Store Dynamics, Differentiation and Determinants of Market Structure*

Florin Maican†
and
Matilda Orth‡

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Abstract

Substantial entry and exit and a trend toward larger but fewer stores constitute a major structural change in retail markets in the last few decades. To study the determinants of market structure in retail markets, this paper uses a dynamic structural oligopoly model of entry and exit that allows for store-level heterogeneity. Using a rich data set on all retail food stores in Sweden, we estimate entry cost of potential entrants and sell-off values for exit for small and large stores. We find empirical evidence of type competition. An additional large store in the market decreases the profits of large stores about three percentage points more than for small stores. For small stores, the average entry cost is about two times larger than the sell-off value of exit. Using structural estimates, we evaluate the impact of different policies on the cost structure for each store type and market structure dynamics. Small stores are negatively affected by more efficient incumbents, whereas large stores incur higher entry costs due to other factors such as higher rent or cost of buildings. The findings have a direct link to competition policy because the majority of OECD countries have entry regulations, and the consequences of regulation in retail food are frequently debated among policy makers in the EU.

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†Research Institute of Industrial Economics (IFN) and University of Gothenburg, Box 640, SE-405 30, Göteborg, Sweden, Phone +46-31-786 4866, Fax: +46-31-786 4154, E-mail: florin.maican@economics.gu.se

‡Research Institute of Industrial Economics (IFN), Box 55665, SE-102 15, Stockholm, Sweden, Phone +46-8-665 4531, Fax: +46-8-665 4599, E-mail: matilda.orth@ifn.se

1 Introduction

Firm turnover and the cost structure of an industry are key determinants of market structure and its evolution over time. Markets are characterized by substantial simultaneous entry and exit that affect the market structure. In addition, product differentiation is central in many markets. One example is retail food, where store type and location are key dimensions. The degree of differentiation influences both competition and the cost structure of an industry, which in turn determine market structure. We present a dynamic model of entry and exit with product differentiation, recovering both entry cost of potential entrants and sell-off values of exit.

A central feature of our model is that it generalizes two-period static models of differentiation into a dynamic context.[1] The model builds on Pakes et al. (2007) (POB) but allows for differentiation in store type. We apply the model to a panel data set covering detailed information of all retail food stores in Sweden during 2001-2008. A dynamic approach is central because the market has undergone a structural change towards larger but fewer stores (Figures 1-2). Store type differentiation is essential as large stores cover only 20 percent of the total number of stores but over 60 percent of aggregate sales and sales space (Table 1). The retail food market has a number of characteristics that are appropriate for an application of our theoretical model: First, stores operate well-defined store types, are highly independent of the firm and decide their own prices. Second, entry and exit of stores are main determinants of market structure.[2] Third, demand is closely tied to population. Fourth, the trend towards larger but fewer stores did not change during the last few decades.[3]

The present paper contributes with information on the dynamics of store type competition and asymmetries between store types. The evaluation of entry costs for different store types and understanding the factors affecting entry cost provide crucial information in markets where the average travel distance with the main purpose of buying food increases.[4] The retail food market is important not only because food products constitute a high share of private consumption, but also because en-

[1]Berry and Reiss (2007) survey static entry literature, and Berry and Tamer (2007) discuss identification in static entry games.

[2]Entry and exit are often claimed to play a greater role for economic performance in retail than in many other industries. Store turnover are, for example, found to contribute more severely to productivity growth in retail markets compared to manufacturing industries (Foster et al., 2006).

[3]The model requires construction of consistent transition probabilities only once based on what is observed in the data. In markets with various structural changes over time we might not obtain consistent transition probabilities if the period is not sufficiently long.

[4]In Sweden, average travel distance with the main purpose of buying food was about 9.83 kilometers during 1995-2002 (The Swedish Institute of Transport and Communication).

try is regulated. Regulations are in effect in most OECD countries, and Europe has more restrictive regulations than the U.S., and the consequences of regulation in retail food are frequently debated among policy makers in the EU (European Parliament, 2008; European Competition Network, 2011). From the perspective of competition policy, it is therefore central to obtain information on the sunk costs of entry and how these vary with different degrees of regulation. Because our model allows for counterfactuals using estimated structural parameters, it can be used to design policies to encourage entry of small stores that is beneficial to consumers and to investigate the trade-off between costs for large and small stores. From a welfare point of view, it is key to understand players' incentives and the subsequent market outcomes, and hence to secure that various consumer groups have access to a wide range of products and store types.[5]

The model connects to two areas of literature: The first comprises recent studies using dynamic structural models of entry and exit (Aguirregabiria and Mira, 2007; Bajari et al., 2007 [BBL]; Pakes et al., 2007; Pesendorfer and Schmidt-Dengler, 2008).[6] However estimating demand and cost, and then recovering the structural parameters is demanding from both a data and a computational perspective. This is certainly true for complex markets such as retailing.[7] To use an approach based on POB, which instead requires a good measure of profits, is then a valid alternative. The second strand of literature concerns two-period static entry models with differentiation. These models ignore the presence of sunk costs as they cannot be separately identified from fixed costs (Bresnahan and Reiss, 1987; Bresnahan and Reiss, 1990; Berry, 1992; Mazzeo, 2002; Toivanen and Waterson, 2005; Seim, 2006; Jia, 2008).[8]

We model the long-run equilibrium using a model that allows for store heterogeneity. The model relies on a reduced form (observed) profit function. We follow POB but relax the assumption of identical firms, and recognize differentiation in

[5]Our approach (as POB) does not allow for a complete welfare analysis. A common constraint for the use of fully dynamic models is data limitations. We do not have access to household and price data to estimate demand.

[6]See also Asplund and Nocke (2006). Ackerberg et al. (2007) survey recent econometric methods in Industrial Organization including dynamic games.

[7]Maican (2010) uses a dynamic framework to analyze store format repositioning in the Swedish retail food market. There is a growing literature that analyzes retail chain expansion (e.g., Holmes, 2011; Toivanen and Waterson, 2005). Most of this literature investigates industries where exit is extremely rare. Holmes (2011) analyzes the diffusion of Walmart in the U.S. Toivanen and Waterson (2011) study the expansion of McDonalds in the U.K.

[8]There are studies that investigate store location in retail markets (e.g., Seim, 2006; Jia, 2008; Ellickson et al., 2010; Nishida, 2010; Holmes, 2011; Orth, 2011). In future versions of the paper, we aim to account explicitly for location differentiation in our dynamic framework (Berry et al., 1995; Berry et al., 2004; Davis, 2006; Seim, 2006).

store type. Dunne et al. (2011) model identical firms using data on dentists and chiropractors. They estimate an average firm profit function, sunk and fixed costs, and then perform a counterfactual exercise of a change in regulation which shifts the entry cost. Many markets, like retail food, are characterized by heterogenous players, which calls for models with less restrictive assumptions. However, these assumptions need to be balanced against the computational burden and presence of multiple equilibria. In the proposed model, data pick up the equilibrium played. Separating large stores from small stores is important in our application because large stores stand for the majority of sales and sales space but only for a minor share of all stores. We are only aware of a few empirical applications of POB with heterogenous players. Elejalde (2011) investigates U.S. banks and finds that single-market banks have higher sunk costs of entry than multi-market banks. Fan and Xiao (2011) also find differences in cost structure across heterogenous firms using data on the telephone market in the U.S.

An advantage of our model is that it is based on the actions that actually take place in the market. This comes at the cost that we need information on profits. We cannot obtain accurate policy experiments if there are multiple equilibria in the data. Pakes et al. (2007) claim that the correct equilibrium will be picked for large enough samples. To address this issue, we take advantage of our data, which have the advantage of containing all stores active in the Swedish retail food market for a long period of time. The structural parameters of the distribution of entry costs and sell-off values are estimated by matching the observed entry and exit rates in the data to the ones predicted by the model.[9]

Our empirical results are based on differentiation in type. We find empirical evidence of type competition and significant differences in the cost structure for small and large types. The estimates indicate that entry of an additional large store decreases the profits of small stores by about 6 percent and profits of large stores by about 9 percent. These findings are in line with the results from the static entry literature (Mazzeo, 2002). The average entry cost is about two times larger than the sell-off value for small stores. This result is reasonable due to the drastic fall in small stores and that most small entrants belong to other firms than the national ones. Asymmetries between store types are present. More efficient incumbents increase costs for small stores whereas higher cost of buildings (rent) increase the costs for large stores. Entry cost increases less than the sell-off value for small stores when the number of potential entrants increases.

[9]Another advantage is that our model can allow for correlated draws for each store type (firm), apart from the standard assumption that entry costs have a known distribution.

The next section presents the model, followed by the data and market information. Section 4 discusses the empirical implementation of the model, Section 5 presents the empirical results, and Section 6 reports the results of several counterfactual exercises that highlight the importance of factors in generating turnover and the level of long-run profitability. Section 7 conclude the paper.

2 A dynamic model of entry and exit

This paper uses a dynamic model to learn about the distribution of retail stores' entry and exit costs. The framework is based on Pakes et al. (2007) (POB) and accounts for differentiation in type/location, which is common in retail markets. Importantly, we exploit the fact that store concepts in retail food are well-defined and differ from POB in that store types are known.[10]

In the beginning of each period, a set of incumbents $\mathbf{J} = (J_z, J_{-z})$ and potential entrants $\boldsymbol{\mathcal{E}} = (\mathcal{E}_z, \mathcal{E}_{-z})$ simultaneously decide their actions. Incumbents choose whether to continue to operate with type (or in location) $z \in \mathcal{Z}$ or exit.[11] Incumbents of type $z \in \mathcal{Z}$ receive a draw of the sell-off value ϕ_z from the distribution $F^{\phi_z}(\cdot|\boldsymbol{\theta})$ upon exit, where $\boldsymbol{\theta}$ is a parameter to be estimated. We follow the common assumption that exit draws are i.i.d. across markets and time. Stores only observe their own draws of the sell-off value but not their rivals' draws, which induces asymmetric information across stores. The distribution is, however, known to all players. The draw of the exit fee depends on the store type (location) of the store, i.e., stores of different types receive sell-off values from different distributions. This stands in contrast to POB, where all incumbents are ex-ante identical and receive draws of their sell-off values from the same distribution.

Potential entrants decide whether to enter their store type $z \in \mathcal{Z}$ or stay out. Entrants' decisions are made one period ahead of the period in which they start to operate. The entry cost for potential entrants of store type z, κ_z, is a draw from the

[10] In the extended version of POB, which considers product differentiation, cost draws are taken from the same distribution for the different store types. The possibility to allow for correlation in cost draws across store types might be particularly important to control for ownership.

