Store Dynamics, Differentiation and Determinants of Market Structure*

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Abstract

Entry, exit and the cost structure are key determinants of market structure. This paper uses a dynamic oligopoly model that allows for type differentiation to estimate the sunk costs of entry and sell-off values of exit in retail markets. Using a rich data set on all retail food stores in Sweden, we find empirical evidence of type competition and significant differences in the cost structures for small and large types. An additional large store in the market decreases profits of large types about seven 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. 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.

Keywords: Retail markets; imperfect competition; product differentiation; entry; exit; sunk costs.
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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 sunk costs of entry and sell-off values of exit.

A central feature of our model is that it generalizes two-period static models of differentiation (Mazzeo, 2002; Seim, 2006) into a dynamic context. The model builds on Pakes, Ostrovsky, and Berry (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 store 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 only cover 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, firms operate the well-defined store types. Second, entry and exit of stores are main determinants of market structure.[1] Third, demand is closely tied to population. Fourth, the trend towards larger but fewer stores is constant over time.[2]

The retail food market is important not only because food products constitute a high share of private consumption, but also because entry is regulated. Regulations are in affect in most OECD countries, where Europe has more restrictive regulations than the U.S. From the perspective of competition policy, it is, therefore, central to obtain information about the sunk costs of entry (and potentially how these vary with different degrees of regulation). From a welfare point of view,

[1]Entry and exit play a more severe 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, Haltiwanger, and Krizan, 2006).

[2]The model requires to construct 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 sufficient long.

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.[3]

The model connects with two areas of literature: The first is recent studies using structural models of entry and exit (Ackerberg, Benkard, Berry, and Pakes, 2007; Pakes, Ostrovsky, and Berry, 2007; Bajari, Benkard, and Levin, 2007; Pesendorfer and Schmidt-Dengler, 2008; Dunne, Klimek, Roberts, and Xu, 2009; Maican, 2010). To start to estimate demand and cost, and then recover the structural parameters is, however, demanding from both a data and computational perspective. This is certainly true in complex markets such as retailing.[4] The second literature is two-period static entry models with differentiation. These models abstract from 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; Toivonen and Waterson, 2005; Seim, 2006; Jia, 2008).[5]

This paper estimates a dynamic structural model of firm entry and exit decisions in an oligopolistic industry. The proposed framework distinguishes the decisions of an incumbent firms from potential entrants. We model the long-run equilibrium using a model that allows for firm heterogeneity. The model relies on a reduced form (observed) profit function and lets the data pick up the equilibrium played. Dunne, Klimek, Roberts, and Xu (2009) apply a similar approach to data on dentists and chiropractors. They estimate an average firm profit function along with sunk costs and sell-off values. As the baseline model in POB, they abstract from any differentiation. We follow POB but relax the assumption of identical firms and recognize differentiation in store type. Many markets, like retail food, are characterized by heterogenous players which calls for models with less restrictive assumptions. These assumptions need, however, to be balanced against the computational burden and presence of multiple equilibria. To separate large stores from small is important in our application because large stores stand for the ma-

[3]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.

[4]To use an approach based on POB, that instead requires a good measure of profits, is a valid alternative.

[5]Store location has not yet been much investigated in the light of retail chains, though a few examples exist (Seim, 2006; Jia, 2008; Holmes, 2010; Nishida, 2010). In future versions of the paper, we aim to account explicitly for location differentiation in our dynamic framework, i.e., to extend Seim (2006) to a dynamic framework.

jority of sales and sales space but only for a minor share of all stores.

An advantage of our model is that it bases on the actions that actually take place in the market. This comes at the cost that we need information about profits. We cannot obtain accurate policy experiments if there are multiple equilibria in the data. Pakes, Ostrovsky, and Berry (2007) claim that the correct equilibrium will be picked for large enough samples. To address this issue, we take advantage of our data that have the favor of containing all stores active in the Swedish retail food market. 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. This is essential when the degree of differentiation increases.

Our empirical results base on differentiation in type. We find empirical evidence of type competition and significant differences in the cost structure for small and large types. Given the complexity of this industry (multiple ownership, spatial differentiation, and regulation), the estimated parameters cannot be used as a direct guide for policies. This paper provides initial estimates of cost structure while future research should consider robustness tests, e.g., including spatial differentiation, and consider the implications of the results. The estimates indicate that an additional large store decreases profits of small stores about 11 percent. The profits of a large store decrease about 18 percent due to entry of an additional large store. These findings are in line with the results from the static entry literature (Mazzeo, 2002). The average entry cost is about 2 times larger than the sell-off value for small stores. Entry cost increases less than the sell-off value for small stores when the number of potential entrants increases.

