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The Impact of Wal-Mart Supercenters on Supermarkets' Profit Margins

Xiaoou Liu
School of Agricultural Economics and Rural Development
Renmin University of China
Beijing, China 100872

Rigoberto Lopez
Department of Agricultural and Resource Economics
University of Connecticut
W.B. Young Building, 1376 Storrs Road
Storrs, CT 06269

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ABSTRACT

The Impact of Wal-Mart Supercenters on Supermarkets' Profit Margins. XIAOOU LIU (Email: xiaoou2010@gmail.com, School of Agricultural Economics and Rural Development, Renmin University of China, Beijing, China 100872) RIGOBERTO LOPEZ (Professor and Department Head, Department of Agricultural and Resource Economics, Storrs, CT 06269)

This paper quantifies the impact of Wal-Mart Supercenters on supermarkets' profitability via a two-stage dynamic entry game, using simulated methods of moment 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 of 50% decreases in profit margins for incumbent supermarkets. The effect of scale of economies is found to be more significant for Wal-Mart Supercenters than for incumbent supermarkets.

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

1 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 incumbent supermarkets. Besides the low prices for individual food items, economies of scale 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 large, multiple units near one another can benefit a store's profit by splitting the cost of operation, delivery, and advertising among nearby outlets and sharing knowledge of local markets.

While the price reductions induced by WMS' lower prices are well documented, (Hausman, 2007; Basker & Noel, 2007; Capps and Griffin, 1998; Currie and Jain, 2002), Basker (2005b) argues that previous studies are devoid of structural models and have not gone beyond prices and/or employment effects, particularly with respect to incumbent supermarkets.

The first objective of this paper is to quantify the impact of WMS on incumbent supermarkets' profit margins and profitability through a structural model. 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, so this paper follows the convention in the entry literature and directly starts from a linear profit function.

The second objective is to assess the effect of economies of scale stemming from being able to provide shopping convenience and to optimally operate multiple stores over an entire set of markets. This paper defines the term "scale of economies" as the benefit of operating large supercenters from both demand shock and supply shock. The demand shock is from the perspective of providing more shopping convenience to consumers, the supply shock from that of the cost-splitting effect of operating multiple stores over the entire set of markets. Studying this effect requires a model to analyze retailers' joint entry decisions across all markets rather than, as in most entry literature, assuming independent entry decisions across markets.

Following Jia (2008), we utilize a two-stage dynamic entry game with complete information to formulate the impact of WMS's entry on its rival chains and compare the effect of economies of scale on WMS with that on traditional food chains. The first-stage of the game is the pre-WMS period, when incumbent supermarkets compete in a market without anticipating the future entry of WMS. The incumbent supermarkets are assumed to maximize their profit as Nash-Bertrand players. Based on these assumptions, researchers can estimate profit margins of incumbent supermarkets following the standard method suggested in Villas-Boas (2007).

The second stage is the post-WMS period, when WMS emerges and optimally locates their stores across all markets. Because all players are assumed to have complete information, incumbent supermarkets are well informed about the payoff structure of WMS. They respond to its entry by price reductions with the hope of maintaining their market share and a fixed profit goal.[1] Meanwhile, WMS is assumed to be aware that incumbent chains' reaction is a well defined function of its entry decisions, so it will optimally make its entry decision by incorporating rival chains' reactions. The corresponding profit margin is specified as the marginal contribution of dollar sales to the profit function. Once WMS makes its entry decisions, all profits are realized and thereby one can estimate profit margins directly from parameter estimates of the profit function.

To address the issue of market dependence, this model adapts an econometric technique proposed by Conley (1999), analogizing time dependence through cross-sectional dependence, and proposes an asymptotically normally distributed and consistent Generalized Method of Moments (GMM) estimator.

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[1] This assumption allows Wal-Mart to be the only one to maximize its profit in the second stage. All incumbent supermarkets have to give up this goal and target a lower fixed profit under the competition pressure imposed by the entry of WMS. The implementations are true for some markets but may be far away from reality for other markets, because the response of incumbent supermarkets to WMS is mixed (Barnes et al., 1996; Artz and Stone, 2006). To solve this issue, the model allows for a fixed profit goal that could be zero or significantly high.

This model is applied empirically via simulation based on an Information Resources Infoscan (IRI) database of supermarket fluid milk sales in the Dallas/Fort Worth metropolitan area. The dataset includes 58 four-week-ending fluid milk observations covering March 1996 to July 2000. For each time period, the database reports the values of fluid milk sales and the quantity sold by five major supermarket chains in this area. The demographic profile of a market, each supermarket's gross market share and the number of WMS' were collected from Market Scope. The variable of average store size used for evaluating the effect of economies of scale was calculated based on store size data from Dun & Bradstreet's Million Dollar Database.