[11] In Sweden, individual stores decide over their own prices and a majority of stores operate as independent or franchise units. The degree to which firms are part of individual stores' strategic decisions varies somewhat among firms. Coop is the only firm that operates as a cooperation at the local or national level. The simplest version of the model only incorporates differentiation in store type. The model can however be generalized to account for location and firm but the computational burden will increase due to the large state space. Note however that the distribution of size and sales in Sweden are similar for stores associated to different firms.

distribution $F^{\kappa_z}(\cdot|\boldsymbol{\theta})$. Sunk costs are private information known prior to players' decisions and are i.i.d. distributed from a known distribution (Bajari et al., 2007; Pakes et al., 2007). We thus have two different pools of potential entrants (one for each type), that receive sunk cost draws from different distributions, upon deciding whether to enter or not. The entry costs might be higher the larger the store type. In POB, all potential entrants receive draws from the same distribution. The entry assumption, that entrants decide to enter a period ahead of the period in which they start to operate, allows us to obtain continuation and entry values that are independent of entry costs.

A store is described by a vector of state variables $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$ that consists of the number of stores of each type active in a local market, (n_z, n_{-z}) and exogenous profit shifters specific to each type, $\mathbf{y}$. The index $-z$ includes other types except z. Furthermore, we assume independent local markets, i.e., a separate game is played in each local market. For notational simplicity, the presentation omits from the market index m.[12] The number of stores of type z, n_z, evolves endogenously over time according to $n'_z = n_z + e_z - x_z$, where e_z and x_z are the number of entrants and exiters. The exogenous profit shifters that cover both demand and cost are public information to firms and evolve exogenously according to a first-order Markov process $\mathbb{P}(\mathbf{y}'|\mathbf{y})$.

All stores of type z are identical up to the draw of the sell-off value and entry fee. Profits of firms of the same type are therefore identical. We do not allow firms to invest or change owner or format. The fact that store concepts are rather uniform in the retail food market justifies this assumption. The model requires having observed profits in contrast to the literature on static entry and dynamic games that estimates the underlying primitives of demand and cost. Since it is difficult to collect data on prices and because store types are well-defined, we believe this approach is appropriate for our application to the Swedish retail food market.

□ **Incumbents.** The value function of an incumbent store of type z is given by the Bellman equation

$$\begin{aligned} V_z(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}) = \quad & max\{\pi_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) + \beta\phi_z, \pi_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) + \\ & \beta VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})\}, \end{aligned} \tag{1}$$

[12]Since stores decide over their own prices in Sweden and a majority of stores operate as independent or franchise units, multi-market contact is not as crucial as in many other countries. To relax the independence assumption across markets would severely increase the complexity and computational burden of the model. There are only a few attempts that recognize the issue of the chain effect across local markets, and they all use a small number of players (Jia, 2008; Nishida, 2010; Holmes, 2011).

where $\pi_z(\cdot)$ is the profit function; $VC_z(\cdot)$ is the continuation value; ϕ_z is the sell-off value; and $0 < \beta < 1$ is the discount factor. Incumbents know their scrap value ϕ_z but not the number of entrants and exits, prior to making their decision. The continuation value, $VC_z(\cdot)$, is obtained by taking the expectation over the number of entrants, exits, and possible values of the profit shifters

$$\begin{aligned} VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) = \ & \textstyle\sum_{e_z, e_{-z}, x_z, x_{-z}, \mathbf{y}} \int_{\phi'_z} V_z(n_z + e_z - x_z, n_{-z} + e_{-z} - x_{-z}, \\ & \mathbf{y}, \phi'_z; \boldsymbol{\theta}) p^c_z(e_z, e_{-z}, x_z, x_{-z} | n_z, n_{-z}, \mathbf{y}, \lambda^c_z = 1) \\ & p(\mathbf{y}'|\mathbf{y}) p(d\phi'_z), \end{aligned} \tag{2}$$

where $p^c_z(\cdot)$ is a z - incumbent's perception of rivals' type decisions $(e_z, e_{-z}, x_z, x_{-z})$ conditional on itself continuing, i.e., that $\lambda^c_z = 1$. The optimal policy for an incumbent is to exit if the draw of the sell-off value is larger than the value of continuing, which gives the probability to exit $Pr(\phi_z > VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})) = 1 - F^{\phi_z}(VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}))$.

□ **Entrants.** Potential entrants maximize the expected discounted future profits and enter if they can cover sunk costs. They start to operate in the next period. The value of entry is

$$\begin{aligned} VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) = \ & \textstyle\sum_{e_z, e_{-z}, x_z, x_{-z}, \mathbf{y}} \int_{\kappa'_z} V_z(n_z + e_z - x_z, n_{-z} + e_{-z} - x_{-z}, \\ & \mathbf{y}, \phi'_z; \boldsymbol{\theta}) p^e_z(e_z, e_{-z}, x_z, x_{-z} | n_z, n_{-z}, \mathbf{y}, \lambda^e_z = 1) \\ & p(\mathbf{y}'|\mathbf{y}) p(d\kappa'_z), \end{aligned} \tag{3}$$

where $p^e_z(\cdot)$ is a potential entrant's perceptions of the number of entrants and exits of each type conditional on entering. Entry occurs if the draw from the distribution of sunk costs is smaller than the value of entry, which results in the probability of entry being $Pr(\kappa_z < VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})) = F^{\kappa_z}(VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}))$. Potential entrants choose to operate a store of type z if the expected profits are higher than for all other types and the outside option. Hence, we have first the condition that the entry value needs to be larger than the draw of the entry cost. Then we have that the type (location) choice needs to give the highest expected discounted future profits among all type alternatives:

$$VE_z(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}) \geq \kappa_z \tag{4}$$

$$\beta VE_z(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}) \geq \beta VE_{-z}(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}). \tag{5}$$

■ **Equilibrium.** Incumbents and potential entrants make simultaneous moves and they both form perceptions of entry and exit among rivals. In equilibrium, these perceptions need to be consistent with actual behavior. The incumbents' perception of rival incumbents' behavior needs to be the same for all rivals of the same type. That is, all incumbents of a given type have the same probability of exit and this probability is indicated by the probability that the draw of the exit fee is larger than the value of continuing. Similarly, all potential entrants have the same probability to enter with a given type, i.e., they have the same probability that the draw of the entry cost is smaller than the value of entry. So again perceptions are the same for all rivals of the same store type.

For incumbents we need to construct the perceptions of p_z^c in equation (2). Conditional on that a z-incumbent continues, we have to compute the perceived probabilities of facing a particular number of entrants and exits of each type $p_z^c(e_z, e_{-z}, x_z, x_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^c = 1)$. That is, the probability that the exit draw is larger than the type-location continuation value, $\phi_z > VC_z(n_z, n_{-z}, \mathbf{y}, \phi_z; \boldsymbol{\theta})$ is

$$\begin{aligned} p_z^c(e_z, e_{-z}, x_z, x_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^c = 1) = \; & p_z^c(e_z, e_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^e = 1) \\ & g_z^c(x_z, n_z - 1|n_z, n_{-z}, \mathbf{y}) \\ & g_{-z}^c(x_{-z}, n_{-z}|n_z, n_{-z}, \mathbf{y}). \end{aligned} \tag{6}$$

The perceptions of entry conditional on that they enter $p_z^c(\cdot)$ and the perceptions of exit of the same type $g_z^c(\cdot)$ and of the rival type $g_{-z}^c(\cdot)$ all need to be consistent with equilibrium behavior. The assumption of identical type competitors implies that incumbents' perceptions of competitors' exit from each type is given by the multinomial logit probabilities in case of more than two choices, and by the binomial distribution in case of two choices.

Potential entrants of each type are identical up to the draw of the sunk cost, so in equilibrium all potential entrants of each type need to have the same probability to enter. The perceptions are given by

$$\begin{aligned} p_z^e(e_z, e_{-z}, x_z, x_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^e = 1) = \; & p_z^e(e_z, e_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^e = 1) \\ & g_z^e(x_z, n_z|n_z, n_{-z}, \mathbf{y}) \\ & g_{-z}^e(x_{-z}, n_{-z}|n_z, n_{-z}, \mathbf{y}), \end{aligned} \tag{7}$$

where $p_z^e(\cdot)$ are the perceptions of the entry distribution conditional on that they enter, while $g_z^e(\cdot)$ and $g_{-z}^e(\cdot)$ are perceptions of exit of the same and rival types.

The solution concept is a Markov Perfect Equilibrium. Yet there might exist more than one equilibrium. As in POB, it is guaranteed that in the recurrent class there is not more than one profile of equilibrium policies that are consistent with a given data-generating process. The data will thus select the equilibrium to be played. As POB argue, the correct equilibrium will be picked if samples are large enough. For this purpose, the present paper takes advantage of the detailed data we have access to, covering the total population of stores in Sweden for a long period of time.

■ **Transition probabilities: Incumbents.** An incumbent that continues will get the continuation value

$$VC_z(\mathbf{s};\theta) = E^c_{\mathbf{s}'}[\pi_z(\mathbf{s}';\boldsymbol{\theta}) + \beta E_{\phi'_z}(\max\{VC_z(\mathbf{s}';\boldsymbol{\theta}), \phi'_z\}\,|\mathbf{s}')], \tag{8}$$

where $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$ and $\mathbf{s}' = (n'_z, n'_{-z}, \mathbf{y}')$. An incumbent will exit if the draw of the sell-off value is larger than the continuation value in a given state $\mathbf{s}$, i.e., $p^x_z(\mathbf{s}) = Pr(\phi'_z > VC_z(\mathbf{s}';\boldsymbol{\theta}))$. Thus,

$$E_{\phi'_z}(\max\{VC_z(\mathbf{s}';\boldsymbol{\theta}), \phi'_z\}\,|\mathbf{s}') = (1-p^x_z)VC_z(\mathbf{s}';\boldsymbol{\theta}) + p^x_z E[\phi'_z|\phi'_z > VC_z(\mathbf{s}';\boldsymbol{\theta})]. \tag{9}$$

If we assume that ϕ_z has an exponential distribution, we get $E[\phi'_z|\phi'_z > VC_z(\mathbf{s}';\boldsymbol{\theta})] = VC_z(\mathbf{s}') + \sigma_z$, which we substitute into (9). Using (8) we then get

$$VC_z(\mathbf{s};\boldsymbol{\theta}) = E^c_{\mathbf{s}'}[\pi_z(\mathbf{s}';\boldsymbol{\theta}) + \beta E_{\phi'_z}(\max\{(1-p^x_z)VC_z(\mathbf{s}';\boldsymbol{\theta}) + p^x_z(VC_z(\mathbf{s}';\boldsymbol{\theta}) + \sigma_z)\})], \tag{10}$$

where σ_z is a parameter in the exponential distribution representing the inverse of the mean. We now define the continuation values, profits, and exit probabilities as vectors, i.e., $\boldsymbol{VC}_z(\cdot)$, $\boldsymbol{\pi}_z$, and $\boldsymbol{p}^x_z$. Furthermore, let the perceptions be a matrix of transition probabilities $\boldsymbol{W}^c_z$ that indicates the transition from state $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$ to state $\mathbf{s}' \neq \mathbf{s}$ for type z

$$\boldsymbol{VC}_z(\cdot) = \boldsymbol{W}^c_z[\boldsymbol{\pi}_z + \beta\boldsymbol{VC}_z(\cdot) + \beta\sigma_z\boldsymbol{p}^x_z]. \tag{11}$$

There is no dependence over time in the transition probabilities.[13]

To compute the continuation value we need to calculate the expected discounted future profits that the store would gain in alternative future states. We then take weighted averages for those stores that actually continued from state $\mathbf{s}$. The idea is to use average discounted profits actually earned by stores that continue from

[13]The presence of serially correlated unobservables is discussed in detail in the empirical implementation in Section 4.

state $\mathbf{s}$, i.e., to plug consistent estimates of $\boldsymbol{W}_z^c$ and $\boldsymbol{p}_z^x$ into (11) in order to get consistent estimates of $\boldsymbol{VC}_z(\cdot)$.

