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ABSTRACT

This article quantifies the impact of Wal-Mart Supercenters on supermarkets' profitability via a two-stage dynamic entry game, using method of simulated moments and milk scanner data from Dallas/Fort Worth supermarkets. The empirical findings show that the entry of Wal-Mart Supercenters accounts for about an average 50% decrease in milk profit margins for incumbent supermarkets. Effects of scale are found to be more significant for Wal-Mart Supercenters than for incumbent supermarkets, granting Wal-Mart a competitive edge.

Key words: Wal-Mart, entry, profit margins, milk, dynamic games

JEL codes: L1, L66, L81, D4, C73

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INTRODUCTION

Since the first Wal-Mart Supercenter (hereafter WMS) opened in Washington, Missouri, in 1988, the expansion of WMS entry into food retail markets has induced significantly lower market prices as well as some consumers switching away from traditional supermarkets, putting competitive pressure on supermarkets' profit margins. Besides low prices for individual food items, economies of scope have supported WMS penetration, as a typical WMS sells over 100,000 products under one roof, thereby introducing the convenience of one-stop shopping. On the supply side, operating multiple large units near one another can support network economics by leveraging the costs of operation, warehousing, delivery, and advertising among nearby outlets.

WMSs' lower prices and their impact on incumbents' prices are well documented. Basker and Noel (2009) find that prices for 24 grocery products in 175 cities are 10% lower at WMSs than at competing grocery stores. Hausman and Leibtag (2007) find a 30% premium at incumbent supermarkets over supercenters, mass merchandisers, and club stores in 34 cities. Basker (2005) finds that Wal-Mart's entry reduces average retail prices by as much as 7-13% for 10 grocery products in 165 cities. Volpe and Lavoie (2008) reveal that prices decrease by 6-7% for national brands and 3-7% for private label products in a sample of New England WMSs.

WMSs' impact on units or dollar sales has not been extensively documented. Artz and Stone (2006) point out that WMSs have a greater impact on local food stores in

metropolitan areas than in rural ones, causing on average 8% loss in sales at metropolitan food stores and approximately 4% at rural ones. Singh, Hanson, and Blattberg (2006) in a case study in the Northeast find that a WMS lures away large-basket buyers, leading to fewer store visits and a 17% decline in sales at nearby supermarkets. Cleary and Lopez (2011) document the decline in supermarket milk demand due to the expansion of WMSs in Dallas/Fort Worth. For 46 product categories, Ailawadi, Zhang, Krishna and Kruger (2010) find that incumbents suffer substantial sales losses as a result of a Wal-Mart entry, with a median 17% loss for supermarkets and 40% for other mass merchandisers.

The purpose of this article is to quantify the impact of WMS entry on incumbent supermarkets' profit margins through a structural model of entry. One way to achieve this objective is to start from primitive assumptions of supply and demand in a retail market and derive the profit function from equilibrium conditions. However, since this approach cannot proceed without retail data from WMS and restrictive assumptions on competition patterns among retailers, this article follows the convention in the entry literature which directly starts from a linear profit function. In addition, this article assesses the effect of what Jia (2008) terms 'scale economies' stemming from being able to provide shopping convenience to consumers and to optimally operate multiple stores near each other. Scale economies in this case sub-sums economies of scope (e.g., Bonanno and Lopez, 2009) as well as network economies from the proximity of locations.

Adapting the model developed by Jia (2008), we utilize a two-stage dynamic entry game with complete information to formulate the impact of WMS entry on its rival chains and compare the effect of scale economies of WMSs with that of traditional supermarkets. The first stage of the game is the pre-WMS period, when incumbent

supermarkets compete as Nash-Bertrand players in a market without anticipating the future entry of WMS. The second stage is the post-WMS period, when WMSs emerge and locate their stores optimally across all markets.

This model applies scanner data on supermarket fluid milk sales in the Dallas/Fort Worth metropolitan area provided by the Food Marketing Policy Center at the University of Connecticut. The dataset includes 58 four-weekly observations on fluid milk sold by five major supermarket chains from March 1996 to July 2000.

The Dallas/Fort Worth milk market provides an interesting case study for this model. First, the expansion path of WMSs in this metropolitan area is easily divided into “pre-WMS” and “post-WMS” periods. Second, the Dallas/Fort Worth area is characterized by few, large incumbent supermarkets. The top two supermarket chains (Albertson’s and Kroger) in this market were also the contemporary top two food-retailers in the U.S., making the general conclusions transferable to other geographic markets. Third, milk, being a relatively homogeneous good, allows for ready identification of a demand function for the first stage of the game. Fourth, the fluid milk price has been a key strategic variable in reacting to entry. For instance, milk was rather oligopolistic in the Dallas/Fort Worth market before WMSs aggressive entry, and then a price war was triggered in 1999 as WMSs entry accelerated (Cotterill and Brundage, 2001; Cleary and Lopez, 2011). Thus, milk sales can be used as a vivid indicator of competitive pressure as its price and, by extension, sales are sensitive to entry, particularly to Wal-Mart. For instance, Volpe and Lavoie (2008) find that Wal-Mart’s presence has the largest competitive effect on dairy products among the grocery products analyzed.

