Better Together? Performance Dynamics in Retail Chain Expansion before and after Mergers[*]

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Abstract

This paper evaluates how mergers affect the performance efficiency of retail chains. We estimate a dynamic model of retail expansion using data on convenience-store chains in Japan before and after an actual merger event. Our estimation allows for the presence of performance efficiency, in the form of serially correlated state variables that evolve both endogenously and stochastically. The estimates reveal that although the merged firm benefited from lower expansion costs, underlying performance efficiency for the merged entity did not improve following the merger, and such changes in performance varied across markets. Simulation analysis reveals the dampened performance is associated with the merged firm's diminished ability to retain efficiency gains from one year to the next. However, these negative effects can be mitigated if the merged firm inherits the primitives behind the performance efficiency of the more dominant merging party.

Keywords: Dynamic Discrete Choice; Entry; Industry Dynamics; Learning-by-Doing; Market Concentration; Merger Analysis; Organizational Forgetting; Particle Filter; Revenue Regression; Serial Correlation; Retailing.

1 Introduction

> Achieving synergy is easier said than done - it is not automatically realized once two companies merge. Sure, there ought to be economies of scale when two businesses are combined, but sometimes a merger does just the opposite. In many cases, one and one add up to less than two. *Basics of Mergers and Acquisitions* Investopedia (2010)

Ownership changes, such as mergers and acquisitions, affect the profitability of merging firms through various mechanisms. These mechanisms, as pointed out by Williamson (1968), may include enhanced cost or revenue-based *performance efficiency*. Performance efficiency likely has two dimensions, á la Benkard's (2000, 2004) empirical framework for efficiency in production. The first dimension is when a firm becomes more efficient with scale (i.e., *size spillovers*), while the second dimension is the extent to which a firm is able to preserve its efficiency gains (i.e., *retention*). This notion of supply-side efficiency is particularly relevant for the retail industry, as a key instrument retail chains rely on to increase their production is via retail outlet expansion. One critical challenge of studying efficiency, which is well acknowledged in past literature, is that this efficiency component of profitability is not directly observable in data (e.g., Griliches, 1957); that is, in addition to the two dimensions, there may be a third dimension that is entirely *stochastic*. In light of such challenges, this paper's objective is to propose and implement an empirical strategy in order to investigate how mergers affect firms' performance dynamics, while acknowledging that efficiency likely evolves both endogenously and stochastically.

Uncovering these performance dynamics is especially important for firms and policy makers in most industries in which mergers occur. For instance, a retail chain may be interested in understanding whether a merger boosts or disrupts such dynamics.[1] Similarly, policy makers may be interested in evaluating how market structure and efficiencies evolve after the merger.[2] Unfortunately, despite the importance of such potential effects of mergers, few empirical studies have examined how changes in ownership lead to changes in performance over time. A prominent reason for this gap in the literature is the difficulty in observing

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[1] For example, 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 because of unexpectedly sluggish growth.

[2] From a policy perspective, antitrust authorities may block a merger between multistore retailers when verifying the purported efficiencies from the merging firms is difficult. 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. One of the major debates in the litigation concerned projected cost savings and the extent to which such efficiencies would be passed on to consumers (Baker, 1999). In fact, Blonigen and Pierce's (2016) research demonstrate that such efficiency gains may not exist.

such dimensions of profitability. Because various tangible and intangible assets drive a firm's performance, observing and quantifying the performance efficiency is difficult. Making such studies even more difficult, performance can evolve both endogenously and stochastically over time.

This study analyzes firm-performance dynamics in retail growth, before and after a merger. Unlike previous studies that rely on detailed information on inputs and outputs (e.g., Braguinsky, Ohyama, Okazaki, and Syverson, 2014), this paper adopts a different approach. Namely, we use a dynamic oligopoly model to recover the data-generating process behind performance efficiency that rationalizes the observed data on store counts and sales by market, which are often publicly available through financial statements.

One of the interesting features of our setting is that we allow the equilibrium played to be different before and after year 2001 - the year in which sunkus and circle K are financially integrated into one entity. Namely, we estimate the model of dynamic expansion in our sample separately for pre- and post-merger time periods. This empirical strategy departs from existing studies, such as Benkard, Bodoh-Creed, and Lazarev (2010), who assume the equilibrium being played *does not change* after the merger. We are able to depart from this assumption, because the merger between sunkus and circle K is *factual* and not merely a proposed *counterfactual*.

Our model allows for performance efficiency to operate flexibly through a serially correlated, endogenous, and stochastic process. We estimate this model using an extensive and manually collected data set on all six major convenience-store chains in Japan in all 47 prefectures in Japan from 1982 to 2012.[3] Note that our model captures both inter-firm (i.e., firm-specific model primitives)[4] and intra-firm (i.e., market- and time-specific model primitives) heterogeneity in performance efficiency. 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 (2015) that combines particle-filtering methods with two-step estimation of dynamic-discrete choice games in a setting that has retail expansion and contraction. Because both revenue and store counts are observed in our data, the estimated model helps us determine the extent to which performance dynamics operate through demand (e.g., customer goodwill, brand awareness) or fixed costs (e.g., scale economies, learning-by-doing). A typical challenge of incorporating revenue into entry models is the inherent selection bias (i.e., we only observe non-zero revenues for markets in which the firms have at least one

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[3]To be precise, our estimation sample omits observations from 1998 to 2000, as the surprise and unexpected merger announcement was made in 1998.

[4]Inter-firm heterogeneity is largely motivated by the extensive literature that demonstrates inter-firm heterogeneity in performance. We refer the reader to Syverson (2011) for a summary of such work in the context of productivity.

store). To address this challenge, we augment the particle-filtering method with the control function approach (e.g., Heckman, 1979) as proposed by Ellickson and Misra (2012) to correct for selection biases when we estimate revenue equations.

With the estimated structural model, we evaluate how the actual merger between circle K and sunkus in 2001 affected performance dynamics for two reasons. First, evaluating the dynamic aspect of performance for this merger is particularly relevant, because the publicized motive for this merger was to pursue "efficiencies of scale by integrating information systems and improving product margins through joint-purchasing negotiations,"[5] while media observes that "many argue that it is [still] cost heavy," even six years after the merger.[6] Because of the prolonged merging process after the financial integration, the Japanese convenience-store expansion and revenue dynamics before and after the merger provide us an appropriate setting for evaluating performance improvements or deterioration. Second, because this industry adopts uniform pricing, we are able to avoid the typical issue of confounding the effects of mergers on prices and on outlet expansion/contraction.

Our analysis yields three main findings. First, the estimates reveal that we do observe the merged entity has lower sunk costs of expansion. However, no noticeable improvements to the process behind performance dynamics following the merger existed. We associate the latter finding with the merged firm's reduced ability to retain its performance efficiency from one year to the next after merger. Namely, the posterior distribution of unobserved performance dynamics does not improve for the newly merged firm, because both the level and growth rate of efficiency gains actually decreases after the merger. Second, exploratory analysis of a hypothetical scenario in which the merged firm inherits the performance efficiency of circle K, the more dominant firm pre-merger (relative to sunkus), appears to better preserve efficiency in the years following the merger. Finally, we find heterogeneity in the performance dynamics across various markets. In particular, we show that the drop in performance dynamics is most pronounced in markets with stagnated growth in the number of outlets, such as rural markets.

The rest of the paper is organized as follows. The remainder of Section 1 discusses the related literature. Section 2 provides details about the data and explains the institutional features of the industry and merger. Section 3 lays out the model we use for estimation and simulations. Section 4 goes over our estimation approach. Section 5 reports our parameter estimates and subsequent merger analysis. Section 6 concludes.

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

[6]See, for example, "Circle K Sunkus: a disappointing merger?" *Japan Consuming*, July 1, 2007, available at http://www.japanconsuming.com/circle-k-sunkus-a-disappointing-merger/.

1.1 Related Literature

We contribute to the large literature on the relationship between ownership and firm performance. The existing studies offer mixed evidence. To support the notion of performance improving mergers, empirical work by Braguinsky, Ohyama, Okazaki, and Syverson (2014) and Maksimovic and Phillips (2001) suggest mergers may lead to increased profitability through more efficient use of capital. In fact, some governments are pursuing policies to consolidate state-owned businesses as a means to boost profitability.[7] However, a merger need not necessarily lead to synergies and efficient re-allocation of resources, because the newly combined firm will have the difficult task of integrating its corporate culture, logistics, marketing, and overall strategy (e.g., Larsson and Finkelstein, 1999; Weber and Camerer, 2003). For example, Schoar (2002) demonstrates that mergers lead to mixed results in performance, depending on whether the production plants within a conglomerate are incumbents or recently acquired, which ultimately leads to a net decrease in firm performance. In terms of incorporating mergers into dynamic oligopoly models, this paper is related to Benkard, Bodoh-Creed, and Lazarev (2010), Gayle and Le (2014), Hollenbeck (2013a), and Jeziorski (2014).[8]

This paper contributes to the growing literature on mechanisms behind retail firms' entry and expansion strategies. Retail chains may become increasingly profitable over time through performance dynamics such as improved customer goodwill (e.g., Basker, Klimek, and Van, 2012; Jovanovic and Rob, 1987; Pancras, Sriram, and Kumar, 2012; Shen and Xiao, 2014) or scale and network economies (e.g., Aguirregabiria and Ho, 2012; Ellickson, Houghton, and Timmins, 2013; Holmes, 2011; Jia, 2008; Nishida, 2015b). In data, such dynamics may materialize through persistence in market shares (e.g., Bronnenberg, Dhar, and Dubé, 2009). Furthermore, some of these performance advantages may persist over time via firm-specific abilities to retain efficient organizational-level processes (e.g., Darr, Argote, and Epple, 1995).[9] However, a formidable challenge that empiricists face is that the underlying performance dynamics are inherently unobservable. This paper addresses such issues by estimating a dynamic model of expansion that explicitly deals with the unobserved nature of performance dynamics.