The next section presents the model, followed by the data and market information. Section 4 discuses the empirical implementation of the model. Section 5 presents the empirical results whereas Section 6 concludes.

2 A dynamic model of entry and exit

This paper uses a dynamic model to learn about distribution of retail firms' entry and exit costs. Our framework, based on Pakes, Ostrovsky, and Berry (2007) (POB), accounts for differentiation in type/location that is common in retail markets. Dunne, Klimek, Roberts, and Xu (2009) also uses the basic POB framework (no differentiation) to study entry, exit and the determinants for markets structure for two U.S. service industries, dentists and chiropractors.

In the beginning of each period, a set of incumbents $\mathbf{J}$ and potential entrants $\mathcal{E}$ simultaneously decide their actions. Incumbents choose whether to continue to operate with type (or in location) $z \in \mathcal{Z}$ or exit.[6] Incumbents of type z receive a draw of the sell-off value ϕ_z from the distribution $F_z^{\phi}(\cdot|\boldsymbol{\theta})$ upon exit, where $\boldsymbol{\theta}$ is a parameter vector which might need to be estimated. The common assumption is that the exit draws are i.i.d across markets and time. Stores only observe their own draw of the sell-off value but not their rivals' draws, which induce asymmetric information across stores. The distribution is, however, known to all players. The draw of the exit fee depends on the type/location of the store.

Potential entrants decide whether to enter store type $z \in \mathcal{Z}$ or to stay out. Entrant decisions are made one period ahead of the period they start to operate. The entry cost for potential entrants, κ_z, is a draw from the distribution $F_z^{\kappa}(\cdot|\boldsymbol{\theta})$. The sunk costs are private information known prior to players' decisions and are i.i.d. distributed from a known distribution (Pakes, Ostrovsky, and Berry 2007; Bajari, Benkard, and Levin 2007). The entry costs might be higher the larger the store type. The entry assumption, that entrants decide to enter a period ahead of the period they start to operate, allow 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 paper abstracts from the market index m.[7]

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 exits. We

[6]The decision to exit or continue depends on store's performance. In practice, firms that operate several stores can influence the decision of each store through possible chain effects. However, the firm takes the decision based on store performance.

[7]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 all use a small number of players (Jia, 2008; Holmes, 2010; and Nishida, 2010).

do not allow firms to invest, change owner or format. The fact that store concepts are well defined in the retail-food market justifies this assumption. 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. Moreover, the model requires to have observed profits in contrast to the literature on static entry and dynamic games that estimate the underlying primitives of demand and cost.

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

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

where $\pi_z(\cdot)$ is the profit function; $VC_z(\cdot)$ is the continuation value; ϕ is the sell-off value; and $0 < \beta < 1$ the discount factor. Incumbents know their scrap value ϕ, 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

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

where $p_z^c(\cdot)$ is a z-incumbents' perception of rivals' type decisions $(e_z, e_{-z}, x_z, x_{-z})$ conditional on continuing, i.e., that $\lambda_z^c = 1$. 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 $Pr(\phi > VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})) = 1 - F_z^{\phi}(VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}))$.

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

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

where g_z^x and g_{-z}^x are a potential entrants' 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 result in the probability of entry $Pr(\kappa < VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})) = F_z^{\kappa}(VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}))$. Potential entrants choose to operate a store of type z if the expected profits are higher than 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 both form perceptions over entry and exit by rivals. In equilibrium, these perceptions need to be consistent with actual behavior. The incumbents' perception over rival incumbents behavior needs to be the same for all rivals with the same type. That is, all incumbents of a given type have the same probability of exit 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.

