Entry Regulations, Product Differentiation and Determinants of Market Structure*

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Abstract

Consequences of regulations are of great importance for both economists and policy makers. Accurate evaluations of regulations need to consider the nature of demand, the incentives given to firms and strategic interaction over time. To evaluate how entry regulations affect profitability and market structure in retail food, 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 demand, entry cost of potential entrants and sell-off values for exit for small and large stores. We find empirical evidence of strong competitive effects from large stores. An additional large store decreases short and long-run profits about four times more than an additional small store. The average entry cost for large stores is 30 percent higher in markets with a restrictive than a liberal regulation. The corresponding difference for small stores is 20 percent. Counterfactual simulations show that decreasing the entry costs of small and large stores in restrictive markets to those in liberal markets result in higher entry rates and lower long-run profits of incumbents. The findings have a direct link to competition policy because regulations in retail food are frequently debated among policy makers.

Keywords: Retail markets; imperfect competition; product differentiation; entry; exit; sunk costs.
JEL Classification: L11, L13, L81.

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1 Introduction

The consequences of regulations on profitability and market structure is a topic of great concern to both economists and policy makers. Entry regulations in retail food, being more restrictive in Europe than in the US, is one example of a widely debated policy question.[1] The total annual food expenditure in the US is over USD 1,100 billion, the average household purchases groceries every week and spends up to an hour per trip. Food stands for about 10 percent of the private consumption in the US, and up to 20 percent in most European countries. This emphasizes the importance of the industry and that the welfare effects of different policies are likely to be severe. A careful analysis of regulations needs to consider comprehensive modeling of both the demand and supply side which, from an empirical point of view, requires extensive data. We present a dynamic model of entry and exit with product differentiation, incorporating demand, and recovering both entry cost of potential entrants and sell-off values of exit in markets with different degrees of regulation. A unique data set on both store characteristics and prices, together with structural estimates, allow us to quantify the impact of entry regulations on long-run profits and market structure.

Our data consist of an extensive panel covering detailed information of store characteristics of all retail food stores in Sweden, together with prices, during 2001-2008. This combination of data is rare due to, e.g., the complexity of measuring retail food prices, and allows us to carefully evaluate regulations and local market industry dynamics. Product differentiation and substantial simultaneous entry and exit characterize almost all retail markets. The degree of differentiation depends crucially on local demand and influences both competition and the cost structure of an industry, which in turn determine market structure and its evolution over time. 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 the main determinants of market structure.[2] Third, the trend toward larger but fewer

[1] See, e.g., European Parliament (2008); European Competition Network (2011); European Commission (2012).

[2] Entry and exit are often claimed to play a greater role for economic performance in retail than in many other industries. Store turnover is, for example, found to contribute more severely to

stores did not change during the last few decades.[3]

A central contribution is that we quantify the impact of entry regulations on long-run profits and market structure using a dynamic oligopoly model. The model explicitly incorporates demand, local markets, differentiation in store type, strategic interactions between stores, and presence of regional entry regulations. The paper fills a gap in the literature by considering trade-offs between small and large stores and adding a demand model, which is critical for investigating welfare effects and correctly evaluating the consequences of the regulation. We use unique combinations of data on store characteristics of all retail food stores in Sweden with data on store-level prices, regional and regulatory information. To the best of our knowledge, there are no other studies combining detailed store characteristics for the total population of stores and price data of food products for evaluating the consequences of regulations in retail.[4] 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.[5] From the perspective of competition policy, it is central to obtain information on the sunk costs of entry and how these vary with different degrees of regulation. From a welfare point of view, it is key to understand demand, players' incentives and the subsequent market outcomes, and hence to ensure that various consumer groups have access to a wide range of products and store types. 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 large and small stores. Although the institutional details differ across industries, the proposed model can be applied on other regulated industries where extensive data is available.

The paper relates to recent studies using dynamic structural models of entry and exit (Aguirregabiria and Mira, 2007; Bajari et al., 2007; Pakes et al., 2007; Pesendorfer and Schmidt-Dengler, 2008; Collard-Wexler, 2012; Ryan, 2012).[6] We

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]Beresteanu et al. (2010) combine store characteristics and prices for a single cross-section of data in their study of Walmart. In contrast to their study, we observe panel data on prices and focus on the role of entry regulations.

[5]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).

[6]See also Asplund and Nocke (2006). Ackerberg et al. (2007) survey recent econometric methods in Industrial Organization including dynamic games. Maican (2010) uses a dynamic framework to analyze store format repositioning in the Swedish retail food market. There is a growing

model the long-run equilibrium using a model that allows for store heterogeneity. Our model relates to Pakes, Ostrovsky and Berry (2007) [POB] and explicitly incorporates a static demand model and allows for differentiation in store type. Dunne et al. (2013) 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 where a change in regulation 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, the actual equilibrium played is picked out from the data. 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. Fan and Xiao (2013) find differences in cost structure across heterogenous firms using data on the telephone market in the U.S.[7]

An advantage of our model is that it is based on the actions that actually take place in the market. Having data on all Swedish retail food stores for a long period of time allow us to consistently estimate transition probabilities across the states for incumbents and entrants in the dynamic problem.[8] Another advantage is that our model allows for correlations in the entry costs between store types. 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.

We find empirical evidence of significant differences in the cost structure for small and large types across markets with different degrees of regulation. The estimates of own and cross price elasticities show asymmetries between store types. The results show strong competitive effects from large stores. An additional large store decreases short-run profits about four times more than an additional small store. In the long-run an additional small or large competitor reduces incumbents' continuation values somewhat less, though the relative magnitude remains about

literature that analyzes retail chain expansion where exit is extremely rare (e.g., Toivanen and Waterson, 2011; Beresteanu et al., 2010; Holmes, 2011; Basker et al., 2012). There are studies that investigate store location in retail markets mostly building on static models (e.g., Seim, 2006; Jia, 2008; Nishida, 2010; Holmes, 2011; Orth, 2011; Ellickson et al., 2013). In Appendix C, we account explicitly for location differentiation in our dynamic framework (Berry et al., 1995; Berry et al., 2004; Davis, 2006; Seim, 2006).

[7]Elejalde (2012) investigates U.S. banks and finds that single-market banks have higher sunk costs of entry than multi-market banks.

[8]Pakes et al. (2007) claim that the correct equilibrium will be picked for large enough samples.

four times. The average entry cost for large stores is 30 percent higher in markets with a restrictive than a liberal regulation. The corresponding difference is 20 percent for small stores. The average entry cost is substantially larger than the sell-off values for both store types. 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. Counterfactual simulations show that decreasing the entry costs of small and large stores in restrictive markets to those in liberal markets result higher entry rates and lower long-run profits of incumbents.

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 concludes the paper.

2 A dynamic oligopoly model

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) to which we augment a discrete choice demand model and account 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.[9] The model consists of a discrete choice demand model, which we use to construct per-period profits, along with a dynamic game of entry and exit.

2.1 Demand and per-period profits

To construct per-period profits, we rely on a static discrete choice demand model. We use a nested logit specification with correlation τ across stores belonging to the same group of store types $z \in \mathcal{Z}$. Following Berry (1994), the utility of consumer i of store j in local market m is given by[10]

$$u_{ijm} = \delta_{jm} + \zeta_{izm} + (1-\tau)\epsilon_{ijm}, \tag{1}$$

[9]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.

[10]For simplicity we abstract from the index for time t.

where ϵ_{ijm} is identically and independently distributed extreme value; ζ_{izm} is common to all stores in group z and has a distribution function such that if ϵ_{ijm} is a random variable, $[\zeta + (1 - \tau)\epsilon]$ is extreme value distributed with $\tau \in [0, 1]$ measuring the within-group correlation in idiosyncratic preferences. Defining δ_{jm} as

$$\delta_{jm} = x_{jm}\beta - \alpha p_{jm} + \eta_f + \eta_m + \xi_{jm}, \tag{2}$$

where x_{jm} is store characteristics, p_{jm} is the basket price, ξ_{jm} captures unobserved quality, and η_f and η_m are fixed effects for firms and local markets. Integrating out over the idiosyncratic preferences yields the estimable equation

$$ln(s_{jm}) - ln(s_{0m}) = x_{jm}\beta - \alpha p_{jm} + \tau ln(s_{jm|z}) + \eta_f + \eta_m + \xi_{jm}, \tag{3}$$

where $s_{jm|z}$ is the within-group share of store j in group z in market m, and s_{0m} is the outside option. If τ is equal to zero the model collapses to a standard logit whereas if τ approaches one, only the within share in nests matter. We need to instrument for the endogenous variables price p_{jm} and the within-group share $s_{jm|z}$.

