IFN Working Paper No. 984, 2013

Entry Regulations, Product Differentiation and Determinants of Market Structure

Florin Maican and Matilda Orth

Research Institute of Industrial Economics
P.O. Box 55665
SE-102 15 Stockholm, Sweden
info@ifn.se
www.ifn.se

Entry Regulations, Product Differentiation and Determinants of Market Structure*

Florin Maican[†] and Matilda Orth[‡]

September 29, 2013

Abstract

We use a dynamic oligopoly model of entry and exit to evaluate how entry regulations affect profitability and market structure in retail. The model incorporates demand and store-level heterogeneity. Based on unique data for all retail food stores in Sweden, we find that the average entry costs for small and large stores are 10 and 18 percent lower, respectively, in markets with liberal compared with restrictive regulations. Counterfactual simulations show that lower entry costs in restrictive markets result in higher entry rates and allow us to quantify the consequences of regulations in light of trade-offs between small and large stores.

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

*We would like to thank Christoph Bauner, Gregory Crawford, Uli Doraszelski, Igal Hendel, Ariel Pakes, Amil Petrin, Mark Roberts, Yuya Takahashi, Otto Toivanen and seminar participants at the Swedish National Conference in Economics 2011 (Uppsala), the thirteen CEPR/JIE Conference on Applied IO 2012, EEA-ESEM 2013, EARIE 2013, and IIOC 2013 for their valuable comments and discussions. Special thanks to DELFI Marknadspartner, the Swedish Consumer Agency, Värderingsdata and the Swedish National Organization of Pensioners (PRO) for providing the data. Financial support from the Swedish Retail and Wholesale Development Council, Torsten Söderbergs Stiftelse, and the Swedish Competition Authority is gratefully acknowledged.

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

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

1 Introduction

The effect of regulations on profitability and market structure is a topic of great concern for both economists and policy makers. Entry regulations in the retail food industry, which are more restrictive in Europe than in the US, are one example of a widely debated policy issue.[1] The total annual food expenditure in the US is over USD 1,100 billion, and the average household purchases groceries every week and spends up to an hour per trip. Food consumption represents about 10 percent of private consumption in the US and up to 20 percent in most European countries. Because of the importance of the food industry, highlighted by these statistics, the welfare effects of different policies are likely to be severe. A careful analysis of regulations requires 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 that incorporates demand and recovers both the entry costs of potential entrants and the sell-off values of exit in local markets with different degrees of regulation. A unique data set of both store characteristics and prices, together with structural estimates, allows us to quantify the impact of entry regulations on long-run profits and market structure.

Our data consist of an extensive panel of detailed information of store characteristics of all retail food stores in Sweden, together with prices, during the 2001-2008 period. This combination of store characteristics and prices is rare because of, e.g., the complexity of measuring retail food prices and allows us to carefully evaluate the effect of regulations and the dynamics of the local market industry. Product differentiation and substantial simultaneous entry and exit characterize almost all retail markets. The degree of differentiation depends on local demand and influences both competition and the cost structure of an industry, which in turn determine the market structure and its evolution over time. A dynamic approach is crucial because the market has undergone a structural change toward larger but fewer stores (Figures 1-2). Store type differentiation is essential as large stores compose 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 make the application of our theoretical model appropriate: First, stores operate well-defined store types, are highly independent of the firm and decide their own prices. Second, the entry and exit of stores are the main determinants of the market structure.[2] Third, the trend toward larger but fewer stores has not changed over the last few decades in most OECD countries.[3]

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

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

[3] The model requires consistent transition probabilities to be constructed only once based on what is observed in the data. In markets with various structural changes over time, we might not obtain consistent

A central contribution of this paper 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 the 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 regulations. We use a unique combination of data on the store characteristics of all retail food stores in Sweden and data on store-level prices as well as regional and regulatory information. To the best of our knowledge, no other study has combined detailed information on store characteristics for the total population of stores with price data on food products to evaluate the consequences of regulations in the retail industry.[4] Focusing on store types is appropriate for Sweden because, to a large extent, stores are operated by independent store owners, reducing the influence by national firms, and all stores (not just large stores) are affected by regulations. The evaluation of entry costs for different store types and the factors affecting entry costs provides crucial information in markets where the average travel distance for buying food increases.[5] From the perspective of competition policy, it is important 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 the entry of small stores, which is beneficial to consumers, and to investigate the trade-off between large and small stores. The proposed model is quite general and can be applied to other regulated industries where data on both prices and firm characteristics are available.

The paper, which relates to Pakes, Ostrovsky and Berry (2007) [POB], 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 and sunk and fixed costs and then perform a counterfactual exercise where a change in regulation shifts the entry cost. Many markets, such us the retail food, are characterized by heterogeneous players and thus require 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

transition probabilities if the period is not sufficiently long.

[4]Beresteanu et al. (2010) combine store characteristics for a panel 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, the average travel distance for buying food was about 9.83 kilometers during the 1995-2002 period (The Swedish Institute of Transport and Communication).

equilibrium played is picked out from the data. Separating large stores from small stores is important in our study because large stores account for the majority of sales and the sales space but compose only a minor share of all stores. Fan and Xiao (2013) find differences in cost structure across heterogeneous firms in a POB framework using data on the telephone market in the U.S.[6] More generally, our paper is also related to other recent studies that use dynamic structural models of entry and exit (Aguirregabiria and Mira, 2007; Bajari et al., 2007; Pesendorfer and Schmidt-Dengler, 2008; Ryan, 2012; Collard-Wexler, 2013; Sweeting, 2013).[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 distributions 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 stores across markets with different degrees of regulation. Controlling for store affiliation in the demand model and estimating costs for different store types, we provide considerable information on market dynamics. 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 than in the short run, though the relative magnitude remains about four times. The average entry costs for large stores are 18 percent lower in markets with liberal compared with restrictive regulations. The corresponding difference is 10 percent for small stores. The average entry costs are substantially larger than the sell-off values for both store types. This result is not surprising because the number of small stores has drastically decreased. Counterfactual simulations show that decreasing the entry costs of small and large stores in restrictive markets to those in liberal markets results in higher entry rates and lower long-run profits for incumbents. Decreasing

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

[7]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 body of 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 that mostly build on static models (e.g., Seim, 2006; Jia, 2008; Nishida, 2010; Holmes, 2011; Orth, 2011; Ellickson et al., 2013). In Appendix D, we explicitly show how to account for location differentiation in our dynamic framework (Davis, 2006; Seim, 2006).

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

only the entry costs for small stores in all markets results in not only an increase in entry rates for small stores but also an increase in exit. In addition, the long-run competitive effect of large stores on small stores decreases when only the entry costs of small stores are reduced. Our counterfactual simulations show that understanding the cost differences between different store types in markets with various degrees of regulation plays a key role in designing policies that favor the entry of small stores. For example, we can design entry cost reductions that increase the likelihood of entry for small stores without inducing the exit of other small stores. Increasing the number of small stores is beneficial for consumers because it increases product differentiation and decreases the transportation cost (travel distance) for buying food. The findings help us to understand and to quantify the consequences of entry regulations in light of the trade-offs between small and large stores.