More broadly, this paper is related to the literature on retail chains' expansion. Large

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[7]For example, "China Prepares Mergers for Big State-Owned Enterprises," *Wall Street Journal*, March 11, 2015.

[8]For analysis of the incentives behind the mergers themselves, see Akkus, Cookson, and Hortacsu (2014), Gugler and Siebert (2007), Park (2013), Perez-Saiz (2014), Rhoades and Yeats (1974), Sheen (2014), and Uetake and Watanabe (2013). For analysis of mergers and product repositioning, see Gandhi, Froeb, Tschantz, and Werden (2008), Sweeting (2010), Fan (2013), and Jeziorski (2014).

[9]We refer the reader to Besanko, Doraszelski, Kryukov, and Satterthwaite (2010) for the theoretical framework behind learning-by-doing and organizational forgetting in industry dynamics.

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 literature has received increasing interest from researchers (e.g., Beresteanu, Ellickson, and Misra, 2010; Blevins, Khwaja, and Yang, 2015; Hollenbeck, 2013b; Holmes, 2011; Igami and Yang, 2015; Nishida, 2015a; Orhun, 2013; Suzuki, 2013; Toivanen and Waterson, 2005, 2011; Varela, 2013; Vitorino, 2012; and Yang, 2012, 2016).[10] In particular, an increasing number of empirical applications of industry dynamics now exploit information about revenues (Dunne et. al., 2013; Hollenbeck, 2013b; Suzuki, 2013).

Finally, this paper relates to the literature on applying particle-filtering methods to dynamic games. Blevins (2014) was the first to incorporate particle-filtering in the estimation of dynamic-discrete choice games of imperfect information, whereas Gallant, Hong, and Khwaja (2015) were the first to incorporate particle filtering in dynamic discrete-choice games of complete information. Recently, such methods have been also used in single-agent dynamic discrete-choice models such as Fang and Kung (2012).[11]

2   Industry and Data

This section describes our data from the convenience-store chains in Japan. 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 performance dynamics that affect the firms' future decisions, in that past size has 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.

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[10]See Aguirregabiria and Suzuki (2015) for a recent survey of retail entry models.

[11]Marketing research has used linear and non-linear particle filtering methods 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).

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 come 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. For each variable, we observe heterogeneity across chains, markets, and years.

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 businesses 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

United States, established circle K Japan Co., Ltd. and opened its first outlet. Since then, circle K in Japan has been a subsidiary of UNY Co., Ltd. Meanwhile, sunkus experienced two ownership turnovers. In 1994, Nagasakiya Co., Ltd sold its shares of sunkus to Ono group. Four years later, 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. Although both sunkus and circle K are kept as separate chain brands, they increased the joint operations and management decisions under the holding company. The complete integration at the operation level took longer than the capital integration– in 2007 circle K and sunkus fully integrated their vendor and logistics networks.

2.2 Suggestive Evidence of Performance Efficiency

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 the total number of existing outlets, affect the subsequent year's evolution of chains in the number of new outlets. Figure 1 plots the annual change in the number of outlets and the cumulative number of outlets for each chain. The horizontal and vertical axes are the cumulative number of outlets and the change in the number of outlets, respectively. These figures suggest this industry has faced competition in expanding a chain's size in store counts in the data period.

To build on the findings from the diagram, we consider a simple linear regression specification that includes market fixed effects. Table 2 confirms that the lagged number of outlets positively affects the change in the number of outlets in the following year. Overall, these findings are suggestive of *size spillovers* in the industry. Furthermore, a comparison of our results across the chains demonstrates noticeable heterogeneity in these effects. In addition to potential size spillovers, our data suggests that there may be persistence in market expansion, which may materialize from *retention* of efficiency gains. Considering a similar regression as the one used in Blevins, Khwaja, and Yang (2015), we demonstrate a positive association between the lagged change in the number of outlets and the current change in the number of outlets (Table 3).

2.3 Expansion and Sales Dynamics for Merging Chains

We now direct our attention onto the expansion dynamics for circle K and sunkus, the two chains that financially integrated in 2001. A simple plot of the expansion patterns

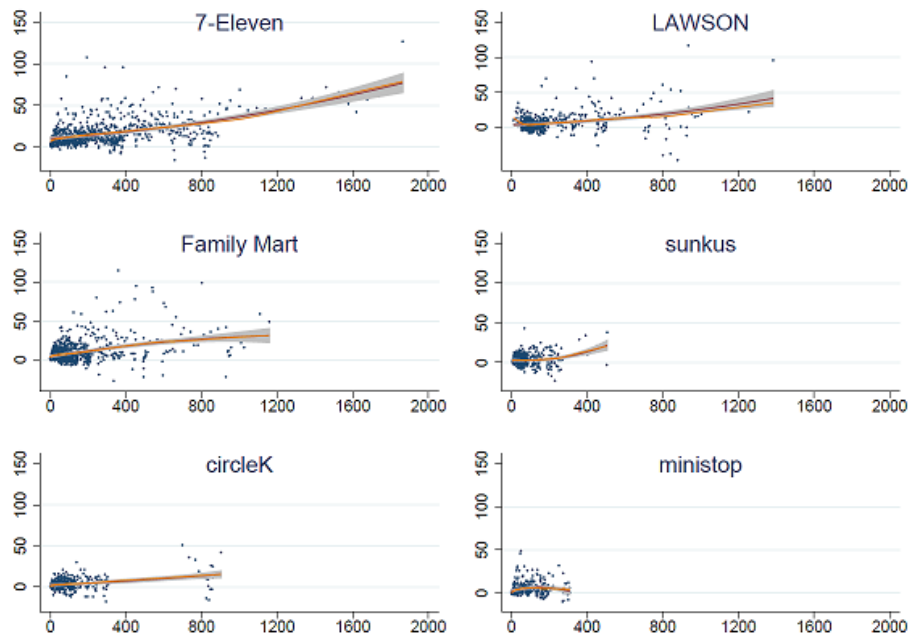Figure 1: Outlet Expansion/Contraction Patterns
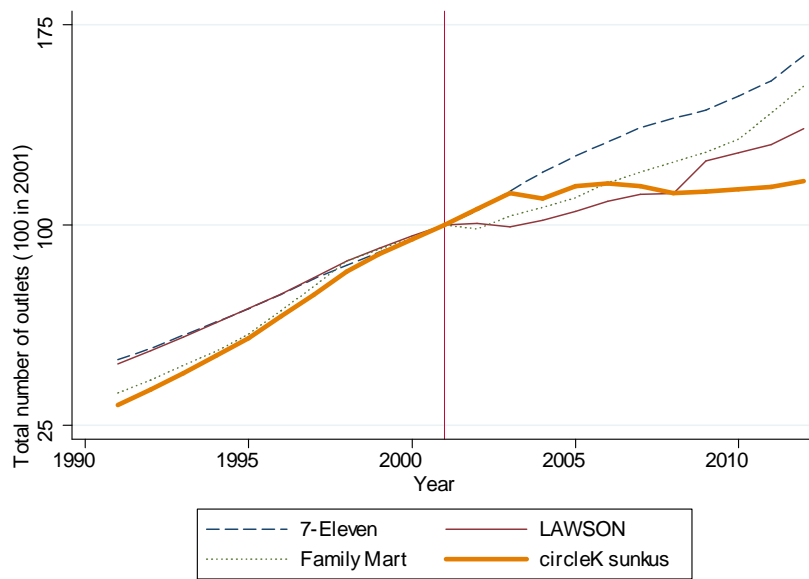

Figure 2: Total Number of Outlets

Table 2: 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 3: Effects of Lagged Change in Number of Stores on Change in Number of New Stores