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, $\phi_z > VC_{zl}(n_z, n_{-z}, \mathbf{y}; \phi, \theta)$:

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

The perceptions of entry conditional on that they enter $p^c_z(\cdot)$, the perceptions of exit of the same type $p^c_z(\cdot)$ and rival type $p^c_{-z}(\cdot)$ 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 are identical up to the draw of the sunk cost, so in equilibrium all potential entrants need to have the same probability to enter with a type. The perceptions of the probability to enter is

$$\begin{aligned} p^e_z(e_z, e_{-z}, x_z, x_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda^e_z = 1) = \;& p^e_z(e_z, e_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda^e_z = 1) \\ & g^e_z(x_z, n_z|n_z, n_{-z}, \mathbf{y}) \\ & g^e_{-z}(x_{-z}, n_z|n_{-z}, \mathbf{y}), \end{aligned} \tag{7}$$

where $p^e_z(\cdot)$ are the perceptions of the entry distribution conditional on that they enter while $g^e_z(\cdot)$ and $g^e_{-z}(\cdot)$ are perceptions of exit of same and rival type.

The solution concept is a Markov Perfect equilibrium. There might, however, exist more than one equilibria. As in POB, there 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 argues, the correct equilibrium will be picked if samples are large enough. For this purpose, this paper takes advantage of the detailed data we have access to, covering the total population of stores in Sweden 2001-2008.

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

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

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

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

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

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

where σ 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; $\boldsymbol{VC}_z(\cdot)$, $\boldsymbol{\pi}_z$, and $\boldsymbol{p}^x_z$. Furthermore, let the perceptions be a matrix of transition probabilities $\boldsymbol{W}^c_z$ which indicates the transition from state $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$ to state $\mathbf{s}' \neq \mathbf{s}$.

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

There is no dependence over time in the transition probabilities.[8]

To compute the continuation value we need to calculate the expected discounted future profits that the firm would gain in alternative future states. We then take weighted averages for those firms that actually continued from state $\mathbf{s}$. The idea is to use average discounted profits actually earned by stores that continue from state $\mathbf{s}$. Hence to plug consistent estimates of $\boldsymbol{W}^c$ and $\boldsymbol{p}^x_z$ into (11) in order to get consistent estimates of $\widehat{\boldsymbol{VC}}_z(\cdot)$.

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 Markov property and summing over the independent draws of the probability of exit, we obtain consistent estimates of exit probabilities.

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

Let $W^c_{\mathbf{s},\mathbf{s}'}$ 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 incumbent's

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

transition proability from state $\mathbf{s}$ to $\mathbf{s}'$ are given by

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

Both $\tilde{p}^x_z(\mathbf{s})$ and $\tilde{W}^c_{\mathbf{s},\mathbf{s}'}$ will converge in probability to $p^x_z(\mathbf{s})$ and $W^c_{\mathbf{s},\mathbf{s}'}$ as $R(\mathbf{s}) \to \infty$. The transitions are weighted by the number of incumbents that continues 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 $\boldsymbol{\pi}_z$, $\tilde{\boldsymbol{p}}^x_z$ and $\tilde{\boldsymbol{W}}^c$.

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

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. Because $\boldsymbol{W}^c$ and $\boldsymbol{p}^x_z$ 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.[9]

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

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

■ **Unobservables.** The model requires the use of observed profits. Correlated unobserved variables such as persistent demand shocks would bias the estimates.

[9] 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.

The 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. Although the presence of serially correlated unobservables cannot be ruled out, this paper provides conservative estimates.

3 Data and characteristics of the Swedish retail food market

Retail food markets in the OECD countries are fairly similar, consisting of firms operating uniformly designed store types. In Sweden, the food market is dominated by four firms that together had 92% of the market shares in 2002: 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 mostly of independently owned stores with centralized decision making. Coop, on the other hand, consists of centralized cooperatives with decisions made at national or local level. Axfood and Bergendahls each have a mix of franchises and centrally owned stores, the latter mainly in the south and southwest of Sweden.[10]

A majority of OECD countries have entry regulations that give power to local authorities. The regulations differ substantially across countries, however (Hoj, Kato, and Pilat 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. In case of inter-municipality questions of entry, they are handled by the 21 county administrative boards. PBA is claimed to be one of the major barrier 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,

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

Swedish Competition Authority 2001:4, Swedish Competition Authority 2004:2). Large entrants are often newly built stores in external locations, making regulation highly important.[11] Appendix A describes PBA in greater detail.

■ **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 include all retail food stores in the Swedish market during 2001-2008 and contain 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. We drop gas-station stores due to that these are located at special places, with a limited product assortment of groceries and offer another product bundle than ordinary stores.[12]

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 kids and pensioners) and the distribution of income across age groups. We also use average wages for municipality workers in the municipality[13] Finally, we use data on average and median price per square meter for houses sold for each municipality and year provided by Värderingsdata AB.