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

The remainder of this paper is structured as follows. Section 2 reviews the literature. Section 3 discusses the model and section 4 proposes a solution algorithm. Section 5 describes the empirical implementation. Section 6 explains the data and estimation approach. Section 7 presents the empirical results and possible extensions. Section 8 presents conclusions.

2 LITERATURE REVIEW

The literature on Wal-Mart's economic impact on existing business is growing. WMS's low price strategy is a frequently visited topic. Basker and Noel (2007) find that food prices at WMS are 10% lower than those at competing grocery stores. Hausman and Leibtag (2007) find a 30% premium at incumbent supermarkets over supercenters, mass merchandisers, and club stores.

At a more detailed level, Basker (2005b) uses data on 10 products at Wal-Mart discount stores and finds that the price effect of Wal-Mart's entry differs by product and city size. For some products, Wal-Mart's entry reduces average retail prices by an economically large and statistically significant 7-13%. Volpe and Lavoie (2006) reveal that WMSs decrease prices by 6-7% for national brands and 3-7% for private label products by focusing on the competitive price effects of six WMSs on national brand and private label supermarket prices in New England. Stone (1995), and 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.

Price is not the only competitor attribute affected by Wal-mart's entry. Singh et al. (2006) find that a WMS lures away large-basket buyers, leading to fewer store visits and a 17% decline in sales at northeastern supermarket chains. Basker (2005a) finds that Wal-Mart adds 100 jobs in the year of entry. Neumark et al. (2008) estimate the effects of Wal-Mart on county-level retail employment and earnings and find that a Wal-Mart store opening reduces county-level retail employment by about 2.7%.

Jia (2008) evaluates Wal-Mart's expansion from the late 1980s to the late 1990s, and reveals that Wal-Mart's expansion explains about 40 to 50% of the net decrease in the number of single-unit local retailers. Instead of analyzing a retailer's profit function by looking for equilibrium conditions of supply and demand, Jia (2008) develops a three-stage entry model assuming a linear profit function for spatially competing retailers. Without assuming any competition pattern among all players, the model has great flexibility to formulate players' behaviors.

Regarding the case of the Dallas/Fort Worth metropolitan area, Cotterill and Brundage (2001) argue that the considerable expansion of Wal-Mart in 1999 triggered a milk price war. Capps and Griffin (1998) conducted a study of the urban/rural fringe of the Dallas/Fort Worth metropolitan area and find Wal-Mart to decrease David's Supermarket sales by 21%. They predict that mass merchandisers like Wal-Mart will be responsible for a 14% sales reduction at existing grocery chains in this area.

3 MODEL

This section describes a two-stage dynamic game to analyze the impact of WMS. The first stage refers to the "pre-WMS" period when incumbent supermarkets compete in a market to maximize their profits, without anticipating the entry of WMS in the second stage. The Nash-Bertrand market equilibrium could be obtained in this stage by solving each supermarket's profit maximization problem.

In the second stage, WMS simultaneously chooses store locations to maximize its total profits over all markets. Incumbent supermarkets quickly obtain full knowledge 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.

The reaction function of incumbent supermarkets is a well-defined function of WMS's entry decisions. Meanwhile, WMS is fully informed about the reaction function of incumbent supermarkets and optimally make location choices by maximizing its profit over all markets collectively. Once the entry decisions are made by WMS, profits of all players are realized.[2]

In the first stage, the profit function of incumbent supermarkets i that operate in the market m is:

$$\Pi_{i,m}^{0} = \gamma_i^0 * \left(p_{i,m}^0 Q_{i,m}^0\right) + X_m^0 \beta_i + \alpha_{i,i} s_{i,m}^0 + \sum_{j \neq i} \alpha_{i,j} s_{j,m}^0 \tag{1}$$

$$+ \sigma_{ii} \sum_{n \neq m} \frac{ss_i}{Z_{m,n}} + \sqrt{1-\rho^2}\,\varepsilon_m^0 + \rho \eta_{i,m}^0, i, j = \{1,2,\ldots,\mathrm{N}_r\}$$

and that of staying outside the market is normalized to 0. N_r is the number of incumbent

[2] 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.

supermarkets, γ^0 refers to profit margins in the first stage, and $p_{i,m}^0 Q_{i,m}^0$ is the value of retail sale for retailer i in market m. In this stage, $p_{i,m}^0 Q_{i,m}^0$ is independent of WMS's future entry in the second stage. $X_m^0 \beta_i$ is the vector of parameterized market features such as population, urbanization ratio, percentage of white or hispanic, etc. X_m^0 is allowed to vary across both players and markets, and the coefficient β_i could vary across retailers.