	(1)	(2)	(3)	(4)
Population	-0.00174	-0.00528***	-0.00701***	-0.000674
	(0.00149)	(0.00136)	(0.00138)	(0.00126)
Income per capita	-0.000899	-0.00118	-0.00217*	
	(0.000985)	(0.000989)	(0.00100)	
Time trend	-0.229***			
	(0.0401)			
Lagged change in # of stores	0.390***	0.405***	0.483***	0.546***
	(0.0164)	(0.0163)	(0.0156)	(0.0151)
7-Eleven	6.944***	7.762***		
	(0.841)	(0.833)		
LAWSON	1.998*	2.106*		
	(0.820)	(0.825)		
Family Mart	2.926***	3.603***		
	(0.794)	(0.789)		
sunkus	-0.387	-0.280		
	(0.879)	(0.884)		
circle K	-0.494	-0.267		
	(0.921)	(0.925)		
circle K sunkus	-1.663	-2.368*		
	(1.190)	(1.190)		
Constant	17.56***	22.75***	33.51***	5.759
	(4.791)	(4.729)	(4.711)	(4.178)
Observations	3056	3056	3056	3623
R^2	0.43	0.43	0.39	0.40

Standard errors in parentheses

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

Figure 3: Total Sales
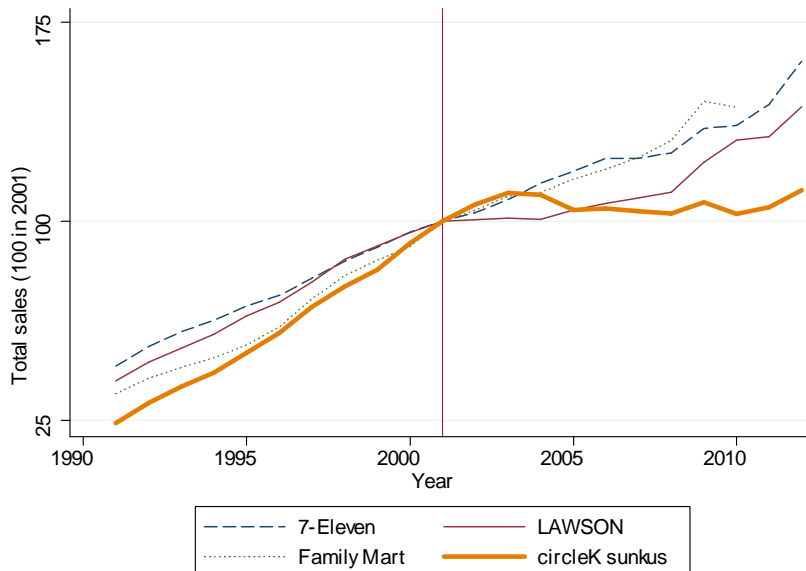
for the four largest chains with normalizing the number of outlets in 2001 as 100 (Figure 2) reveals an apparent decline for circle K's and sunkus' expansion trends after 2001; we see a similar slowdown for these two chains before and after the merger for aggregate sales (Figure 3).[12] Prior to the merger, the total number and total sales of circle K and sunkus have been increasing the most rapidly among those four chains. After the merger, however, both the total sales and outlet counts for circle K and sunkus stagnated, unlike the other three chains, which continued to expand in size. To further investigate the possibility of a structural break in the expansion dynamics, we conduct a Chow test using the market-level sales and number of outlets 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 4). We conduct a similar Chow test to see if the persistence in outlet (or sales) growth changes after the merger. Similar to our previous test, we demonstrate that the null hypothesis is rejected at the 1% level (Table 5).

Next, we explore further the slower growth in expansion and sales following the merger. In particular, we investigate the extent to which some of the decelerated expansion is an artifact of cannibalization concerns. If cannibalization concerns are a driving force behind rapid contraction, then we should see markedly negative growth with respect to outlets and sales in local markets that are already overly saturated (e.g., Igami and Yang, 2015). Figures 4 and 5 reveal that store contractions *post-merger* are unlikely driven by cannibalization

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[12]We interpret all years from 2002 onward as being post-merger years.

Table 4: 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

Table 5: Results from Chow Test for Structural Break in Relationship with Persistence in Outlet or Sales Growth

	Expansion	Change in sales
F statistic	144.06***	34.22***
Controls	Yes	Yes
Market fixed effects	Yes	Yes
Time trend	Yes	Yes

concerns *alone*, as the contraction in outlets and sales does not appear to be a function of the existing number of outlets or sales in the years following the merger.

Although such patterns suggest that mergers have an impact on performance dynamics, we are cautious about jumping 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 our estimable model that allows for strategic and forward-looking expansion/contraction decisions, selection in revenue, and unobservable performance dynamics.

3 Model

This section describes the dynamic retail expansion model we estimate. The model builds on and extends the retail expansion framework originally proposed by Blevins, Khwaja, and Yang (2015). We first describe the underlying primitives, followed by the equilibrium concept used to analyze the model.

3.1 Basic Setting

We consider an environment 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

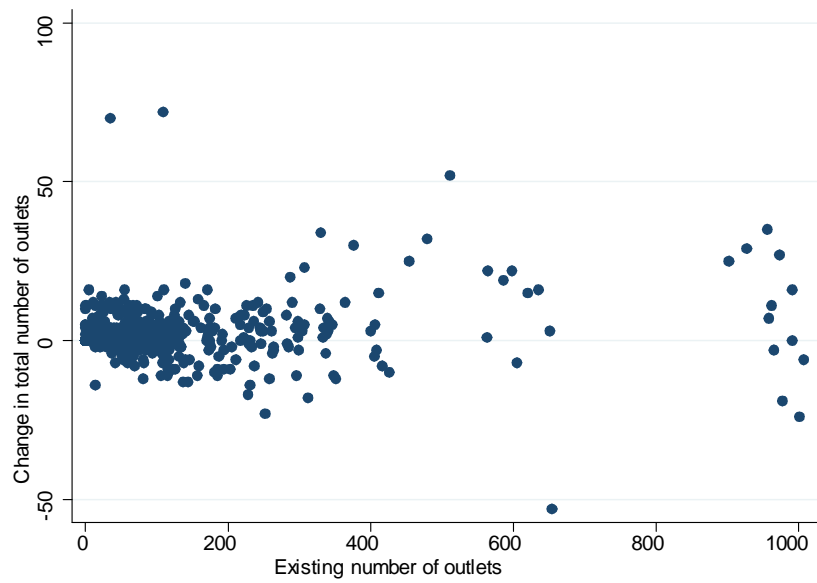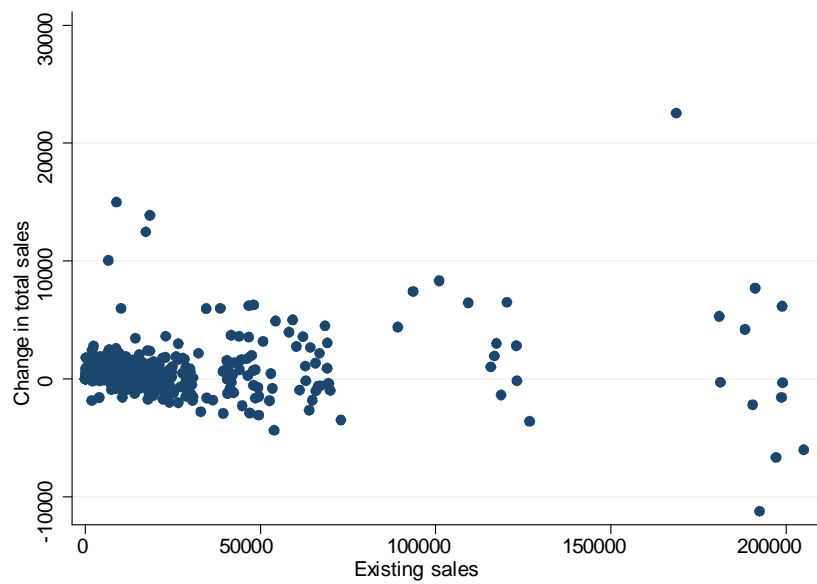Figure 4: Relationship Between Growth in Outlets and Level of Saturation

Figure 5: Relationship Between Growth in Outlets and Level of Saturation

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 $N_{mt} = \{N_{imt}\}_i$.

Firms are forward-looking and 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

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

where θ denotes a set of parameters. The one-shot payoff consists of two main components: the revenue and the 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}). The market characteristics may be categorized as being specific to revenue (X_{mt}^R) or cost (X_{mt}^C). We assume here that firms play a game of incomplete information, as in Seim (2006), so $\zeta_{imt} = (\zeta_{imt}^R, \zeta_{imt}^C)$ can be interpreted as private information that is i.i.d. (across markets and time) with Type I Extreme Value distribution. As in Ellickson and Misra (2012), we also include optimization error, $\xi_{imt} = (\xi_{imt}^R, \xi_{imt}^C)$. 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. There is also firm-specific profitability that varies across markets and time and is unobserved by the econometrician, 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 $C_i(\cdot)$:

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

where $\theta_1^C, \theta_2^C, \theta_3^C$, and θ_4^C are parameters for market characteristics, entry costs, expansion costs, and contraction costs, respectively. Similar to revenue specification, we allow for a private-information shock and optimization error. 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.[13]

A key difference between our model and typical dynamic oligopoly models of entry is the inclusion of a serially correlated and unobserved state that captures performance efficiency (Z_{imt}). We assume this unobserved profitability follows a simple autoregressive process, which the following transition equation captures:

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

where $\epsilon_{imt} \sim \mathrm{N}(0, \psi_\epsilon^2)$ are i.i.d. This performance efficiency measure has two main components. The first component, δ_i, is the persistence of profitability (i.e., retention of efficiency gains). 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).[14] Finally, ϵ_{imt} are normally distributed i.i.d. innovations to unobserved profitability with standard deviation ψ_ϵ. Different parameters across firms capture heterogeneity 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 allows for some elements of a firm's profitability to be private information incorporated in ζ_{imt}.