Empirical results show that Wal-Mart Supercenter entry accounts for an average decrease of 50% in milk profit margins for incumbent supermarkets in the transition from the first to the second stage. The profit margins of incumbent supermarkets in the second stage are not significantly different from zero. The competition between incumbent supermarkets is found to be only 45% of their degree of competition with respect to WMSs, which may imply the possibility of tacit collusion among incumbent supermarkets in response to the presence of WMSs in food markets.

A TWO-STAGE ENTRY MODEL

This section describes a two-stage (pre- and post-entry) dynamic game to analyze the entry impact of a WMS on incumbent supermarket profit margins.

In the first stage, incumbent supermarkets compete in a market to maximize their profits, without anticipating the entry of a WMS in the second stage. The Nash-Bertrand market equilibrium is obtained in this stage by solving each supermarket's profit maximization problem. The profit function of incumbent supermarkets i that operate in the market m is given by:

$$\begin{aligned} \Pi_{im}^0 = & \gamma_i^0 (p_{im}^0 Q_{im}^0) + X_m^0 \beta_i + \alpha_{ii} s_{im}^0 + \sum_{j \neq i} \alpha_{ij} s_{jm}^0 & (1) \\ & + \sigma_{ii} \sum_{n \neq m} \frac{ss}{Z_{mn}} + \sqrt{1 - \rho^2} \varepsilon_m^0 + \rho \eta_{im}^0, i, j = \{1, 2, \dots, N_r\} \end{aligned}$$

where N_r is the number of incumbent supermarkets, γ^0 is a supermarket's profit margins in the first stage and p_{im}^0, Q_{im}^0 is sales by supermarket i in market m . In this stage, p_{im}^0, Q_{im}^0 is independent of WMS's future entry in the second stage. X_m^0 is the α vector of market characteristics, which is allowed to vary across both players and

markets, and the coefficient β_i varies across retailers. Note that equation (1) includes market shares (s_i, s_j) for both retailer i and its rival competitors j , and their effects are assumed to be $\alpha_{ii} > 0$ and $\alpha_{ij} < 0$ ($i \neq j$). The unobserved profit shock is $\sqrt{1-\rho^2} \varepsilon_m^0 + \rho \eta_{im}^0$ is known to the retailers but unknown to econometricians.

Scale economies are captured by two variables. The first variable ss_i is the average store size of retailer i as bigger stores are assumed to lure more consumers by providing a wider range of products and brand choices. The second variable, Z_{mn} , designates the distance from market m to market n , which is used to evaluate the cost splitting effect of operating a chain. By construction, the profit in market m increases by $\sigma_{ii} \frac{1}{Z_{mn}}$ if there is a store in market n that is Z_{mn} miles away. The effect is assumed to decrease with distance.

The profit maximization condition for retailer i is

$$Q_{im}^0 + \gamma_i^0 P_{im}^0 \frac{\partial Q_{im}^0}{\partial p_{im}^0} = 0. \quad (2)$$

The profit margin γ_i^0 can then be calculated from quantity sales, the retail price and the demand estimate for $\frac{\partial Q_{im}^0}{\partial p_{im}^0}$, as suggested by Villas-Boas (2007).

In the second stage, the profit function of a WMS is specified as

$$\Pi_{wm} = D_m [\theta_w (\frac{1}{N_r} \sum_{i=1}^{N_r} \frac{ss_w}{ss_i} sale_{im}) + X_m \beta_w + \sum_{i=1}^{N_r} \alpha_{wi} s_{im}] \quad (3)$$

$$+ \sigma_{ww} \sum_{m \neq n} \frac{ss_w D_n}{Z_{mn}} + \sqrt{1 - \rho^2} \varepsilon_m + \rho \eta_{wm}] .$$

The variable $D_m \in \{0,1\}$ refers to the WMS entry strategy in market m , where $D_m = 1$ if WMS operates in market m and $D_m = 0$ otherwise. $D = \{D_1, \dots, D_M\}$ is a vector indicating the location choices for WMSs over the entire set of markets. Similar to other players, the effect of economies of scale on WMS is measured by two variables: ss_w and $\frac{ss_w D_n}{Z_{mn}}$, the average store size of WMSs, and $\frac{D_n}{Z_{mn}}$, which indicates that if Wal-Mart decides to operate a WMS in market n $Z_{m,n}$ miles away from market m , the profit of market m will be raised by $\sigma_{ww} \frac{ss_w D_n}{Z_{mn}}$. The summation of $\frac{ss_w D_n}{Z_{mn}}$ over all markets except m implies that the profit in market m depends on the number of other markets that Wal-Mart decides to enter.