Another set of explanatory variables in equation (3.1) includes gross market shares for both retailer i and its rival competitors. The profit of retailer i is presumed to benefit from a higher gross market share through its market power. $\alpha_{ii} s_{i,m}$ describes the contribution of retailer i's gross market share to its profit. The coefficient α_{ii} is assumed to be positive. $\sum_{i \neq j} \alpha_{i,j} s_{j.m}$ is the negative profit shock from retailer i's rivals. The unobserved profit shock is $\sqrt{1-\rho^2}\varepsilon_m^0 + \rho \eta_{i,m}^0$, which is known to the retailers and unknown to econometricians.

The economies of scale is captured by two variables. The first variable ss_i is the average store size of retailer i as a measurement of the demand shock. This implementation assumes bigger stores lure more consumers by providing a wider range of products and brand choices and thereby exhibit positive demand shocks to a retailer's profit. The second measurement, $Z_{m,n}$, designates the distance from market m to market n in miles, which is used to evaluate the cost splitting effect of operating a chain. By construction, the profit in market m increases by $\sigma_{ii} \dfrac{1}{Z_{m,n}}$ if there is a store in market n that is $Z_{m,n}$ miles away. The effect is assumed to decrease with the distance.

The profit maximization condition for retailer i is

$$Q_{i,m}^0 + \gamma_i^0 p_{i,m}^0 \frac{\partial Q_{i,m}^0}{\partial p_{i,m}^0} = 0. \qquad (2)$$

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

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

$$\Pi_{w,m} = D_m * [\theta_w (\frac{1}{N_r}\sum_{i=1}^{N_r}\frac{ss_w}{ss_i} sale_{i,m}) + X_m \beta_w + \sum_{i=1}^{N_r}\alpha_{w,i}s_{i,m} \tag{3}$$

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

The variable $D_m \in \{0,1\}$ refers to the entry strategy of WMS in market m, where $D_m = 1$ if WMS operates a store in market m and $D_m = 0$ otherwise. $D = \{D_1,...,D_M\}$ is a vector indicating the location choices for WMS's 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 $\frac{D_n}{Z_{m,n}}$. ss_w, the average store size of WMSs. $\frac{D_n}{Z_{m,n}}$ indicates that if Wal-Mart decides to operate a WMS in market n which is $Z_{m,n}$ miles away from market m, the profit of market m will be raised by $\sigma_{ww}\frac{ss_w * D_n}{Z_{m,n}}$. The summation of $\frac{ss_w * D_n}{Z_{m,n}}$ 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 $sale_{i,m}$ is the value of sales for retailer i in market m. Because the sale data for WMS is not always accessible to researchers, this paper assumes the decision rule of 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 WMS is not available. The weight of dollar sales is determined by the relative store size of a supercenter to that of incumbent supermarkets. The value of θ_w is the marginal contribution of the estimated sales to the profit of WMS, which is similar to profit margins but is taken with respect to estimated sales instead.

Similar to $X^0_m\beta_i$ in (3.1) for incumbent supermarkets, $X_m\beta_w$ is the impact of market features on the profit of WMS. The competition effect of other supermarkets on

WMS is captured by $\Sigma_{i=1}^{N_r}\alpha_{w,i}s_{i,m}$. $\alpha_{w,i}$ and is presumed to be non-positive. $\sqrt{1-\rho^2}\varepsilon_m+\rho\eta_{w,m}$ is unobserved market shocks occurring in the second stage.

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

$$\Pi_{i,m}=\gamma_i sale_{i,m}+X_m\beta_i+\alpha_{i,i}s_{i,m}+\sum_{j\neq 1}\alpha_{i,j}s_{j,m} \tag{4}$$

$$+\alpha_{i,w}*\frac{ss_w}{ss_i}D_m+\sigma_{ii}\sum_{n\neq m}\frac{ss_i}{Z_{m,n}}+\sqrt{1-\rho^2}\varepsilon_m+\rho\eta_{i,m}$$

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

4 SOLUTION ALGORITHM

This section proposes a solution algorithm to find the Nash equilibrium for the problem in the second stage. For simplicity, this section uses X_m to refer to

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

WMS's problem becomes

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

where M denotes the total number of markets.

Let $\mathbf{D}=\{0,1\}^M$ denote the choice set of WMS over M markets. Any element of the set $\mathbf{D}$ is an M-coordinate vector $D=\{D_1,...,D_M\}$. The choice variable D_m directly determines the profit of WMS in market m, that is, it earns profit $(X_m+\sigma_{ww}\sum_{m\neq n}\frac{ss_w\times D_n}{Z_{m,n}})$ if $D_m=1$, and zero if $D_m=0$. Hence, the decision to open a store 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. A naive way to solve this problem is to try all the 2^M 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 $2^{29}=536{,}870{,}912$.

