196	-0.1784	0.0266
	(0.0054)	(0.0005)	(0.0015)	(0.0045)	(0.0017)
N_{-i} (θ_4^R)	-0.0754	-0.0008	-0.0021	0.0255	-0.0042
	(0.0034)	(0.0000)	(0.0006)	(0.0004)	(0.0004)
Unobserved profitability (γ^R)	-51.9362	13.7909	-1.3362	-6.3835	0.6484
	(0.3452)	(0.1973)	(0.0348)	(0.0830)	(0.1357)

different revenue regressions depending on whether the policy functions are pre-merger or post-merger. Having separate revenue regressions seems appropriate as the underlying selection issues that the control function approach is meant to address may be systematically different before and after the merger.

First note that revenues are a positive function of the number of own outlets, as one would expect. Furthermore, this positive relationship with size prior to the merger is magnified in markets with higher incomes, and for some chains such as 7-Eleven, Family Mart, and circle K, higher population accentuates the positive effect of own size. After the merger, income has a positive effect for all of the chains. Competition appears to have a dampening effect on the own size effect for some chains, both before and after the merger. Interestingly, sensitivity to competition is elevated after the merger. Finally, we see that the unobserved profitability is positively associated with revenue for a number of the chains, both before and after the merger. In particular, unobserved profitability has a positive effect on revenue for 7-Eleven, LAWSON, sunkus, and ministop prior to the merger, and LAWSON as well as the merged firm after the merger. This finding suggests that the unobserved profitability process may also operate through revenue, in addition to sunk costs (which we demonstrate in the next set of results).

From the estimates, we can also evaluate how the determinants of revenue changes for sunkus and circle K after the merger. There are a few noticeable changes. First, the relationship between the number of stores and revenue lies somewhere between that of sunkus and circle K as individual firms. Second, the competition effect as measured through the interaction between number of own and rival stores becomes negative after the merger, such that rival firms exert business stealing effects. As the merger appears to spur the unobserved profitability processes for rival chains, competition may be somewhat intensified after the merger. Third, we see that the own-brand cannibalization effects that sunkus experience prior to the merger dampens after the merger, as the quadratic effect of the number of outlets on revenue for the merged firm becomes positive. This finding suggests that as the merged firm maintains the individual branding for sunkus and circle K, expansion into markets can be done so as to minimize cannibalization by entering using a combination of the two brands, as opposed to just one. Finally, we see that the role of unobserved profitability in revenue is now overwhelmingly positive.

We now move on to the second stage estimates (Table 7). The estimates reveal that unobserved profitability contributes heavily to the one-shot payoff for LAWSON, and contributes the least to ministop. Family Mart appears to experience the largest sunk costs, as its entry, expansion, and contraction costs are the largest among all of the chains, which amount to 8, 4, and 1 million Yen respectively. Finally, we see that minimum wage and land price has a negative effect on profits for most of the chains, with the exception of 7-Eleven and LAWSON. One reason for the positive effects of these cost-side variables is that minimum wage and land price may be tied with the market's economic growth.

Focusing on the merged firm, the contribution of unobserved profitability lies somewhere between the firms as individual entities. Similarly, the entry costs and contraction costs also lie somewhere in between the firms as individuals. However, the cost of expansion increases significantly after the merger. The lack of savings in the sunk costs of operation and expansion seem to fit

Table 7: Second Stage Estimates for the Profit Function

	7-Eleven	LAWSON	Family Mart	sunkus	circle K	ministop	CK+SKS
Unobserved profitability	0.6778	0.9818	0.3524	0.8744	0.2032	0.2478	0.6866
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Entry cost	0.2728	0.8160	0.9725	0.2451	0.5748	0.2790	0.5533
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Expansion cost	0.4005	0.4097	0.9382	0.0025	0.1301	0.2826	0.9933
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Contraction cost	0.3643	0.1499	0.0947	0.7042	0.0569	0.2586	0.2130
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Minimum wage	0.5574	1.8858	-0.5788	-0.1226	-4.5708	-2.0930	-0.6934
	(0.0184)	(0.0252)	(0.0145)	(0.0015)	(0.0532)	(0.0309)	(0.0188)
Land price	1.9141	6.4760	-1.9878	-0.4209	-15.6966	-7.1876	-2.3811
	(0.0611)	(0.0834)	(0.0476)	(0.0048)	(0.1836)	(0.1058)	(0.0615)

in with the overall story thus far that performance dynamics in store expansion does not improve.