The variable $sale_{im}$ is the value of sales for retailer i in market m . Because the sales data for WMSs is not always accessible to researchers, it is assumed that the decision rule of a WMS on its sales is to estimate a weighted average of its rivals' dollar sales. This specification ensures that the model can be evaluated even if the sales data for WMSs is not available. The weight of dollar sales is determined by the relative store size of a WMS to that of incumbent supermarkets. The value of θ_w is the marginal contribution of estimated sales to the profit of a WMS, which is similar to profit margins. $X_m \beta_w$ is the impact of market features on WMS profit. The competition effect of other supermarkets on WMS is captured by $\sum_{i=1}^{N_r} \alpha_{wi} s_{im}$ (α_{wi} is non-positive). $\sqrt{1 - \rho^2} \varepsilon_m + \rho \eta_{wm}$ is unobserved market shocks occurring in the second stage.

The profit of retailer i in the second stage is specified as:

$$\begin{aligned} \Pi_{im} = & \gamma_i \text{sale}_{im} + X_m \beta_i + \alpha_{ii} s_{im} + \sum_{j \neq i} \alpha_{ij} s_{jm} \\ & + \alpha_{iw} \frac{SS_w}{SS_i} D_m + \sigma_{ii} \sum_{n \neq m} \frac{SS_i}{Z_{mn}} + \sqrt{1 - \rho^2} \varepsilon_m + \rho \eta_{im} \end{aligned} \quad (4)$$

where γ_i refers to the new profit margin of retailer i , $\alpha_{iw} \frac{SS_w}{SS_i} D_m$ is the impact of WMS on retailer i , and $\frac{SS_w}{SS_i}$ describes the competition advantage of operating a supercenter instead of a traditional food supermarket. The fixed profit goal π_i indicates that retailer i will set its profit Π_{im} equal to π_i under the competitive pressure of a WMS. In equilibrium, retailer i 's dollar sales, sale_{im} , is a well-defined reaction function of WMS's entry decision; that is, $\text{sale}_{im} = \text{sale}_{im}(D_m)$.

In the second stage, Wal-Mart simultaneously chooses WMS locations to maximize its total profits over all markets. Incumbent supermarkets quickly obtain full knowledge of a WMS's payoff structure and adjust their goal from profit maximization to targeting a fixed profit level. For some markets, this fixed profit level may prove to be equivalent to the maximized profit, but for most markets, where WMS imposes significant competition pressure, this targeted profit level is assumed to be less than the profit maximization level. Meanwhile, Wal-Mart is fully informed about the reaction function of incumbent supermarkets and optimally makes location choices by maximizing its profit over all markets collectively. Once the entry decisions are made by Wal-Mart, profits of all players are realized.¹

DATA AND ESTIMATION

An ideal application of this model is to analyze Wal-Mart's joint entry decisions in all markets. The definition of "market" is critical. For example, Jia (2008) defines a market as a county and extracts 2,065 markets from a total 3,140 counties in the U.S. For the model discussed in this article, two conditions are worth noticing for a valid definition of "market". The first is that all markets included in the study must contain the same incumbent supermarkets because the model does not allow parameters to vary across markets. Second, a market must include only one WMS. For example, one could define a market by county or zip code, but if there is more than one WMS in such a market, one may need to consider a more detailed division.

Due to lack of data availability, this article applies simulation to define markets. In the literature on panel data analysis, when observations are independent over time, the time-series dimension of the panel data may be treated as another set of cross-sectional data. Based on this rationale, an empirical application maps time-series data onto the cross-sectional dimension to simulate geographically different markets. A basic assumption of this approach is that the original observations are independent over time.

The fluid milk database used in this study is an Information Resources Infoscan (IRI), provided by the Food Marketing and Policy Center at the University of Connecticut.² The database includes 58 four-week-ending observations covering the period from March 1996 to July 2000 in the Dallas/Fort Worth metropolitan area. The number of WMSs and demand shifters such as population, age, and Hispanic percentage are collected from Market Scope. The average store sizes of all players are calculated based on store sizes provided by a Dun & Bradstreet's Million Dollar Database (2006).

Figure 1 shows the market simulation results. For the 58 time-series observations in

the Dallas/Fort worth area. Then in Figure 2 the first 29 observations of this series are defined as 29 markets for the “pre-WMS” period, as shown by the dashed line. Thus, the first observation corresponds to market 1, the second to market 2, and so on. The rest of the observations (30 through 58) are defined as the evolution of these markets in the second stage, as shown by the solid line in Figure 2. Thus, the 30th observation corresponds to market 1, the 31st observation to market 2, and so on.

For the location choice of WMSs, Market Scope gives only the total number of WMSs over all markets rather than exact locations and densities; therefore the distance between any nearby markets is normalized to be 1 mile. To cover as many as possible location choices made by WMS, this application applies a bootstrapping technique to generate another 1,000 samples with possible WMS location choices³.