We average over the states in the recurrent class. Let R be the set of periods in state $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$:

$$R(\mathbf{s}) = \{r : \mathbf{s}_r = \mathbf{s}\},$$

where $\mathbf{s}_r = (n_{r,z}, n_{r,-z}, \mathbf{y}_r)$. Using the Markov property and summing over the independent draws of the probability of exit, we obtain consistent estimates of exit probabilities:

$$\tilde{p}_z^x(\mathbf{s}) = \frac{1}{\#R(\mathbf{s})} \sum_{r \in R(\mathbf{s})} \frac{x_{r,z}}{n_z}.$$

Let $W_{\mathbf{s},\mathbf{s}'}^c$ be the probability that an incumbent transits to $\mathbf{s}' = (n'_z, n'_{-z}, \mathbf{y}')$ conditional on continuing in $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$. Consistent estimates for incumbents' transition probability from state $\mathbf{s}$ to $\mathbf{s}'$ are given by

$$\tilde{W}_{\mathbf{s},\mathbf{s}'}^c = \frac{\sum_{r \in R(\mathbf{s})} (n_z - x_{r,z}) \mathbf{1}_{\mathbf{s}_{r+1} = \mathbf{s}'}}{\sum_{r \in R(\mathbf{s})} (n_z - x_{r,z})}. \tag{12}$$

Both $\tilde{p}_z^x(\mathbf{s})$ and $\tilde{W}_{\mathbf{s},\mathbf{s}'}^c$ will converge in probability to $p_z^x(\mathbf{s})$ and $W_{\mathbf{s},\mathbf{s}'}^c$ as $R(\mathbf{s}) \to \infty$. The transitions are weighted by the number of incumbents that continue in order to capture that incumbents do their calculations conditional on continuing. Now we use (11) to get estimates of $\boldsymbol{VC}_z(\cdot)$ as a function of $\boldsymbol{\pi}_z$, $\tilde{\boldsymbol{p}}_z^x$ and $\tilde{\boldsymbol{W}}_z^c$:

$$\widehat{\boldsymbol{VC}}_z(\cdot) = [I - \beta \tilde{\boldsymbol{W}}_z^c]^{-1} \tilde{\boldsymbol{W}}_z^c [\boldsymbol{\pi}_z + \beta \sigma_z \tilde{\boldsymbol{p}}_z^x], \tag{13}$$

where I is the identity matrix. Calculation of the continuation values includes inversion of the transition matrix. $\widehat{\boldsymbol{VC}}_z(\cdot)$ is the mean of discounted values of the actual returns by players, creating a direct link to the data. Since $\boldsymbol{W}_z^c$ and $\boldsymbol{p}_z^x$ are independent of the parameters (for a known β), they only need to be constructed once. The computational burden decreases because the transitions are only constructed in the beginning of the estimation routine. The burden increases, on the other hand, in the number of states, mainly due to the inversion of the transition matrix.[14]

■ **Transition probabilities: Entrants.** We follow the same approach for entrants as for incumbents and define $\boldsymbol{W}_z^e$ as the transition matrix that gives the

[14] The number of states depends directly on the number of types/locations and on the way in which we discretize the exogenous demand and cost shifters.

probability that an entrant starts operating at $\mathbf{s}'$ conditional on continuing in $\mathbf{s}$:

$$\tilde{W}^{e}_{\mathbf{s},\mathbf{s}'} = \frac{1}{\#R(\mathbf{s})} \frac{\sum_{r\in R(\mathbf{s})} (e_{r,z}) \mathbf{1}_{\mathbf{s}_{r+1}=\mathbf{s}'}}{\sum_{r\in R(\mathbf{s})} (e_{r,z})}. \tag{14}$$

The expected value of entry is then

$$\begin{aligned}\widehat{\boldsymbol{VE}}_z(\cdot) = \; & \left[\tilde{\boldsymbol{W}}^{e}_{z} + \beta\tilde{\boldsymbol{W}}^{e}_{z}[I - \beta\tilde{\boldsymbol{W}}^{c}_{z}]^{-1}\tilde{\boldsymbol{W}}^{c}_{z}\right]\boldsymbol{\pi}_z \\ & + \left[\beta\tilde{\boldsymbol{W}}^{e}_{z}\beta\tilde{\boldsymbol{W}}^{c}_{z}[I - \beta\tilde{\boldsymbol{W}}^{c}_{z}]^{-1}\tilde{\mathbf{p}}^{x}_{z} + \beta\tilde{\boldsymbol{W}}^{e}_{z}\tilde{\mathbf{p}}^{x}_{z}\right]\sigma_z.\end{aligned} \tag{15}$$

■ **Unobservables.** The model requires the use of observed profits. Although using a rich profit function specification, there are likely persistent differences in profits across markets due to unobserved factors. Correlated unobserved variables such as persistent demand shocks would then bias the estimates. Theory predicts an expected negative effect of the number of incumbents on profit. The presence of the serially correlated unobservables implies a positive bias in the estimated parameters. Therefore, a stronger competitive impact is anticipated in the presence of correlated unobservables.

It is possible to include a market fixed effect to control for unobserved profit differences across markets. Adding a market effect in the profit function implies that we need to model an additional state variable in stores' dynamic problem (Ackerberg et al., 2007). Our local market definition suggests the use of as many as 290 fixed effects. To reduce the dimensionality of the transition matrices in this context, geographic markets can be classified into smaller groups and one can use the fact that the market fixed effect does not change over time (Dunne et al., 2011). Although presence of serially correlated unobservables cannot be ruled out without fixed effects, the results in the current version of the paper provide conservative estimates.

3 Data and characteristics of the Swedish retail food market

The retail food markets in the OECD countries are fairly similar, consisting of firms operating uniformly designed store types. In Sweden, the food market consists of stores that to a large extent operate as independent or franchise units. Individual stores decide over prices and inputs. Firms work mainly as wholesale providers and the degree of centralization varies somewhat across firms. In 2002, over 90% of all stores were connected to one of four firms: ICA(44%), Coop(22%), Axfood(23%), and Bergendahls(3%). Various independent owners make up the remaining 8% market share. International firms with hard discount formats entered the Swedish market in 2002 (Netto) and 2003 (Lidl). ICA consists mainly of independently owned stores with centralized decision making. Coop, on the other hand, consists of centralized cooperatives with decisions made at the national or local level. Axfood and Bergendahls each have a mix of franchises and centrally owned stores, the latter located mainly in the south and southwest of Sweden.[15]

■ **Entry regulation.** A majority of OECD countries have entry regulations that give power to local authorities. However, the regulations differ substantially across countries (Hoj et al., 1995; Boylaud and Nicoletti, 2001; Griffith and Harmgart, 2005; Pilat, 2005). While some countries strictly regulate large entrants, more flexible zoning laws exist for instance, in the U.S. (Pilat, 1997). The Swedish Plan and Building Act (PBA) gives power to the 290 municipalities to decide over applications for new entrants. All stores are under the regulation in Sweden, which stands in contrast to for example U.K. that explicitly focus on large stores. Each store needs to send a formal application to the local government. The local governments approve applications after evaluating the potential impact on market structure, prices, traffic and broader environmental issue etc., caused by the new store. Inter-municipality questions of entry are handled by the 21 county administrative boards. The PBA is claimed to be one of the major barriers to entry, resulting in diverse outcomes, e.g., in price levels, across municipalities (Swedish Competition Authority, 2001:4). Several reports stress the need to better analyze how regulation affects market outcomes (Pilat, 1997; Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2). Large entrants are often newly built stores in external locations, making regulation highly important.[16] Appendix A describes the PBA in greater detail.

We use several measures to capture the degree of local market entry regulation. First, we follow previous literature and use political preferences of the share of non-socialist seats in the local government (Bertrand and Kramarz, 2002; Schivardi and Viviano, 2011). The anticipation for Sweden is that non-socialist local govern-

[15]In 1997, Axel Johnson and the D-group merged, initiating more centralized decision making and more uniformly designed store concepts.

[16]Possibly, firms can adopt similar strategies as their competitors and buy already established stores. As a result, more productive stores can enter without PBA involvement and, consequently, the regulation will not work as an entry barrier that potentially affects productivity. Of course, we cannot fully rule out the opportunity that firms buy already established stores.

ments are more liberal towards new entry.[17] Municipal elections imply two shifts in the number of seats during the study period. The number of markets with a non-socialist local government increases from 57 in 2001 to 102 in 2008. Second, we use the total number of new applications being approved, and their share of the accumulated number of approvals for each municipality and year.

■ **Data.** The store data is collected by Delfi Marknadsparter AB (DELFI) and defines a unit of observation as a store based on its geographical location, i.e., its physical address. The data set includes all retail food stores in the Swedish market during 2001-2008 (1993-2008) and contains the geographic location (geo-coordinates) of each store, store type, chain affiliation, revenue class, sales space (in square meters), wholesaler and the location (geo-coordinates) of the wholesaler. The store type classification (12 different) depends on size, location, product assortment, etc. Advantages of the data are that it is collected yearly and include the total population of stores. We drop gas station stores since that these are located at special places and offer a limited product assortment of groceries and a different product bundle than ordinary stores.[18]

We also merge demographic information (population, population density, average income, and political preferences) from Statistics Sweden (SCB) to DELFI. We consider information on the demographic distribution of population (e.g., share of children and pensioners), and the distribution of income across age groups. We also use average wages for municipality workers in the municipality.[19] Finally, we use data provided by Värderingsdata AB on average and median price per square meter for houses sold for each municipality and year. In future versions of this paper, we will also use accounting data on store profits from the Swedish Companies Registration Office (Bolagsverket). The data contain accounting information of all retail food stores in Sweden and is gathered and validated by PAR.