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 turnover, long-run profitability and trade-offs between different store types. 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. We augment Pakes, Ostrovsky, and Berry's (2007) framework by using a discrete choice demand model and accounting for differentiation in type/location, which is common in retail markets. Importantly, we exploit the fact that store concepts in the retail food market are well defined and allow for correlations in cost draws across store types in markets with different degrees of regulation. 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[9]

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

[9]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.[10] We define δ_{jm} as

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

where $\mathbf{x}_{jm}$ represents the 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

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

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 matters. We need instruments 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

$$\xi_{jm} = ln(s_{jm}) - ln(s_{0m}) - \mathbf{x}_{jm}\beta + \alpha p_{jm} - \tau ln(s_{jm|z}) - \eta_f - \eta_m, \tag{4}$$

which is used to form moment conditions in the estimation.

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

$$\pi_{jm} = (p_{jm} - mc_{jm}) M s_{jm}(\mathbf{p}, \mathbf{x}; \boldsymbol{\psi}), \tag{5}$$

where mc_{jm} is the marginal cost of store j, defined as $ln(mc_{jm}) = \mathbf{w}_{jm}\gamma + \omega_{jm}$, where $\mathbf{w}_{jt}$ are the cost shifters; M is the total market size; $\mathbf{p}$ is the price vector; $\mathbf{x}$ is the store characteristics matrix; and $\boldsymbol{\psi}$ represents parameters to be estimated. The main cost shifters for retail food stores are labor costs, building costs (rent), and the 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 that p_{jm} is the result of a pure strategy Nash equilibrium. The fact that individual stores decide their own prices in Sweden supports this assumption. The first-order conditions then imply

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

[10] Berry et al. (1995) and Berry et al. (2004) provide rich discrete choice frameworks to model demand.

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

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

The demand equation (3) can be estimated separately from or jointly with equation (7), the latter of which 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 an 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 a valid instrument.

We use the demand estimates to construct per-period profits for large and small stores. The average per-period profits of a store of type z in market m are

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

where n_{zm} is the number of stores of type z. Sections 4 and 5 discuss the empirical implementation and the results of the demand estimation.

2.2 Entry and exit

In the beginning of each period, a set of incumbents $\mathbf{J}$ and potential entrants $\boldsymbol{\mathcal{E}}$ 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 known to all players, however.

Potential entrants decide whether to enter a store of type $z \in \mathcal{Z}$ or to not enter the market. Entrants' decisions are made one period ahead of the period in which they start to operate. The entry costs for potential entrants that choose store type z, κ_z, are a draw

[11] The simplest version of the model only incorporates differentiation in store type. The model can be generalized to account for location and firm, but the computational burden will increase because of the large state space. In Sweden, individual stores decide their own prices, the majority of stores operate as independent or franchise units, and the distributions of size and sales are similar for stores associated with 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 it is in many other countries. Only a few studies 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).

from the distribution $F^{\kappa_z}(\cdot|\boldsymbol{\theta})$. Sunk costs are private information that is known prior to players' decisions and are i.i.d. from a known distribution (Bajari et al., 2007; Pakes et al., 2007). The entry costs might be higher for larger store types. 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 that is active in a local market, (n_z, n_{-z}) and exogenous profit shifters that are specific to each type, $\mathbf{y}$. The index $-z$ includes all types except z. Furthermore, we assume that local markets are independent, 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 exits. The exogenous profit shifters that cover both demand and variable 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. The profits of stores of the same type are therefore identical. We do not allow stores to invest or change owner or format. The fact that store concepts are rather uniform in the retail food market justifies this assumption.

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

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

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 the rivals' type decisions $(e_z, e_{-z}, x_z, x_{-z})$ conditional on itself continuing, i.e., $\lambda^c_z = 1$. The optimal policy for an incumbent is to exit if the draw of the sell-off value is larger than the value of continuing in the market, which gives the probability of 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 their 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 the market. 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 those for all other types and the outside option. Hence, first, we have the condition that the entry value needs to be larger than the draw of the entry cost. Then, we have that the type (location) decision needs to give the highest expected discounted future profits among all type alternatives:

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

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

Equilibrium. Incumbents and potential entrants make simultaneous moves, and they both form the perceptions of entry and exit among rivals. In equilibrium, these perceptions need to be consistent with stores' actual behavior. The incumbents' perceptions of rival incumbents' behavior need 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, which is the probability that the draw of the exit cost is larger than the value of continuing. Similarly, all potential entrants have the same probability of entering 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. Thus, again the perceptions are the same for all rivals of the same store type.

For incumbents, we need to construct the perceptions of p^c_z in equation (10). Conditional on a z-incumbent continuing, we have to compute the perceived probabilities of facing a particular number of entrants and exits of each type $p^c_z(e_z, e_{-z}, x_z,\ x_{-z} | n_z, n_{-z}, \mathbf{y}, \lambda^c_z = 1)$. That is, the probability that the exit draw is larger than the type-location continuation

value $\phi_z > VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})$ 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 the equilibrium behavior. The assumption that competitors are identical in type implies that incumbents' perceptions of competitors' exit from each type are given by the multinomial logit probabilities in the case of more than two choices and by the binomial distribution in the 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 of entry. 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 entrants conditional on that they enter, while $g_z^e(\cdot)$ and $g_{-z}^e(\cdot)$ are the 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 only one profile of equilibrium policies that is consistent with a given data-generating process. The data will thus select the equilibrium that is played. As POB argue, the correct equilibrium will be selected if samples are large enough. For this purpose, the present paper takes advantage of the detailed data that 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

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

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., $p_z^x(\mathbf{s}) = Pr(\phi_z' > VC_z(\mathbf{s}'; \boldsymbol{\theta}))$. Thus,

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

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

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

where σ_z is a parameter in the exponential distribution that represents 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, we define 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

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

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 that are actually earned by stores that continue from state $\mathbf{s}$, i.e., to insert 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 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 transitions 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

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

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 the fact that incumbents' calculations are conditional on continuing. Now, we use equation (19)

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

to get estimates of $\boldsymbol{VC}_z(\cdot)$ as a function of $\boldsymbol{\pi}_z$, $\tilde{\boldsymbol{p}}_z^x$ and $\tilde{\boldsymbol{W}}_z^c$:

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

where I is the identity matrix. The calculation of the continuation values includes inversion of the transition matrix. $\widehat{\boldsymbol{VC}}_z(\cdot)$ is the mean of the discounted values of the actual returns by players, creating a direct link to the data. Since $\boldsymbol{W}_z^c$ and $\boldsymbol{p}_z^x$ are independent of the parameters (for a known β), they only need to be constructed once. The computational burden decreases because the transitions are only constructed in the beginning of the estimation routine. The burden increases, on the other hand, in the number of states, mainly due to the inversion of the transition matrix.[13]

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

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

The expected value of entry is then

$$\begin{aligned}\widehat{\boldsymbol{VE}}_z(\cdot) = \; & \left[\tilde{\boldsymbol{W}}_z^e + \beta\tilde{\boldsymbol{W}}_z^e[I - \beta\tilde{\boldsymbol{W}}_z^c]^{-1}\tilde{\boldsymbol{W}}_z^c\right]\boldsymbol{\pi}_z \\ & + \left[\beta\tilde{\boldsymbol{W}}_z^e\beta\tilde{\boldsymbol{W}}_z^c[I - \beta\tilde{\boldsymbol{W}}_z^c]^{-1}\tilde{\mathbf{p}}_z^x + \beta\tilde{\boldsymbol{W}}_z^e\tilde{\mathbf{p}}_z^x\right]\sigma_z.\end{aligned} \tag{23}$$