We represent the model's structural parameters as $\alpha = \{\alpha_i\}_{i=1}^I$, where

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

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

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[13]Knowing the relative size of γ^R to γ^C allows us to conjecture the possible sources of performance dynamics. For instance, γ^R is informative regarding how an increase in a retail chain's size of operation and duration of active operation in a given market might lead to an increase in brand recognition (Pancras, Sriram, and Kumar, 2012; Shen and Xiao, 2014), better knowledge of local demand and thus higher sales per outlet, and improved product quality or scope over time (Basker, Klimek, and Van, 2012; Jovanovic and Rob, 1987). Similarly, increased γ^C may imply reduced transportation costs through a denser distribution network (Holmes, 2011; Jia 2008; Nishida 2015b), better negotiating of rent with land-developers (Gould, Pashigian, and Prendergast, 2005), better ensuring minimal employee turnover (Benkard, 2000), better recruiting of potential franchisee owners of higher quality, and better financing of future expansion if it already has an extensive real estate portfolio; such scale in real estate assets was critical for McDonald's early growth efforts (Love, 1995).

[14]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.

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 are 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.

3.2 Equilibrium

We analyze the dynamic game of incomplete information using the solution concept of pure strategy Markov perfect equilibria (MPE),[15] and use the following notation to set up the MPE. A Markov strategy for a firm is a map from its payoff-relevant state variables and private information to its set of actions, that is, $\sigma_{imt} : S \times \mathbb{R} \to \mathcal{N}_i$. Furthermore, a profile of Markov strategies is the vector $\sigma_{mt} = (\sigma_{1mt},\ldots,\sigma_{Imt})$, where $\sigma : S \times \mathbb{R}^I \to \mathcal{N}$. 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 an 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 equation for the present discounted value of the stream of profits for firm i can be written as,

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

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.

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

4   Estimation

To estimate the model of retail dynamics, we combine recently developed particle-filtering methods for dynamic games and control-function methods in revenue regressions, which will address the following two key issues. First, we follow Blevins, Khwaja, and Yang (2015) to pair flexible particle-filtering techniques with the Bajari, Benkard, and Levin's (2007) two-step method. This approach allows for serially correlated and firm-specific unobservable states in a dynamic model of retail expansion.[16] Second, because our analysis makes use of revenue data, controlling for potential selection biases in revenues is important. To address this issue, we employ propensity-score methods proposed by Ellickson and Misra (2012).

Our estimation approach proceeds in the following three steps. First, we estimate each firm's beliefs via pre-merger and post-merger policy-function approximation, while employing particle filtering to obtain the posterior distribution of the serially correlated performance measure. 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.[17] Finally, using the calibrated revenue equations, we construct trajectories of profits using forward simulations, and estimate remaining cost parameters via Bajari, Benkard, and Levin (2007). We obtain standard errors using block bootstrapping.

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 unobservable state Z_{imt}, as well as the reduced-form policy functions for each of the retail chains. These reduced-form policy functions are meant to approximate 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, such as population, income, whereas $Z_{mt} = \{Z_{imt}\}_{\forall i}$ 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, 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:

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

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[16] Similar to Blevins (2014), we use a bootstrap particle filter (Gordon, Salmond, and Smith, 1993).

[17] Appendix D discusses the details regarding how we incorporate the merger event.

The likelihood consists of three main components. First, we estimate the firm-specific choice probabilities l_m via an ordered probit (see Appendix B for details).[18] The order probit uses sieve maximum likelihood that includes all exogenous variables and relevant interactions. Second, we have the transition probabilities for the exogenous characteristics, $p(X_{mt}|X_{mt-1}, \phi)$; we estimate these transition probabilities using a seemingly unrelated regression (SUR), because the evolution of these characteristics may be correlated across markets.[19] 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:

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

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:

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

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.[20] We use $R = 1,000$ simulation draws (i.e., particle "swarms").

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[18] In this likelihood, we are also taking a product across all firms i. To maintain consistency in our notation regarding the actions and pay-off relevant states, we omit $\prod_i$ and chain subscript i in the paper's exposition.

[19] See Appendix A for more details.

[20] An alternative way to integrate out the unobserved states is the expectation-maximization method by

4.2 Estimating the Revenue Function

Our analysis makes use of the fact that we observe firm-specific revenues across markets and time. In general, the realized revenues may suffer from selection bias that is induced by the underlying dynamic game of expansion, because 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_{imt}^R. Denoting the composite shock as $\omega_{imt}^R = \zeta_{imt}^R + \xi_{imt}^R$, it becomes clear that given this selection bias, $\mathbb{E}(\omega_{imt}^R | n_{imt} = k) \neq 0$.

To address the selection bias described above, we follow Ellickson and Misra (2012) and adopt a propensity-based method. This procedure amounts to running revenue regressions, with the inclusion of a control function $\Lambda(\hat{n}_{imt})$. The argument for how a control function addresses the selection bias is laid out in the Appendix of Ellickson and Misra (2012); in their discussion, they demonstrate equivalence between the control function, and the expectation of ω_{imt}^R conditional on being active. Here, the control function depends on $\hat{n}_{imt}$, which is the predicted number of opened/closed outlets as determined using the first-stage policy approximation. The main revenue regression is therefore defined as

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

where we choose a simple third-order polynomial for $\Lambda(\hat{n}_{imt})$.[21]

4.3 Estimating the Cost Function

The final stage of our estimation proceeds using Bajari, Benkard, and Levin's (2007) forward simulation approach, which allows us to recover the cost parameters given the estimated first-stage parameters ϕ and the revenue parameters. The estimated first-stage parameters allow us to forward simulate the policies, exogenous state variables, and serially correlated performance efficiency. To proceed with the inference, we assume the data are generated by a single MPE strategy, which is a typical assumption when using two-step estimation methods. Unlike nested fixed-point estimation methods, this assumption does not require us

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Arcidiacono and Miller (2011). We choose to deviate from popular convention for the following reasons. First, incorporating 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, is practically easier. However, the incorporation of discrete unobserved states will require an *a priori* assumption about the number of unobserved types. 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}).

[21] See Appendix C for more details on the implementation.

to state anything about the particular equilibrium selection; we are assuming the equilibrium selection is the same across markets.

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

$$\bar{V}_i(S_1; \sigma, \alpha) = \mathbb{E}\left[\sum_{\tau=1}^{\infty} \rho^{\tau-1} \Pi_i(\sigma(S_\tau, \nu_\tau), S_\tau, \nu_{i\tau}; \alpha) \mid S_1, \sigma\right]$$

$$\simeq \frac{1}{\bar{S}} \sum_{s=1}^{\bar{S}} \sum_{\tau=1}^{T} \rho^{\tau-1} \Pi_i(\sigma(S_\tau^s, \nu_\tau^s), S_\tau^s, \nu_{i\tau}^s; \alpha).$$

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:

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

We use $B = 1,000$ simulated inequalities.

4.4   Incorporating the Merger Event

Our estimation makes use of the pre- and post-merger states. Before the merger, we use 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 sunkus and circle K have merged.

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 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 total revenues in Figures 2 and 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 total sales, but our analysis explicitly takes this change into account because we are estimating policy functions separately before and after the merger.

Finally, there are concerns that the merger itself may not be exogenous. To avoid such concerns, we omit all observations between 1998 to 2000 for estimating our model. Our argument revolves around the fact that the merger itself was a complete surprise to virtually all industry players in 1998, and thus, the alliance between circle K and sunkus can be considered exogenous in October 1998 to the rest of all industrial participants. We have obtained a few pieces of anecdotal evidence that support this claim. First, in an interview with the CEO of sunkus on January 1999:[22] "It was October 22th 1998 that a shocking news was delivered in the distribution and retailing industry when two semi-major chains, sunkus and circle K, made an agreement of an alliance. They say the merger between them is possible in the near future." Another article describes the shocking nature of this event in 1998:[23] "In October 1998, it was a big surprise when circle K Japan and sunkus associated announced they decided to form an alliance with a merger in sight in the near future." These anecdotes are also consistent with our empirical findings that show that store counts and total sales do not exhibit erratic behavior in the years leading up to the merger.