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. The algorithm proceeds as follows:

Let $D^*=\arg\ \max_{D\in\mathrm{D}}\Pi(D)$ denote the profit maximizer. The optimality of D^* implies that the profit at D^* must be weakly higher than the profit at any one-market deviation[3]:

$$\Pi(D_1^*,...,D_m^*,...,D_M^*)\geq\Pi(D_1^*,...,D_m,...,D_M^*),\forall M, D_m^*\neq D_m. \tag{5}$$

[3] Similar to Jia (2008), this paper defines a vector D is bigger than vector D' if and only if every element of D is weakly bigger: $D\geq D'$ if and only if $D_m\geq D_m'\forall m$. D and D' are unordered if neither $D\geq D'$ nor $D\leq D'$, and $D=D'$ if $D\geq D'$ and $D\leq D'$

Let $\hat{D}$ equal $\{D_1^*,...,D_m,...,D_M^*\}$. The difference between $\Pi(D^*)$ and $\Pi(\hat{D})$ comes from two parts: the profit of market m, and the profit of all other markets through the economies of scale effect:

$$\Pi(D^*)-\Pi(\hat{D}) = D_m^*[X_m+\sigma_{ww}\sum_{m\neq n}\frac{ss_w D_m^*}{Z_{m,n}}] \tag{6}$$

$$-D_m[X_m+\sigma_{ww}\sum_{m\neq n}\frac{ss_w D_m}{Z_{m,n}}]$$

$$=(D_m^*-D_m)[X_m+\sigma_{ww}\sum_{m\neq n}\frac{ss_w D_n^*}{Z_{m,n}}]$$

$$+\sigma_{ww}\sum_{m\neq n}ss_w\frac{D_n^* D_m^*}{Z_{n,m}}-\sigma_{ww}\sum_{m\neq n}ss_w\frac{D_n^* D_m}{Z_{n,m}}$$

$$=(D_m^*-D_m)[X_m+2\sigma_{ww}\sum_{m\neq n}\frac{ss_w D_n^*}{Z_{m,n}}]$$

where $Z_{m,n}=Z_{n,m}$ by symmetry. Because $\Pi(D^*)-\Pi(\hat{D})\geq 0$ and $D_m^*\neq D_m$, the following statement must be true: $D_m^*=1$, $D_m=0$ if and only if $X_m+2\sigma_{ww}\sum_{m\neq n}\frac{ss_w D_n^*}{Z_{m,n}}\geq 0$; and $D_m^*=0$, $D_m=1$ if and only if $X_m+2\sigma_{ww}\sum_{m\neq n}\frac{ss_w D_n^*}{Z_{m,n}}<0$. Equation (5) then leads to:

$$D_m^*=1[X_m+2\sigma_{ww}\sum_{m\neq n}\frac{ss_w D_n^*}{Z_{m,n}}\geq 0],\forall m \tag{7}$$

Equation (7) is a set of necessary conditions for the optimal vector D^*. $[X_m+2\sigma_{ww}\sum_{m\neq n}\frac{ss_w D_n^*}{Z_{m,n}}]$ is market m's marginal contribution to total profit. Not all vectors that satisfy equation (7) maximize profit, but if D^* maximizes profit, it must satisfy the conditions.

Define $V_m(D) = 1[X_m + 2\sigma_{ww}\sum_{m \neq n} \frac{ss_w D_n}{Z_{m,n}} \geq 0]$. Because σ_{ww} is non-negative, $V(D) = \{V_1(D),...,V_M(D)\}$. $V(\cdot)$ is an increasing function that maps from **D** into itself: V:$\mathbf{D} \rightarrow \mathbf{D}$, that is, $V(D') \geq V(D")$ whenever $D' \geq D"$. The profit maximizer D^* is then interpreted as one of $V(\cdot)$'s fixed points.[4]

The problem of finding a lower bound and an upper bound for the choice set D^* is equivalent to find a greatest fixed point and a least fixed point for the set of fixed points of $V(D)$. The conditions for existence of supremum (the greatest fixed point) and infimum (the least fixed point) for a set of fixed points are given by Tarski's (1955) fixed point theorem.[5] The theorem illustrates that the set of fixed points of an increasing function that maps from a lattice into itself is a lattice and has a greatest point and a least point.[6]