3 Data and characteristics of the Swedish retail food market

Many retail food markets in OECD countries consist 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 their own prices. This contrasts national pricing, which exist, for example, in the UK. The centralized decision making, and thus the concern about national strategies, in the Swedish retail food market is thus less pronounced than that 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 that traditionally collaborate on wholesale provision and logistics. Axfood and Bergendahls each have a mix of franchises and centrally owned stores, the

[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.

latter of which are mainly located in the south and southwest of Sweden.[14] Coop, on the other hand, consists of centralized cooperatives, and decisions are made at the national or local level. In 2011, about 90 percent of all stores were connected to one of four firms: ICA (49 percent), Coop (22 percent), Axfood (15 percent), and Bergendahls (7 percent). Various independent owners make up the remaining 7 percent market share. International firms with hard discount formats entered the Swedish market in 2002 (Netto) and 2003 (Lidl).

Entry regulation. The majority of OECD countries have entry regulations that give power to local authorities to decide on store entry. 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 on applications for new entrants. All stores are regulated by the PBA in Sweden, contrasting, for example, the regulations in U.K., which explicitly focus on large stores. Each store that wants to enter the market needs to send a formal application to the local government. The local governments approve or reject applications after evaluating the potential impact of the store's entry on the market structure, prices, traffic, broader environmental issues and so forth. Inter-municipality questions of entry are handled by the 21 county administrative boards. The PBA is considered 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 entry regulation affects market outcomes (Pilat, 1997; Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2). Appendix A describes the PBA in greater detail.

We use several measures to capture the degree of entry regulation in the local market. 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). For Sweden, we expect that non-socialist local governments are more liberal regarding new entry.[15] This is confirmed by simple reduced-form regressions. In all, 117 of the 290 municipalities have had a non-socialist local government for at least one of the years in our study period. With local government (municipal) elections, there are 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 (PBA) to local authorities for each municipal-

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

[15] 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.

ity and year. This includes applications to change land-use plans and the total number of existing land-use plans.[16] The data are collected by the Swedish Mapping, Cadastral and Land Registration Authority (Lantmäteriet).

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.[17] In detail, we use an index in which half the weight is the share of non-socialist seats in local governments, one quarter is the number of approved applications over the total number of stores and one quarter is the number of approved applications over the number of existing land-use plans. It is important to point out that our regulation index is not sensitive to the size of the market by construction. The higher the index is, the more liberal regulations are. The lower and upper bounds of the index are 0.032 and 1.28, respectively. The median is 0.28, and the standard deviation is about 0.14. We define municipalities to have restrictive (liberal) regulations if the index is below (above) the median. The empirical findings are robust to different definitions and cut-off points on the regulation index. To keep the exposition tractable, we report results using only one index definition.[18]

Data. Three different data sets covering stores, demographics, and prices are incorporated in our empirical application. The store data are collected by Delfi Marknadsparter AB (DELFI), where a unit of observation is 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 the 2001-2008 period and contains the store's geographic location (geo-coordinates), store type, firm affiliation, revenue class, sales space (in square meters), wholesaler and the quarter location (geo-coordinates). The store type classification (12 different) depends on size, location, product assortment, and so forth. Advantages of the data are that they are collected yearly and include the total population of stores. We drop gas station stores from the data since these stores are located in special places and offer a limited 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) with the data from DELFI. We include information on the demographic distribution of the population (e.g., share of

[16]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 of the 290 municipalities and are available 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.

[17]See Suzuki (2013).

[18]The results using different regulation indexes are available from the authors upon request.

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

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

Prices. The data on product prices are 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 2003-2008 period. The sample thus covers roughly 20 percent of the total number of stores. Stores of different sizes, formats and firms are investigated across the entire country.[20] The surveyed products cover a wide range of frequently purchased items of well-defined brands and pack sizes. The "regular price", i.e., the price is without temporary promotions or discount campaigns (due to, for example, loyalty cards) is collected for each product. Based on the name and address of the stores in DELFI, we identify the stores that are included in the PRO survey. Because the empirical implementation of our model relies on all stores, we define a product basket for which we construct a price index by store type, firm, local market and year. In the empirical implementation, we use a basket containing eleven products. For robustness, we also use a basket with only three products. Our main results are robust to the basket choice. The results only indicate changes in the size of profits and costs but the cost ratio for small and large remains the same. Appendix B provides details about the components of the product basket and descriptive statistics of the price.

Store types. DELFI relies on geographical location (address) and classifies store types, making this data set appropriate for defining store types. Store types are similar for stores that are affiliated with different firms and we analyze several store types together. We define the five largest types (hypermarkets, department stores, large supermarkets, large grocery stores, and other[21]) 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 analysis. We believe that these types are representative of small and large stores in the Swedish retail food market.

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 estimating sunk cost

[20] 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.

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

and fixed cost. Thus, we do not include stores that switch owners but continue to operate at the same address.

Table 1 shows aggregate statistics for the 2001-2008 period. The total number of stores decreases by 16 percent to 5,240 at 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 account for the majority of the 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 improvements in efficiency. The total number of entrants is rather constant over time, with the number of exits being slightly less than double the number of entrants.

The majority of entrants and exits are small stores (Table 2). Among small entrants, between 25 and 75 percent were not affiliated with any of the main four firms during the 2001-2008 period (higher at the beginning of the period). In comparison, the share of large entrants without an affiliation to any of the main firms varies between 14 and 21 percent. Regarding exits, up to half of the small stores do not belong to one of the main firms, whereas up to 20 percent is found for large.

Table 3 shows that the distributions 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 without an affiliation to the main firms are substantially smaller and have lower sales.

Figures 1 and 2 show how the number of stores evolves for the different firms over 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 stores affiliated to three of the main firms: 28 percent for ICA, 26 percent for Coop, and 11 percent for Axfood. The reverse trend is found for Bergendahls and hard discounters. The number of large stores increases for ICA and Bergendahls and is fairly constant for Coop, while it decreases for Axfood and Others. There is a substantial decline in stores that are affiliated with ICA, Coop, and Others, whereas the changes are smaller in magnitude for small stores that are affiliated with 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 consists of mainly stores affiliated to ICA, Axfood, Coop, and Others, i.e., well established players in the market. Hard discounters and small stores that are owned by Others dominate entry, together with Axfood. Note, however, that these observations concern only the number of stores and not capacity (size/type of store).

Table 4 presents the entry and exit rates across markets and owners for the 2002-2007 period. 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 that for exit. Since entry and exit do not occur in all markets, we observe variation in the upper percentiles. For example, the entry rate for the 75th percentile varies substantially over time (0-0.06).