4.5   Identification of Model Parameters

We now discuss the identification of strategic effects, revenue regression parameters, and the unobserved profitability process.

Identification conditions for models with strategic interactions (i.e., θ_4^R) are 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, because 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

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[22] Based on translated article "Interview with Kittaka Takaya, CEO of sunkus & Associates Inc.", *Gekiryu Magazine* 24 (1), 86-90.

[23] Based on translated article "Another start for all-out battle", *Monthly Conbini* 77 (January).

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 $(X_{mt}^C \neq X_{mt}^R)$, but not revenue. These cost-side variables have an impact on the strategies, but can be excluded from the regression specification. As Ellickson and Misra (2012) suggested, property value is likely the better candidate as an exclusion restriction, because we can better interpret it as a market characteristic that affects sunk costs.

For the unobserved performance dynamics, we follow similar arguments as Blevins, Khwaja, and Yang (2015). First, our data has variation in expansion/contraction across and within markets. Paired with a distributional assumption regarding the dynamics of the unobserved profitability process, the particle filtering method can be implemented. Moreover, the distribution for performance efficiency 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. With these exclusion restrictions, the posterior distribution for the performance efficiency can be identified, which can then be used to obtain the underlying parameters associated with performance. In the absence of such exclusion restrictions, the identification strategy presented by Hu, Shum, and Tan (2010) suggests that a necessary (but not sufficient) requirement for identification of dynamic games with serial correlation includes a long panel, and rich transitions in the observed states, both of which our data easily satisfy. Once unobserved heterogeneity is integrated out, the remaining model primitives can be identified as in typical entry/exit models.

Retention (δ_i) is identified by projecting Z_{imt} onto its lagged value (Z_{imt}). This is possible provided that we make an assumption about the initial distribution for Z_{im0}. Regarding the initial distribution, there is the issue of initial conditions for the performance efficiency. For this reason, we need to make use of a parametric estimation method; and to reiterate, we estimate the distribution of the performance efficiency, not the actual values. Furthermore, the fact that our data encompass the entire evolution of the convenience-store industry, we do observe the initial period of data in each market. Lastly, the importance-sampling aspect of particle filtering exponentially reduces the impact of our parametric initial distribution assumption with each updating and re-sampling iteration (Whiteley, 2012), whereby Blevins (2014) demonstrates such features of particle filtering in his Monte Carlo experiments. Ultimately, the correlations between present and past performance efficiency will contribute to the retention rate.

To identify the size spillover effect (β_i) in performance, we rely on the assumption that

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revenue and cost shifters, such as population, income, minimum wage, and property value, enter the payoffs, but not the unobserved profitability. So if short term fluctuations in the observed market conditions lead to both short term and long term changes in the total number of outlets, the continued change in the growth of outlets can only be explained by the size spillovers given that the law of motion for performance efficiency is independent of observable market conditions. Furthermore, within-market intertemporal volatility of these exogenous states also ensure they do not mirror the market fixed effect found in the evolution of unobserved profits.

Note that unlike Blevins, Khwaja, and Yang (2015), one added layer of richness in our specification is that the performance efficiency is weighted differently in revenue (γ^R) than in cost (γ^C). Consequently, our estimation method aims to identify these weights. To identify the role of performance efficiency in revenue, we make use of the fact that the posterior distribution of performance efficiency is identified via our earlier arguments. Knowing the posterior distribution, we can then project them onto revenue and obtain γ^R via our revenue regressions. With the revenue portion of profit identified, we can identify the relative role of unobserved profitability on cost via similar identification arguments used to identify the various sunk costs (i.e., revealed preferences in the sequence of actions). In particular, γ^C is identified separately from the other parameters in sunk cost given its autoregressive structure that incorporates information about firm size well before the previous year. Another important point of departure we make from the standard literature is that we employ policy functions with structural breaks (i.e., merger event). We are able to identify, in a flexible manner, the policy functions as we observe a large number of years both before and after the merger event.

5   Empirical Results

5.1   Parameter Estimates

We begin by reporting the estimates from the first stage pertaining to the data generating process behind performance dynamics (see Tables 6 and 7).[24]

As for the merged firms, sunkus and circle K, 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 no evidence that the merger improved the underlying performance dynamics for sunkus and circle K. For instance, the merged firms' increased size may not fully exploit cost efficiencies from size in the number of outlets,

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[24]The full set of estimates for the parametrized first stage are available upon request.

Table 6: Estimates for the Performance Efficiency 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)

Standard errors in parentheses

Table 7: Estimates for the Performance Efficiency after Merger

	7-Eleven	LAWSON	Family Mart	ministop	cK+sunkus
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)

Standard errors in parentheses

such as reducing transportation costs through a denser distribution network. We come back to this issue in the next subsection when we quantify how these changes in the magnitude will drive the trajectory of the performance efficiency in monetary units.

We observe two patterns for all the chains. First, noticeable inter-firm heterogeneity exists in these estimates across chains.[25] For instance, before the merger, the retention effect (δ) is largest for circle K, whereas the size-spillover (β) is largest for ministop. After the merger, Family Mart and 7-Eleven have the largest retention and size spillover estimates, respectively. Second, we observe noticeably different unobserved profitability processes before and after the merger for all chains.

We turn to the main results from our revenue regressions before and after the merger in Tables 8 and 9, respectively.

First note that performance efficiency has a noticeable effect through revenue for all chains except circle K and Family Mart prior to the merger, but only LAWSON after the merger. This finding suggests a diminishing role that the performance efficiency plays through revenue.[26]

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[25]These estimates are comparable across chains because the process is initialized using the same initial standard normal distribution.

[26]Having this piece of knowledge allows us to speculate on the possible sources of performance dynamics through demand. For instance, an increase in a retail chain's size of operation and duration of active

Table 8: Estimates from the Revenue Regressions before Merger

	7-Eleven	LAWSON	Family Mart	sunkus	circle K	ministop
Constant (θ_1^R)	142.1540	255.6441	138.4241	344.2807	116.4463	282.2633
	(0.7648)	(2.5883)	(2.8734)	(6.4406)	(5.4231)	(4.8736)
Population ($\theta_{2,population}^R$)	-0.0068	-0.0195	-0.0053	-0.0371	-0.0474	-0.0231
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0003)	(0.0002)
Income ($\theta_{2,income}^R$)	0.0304	-0.0651	0.0043	-0.0733	0.0056	-0.0456
	(0.0003)	(0.0011)	(0.0006)	(0.0018)	(0.0021)	(0.0077)
N_i (θ_3^R)	0.0667	0.1434	0.1302	-0.0323	0.2737	0.2978
	(0.0007)	(0.0067)	(0.0029)	(0.0254)	(0.0088)	(0.0065)
N_{-i} (θ_4^R)	0.0011	0.0972	-0.0046	0.2112	0.1973	0.0938
	(0.0001)	(0.0014)	(0.0013)	(0.0046)	(0.0059)	(0.0013)
Unobserved performance (γ^R)	2.9781	1.1883	7.832e-07	0.4181	1.214e-08	0.2247
	(0.0702)	(0.0698)	(0.0000)	(0.0075)	(0.0000)	(0.0092)

Standard errors in parentheses

Table 9: Estimates from the Revenue Regressions after Merger

	7-Eleven	LAWSON	Family Mart	ministop	cK+sunkus
Constant (θ_1^R)	4.8152	57.2905	60.1369	106.5308	148.7529
	(1.4622)	(1.5969)	(1.1258)	(0.8825)	(0.7558)
Population ($\theta_{2,population}^R$)	0.0297	-0.0101	-0.0019	-0.0074	0.0032
	(0.0006)	(0.0001)	(0.0001)	(0.0003)	(0.0002)
Income ($\theta_{2,income}^R$)	0.0220	0.0489	0.0414	0.0272	0.0015
	(0.0002)	(0.0002)	(0.0001)	(0.0004)	(0.0000)
N_i (θ_3^R)	-0.0923	0.0507	-0.0157	-0.1920	0.0274
	(0.0066)	(0.0006)	(0.0018)	(0.0092)	(0.0057)
N_{-i} (θ_4^R)	-0.0798	-0.0013	-0.0041	0.0246	-0.0039
	(0.0085)	(0.0000)	(0.0005)	(0.0004)	(0.0002)
Unobserved performance (γ^R)	4.195e-12	5.2619	3.857e-11	3.734e-11	7.309e-06
	(0.0000)	(0.2126)	(0.0000)	(0.0000)	(0.0000)

Standard errors in parentheses

Table 10: Second-Stage Estimates for the Cost Function

	7-Eleven	LAWSON	Family Mart	sunkus	circle K	ministop	cK+sunkus
Unobserved performance (γ^C)	0.8667	0.4886	0.2365	0.0928	0.6018	0.0514	0.8158
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Entry cost (θ_2^C)	0.1300	0.6070	0.4383	0.8589	0.7558	0.6962	0.0926
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Expansion cost (θ_3^C)	0.8403	0.0190	0.2015	0.7096	0.9368	0.3573	0.6320
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Contraction cost (θ_4^C)	0.4169	0.2364	0.7388	0.6292	0.1337	0.2193	0.0837
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Minimum wage ($\theta_{1,wage}^C$)	0.3849	0.9664	-0.6193	-3.2557	5.1401	-1.4011	-1.9060
	(0.0191)	(0.0241)	(0.0139)	(0.0028)	(0.0524)	(0.0323)	(0.0180)
Land price ($\theta_{1,land}^C$)	1.3217	3.3189	-2.1268	-11.1804	17.6518	-4.8115	-6.5455
	(0.0609)	(0.0934)	(0.0469)	(0.0083)	(0.1932)	(0.1064)	(0.0552)

Standard errors in parentheses

As for the merged firms, three noticeable changes emerge. First, the lack of contribution from the demand side may be related to the fact that both chain brands are kept separate after the merger, such that they might have been unable to fully exploit the merger event to increase sales. Second, we see that the own-brand cannibalization effects that sunkus experiences prior to the merger dampens after the merger, as the number of outlets on revenue for the merged firm becomes positive. This finding suggests that the merged chains may expand and locate in such a way that they minimize cannibalization of the two brands. Finally, the competition effect θ_4^R 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.