The algorithm that delivers the greatest and the least fixed point of $V(D)$ starts with $D^0 = \sup(\mathrm{D}) = \{1,...,1\}$. The supremum exists because **D** is a complete lattice. Define a sequence $\{D^t\}: D^1 = V(D^0)$, and $D^{t+1} = V(D^t)$. By the construction of D^0 , one can obtain $D^0 \geq V(D^0) = D^1$. The increasing property of $V(\cdot)$ applies here and one obtains $V(D^0) \geq V(D^1)$, or $D^1 \geq D^2$. Iterating this process several times generates a decreasing sequence: $D^0 \geq D^1 \geq \cdots \geq D^t$. Given that D^0 has only M distinct elements and at least one element of the D vector is changed from 1 to 0 in each iteration, the process converges within M steps: $D^T = D^{T+1}$, with $T \leq M$. Let D^U denote the convergent vector instead of D^T . By construction, D^U is a fixed point of the function

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[4] The fixed point of a function is defined as if g is a continuous function $g(x) \in [a,b]$ for all $x \in [a,b]$, then there exists a $c \in [a,b]$ such that $g(c) = c$.

[5] Tarski (1955)'s fixed point theorem: suppose that $Y(X)$ is an increasing function from a nonempty complete lattice **X** into **X** : (a). the set of fixed points of $Y(X)$ is nonempty, $\sup_{\mathrm{X}}(\{X \in \mathrm{X}, X \leq Y(X)\})$ is the greatest fixed point, and $\inf_{\mathrm{X}}(\{X \in \mathrm{X}, Y(X) \leq X\})$ is the least fixed point; (b). the set of fixed points of $Y(X)$ in **X** is a nonempty complete lattice. A lattice in which each nonempty subset has a supermum and an infimum is complete, and a nonempty complete lattice has a greatest and a least element.

[6] The choice set **D** is a complete and a non-empty lattice. Any subset of **D** is also a complete and non-empty lattice.

$V(\cdot): D^U = V(D^U)$. To show that D^U is indeed the greatest element of the set of fixed points, let D′ denote an arbitrary element of the set of fixed points. Note that $D^0 \geq D^{'}$. Applying the function $V(\cdot)$ to the inequality T times, we have $D^U = V^T(D^0) \geq V^T(D^{'}) = D^{'}$.

Using the dual argument, one can show that the convergent vector D^L derived from $D^0 = \inf(\mathrm{D}) = \{0,...,0\}$ is the least element in the set of fixed points, as well as the lower bound of D^*.[7] Once the upper and lower bounds are determined, an exhaustive search among all choice vectors between the bounds can be conducted to find the optimal choice set D^*.

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

$$sale_{i,m}(D_m) = \frac{1}{\gamma_i}[\pi_i - (X_m\beta_i + \alpha_{i,i}s_{i,m} + \sum_{j \neq i} \alpha_{i,j}s_{j,m} + \alpha_{i,w} * \frac{ss_w}{ss_i} D_m + \sigma_{ii} \sum_{n \neq m} \frac{ss_i}{Z_{m,n}} + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{i,m})] \tag{8}$$

The profit of WMS then becomes

$$\Pi_{w,m} = D_m * [\theta_w(\frac{rs_w}{N_r} \sum_{i=1}^{N_r} sale_{i,m}(D_m)) + X_m\beta_w + \sum_{i=1}^{N_r} \alpha_{w,i}s_{i,m} + \sigma_{ww} \sum_{m \neq n} \frac{ss_w \times D_n}{Z_{m,n}} + \sqrt{1-\rho^2}\varepsilon_m + \rho\eta_{w,m}] \tag{9}$$

[7] One can obtain tighter upper and lowers bound by maximizing a profit function with the constraints if $D_m = 1$, then $X_m + \sigma_{ww} \sum_{m \neq n} \frac{ss_w D_n}{Z_{m,n}} > 0$ for lower bound and if $X_m + 2\sigma_{ww} \sum_{m \neq n} \frac{ss_w D_n}{Z_{m,n}} < 0$, then $D_m = 0$ for upper bound. For more details, See Jia (2008).

5 EMPIRICAL IMPLEMENTATION

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

$$\theta_0 = \{\theta_w, \beta_i, \beta_w, \alpha_{i,w}, \alpha_{w,i}, \sigma_{i,i}, \sigma_{ww}, \gamma_i, \rho, \pi_i\}_{(i=1,\ldots,N_r)} \in R^P .$$

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.[8]

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

$$\hat{\theta} = \arg\ \min \frac{1}{M} [\sum_{m=1}^{M} \hat{g}(X_m, \hat{\theta})]' \Omega_M [\sum_{m=1}^{M} \hat{g}(X_m, \hat{\theta})] \tag{10}$$

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

$$\sqrt{M}\,(\hat{\theta} - \theta_0) \to N(0, (1 + R^{-1}) * A_0^{-1} B_0 A_0^{-1}) \tag{11}$$

holds under the conditions that $\Omega_M \to \Omega_0$. 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 $G_0 = E[\Delta_{\theta^{'}} g(X_m, \theta_0)]$.