Having the demand estimates, we can back-out a price-adjusted quality according to

$$\xi^*_{jm} = ln(s_{jm}) - ln(s_{0m}) - x_{jm}\beta + \alpha p_{jm} - \tau ln(s_{jm|z}) - \eta_f - \eta_m \tag{4}$$

■ **Profits.** The per-period profits of store j are given by

$$\pi_{jm} = (p_{jm} - mc_{jm})Ms_{jm}(\mathbf{p}, \mathbf{x}, \theta), \tag{5}$$

where mc_{jm} is marginal cost of store j defined as $ln(mc_{jm}) = \mathbf{w}_{jm}\gamma + \omega_{jm}$, M is total market size, $\mathbf{p}$ and $\mathbf{x}$ are vectors, and θ are parameters to be estimated. The main cost shifters for retail food stores are costs of labor, buildings (rent), and wholesale distribution. Note that the marginal cost function is linear in characteristics and constant in output. We assume that stores compete in prices, deciding the basket price, and p_{jm} is the result of a pure strategy Nash equilibrium. That individual stores decide over their own prices in Sweden support this assumption. The first-order conditions then imply

$$s_{jm}(\mathbf{p}, \mathbf{x}; \theta) + (p_{jm} - mc_{jm})\frac{\partial s_{jm}(\mathbf{p}, \mathbf{x}, \theta)}{\partial p_{jm}} = 0. \tag{6}$$

In the standard nested logit specification, derived in Berry (1994), the pricing equation takes a simple analytical form

$$p_{jm} = w_{jm}\gamma + \left[\frac{(1-\sigma)}{\alpha}/[1 - \sigma\overline{s}_{jm|z} - (1-\sigma)s_{jm}]\right] + \omega_{jm}. \tag{7}$$

The demand equation (3) can be estimated separate from or jointly with equation (7), the latter by forming moments on ξ_{jm} and ω_{jm}. Price and the within-group share are endogenous variables. There is variation in prices across store types, firms, markets and years. For prices, we use the average prices for stores of the same type in other local markets as instrument. For $s_{jm|z}$, we use the average number of stores of each type in other local markets. Moreover, any function of these variables is valid instruments.

Our goal is to use the demand estimates for constructing per-period profits for large and small stores. Average per-period profits of a store of type z in market m is

$$\pi_{zm} = \frac{1}{n_{zm}} \sum_{r=1}^{n_{zm}} (p_{rm} - mc_{rm}) M s_{rm}(\mathbf{p}, \mathbf{x}, \theta), \tag{8}$$

where n_{zm} is the number of stores of type z.

2.2 Entry and exit

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 store type (or in location) $z \in \mathcal{Z}$ or exit.[11] Incumbents 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.

[11]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. In Sweden, individual stores decide over their own prices, a majority of stores operate as independent or franchise units, and the distribution of size and sales are similar for stores associated to different firms (see Section 3 for details). Exit by all stores belonging to the same firm is extremely rare and multi-market contact is not as crucial as in many other countries. 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).

Potential entrants decide whether to enter a store of 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 that choose store type z, κ_z, is a draw from the 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). 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 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. 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.

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

$$\begin{aligned} V_z(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}) = \quad & max\{\pi_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) + \beta\phi_z, \pi_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) + \\ & \beta VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})\}, \end{aligned} \tag{9}$$

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

$$\begin{aligned} VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) = & \textstyle\sum_{e_z, e_{-z}, x_z, x_{-z}, \mathbf{y}} \int_{\phi'_z} V_z(n_z + e_z - x_z, n_{-z} + e_{-z} - x_{-z}, \\ & \mathbf{y}, \phi'_z; \boldsymbol{\theta}) p^c_z(e_z, e_{-z}, x_z, x_{-z} | n_z, n_{-z}, \mathbf{y}, \lambda^c_z = 1) \\ & p(\mathbf{y}'|\mathbf{y}) p(d\phi'_z), \end{aligned} \tag{10}$$

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

$$\begin{aligned} VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) = & \textstyle\sum_{e_z, e_{-z}, x_z, x_{-z}, \mathbf{y}} \int_{\phi'_z} V_z(n_z + e_z - x_z, n_{-z} + e_{-z} - x_{-z}, \\ & \mathbf{y}, \phi'_z; \boldsymbol{\theta}) p^e_z(e_z, e_{-z}, x_z, x_{-z} | n_z, n_{-z}, \mathbf{y}, \lambda^e_z = 1) \\ & p(\mathbf{y}'|\mathbf{y}) p(d\phi'_z), \end{aligned} \tag{11}$$

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:

$$VE_z(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}) \geq \kappa_z \tag{12}$$

$$\beta VE_z(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}) \geq \beta VE_{-z}(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}). \tag{13}$$

■ **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 (10). 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

$$\begin{aligned} p_z^c(e_z, e_{-z}, x_z, x_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^c = 1) = \; & p_z^c(e_z, e_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^e = 1) \\ & g_z^c(x_z, n_z - 1|n_z, n_{-z}, \mathbf{y}) \\ & g_{-z}^c(x_{-z}, n_{-z}|n_z, n_{-z}, \mathbf{y}). \end{aligned} \tag{14}$$

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

$$\begin{aligned} p_z^e(e_z, e_{-z}, x_z, x_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^e = 1) = \; & p_z^e(e_z, e_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^e = 1) \\ & g_z^e(x_z, n_z|n_z, n_{-z}, \mathbf{y}) \\ & g_{-z}^e(x_{-z}, n_{-z}|n_z, n_{-z}, \mathbf{y}), \end{aligned} \tag{15}$$

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

$$VC_z(\mathbf{s};\theta) = E^c_{\mathbf{s}'}[\pi_z(\mathbf{s}';\boldsymbol{\theta}) + \beta E_{\phi'_z}(\max\{VC_z(\mathbf{s}';\boldsymbol{\theta}), \phi'_z\}\,|\mathbf{s}')], \tag{16}$$

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,

$$E_{\phi'_z}(\max\{VC_z(\mathbf{s}';\boldsymbol{\theta}), \phi'_z\}\,|\mathbf{s}') = (1-p^x_z)VC_z(\mathbf{s}';\boldsymbol{\theta}) + p^x_z E[\phi'_z|\phi'_z > VC_z(\mathbf{s}';\boldsymbol{\theta})]. \tag{17}$$

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 (17). Using (16) we then get

$$VC_z(\mathbf{s};\boldsymbol{\theta}) = E^c_{\mathbf{s}'}[\pi_z(\mathbf{s}';\boldsymbol{\theta}) + \beta E_{\phi'_z}(\max\{(1-p^x_z)VC_z(\mathbf{s}';\boldsymbol{\theta}) + p^x_z(VC_z(\mathbf{s}';\boldsymbol{\theta}) + \sigma_z)\})], \tag{18}$$

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

$$\boldsymbol{VC}_z(\cdot) = \boldsymbol{W}^c_z[\boldsymbol{\pi}_z + \beta\boldsymbol{VC}_z(\cdot) + \beta\sigma_z\boldsymbol{p}^x_z]. \tag{19}$$

There is no dependence over time in the transition probabilities.[12]

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 state $\mathbf{s}$, i.e., to plug consistent estimates of $\boldsymbol{W}^c_z$ and $\boldsymbol{p}^x_z$ into (19) 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

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

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:

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

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

$$\tilde{W}^c_{\mathbf{s},\mathbf{s}'} = \frac{\sum_{r \in R(\mathbf{s})} (n_z - x_{r,z}) \mathbf{1}_{\mathbf{s}_{r+1}=\mathbf{s}'}}{\sum_{r \in R(\mathbf{s})} (n_z - x_{r,z})}. \tag{20}$$

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 continue in order to capture that incumbents do their calculations conditional on continuing. Now we use (19) to get estimates of $\boldsymbol{VC}_z(\cdot)$ as a function of $\boldsymbol{\pi}_z$, $\tilde{\boldsymbol{p}}^x_z$ and $\tilde{\boldsymbol{W}}^c_z$:

$$\widehat{\boldsymbol{VC}}_z(\cdot) = [I - \beta \tilde{\boldsymbol{W}}^c_z]^{-1} \tilde{\boldsymbol{W}}^c_z [\boldsymbol{\pi}_z + \beta \sigma_z \tilde{\boldsymbol{p}}^x_z], \tag{21}$$

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 $\boldsymbol{W}^c_z$ 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.[13]

■ **Transition probabilities: Entrants.** We follow the same approach for entrants as for incumbents and define $\boldsymbol{W}^e_z$ as the transition matrix that gives the probability that an entrant starts operating at $\mathbf{s}'$ conditional on continuing in $\mathbf{s}$:

$$\tilde{W}^e_{\mathbf{s},\mathbf{s}'} = \frac{1}{\#R(\mathbf{s})} \frac{\sum_{r \in R(\mathbf{s})} (e_{r,z}) \mathbf{1}_{\mathbf{s}_{r+1}=\mathbf{s}'}}{\sum_{r \in R(\mathbf{s})} (e_{r,z})}. \tag{22}$$

[13]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 expected value of entry is then

$$\widehat{\boldsymbol{VE}}_z(\cdot) = \left[\tilde{\boldsymbol{W}}^e_z + \beta\tilde{\boldsymbol{W}}^e_z[I - \beta\tilde{\boldsymbol{W}}^c_z]^{-1}\tilde{\boldsymbol{W}}^c_z\right]\boldsymbol{\pi}_z + \left[\beta\tilde{\boldsymbol{W}}^e_z\beta\tilde{\boldsymbol{W}}^c_z[I - \beta\tilde{\boldsymbol{W}}^c_z]^{-1}\tilde{\mathbf{p}}^x_z + \beta\tilde{\boldsymbol{W}}^e_z\tilde{\mathbf{p}}^x_z\right]\sigma_z. \tag{23}$$

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. Importantly, individual stores decide over their own prices. This stands in contrast to national pricing, which exist for example in the UK. The centralized decision making, and thus the concern about national strategies, in Swedish retail food is thus less pronounced than in many other countries. Firms work mainly as wholesale providers and the degree of centralization varies somewhat across firms. ICA consists of independently owned stores traditionally collaborating on wholesale provision and logistics. Axfood and Bergendahls each have a mix of franchises and centrally owned stores, the latter located mainly in the south and southwest of Sweden.[14] Coop, on the other hand, consists of centralized cooperatives with decisions made at the national or local level. In 2011, about 90% of all stores were connected to one of four firms: ICA(49%), Coop(22%), Axfood(15%), and Bergendahls(7%). Various independent owners make up the remaining 7% market share. International firms with hard discount formats entered the Swedish market in 2002 (Netto) and 2003 (Lidl).