Revenues are a positive function of the income for some chains such as 7-Eleven, Family Mart, and circle K. After the merger, income has a positive effect on 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.

We now move on to the cost function estimates (Table 10). Sunkus experiences the largest entry cost, whereas circle K has the largest expansion costs, and Family Mart has the largest contraction costs; these costs are roughly 9 million, 9 million, and 7 million Yen, respectively. We see that minimum wage and land price have 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 could be that minimum wage and land price may be tied to the market's economic growth.

operation in a given market might leads to an increase in brand recognition (Pancras, Sriram, and Kumar, 2012; Shen and Xiao, 2014), better knowledge of local demand and thus higher sales per outlet, and improved product quality or scope over time (Basker, Klimek, and Van, 2012; Jovanovic and Rob, 1987).

Focusing on the merged firm, increased γ^C and reduced γ^R reveal that performance efficiency operate heavily through costs (as opposed to revenue) for circle K and sunkus after merger. The entry costs and contraction are lower than those of circle K and sunkus as individuals (i.e., before merger). These findings, together with the reduced entry costs after the merger, suggest the presence of savings in the sunk costs of operation and expansion. In other words, the merger had a cost-reducing effect at least partially. Because we observe a decline in the size spillover and retention in performance dynamics, however, the overall evaluation of the merger needs to rely on a simulation that we develop in the next subsection.

5.2 Merger Analysis: Better Together?

Using the estimated model, we now look more closely at the merger between sunkus and circle K. In particular, we simulate trajectories of performance efficiency over time for sunkus, circle K, and the merged firm. Simulations are necessary because we do not know the exact values of the performance efficiency, but rather their posterior distributions based on the inferred autoregressive transition equations that governs their evolution.

To illustrate the effect that the merger has on performance dynamics, we plot their trajectories prior to the merger, as well as the trajectories after the merger, in Figure 6. For example, in 1990, the average monetary value of performance efficiency across active markets is around 5 billion Yen (about US$50 million), which amount to 3% of total sales of circle K and sunkus in 1990. We see that by the year 2000, the unobserved profitability level is over 150 billion Yen; however, the level decreases to around 50 billion Yen immediately after the merger, amounting to a 66% drop.

Also noticeable are changes in the dynamics of performance. The thick solid line "circle K and sunkus (actual)" in Figure 6 reveals that the actual merger led to much slower growth in performance efficiency; for instance, from 2003 onwards, the growth rate for performance efficiency is virtually zero. This slower growth is largely associated with the merged firm's diminished ability to retain its efficiency gains from the previous period.

Alternative Merger Scenario. To further investigate the lack of improvements in the growth of unobserved profitability, we consider an exploratory simulation analysis of a hypothetical scenario in which the merged firm inherits the performance efficiency of circle K, which is the larger of the two firms. We think of this scenario as one in which the dominant firm, circle K, imposes its tangible and intangible assets, including corporate culture, and supply-chain processes onto sunkus, the smaller firm. Such an inheritance of corporate process seems plausible, because we have seen similar integration strategies in other past

Figure 6: Trajectories for the Performance Efficiency of sunkus and circle K before and after the Merger
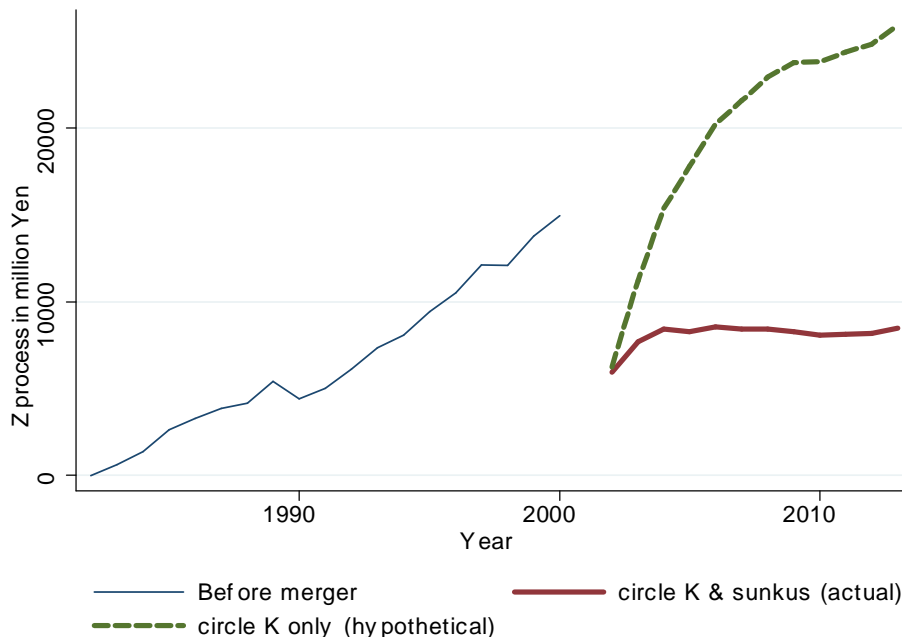
mergers (e.g., Cisco, General Electric, and Teva).[27] We proceed by following a similar forward-simulation approach as Benkard, Bodoh-Creed, and Lazarev (2010) and Jeziorski (2014), who also evaluate hypothetical scenarios in models estimated using two-step methods.

Under this hypothetical scenario, we repeat the same simulation exercise as in the previous section, and plot the trajectory of performance dynamics in Figure 6, which is the dashed line "circle K only (hypothetical)." The graph illustrates that imposing circle K's performance efficiency onto the merged firm will lead to comparable growth rates in the long-run, despite an initial drop in performance efficiency immediately following the merger. Even though the pre-merger circle K has smaller size-spillover effects than sunkus, its larger retention effects allow the merged firm to eventually achieve similar trajectories in performance as prior to the merger.

Heterogeneity in Performance across Markets. We further investigate potential intra-firm heterogeneity in the dynamics of unobserved profitability across various cities for the actual merger case and the alternative merger case. For this purpose, we focus on a handful of representative markets in Figure 7: two markets from the largest and the

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[27]Refer to "Synergy springs from cultural revolution," *Financial Times*, October 6, 2006, for some anecdotes.

Figure 7: Trajectories for the Performance Efficiency of sunkus and circle K before and after the Merger across Different Markets
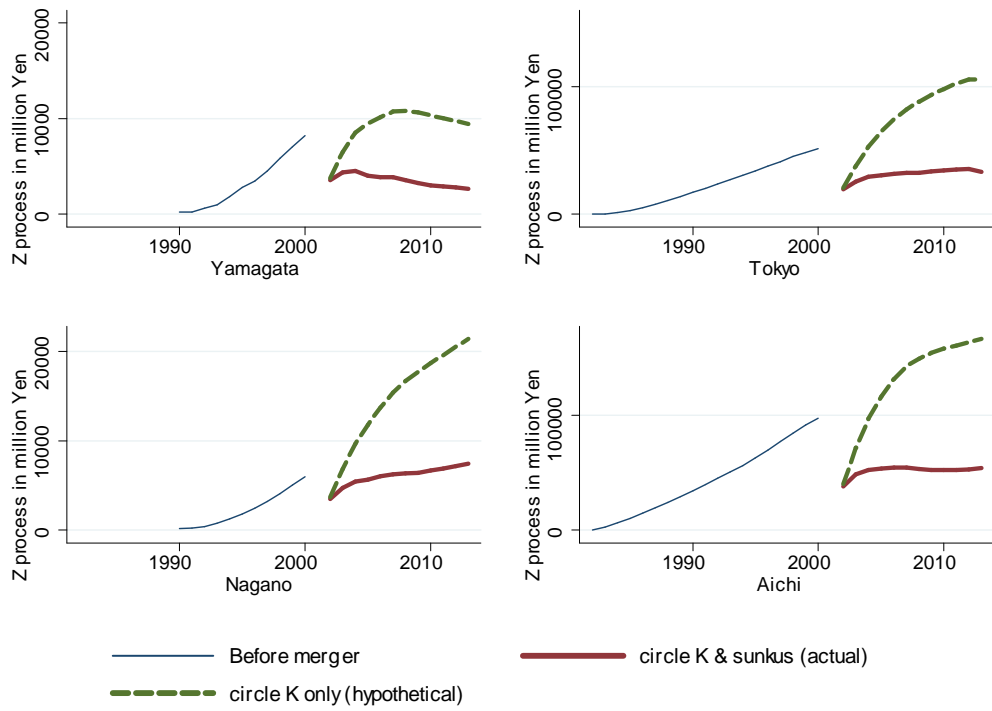
Table 11: Aggregate Comparisons between Actual Merger and Hypothetical Merger Scenarios Five Years after the Merger Event