Figures 5 and 6 show that the average entry and exit rates share similar trends for national chains, whereas the entry rate is very 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 entry is 15-30 percent. The overall correlation between entry and exit rates is 0.04, whereas the correlation between the number of entrants and the number of 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 for buying food is relatively short (except if prices are sufficiently low), and nearness to home or work is therefore a key concern for consumers in choosing where to shop, though distance likely increases with store size.[22] 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, in which stores in one market competitively interact only with other stores in the same local market. The 21 counties in Sweden are clearly too large to be considered local markets for our purposes, while the 1,534 postal areas are likely 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 stores, such as hypermarkets and department stores, while municipalities seem more suitable for large supermarkets. As noted, municipalities are also where local government decisions regarding new entrants are made. We therefore use municipalities as local markets.

[22]The importance of these factors is confirmed by discussions with representatives from ICA, Coop, and Bergendahls.

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 the continuation value. To compute the value functions for each market configuration (liberal and restrictive), we need an estimation of the profit function for small and large stores in those markets. Evaluating 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.

Modeling firm. Because our main focus on small and large stores implies increasing computational complexity, this paper controls for firm/owner only in the static part of the model, i.e., the discrete choice demand. Using the framework to understand store dynamics by firm/owner is straightforward, however. A simple choice would be to drop the store type differentiation and only model the dynamics of the number of stores that are affiliated with ICA and Coop, for example. For an examination of entry regulation and application to the Swedish retail food market, modeling store type differentiation is more interesting since it provides information concerning the trade-offs between small and large stores in a market where all stores are regulated. 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 (m^2) and dummies for the main firms (ICA, Axfood, Coop, and Bergendahls). In addition, we use specifications with controls for local market characteristics, such as income, population, share of children, and pensioners. For all estimates, the large product basket is used to measure price (see the data section for details). Buying food from stores other than those affiliated with the four main firms is our outside option (s_{0m}). 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 $s_{jm|z}$. As an 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 costs. As an instrument for the within-group share, we use the log of the number of stores of each type in the local market, which is correlated with the number of stores.

Estimation of profit generating function. We use our demand estimates to construct profits for each store type and market (equation (8)).[23] The parameters of the profit function are estimated statically and are a primitive in the second part of the estimation when

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

the parameters of the cost distributions are estimated. The profit of a store type is a function of state variables. For each state that is part of the transition probability matrices, a profit measure for each store type can be obtained. We estimate a reduced form per-period profit-generating function as a function of the state variables by regressing profits on the number of competitors of different types, all exogenous state variables (discussed in detail below), and local market fixed effects. Profits for stores of type z in market m in year t are

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

where n_{ztm} 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); $\mathbf{y}_{tm}$ includes exogenous state variables (profit shifters) and market-year fixed effects; and ϵ_{ztm} is a type-market specific error term that is i.i.d. Controlling for type implies different profit functions for types, and the goal is to estimate the parameter vector of the profit function $\boldsymbol{\gamma}$.

The numbers of stores of each type are the endogenous state variables. To obtain accurate cost estimates, we use a rich specification of the exogenous state variables that includes profit shifters of both demand and variable costs. The nature of retail food products implies that population and income are key variables that shift demand. On the cost side, we add the median of each stores' minimum distance to its nearest distribution center for each store type and market.[24] We also control for the degree of local market regulation and for unobserved heterogeneity using market fixed effects.

To better control for unobserved market effects when estimating the cost parameters, we use the 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 include the following profit shifters: population, income, average distance of the store type to the nearest distribution center, squared population, squared income, squared distance, regulation (index), and local market fixed effects, i.e., $y_{mt} = \hat{\gamma}_{pop} pop_{mt} + \hat{\gamma}_{inc} income_{mt} + \hat{\gamma}_{dist} dist_{mt} + \hat{\gamma}_{pop}^2 pop_{mt}^2 + \hat{\gamma}_{inc}^2 income_{mt}^2 + \hat{\gamma}_{dist}^2 dist_{mt}^2 + \hat{\gamma}_{reg} regulation_{mt} + \hat{f}_m$. The market index y_{mt} helps us to reduce the dimensionality of the state space. An alternative approach to reduce the dimensionality of the transition matrices is to classify geographic markets into smaller groups and to use the fact that the market fixed effect does not change over time (Dunne et al., 2013).

The advantage of a static profit estimation approach is that it allows for a better control for unobserved heterogeneity. Even if a rich profit function specification including local mar-

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

ket fixed effects is used, there might still be 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.

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 entry regulations 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 that we consider trade-offs between small and large stores. The approach follows the strategy of 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 entry regulations are, and the cost distributions for each store type are allowed to vary by market group. As explained in Section 3, we define municipalities to have a restrictive (liberal) implementation of the PBA if our regulation index is below (above) the median.[25] The grouping of local markets is considered exogenous to the stores, and we consequently do not try to model expected changes in regulations over time. We then make detailed comparisons of the link between the regulations, store size, and cost structures.

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 cities, such as 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 is part of the state space, we discretize the index 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 probability matrices ($\boldsymbol{W}_z^c$) and ($\boldsymbol{W}_z^e$) are computed for each store and market type using the observed states in the data and equations (20) and (22). After the transition matrices are computed, they are kept in memory to increase the computation efficiency. Calculating the inverses of the transition matrices is the most demanding computational task.[26] For stores that continue

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

[26] 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 that are needed to evaluate the value functions on an

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 equations (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 probability matrices are consistent.

The dynamic model assumes that the transition matrices are stationary (Ericson and Pakes, 1995). Nonstationarity is not a problem in our retail application. First, all state variables are stationary.[27] Even if the number of stores is stationary around a trend, this does not change during the study period. Second, we believe that there are no factors that drive nonstationarity in the retail data. During the study period, there were no major economic events that created structural changes in the Swedish retail industry that could lead to non-stationarity in the data.

Structural parameters. The final stage of estimation involves the parameter estimation for the distributions of sunk costs and sell-off values of exit. We assume that the sell-off values follow an exponential distribution. For the entry costs, we assume that the distribution is unimodal, i.e.,

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

for $\mu \in (1/a, \infty)$, 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., the cost of buildings and logistics, and we expect that $\kappa_{large} > \kappa_{small}$. To allow for a correlation in entry costs, we assume that $\kappa_{large} = \kappa_{small} + \mu$, where κ_{small} and μ follow unimodal distributions with parameters a_1 and a_2, respectively.

The continuation value is computed for each state and is 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 that are observed in the data for each type and that are, 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

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

ordinary laptop with a dual-core processor.

[27] The nonstationarity in the state variables can be rejected using simple unit-root tests.

where $\mathbf{A}_R$ is the weighting matrix that is 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, but is not the asymptotic optimal matrix.

5 Results

This section discusses the estimated results for the profit-generating function and the cost parameters. In our sample, the median store size is about 215 square meters for small stores and about 1,725 square meters for large stores, i.e., a median large store is about eight times larger than a small store. In terms of revenue, a median large store sells about ten times more than a median small store. The revenue per square meter of a median large store is about 21 percent higher than that for a median small store. These figures emphasize the importance of estimating costs separately for small and large stores, 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 (m^2) and dummies for the main firms (ICA, Axfood, Coop, and Bergendahls), 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 the coefficient is smaller after we control for local market characteristics that shift the demand.[28] In the OLS specifications, the coefficient of the within store type (group) share is about 0.90. It decreases to 0.14 when instrumenting within-type share, which is consistent with the existence of demand shocks that affect both total demand and within-type share. The coefficients for store size and dummies for major firms are positive, as anticipated.