■ **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; Schivardi and Viviano, 2011). 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

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

regulation in Sweden, which stands in contrast to for example U.K. that explicitly focus on large stores. Each store that wants to enter needs to send a formal application to the local government. The local governments approve or reject 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.[15] Appendix A describes the PBA in greater detail.

We use several measures to capture the degree of local market entry regulation. First, we access data on political preferences, i.e., 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 governments are more liberal towards new entry.[16] 117 out of the 290 municipalities have a non-socialist local government for at least one of the years. Local government (municipal) elections imply two shifts in the number of seats over time 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). Second, we have data on the number of approved applications to local authorities for each municipality and year. This includes applications to change land-use plans, and the total total number of existing land-use plans.[17] The data are collected by the Swedish Mapping, Cadastral and Land registration Authority (Lantmäteriet).

[15]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.

[16]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. The Center Party is traditionally strong in rural areas. For our purposes, we therefore only consider the Moderate Party, the Liberal Party and Christian Democrats in the non-socialist group.

[17]In addition, we have data on the number of approved PBA applications that allow the entry of retail stores. A high number of approved applications that allow retail stores to enter the market indicates a more liberal application of the PBA. The data are collected by surveys of 163 out of the 290 municipalities and exist for three time periods: 1987-1992, 1992-1996, and 1997-2000 (Swedish Competition Authority, 2001:4). The survey was unfortunately not carried during our study period, i.e., 2001-2008. Importantly, the correlation between the number of approved applications for retail stores and the total number of approved applications is as high as 0.83.

To accurately measure the degree of local market regulation over time, we construct index variables using the share of political seats and various measures of the number of approved PBA applications. In detail, we use an index with half the weight to the share of non-socialist seats in local governments, and one quarter each to the number of approved applications over the total number of stores and the number of approved applications over the number of existing land-use plans. The higher the index, the more liberal the regulation. We define municipalities as having a restrictive (liberal) implementation of the regulation if the index is below (above) the median.[18]

■ **Data.** Three different data sets covering stores, demographics, and prices are incorporated in our empirical application. 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.[19]

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.[20] Furthermore, we use data provided by Värderingsdata AB on average and median price per square meter for houses sold for each municipality and year.

■ **Prices.** The data on prices is collected by the Swedish National Organization of Pensioners (PRO) and contain yearly price information for approximately 30 products in about 1,000 stores during the period 2003-2008. The sample thus covers roughly 20 percent of the total number of stores. Stores of different sizes, formats

[18]The empirical findings are robust to different definitions and cut-off points on the regulation index.

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

[20]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.

and firms are investigated across the whole country.[21] The surveyed products cover a wide range of frequently purchased items of well-defined brands and pack-sizes. The "regular price" is collected for each product, i.e., the price without temporary promotions and discount campaigns (due to for example loyalty cards). Based on the name and address of the stores in DELFI, we identify the identity of the stores included in the PRO-survey. Because the empirical implementation of our model relies on all stores, we define two product baskets for which we construct a price index by store type, firm, local market and year.

■ **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.

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.[22]

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

[21] PRO is divided into a number of geographic districts, roughly corresponding to the 21 counties, which are each responsible for the survey in their geographic area. See Asplund and Friberg (2002) for previous work using the same data source.

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

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 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.[23] 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 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[24]) 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.

[23]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).

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

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.

Because our main focus on small and large stores imply increasing computational complexity, this paper controls for owner only in the static part, i.e., the discrete choice demand. It is, however, straightforward to use the framework to understand store dynamics by owner. A simple choice would be to drop the store type differentiation and only model the dynamics of the number of stores by ICA and Coop, for example. From the point of view of regulation and our application to the Swedish retail food market, modeling store type differentiation is more interesting since it provides information of trade-offs between small and large types. This is important for both consumers and firms.

■ **Demand estimation.** The control variables when estimating equation (3) are the logarithm of the size of the store and dummies for the main firms (ICA, COOP, and Bergendahls). In addition, we show specifications using controls for local market characteristics such as income, population, share of children, and pensioners. For all estimates, the large product basket is used to measures prices (see data Section for details). After controlling for various fixed effects, we assume that the remaining demand shocks ξ_j are not correlated across markets.

To estimate equation (3), we need instruments for the endogenous variables price p_{jm} and the within-group share $s_{jm|z}$. To instrument for p_{jm}, we use average prices of stores of the same type in other local markets. This instrument is correlated with the store's price because of the production cost. To instrument for the within-group share, we use the log of number of stores of each type in the local market, which is correlated with the number of stores.

■ **Estimation of profit generating function** 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. We use our demand estimates to construct profits for each store type and market (equation

(8)).[25] 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. Although using a rich profit function specification, there are likely persistent differences in profits across markets due to unobserved factors. The presence of serially correlated unobservables can 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 estimates for the competition effects.

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., 2013).

We estimate a reduced form per-period profit-generating function as a function of the state variables. In other words, we regress 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

$$\begin{aligned}\tilde{\pi}_{ztm} = \quad & \gamma_0 + \gamma_z n_{ztm} + n_{ztm}\mathbf{dm}_z\boldsymbol{\gamma}_{zd} + \gamma_{z,2}n_{ztm}^2 + \\ & \mathbf{n}_{-ztm}\boldsymbol{\gamma}_{-z} + \mathbf{n}_{-ztm}\mathbf{dm}_z\boldsymbol{\gamma}_{-zd} + \mathbf{n}_{-ztm}^2\boldsymbol{\gamma}_{-z,2} + \\ & \mathbf{dm}_z\boldsymbol{\gamma}_d + \mathbf{y}_{tm}\boldsymbol{\gamma}_y + \xi_m + \tau_t + \epsilon_{ztm},\end{aligned} \tag{24}$$

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 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 $\boldsymbol{\gamma}$. Although the nature of retail food products creates a close link between population and aggregate demand, we also want to include additional exogenous state variables. For each store type

[25] An alternative to estimating a demand model is to use observed profits or to construct operating profits (Dunne et al., 2013). Therefore, we use a constructed measure of operating profits for robustness (Appendix B).

and market, we add the median of each stores' minimum distance to its nearest distribution center.[26]

The numbers of stores of each type are the endogenous state variables. To control better for unobserved market effects, we create an index variable y_{mt} as the third state variable in the dynamic model. We construct the index variable based on the estimates from the profit function and includes population, average distance of the store type to the nearest distribution center, squared population, squared distance, and local market fixed effects, i.e., $y_{mt} = \hat{\gamma}_{pop} POP_{mt} + \hat{\gamma}_{dist} DIST_{mt} + \hat{\gamma}^2_{pop} POP^2_{mt} + \hat{\gamma}^2_{dist} DIST^2_{mt} + \hat{f}_m$.

■ **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 2 and 55, and there are between 2 and 19 large stores in each market. Since the exogenous index variable 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. The dimensionality of the generated state space is 2,548 states in markets with restrictive entry regulations and 3,888 states in markets with liberal entry regulations (explained below). The transition probabilities matrices ($\boldsymbol{W}^c_z$) and ($\boldsymbol{W}^e_z$) are computed for each store type using the observed states in the data and (20) and (22). 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.[27] 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 (21) and (23). 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 final stage of estimation deals with parameter estimation for the distributions of sunk costs and sell-off values of exit. We assume the sell-off values follow an exponential distribution. For the entry cost we assume

[26] The minimum distance to the nearest distribution center is calculated for each store and owner (firm).

[27] Our code, which is written in Java uses sparse matrices and parallel computing. For two types, 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.

a unimodal distribution, i.e.,

$$f(\kappa = x) = a^2(x - \frac{1}{a})exp(-a(r - \frac{1}{a})),$$

for $x \in (1/a, \infty)$, where the parameter a defines the boundary support for the entry cost κ. Because of the boundary support there will be no entry if the number of incumbents is very large. The entry costs for small (κ_{small}) and large stores (κ_{large}) in a local market are correlated. This is due to, e.g. cost of buildings, logistic, and we expect that $\kappa_{large} > \kappa_{small}$. To allow for correlation in entry costs, we assume that $\kappa_{large} = \kappa_{small} + x$, where κ_{small} and x follow unimodal distributions with parameters a_1 and a_2, respectively.