■ **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 exit 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.

We only consider physical entry and exit since this is what matters for estimation of sunk cost and fixed cost. This implies that we abstract from stores that

[11]Possibly, firms can adopt similar strategies as their competitors and buy already established stores. As a result, more productive stores can enter without involvement of PBA 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.

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

[13]Statistics Sweden collect 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.

switch owner but that continues to operate in the store on the same address.[14]

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

The majority of entrants and exists are small stores (Table 2). Among small entrants, many are owned by others. For example, as high as 78 percent of the small entrants are owned by others in 2002. In comparison, the share of large entrants owned by others than national chains is substantially smaller. For exitors, about half of the small 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 than they enter.

Figures 1 and 2 show how the number of stores evolves for different players across time. The number of small stores decreases 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, 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 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 decline, while the number of stores that exit reaches its peak in 2004. Figure 4 shows that the substantial outflow of stores are mainly owned by ICA, Axfood, Coop and Others. That is, well established players in the market. Hard dis-

[14]See Maican 2010 for an analysis of stores switching format.

counters and small stores by Others dominate entry, together with Axfood. Note however that this is evidence for the number of stores and not for the total capacity (size/type of store).

Table 3 presents entry and exit rates across markets and owners for the period 2002-2007. On average, the exit rate is two to three times larger than the entry rate but the standard deviation is 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. The 75th percentile entry rate varies for example substantially across 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 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 whereas 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. Abstracting from the three metropolitan areas (Stockholm, Göteborg and Malmö), the correlation is weaker, 0.17. There is, as we expect, a positive correlation between entry and exit which supports our approach of using a dynamic model.

■ **Local markets.** Food products fulfill daily needs, are often of relatively short durability, and stores are thus 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 thus key aspects for consumers choosing where to shop, though distance likely increases with store size.[15] 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

[15]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).

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 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[16]) 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 boarders in line with Seim (2006) that uses census tracts. The zip codes are irregular areas that vary in size. The advantage to 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 intense with competitors in the same cell. The intensity of competition declines for competitors in the second (cell 2, 5 and 4), followed by even lower intensity in the third neighboring (cell

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

3, 6, 9, 8 and 7).[17] We expect the competition intensity to be strongest in the first neighboring and then to decrease as we move to further away from the actual location.

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. The 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. The future versions will include differentiation in both type and location.

■ **Estimation of profit generating function.** Our structural framework requires the use of a good measure of profits. Although this paper uses a rich store level data set, a direct measure of profits is not provided. Detailed data on a wide range of variables for each store provide, however, good opportunities to construct a profit measure. First, the data include the revenues at the store level. Second, the paper assumes that stores of the same type have identical cost. 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 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 static profit es-

[17] Following Seim (2006), distances between zip codes are computed using the Haversine formula. The distance d between two points A and B is given by
$d_{A,B} = 2R arcsin(min((sin(0.5(x_B - x_A)))^2 + cos(x_A)cos(x_B)(sin(0.5(y_B - y_A)))^2)))^{0.5}, 1)$
where x is longitude and y latitude.

timation approach is a better control for unobserved heterogeneity. The presence of serially correlated unobservables might induces 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 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 in 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 both across 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 therefore assume that they are proportional to store size (square meter, 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, 2010). The difference between the gross profit margin and cost of rent and wages defines operating profits. In the estimation, this paper uses a gross profit margin of 17 percent. Constructing Wal-Mart's operating profits, Holmes (2010) uses a gross profit margin of 24 percent from which he takes out 7 percent that accounts for the cost of running the distribution system, the fixed cost of running central administration, and other costs. These costs are not viewed like variable costs.[18]

The average price per square meter for houses sold times the median square meters of each store type is a reasonable approximation for the cost of buildings. The paper assumes stores pay a rent of 12 percent of total costs of buildings. The cost of labor is measured as average wages in the municipality times size of the store. Instead of square meters, the paper uses the number of employees to measure size.[19] The total cost of labor is then calculated as wages times 3 employees for small store types and 5 employees for large types. Relying on these

[18]The future version of this paper will also include distribution costs. The minimum distance from each location to the nearest distribution center for each store type is an acceptable approximation for distribution costs.