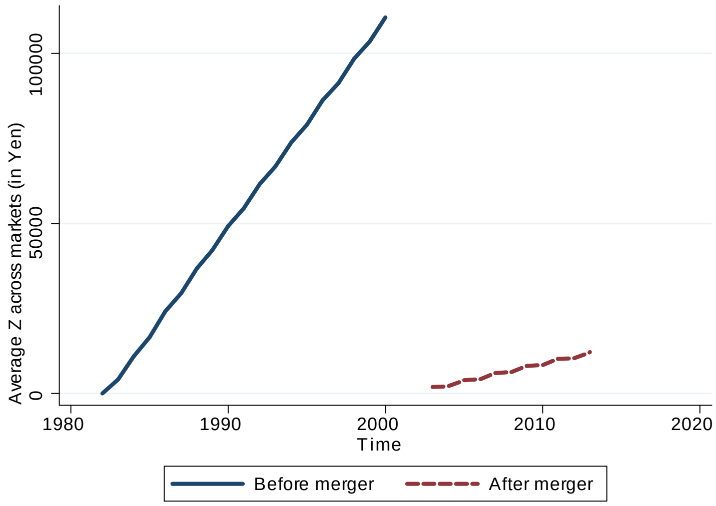
5.2 Merger Analysis

Using the estimated model, we now look more closely at the merger between sunkus and circle K. In particular, we simulate trajectories of the key variables (i.e., unobserved profitability, number of outlets, revenue, and overall profits) over time for sunkus, circle K, and the merged firm. For sunkus and circle K, we simulate their dynamics until 2001, and for the merged firm, we simulate the merged firm dynamics from 2002 onwards.

To illustrate the impact that the merger has on performance dynamics, we plot the unobserved profitability trajectories prior to the merger, as well as the trajectories after the merger. This illustration is provided in Figure 4. For example, in 1990, the monetary value of the average unobserved profitability is around 50,000 Yen per year. Note that one caveat of comparing the trajectories before and after the merger is that one needs to make an assumption about the initialization for the unobserved profitability dynamics after the merger; that is, will the merged firm be endowed with the performance dynamics accumulated by sunkus and circle K, or does the merged firm restart the process. For our analysis, we assume that the performance dynamics restart after the merger, as this assumption would be most consistent with our use of pre-merger and post-merger policy functions. However, this assumption means that the level effects of the merger on performance dynamics will be hard to interpret.

Consequently, our focus will be on changes in the growth of unobserved profitability. A nice

Figure 4: Trajectories for the Unobserved Profitability of sunkus and circle K Before and After the Merger



feature of such a comparison is that the pre-merger and post-merger dynamics begin at roughly the same point. That said, the figure reveals to us that the merger leads to much slower growth in performance dynamics. Such a decline is consistent with a diminished size spillover effects, as well as the merged firm's inability to retain gains from the unobserved profitability process. This decline in the unobserved profitability growth suggests that both companies are unable to generate and maintain performance gains after merger, either through the demand or cost side (or both), and this result is consistent with both stories. For instance, as we describe in the earlier section, fully integrating the operations took six more years after 2001. Also, from the demand side, both chain brands are kept separate, such that they might have been unable to fully exploit economies of scope and scale due to merger, such as a joint advertising on TV.

Table 8 provides the average growth rates across markets and time for the other variables we are interested in. We see that the merger does not lead to rapid growth in terms of the number of outlets per market. Although the percentage rate of outlet growth for the merged firm is larger than each of the individual firms prior to the merger, the merged firm does not grow faster than the combined growth rate of the individual firms.

The most striking findings emerge when we investigate the revenue and profit trajectories. Notice that prior to the merger, revenue and profit growth is stagnant. However, after the merger, we see noticeable increases in both revenue and profit growth, especially so in revenue. Thus,

Table 8: Growth of Key Variables Before and After the Merger (in Percentages)

	sunkus	circle K	CK+SKS
Z process	2.1862	1.5503	0.9339
Number of outlets	2.0336	2.0857	3.4306
Revenue	0.0000	0.0000	9.7252
Profits	-0.0000	-0.0000	5.3554

despite the slower growth in the underlying unobserved profitability process, the merged firm is able to enjoy increased profits. Going back to the revenue regression estimates, one important finding to note is that the role of unobserved profitability in revenue becomes more pronounced after the merger. One example that could rationalize this result is that the merged firm is better at exploiting efficiencies associated with unobserved profitability in order to generate higher sales, as opposed to simply reducing the costs of expansion.