In the first stage, a log demand function is estimated to calculate retailer i 's retailing margin, applying the equilibrium condition in (2):

$$\begin{aligned} \log Q_{im} = & \delta_0^i + \delta_1^i \log p_{im} + \delta_2^i hhsizem + \delta_3^i agem + \delta_4^i hispm \\ & + \delta_5^i \log(inc_m) + \delta_6^i avgprice_{jm} + \delta_7^i \log(pop_m) + \varepsilon_{im} \end{aligned} \quad (5)$$

for $m=1,\dots,29$. Q_{im} is the quantity sold in market m , and p_{im} is the retail price. The set of variables $\{hhsizem, agem, hispm, inc_m, avgprice_{jm}, pop_m\}$ are demand shifters in market m , referring to the average household size, average age of the population, percentage of the population that is Hispanic, per capita consumer income, average price of rival competitors, and population, respectively. The estimate of δ_1^i is used to calculate the retailing margins in the first stage.

A solution algorithm is used to find the Nash equilibrium for the problem in the

second stage. For simplicity, this section uses X_m to refer to

$$\theta_w \left(\frac{rs_w}{N_r} \sum_{i=1}^{N_r} sale_{i,m} \right) + X_m \beta_w + \sum_{i=1}^{N_r} \alpha_{w,i} s_{i,m} + \sqrt{1-\rho^2} \varepsilon_m + \rho \eta_{wm}. \quad (6)$$

WMS's problem becomes

$$\underset{D_1, \dots, D_M \in \{0,1\}}{\text{Max}} \Pi = \sum_{m=1}^M [D_m (X_m + \sigma_{ww} \sum_{m \neq n} \frac{ss_w \times D_n}{Z_{mn}})], \quad (7)$$

where M denotes the total number of markets.

Let $\mathbf{D} = \{0,1\}^M$ denote the choice set of a WMS over M markets. Any element of the set \mathbf{D} is an M -coordinate vector $D = \{D_1, \dots, D_M\}$. The choice variable D_m directly determines the profit of the WMS in market m ; that is, it earns a profit $(X_m + \sigma_{ww} \sum_{m \neq n} \frac{ss_w \times D_n}{Z_{mn}})$ if $D_m = 1$, none if $D_m = 0$. Hence, the decision to open a WMS in market m increases profits in other markets through the economies of scale effect.

This maximization problem is a discrete problem of large dimension. In each market, WMS has two choices taking values 1 and 0. The total dimension of the choice set is thereby 2^M .⁴ To address this issue, Jia (2008) suggests an algorithm that transforms the profit maximization problem into a search for the fixed points of a necessary condition. This algorithm suggests obtaining lower and upper bounds of the choice set, then evaluating all choice vectors between the bounds to find the profit-maximizing one.

In the second stage, the parameters are estimated via the method of simulation moments (McFadden, 1989; Pakes and Pollard, 1989), correcting for spatial dependence

(Jia, 2008; Conley, 1999). In this application, B_m is equivalent to m because the farthest distance between two markets is only 28 miles and this application assumes the spatial dependency is still effective within this distance.⁵

The simulated data set used in this application contains 145 observations (29 markets \times 5 supermarkets). To gain degrees of freedom, the parameters of market feature variables β_i are restricted to be identical across all players. The reaction of WMS to competition from incumbent supermarkets σ_{wi} , the effect of scale of economies on incumbent supermarkets σ_{ii} , incumbent supermarkets' competitive advantage through their gross market share α_{ii} , rival supermarkets' competitive advantage through their gross market share α_{ij} , as well as their profit goal π_i , are restricted to be identical across the five incumbent supermarkets. By these restrictions, the total number of estimated parameters is reduced to 20.

The market feature variables X_m include log population and log Hispanic percentage for all players. The moments conditions that match the model-predicted and the observed values include the number of WMSs, dollar sales of retailer i with $i = 1, \dots, 5$, their interaction terms with market features and the difference in the dollar sales of incumbent supermarkets between stage 1 and stage 2, interacted with the changes in the market feature variables between the two stages.

The unobserved market shocks $\sqrt{1 - p^2} \varepsilon_m + pn_{wm}$ are obtained from 150 Halton draws instead of the usual machine-generated pseudo-random draws. As discussed in Train (2000), 100 Halton draws achieves greater accuracy in a mixed logit estimation than 1000 pseudo-random draws.

EMPIRICAL RESULTS

Table 1 reports the estimates of δ_1 in equation (5). The consistent estimators of profit margins in the first stage (pre-WMS periods) are calculated from $-\frac{1}{\hat{\delta}_1}$. Albertson's and Kroger exert 86.85% and 66.82% margins while Tom Thumb has the lowest profit margins with 23.83%. The profit margin of Winn Dixie is greater than 1 because its price elasticity is estimated as -0.7899 .⁶

The first line of table 2 reports the estimates of profit margins γ_i in the second stage (post-WMS period). Winn Dixie exhibits the highest profit margins with 24.74%, followed by Albertson's with 24.66%. Kroger experiences the lowest profit margin among all incumbent supermarkets with only 16.98%.