[19]The number of employees is taken from Statistics Sweden.

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

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

where n_{tm}^z 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 2 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. 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 there main dimensions: firm, 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 used in the empirical literature (Figure 7). In this case, the profit function can then be specified as

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

where n_{zlt} and $\mathbf{n}_{-zlt}$ are the number of stores of own and rival types in location l; $\mathbf{d}_{-zl}$ 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. This paper estimates the transition probabilities using all municipalities in Sweden with a population less than 200,000, i.e., large cites like Stockholm, Goteborg, and Malmo are excluded. The number of small store types in each market varies between 3 and 55. There are between 2 and 18 large stores in each market. Since the population is part of the state space and is a continuous variable, the paper discretizes population in 5 groups based on quantiles to reduce the state space dimensionality.[20] 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.[21] 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 $\mathbf{y}_{tm}$ evolve 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. This paper assumes that the sell-off value 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 $F_z^{\phi}(\cdot|\boldsymbol{\theta})$. The

[20]For robustness, this paper also considers regrouping of population using 10 and 20 groups. However, increasing the number of states has the disadvantage of decreasing the number of visited states.

[21]Our code that is written in Java uses sparse matrices and parallel computing. For 2 types and 3,604 states, it takes less than 1 minute to compute all the matrices needed to evaluate the value functions on an ordinary laptop with Dual-Core processor.

value of entering depends on the entry cost draw from the distribution $F_z^{\kappa}(\cdot|\boldsymbol{\theta})$. 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 all types since after a store decides to enter it chooses its type. However, the estimated results, presented in Section 5, are robust to the choices of the number of potential entrants for each type. This paper estimates the cost distribution parameters using a minimum distance estimator, i.e., minimize the distance between theoretical and observed probabilities. Let $\hat{\mathbf{p}}$ be the vector 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 observation in state $\mathbf{s}$ and R is the total number of observations. The matrix $\mathbf{A}_R$ reduces the fine bias, but it is not the asymptotic optimal matrix.

5 Results

This section discusses the estimated results for profit generating function and 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 8 times larger than a small store. In terms of revenues, a median large store sells about 10 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. Those figures emphasize the importance of estimating costs separate for small and large types. Therefore, this paper estimates the parameters of the exit and entry costs for each type.

■ **Estimation of profit function.** Table 4 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 the mean of 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 that 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 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 profits of small stores becomes positive (under 1 percent) for an average market.[22] 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 results is that stores might choose their location to avoid competition (spatial differentiation effect) in large markets.

Like for small, the coefficient of the number of large stores and the marginal ef-

[22]Note that the net effect is small but positive in (1), (-0.017+0.021=0.004) which might be due to that we do not control for market heterogeneity.

fect 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 profits of small stores about 11 percent. 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 about 18 percent due to entry of an additional large store. That is, large competitors decrease payoffs of large stores more than they induce a fall in profits for small. These findings are in line with the results from the static entry literature (Mazzeo, 2002) and holds 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 seems not to influence profits of large stores significantly different from small. 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.

■ **Costs estimates.** Table 5 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 2 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 exit by small are owned by others than the national chains. Those figures might also explain why entry cost for small stores is higher than entry costs 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.

■ **Robustness.** Tables 5 also shows how the estimated results change when the initial assumptions are modified. Increasing the number of potential entrants results in higher entry cost and sell-off value for small stores but the gap between them decreases (specification 2). In other words, entry cost increases less than the sell-off value for small stores when the number of potential entrants increases. Contrary, 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 3, 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 implies also an increase in the sell-off value for large stores. But it does not affect the entry cost for large stores. Those results might suggest that large types enter strategically, e.g., they might have better location.

Another strategy is to decrease the rent for all stores, e.g., a decrease with 5 percentage points in specification 4. 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.

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. Reliable data for profits exist at the level of an organization number for tax reporting (provided by Statistics Sweden). To check the robustness of our results of profits, we therefore use an aggregated measure of profits for two different store sizes (results not reported).

6 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, that builds on

Pakes, Ostrovsky, and Berry (2007), allows for differentiation in store type. This paper contributes 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 between 2001 and 2008, we find strong store type competition and different cost structures for small and large types. An additional large store decreases profits of large types about seven 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. 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, for example. Simulations using the estimated model show that increasing pressure from potential entrants implies a smaller increase in entry cost than in the sell-off value of exit for small types.