6 Conclusion

This paper investigates the role of performance dynamics in the long-run evolution of retail expansion. By combining particle filtering, control functions, and forward simulations, we are able to push the frontier by understanding not only whether such dynamics exist, but what channel these dynamics operate in. Such an approach is especially applicable when revenue information is available to the researcher. We apply these methodological innovations to a setting involving convenience store expansion in Japan, which offers us the unique opportunity to look at dynamics both before and after an actual merger.

Two key findings emerge. First, our estimates suggest that the size spillover and retention effects operate through both the sunk cost component of profits, as well as revenue. Knowing that these performance dynamics are related to both channels further justifies the use of revenue data when analyzing such markets. Second, simulations using the estimated model suggests that the merger has a detrimental effect on the underlying performance dynamics for the merged entities; that is, the joint unobserved profitability for the two firms as un-merged entities grows at a higher rate than the unobserved profitability growth for the two firms as a merged entity. However, despite the seemingly negative impact that the merger has on these performance dynamics, the merged firm still emerges to become very profitable.

We believe that our findings allows one to refine the economic interpretation of performance dynamics. In particular, Igami and Yang (2014) recently conjectured that a merger between two horizontally differentiated retail chains may allow the merged firm to expand and preempt markets, while mitigating potential cannibalization costs via differentiated brand expansion. More generally, mergers may have an effect on the merged firm's positioning so as to minimize cannibalization (Sweeting, 2010). While deeper exploration of such incentives is beyond the scope of our paper, we highlight a few results that would support such conjecture. First, we find that after the merger, own-brand competition effects dampen, suggesting a softened cannibalization costs. Second, the performance dynamics operate primarily through the revenue channel after the merger. Finally, revenue growth markedly improves after the merger. Collectively, these findings motivate further analysis of potential strategic opportunities that mergers allow retail chains to engage in. Although the detection of preemptive motives is inherently difficult, we believe simple approaches that test for non-monotonic relationships between strategic investments and market size (e.g., Ellison and Ellison, 2011; Yang, 2014) provide one promising avenue for confirming the existence of such benefits from mergers.

In terms of caveats, our current analysis abstracts away two features of the industry. First, we take the 2001 merger as an exogenous event. Although we believe this assumption is a reasonable one to make because mergers and acquisitions rarely happen in this industry, firms in general endogenously choose when and with whom to merge. Second, we do not consider the ownership composition of the stores; that is, the dynamics of franchisee versus chain managed outlets. We believe future research in this direction is fruitful for a few reasons. The performance dynamics may differ between franchisee and chain-run stores. Furthermore, the merger may have a differential impact on stores, depending on ownership structure. Finally, the value of store closures may vary across franchisee and chain-run stores. However, to investigate such issues, one would need a new framework for estimating models of dynamic retail expansion with ownership structure decisions. We defer the development of this new framework for future research.

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Appendix A. Seemingly Unrelated Regression (SUR)

We employ an SUR model to capture the dynamics of our exogenous demand and cost-side variables. Such an approach allows for some potential correlation between the key variables. For example, income and property value often move along similar trends. The SUR specification we use can be described as:

$$\begin{bmatrix} X_{1t} \\ X_{2t} \\ ... \\ X_{kt} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ ... \\ c_k \end{bmatrix} + \begin{bmatrix} A_{11} & A_{12} & ... & A_{1k} \\ A_{21} & A_{22} & ... & A_{2k} \\ ... & & & \\ A_{k1} & A_{k2} & ... & A_{kk} \end{bmatrix} \cdot \begin{bmatrix} X_{1t-1} \\ X_{2t-1} \\ ... \\ X_{kt-1} \end{bmatrix} + \begin{bmatrix} e_{1t-1} \\ e_{2t-1} \\ ... \\ e_{kt-1} \end{bmatrix}$$

where $E[e_t e_t'] = \Omega$ and where $c = (c_1, \ldots, c_k)$, $A = (a_{ij})$, and Ω are parameters to be estimated. The estimated SUR model estimates and covariance matrix are shown in Tables 9 and 10.