Having the demand estimates, we compute the implied price elasticities. We calculate unweighted average own and cross price elasticities for 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 stores and 0.012 for large stores. These findings indicate that asymmetric

[28] Note that the price enters the demand equation with a negative sign.

competition exists within store types, i.e., the own price elasticities are larger (in absolute terms) than the cross price elasticities. For example, the impact of increasing the prices of a large store on the market share of another large store is substantially larger than the impact of increasing the prices 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 prices of small stores on the market shares of large stores is smaller than that of increasing the prices 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.

We use the demand estimates to construct average per-period profit for small and large stores according to equation (8). 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 are a good approximation of the annual reported profits. The reported average annual profit for small stores belonging to ICA is SEK 230,000. The average annual profit range for large stores is SEK 1.1 to 4.3 million (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 stores, and SEK 2.1-2.35 (5.33-7.91) million for large stores. The next step is to use these profits to estimate a profit generating function and to obtain an estimate of stores' profits for each value of the state space.

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 the mean operating profits for each store type in different geographical markets. We present the results of four different specifications. The covariates in specification $\mathcal{M}_1$ are the number of small stores, the number of large stores, the number of small and large stores squared, a store type dummy, the store type dummy interacted with the number of small and large stores, the population and population squared, and the average distance and distance squared to the nearest distribution center for each store type and market. Specification $\mathcal{M}_2$ adds local market fixed effects to $\mathcal{M}_1$, specification $\mathcal{M}_3$ includes average local market income and income squared in $\mathcal{M}_2$, and specification $\mathcal{M}_4$ adds the local market regulation index to $\mathcal{M}_3$.

The OLS estimator with robust standard errors is used to estimate specifications $\mathcal{M}_1$-$\mathcal{M}_4$. It is important to make the following remarks. First, these estimates come from aggre-

gate data at the type level that are based on our nested logit demand estimates.[29] Second, the reported results are averages of the estimated operating profits over markets. Third, the relative difference between the profits of small and the profits of large stores is more valuable than our absolute estimation, which depends on our assumptions presented in the previous section.

In all specifications, the coefficient for the number of small stores is negative and statistically significant at the 1 percent level. On average, an additional small competitor decreases the profits of a small store by about 7 percent (specification $\mathcal{M}_1$).[30] The coefficients for the number of large stores and the marginal effect of the number of large stores on profits are also negative in all specifications. The coefficient of the number of large stores squared is statistically significant at conventional levels. The marginal effects show that the decrease in the profits of small/large stores from the addition of a large store is about five times greater than that caused by the addition of a small store. The marginal effects for both the number of small and the number of large stores decrease by about 1-2 percentage points when we control for local market fixed effects.

The positive and significant coefficient for the dummy for large stores indicates that large stores make higher profits than small stores. Turning to the interactions of the number of small/large competitors and the dummy for large stores, we find evidence of competition from large stores. Large competitors decrease profits to a greater extent for small stores than for large ones. With the addition of a large store, the decrease in profits is almost 3 percentage points greater for small stores than for large stores. This result indicates that the short-run profits of small stores decrease owing to the entry of large competitors, which is consistent with the long-run trend of larger but fewer stores in the market.

The coefficient for the distance to the nearest distribution center is negative and statistically significant at the 1 percent level in all specifications. That is, lower logistics and distribution costs clearly increase profits. This finding is consistent with previous findings related to Walmart (Basker and Noel, 2009, Holmes, 2011). The coefficients for population and income are not significant at conventional levels when market fixed effects are included. Limited variation over time in these variables is a possible explanation for this finding.

5.3 Structural parameter estimates

Table 8 presents parameter estimates for the distributions of sell-off value and entry costs for each store type (panel A) and the average sell-off value and entry costs in monetary units, i.e., Swedish kronor (panel B).[31] We estimate the entry cost parameters for markets

[29] Section 5.3 and Appendix C discuss an alternative methodology to construct profits.

[30] Marginal effects are computed using averages of the continuous variables.

[31] The mean values in panel B are in millions of 2001 SEK (1 USD=9.39 SEK, 1 EUR=8.34 SEK).

with restrictive and liberal entry regulations. The estimates are obtained using a minimum distance estimator, as presented in the previous section.

We present results for the four different profit function specifications (Table 7). As expected, large stores have higher sell-off values and entry costs than small stores. This result is robust across all specifications. For expositional simplicity and because the differences across markets are fairly similar, we focus on the most complex specification, $\mathcal{M}_4$. Our findings indicate that the average sell-off value is about 10 times higher for large than for small stores. Small stores have entry costs of SEK 12.11 and 13.56 million in liberal and restrictive markets. The entry costs for small stores are thus 10 percent lower in liberal than in restrictive markets. For large stores, the corresponding entry costs are SEK 110.9 and 136.5 million, i.e., the entry costs for large stores are 18 percent lower in liberal than in restrictive markets. Publicly available investment costs for constructing a completely new store, including the land, buildings, and equipment are consistent with our estimates of the average entry costs. The reported cost is 8.5 million for a small Coop store in a small market (Årjäng), 80 million for a large ICA store in a relatively large market (Malmö), and 123 million for the 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 the reported costs for land and buildings. Related to the existing entry regulations in the EU, our results suggest that the trade-off between small and large stores plays a key role in decisions regarding which stores are allowed to enter the market.

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 costs follow a unimodal distribution. The value functions are computed for each state and are expressed in millions of 2001 SEK. VE_z does not depend on the estimated parameter of the entry cost distribution. However, lower entry rates imply larger entry costs. The implications of differences in entry costs are explored in the counterfactual analysis. The slopes of the profit function show the toughness of short-run competition, and entry and exit have a long-run impact on store profits.

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. These descriptive statistics are computed using all observed states in the data. For both store types, the average VC_z and VE_z are lower in liberal than in restrictive markets. For incumbents, all distribution measures of VC_z are lower in liberal than in restrictive markets. The lower percentiles of VE_z (below median) are higher in liberal markets than in restrictive markets.

Table 10 shows the continuation values (VC_z) and entry values (VE_z) for a selection of states. Both the continuation and the entry values increase with the exogenous market index y_{mt}. This includes profit shifters and accounts for unobserved market heterogeneity. Increasing the market index from 1 to 2 (high profit regime) in liberal (restrictive) markets, with 4 small and 3 large stores, increases VC_{small} from SEK 5 to 32 (13 to 18) million and VC_{large} from SEK 36 to 261 (121 to 163) million. The values of entry in liberal (restrictive) markets also increases: VE_{small} increases from SEK 0.8 to 5.4 (1.7 to 9.9) million and VE_{large} increases from SEK 6 to 44 (15 to 81) million. 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 a market index of 4, the continuation and entry values in restrictive markets decrease from SEK 7.7 to 5.6 million for small stores, and from SEK 73 to 51 for large stores. For several states, an increase in exogenous profit shifters (part of market index y_{mt}) outweighs more intense competition. The net effect of increasing the number of large stores from 2 to 3 and increasing the market index from 1 to 2 in a market with 4 small stores, for example, is an increase in continuation values. These findings highlight the complexity of the market dynamics when two store types are used and local market heterogeneity is allowed for.