Future research needs to assess the importance of spatial differentiation and ownership for the observed differences in the cost structure. This will provide additional information about type competition. Another key aspect is to understand how the cost of labor and new technology affect the markets 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	sh. of large	entrants	exits	total	sh. of large	total	sh. of 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 exits 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 owned by other than the national chains ICA, Coop, Axfood and Bergendahls.

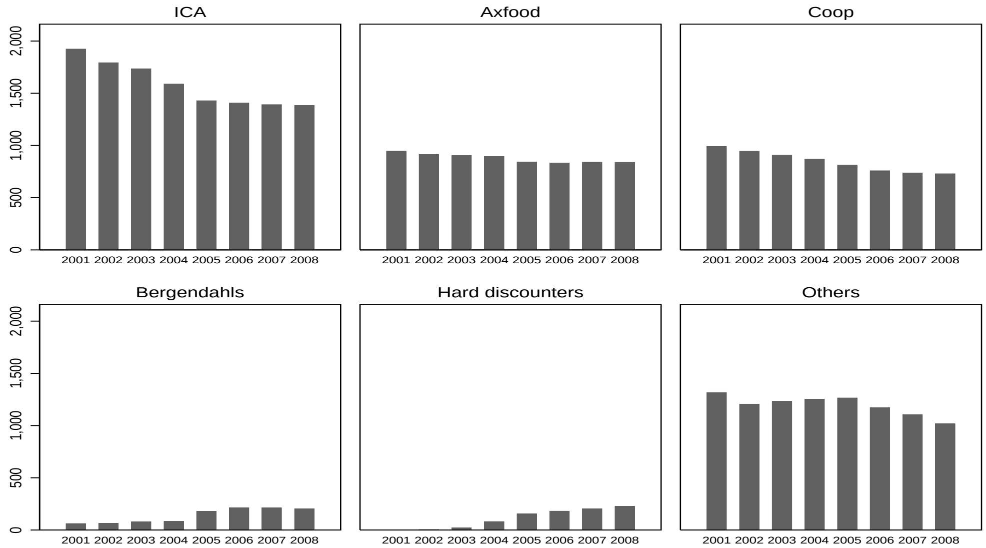

Figure 1: Total number of stores by owner 2001-2008.

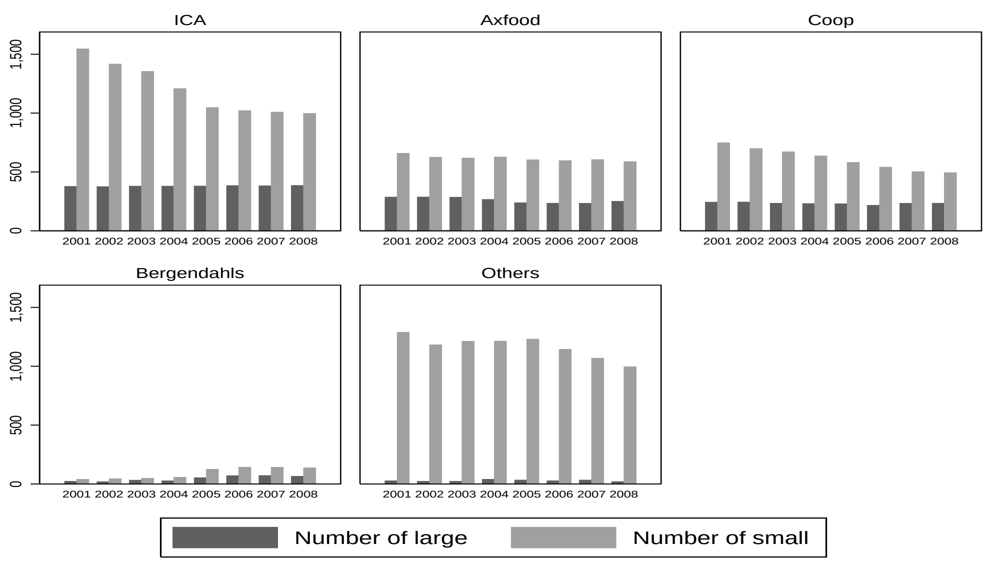

Figure 2: Number of large and small stores by national chains 2001-2008.