Table 9: SUR Model Estimates

	Population	Income	Minimum Wage	Property Value
Lagged Population	1.0065	0.0196	-0.0021	7.1895
Lagged Income	0.0025	0.9266	0.0989	5.4031
Lagged Minimum Wage	-0.0000	0.0001	-0.0001	0.8886
Lagged Property Value	-0.0636	-1.9223	0.5645	-246.2148
Intercept	22.7977	1157.1271	15.9366	127278.0673

Table 10: Estimated SUR Covariance Matrix

	Population	Income	Minimum Wage	Property Value
Lagged Population	225.2762	453.0557	-207.6054	71163.0193
Lagged Income	453.0557	202015.2184	-5083.1525	-1581870.1842
Lagged Minimum Wage	-207.6054	-5083.1525	10503.9747	1357847.5730
Lagged Property Value	71163.0193	-1581870.1842	1357847.5730	3791892717.3799

Appendix B. More Details about Policy Function Estimation

In particular, we estimate an ordered probit model where the choice set is $\mathcal{K}_i = \mathcal{K} = \{k_1, k_2, \ldots, k_K\}$ with $k_1 < k_2 < \cdots < k_K$. These values may range from negative to positive, representing expansion and contraction decisions by firms. With an ordered probit, there is a potential complication in terms of the large number of choices each chain has. For example, a chain may expand by adding as many as 127 outlets in a given market and year. To address such computational issues, we make discrete the actions available based on the raw distributions of n_{mt}. A similar solution is used by Blevins, Khwaja, and Yang (2014). In our application, we choose $\mathcal{K} = \{-5, 0, 2, 5, 10, 20, 50\}$. This discretization is chosen based on the most commonly observed expansion decisions we see the retail chains make.

The term y^*_{imt} captures each firm's latent index, for which we use a flexible functional form to capture. Exogenous state variables are summarized as W_{mt} denote the vector of exogenous state variables that include X_{mt} and relevant interactions between variables. For tractability, we consider a flexible linear specification for y^*_{imt} that includes higher-order terms and interactions:

$$y^*_{imt} = \phi^W \cdot W_{mt} + \phi^Z Z_{imt} + \zeta_{imt}.$$

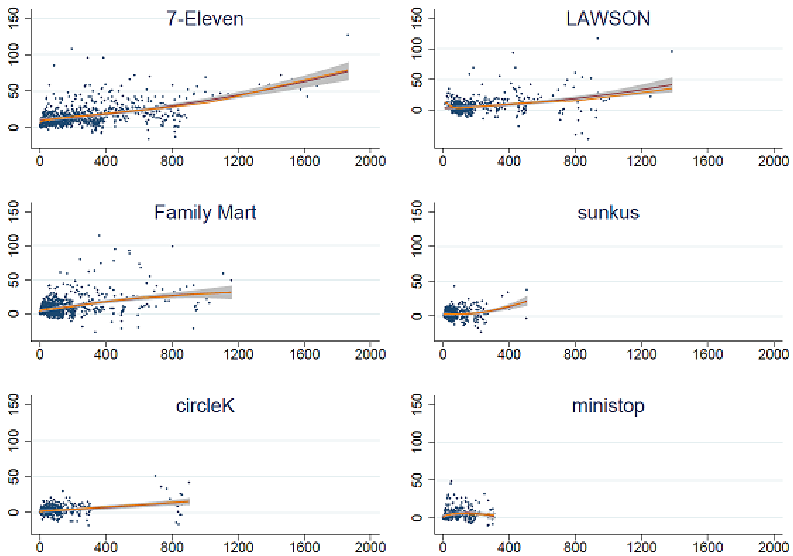
The serially correlated performance dynamic measure is captured by Z_{imt}, firm-specific profitability which is based on the specification for the Z process and is integrated out via particle filtering. Finally, we use ζ_{imt} to denote an independent and normally distributed error term with mean zero and unit variance. Firm and market fixed effects are also included, as per the specified Z process.

The order probit specification is summarized by a collection of threshold-crossing conditions:

$$n_{imt} = \begin{cases} k_1 & \text{if } y^*_{imt} \leq \vartheta_1 \\ k_2 & \text{if } \vartheta_1 \leq y^*_{imt} \leq \vartheta_2 \\ \vdots & \vdots \\ k_K & \text{if } \vartheta_{K-1} \leq y^*_{imt} \leq \vartheta_K \end{cases}.$$

The values $\vartheta_1, \ldots, \vartheta_K$ are the K cutoff parameters corresponding to each outcome. These cutoffs are estimated using sieve maximum likelihood along with the index coefficients, and the parameters in the law of motion for Z_{imt}.

Figure 5: Outlet Expansion/Contraction Patterns



Appendix C. Evidence of Expansion and Sales

This subsection presents descriptive evidence on the expansion patterns of the convenience-store chains over years. Our interest here is to examine how a chain's past size in a given market, measured by either total sales or total number of outlets, affect the subsequent year's evolution of chains in the number of outlets and total sales.