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[8] X_m here refers to all explanatory variables.

Λ_0 is defined as $\Lambda_0 = E[g(X_m,\theta_0)g(X_m,\theta_0)'] = Var[g(X_m,\theta_0)]$. 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 $A\,\mathrm{var}(\hat{\theta}) = (1+R^{-1})*(G_0^{'}\Lambda_0^{-1}G_0)^{-1}/M$.

The issue in 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.[9]

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 distance 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 in equation (11) 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:

$$\hat{\Lambda} = \frac{1}{M}\sum_{m}\sum_{s\in B_m}[\hat{g}(X_m,\theta)\hat{g}(X_s,\theta)'], \tag{12}$$

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

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[9] The distance reduces the value of $\frac{1}{Z_{m,n}}$. When $\frac{1}{Z_{m,n}}$ becomes small enough, the effect becomes zero.

$$\hat{\Lambda} = \frac{1}{M}\sum_m \sum_{s \in B_m}[\hat{g}(X_m, \tilde{\theta})\hat{g}(X_s, \tilde{\theta})'], \tag{13}$$

where $\tilde{\theta}$ is a preliminary estimate of θ_0 using either 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 $\{\hat{\varepsilon}_m\}$ and profit shocks for WMS $\{\eta_w, m\}$ and incumbent supermarkets $\{\eta_{i,m}\}_{i=1}^{N_r}$, where $m = 1,..., M$.[10]

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

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 $\hat{\Lambda}^{-1}$.

6 AN EMPIRICAL APPLICATION

An ideal application of this model is to analyze joint entry decisions of WMS including all markets that a WMS may enter. The definition of "market" is critical. For example, Jia (2008) defines a market as a county and extracts 2065 markets from total 3140 in the U.S. For the model discussed in this paper, two conditions are worth noticing for a valid definition of market. The first is that all markets included in the study must

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[10] This essay applies 150 simulation Halton draws to the empirical application instead of the usual machine-generated pseudo-random draws. As discussed in Train (2000), 100 Halton draws achieves greater accuracy in his mixed logit estimation than 1000 pseudo-random draws.

contain the same incumbent supermarkets because the model does not allow parameters to vary across markets.[11] Second, one 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 a market, one may need to consider a more detailed division.

Due to data availability, this paper only applies a simulated study to illustrate how the model works. Interested researchers could conduct a more practical application by following the procedure discussed in this paper.

6.1 Data

In the literature on panel data analysis, when observations are independent over time, the time series dimension of the panel data could 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 original data set in this study is an Information Resources Infoscan (IRI) fluid milk database provided by the Food Marketing and Policy Center at the University of Connecticut. The database includes 58 four-week-ending observations covering the periods from March 1996 to July 2000 in the Dallas/Fort Worth metropolitan area. The number of WMSs and demand shifters such as population, age, hispanic percentage are collected from Market Scope. The average store sizes of all players are calculated based on store sizes provided by Dun & Bradstreet's database.

In the Dallas/Fort Worth metropolitan market area, WMS has been growing since 1995, but did not seem to pose a real threat to incumbent supermarkets until March 1999, when the pace of openings accelerated. The considerable expansion of WMS in 1999 may have triggered the milk price war (Cotterill and Brundage, 2001). According to Kopenec (Associated Press, 6/16/99), Kroger, with a retail market share of 24%, followed by Albertson's and Tom Thumb grocers, with respectively 24.8% and 18.1% market shares, cut the price at their stores in this market area to $0.99/gallon.

These facts provide a good case study for this model. First, the expansion path of

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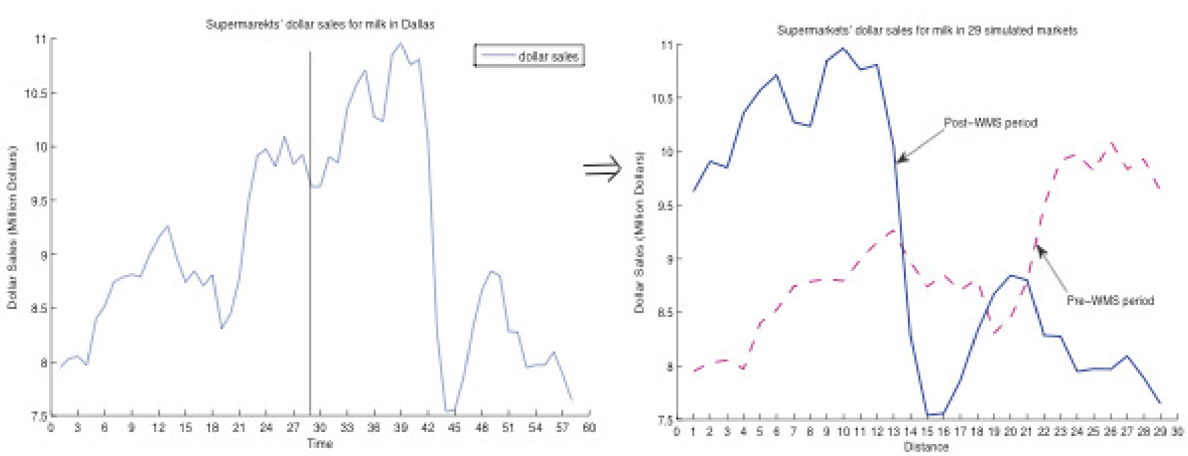
[11] Or one can use an integrated supermarkets instead.