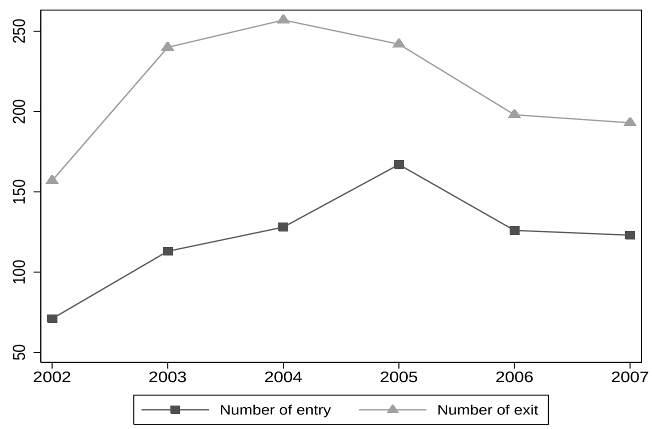

Figure 3: Total number of entry and exit in Sweden 2002-2007.

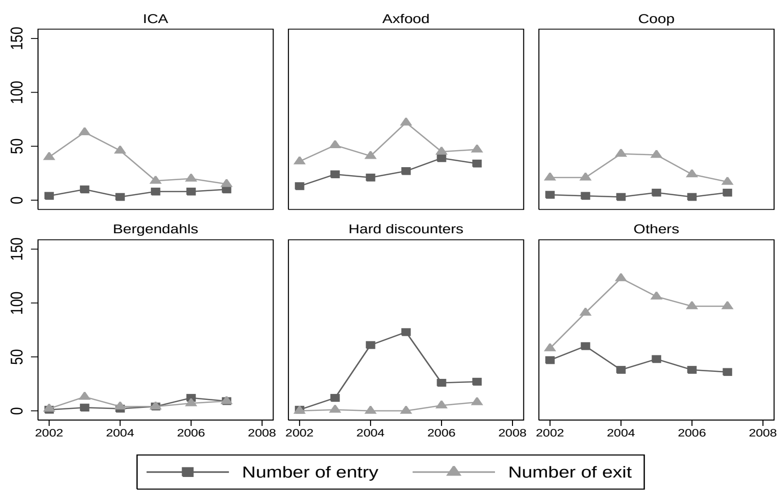

Figure 4: Total number of entry and exit by owner 2002-2007.

Table 3: 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.

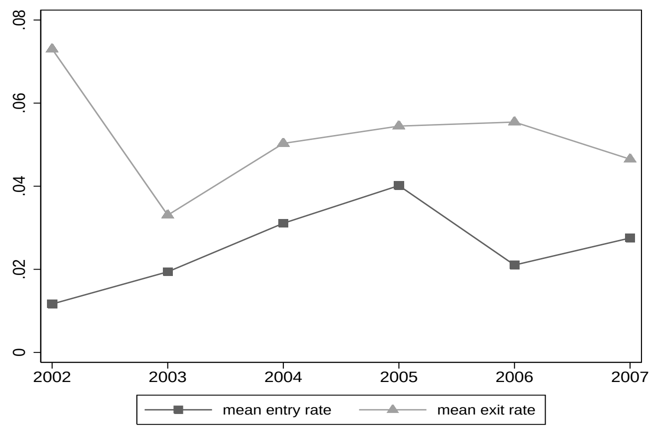

Figure 5: Mean entry and exit rates across local markets 2002-2007.