■ **Entry and exit.** As we have annual data on all Swedish retail stores based on address, we observe the physical entry and exit of stores. We define an entrant e_{mt} in market m in year t as a store that operates in year t but not in $t-1$. We define a store that exits, x_{mt}, from market m in year t as a store that operates in year $t-1$ but not in t. The total number of stores n_{mt} is given by $n_{mt} = i_{mt} + e_{mt} - x_{mt}$, where i_{mt} is the number of incumbent stores.

[17] The Social Democratic Party collaborates with the Left Party and the Green Party. The non-socialist group consists of the Moderate Party, most often together with the Liberal Party, Christian Democrats, and the Center Party.

[18] There are about 1,300 gas stations in the data every year; 1,317 (2001) and 1,298 (2008).

[19] Statistics Sweden collects information on wages for employees in the retail sector using surveys. The sample is not large enough to provide data at the municipality level. We therefore use wages for municipality workers as a proxy for retail sector wages.

We only consider physical entry and exit since this is what matters for estimation of sunk cost and fixed cost. This implies that we do not include stores that switch owners but continue to operate at the same address.[20]

Table 1 shows aggregate statistics for the period 2001-2008. The total number of stores decreases by 16 percent to 5,240 in the end of the period. While total sales increases by over 24 percent, the total number of square meters increases by only about 10 percent. The share of large stores increases by 3.5 percentage points to almost 22 percent in 2008. Large stores constitute for the majority of sales and sales space. Their sales increases by 3.8 percentage points to 61.8 percent in 2008, whereas their sales space increases by 2.7 percentage points to 60.5 percent. Thus, large stores had higher growth in sales than in sales space and number of stores, indicating efficiency improvements. The total number of entrants is rather constant over time with the number of exiters being slightly less than double the number of entrants.

The majority of entrants and exiters are small stores (Table 2). Among small entrants, many are owned by Others. For example, as many as 78 percent of the small entrants were owned by Others in 2002. In comparison, the share of large entrants that are not owned by national chains is substantially smaller. For exiters, about half of the small ones do not belong to a national chain, whereas a much lower share is found for large. Note that "other" owners exit a higher share of large stores than they enter. Table 3 shows that the distribution of sales space and sales are surprisingly similar across stores that belong to different firms. The median store size is 350-450 square meters for stores that the belong to the three major firms. Stores owned by Others are substantially smaller and have lower sales.

Figures 1 and 2 show how the number of stores evolves for different players across time. The number of small stores decreases by about 20 percent to 3,215 in 2008, but the number of large stores is fairly constant. There is a fall in the total number of stores for the three main players: 28 percent for ICA, 26 percent for COOP, and 11 percent for Axfood. The reverse trend is found for Bergendahls and hard discounters. Large stores increase for ICA and Bergendahls and are fairly constant for COOP, while they decrease for Axfood and Others. Mainly national chains operate large stores, while almost all stores owned by Others are small. Small stores decline substantially for ICA, COOP, and Others, whereas the changes are smaller in magnitude for small stores owned by Axfood.

Figure 3 shows that the total number of entrants increases until 2005 and then declines, while the number of stores that exit peaks in 2004. Figure 4 shows that

[20] See Maican (2010) for an analysis of stores switching format.

the substantial outflow of stores are mainly owned by ICA, Axfood, Coop, and Others, i.e., well established players in the market. Hard discounters and small stores owned by Others dominate entry, together with Axfood. Note however that these observations concern only number of stores and not capacity (size/type of store).

Table 4 presents entry and exit rates across markets and owners for the period 2002-2007. On average, the exit rate is two to three times higher than the entry rate, but the standard deviations are about the same. The mean exit rate varies between 0.03 and 0.07 with a standard deviation of 0.05-0.08. The mean entry rate ranges between 0.01 and 0.04 and the standard deviation is somewhat lower than for exit. Since entry and exit do not occur in all markets, we observe a variation in the upper percentiles. For example, the 75th percentile entry rate varies substantially over time (0-0.06).

Figures 5-6 show that the average entry and exit rates share common trends for national chains, whereas the entry rate is remarkably high for hard discounters and the mean exit rate is high for Others.

Exit takes place in 9-40 percent of the markets in a given year, while the corresponding number for entrants is 15-30 percent. The overall correlation between entry and exit rates is 0.04 whereas the correlation between number of entrants and exits is 0.43. If we exclude the three metropolitan areas (Stockholm, Gothenburg, and Malmö), the correlation is weaker, 0.17. There is, as we expected, a positive correlation between entry and exit, which supports our approach of using a dynamic model.

■ **Local markets.** Food products fulfill daily needs and are often of relatively short durability. Thus stores are generally located close to consumers. The travel distance when buying food is relatively short (except if prices are sufficiently low), and nearness to home and work are therefore key aspects for consumers when choosing where to shop, though distance likely increases with store size.[21] The size of the local market for each store depends on its type. Large stores attract consumers from a wider area than do small stores, but the size of the local market also depends on the distance between stores. We assume that retail markets are isolated geographic units, with stores in one market competitively interacting only with other stores in the same local market. A complete definition of local markets requires information about the exact distance between stores. Without this information we must rely on already existing measures. The 21 counties in Sweden are clearly too

[21]The importance of these factors is confirmed by discussions with representatives from ICA, COOP, and Bergendahls. According to surveys made by the Swedish Institute for Transport and Communication Analysis, the average travel distance for trips with the *main* purpose of buying retail food products is 9.83 kilometers (1995-2002).

large to be considered local markets for our purposes, while the 1,534 postal areas are probably too small, especially for large stores. Two intermediate choices are the 88 local labor markets or the 290 municipalities. Local labor markets take into account commuting patterns, which are important for the absolutely largest types such as hypermarkets and department stores, while municipalities seem more suitable for large supermarkets. As noted, municipalities are also the location of local government decisions regarding new entrants. We therefore use municipalities as local markets.

■ **Store types.** DELFI relies on geographical location (address) and classifies store types, making it appropriate for defining store types. Because of a limited number of large stores, we need to analyze several of the largest store types together. We define the five largest types (hypermarkets, department stores, large supermarkets, large grocery stores, and other[22]) as "large" and four other types (small supermarkets, small grocery stores, convenience stores, and mini markets) as "small." Gas stations, seasonal stores, and stores under construction are excluded. From the point of view of the Swedish market, we believe that these types are representative of being small and large.

■ **Locations.** We divide each market using five-digit zip codes that provide us with a number of locations that share borders in line with Seim (2006), who uses census tracts. The zip codes are irregular areas that vary in size. The advantage of use zip codes is that they are constructed for mail delivery and therefore consider geographical characteristics such as big roads, water, and forest areas. Hence, we believe zip codes are an appropriate way of dividing markets. In order to calculate distances between cells, we place all stores at the population-weighted midpoint of the zip code. Based on the idea of distance bands in Seim (2006), we calculate a radius from the midpoint of each zip code, which gives us distance bands within a certain distance from each cell. The splitting of markets into locations (cells) is illustrated in Figure 7. The general idea of spatial differentiation is that stores located in the first neighboring (cell 1) compete most intensely with competitors in the same cell. The intensity of competition declines for competitors in the second neighboring (cells 2, 5, and 4), followed by even lower intensity in the third (cells 3, 6, 9, 8, and 7).[23] Thus, we expect the competition intensity to be strongest in the

[22]Stores classified as "other" stores are large and externally located.

[23]Following Seim (2006), distances between zip codes are computed using the Haversine formula. Based on latitude-longitude coordinate data, the distance d between two points A and B is given by

$d_{A,B} = 2\text{Rarcsin}\left[\min\left((\sin(0.5(x_B - x_A)))^2 + \cos(x_A)\cos(x_B)(\sin(0.5(y_B - y_A)))^2\right)^{0.5}, 1\right]$

where R = 6,373 kilometers denotes the radius of the earth, and x_A is longitude and x_B latitude.

first neighboring and then to decrease as we move to further away from the actual location.[24]

4 Empirical implementation

This section presents the empirical strategy for recovering the cost parameters. The cost distributions of entry and exit are functions of the value of entry and continuation value. To compute the value functions for each market configuration, we need an estimation of the profit function for small and large types in those markets. Estimation of the value functions for a given set of parameters requires consistent estimation of the transition probabilities for continuing incumbents and entrants. The structural parameters of the distribution of entry costs and sell-off values are estimated by matching the observed entry and exit rates in the data to the ones predicted by the model. The current version of the paper presents only the implementation that captures differentiation in type.

■ **Estimation of profit generating function.** Our structural framework requires a good measure of profits. Although DELFI is a very rich store-level data set, a direct measure of profits is not provided. Therefore, we will also use accounting data on observed profits from the Swedish Companies Registration Office (Bolagsverket). In the current version, we exploit the fact that DELFI contains detailed data on a wide range of variables for each store which provide good opportunities to construct a profit measure. First, the data include revenues at the store level. Second, we assume that stores of the same type have identical costs. Third, a wide range of cost measures at the store level helps us to construct the total costs for each type.

The parameters of the profit function can be estimated statically and be a primitive in the second part of the estimation when the parameters of the cost distributions are estimated. The profit function is estimated as a function of state variables. For each state that is part of the transition probability matrices, a profit measure for each type can be obtained. The advantage of a static profit estimation approach is that it facilitates a better control for unobserved heterogeneity. The presence of serially correlated unobservables might induce a positive bias on competition parameters in the profit regression. Thus, the expected negative effect of competition on profit might be underestimated due to unobserved heterogeneity, e.g., persistent demand shocks. In other words, the paper provides conservative

[24]Descriptive statistics show that 85 (95) percent of all Swedish consumers have the nearest store within 5 (10) kilometers in 2001, whereas the corresponding figure is 83 (94) percent in 2008.

estimates for the competition effects.

The primary costs of retail chains include rent (cost of buildings), wages (cost of labor), distribution (logistics), stock of products, machinery/equipment, and other costs such as marketing and costs of promotion. Most of these costs enter as variable costs in the profit function and we divide them into two groups: (i) costs that vary across both store types and markets, and (ii) costs that only vary across store types and are constant across markets. Rent, wages, and distribution costs all vary across both types and markets because they, apart from store size, depend on the geographic location of the store. The remaining costs might only vary across types and we therefore assume that they are proportional to store size (in square meters and sales).