WMS in this metropolitan area is easily divided into “pre-WMS” and “post-WMS” periods. Secondly, the Dallas/Fort Worth area is characterized by few, large incumbent supermarkets (Albertson’s, Kroger, Minyard, Tom Thumb, and Winn Dixie). The top two supermarket chains (Albertson’s and Kroger) in this market are also the contemporary top two food-retailers in the U.S., making the general conclusions transferable to other geographic markets.

Figure 1 shows how the simulation works. The lefthand graph shows the 58 time series observations in the Dallas/Fort worth area. Then, the first 29 observations of the series are defined as 29 markets uniformly located in a horizontal line for the “pre-WMS” period, as shown by the dashed line in the righthand graph. For example, the 1st observation corresponds to market 1, the 2nd observation to market 2, etc. The distance between any nearby markets is assumed to be 1 mile. The rest of the observations are defined as the evolution of these markets in the second stage, as shown by the solid line in the righthand graph. The 30th observation corresponds to market 1, and the 31st observation to market 2, etc.

For the location choice of WMSs, Market Scope only gives the total number of WMSs over all markets rather than exact locations and densities. To cover as many as possible location choices made by WMS, this application applies the bootstrapping technique to generate another 1,000 samples with a prior density assumption that WMS stores are more concentrated in markets 14–17 and 23–29.

Figure 1. Simulated Milk Markets



6.2 ESTIMATION

In the first stage, a log demand function is estimated to calculate retailer i's retailing margin according to equation (3.1):

$$\log Q_{i,m} = \delta_0^i + \delta_1^i \log p_{i,m} + \delta_2^i hhsize_m + \delta_3^i age_m + \delta_4^i hisp_m \qquad (14)$$
$$+ \delta_5^i \log(inc_m) + \delta_6^i avgprice_{j.m} + \delta_7^i \log(pop_m) + \varepsilon_{i,m}$$

for $m = 1,...,29$. $Q_{i,m}$ is the quantity sold in market m, and $p_{i,m}$ is the retail price. The set of variables $\{hhsize, age, hisp, inc, avgprice, pop\}$ 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 is used to calculate the retailing margins in the first stage.

At the second stage, the primary parameter $\tilde{\theta}$ in equation (10) is estimated through MSM with $(XX')^{-1}$ weight matrix $\hat{\Lambda}^{-1}$, which is calculated and plugged into the objective function in equation (10) to correct for spatial dependence. 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.[12]

The simulated data set used in this application contains 145 observations (29 markets ×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 $\sigma_{w,i}$, the effect of scale of economies on incumbent supermarkets $\sigma_{i,i}$, incumbent supermarkets' competitive advantage through their gross market share $\alpha_{i,i}$, rival supermarkets' competitive advantage through their gross market share $\alpha_{i,j}$, as well as their profit goal π_i, are restricted to be identical across

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

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 includes numbers of WMSs, dollar sales of retailer i with $i = 1,...,5$, their interaction terms and the above items, 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.

6.3 RESULTS

Table 1 reports the estimates of δ_1 in equation (15). Profit margins 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.[13]

[13] 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.

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 delta method.

The first line of Table 2 reports the estimates of profit margins γ_i in the second stage. 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%.

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.

The third line of Table 2 reports the percentage change in profit margins from the first stage to the second stage. All incumbent supermarkets experience significant decreases in retail margins after the expansion of WMS occurred 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%.[14] The second largest retailer, Albertson's, exhibits a 71.61% reduction after the entry of WMS. Tom Thumb shows the most modest response to the entry of WMS, reducing its profit margin by only 7.79%.

Table 3 reports estimates of the other 15 parameters in equation (10). 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 only accounts for 44.5% of the effect they impose on WMS.

The marginal benefit of an incumbent supermarket from its economies of scale is 0.1205, which is only 30% of the 0.3913 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 WMS is roughly only 1% of that on incumbent supermarkets.