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 $F^{\kappa_z}(\cdot|\boldsymbol{\theta})$. 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 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

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} [\hat{\mathbf{p}} - \hat{\mathbf{q}}(\boldsymbol{\theta})]' \mathbf{A}_R [\hat{\mathbf{p}} - \hat{\mathbf{q}}(\boldsymbol{\theta})], \tag{25}$$

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 restrictive or liberal entry regulation.** A central goal of this study is to quantify the impact of entry regulations on profits and market structure, a concern of direct interest for policy makers. 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. A main advantage of our model compared to previous work is the possibility to consider trade-offs between small and large types. The approach builds on and extends Dunne et al. (2013) 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 how restrictive the entry regulation is, and the cost distributions for each store type are allowed to vary by market group. As explained in Section 3, we define municipalities as having a restrictive (liberal) implementation of the regulation if our regulation index is below (above) the median.[28] 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. We then do detailed comparisons of the link between the regulation, store size, and cost structures.

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.

5.1 Demand estimates

Table 5 shows the estimates of the demand equation using OLS and two-stage least squares. The first specification (Columns 1-2) contains store size and dummies for the three main firms, whereas the second specification (Columns 3-4) adds income, population, share of children and pensioners. The price coefficient (α) is positive and significant in all specifications, although smaller after controlling for local market characteristics that shift the demand. In the OLS specifications, the coefficient of the within store type (group) share is about 0.90. It decreases to 0.14 when

[28]Our empirical findings are robust to different definitions and cut-off points on the regulation index.

instrumenting within-type share, which is consistent with the existence of demand shocks that affect both total demand and within-type share. The coefficients of store size and dummies for major firms are, as anticipated, positive.

Having the demand estimates, we compute the implied price elasticities. We calculate unweighted average own and cross price elasticities over all markets. Table 6 presents the own and cross price elasticities for small and large stores, showing cross elasticities both within and between store types. The average own price elasticity is about -0.17 for a small store and -0.14 for a large store. The average cross price elasticity for the same store type is about 0.0012 for small and 0.012 for large. These findings indicate asymmetric competition within store types. For example, the impact of increasing the price of a large store on the market share of another large store is substantially larger than the impact of increasing the price of a small store on the market share of another small store (0.01 versus 0.001). The next step is to analyze the average cross price elasticities between small and large stores. The impact of increasing the price of small stores on the market shares of large stores is smaller than that of increasing the price of large stores on the market shares of small stores, i.e., 0.001 versus 0.007. In other words, consumers prefer large stores if prices are sufficiently low to compensate for the transportation costs.

5.2 Estimation of profit function

Table 7 shows the estimates of the profit-generating function. 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 and population squared, and average distance and distance squared to the nearest distribution center for each store type and market.

The OLS estimator with robust standard errors is used to estimate this specification. Marginal effects are computed using averages of the continuous variables. It is important to point out the following remarks. First, these estimates come from aggregate data at the type level based on our nested logit demand estimates.[29] Second, the findings are averages of the estimated operating profits over markets.

[29] Appendix B provides and discusses an alternative methodology to construct profits.

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. On average, an additional small competitor decreases profits of a small store by about 6 percent. The coefficient of the number of large stores and the marginal effect of the number of large stores on profits are also negative. The coefficient of the number of large stores squared is statistically significant at conventional levels. Marginal effects show that an additional large store decreases profits of small/large about five times more than an additional small store.

Large stores make higher profits than small ones as indicated by the positive and significant coefficient on the dummy for large. Turning to the interactions of the number of small/large competitors and the dummy for large types, we find evidence of strong competition from large store types. Large competitors decrease the payoffs of small stores more than they induce a fall in profits for large ones. An additional large store decreases profits about 3 percentage points more for small stores than of large stores. This indicates that small store's short-run profits fall as a consequence of large competitors, which is in line with the long-run trend of larger but fewer stores in the market.

The coefficient on the distance to the nearest distribution center is negative and statistically significant at the 1 percent level. That is, lower logistics and distribution costs clearly increase profits. This finding is consistent with previous literature on Walmart (Basker and Noel, 2009, Holmes, 2011). The coefficient of population is negative and the one on population squared is positive. Limited variation over time, lack of controlling for spatial differentiation and differences in market size by store type are possible explanations for this unexpected finding.

5.3 Structural parameter estimates

Table 8 presents parameter estimates for the distributions of sell-off value and entry cost for each store type (panel A), and average sell-off value and entry cost in monetary units, i.e., Swedish kronor (panel B).[30] We estimate the entry cost parameters for markets with a restrictive and liberal entry regulation. The estimates are obtained using a minimum distance estimator presented in the previous section.

As expected, large stores have higher sell-off values and entry costs than small

[30]The mean values in panel B are in millions of 2001 SEK (1USD=6.71SEK, 1EUR=8.63SEK).

stores. Our findings indicate that the average sell-off value is about 10 times higher for large than for small, i.e., 11 times higher in restrictive markets and 9 times higher in liberal markets. Small stores have an entry costs of SEK 11 and 14 millions in restrictive and liberal markets, i.e., a difference of 20 percent. For large stores, the corresponding entry costs are SEK 109 and 158 millions, i.e., a difference of 30 percent. Publicly available investment costs for putting up a completely new store, including land, buildings, equipment etc., confirm that our estimates of the average entry costs are reasonable. The reported cost is 8.5 millions for a small Coop store in a small market (Årjäng); 80 millions for a large ICA store in a relatively large market (Malmö); and 123 millions for the absolutely largest ICA store in a relatively large market(Västerås). Since our estimates of sunk entry costs include other costs such as those related to the regulatory process, we expect them to be larger than reported costs for land and building. Related to the existing entry regulations in the EU, our results suggest that the trade-off between entry of small and large stores plays a key role when deciding which stores should be allowed to enter.

■ **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. As noted, we assume that the sell-off value follows an exponential distribution, and that the entry cost follows a unimodal distribution. The value functions are computed for each state and are expressed in millions of 2001 SEK. The estimated structural parameters are the associated cost of operating based on yearly data. 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. 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' pay-offs.

The calculations of the continuation and entry values rely, apart from the distributional assumptions, on short-run profits. To evaluate how well our predicted per-period profits correspond to stores' actual profits, we compare the predicted profits with accounting information of reported profits. Overall, our estimates correspond very well with reported profits. Reported average profit for small stores belonging to ICA stores is SEK 230,000. The average profit range for large stores is SEK 1.1 to 4.3 millions (Annual report, ICA 2011). Our findings for restrictive and liberal markets show median (average) per-period profits of SEK 248,000-258,000 (644,000-921,000) for small, and SEK 2.1-2.35 (5.33-7.91) millions for large.

Table 9 shows the distribution of the value functions (VC_z, VE_z) for small and large incumbents and entrants in markets with restrictive and liberal regulations. We calculate the values based on all observed states in the data. For both store types and all distribution measures, VC_z and VE_z are lower in restrictive than in liberal markets. The median continuation values in restrictive markets are 25 percent lower for small and 35 percent lower for large. The differences in the value of entry are similar, the median is 26 percent lower for small and 34 percent lower for large in restrictive markets.

Table 10 shows continuation values (VC_z), entry values (VE_z), and probabilities of entry (p_e) and exit (p_x) for a selection of states. Both the continuation and entry values increase with the exogenous index variable. Increasing the market index from 1 to 2 in liberal (restrictive) markets, with 4 small and 2 large stores, increases VC_{small} from SEK 26 to 31 (12 to 14) millions and VC_{large} from SEK 218 to 256 (104 to 124) millions. The values of entry in liberal (restrictive) markets also increases, VE_{small} from SEK 1.1 to 6.7 (0.6 to 1.7) millions and VE_{large} from SEK 9.9 to 48.9 (5.2 to 15.6) millions. Additional large stores decrease the continuation and entry values, conditional on the index variable and the number of small stores. For example, in a market with 32 small stores and the index variable 4, the continuation and entry values in restrictive markets decrease from SEK 20 to 7 millions for small, and from SEK 103 to 70 for large. For several states, an increase in exogenous profit shifters outweighs more intense competition. The net effect of increasing the number of large from 3 to 4 and the market index from 1 to 2 in a market with 4 small stores, for example, is higher continuation values. Considering several store types allows us to analyze trade-offs between large and small stores and investigate the relative importance of each store type for long-run profits and market structure. For example, an additional large store decreases the continuation values more than two additional small stores in a market with 7 small, 2 large and a market index equal to 1 (low profit regime). While an additional large competitor reduces incumbents' long-run profits by 17 percent for small and 11 percent for large in liberal markets, the corresponding continuation values reduce to half in restrictive markets. Two additional small stores, on the contrary, have a modest impact on the continuation values in both liberal and restrictive markets. The unique possibilities we have to evaluate these trade-offs across states clearly highlights the richness of our proposed dynamic framework and how it can be used to improve our understanding of industry dynamics.