Figure 5 plots the annual change in the number of outlets and the cumulative number of outlets for each chain. The horizontal and vertical axis is the cumulative number of outlets and the change in the number of outlets, respectively. These figures suggest the higher the size variable, the higher the increase in the total sales in that market.

To examine how past size affects expansion in outlets, Table 11 presents the linear regression of the change in the number of total stores on lagged sales, chain-brand fixed effects, and market characteristics, such as population and income per capita. All specifications include market fixed effects. The first column suggests that the lagged sales positively affects the change in the number of outlets, and this effect is statistically significant at the 1% level. Similarly, Table 12 confirms that the lagged number of outlets, another size variable, positively affects the change in the number of outlets in the following year.

Tables 13 and 14 provide the effect of lagged sales and lagged number of stores on the change

Table 11: Effects of Lagged Sales on Number of New Stores

	(1)	(2)	(3)	(4)
Population	-0.00204	-0.00727***	-0.0156***	-0.0132***
	(0.00184)	(0.00173)	(0.00176)	(0.00166)
Income per capita	0.00119	0.000990	-0.00214	
	(0.00117)	(0.00118)	(0.00121)	
Time trend	-0.421***			
	(0.0539)			
Lagged sales	0.0000376***	0.0000132	0.0000898***	0.000101***
	(0.00000965)	(0.00000924)	(0.00000808)	(0.00000824)
7-Eleven	9.757***	13.75***		
	(1.186)	(1.082)		
LAWSON	1.767	2.546**		
	(0.962)	(0.968)		
Family Mart	3.445***	4.944***		
	(0.926)	(0.916)		
sunkus	-0.520	0.352		
	(1.036)	(1.041)		
circle K	-0.644	0.637		
	(1.097)	(1.097)		
circle K sunkus	-3.666**	-4.339***		
	(1.232)	(1.243)		
Constant	20.37***	25.20***	64.64***	49.18***
	(6.155)	(6.194)	(6.021)	(5.554)
Observations	2668	2668	2668	2927
R^2	0.33	0.31	0.22	0.21

Standard errors in parentheses
$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 12: Effects of Lagged Number of Stores on Number of New Stores

	(1)	(2)	(3)	(4)
Population	-0.00366*	-0.00890***	-0.0151***	-0.00990***
	(0.00152)	(0.00143)	(0.00148)	(0.00136)
Income per capita	0.00104	0.000625	-0.00220*	
	(0.000971)	(0.000983)	(0.00102)	
Time trend	-0.398***			
	(0.0420)			
Lagged # of stores	0.00357*	-0.00155	0.0117***	0.0205***
	(0.00174)	(0.00167)	(0.00154)	(0.00150)
7-Eleven	9.619***	12.52***		
	(0.980)	(0.943)		
LAWSON	1.909*	3.034***		
	(0.900)	(0.904)		
Family Mart	3.156***	5.020***		
	(0.860)	(0.848)		
sunkus	-0.996	-0.569		
	(0.914)	(0.925)		
circle K	-1.515	-0.666		
	(0.969)	(0.978)		
circle K sunkus	-3.660**	-4.312***		
	(1.188)	(1.202)		
Constant	25.84***	31.84***	62.60***	37.13***
	(4.853)	(4.876)	(4.783)	(4.404)
Observations	3307	3307	3307	3877
R^2	0.32	0.30	0.21	0.21

Standard errors in parentheses
$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 13: Effects of Lagged Sales on Changes in Sales

	(1)	(2)	(3)	(4)
Population	0.600	-0.130	-1.878***	-2.478***
	(0.438)	(0.409)	(0.413)	(0.375)
Income per capita	-0.155	-0.165	-1.128***	
	(0.278)	(0.279)	(0.282)	
Time trend	-59.69***			
	(13.03)			
Lagged sales	0.0128***	0.00919***	0.0282***	0.0279***
	(0.00238)	(0.00225)	(0.00196)	(0.00190)
7-Eleven	2920.1***	3521.2***		
	(288.0)	(257.4)		
LAWSON	733.9**	846.6***		
	(228.6)	(228.2)		
Family Mart	1099.9***	1314.6***		
	(219.3)	(215.0)		
sunkus	125.9	253.9		
	(249.4)	(248.8)		
circle K	442.6	631.0*		
	(264.5)	(262.3)		
circle K sunkus	785.0**	691.6*		
	(291.8)	(292.2)		
Constant	702.0	1291.0	10758.7***	9471.2***
	(1467.7)	(1467.8)	(1407.4)	(1260.5)
Observations	2611	2611	2611	2755
R^2	0.36	0.35	0.28	0.27