Having the revenues and the variable costs for each type, the first step is to construct the operating profits for each type and market (Holmes, 2011). The difference between the gross profit margin and costs of rent and wages defines operating profits. In the estimation, this paper uses a gross profit margin of 17 percent. Constructing Walmart's operating profits, Holmes (2011) uses a gross profit margin of 24 percent from which he takes out 7 percent, which accounts for the cost of running the distribution system, the fixed cost of running central administration, and other costs. These costs are not considered variable costs.[25]

The average price per square meter for houses sold times the median the number of square meters of each store type is a reasonable approximation for the cost of buildings. The paper assumes that stores pay a rent of 12 percent of the total cost of buildings. The cost of labor is measured as average wages in the municipality times the size of the store. Number of employees, rather than number of square meters, is taken as a measure of store size.[26] The total cost of labor is then calculated as wages times three employees for small store types and five employees for large types. Relying on these assumptions, we calculate a measure of operating profits $\tilde{\pi}_z$. This paper estimates a reduced form per-period profit-generating function as a function of the state variables using operating profits. In other words, we regress operating profits on the number of competitors of different types, all exogenous state variables, and local market fixed effects. Profits for stores of type z in market m in year t are

[25] Future versions of this paper will also include distribution costs. The minimum distance from each location to the nearest distribution center for each store type will be used as an approximation of distribution costs.

[26] The number of employees is from Statistics Sweden.

$$\begin{aligned}\tilde{\pi}_{ztm} = \quad & \gamma_0 + \gamma_z n_{ztm} + n_{ztm}\mathbf{dm}_z\boldsymbol{\gamma}_{zd} + \gamma_{z,2}n^2_{ztm} + \\ & \mathbf{n}_{-ztm}\boldsymbol{\gamma}_{-z} + \mathbf{n}_{-ztm}\mathbf{dm}_z\boldsymbol{\gamma}_{-zd} + \mathbf{n}^2_{-ztm}\boldsymbol{\gamma}_{-z,2} + \\ & \mathbf{dm}_z\boldsymbol{\gamma}_d + \mathbf{y}_{tm}\boldsymbol{\gamma}_y + \xi_m + \tau_t + \epsilon_{ztm},\end{aligned} \tag{16}$$

where n^z_{tm} is the number of stores of the own type; $\mathbf{dm}_z$ is a dummy matrix for types; $\mathbf{n}_{-ztm}$ is the number of rival type stores (it is a matrix if there are more than two types); $\mathbf{y}_{tm}$ is exogenous state variables; ξ_m and τ_t are fixed effects for markets and years; and ϵ_{ztm} is a type-market specific error term that is i.i.d. distributed. Controlling for type implies different profit functions for types, and the goal is to estimate the parameter vector of the profit function $\boldsymbol{\gamma}$. Population is our exogenous variable that is part of the state space. Although the nature of retail food products creates a close link between population and aggregate demand, it can be informative to include additional exogenous state variables. The numbers of stores of each type are the endogenous state variables. Section 5 discusses the estimation results for the profit-generating function.

■ **Extension: differentiation in location.** The present model can be extended by including differentiation in location. This new model has three main dimensions: store, location, and type. To account for spatial differentiation in detail, we use a large number of locations. Grouping locations based on distance reduces the dimensionality of the competition parameters. Adding the following assumption reduces the competition parameter space: a store faces competition not from the stores in each location of the market but from neighboring locations, which are defined by the distance between locations (Seim, 2006). For example, three distance bands specification is the most commonly used in the empirical literature (Figure 7). In this case, the profit function can then be specified as

$$\begin{aligned}\tilde{\pi}_{zlt} = \quad & \gamma_0 + \gamma_{zl} n_{zlt} + n_{zlt}\mathbf{dm}_{zl}\boldsymbol{\gamma}_{zl} + \textstyle\sum_{k\in L} n_{zkt}\gamma_{zk} + \\ & \mathbf{n}_{-zlt}\boldsymbol{\gamma}_{-zl} + \mathbf{n}_{-zlt}\mathbf{dm}_{zl}\boldsymbol{\gamma}_{-zld} + \textstyle\sum_{k\in L} \mathbf{n}_{-zkt}\boldsymbol{\gamma}_{-zk} + \\ & \mathbf{dm}_{zl}\boldsymbol{\gamma}_d + \mathbf{y}_{lt}\boldsymbol{\gamma}_y + \xi_l + \tau_t + \epsilon_{zlt},\end{aligned} \tag{17}$$

where n_{zlt} and $\mathbf{n}_{-zlt}$ are the number of stores of own and rival types in location l; $\mathbf{dm}_{zl}$ is a dummy matrix for types in location l; n_{zkt} and $\mathbf{n}_{-zkt}$ are own and rival store types within distance band k from location l; L is the number of locations in a market; $\mathbf{y}_{lt}$ is exogenous state variables; and ϵ_{zlt} is an i.i.d. error term.

■ **Estimation of transition matrices and value functions.** The next step is to compute continuation and entry values for each store type at each state in the state space. We estimate the transition probabilities using all municipalities in Sweden with a population of less than 200,000, i.e., large cites like Stockholm, Gothenburg, and Malmö are excluded. The number of small store types in each market varies between 3 and 55, and there are between 2 and 18 large stores in each market. Since population is a continuous variable and part of the state space, the paper discretizes population in five groups based on quantiles to reduce the state space dimensionality.[27] The dimensionality of the generated state space is 3,604 states. The transition probabilities matrices ($\boldsymbol{W}_z^c$) and ($\boldsymbol{W}_z^e$) are computed for each store type using the observed states in the data and (12) and (14). After the transition matrices are computed, they are kept in memory to increase the computation efficiency. The inverses of the transition matrices are the most demanding computational task.[28] For stores that continue from state $\mathbf{s}$, we compute the expected discounted future profits for alternative future states $\mathbf{s}' \neq \mathbf{s}$. For each state and type, we hence construct the actual $\mathbf{VC}_{z,m}(\cdot)$ and $\mathbf{VE}_{z,m}(\cdot)$ using (13) and (15). The exogenous state variable $\mathbf{y}_{tm}$ evolves as a Markov process that is independent of n_{ztm} and $\mathbf{n}_{-ztm}$. Since there is a constant trend over time in our data, the estimated transition probabilities matrices are consistent.

■ **Structural parameters.** The second and final stage of estimation deals with parameter estimation for the distributions of sunk costs and sell-off values of exit. We assume that the sell-off values and entry costs follow an exponential and a logistic distribution, respectively. The parameters of the distributions are estimated for each type z. The continuation value is computed for each state and are known up to the parameter of the distribution of sell-off values $F^{\phi_z}(\cdot|\boldsymbol{\theta})$. The value of entering depends on the entry cost draw from the distribution $F^{\kappa_z}(\cdot|\boldsymbol{\theta})$. The potential entrants in each market can be defined in two ways: (i) the maximum number of stores in each market observed during the study period; (ii) the observed number of stores in each market multiplied by a constant, e.g., 2 for both types or 3 for small and 2 for large. However, the estimated results, presented in Section 5, are robust to the choices of number of potential entrants of each type. A minimum distance estimator that minimizes the distance between theoretical and observed probabilities is used to estimate the cost distribution parameters. Let $\hat{\mathbf{p}}$ be the vec-

[27] For robustness, we also consider regrouping population in 10 and 20 groups. However, increasing the number of states has the disadvantage of decreasing the number of visited states. To handle additional exogenous state variables, one can use the estimated profit function parameters and measure the combined effect by defining a single exogenous aggregated state variable (Dunne et al., 2011).

[28] Our code, which is written in Java uses sparse matrices and parallel computing. For two types and 3,604 states, it takes less than one minute to compute all the matrices needed to evaluate the value functions on an ordinary laptop with a dual-core processor.

tor of exit and entry probabilities observed in the data for each type and, therefore, used to estimate the transition matrices. The vector of theoretical probabilities $\hat{\mathbf{q}}$ is obtained from the assumed cost distributions and computed value functions. The minimum distance estimator is defined as

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} [\hat{\mathbf{p}} - \hat{\mathbf{q}}(\boldsymbol{\theta})]' \mathbf{A}_R [\hat{\mathbf{p}} - \hat{\mathbf{q}}(\boldsymbol{\theta})], \tag{18}$$

where $\mathbf{A}_R$ is the weighting matrix defined by the following blocks

$$\mathbf{A}_R(j,j) = \begin{bmatrix} \frac{\#R(\mathbf{s}_1)^2}{R^2} & \frac{2\#R(\mathbf{s}_1)\#R(\mathbf{s}_2)}{R^2} & \cdots & \frac{2\#R(\mathbf{s}_1)\#R(\mathbf{s}_S)}{R^2} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\#R(\mathbf{s}_S)\#R(\mathbf{s}_1)}{R^2} & \frac{2\#R(\mathbf{s}_S)\#R(\mathbf{s}_2)}{R^2} & \cdots & \frac{\#R(\mathbf{s}_S)^2}{R^2} \end{bmatrix}$$

where $\#R(\mathbf{s})$ is the number of observations in state $\mathbf{s}$ and R is the total number of observations. The matrix $\mathbf{A}_R$ reduces the fine bias, yet is not the asymptotic optimal matrix.

■ **Markets with and without restrictive entry regulation.** A concern of direct interest for policy makers is the extent to which entry costs vary with the degree of regulation in geographic markets. Therefore, we explicitly incorporate the entry regulation into the model by allowing the distributions of entry costs to vary across local markets with different degrees of entry regulation. The approach builds on Dunne et al. (2011) who estimate entry costs for homogenous stores in markets with and without entry subsidies to underserved markets. In our application, local markets are grouped by political preferences (socialist and non-socialist local governments), and the cost distributions for each store type are allowed to vary by market group. We can then do detailed comparisons of the link between the regulation, store size, and cost structures.

The grouping of local markets are taken as exogenous to the stores, and we consequently do not try to model expected changes in the regulation over time. A main advantage of our model compared to previous work is the possibility to consider trade-offs between small and large types. These features will be considered in the counterfactual exercises, where we aim to investigate market structure responses of a more liberal regulation. 117 out of the 290 municipalities have a non-socialist local government for at least one of the years. Local government elections imply two shifts over time in political preferences during the study period. The number of markets with a non-socialist local government increases over time: 57 (2001-2002), 104 (2003-2006), and 102 (2007-2008).