Since considering several store types makes the presentation by individual states quite complex, we also run simple regressions. Table 11 shows the marginal effects evaluated at observed number of rival type stores, and the exogenous state variable. On average, profits decrease when the number of rivals increase (by one store). An additional large store decreases profits around five times more than an additional small store. The reduction in profits is, moreover, larger for small than for large incumbents. These findings are consistent with our profit generating function estimates. The probability to exit increases, for both small and large incumbents, when an additional store operates in the market and the impact is stronger if the store is large than if it is small. The magnitudes of the marginal effects on both the continuation values and exit are (in absolute terms) larger in markets with a restrictive than with a liberal regulation.[31]

For potential entrants, the value of entry decreases with additional large or small store. Furthermore, more intense competition stores makes potential entrants less likely to enter. An additional large store decreases the probability to enter more than a small store. Large stores prefer to enter large markets consisting of a relatively high number of small stores. The competitive effects on the entry values and probability of entry are only slightly higher (in absolute terms) in restrictive than in liberal markets.

6 Counterfactuals

Once we have estimated our model, we can use it for counterfactual exercises and evaluate how changes in the underlying cost distributions influence the endogenous long-run profits, the continuation value, value of entry, probabilities to enter and exit, and the net change in market structure. Before turning to the main counterfactual exercise on costs that quantifies the impact of regulations, we show how the profit function results change when the initial assumptions are modified. This exercise is based on the constructed operating profits and is thus supposed to be interpreted as "semi-counterfactuals" (Table B.2 in Appendix B). In addition, we decrease the costs of small stores.

■ **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

[31]One explanation to this result is that restrictive markets tend to consist of fewer stores and we, therefore, expect that the continuation values fall relatively more.

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 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.[32]

[32]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

6.1 Entry regulations and industry dynamics

Our main goal is to evaluate how entry regulations influence long-run profits and market structure. Therefore, we evaluate differences in the determinants of market structure in local markets with liberal and restrictive regulations. In the counterfactual exercise, we focus on local markets with a restrictive implementation of the regulation. In these markets, we replace the parameter estimates of the entry cost distributions for each store type by those that we obtain in the liberal markets. Based on the new entry cost parameters, i.e., if the restrictive markets would have a liberal regulation, we compute the new equilibrium values for small and large stores. This gives new values of incumbent stores continuing in operation (VC_z^{cf}), values of potential entrants (VE_z^{cf}), and the probabilities of exit ($p_z^{x,cf}$) and entry ($p_z^{e,cf}$) for small and large stores. We then evaluate the change in long-run profits and market structure that is due to a restrictive regulation. For each store type in restrictive markets, we compute the difference between predicted long-run profits based on the new entry costs (from liberal markets) and our long-run profits obtained from the estimated entry costs in restrictive markets. Our structural estimates thus allow us to quantify how more liberal regulations change 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 quantify the consequences of the entry regulation in light of trade-offs between small and large stores.

Table 12 shows the changes in the value functions (VC_z and VE_z), exit and entry probabilities (p_z^x and p_z^e) when cost of entry in restrictive markets is reduced to be equal to the cost of entry in liberal markets for both small and large stores. In other words, we reduce the entry cost by 21 percent, i.e., from SEK 14 million to SEK 11 million for small stores. For large stores, we reduce the entry cost by 30 percent, i.e., from SEK 158 million to SEK 108 million (Table 8).

The reduction in entry cost for small stores induces a median decrease in the continuation value VC_{small} by 4 percent in markets with low y (i.e. low profit regime) and a median increase by 0.8 percent in markets with high y value. While we observe a large dispersion in changes of VC_z across the states, the sum of the changes ($VC_z^{cf} - VC_z$) across the observed states is negative for both small and large stores. On aggregate, this suggests that there is an increase in competitive pressure from new entrants inducing a decrease in store value. However, the changes

potential changes in results when using observed profits.

in probability to exit is small suggesting that an even higher increase in the competitive pressure would be needed to increase exit for both small and large stores. The 21 percent entry cost reduction in the restrictive markets induces an increase by 4 percentage points in the entry probability for small stores in markets with both low and high profits based on y. In the upper part of the distribution, the increase is as high as 15 percentage points. The value function (VE_{small}) of small potential entrants increases by 0.08 percent in low y markets and by about 6 percent in high profit markets. However, we observe large dispersion in VE_{small}, e.g., a reduction by about 3 percent for some states and an increase of up to 40 percent (larger in high y markets) for other states. This is not surprising because competition from the entry of large stores increases as a result of lower entry costs for large stores.

For large stores, the decrease in entry cost by 30 percent decreases the store value function (VC_{large}) by about 3 percent (median). The reduction is larger in states with low y, where the increase in exit probability is somewhat larger than in high y markets. For the observed states in the data, the sum of cumulated changes in VC_{large} is negative suggesting an increase in competition in long-run due to new entrants of both store types. By reducing the entry costs of small and large stores, the median reduction in VE_{large} is about 1 percent in low profit markets. The largest reduction is about 7 percent in low profit markets and about 4 percent in high profit markets. The complexity of the dynamics when reducing the entry costs of two store types makes the value of entry increase in some states (larger in high profit markets). This translates to small changes in entry probability of large stores.

Summarizing, by reducing the entry costs of both small and large store types we find an increasing in long-run competition in restrictive markets. First, competition among incumbents is more intense in restrictive markets with a low rather than a high profit regime. Second, it is important to consider the trade-off by both store types. To differentiate the cost reductions by store type plays a crucial role in successfully increasing entry, which in turn translates into lower continuation values of incumbents. In addition, the change in entry cost policy needs to take exogenous features driving profitability of the market into account.

7 Conclusions

This paper deals with store dynamics and cost structure in the retail food market using a structural model of demand, entry and exit. The framework, which builds on Pakes et al. (2007), allows for differentiation in store type. We estimate sunk costs of entry and sell-off values of exit for small and large store types in markets with different degrees of regulation. Based on the structural estimates, we use counterfactual simulations to quantify the impact of entry regulations on long-run profits and market structure.

Using unique data on all retail food stores in Sweden from 2001 to 2008, we find strong competitive effects of large stores and different cost structures for small and large types. The estimates of own and cross price elasticities show asymmetries between store types. An additional large store decreases short-run profits about four times more than an additional small store. In the long-run an additional small or large competitor reduces incumbents' continuation values somewhat less, though the relative magnitude remains about four times. The average entry cost for large stores is 30 percent higher in markets with a restrictive than a liberal regulation. The corresponding difference is 20 percent for small stores. The average entry cost is substantially larger than the sell-off values for both store types. 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. Counterfactual simulations show that decreasing the entry costs of small and large stores in restrictive markets to those in liberal markets result higher entry rates and lower long-run profits of incumbents.

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 yet 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.

References

Ackerberg, D., L. Benkard, S. Berry, and A. Pakes (2007): "Econometric Tools for Analyzing Market Outcomes," *Handbook of Econometrics*, 6, 4171–4276.

Aguirregabiria, V., and P. Mira (2007): "Sequential Estimation of Dynamic Discrete Games," *Econometrica*, 75(1), 1–53.

Asplund, M., and R. Friberg (2002): "Food Prices and Market Structure in Sweden," *Scandinavian Journal of Economics*, 104(4), 547–567.

Asplund, M., and V. Nocke (2006): "Firm Turnover in Imperfectly Competitive Markets," *Review of Economic Studies*, 73, 295–327.

Bajari, P., L. Benkard, and J. Levin (2007): "Estimating Dynamic Models of Imperfect Competion," *Econometrica*, 75(5), 1331–1370.

Basker, E., S. Klimek, and P. Van (2012): "Supersize It: The Growth of Retail Chains and the Rise of the Big-Box Store," *Journal of Economics and Management Strategy*, 21(3), 541–582.

Basker, E., and M. Noel (2009): "The Evolving Food Chain: Competitive Effects of Wal-Mart's Entry into the Supermarket Industry," *Journal of Economics and Management Strategy*, 18(4), 177–198.

Beresteanu, A., P. Ellickson, and S. Misra (2010): "The Dynamics of Retail Oligopoly," Mimeo, University of Rochester.

Berry, S. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *The RAND Journal of Economics*, 25(2), 242–262.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4), 841–890.

——— (2004): "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Vehicle Market," *Journal of Political Economy*, 112(1), 68–104.

Bertrand, M., and F. Kramarz (2002): "Does Entry Regulation Hinder Job Creation? Evidence from the French retail industry," *Quarterly Journal of Economics*, 117(4), 1369–1413.

Boylaud, O., and G. Nicoletti (2001): "Regulatory reform in retail distribution," OECD Working Paper 32.

Collard-Wexler, A. (2012): "Demand Fluctuations in the Ready-Mix Concrete Industry," *Econometrica (*forthcoming*)*.

Davis, P. (2006): "Spatial Competition in Retail Markets: Movie Theaters," *RAND Journal of Economics*, 37(4), 964–982.

Dunne, T., S. Klimek, M. Roberts, and Y. Xu (2013): "Entry, Exit and the Determinants of Market Structure," Mimeo, Pennsylvania State Univeristy.