Standard errors in parentheses
$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 14: Effects of Lagged Number of Stores on Changes in Sales

	(1)	(2)	(3)	(4)
Population	0.531	-0.318	-2.025***	-2.593***
	(0.436)	(0.408)	(0.413)	(0.375)
Income per capita	-0.204	-0.233	-1.091***	
	(0.275)	(0.277)	(0.282)	
Time trend	-68.47***			
	(12.93)			
Lagged number of stores	3.985***	3.155***	6.521***	6.468***
	(0.514)	(0.492)	(0.436)	(0.421)
7-Eleven	2635.8***	3287.8***		
	(278.6)	(251.3)		
LAWSON	446.9	590.6*		
	(232.7)	(232.4)		
Family Mart	849.1***	1107.9***		
	(222.4)	(218.1)		
sunkus	77.99	221.2		
	(248.6)	(248.4)		
circle K	265.5	488.8		
	(264.8)	(262.8)		
circle K sunkus	588.5*	490.3		
	(292.5)	(293.5)		
Constant	1279.4	2068.7	10942.6***	9658.2***
	(1457.5)	(1457.5)	(1409.2)	(1261.9)
Observations	2601	2601	2601	2745
R^2	0.36	0.36	0.29	0.28

Standard errors in parentheses

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Table 15: Effects of Lagged Number of Stores on Sales per Store

	(1)	(2)	(3)	(4)
Population	-0.0152***	0.0136***	-0.00121	0.00100
	(0.00360)	(0.00367)	(0.00410)	(0.00373)
Income per capita	0.0100***	0.0128***	0.000640	
	(0.00224)	(0.00244)	(0.00274)	
Time trend	2.330***			
	(0.104)			
Lagged number of stores	0.0667***	0.0950***	0.129***	0.127***
	(0.00421)	(0.00437)	(0.00432)	(0.00419)
7-Eleven	61.23***	39.78***		
	(2.258)	(2.228)		
LAWSON	10.08***	4.893*		
	(1.901)	(2.056)		
Family Mart	0.0490	-8.601***		
	(1.819)	(1.937)		
sunkus	17.02***	12.36***		
	(2.044)	(2.215)		
circle K	6.994**	-0.241		
	(2.183)	(2.352)		
circle K sunkus	5.393*	9.510***		
	(2.447)	(2.659)		
Constant	87.00***	55.85***	143.7***	139.3***
	(11.88)	(12.85)	(13.72)	(12.40)
Observations	2744	2744	2744	2889
R^2	0.59	0.52	0.35	0.34

Standard errors in parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 16: Effects of Lagged Sales on Sales per Store

	(1)	(2)	(3)	(4)
Population	-0.00782*	0.0171***	-0.000419	-0.000383
	(0.00307)	(0.00312)	(0.00354)	(0.00324)
Income per capita	0.00833***	0.00863***	-0.00495*	
	(0.00195)	(0.00213)	(0.00242)	
Timetrend	2.035***			
	(0.0917)			
Lagged sales	0.000265***	0.000386***	0.000603***	0.000591***
	(0.0000166)	(0.0000172)	(0.0000168)	(0.0000164)
7-Eleven	60.21***	39.74***		
	(2.022)	(1.965)		
LAWSON	8.984***	5.129**		
	(1.604)	(1.742)		
Family Mart	1.540	-5.865***		
	(1.544)	(1.647)		
sunkus	12.85***	8.431***		
	(1.750)	(1.899)		
circle K	6.124***	-0.348		
	(1.857)	(2.003)		
circle K sunkus	4.541*	7.674***		
	(2.047)	(2.230)		
Constant	81.65***	61.39***	162.6***	149.2***
	(10.31)	(11.22)	(12.11)	(10.93)
Observations	2600	2600	2600	2744
R^2	0.66	0.59	0.43	0.42

Standard errors in parentheses
$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

in sales, respectively. Both results suggest that the size of a chain positively affects the change in the total sales of the chain in the following year. Appendix Tables 15 and 16 examine whether a chain's past size affect the sales per outlet, another performance measure of a chain. Both tables suggest that the size of a chain, either in the number of stores or total sales, positively affect the sales per store in the following year.