The third line of table 2 reports the percentage change in profit margins from the first stage to the second stage. All incumbent supermarkets⁷ experience significant decreases in retail margins after the expansion of WMS in the second stage. Kroger, the top food retailer in all markets, has the largest percentage decrease of profit margins, with as much as 74.59%. The second largest retailer, Albertson's, exhibits a 71.61% reduction after the entry of a WMS. Tom Thumb shows the most modest response to the entry of a WMS, reducing its profit margin by only 7.79%.

Table 3 reports parameter estimates in the second stage. Log population is beneficial to a retailer's profit with a marginal contribution equal to 0.5071, while a higher Hispanic percentage in the neighborhood discourages the profitability of a retailer by a marginal effect of -0.6836. A 1% increase in a supermarket's gross market share increases its profit by 12.39%, while a 1% increase in its rivals' gross market share decreases the

supermarket's profit by 12.81%. The competition pressure that incumbent supermarkets impose on their rival supermarkets has a value of -5.6981, which accounts for only 44.5% of the effect they impose on WMSs.

The marginal benefit of an incumbent supermarket from its economies of scale is 0.1205, which is only 30% of the 0.3913 a WMS receives. This difference indicates that the scale of economies is more important for WMS than for incumbent supermarkets. In contrast, $\hat{\theta}_w$ has the value 0.0284, which implies that the contribution of direct dollar sales on the profit of WMSs is roughly only 1% of that on incumbent supermarkets.

The estimate of α_{iw} illustrates that the entry of a WMS has the most significant impact on Kroger's profitability. When a WMS enters a market, Kroger's profit decreases by 10.62 %, followed by Tom Thumb with a decrease of 8.15%. WMSs have the least significant impact on Winn Dixie. The profit goal, π_i is not statistically significantly different from zero, which indicates that once a WMS enters a market, incumbent supermarkets attempt to keep their consumers away from WMS by scarifying their positive profitability.

CONCLUDING REMARKS

This article evaluates the competitive impact of WMSs on incumbent supermarkets as well as the role of economies of scale in a player's payoff structure. The empirical application to 29 simulated markets reveals the fact that WMS expansion accounts for significant reductions in profit margins for all incumbent supermarkets. These results reinforce concerns raised by the public and particularly by the unionized workforce of incumbent supermarkets.

The presence of economies of scale is found to generate substantial benefits for all

retailers but is more beneficial to the profitability of WMSs than to that of incumbent supermarkets. This result can help explore the potential effects of retail merger policies or other regulations that involve Wal-Mart.

Another empirical finding is that the competition among incumbent supermarkets is found to be only 44.5% of the competition effect that they direct to WMSs, which implies possibility of partial collusion among incumbent supermarkets under the competitive pressure of WMSs.

A possible extension of this article is to solve the issue of multiple equilibria, as discussed in Jia (2008). In this model, we assume that all players have complete information and make simultaneous entry decisions. This assumption can lead to a simulated value of WMS location choice D less than 1 mile. One solution of this issue is to look for features that are common among different equilibria (Bresnahan and Reiss, 1990, 1991; Berry, 1992). Another solution is to search for bounds of parameters instead of identifying the point estimates. These approaches may however, become computationally intensive for the model specified here because of extremely large choice dimensions.

Another possible extension is to incorporate vertical competition in the model when retailing data at the brand level is available because WMS entry may also change a vertical competition pattern. A straightforward method to evaluate this possibility is to compare manufacturers' profit margins between the "pre-WMS" and "post-WMS" periods.

Finally, the results for milk, being an entry-sensitive commodity in a pre-existing oligopolistic setting, should not be readily generalized to other products and cities.

Whether the results of this study can be extended to other products and cities beyond our sample is a question that awaits further empirical analysis.

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APPENDIX

The problem for incumbent supermarket i can be obtained by backward induction. In the equilibrium, the reaction function of retailer i is a well-defined function of D_m :

$$\begin{aligned} sale_{im}(D_m) = & \frac{1}{\gamma_i} [\pi_i - (X_m \beta_i + \alpha_{ii} s_{im} + \sum_{j \neq i} \alpha_{ij} s_{jm}) \\ & + \alpha_{iw} * \frac{SS_w}{SS_i} D_m + \sigma_{ii} \sum_{n \neq m} \frac{SS_i}{Z_{mn}} + \sqrt{1 - \rho^2} \varepsilon_m + \rho \eta_{im}] \end{aligned} \quad (A1)$$

The profit of WMS then becomes

$$\begin{aligned} \Pi_{wm} = & D_m * [\theta_w (\frac{rS_w}{N_r} \sum_{i=1}^{N_r} sale_{im}(D_m)) + X_m \beta_w + \sum_{i=1}^{N_r} \alpha_{wi} s_{im}] \\ & + \sigma_{ww} \sum_{m \neq n} \frac{SS_w \times D_n}{Z_{mn}} + \sqrt{1 - \rho^2} \varepsilon_m + \rho \eta_{wm}] \end{aligned} \quad (A2)$$

The method of simulated moments (MSM) is applied to estimate the model because a closed form solution of the model does not exist. The set of parameters that need to be estimated is

$$\theta_0 = \{\theta_w, \beta_i, \beta_w, \alpha_{iw}, \alpha_{wi}, \sigma_{ii}, \sigma_{ww}, \gamma_i, \rho, \pi_i\}_{(i=1, \dots, N_r)} \in R^P. \quad (A3)$$

The following moment condition should at the true parameter value θ_0 :

$$E[g(X_m, \theta_0)] = 0,$$

where $g(X_m, \cdot) \in R^L$ with $L \geq P$ is a vector of moment functions that specifies the differences between the observed equilibrium market structures and those predicted by the model. X_m here refers to the explanatory variables.