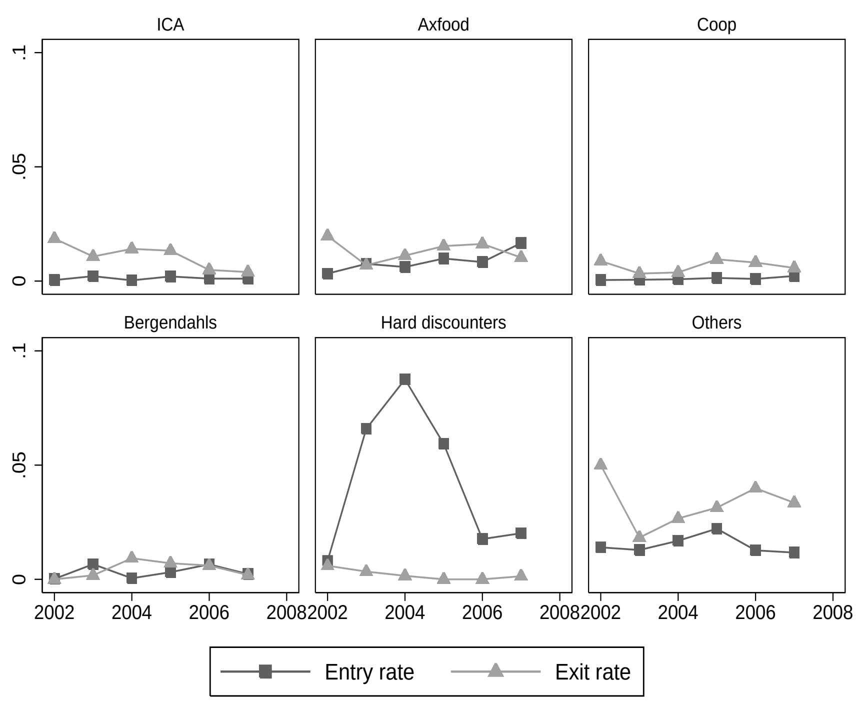

Figure 6: Mean entry and exit rates across owners and local markets 2002-2007.

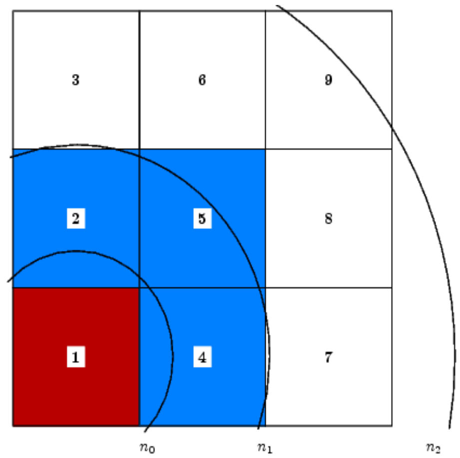

Figure 7: Illustration of distance bands

Table 4: Profit generating function estimates

	(1)	(2)
Number of small stores	-0.017	-0.060
	(0.008)	(0.021)
Number of small stores × Large type	0.021	0.021
	(0.005)	(0.004)
Number of small stores squared	-0.0001	0.0007
	(0.0001)	(0.0003)
Number of large stores	-0.189	-0.118
	(0.034)	(0.103)
Number of large stores × Large type	-0.062	-0.062
	(0.023)	(0.015)
Number of large stores squared	0.009	0.006
	(0.001)	(0.006)
Population	0.533	-2.355
	(0.099)	(0.985)
Population × Large type	-0.041	-0.041
	(0.125)	(0.084)
Large type	2.941	2.941
	(1.170)	(0.794)
Intercept	2.476	32.85
	(0.888)	(10.26)
Year fixed effects	yes	yes
Market fixed effects	no	yes
Adjusted R^2	0.832	0.896
Root of mean squared errors	0.559	0.443
Absolute mean errors	0.312	0.196
Number of observation	1,240	1,240

NOTE: The dependent variable is the log of estimated profits. The standard errors are in parenthesis. 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 5: Sell-off value and entry cost parameter estimates

Specification	Small type		Large type	
	Sell-off value ϕ	Entry cost κ	Sell-off value ϕ	Entry cost κ
1	2.576	4.873	4.178	3.543
	(1.287)	(0.957)	(1.837)	(1.496)
2	4.938	5.711	4.141	3.446
	(2.031)	(1.355)	(1.951)	(1.572)
3	7.891	9.245	6.497	3.280
	(1.456)	(2.466)	(2.941)	(1.340)
4	5.594	6.497	4.665	2.520
	(2.046)	(1.245)	(1.715)	(1.182)

NOTE: The standard errors are in parenthesis. 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 follows an exponential distribution. Entry cost follows a logistic distribution. Specification 1 (Section 4): number of potential entrants is 2 times number of actual stores. Specification 2: number of potential entrants is 3 times number of actual stores. Specification 3: number of potential entrants is 2 times number of actual stores and the gross profit margin increases with 3 percent. Specification 4: number of potential entrants is 2 times number of actual stores and the rent of buildings decreases with 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 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, 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 because of the policy change seem small (Swedish Competition Authority 2001:4). Nevertheless, 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 deals 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: 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 stores' 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.