	Equilibrium	Hypothetical
Total number of outlets	5482	6578
Total revenue (in billion Yen)	197	237
Total profit (in billion Yen)	19	22

third-largest metropolitan areas (Tokyo and Aichi), and two markets from more rural areas (Yamagata and Nagano). These four panels display heterogeneity across markets in how the merger affects performance dynamics. For instance, Yamagata exhibits negative growth in performance efficiency, reflecting the decreasing number of outlets in that market, whereas in Nagano, the performance increases over years after merger. Meanwhile, performance dynamics in Tokyo and Aichi exhibit a similar flat pattern following the merger. When the contribution from the size spillover diminishes as the number of outlets decreases, the relative gap between the baseline actual merger case and the hypothetical case (combine everything into circle K), measured by the ratio of actual performance to performance in the alternative scenario, the effect of a reduced retention rate is more pronounced. For instance, the performance in Yamagata for the hypothetical case is 3.48 times larger than the performance in the actual merger case, whereas the ratio decreases to 2.87 in Nagano. This market-specific heterogeneity in performance dynamics can then provide some guidance regarding markets that may be vulnerable to negative effects from mergers. For example, if a merged chain is reducing the number of outlets in a market, as in Yamagata, the chain suffers more from the reduced retention rate.

Overall, the merged firm's performance improves in light of this alternative merger scenario. Motivated by this finding, we investigate how the improved performance dynamics translate into other aggregated measures, such as the merged firm's total number of outlets, total revenue, and total profit, five years after the merger in 2006. Table 11 shows that not only do performance dynamics improve in light of the hypothetical merger, but so do store counts, revenue, and overall profits. A comparison between the equilibrium and hypothetical scenarios suggest that imposing circle K's process onto the merged firm will improve store counts, revenue, and profits by about 20%, 20%, and 16% respectively.

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 the channel through which these dynamics operate. 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 industry dynamics both before and after an actual merger.

A few key findings emerge. First, our estimates suggest the size-spillover and retention effects both operate through the sunk-cost component of profits. Knowing how these performance dynamics relate to either demand or supply channels further justifies the use of revenue data when analyzing such markets. Second, simulations using the estimated posterior distribution for performance efficiency and model primitives suggests the merger has a detrimental effect on the underlying performance dynamics for the merged entities; that is, the joint performance efficiency for the two firms prior to the merger grows at a higher rate than after the merger. Finally, exploratory analysis suggests performance dynamics may be preserved (and even improved) if the dominant firm successfully imposes its performance efficiency onto the merged firm.

More broadly, although a data limitation prohibited us from further nailing down the specific sources of the performance efficiency, our model has shown that employing publicly available data on store counts and sales serves as the first step to investigate how mergers have affected market participants' unobserved profitability processes. We hope this approach will encourage researchers and practitioners to explore other industries and study effects of mergers on market structure and performance when access to private information, such as inputs, prices, and costs, is limited.

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 such an assumption is reasonable for this particular industry, because mergers and acquisitions rarely happen in the 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 fraction of franchised versus corporate-owned outlets. We believe future research in this direction would be fruitful because mergers may have a differential impact on stores, depending on ownership structure. We defer the development of this new framework for future research.

References

AGUIRREGABIRIA, V., AND C.-Y. HO (2012): "A dynamic oligopoly game of the US airline industry: Estimation and policy experiments," *Journal of Econometrics*, 168(1), 156–173.

AGUIRREGABIRIA, V., AND J. SUZUKI (2015): "Empirical games of market entry and spatial competition in retail industries," Discussion paper, University of Toronto.

AKKUS, O., J. A. COOKSON, AND A. HORTAÇSU (2014): "The determinants of bank mergers: A revealed preference analysis," Discussion paper, University of Chicago.

ARCIDIACONO, P., AND R. A. MILLER (2011): "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity," *Econometrica*, 79(6), 1823–1867.

BAJARI, P., C. BENKARD, AND J. LEVIN (2007): "Estimating Dynamic Models of Imperfect Competition," *Econometrica*, 75(5), 1331–1370.

BAKER, J. (1999): "Econometric Analysis in FTC v. Staples," *Journal of Public Policy and Marketing*, 18(1), 11–21.

BASKER, E., S. KLIMEK, AND P. HOANG VAN (2012): "Supersize It: The Growth of Retail Chains and the Rise of the "Big-Box" Store," *Journal of Economics & Management Strategy*, 21(3), 541–582.

BASS, F. M., N. BRUCE, S. MAJUMDAR, AND B. MURTHI (2007): "Wearout effects of different advertising themes: A dynamic Bayesian model of the advertising-sales relationship," *Marketing Science*, 26(2), 179–195.

BENKARD, C. L. (2000): "Learning and Forgetting: The Dynamics of Aircraft Production," *The American Economic Review*, 90(4), 1034–1054.

——— (2004): "A Dynamic Analysis of the Market for Wide-bodied Commercial Aircraft," *The Review of Economic Studies*, 71(3), 581–611.

BENKARD, C. L., A. BODOH-CREED, AND J. LAZAREV (2010): "Simulating the Dynamic Effects of Horizontal Mergers: US Airlines," *Manuscript, Yale University*.

BERESTEANU, A., P. ELLICKSON, AND S. MISRA (2010): "The dynamics of retail oligopoly," *Manuscript, University of Pittsburgh*.

BESANKO, D., U. DORASZELSKI, Y. KRYUKOV, AND M. SATTERTHWAITE (2010): "Learning-by-doing, organizational forgetting, and industry dynamics," *Econometrica*, 78(2), 453–508.

BLEVINS, J. (2014): "Sequential Monte Carlo Methods for Estimating Dynamic Microeconomic Models," *Journal of Appied Econometrics*, forthcoming.

BLEVINS, J., A. KHWAJA, AND N. YANG (2015): "Firm Expansion, Size Spillovers and Market Dominance in Retail Chain Dynamics," *Management Science*, forthcoming.

BLONIGEN, B. A., AND J. R. PIERCE (2016): "Evidence for the Effects of Mergers on Market Power and Efficiency," Discussion paper, National Bureau of Economic Research.

BRAGUINSKY, S., A. OHYAMA, T. OKAZAKI, AND C. SYVERSON (2014): "Acquisitions, Productivity, and Profitability: Evidence from the Japanese Cotton Spinning Industry," *American Economic Review*, forthcoming.

BRONNENBERG, B. J., S. K. DHAR, AND J.-P. H. DUBÉ (2009): "Brand history, geography, and the persistence of brand shares," *Journal of Political Economy*, 117(1), 87–115.

BRUCE, N. I. (2008): "Pooling and dynamic forgetting effects in multitheme advertising: Tracking the advertising sales relationship with particle filters," *Marketing Science*, 27(4), 659–673.

BRUCE, N. I., N. Z. FOUTZ, AND C. KOLSARICI (2012): "Dynamic effectiveness of advertising and word of mouth in sequential distribution of new products," *Journal of Marketing Research*, 49(4), 469–486.

BRUCE, N. I., K. PETERS, AND P. A. NAIK (2012): "Discovering How Advertising Grows Sales and Builds Brands," *Journal of Marketing Research*, 49(6), 793–806.

DARR, E. D., L. ARGOTE, AND D. EPPLE (1995): "The acquisition, transfer, and depreciation of knowledge in service organizations: Productivity in franchises," *Management Science*, 41(11), 1750–1762.

DUNNE, T., S. D. KLIMEK, M. J. ROBERTS, AND D. Y. XU (2013): "Entry, Exit, and the Determinants of Market Structure," *The RAND Journal of Economics*, 44(3), 462–487.

ELLICKSON, P. B., S. HOUGHTON, AND C. TIMMINS (2013): "Estimating network economies in retail chains: a revealed preference approach," *The RAND Journal of Economics*, 44(2), 169–193.