Considering store type differentiation allows us to analyze the trade-offs between large and small stores and to investigate the relative importance of each store type for long-run profits and market structure. For example, in liberal markets, an additional large store decreases the continuation values to a greater degree than two additional small stores in a low profit regime market ($y_{mt} = 1$) with 9 small and, 2 large stores: $VC_{small}(9, 2, 1) = 7.07$, $VC_{small}(9, 3, 1) = 5.56$, and $VC_{small}(11, 2, 1) = 5.81$. The unique possibilities that 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 reduced-form regressions (OLS estimator) to summarize the impact of changes in the state space variables on VC_z, VE_z, p_z^e and p_z^x. Table 11 shows the average marginal effects of an additional store.[32] On average, long-run profits decrease when the number of rivals increases. The decrease in long-run profits from an additional large store is about three times greater than that from an additional small store. Moreover, the reduction in long-run profits is greater for small than for large incumbents. These findings are consistent with our profit generating function estimates, and emphasize asymmetric competition between store types. In addition, the impact of an additional store on long-run profits is

[32]We also compute the whole distribution of the marginal effects. While analyzing the entire distribution provides rich information about competition effects, the average values of marginal effects provide a consistent summary of these effects.

about 1-2 percentage points larger in restrictive than in liberal markets. The greater effects on competition on average in restrictive compared with liberal markets may suggest that restrictive markets fail to attract sufficient additional demand due to insufficient product differentiation. This result might also be explained by the fact that the marginal effect of an additional store on long-run profits is 3-4 percentage points lower for entrants (VE) than for incumbents (VC). Another explanation for this result is that restrictive markets tend to consist of fewer stores, and thus, we would expect the continuation values to decrease to a greater extent. The probability of exit increases, for both small and large incumbents, when an additional small store enters in the market.

More intense competition from stores decreases the probability of entry for potential entrants. An additional large store decreases the probability of entry to a greater degree than an additional small store. However, the competitive effects on the entry values and probability of entry are similar in restrictive and liberal markets.

Robustness. Before turning to the counterfactual exercise on costs that quantifies the impact of regulations, we discuss different robustness specifications regarding the profit measures and the estimation of cost parameters. Appendix C presents an alternative approach to constructing operating profits. Assuming that stores of the same type have identical variable costs, we can construct the operating profits for each store type as the difference between the gross profit margin and the costs of rent and wages (Holmes, 2011). Using this profit measure, our results regarding asymmetric competition between store types remain robust (Table C.1 in Appendix C).

We also provide various semi-counterfactual experiments that use a pseudo-likelihood estimator (Table C.2 in Appendix C).[33] An increase in the number of potential entrants results in higher entry costs and sell-off values for small stores, but the gap between them decreases (Specification 1). In other words, the entry costs increase to a lesser degree compared with the sell-off value for small stores when the number of potential entrants increases. In contrast, increasing the number of potential entrants does not affect the costs for large stores. 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 stores to a greater degree than large stores.

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 the sell-off value and the entry costs 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 costs for large stores. These results suggest that large stores

[33]The optimization problem of using two types is more complex than having one type and using a pseudo-likelihood estimator. For this reason, we use different optimizers, such as Nelder-Mead, CMA-ES, and BOBYQA (Bound Optimization by Quadratic Approximation).

enter strategically, e.g., they might select better locations.

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

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, continuation value, value of entry, probabilities of entry and exit, and net change in market structure. In the first counterfactual exercise, we reduce the costs in restrictive markets to be equal to those in liberal markets. In the second counterfactual, we only decrease the costs of small stores in all markets. 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). In other words, we need to recompute transition matrices for incumbents and entrants of each store type in markets with different regulations. For each store type, we assume that the potential entrants for small and large stores follow different Poisson distributions.[34]

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 the market structure in local markets with liberal and restrictive regulations. In this counterfactual exercise, we focus on local markets with a restrictive implementation of the regulation (Dunne et al., 2013). 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. We assume that there is no change in the regulatory environment or in how the local authorities apply the regulation. Based on the new entry cost parameters, i.e., if the restrictive markets had liberal regulations, we compute the new equilibrium values for small and large stores. This computation yields new values of incumbent stores continuing in operation (VC_z^{cf}), values of potential entrants (VE_z^{cf}), and probabilities of

[34]The parameters of these Poisson distributions are chosen to fit the Swedish local markets, where the expected number of potential entrants for both small and large stores is 9. The procedure automatically performs different test to check whether we obtain reasonable transition probabilities that are consistent with the observed behavior in the local markets. A large value for the expected number of potential entrants increases computational burden substantially when two store types are used (a large number of combinations is required to compute the value of an element in the transition matrices). Based on the discussion with people in the market and given that the number of stores decreases over time, it is unreasonable to assume that there is an infinite (or very large) number of potential entrants in the retail food industry.

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 restrictive regulations. For each store type in restrictive markets, we compute the difference between the 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, entry values, long-run profits, probabilities of entry and exit, and net changes in the number of small and large stores. In contrast to previous work, we quantify the consequences of entry regulations in light of trade-offs between small and large stores.

Table 12 shows the changes in the value functions (VC_z and VE_z) and the exit and entry probabilities (p_z^x and p_z^e) when the 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 costs by 10 percent, i.e., from SEK 13.56 million to SEK 12.11 million for small stores. For large stores, we reduce the entry costs by 18 percent, i.e., from SEK 136.5 million to SEK 110.9 million (Table 8).

The reduction in entry costs induces an average decrease in the continuation value VC_{small} by 0.5 percent in markets with a low profit regime (low index y). In these markets, the changes in VC_{small} varies between -4 percent and +2 percent. While we observe large variation in changes in 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 the aggregate, this result suggests that there is an increase in competitive pressure from new entrants that induces a decrease in store value. The change in the probability of exit is very small, suggesting that an even higher increase in the competitive pressure would be needed to increase the exit rate for both small and large stores.[35] The reduction in entry costs in restrictive markets induces an increase of 3 percentage points in the average probability of entry. In the upper part of the distribution, the increase is as high as 13.5 percentage points. For potential entrants, the average value function of small stores (VE_{small}) increases by 9.2 percent and 8 percent in low and high profit regime markets, respectively. However, we observe large dispersion in VE_{small}, e.g., a reduction by about 4 percent for some states and an increase of up to 53.5 percent for other states. This result is not surprising because competition from the entry of large stores increases as a result of the lower entry costs for large stores. Overall, increasing the likelihood of entry for small stores without inducing the exit of other small stores benefits consumers because of the increased product differentiation and decreased transportation costs (travel distance) for buying food.

For large stores, the reduction in entry costs decreases the average store value function

[35]These results are confirmed by using the profit specification $\mathcal{M}_1$. This specification implies a larger reduction in entry costs for both small and large stores, which results in a more substantial increase in the probability of exit. The results are available from the authors upon request.