The MSM estimator $\hat{\theta}$ is obtained from the following equation:

$$\hat{\theta} = \arg \min \frac{1}{M} \left[\sum_{m=1}^M \hat{g}(X_m, \hat{\theta}) \right]' \Omega_M \left[\sum_{m=1}^M \hat{g}(X_m, \hat{\theta}) \right] \quad (\text{A4})$$

where $\hat{g}(\cdot)$ is a simulated estimate of the true moment function. Ω_M is an $L \times L$ positive semi-definite weighting matrix. Pakes and Pollard (1989), and McFadden (1989) show the relationship

$$\sqrt{M}(\hat{\theta} - \theta_0) \rightarrow N(0, (1 + R^{-1}) * A_0^{-1} B_0 A_0^{-1}) \quad (\text{A5})$$

holds under the conditions that $\Omega_M \rightarrow \Omega_0$. R is the number of simulations, and $A_0 = G_0' \Omega_0 G_0$, $B_0 = G_0' \Omega_0 \Lambda_0 \Omega_0 G_0$ where G_0 is a $L \times P$ matrix with $G_0 = E[\Delta_{\theta'} g(X_m, \theta_0)]$. Λ_0 is defined as $\Lambda_0 = E[g(X_m, \theta_0) g(X_m, \theta_0)'] = \text{Var}[g(X_m, \theta_0)]$. If a consistent estimator of Λ_0^{-1} is used as the weighting matrix, the MSM estimator $\hat{\theta}$ is asymptotically efficient, with its asymptotic variance being $A \text{var}(\hat{\theta}) = (1 + R^{-1}) * (G_0' \Lambda_0^{-1} G_0)^{-1} / M$.

The issue of applying standard MSM methodology to this model is that the moment functions $g(X_m, \cdot)$ are no longer independent across markets when the economies of scale effect induces spatial correlations in the equilibrium outcome. That is, any two entry decisions D_m and D_n are correlated through the economies of scale effect, although the correlation evaporates with distance.

This difficulty of spatial dependence in estimation could be solved by the econometric technique proposed by Conley (1999). The basic assumption in applying this technique is that the dependence between D_m and D_n should die away quickly as the distance increases. In other words, the entry decisions in different markets should be nearly independent when the distances between these markets are sufficiently large.

With the presence of the spatial dependence, this technique replaces the asymptotic covariance matrix of the moment functions Λ_0 with $\Lambda_0^d = \sum_{s \in M} E[g(X_m, \theta_0) g(X_s, \theta_0)']$. Then a non-parametric covariance matrix estimator is formed by taking a weighted average of spatial auto-covariance terms, with zero weights for observations farther than

a certain distance:

$$\hat{\Lambda} = \frac{1}{M} \sum_m \sum_{s \in B_m} [\hat{g}(X_m, \theta) \hat{g}(X_s, \theta)'] \quad (\text{A6})$$

Where B_m is the set of markets whose centroid is within a certain distance, it is assumed the covariance will die out. The spatial correlation is negligible for any market outside the market set B_m . A feasible optimal weight matrix Λ^{-1} is

$$\hat{\Lambda} = \frac{1}{M} \sum_m \sum_{s \in B_m} [\hat{g}(X_m, \tilde{\theta}) \hat{g}(X_s, \tilde{\theta})'] \quad (\text{A7})$$

where $\tilde{\theta}$ is a preliminary estimate of θ_0 using either an identity matrix or $(X_m X_m')^{-1}$ as a weighting matrix.

Using $\hat{\Lambda}^{-1}$ as a weighting matrix, a set of asymptotically normally distributed and consistent estimators can be obtained through three steps:

Step 1: start from some initial guess of the parameter values, and draw independently from the normal distribution the following vectors: the market-level errors $\{\hat{\mathcal{E}}_m\}$ and profit shocks for WMS $\{\eta_w m\}$ and incumbent supermarkets $\{\eta_{im}\}_{i=1}^{N_r}$, where $m = 1, \dots, M$.

Step 2: obtain the simulated profits $\hat{\Pi}_w$ and solve for \hat{D}_w and $sale_{im}$, where $i = 1, \dots, N_r$ and $m = 1, \dots, M$.