5 Results

This section discusses the estimated results for the profit-generating function and the cost parameters. In our sample, a median small store has about 215 square meters and a median large store has about 1,725 square meters, i.e., a median large store is about eight times larger than a small store. In terms of revenues, a median large store sells about ten times more than a median small store. The revenues per square meter of a median large store are about 21 percent higher than for a median small store. In addition, the estimated profits per square meter of a median large store are about 34 percent higher than for a median small store. These figures emphasize the importance of estimating costs separately for small and large types, as done in this paper.

■ **Estimation of profit function.** Table 5 shows the estimates of the profit-generating function, without (1) and with (2) market fixed effects. We use a single form specification for both types but account for type. In this specification, the effect of competition depends on the actual market structure and store type. The dependent variable is the logarithm of mean operating profits for each store type in different geographical markets. The covariates are the number of small stores, number of large stores, number of small and large stores squared, store type dummy, store type dummy interacted with the number of small and large stores, population, population interacted with store type, and year-market fixed effects.

The OLS estimator with robust standard errors is used to estimate this specification. It is important to point out the following remarks. First, these estimates come from aggregate data at the type level. Second, the findings are the average of the mean of estimated operating profits over markets. Third, the relative difference between profits of small and large stores is more valuable than our absolute estimation, which depends on our assumptions made in the previous section.

The coefficient of the number of small stores is negative and statistically significant at the 1 percent level in both specifications. Hence, on average, an additional small competitor decreases profits of a small store by about 2 percent (Column (1)). When we control for market heterogeneity (Column (2)), the non-linearity in the number of small stores becomes important. In this specification, the marginal effect of the number of small stores on the profits of small stores becomes positive (under 1 percent) for an average market. However, the effect is still negative for small markets. In other words, the competition effect of an additional small store is smaller in large markets (high number of small stores). One possible explanation to this result is that stores might choose their location to avoid competition (spatial differentiation effect) in large markets.

Like for small stores, the coefficient of the number of large stores and the marginal effect of the number of large stores on profits are negative. Large stores make higher profits than small ones as indicated by the positive and significant coefficient on the dummy for large. The coefficient of the number of large stores squared is statistically significant at conventional levels in Specification (1) but not in (2). This might be due to high persistency in the number of large stores over time, which in fact corresponds to local market fixed effects. An additional large store decreases the profits of small stores by about 6 percent on average. Turning to the interactions of the number of small/large competitors and the dummy for large types, we find clear evidence of store type competition. The profits of a large store decrease by about 9 percent due to entry of an additional large store. That is, large competitors decrease the payoffs of large stores more than they induce a fall in profits for small ones. These findings are in line with the results from the static entry literature (Mazzeo, 2002) and hold for both specifications.

The coefficient of population is positive and significant at the 1 percent level in (1), but negative when controlling for market fixed effects in (2). This might be due to small changes in population over time, i.e., population is absorbed in the local market fixed effects. Furthermore, population does not seem to influence the profits of large and small stores significantly differently. Apart from market fixed effects, lack of controlling for spatial differentiation and differences in market size by store type are possible explanations for this unexpected finding.

■ **Structural parameter estimates.** Table 6 presents parameter estimates for the distributions of sell-off value and entry cost for each type. The estimates are obtained using a minimum distance estimator presented in the previous section and the Nelder-Mead optimization algorithm. The estimates indicate that the average entry cost is about two times larger than the sell-off value for small stores (Specification 1). For large stores, the average sell-off value is about 17 percent higher than the average entry cost. Furthermore, the average entry cost for small stores is about 30 percent larger than for large stores. This result might be unexpected at first sight. We observe, however, a fall in the number of small stores over time, while the number of large stores increases. In addition, there are few exits of large stores and a majority of exiting stores are not owned by the national chains. These figures might also explain why entry costs are higher for small stores than for large stores. In other words, small stores have low continuation values on average and, therefore, we observe more exits for small stores. Moreover, strong incumbents that are large can continue to operate. Following Dunne et al. (2011), we can estimate the cost distribution parameters for markets with a restrictive and non-restrictive entry regulation (results to be added).

■ **Store values, probability of exit, and probability of entry.** We use the estimated parameters to evaluate the value of an incumbent store continuing in operation (VC_z), the value of a potential entrant (VE_z), and the probabilities of exit (p_z^x) and entry (p_z^e) for small and large stores. The value functions are expressed in millions of 2001 SEK. The estimated structural parameters are the associated cost of operating based on yearly data. Table 7 presents a sample of the results for small and large stores, respectively.

The discounted sum of expected future net profits of small and large stores varies with the state variables. The slopes of the profit function show the toughness of short-run competition, and entry and exit have a long-run impact on stores' payoffs. An increase in the number of stores results in less store turnover, and more exit in the industry. An increasing population and holding the number of small and large stores fixed results in a substantial increase in the continuation values and a decrease in the probability to exit for both small and large stores. Therefore, differences across markets in population create significant differences in the long-run store values. These differences can be more important than the differences in the number of stores. In markets with 4-5 small stores, an additional large entrant decreases the long-run profits by about 2 percent for small stores and by about 3 percent for large stores. In markets with many stores, there is a small increase in the marginal effect of an additional large store on the long-run profits for large stores. For both small and large stores, the probability to exit increases when an additional store enters the market. Using the estimated structural parameters, the probability to exit is computed assuming that the sell-off value follows an exponential distribution for both types.

Assuming that entry costs are logistic distributed and the pool of entrants is two times the number of observed stores, we compute the values of entry (VE_z) for each state. VE_z does not depend on the estimated parameter of entry cost distribution. However, lower entry rates imply larger entry costs. The implications of the entry cost differences are explored in the counterfactual analysis. For both store types, the findings suggest that the probability of entry raises as population increases, and the value of entry decreases with the number of stores. For small stores, the reduction in the value of entry is higher in markets with many small stores. The mean entry cost for stores that choose to enter can be computed easily when the entry cost follows an exponential distribution, i.e., $E[\kappa_z < \beta VE_z(\cdot)] = \theta_z - \beta VE_z(\cdot)(1-p_z^e)/p_z^e$, where θ_z is the estimated parameter of entry cost for type z.[29]

6 Counterfactuals

Once we have estimated our model, we can use it for conterfactual exercises and evaluate how changes in the underlying cost distributions influence the endogenous long-run profits, the continuation value VC, value of entry VE, probabilities to enter and exit, and the net change in market structure.

Before turning to the main counterfactual exercise on costs, we show how the profit function results change when the initial assumptions are modified (Table 8). This exercise is thus supposed to be interpreted as "semi-counterfactuals."

■ **Semi-counterfactuals.** An increase in the number of potential entrants results in a higher entry cost and sell-off value for small stores, but the gap between them decreases (Specification 1). In other words, the entry cost increases less than the sell-off value for small stores when the number of potential entrants increases. In contrast, increasing the number of potential entrants does not affect the costs for large types. A large number of potential entrants implies an increase in competition from the new entrants that decide to enter after the first period. This increase in competition seems to affect small types more than large.

In Specification 2, we increase the gross profit margin for all observed stores by 3 percentage points, i.e., we increase the efficiency of the observed stores in the data. Again, the small stores are affected, e.g., both sell-off value and entry cost increase. This artificial increase in efficiency also implies an increase in the sell-off value for large stores, but it does not affect the entry cost for large stores. These results might suggest that large types enter strategically, e.g., they might have better locations.

Another strategy is to decrease the rent for all stores, e.g., a decrease by 5 percentage points in Specification (3). Large types benefit the most from decreasing the rent. The sell-off value increases and the entry cost decreases for large types. These findings suggest that the cost related to buildings might be an entry barrier.

■ **Decrease in entry cost for small stores.** We evaluate how changes in the entry costs affect the long-run profits, i.e., the value of stores (VC_z) and the value of entry (VE_z), and the probabilities of entry and exit. Because the traveling distance for customers to buy food has increased, the main Swedish retail firms started

[29]The results are not reported, and they are available from authors upon request.

focusing on reinventing small store formats in 2011. Using the structural estimates, we can evaluate the impact of a 30 percent decrease in the entry cost for small stores on long-run profits for small and large stores in various market configurations. For the alternative values of the entry costs, we need to solve the incumbent and entrant stores' optimization problems for VC_z and VE_z at each grid point. We have to compute the equilibrium values of small and large stores' perceptions of the number of entrants and exits for survivors and entrants (Pakes et al., 2007). The results indicate a decrease in the values of incumbent stores (VC_z). Preliminary estimates suggest that due to the increasing competition, the long-run profits decrease on average by about 11 percent for small stores and by about 16 percent for large stores in medium markets. Decreasing entry costs lead to an increase in the exit rate for small stores in large markets. The average entry values (VE_z) for new small stores decrease by about 6 percent. The complexity of market configurations in case of differentiated products calls for additional investigations of these findings.[30]

■ **The impact of entry regulation.** From the perspective of competition policy, it is crucial to quantify how the entry regulation influences market outcomes. Following Dunne et al. (2011), we can focus only on local markets with a restrictive implementation of the regulation, measured as those with a socialist local government. Using parameter estimates of the entry cost distributions in non-restrictive markets, we can then compute the change in the endogenous variables. Our structural estimates thus allow us to quantify how a more liberal regulation changes store values, the value of entry, long-run profits, probabilities to enter and exit, and the net change in the number of small and large stores. In contrast to previous work, we can investigate the entry regulation in the light of trade-offs between small and large stores (results to be added).

7 Conclusions

This paper deals with store dynamics and cost structure in the retail food market using a structural model of entry and exit. The framework, which builds on Pakes et al. (2007), allows for differentiation in store type. The present paper contributes

[30] Our theoretical framework relies on a good measure of profits. The otherwise detailed data from DELFI has the limitation that it lacks a measure of profits. It is therefore central to recognize potential changes in results when using observed profits. Accounting data on store profits will therefore be considered in future work.

to the bridge between the literature on static entry models of differentiation and the literature on dynamic games, as well as to studies on retail markets. We estimate sunk costs of entry and sell-off values of exit for small and large store types.

Using data on all retail food stores in Sweden from 2001 to 2008, we find strong store type competition and different cost structures for small and large types. An additional large store decreases the profits of large types by about 3 percentage points more than for small types. The average entry cost is about two times larger than the sell-off value of exit for small stores. This result can be explained by the drastic fall in the number of small stores along with the fact that most small entrants do not belong to national chains.