(VC_{large}) by about 15 percent. The reduction is larger in states with low profit regime, where the increase in the probability of exit is somewhat larger than in a high profit regime markets. For the observed states in the data, the sum of cumulated changes in VC_{large} is negative, suggesting that competition increases in the long run because of new entrants of both store types. By reducing the entry costs of small and large stores, the median reduction in VE_{large} is about 7 percent in low profit markets. The largest reduction is about 30 percent in low profit regime markets and about 9 percent in high profit regime markets. The complexity of the dynamics when the entry costs of two store types are reduced increases the value of entry in some states (with a larger increase in high profit markets). The reductions in entry costs in restrictive markets induce an average increase in the probability of entry by 1.8-2.8 percentage points for small stores and by 3.1-3.5 percentage points for large stores. In the upper part of the distribution, the increase is as high as 10-14 percentage points. Hence, because the policy of decreasing entry costs in restrictive markets induces a non-trivial increase in entry rates, the markets with high profit regimes have relatively higher entry rates than markets with low profit regimes.

In sum, by reducing the entry costs of both small and large stores, we find an increase 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 between the store types. Differentiating between the cost reductions for the two store types plays a crucial role in successfully increasing entry, which in turn leads to lower continuation values for incumbents. In addition, the policy changes concerning entry costs should account for exogenous features that drive the profitability of the market since we observe large dispersion in the long-run profits within the store type.

Decrease in entry costs for small stores. Because the traveling distance for customers to buy food has increased, the main Swedish retail firms aimed on reinventing small store formats in 2011. Using the structural estimates, we evaluate the impact of a 20 percent decrease in the entry costs for small stores on long-run profits for small and large stores in various market configurations. The difference between this counterfactual and the previous one is that the entry costs of large stores remain unchanged but we reduce the cost of small stores in all markets. In other words, we want to encourage the entry of small stores. Aggregate estimates indicate a median decrease in VC_{small} by 0.1 percent in liberal and restrictive markets. Decreasing entry costs leads to an increase in the probability of exit by about 4 percentage points for small stores and by 3 percentage points for large stores in liberal markets. The average entry value for new small stores (VE_{small}) increases by about 4 percent (0.2 percent) in restrictive (liberal) markets. The decrease in entry costs increases the probability of entry for small stores by 5 percentage points (average across states) in liberal markets and by 8 percentage points in restrictive markets. Since we aim to encourage

the entry of small stores, we find a decrease by 7 percent (median value) in the value of entry for large stores in liberal markets. The long-run profits of small stores decrease by about 1 percent (3 percent) when a small (large) store enters the market.[36] These marginal effects are not sensitive to the degree of regulation in the market.

The findings show the complexity of various effects on the dynamics of the market structure as a result of changes in entry costs of different store types.[37] In sum, our counterfactual results show that there is a trade-off in changes in entry costs between small and large stores when policy aims to increase the number of small stores in a local market. Only reducing the cost of small stores in all markets increases competition between small stores. As a result, we observe increases in both the entry and the exit of small stores, but the net effect is a greater number of stores (net entry). While the local demand conditions are important factors for entry decisions, understanding the cost differences between several store types in markets with different degrees of regulation is important for designing policies that favor the entry of small stores.

7 Conclusions

This paper examines with store dynamics and cost structures in the retail food market by 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 the sunk costs of entry and sell-off values of exit for small and large stores 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 stores. The estimates of own and cross price elasticities show asymmetries between store types. An additional large store decreases short-run profits by 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 between small and large stores remains about four times. The average entry costs for large stores are 18 percent lower in markets with liberal compared with restrictive regulations. The corresponding difference is 10 percent for small stores. The average entry costs are substantially greater than the sell-off values for both store types. This result can be explained by the drastic decrease

[36] These marginal effects are computed by regressing VC_{small} on a linear combination of the state variables (see Table 11).

[37] 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 important to recognize potential changes in the results when using observed profits.

in the number of small stores. 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 for incumbents. We show the importance of the trade-off in entry cost reductions between different store types for product differentiation in local markets with various degrees of regulation. The findings provide suggestions for designing local policies to encourage the entry of small stores.

Future research could assess the importance of spatial differentiation and ownership for the observed differences in the cost structure. These two features are not yet implemented in the dynamic part of the current analysis and could provide additional information regarding the nature of competition and differences in cost structures. Future research could also determine how labor costs 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. (2013): "Demand Fluctuations in the Ready-Mix Concrete Industry," *Econometrica*, 81(3), 1003–1037.

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," *The RAND Journal of Economics (*forthcoming*)*.

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," *The RAND Journal of Economics*, 44(2), 169.193.

Ericson, R., and A. Pakes (1995): "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62(1), 53–83.

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," *The 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 Discrete Dynamic Games (with Entry/Exit Examples)," *The 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," *The RAND Journal of Economics*, 37(3), 619–640.

Suzuki, J. (2013): "Land Use Regulation as a Barrier to Entry: Evidence from the Texas Lodging Industry," *International Economic Review*, 54(2), 495–523.

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.

Sweeting, A. (2013): "Dynamic Product Positioning in Differentiated Product Markets: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry," *Econometrica*, 81(5), 1763–1803.

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 (1 USD=9.39 SEK, 1 EUR=8.34 SEK).

Table 2: Entry and exit by store type and firm affiliation

	All	Small stores		Large stores	
		number	share not affiliated to the main firms	number	share not affiliated to the main firms
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). The main firms are 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 (1 USD=9.39 SEK, 1 EUR=8.34 SEK).

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.

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 of pensioners					-6.008	0.072	-6.524	0.213
Share of children					-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. Pensioners are defined as the population older than 65 years old. Children are defined as the population younger than 12 years old.

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

	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

	Model specification			
	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_4$
Number of small stores	-0.083	-0.071	-0.070	-0.069
	(0.005)	(0.008)	(0.008)	(0.008)
Number of small stores × Large type	-0.001	-0.0008	-0.0008	-0.0008
	(0.004)	(0.003)	(0.003)	(0.003)
Number of small stores squared	0.001	0.0008	0.0008	0.0008
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of large stores	-0.407	-0.361	-0.363	-0.361
	(0.022)	(0.039)	(0.039)	(0.039)
Number of large stores × Large type	0.028	0.026	0.026	0.026
	(0.014)	(0.010)	(0.010)	(0.010)
Number of large stores squared	0.013	0.011	0.011	0.011
	(0.001)	(0.002)	(0.002)	(0.002)
Log of population	-3.676	-2.280	0.983	0.983
	(0.479)	(4.629)	(5.907)	(5.903)
Log of population squared	0.237	0.148	-0.004	-0.007
	(0.023)	(0.217)	(0.278)	(0.277)
Log of distance to DC	-0.308	-1.181	-1.181	-1.181
	(0.179)	(0.260)	(0.260)	(0.260)
Log of distance to DC squared	0.014	0.055	0.055	0.055
	(0.008)	(0.012)	(0.012)	(0.012)
Log of income			-0.311	-0.311
			(0.460)	(0.465)
Log of income squared			0.017	0.017
	No	No	(0.028)	(0.028)
Large type	1.982	1.983	1.983	1.983
	(0.043)	(0.034)	(0.034)	(0.034)
Regulation				0.057
				(0.0121)
Market fixed effects	No	Yes	Yes	Yes
Adjusted R^2	0.750	0.819	0.819	0.819
Root of mean squared errors	0.645	0.530	0.531	0.531
Absolute mean errors	0.121	0.281	0.281	0.281
Number of observations	3,820	3,820	3,820	3,820

NOTE: The dependent variable is the log of estimated average profits by store type, local market and year. OLS estimator is used. Robust standard errors in parentheses. The intercept is included. 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. The index defined in Section 3 is used to measure the degree of regulation in each local market.