Step 3: repeat steps 1 and 2 R times and formulate $\hat{g}(X_m, \theta)$. Search for parameter values that minimize the objective function in equation (10), while using the same set of simulation draws for all values of θ . The weighting matrix Ω_m is the pre-calculated $\hat{\Lambda}^{-1}$.

Figure 1. Simulated Supermarket Milk Sales Over Time

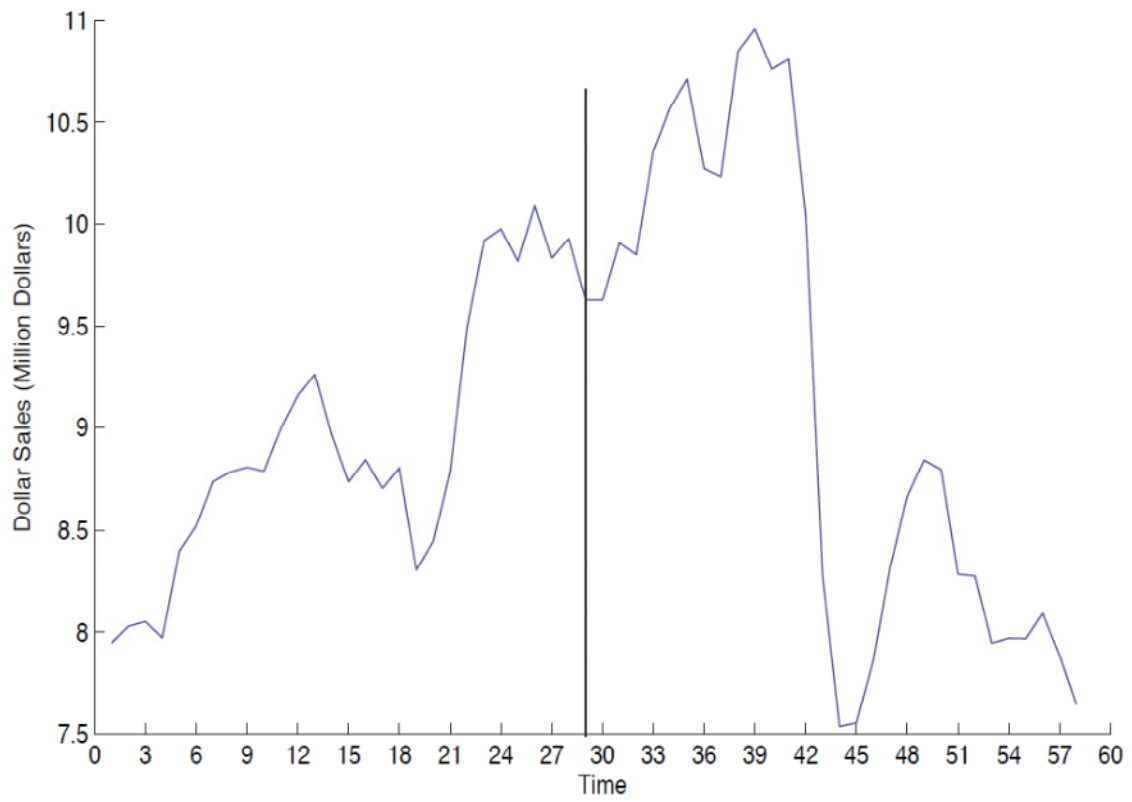


Figure 2. Simulated Supermarket Milk Sales Over 29 Markets

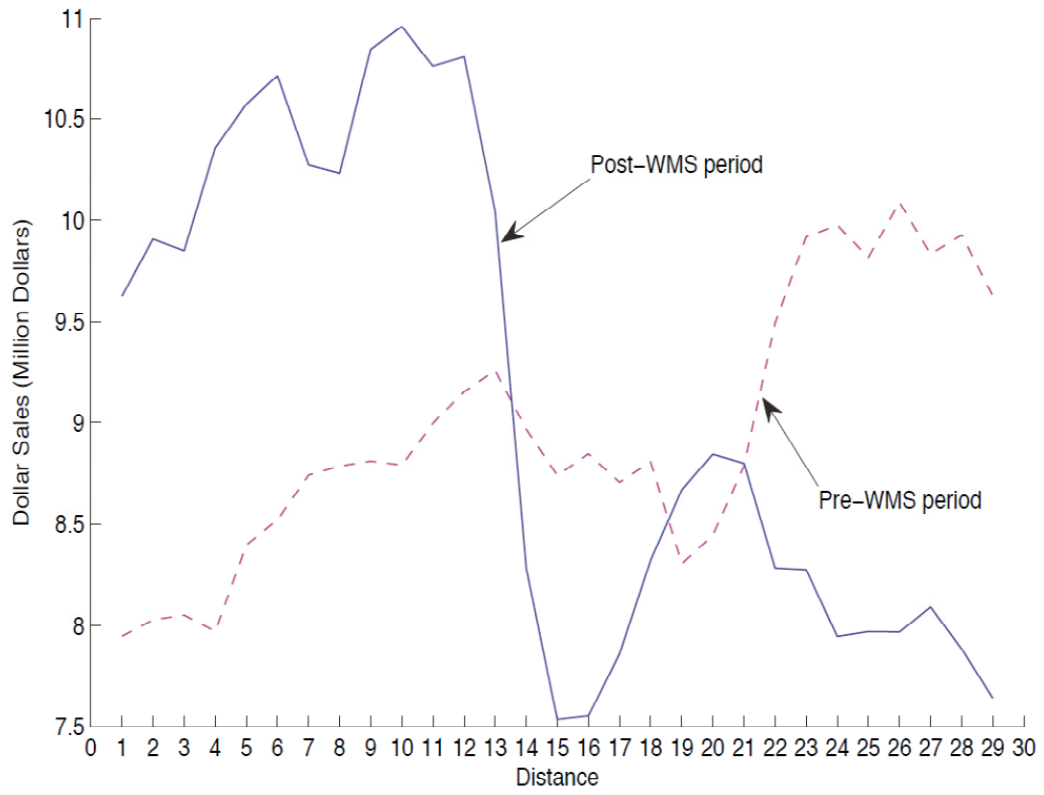


Table 1: Percent Profit Margins in the First Stage

	Albertson's	Kroger	Minyard	Tom Thumb	Winn Dixie
δ_1	-1.1514	-1.4966	-1.4062	-4.1970	-0.7899
	(0.1932)	(0.3414)	(0.2985)	(1.2126)	(0.4032)
Profit Margins	0.8685	0.6682	0.7111	0.2383	1.2660
Std. Errors	(0.1457)	(0.1524)	(0.1510)	(0.0688)	(0.6462)

Note: Standard errors of profit margins are calculated by the delta method.

Table 2. Percent Profit Margins in the Second Stage

	Albertson's	Kroger	Minyard	Tom Thumb	Winn Dixie
Profit Margins	0.2466	0.1698	0.2388	0.2197	0.2474
Std. Errors	(0.0053)	(0.0078)	(0.0142)	(0.0083)	(0.0122)
% changes in margins	-71.61%	-74.59%	-66.42%	-7.79%	(—)

Note: Standard errors of profit margins are calculated by bootstrapping.

Table 3: Parameter Estimates in the Second Stage

Explanatory variables	Parameter	Estimates	Std. Err.
Log population	β^1	0.3071	(0.0285)
Log hispanic percentage	β^2	-0.6836	(0.0033)
Incumbent supermarkets' scale economies	σ_{ii}	0.1205	(0.0006)
Supermarket i 's competitive advantage over WMS	α_{wi}	-12.8075	(0.1845)
Supermarket i 's self competitive advantage over supermarket j	α_{ii}	12.3852	(0.1183)
Supermarket j 's competitive advantage over supermarket i	α_{ij}	-5.6981	(0.0915)
Impact of the entry of WMS on Albertson's profit margins	α_{1w}	-7.8115	(0.0400)
Impact of the entry of WMS on Kroger's profit margins	α_{2w}	-10.6197	(0.1202)
Impact of the entry of WMS on Minyard's profit margins	α_{3w}	-7.905	(0.0459)