Increasing pressure from potential entrants implies a smaller increase in entry cost than in the sell-off value of exit for small types. Semi-counterfactual simulations of changing the operating profits show that small stores are negatively affected by more efficient incumbents. The corresponding results for large stores show unchanged cost of entry but an increase in sell-off values. This indicates that large stores may have good strategic locations. Large stores incur higher entry costs due to other factors such as higher rent or cost of buildings, which thus potentially act as a barrier to entry.

Future research needs to assess the importance of spatial differentiation and ownership for the observed differences in the cost structure. These two features are not part of the current analysis and could provide additional information about the nature of competition and differences in cost structures. Another key aspect is to understand how the cost of labor and new technology affect the market structure and, therefore, market dynamics.

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Table 1: Characteristics of the Swedish retail food market

Year	No. of stores		No. of	No. of	Sales space (m^2)		Sales	
	total	share large	entrants	exits	total	share large	total	share large
2001	5,240	18.2		385	2,783,921	0.578	155,312,368	0.580
2002	4,926	19.3	71	157	2,704,713	0.579	158,576,880	0.596
2003	4,882	19.6	113	240	2,770,370	0.582	167,942,368	0.601
2004	4,770	19.8	128	257	2,791,441	0.579	172,090,400	0.600
2005	4,680	20.0	167	242	2,885,817	0.576	175,726,624	0.600
2006	4,564	20.5	126	198	2,928,130	0.590	181,214,288	0.611
2007	4,489	21.3	123	193	2,983,612	0.604	188,431,040	0.616
2008	4,398	21.7	102		3,082,295	0.605	193,053,040	0.618

NOTE: DELFI is provided by Delfi Marknadspartner AB and contains all retail food stores based on their geographical location (address). Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Sales (incl. 12% VAT) is measured in thousands of 2001 SEK (1USD=6.71SEK, 1EUR=8.63 SEK).

Table 2: Entry and exit by store type and owner

	All	Small stores		Large stores	
		number	share owned by others	number	share owned by others
A. Entrants					
2001					
2002	71	60	0.783	11	0.000
2003	113	93	0.612	20	0.150
2004	128	118	0.305	10	0.200
2005	167	153	0.301	14	0.143
2006	126	96	0.344	30	0.167
2007	123	95	0.316	28	0.214
2008	102	80	0.250	22	0.000
B. Exits					
2001	385	366	0.511	19	0.053
2002	157	142	0.387	15	0.200
2003	240	218	0.408	22	0.091
2004	257	240	0.500	17	0.176
2005	242	209	0.478	33	0.181
2006	198	181	0.530	17	0.059
2007	193	171	0.544	22	0.181
2008					

NOTE: Large entrants and exiters are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). *Others* are stores not owned by the national chains ICA, Coop, Axfood, and Bergendahls.

Table 3: Distribution of store characteristics by firm 2001-2008

	ICA		Axfood		COOP		Others	
	Space (m^2)	Sales	Space (m^2)	Sales	Space (m^2)	Sales	Space (m^2)	Sales
Minimum	20	250	10	20	40	1,500	10	40
10th percentile	130	4,500	100	2,500	198	9,000	55	1,500
25th percentile	235	12,500	150	4,500	310	17,500	80	2,500
50th percentile	450	22,500	350	12,500	400	27,500	116	3,500
75th percentile	858	55,000	1,000	55,000	900	45,000	235	9,000
90th percentile	1,650	110,000	1,800	100,500	1,820	87,500	500	17,500
Maximum	10,000	600,000	11,000	500,000	11,00	580,000	15,000	750,000
Mean	713	46,566	698	38,848	800	44,454	301	12,902
Std. deviation	792	66,716	820	55,283	875	57,080,	772	41,701
No. of obs.	12,857		7,101		6,813		11,678	

NOTE: This table shows the distribution of number of square meters and sales of stores that belong to different firms during the period 2001-2008. Sales (incl. 12% VAT) is measured in thousands of 2001 SEK (1USD=6.71SEK, 1EUR=8.63SEK).

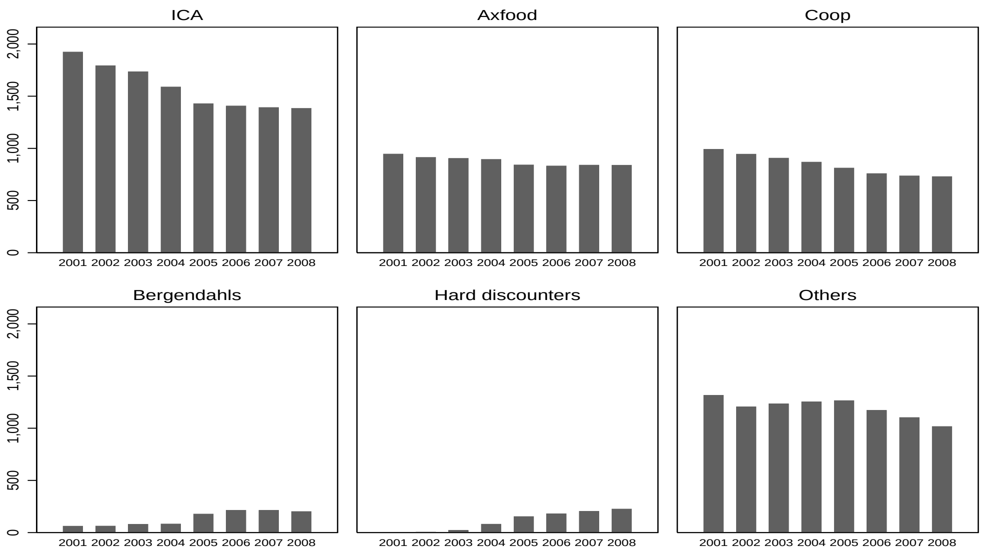

Figure 1: Total number of stores by owner 2001-2008.

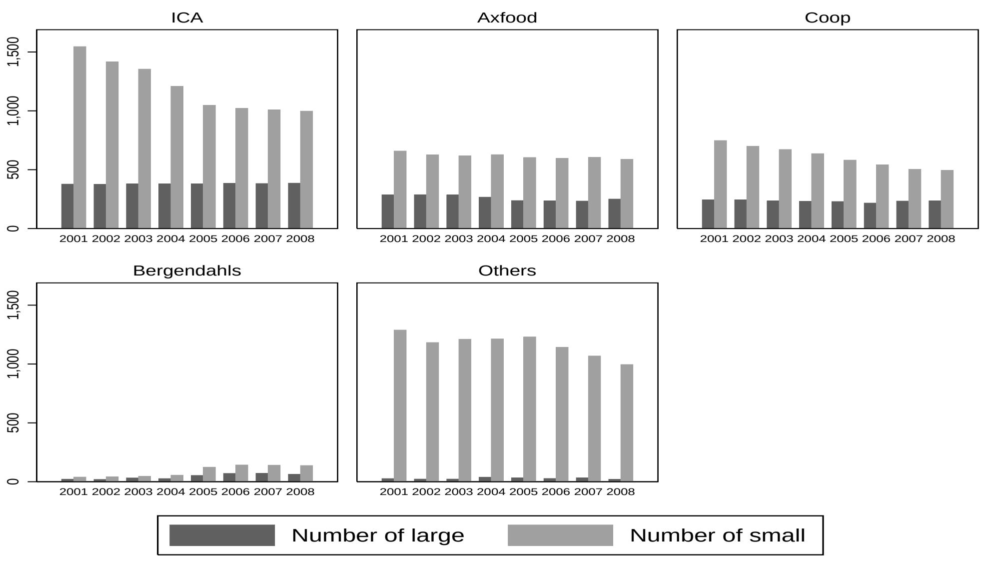

Figure 2: Number of large and small stores by national chains 2001-2008.

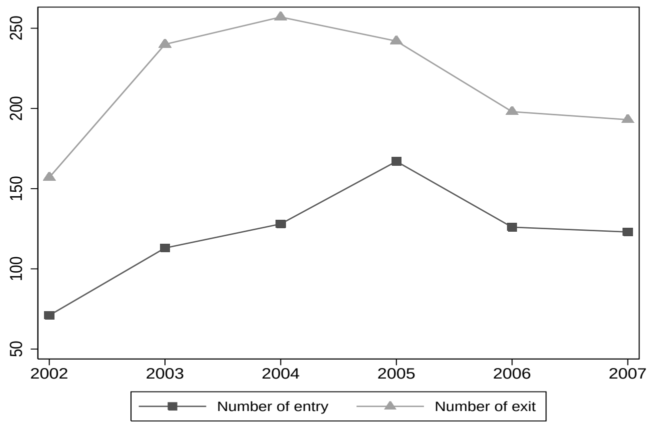

Figure 3: Total number of entries and exits in Sweden 2002-2007.

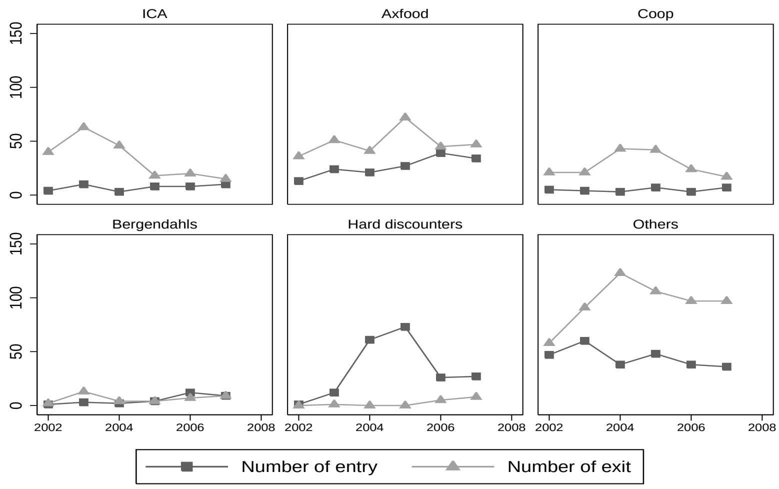

Figure 4: Total number of entries and exits by owner 2002-2007.

Table 4: Entry and exit rates across local markets and years

	p10	p25	Median	p75	p90	mean	sd
A. Entry rate							
2002	0	0	0.0	0.0	0.039	0.012	0.041
2003	0	0	0.0	0.013	0.071	0.019	0.045
2004	0	0	0.0	0.046	0.091	0.031	0.031
2005	0	0	0.0	0.064	0.125	0.040	0.073
2006	0	0	0.0	0.0	0.083	0.021	0.047
2007	0	0	0.0	0.026	0.095	0.027	0.065
B. Exit rate							
2002	0	0	0.062	0.111	0.182	0.073	0.083
2003	0	0	0.0	0.059	0.286	0.033	0.053
2004	0	0	0.0	0.091	0.333	0.050	0.050
2005	0	0	0.0	0.097	0.156	0.054	0.073
2006	0	0	0.0	0.100	0.153	0.055	0.078
2007	0	0	0.0	0.076	0.143	0.046	0.075

NOTE: This table shows descriptive statistics of entry and exit rates across municipalities.