ELLICKSON, P. B., AND S. MISRA (2012): "Enriching Interactions: Incorporating Outcome Data into Static Discrete Games," *Quantitative Marketing and Economics*, 10(1), 1–26.

ERICSON, R., AND A. PAKES (1995): "Markov-perfect industry dynamics: A framework for empirical work," *The Review of Economic Studies*, 62(1), 53–82.

FAN, Y. (2013): "Ownership consolidation and product characteristics: A study of the US daily newspaper market," *The American Economic Review*, 103(5), 1598–1628.

FANG, H., AND E. KUNG (2012): "Why do life insurance policyholders lapse? The roles of income, health and bequest motive shocks," Discussion paper, National Bureau of Economic Research.

GALLANT, A. R., H. HONG, AND A. KHWAJA (2015): "Dynamic entry with cross product spillovers: An application to the generic drug industry," *Management Science*, forthcoming.

GANDHI, A., L. FROEB, S. TSCHANTZ, AND G. J. WERDEN (2008): "Post-Merger Product Repositioning," *The Journal of Industrial Economics*, 56(1), 49–67.

GAYLE, P. G., AND H. B. LE (2014): "Measuring Merger Cost Effects: Evidence from a Dynamic Structural Econometric Model," Discussion paper, Kansas State University.

GORDON, N. J., D. J. SALMOND, AND A. F. SMITH (1993): "Novel approach to nonlinear/non-Gaussian Bayesian state estimation," in *IEE Proceedings F (Radar and Signal Processing)*, vol. 140, pp. 107–113. IET.

GOULD, E. D., B. P. PASHIGIAN, AND C. J. PRENDERGAST (2005): "Contracts, externalities, and incentives in shopping malls," *Review of Economics and Statistics*, 87(3), 411–422.

GRILICHES, Z. (1957): "Specification bias in estimates of production functions," *Journal of Farm Economics*, pp. 8–20.

GUGLER, K., AND R. SIEBERT (2007): "Market power versus efficiency effects of mergers and research joint ventures: evidence from the semiconductor industry," *The Review of Economics and Statistics*, 89(4), 645–659.

HECKMAN, J. J. (1979): "Sample selection bias as a specification error," *Econometrica*, pp. 153–161.

HOLLENBECK, B. (2013a): "Horizontal Mergers and Innovation in Concentrated Industries," *Manuscript, UCLA*.

——— (2013b): "The Spread of Horizontal Chains: Efficiency or Market Power?," *Manuscript, UCLA*.

HOLMES, T. J. (2011): "The Diffusion of Wal-Mart and Economies of Density," *Econometrica*, 79(1), 253–302.

HU, Y., M. SHUM, AND W. TAN (2010): "A simple estimator for dynamic models with serially correlated unobservables," Discussion paper, Johns Hopkins University.

IGAMI, M., AND N. YANG (2015): "Cannibalization and Preemptive Entry in Heterogeneous Markets," *Quantitative Economics*, forthcoming.

JEZIORSKI, P. (2014): "Estimation of Cost Synergies from Mergers: Application to US Radio," *The RAND Journal of Economics*, 45(4), 816–846.

JIA, P. (2008): "What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry," *Econometrica*, 76(6), 1263–1316.

JOVANOVIC, B., AND R. ROB (1987): "Demand-driven innovation and spatial competition over time," *The Review of Economic Studies*, 54(1), 63–72.

KOLSARICI, C., AND D. VAKRATSAS (2010): "Category-versus brand-level advertising messages in a highly regulated environment," *Journal of Marketing Research*, 47(6), 1078–1089.

LARSSON, R., AND S. FINKELSTEIN (1999): "Integrating strategic, organizational, and human resource perspectives on mergers and acquisitions: A case survey of synergy realization," *Organization Science*, 10(1), 1–26.

LOVE, J. F. (1995): *Behind the golden arches*. Bantam Books, New York.

MAKSIMOVIC, V., AND G. PHILLIPS (2001): "The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains?," *The Journal of Finance*, 56(6), 2019–2065.

NISHIDA, M. (2015a): "Estimating a Model of Strategic Store-Network Choice: The Convenience-store Industry in Okinawa," *Marketing Science*, 34(1), 20–38.

——— (2015b): "First-Mover Advantage through Distribution: A Decomposition Approach," *Marketing Science*, forthcoming.

ORHUN, A. Y. (2013): "Spatial differentiation in the supermarket industry: The role of common information," *Quantitative Marketing and Economics*, 11(1), 3–37.

PANCRAS, J., S. SRIRAM, AND V. KUMAR (2012): "Empirical investigation of retail expansion and cannibalization in a dynamic environment," *Management Science*, 58(11), 2001–2018.

PARK, M. (2013): "Understanding Merger Incentives and Outcomes in the US Mutual Fund Industry," *Journal of Banking & Finance*, 37(11), 4368–4380.

PEREZ-SAIZ, H. (2014): "Building New Plants or Entering by Acquisition? Firm Heterogeneity, Identification, and Entry Barriers," *The RAND Journal of Economics*, forthcoming.

RHOADES, S. A., AND A. J. YEATS (1974): "Growth, consolidation and mergers in banking," *The Journal of Finance*, 29(5), 1397–1405.

SCHOAR, A. (2002): "Effects of corporate diversification on productivity," *The Journal of Finance*, 57(6), 2379–2403.

SEIM, K. (2006): "An Empirical Model of Firm Entry with Endogenous Product-type Choices," *The RAND Journal of Economics*, 37(3), 619–640.

SHEEN, A. (2014): "The Real Product Market Impact of Mergers," *The Journal of Finance*, 69(6), 2651–2688.

SHEN, Q., AND P. XIAO (2014): "McDonald's and KFC in China: Competitors or Companions?," *Marketing Science*, 33(2), 287–307.

SUZUKI, J. (2013): "Land Use Regulation as a Barrier to Entry: Evidence from the Texas Lodging Industry," *International Economic Review*, 54(2), 495–523.

SWEETING, A. (2010): "The effects of mergers on product positioning: evidence from the music radio industry," *The RAND Journal of Economics*, 41(2), 372–397.

SYVERSON, C. (2011): "What Determines Productivity?," *Journal of Economic Literature*, 49(2), 326–65.

TOIVANEN, O., AND M. WATERSON (2005): "Market Structure and Entry: Where's the Beef?," *RAND Journal of Economics*, pp. 680–699.

——— (2011): "Retail Chain Expansion: The Early Years of McDonalds in Great Britain," Discussion paper, CEPR Discussion Papers.

UETAKE, K., AND Y. WATANABE (2013): "Entry by Merger: Estimates from a Two-Sided Matching Model with Externalities," *Manuscript, Yale University*.

VARELA, M. J. (2013): "The Costs of Growth: Estimating Entry Costs During Rollouts," *Manuscript, University of Arizona*.

VITORINO, M. A. (2012): "Empirical entry games with complementarities: An application to the shopping center industry," *Journal of Marketing Research*, 49(2), 175–191.

WEBER, R. A., AND C. F. CAMERER (2003): "Cultural conflict and merger failure: An experimental approach," *Management Science*, 49(4), 400–415.

WHITELEY, N. (2012): "Sequential Monte Carlo samplers: error bounds and insensitivity to initial conditions," *Stochastic Analysis and Applications*, 30(5), 774–798.

WILLIAMSON, O. E. (1968): "Economies as an antitrust defense: The welfare tradeoffs," *The American Economic Review*, pp. 18–36.

YANG, N. (2012): "Burger King and McDonald's: Where's the Spillover?," *International Journal of the Economics of Business*, 19(2), 255–281.

YANG, N. (2016): "Learning in Retail Entry," Discussion paper, McGill Desautels Faculty of Management.

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 12 and 13.

Table 12: 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 13: 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. Details about Policy-Function Estimation

We estimate an ordered probit model in which the choice set is $\mathcal{K}_i = \mathcal{K} = \{k_1, k_2, \ldots, k_K\}$ with $k_1 < k_2 < \cdots < k_K$. With an ordered probit, a potential complication arises 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 issues, we make discrete the actions available, based on the raw distributions of n_{mt}, as in 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, which we use a flexible functional form to capture. Exogenous state variables are summarized as W_{mt} denotes 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}, a firm-specific profitability that 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:

$$n_{imt} = \begin{cases} k_1 & \text{if } y^*_{imt} \leq \vartheta_1 \\[2mm] k_2 & \text{if } \vartheta_1 \leq y^*_{imt} \leq \vartheta_2 \\[2mm] \vdots & \vdots \\[2mm] k_K & \text{if } \vartheta_{K-1} \leq y^*_{imt} \leq \vartheta_K \end{cases}.$$

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}.

Appendix C. Revenue-Function Estimation

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, because this assumption allows us to decompose the joint selectivity problem into a collection of individual (firm-specific) selectivity problems. For the control-function specification, we choose a simple third-order polynomial, which is a flexible non-linear function of the predicted number[28] of added or subtracted outlets $\hat{n}_{imt}$:

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

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

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[28] 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.