Elejalde, R. (2012): "Local Entry Decisions in the US Banking Industry," Mimeo, University of Chile.

Ellickson, P., S. Houghton, and C. Timmins (2013): "Estimating Network Economies in Retail Chains: A Revealed Preference Approach," Mimeo, Univeristy of Rochester.

European Commission (2012): "The economic impact of modern retail on choice and innovation in the EU food sector," Written Declaration.

European Competition Network (2011): "ECN Brief Extended Issue," ECN Brief 05/2011, European Competition Network.

European Parliament (2008): "On Investigating and Remedying the Abuse of Power by Large Supermarkets Operating in the European Union," Written Declaration 0088, European Parliament.

Fan, Y., and M. Xiao (2013): "Competition and Subsidies in the Deregulated U.S. Local Telephone Industry," Mimeo, Univeristy of Arizona.

Foster, L., J. Haltiwanger, and C. Krizan (2006): "Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s," *Review of Economics and Statistics*, 88(4), 748–758.

Griffith, R., and H. Harmgart (2005): "Retail Productivity," *International Review of Retail, Distribution and Consumer Services*, 15(3), 281–290.

Hoj, J., T. Kato, and D. Pilat (1995): "Deregulation and privatisation in the service sector," OECD Working Paper 25.

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

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

Maican, F. (2010): "Industry Dynamics and Format Repositioning in Retail," Mimeo, Department of Economics, University of Gothenburg.

Mazzeo, M. (2002): "Product Choice and Oligopoly Market Structure," *RAND Journal of Economics*, 33, 221–242.

Nishida, M. (2010): "Estimating a Model of Strategic Network Choice: The Convenience-Store Industry in Okinawa," Mimeo, John Hopkins University.

Orth, M. (2011): "Entry and Spatial Differentiation in Retail Markets," Mimeo, Research Institute of Industrial Economics (IFN), Stockholm.

Pakes, A., M. Ostrovsky, and S. Berry (2007): "Simple Estimators for the Parameters of Dyscrete Dynamic Games, with Entry/Exit Examples," *RAND Journal of Economics*, 38(2), 373–399.

Pesendorfer, M., and P. Schmidt-Dengler (2008): "Asymptotic Least Squares Estimators for Dynamic Games," *Review of Economic Studies*, 75(1), 901–928.

Pilat, D. (1997): "Regulation and Performance in the Distribution Sector," OECD Working Papers 180.

——— (2005): "Assessing the Productivity of the UK Retail Sector: Some Further Reflections," *The International Review of Retail, Distribution and Consumer Research*, 15(3), 291–296.

Ryan, S. (2012): "The Costs of Environmental Regulation in a Concentrated Industry," *Econometrica*, 8(3), 1019–1061.

Schivardi, F., and E. Viviano (2011): "Entry Barriers in Retail Trade," *Economic Journal*, 121(155), 145–170.

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

Swedish Competition Authority (2001:4): "Kan Kommunerna Pressa Matpriserna? (Can the Municipalities Put Pressure on Prices?)," Technical Report 4, Stockholm.

——— (2004:2): "Konsumenterna, Matpriserna och Konkurrensen (Consumers, Retail Food Prices, and Competition)," Technical Report 2, Stockholm.

Toivanen, O., and M. Waterson (2011): "Retail Chain Expansion: The Early Years of McDonalds in Great Britain," CEPR Discussion Paper 8534.

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).

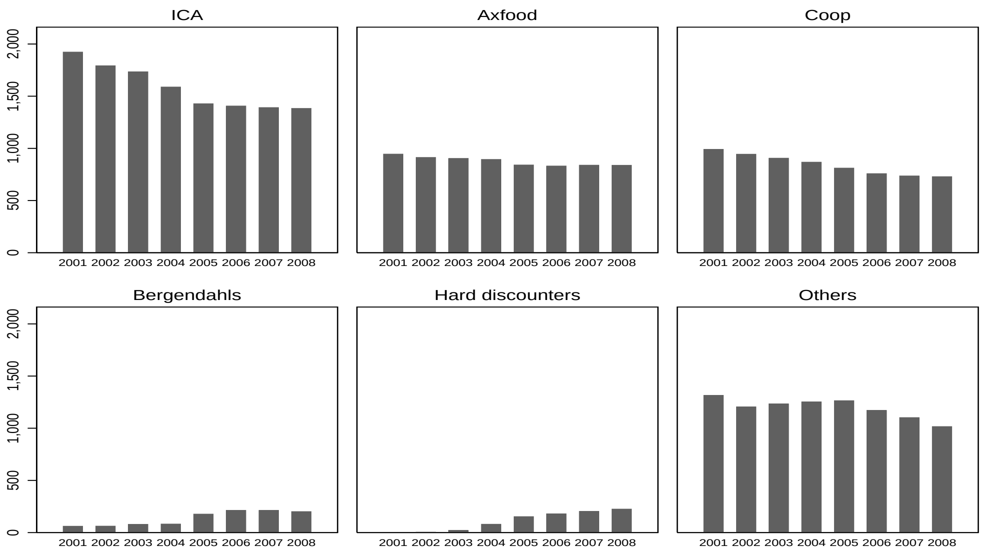

Figure 1: Total number of stores by owner 2001-2008.

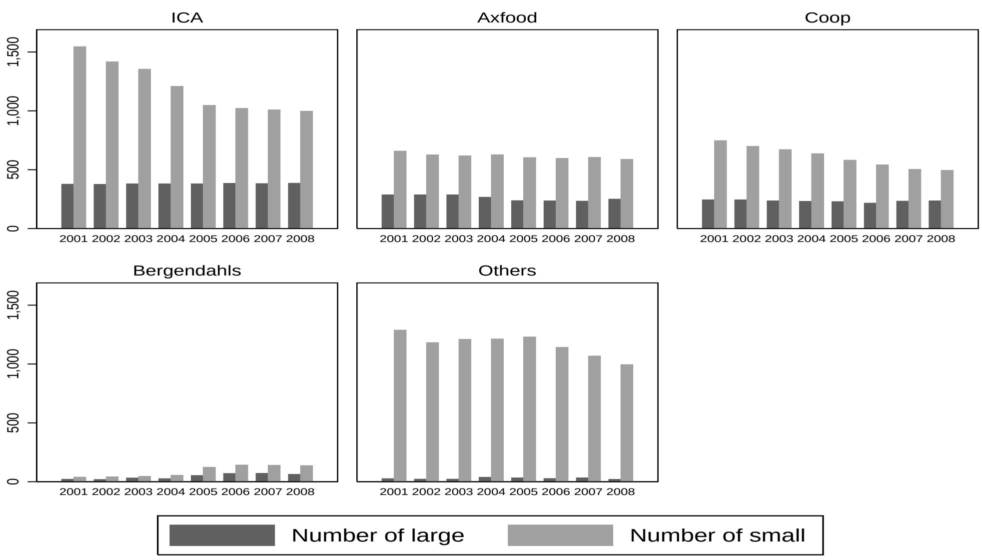

Figure 2: Number of large and small stores by national chains 2001-2008.

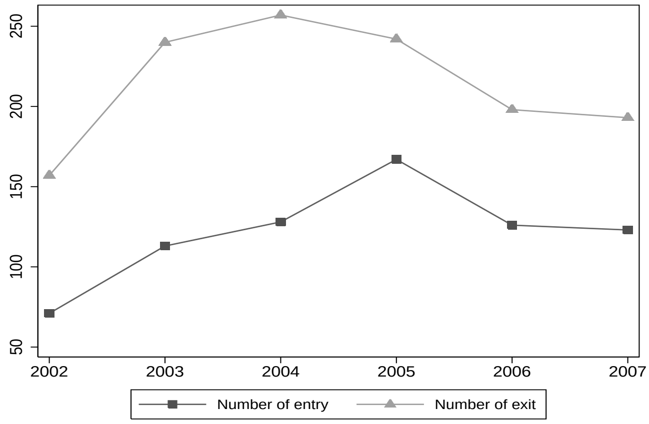

Figure 3: Total number of entries and exits in Sweden 2002-2007.

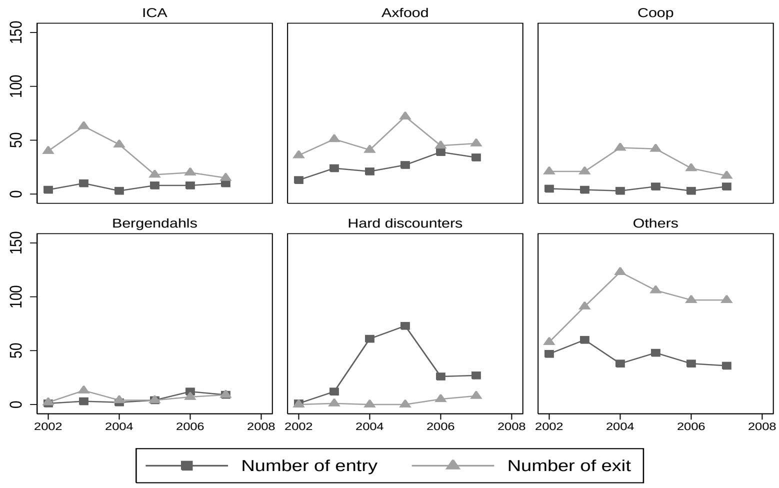

Figure 4: Total number of entries and exits by owner 2002-2007.