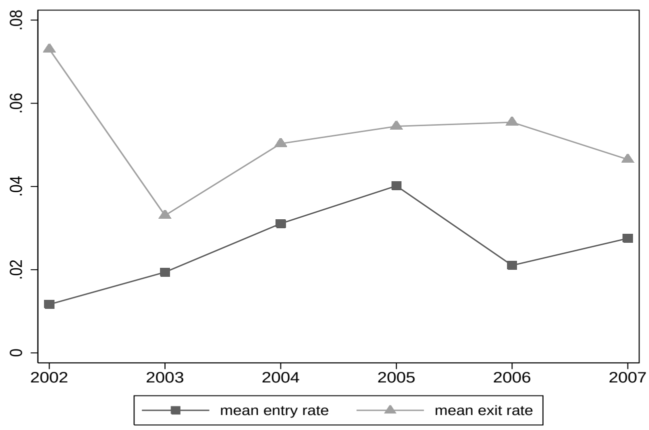

Figure 5: Mean entry and exit rates across local markets 2002-2007.

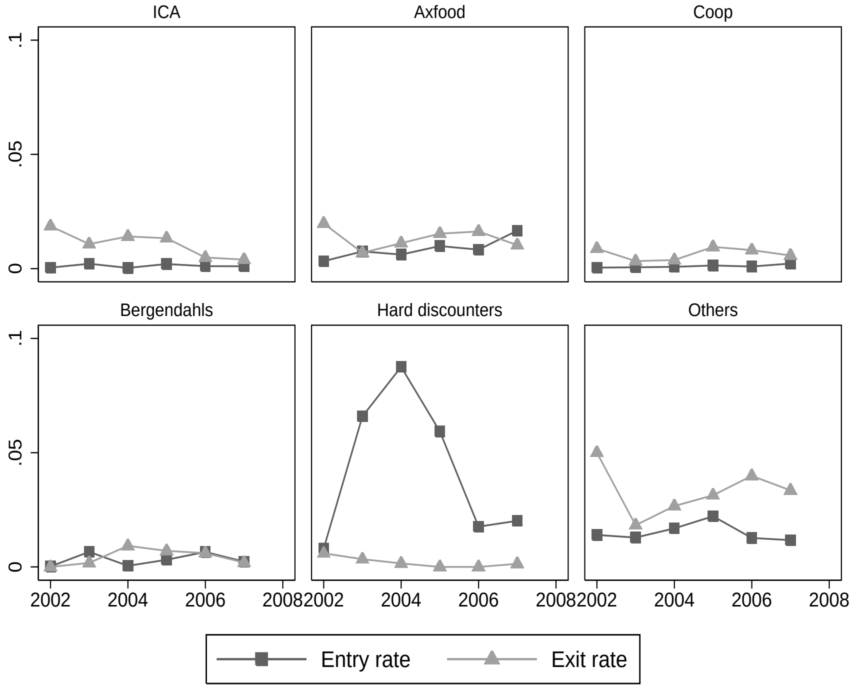

Figure 6: Mean entry and exit rates across owners and local markets 2002-2007.

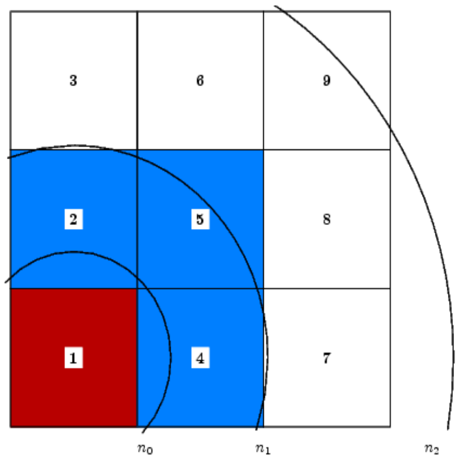

Figure 7: Illustration of distance bands

Table 5: Profit-generating function estimates

	(1)	(2)
Number of small stores	-0.027	-0.060
	(0.006)	(0.021)
Number of small stores × Large type	0.011	0.021
	(0.003)	(0.004)
Number of small stores squared	-0.0003	0.0007
	(0.0001)	(0.0003)
Number of large stores	-0.074	-0.118
	(0.022)	(0.103)
Number of large stores × Large type	-0.036	-0.062
	(0.014)	(0.015)
Number of large stores squared	0.003	0.006
	(0.001)	(0.006)
Population	0.386	-2.355
	(0.099)	(0.985)
Population × Large type	-0.044	-0.041
	(0.079)	(0.084)
Large type	2.547	2.941
	(0.747)	(0.794)
Intercept	2.008	32.85
	(0.563)	(10.26)
Year fixed effects	yes	yes
Market fixed effects	no	yes
Adjusted R^2	0.897	0.896
Root of mean squared errors	0.347	0.443
Absolute mean errors	0.121	0.196
Number of observations	1,240	1,240

NOTE: The dependent variable is the log of estimated profits. Standard errors in parentheses. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). *Large type* is a dummy variable indicating whether the store type is large.

Table 6: Estimation results of structural parameters

	Mean sell-off value ϕ	Mean entry cost κ
Small stores	2.576	4.873
	(1.287)	(0.957)
Large stores	4.178	3.543
	(1.837)	(1.496)

NOTE: Standard errors in parentheses. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Sell-off value of exit follows an exponential distribution. Entry cost follows a logistic distribution. The number of potential entrants is two times the number of actual stores (Section 4).

Table 7: Predicted value of dynamic benefits (VC, VE) and probabilities of exit and entry (p^x, p^e)

No. small stores	No. large stores	Market size Population	VC for incumbents	Probability of exit	VE for potential entrants	Probability of entry
Small type						
4	4	Small	18.86	2.44E-5	20.35	2.99E-7
4	3	Medium	31.36	1.02E-6	31.09	0.6833
4	4	Medium	30.69	1.75E-6	30.42	0.5340
5	3	Medium	31.18	1.18E-6	29.47	8.63E-4
5	4	Medium	30.65	1.82E-6	29.84	1.23E-4
6	4	Medium	25.82	8.96E-5	29.68	1.06E-4
22	5	Large	26.19	6.65E-5	28.06	7.84E-4
22	6	Large	25.61	1.05E-4	27.53	1.03E-5
22	7	Large	25.39	1.26E-4	25.38	9.50E-5
Large type						
4	4	Small	21.50	4.17E-3	26.96	0.0178
4	3	Medium	44.57	1.22E-5	43.43	0.4657
4	4	Medium	43.22	1.71E-5	42.38	0.4410
5	3	Medium	43.71	1.48E-5	49.27	0.0219
5	4	Medium	43.08	1.80E-5	54.36	0.0230
6	4	Medium	30.83	3.91E-4	44.14	0.0209
22	5	Large	46.15	8.22E-6	33.02	0.1114
22	6	Large	40.96	3.02E-5	23.65	0.0489
22	7	Large	31.82	2.40E-5	10.48	0.0391

NOTE: The sell-off value follows an exponential distribution. Entry cost follows a logistic distribution. The value functions are expressed in millions of 2001 SEK. The number of potential entrants is two times the number of actual stores.

Table 8: The impact of various policies on entry cost and sell-off value of exit

Specification	Small type		Large type	
	Sell-off value ϕ	Entry cost κ	Sell-off value ϕ	Entry cost κ
1	4.938	5.711	4.141	3.446
	(2.031)	(1.355)	(1.951)	(1.572)
2	7.891	9.245	6.497	3.280
	(1.456)	(2.466)	(2.941)	(1.340)
3	5.594	6.497	4.665	2.520
	(2.046)	(1.245)	(1.715)	(1.182)

NOTE: The mean values are reported for entry cost and sell-off value of exit. Standard errors in parentheses. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). The value of exit follows an exponential distribution. Entry cost follows a logistic distribution. The number of potential entrants is two times the number of actual stores. Specification 1: increase in number of potential entrants, i.e., number of potential entrants is three times the number of actual stores. Specification 2: increase in sales efficiency, i.e., the gross profit margin increases by 3 percent. Specification 3: change in the local market cost, e.g., the rent of buildings decreases by 3 percent.

Appendix A: PBA and data sources

■ **Entry regulation (PBA).** On July 1, 1987, a new regulation was imposed in Sweden, the Plan and Building Act (PBA). Compared to the previous legislation, the decision process was decentralized, giving local governments power over entry in their municipality and citizens a right to appeal the decisions. Since 1987, only minor changes have been implemented in the PBA. From April 1, 1992 to December 31, 1996, the regulation was slightly different, making explicit that the use of buildings should not counteract efficient competition. Since 1997, the PBA has been more or less the same as prior to 1992. Long time lags in the planning process make it impossible to directly evaluate the impact of decisions. In practice, differences due to the policy change seem small (Swedish Competition Authority, 2001:4). Nevertheless, the PBA is claimed to be one of the major entry barriers, resulting in different outcomes, e.g., price levels, across municipalities (Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2). Municipalities are then, through the regulation, able to put pressure on prices. Those that constrain entry have less sales per capita, while those where large and discount stores have a higher market share also have lower prices.

■ **The DELFI data.** DELFI Marknadspartner AB collects daily data on retail food stores from a variety of channels: (1) public registers, the trade press, and daily press; (2) the Swedish retailers association (SSLF); (3) Kuponginlösen AB (which handles with rebate coupons collected by local stores); (4) the chains' headquarters; (5) matching customer registers from suppliers; (6) telephone interviews; (7) yearly surveys; and (8) the Swedish Retail Institute (HUI). Location, store type, owner, and chain affiliation are double-checked in corporate annual reports.

Each store has an identification number linked to its geographical location (address). The twelve store types, based on size, location, product assortment, etc., are hypermarkets, department stores, large supermarkets, large grocery stores, other stores, small supermarkets, small grocery stores, convenience stores, gas station stores, mini markets, seasonal stores, and stores under construction.

Sales and sales space are collected via yearly surveys. Revenues (including VAT) are recorded in 19 classes. Due to the survey collection, a number of missing values are substituted with the median of other stores of the same type in the same local market. In total, 702 stores have missing sales figures: 508 in 1996 and 194 in later years. For sales space, all 5,013 values are missing for 1996, and are therefore replaced with the mean of each store's 1995 and 1997 values. In addition, 2,810 missing sales space values for later years are replaced similarly. In total, 698 observations are missing both sales and sales space data.