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

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

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	$\sigma_{i,i}$	0.1205	(0.0006)
Supermarket i's competitive advantage over WMS	$\alpha_{w,i}$	-12.8075	(0.1845)
Supermarket i's self competitive advantage over supermarket j	$\alpha_{i,i}$	12.3852	(0.1183)
Supermarket j's competitive advantage over supermarket i	$\alpha_{i,j}$	-5.6981	(0.0915)
Impact of the entry of WMS on Albertson's profit margins	$\alpha_{1,w}$	-7.8115	(0.0400)
Impact of the entry of WMS on Kroger's profit margins	$\alpha_{2,w}$	-10.6197	(0.1202)
Impact of the entry of WMS on Minyard's profit margins	$\alpha_{3,w}$	-7.905	(0.0459)
Impact of the entry of WMS on Tom Thumb's profit margins	$\alpha_{4,w}$	-8.1487	(0.0434)
Impact of the entry of WMS on Winn Dixie profit margins	$\alpha_{5,w}$	-6.2369	(0.0333)
WMS's economies of scale	$\sigma_{w,w}$	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.

7 EMPIRICAL ISSUES AND POSSIBLE EXTENSIONS

One possible extension of this paper is to solve the issue of multiple equilibria. In the entry literature, researchers usually assume that all players have complete information and make simultaneous entry decisions. In an empirical application, this assumption can lead to the simulated value of WMS's location choice D less than 1. One solution of this issue is to look for features that are common among different equilibria, as discussed in Bresnahan and Reiss (1990, 1991) and Berry (1992). Another solution is to search for bounds of parameters instead of identifying the point estimates. These approaches may become computationally intensive for the model specified here because for most empirical applications, the dimension of choice sets is extremely large.

Another possible extension is to release the assumption of a positive effect of scale of economies. The assumption is critical to the solution algorithm proposed in this model, because it ensures that the function $V(D)$, defined by the necessary condition $V_m(D) = 1[X_m + 2\sigma_{ww} \sum_{m \neq n} \frac{ss_w D_n}{Z_{m,n}}]$, is increasing to apply Tarski's fixed point theorem. In reality, the parameter σ_{ww} does not have to be positive. For example, larger sized stores are more costly, and when two stores are too close with a fixed group of consumers, the effect of one stealing from the other business may be dominant and σ_{ww} thereby becomes negative.

The third possible extension is to incorporate vertical competition in the model when retailing data at the brand level is available, because the entry of WMS may also change the vertical competition pattern. A straightforward method to evaluate this possibility is to compare manufacturers' profit margins between the "pre-WMS" and "post-WMS" periods. In the first stage, one can apply the standard method discussed in Villas-Bois (2007) if the wholesale data is not accessible. The wholesale prices, as well as parameterized retailing cost and wholesaling cost can be recovered under different assumptions of vertical competition patterns between retailers and manufacturers.

For the second stage, one can apply the model discussed in this paper to estimate the average retailing margins over all brands. Then the profit margins of manufacturer j

with respect to retailer i can be calculated by $\dfrac{p^r_{i,j}(1-\hat{\gamma}_i)-\tau^r_i c^r_i-\tau^w_i c^w_j}{p^r_{i,j}(1-\hat{\gamma}_i)}$.[15] where c^r_i is the retailing cost of retailer i and c^w_j is the wholesaling cost of manufacturer j. $\hat{\tau}^r_i$ and $\hat{\tau}^w_i$ are estimates of cost parameters in the first stage, which is assumed to be constant over the evolution of a market. In the present model, estimates of profit margins in the second stage only present an average margin over all products sold by retailer i. To identify the specific profit margin $\gamma_{i,j}$ of retailer i on product j provides the fourth possible extension of the model developed in this paper.

8 CONCLUSIONS

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

The presence of economies of scale is found to generate substantial benefits for all retailers and exhibits a more important influence on the profitability of WMSs than on incumbent supermarkets. This information result can help firms explore the potential effects of merger policies or other regulations that affect Wal-Mart.

Another discovery of the empirical implementation is that the competition among incumbent supermarkets is found to be only 44.5% of the competition effect that they impose on WMS, which implies a possibility of collusion among incumbent

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[15] Using $\gamma_i = \dfrac{p^r_{i,j}-p^w_{i,j}-\tau^r_i c^r_i}{p^r_{i,j}} \Rightarrow p^w_{i,j} = (1-\gamma_i)-\tau^r_i c^r_i$ to estimate the manufacturer's margin has the same problem of consistency. The estimate $\hat{\gamma}_i$ appears in the dominator of a fraction so the consistency property of the estimate may not hold. The solution of this issue is left for further research.

supermarkets under the competitive pressure of WMS.

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