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.

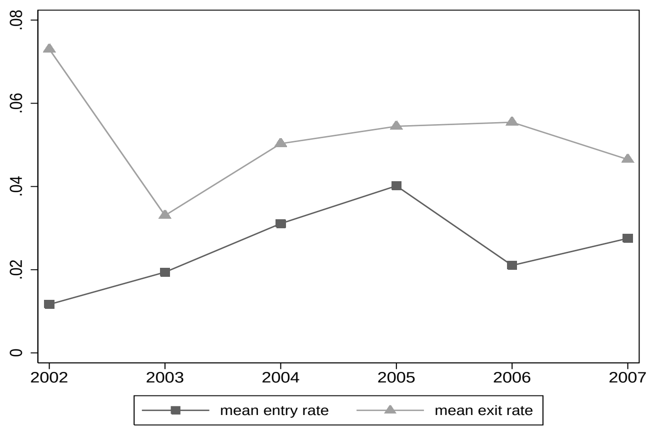

Figure 5: Mean entry and exit rates across local markets 2002-2007.

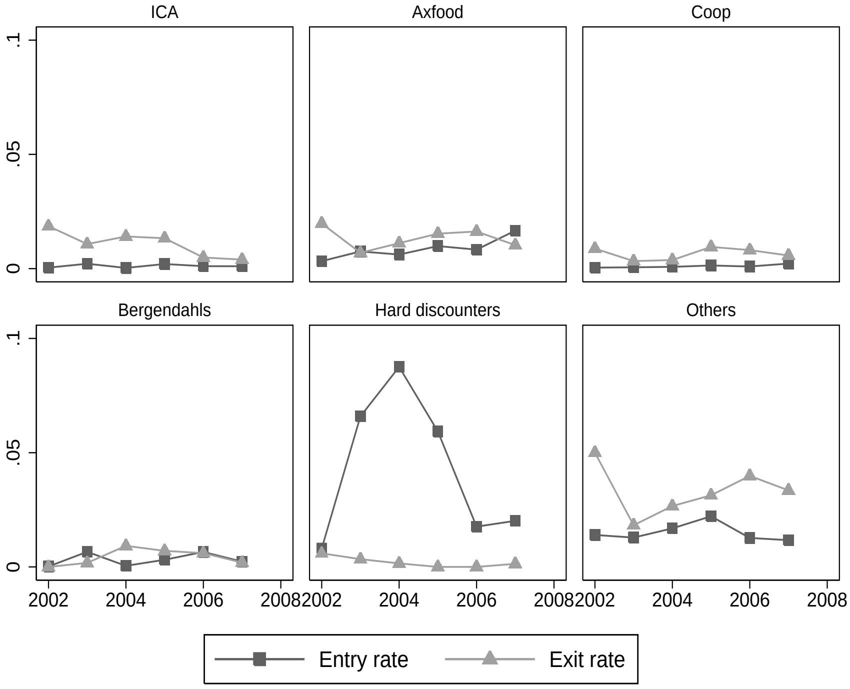

Figure 6: Mean entry and exit rates across owners and local markets 2002-2007.

Table 5: Estimated parameters of the demand equation: Nested logit specification

	OLS		2SLS		OLS		2SLS	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
Log of space(m^2)	0.016	0.003	0.021	0.003	0.278	0.002	0.863	0.027
Log of population					-0.323	0.005	-0.901	0.030
Log of income					0.155	0.005	0.046	0.016
Share pensioners					-6.008	0.072	-6.524	0.213
Share kids					-16.767	0.185	-9.288	0.639
ICA	0.129	0.010	0.152	0.012	0.058	0.007	0.848	0.041
AxFood	0.136	0.010	0.150	0.011	0.032	0.008	0.459	0.030
Coop	0.218	0.011	0.241	0.013	0.051	0.008	0.805	0.042
Bergendahls	-0.061	0.020	-0.047	0.020	-0.063	0.015	0.546	0.052
Price	0.016	0.0001	0.017	0.0002	0.001	0.0001	0.0001	0.00004
Market share (grp)	0.971	0.0015	0.959	0.0040	0.883	0.0014	0.145	0.0331

NOTE: The average price of a type in the other local markets is used as instrument of prices. The number of stores of each type is used as instruments for market share within group.

Table 6: Average estimated own and cross price elasticities by store format

	Small (i)	Small(j)	Large (k)	Large (m)
Small (i)	-0.168	0.0012	0.007	0.007
Small(j)	0.0012	-0.168	0.007	0.007
Large (k)	0.0011	0.0011	-0.138	0.011
Large (m)	0.0011	0.0011	0.011	-0.138

NOTE: Cell entries r,c, where r indexes row and c column, give the percentage change in market share of r with 1% change in price of c.

Table 7: Profit-generating function estimates

Number of small stores	-0.083
	(0.005)
Number of small stores × Large type	-0.001
	(0.004)
Number of small stores squared	0.001
	(0.0001)
Number of large stores	-0.407
	(0.022)
Number of large stores × Large type	0.028
	(0.014)
Number of large stores squared	0.013
	(0.001)
Population	-3.676
	(0.479)
Population squared	0.237
	(0.023)
Distance to DC	-0.308
	(0.179)
Distance to DC squared	0.014
	(0.008)
Large type	1.982
	(0.043)
Intercept	23.701
	(2.494)
Adjusted R^2	0.750
Root of mean squared errors	0.645
Absolute mean errors	0.121
Number of observations	3,820

NOTE: The dependent variable is the log of estimated average profits by store type, local market and year. 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. Distance to the distribution center (DC) is defined as the median (by store type and market) of the minimum distance to the nearest distribution center for each store and firm/owner.

Table 8: Estimation results of structural parameters

	Small stores	Large stores
A. Estimated parameters		
Sell-off value (σ)	1.639	0.167
	(0.673)	(0.561)
Entry cost restrictive markets (a)	0.214	0.021
	(0.023)	(0.008)
Entry cost liberal markets (a)	0.272	0.031
	(0.033)	(0.010)
B. Mean of sell-off value and entry cost		
Sell-off value (ϕ)	0.610	6.000
Entry cost restrictive markets (κ)	14.00	158.0
Entry cost liberal markets (κ)	11.00	109.0

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 for small stores (κ_{small}) follows a unimodal distribution with parameter a_{small}. For large stores, we estimate the parameter of x where k_{large}=$k_{small} + x$, where x follows a unimodal distribution with parameter a_{large}. The mean values in panel B are in millions of 2001 SEK (1USD=6.71SEK, 1EUR=8.63SEK).

Table 9: Descriptive statistics of long-run profits for incumbents and entrants by store-size and regulation

	Small stores		Large stores	
	Restrictive Markets	Liberal Markets	Restrictive Markets	Liberal Markets
A. Value function of incumbents				
Minimum	0.350	0.456	3.410	5.044
10th percentile	1.573	1.826	15.058	18.171
25th percentile	4.430	5.283	40.082	49.225
50th percentile	12.223	14.894	103.021	126.834
75th percentile	18.583	23.288	165.584	188.162
90th percentile	58.779	39.416	486.230	340.623
Maximum	77.352	101.962	630.671	868.996
Mean	17.576	19.035	149.117	161.158
B. Value function of entrants				
Minimum	0.274	0.341	2.270	3.286
10th percentile	0.794	1.398	7.404	13.263
25th percentile	1.791	2.742	15.329	25.352
50th percentile	4.348	5.493	39.874	53.765
75th percentile	13.076	14.828	115.300	131.781
90th percentile	32.055	29.891	273.474	267.043
Maximum	76.882	113.577	627.272	953.441
Mean	10.526	13.159	89.919	119.282

NOTE: Value functions are computed using the estimated parameters for exit and entry distributions. Only observed local markets configurations are included. Numbers are reported in millions of 2001 SEK.