Impact of the entry of WMS on Tom Thumb's profit margins	α_{4w}	-8.1487	(0.0434)
Impact of the entry of WMS on Winn Dixie profit margins	α_{5w}	-6.2369	(0.0333)
WMS's economies of scale	σ_{ww}	0.3913	(0.0076)
Market shock	ρ	0.3147	(0.0068)
WMS's sale scale	θ_w	0.0284	(0.0054)
Supermarket's profit goal	π_i	0.0383	(0.0373)

* Standard errors are obtained by bootstrapping.

End Notes

¹ A critical assumption of this model is that incumbent supermarkets do not compete with WMS by opening more profitable stores in the market. This assumption guarantees WMS is the only player that needs to make entry decisions. The model becomes more complicated if this assumption is not made. See Jia (2008) for a detailed analysis of two competing chains' problem.

² To generalize to overall profit rates, a perfect correlation between milk sales and overall grocery sales would be required.

³ A prior density assumption that WMSs are more concentrated in markets 14-17 and 23-29 is used.

⁴ A naive way to solve this problem is to try all the possibilities and compare the values of profits obtained under each possibility. If an empirical application of this model aims to evaluate the impact including all markets that WMS may enter, the resulting dimension of the choice set will become extremely large. For example, even for the empirical example studied in this paper with 29 simulated markets analyzed, the number of possible elements in the choice set \mathbf{D} is $2^{29} = 536,870,912$.

⁵ Jia (2008) assumes the spatial dependency is negligible for markets 50 miles away.

⁶ The definition of profit margins is $= (p^r - p^w - c^r) / p^r$, where p^r is the retail price, p^w is the wholesale price, and c^r is the retailing marginal cost. The only probability that a profit margin is greater than 1 is for p^w to be less than 0, which is not true even for private label products.

⁷ Because of the paradox raised from Winn Dixie's estimates in stage 1, the discussion excludes the percentage change of Winn Dixie.