Table 10: Predicted value of dynamic benefits (VC, VE) and probabilities of exit and entry (p^x, p^e)

	No. small stores	No. large stores	Market index	VC for incumbents	Probability of exit	VE for potential entrants	Probability of entry
A. Small type							
Liberal	4	2	1	26.2476	0.0001	1.1310	0.0000
Restrictive	4	2	1	12.4099	0.0001	0.6232	0.0000
Liberal	4	2	2	31.4016	0.0001	6.7152	0.0529
Restrictive	4	2	2	14.4011	0.0001	1.7639	0.0000
Liberal	4	3	1	22.0059	0.0001	1.7267	0.0000
Restrictive	4	3	1	15.4312	0.0002	1.7155	0.0000
Liberal	4	3	2	28.4463	0.0001	6.8320	0.0591
Restrictive	4	3	2	13.8914	0.0001	4.5541	0.0144
Liberal	7	3	1	16.6442	0.0001	2.3538	0.0000
Restrictive	7	3	1	15.2731	0.0001	2.1897	0.0000
Liberal	7	4	1	13.7187	0.0001	13.718	0.5350
Restrictive	7	4	1	7.1420	0.0001	1.7773	0.0000
Liberal	9	3	1	16.5772	0.0001	8.2895	0.1515
Restrictive	9	3	1	15.2573	0.0001	5.1046	0.0421
Liberal	32	8	4	10.5836	0.0000	10.549	0.3184
Restrictive	32	8	4	1.5538	0.0783	0.519	0.0000
Liberal	32	10	4	7.4243	0.0000	7.3887	0.0915
Restrictive	32	10	4	2.5798	0.0146	1.2859	0.0000
B. Large type							
Liberal	4	2	1	218.3555	0.0001	9.9321	0.0000
Restrictive	4	2	1	104.7500	0.0000	5.2435	0.0000
Liberal	4	2	2	256.6911	0.0001	48.9687	0.0000
Restrictive	4	2	2	124.6807	0.0000	15.6942	0.0000
Liberal	4	3	1	184.7629	0.0001	15.6817	0.0000
Restrictive	4	3	1	126.4990	0.0000	14.0613	0.0000
Liberal	4	3	2	202.2044	0.0001	53.1273	0.0000
Restrictive	4	3	2	123.5493	0.0001	41.1228	0.0019
Liberal	7	3	1	141.2629	0.0001	20.1998	0.0000
Restrictive	7	3	1	125.5050	0.0001	17.9884	0.0000
Liberal	7	4	1	125.9804	0.0001	125.980	0.3453
Restrictive	7	4	1	64.4310	0.0001	16.1523	0.0000
Liberal	9	3	1	141.2247	0.0001	70.4427	0.0227
Restrictive	9	3	1	125.9187	0.0001	42.1840	0.0029
Liberal	32	8	4	103.4432	0.0001	103.870	0.2082
Restrictive	32	8	4	14.2433	0.0931	4.8621	0.0000
Liberal	32	10	4	70.4557	0.0000	69.5057	0.0226
Restrictive	32	10	4	25.6497	0.0139	11.6321	0.0000

NOTE: The sell-off value follows an exponential distribution. Entry cost follows a unimodal distribution that allows for store type correlation. p^e and p^x are rounded to 4 digits. Market index groups the exogenous variables (population, distance to the distribution center) at the local market level: 1 and 2 corresponds to markets bellow the median of this index, and 3 and 4 values are for markets above the median. The value functions are expressed in millions of 2001 SEK. The number of potential entrants is two times the number of actual stores.

Table 11: Estimation of the long-run competition effects on VC, p^x, VE, p^e

	VC				px				VE				pe			
	Small		Large		Small		Large		Small		Large		Small		Large	
	Restr.	Lib.	Restr.	Lib.	Restr.	Lib.	Restr.	Lib.	Restr.	Lib.	Restr.	Lib.	Restr.	Lib.	Restr.	Lib.
A. Small stores																
Marginal effect	-0.051	-0.041	-0.224	-0.214	0.002	0.001	0.007	0.006	-0.015	-0.0003	-0.151	-0.136	-0.0008	-0.0001	-0.036	-0.035
	(0.007)	(0.007)	(0.033)	(0.027)	(0.0006)	(0.0006)	(0.002)	(0.002)	(0.007)	(0.0009)	(0.034)	(0.029)	(0.002)	(0.002)	(0.009)	(0.007)
R^2	0.353				0.068				0.207				0.202			
B. Large stores																
Marginal effect	-0.046	-0.036	-0.207	-0.197	0.001	0.0009	0.006	0.005	-0.133	-0.119	-0.009	0.004	0.0004	0.0005	-0.032	-0.032
	(0.007)	(0.007)	(0.032)	(0.027)	(0.0001)	(0.0005)	(0.002)	(0.001)	(0.034)	(0.029)	(0.006)	(0.009)	(0.002)	(0.002)	(0.008)	(0.007)
R^2	0.323				0.065				0.190				0.215			

NOTE: The marginal effects show the change in small and large stores' VC, p^x, VE, and p^e (row) of one additional small or large store in restrictive and liberal markets (column). Standard errors are in parentheses. The estimated marginal effects are obtained using average number of observed stores and the following regression specification: ln(y)=$\beta_0 + \beta_1 n_{small} + \beta_2 * n_{large} + \beta_3$MarketType$ + \beta_4 n_{small} \times$ MarketType$ + \beta_5 n_{large} \times$ MarketType$ + \beta_6 n_{small} \times n_{large} + u$, where $y = \{VC, p^x, VE, p^e\}$, n_{small} is the number of small stores in a local market, n_{large} is the number of large stores in a market, $MarketType$ is a dummy variable that indicates type of the market, i.e., liberal or restrictive.

Table 12: Counterfactuals: Changes in VC, p^x, VE, p^e when entry costs in liberal and regulated markets are the same

Statistic	Market type	Growth VC		Change p^x		Growth VE		Change p^e	
		Small	Large	Small	Large	Small	Large	Small	Large
A. Below median aggregated market index									
10th percentile	Restrictive	-0.305	-0.091	-1.137E-4	-4.003E-5	-0.269	-0.068	0.000	-0.006
25th percentile	Restrictive	-0.101	-0.065	-7.318E-10	3.935E-5	-0.042	-0.034	0.000	0.000
50th percentile	Restrictive	-0.043	-0.038	8.541E-12	2.406E-9	0.008	-0.010	0.000	0.000
75th percentile	Restrictive	0.005	-0.018	1.128E-10	5.963E-5	0.276	0.123	0.064	0.009
90th percentile	Restrictive	0.079	0.014	1.146E-6	8.776E-5	0.538	0.247	0.152	0.063
Mean	Restrictive	-0.012	-0.012	-0.004	-0.007	0.092	0.052	0.042	0.008
Sum of changes		-48.454	-417.696	-0.304	-47.527	98.717	192.633	2.787	0.617
B. Above median aggregated market index									
10th percentile	Restrictive	-0.038	-0.061	-0.023	-0.031	-0.026	-0.042	-7.831E-4	-0.013
25th percentile	Restrictive	-0.012	-0.037	-5.233E-4	-3.809E-4	-0.009	-0.031	-1.123E-6	-0.003
50th percentile	Restrictive	0.008	-0.028	-3.053E-14	0.000	0.068	0.036	0.002	0.000
75th percentile	Restrictive	0.091	0.050	0.000	3.665E-10	0.233	0.159	0.052	0.019
90th percentile	Restrictive	0.275	0.261	2.763E-11	5.245E-7	0.433	0.414	0.158	0.068
Mean	Restrictive	0.080	0.043	-0.010	-0.012	0.140	0.018	0.045	0.010
Sum of changes		-1.570	-929.224	-1.496	-1.851	125.490	291.009	5.490	2.282

NOTE: 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 unimodal distribution that allows for type correlation.

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.

Appendix B: Alternative approach to construct operating profits

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. As an alternative approach to demand estimation, 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 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.[33]

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

[33] 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.

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.[34] 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 $\tilde{\pi}_z$.

■ **Results: estimation of alternative profit function** Table B.1 shows the estimates of our alternative profit-generating function, without (1) and with (2) market fixed effects. 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. Estimation is done using OLS with robust standard errors.

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

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

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.

Table B.1: 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 B.2: 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 C: Extended model: 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).[35] Thus, 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.[36]

[35] 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

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

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

[36] 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.

■ **Empirical implementation: locations.** 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

$$\begin{aligned}\tilde{\pi}_{zlt} = \; & \gamma_0 + \gamma_{zl} n_{zlt} + n_{zlt} \mathbf{dm}_{zl} \boldsymbol{\gamma}_{zl} + \textstyle\sum_{k \in L} n_{zkt} \gamma_{zk} + \\ & \mathbf{n}_{-zlt} \boldsymbol{\gamma}_{-zl} + \mathbf{n}_{-zlt} \mathbf{dm}_{zl} \boldsymbol{\gamma}_{-zld} + \textstyle\sum_{k \in L} \mathbf{n}_{-zkt} \boldsymbol{\gamma}_{-zk} + \\ & \mathbf{dm}_{zl} \boldsymbol{\gamma}_d + \mathbf{y}_{lt} \boldsymbol{\gamma}_y + \xi_l + \tau_t + \epsilon_{zlt},\end{aligned} \tag{26}$$

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.

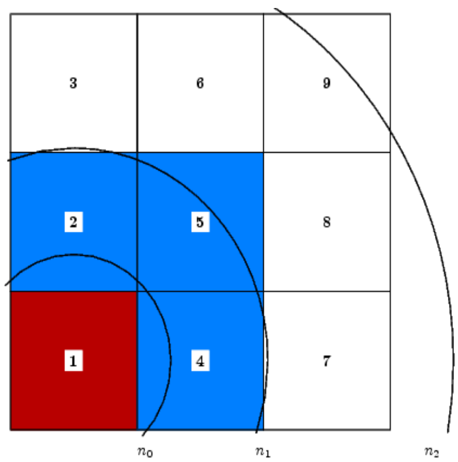

Figure 7: Illustration of distance bands