Table 8: Estimation results of structural parameters

	Small stores				Large stores			
	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_4$	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_4$
A. Estimated parameters								
Sell-off value (σ)	1.639	48.511	23.786	38.255	0.167	4.812	4.850	2.759
	(0.673)	(2.023)	(1.956)	(1.572)	(0.561)	(0.682)	(0.620)	(0.618)
Entry cost restrictive markets (a)	0.214	0.222	0.223	0.221	0.021	0.024	0.024	0.024
	(0.023)	(0.023)	(0.024)	(0.027)	(0.008)	(0.007)	(0.007)	(0.007)
Entry cost liberal markets (a)	0.272	0.248	0.248	0.247	0.031	0.033	0.029	0.030
	(0.033)	(0.040)	(0.041)	(0.041)	(0.010)	(0.011)	(0.011)	(0.011)
B. Mean of sell-off value and entry cost								
Sell-off value (ϕ)	0.610	0.021	0.042	0.026	6.000	0.207	0.206	0.362
Entry cost restrictive markets (κ)	14.00	13.48	13.43	13.56	158.0	135.82	135.46	136.51
Entry cost liberal markets (κ)	11.00	12.10	12.10	12.11	109.0	102.69	116.66	110.99

NOTE: Standard errors in parentheses. $\mathcal{M}_1 - \mathcal{M}_4$ are different specification of the profit generating function (see Table 7). Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Municipalities are defined to have restrictive (liberal) regulations if the regulation index, defined in section 3, is below (above) the median. 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 μ where k_{large}=k_{small} + μ, where μ follows a unimodal distribution with parameter a_{large}. The mean values in panel B are in millions of 2001 SEK (1 USD=9.39 SEK, 1 EUR=8.34 SEK).

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	0.123	0.012	1.052	0.287
10th percentile	1.112	1.080	8.907	10.158
25th percentile	3.516	3.095	28.698	30.314
50th percentile	12.952	9.528	110.120	78.457
75th percentile	25.682	21.022	206.256	169.943
90th percentile	57.301	41.885	467.575	295.145
Maximum	200.659	92.566	1532.847	709.536
Mean	19.774	14.947	160.897	121.584
B. Value function of entrants				
Minimum	0.110	0.010	0.766	0.082
10th percentile	0.655	1.026	5.310	9.604
25th percentile	1.637	2.349	14.558	20.730
50th percentile	4.645	5.040	39.264	47.705
75th percentile	12.896	12.295	105.474	117.036
90th percentile	34.679	24.611	277.776	218.119
Maximum	100.329	117.986	766.423	1019.193
Mean	12.242	10.280	99.086	92.873

NOTE: Value functions are computed using the estimated parameters for exit and entry distributions and the most complex profit generating function specification ($\mathcal{M}_4$). Only observed local markets configurations are included. Municipalities are defined to have restrictive (liberal) regulations if the regulation index, defined in section 3, is below (above) the median. Numbers are reported in millions of 2001 SEK.

Table 10: Predicted value of dynamic benefits (VC, VE)

Regulation	No. small stores	No. large stores	Market index	Small: VC for incumbents	Small: VE for potential entrants	Large: VC for incumbents	Large: VE for potential entrants
Liberal	4	2	2	35.7615	2.4713	284.0939	21.8547
Restrictive	4	2	2	27.1464	3.1285	228.0202	25.3365
Liberal	4	3	1	4.9464	0.8368	36.3578	6.0592
Restrictive	4	3	1	13.8529	1.7317	121.3900	15.1759
Liberal	4	3	2	32.4546	5.4598	261.9207	44.2216
Restrictive	4	3	2	18.3948	9.9998	163.4181	81.6881
Liberal	9	2	1	7.0755	0.7993	63.7712	7.0874
Restrictive	9	2	1	6.6893	0.7708	55.9924	7.9986
Liberal	9	3	1	5.5633	1.0837	45.8437	9.1689
Restrictive	9	3	1	8.8128	2.9406	79.1162	26.3689
Liberal	11	2	1	5.8128	1.4569	52.9324	13.2308
Restrictive	11	2	1	0.8027	0.4100	6.8217	2.7650
Liberal	32	8	4	7.7899	7.7885	73.7521	73.7780
Restrictive	32	8	4	1.6271	0.5430	13.9804	4.7757
Liberal	32	10	4	5.6536	5.6521	51.8410	51.7837
Restrictive	32	10	4	2.7220	1.3574	24.8102	11.3837

NOTE: The sell-off value follows an exponential distribution. Entry cost follows a unimodal distribution that allows for store type correlation. Municipalities are defined to have restrictive (liberal) regulations if the regulation index, defined in section 3, is below (above) the median. Market index groups the exogenous variables (population, income, and distance to the distribution center) at the local market level: 1 and 2 correspond to markets below the median of this index, and 3 and 4 are for markets above the median. The value functions are expressed in millions of 2001 SEK.

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																
	-0.079	-0.059	-0.279	-0.259	0.0006	0.001	-0.002	-0.001	-0.049	-0.026	-0.214	-0.191	-0.005	-0.002	-0.044	-0.041
	(0.005)	(0.007)	(0.032)	(0.027)	(0.0001)	(0.0006)	(0.0016)	(0.001)	(0.004)	(0.010)	(0.034)	(0.028)	(0.002)	(0.002)	(0.009)	(0.007)
R^2	0.477				0.088				0.407				0.276			
B. Large stores																
	-0.076	-0.053	-0.267	-0.244	0.0005	0.001	-0.001	-0.001	-0.047	-0.023	-0.199	-0.175	-0.003	-0.001	-0.037	-0.034
	(0.005)	(0.009)	(0.031)	(0.026)	(0.0001)	(0.0005)	(0.001)	(0.001)	(0.004)	(0.010)	(0.033)	(0.028)	(0.002)	(0.002)	(0.008)	(0.007)
R^2	0.467				0.096				0.394				0.268			

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: $\ln(y)=\beta_0 + \beta_1 n_{small} + \beta_2 n_{large} + \beta_3 \text{MarketIndex} + \beta_4 \text{Regulation} + \beta_5 n_{small} \times \text{Regulation} + \beta_6 n_{large} \times \text{Regulation} + \beta_7 n_{small} \times n_{large} + u$, 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, *Regulation* 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	Regulation	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	-0.039	-0.402	0.000	0.000	-0.041	-0.305	0.000	0.000
25th percentile	Restrictive	-0.002	-0.199	0.000	0.000	-0.002	-0.163	0.000	0.000
50th percentile	Restrictive	-0.001	-0.142	0.000	0.000	-0.001	-0.073	0.000	0.000
75th percentile	Restrictive	0.001	-0.034	0.000	0.000	0.030	0.020	0.000	0.001
90th percentile	Restrictive	0.013	0.001	0.000	0.000	0.535	0.470	0.135	0.009
Mean	Restrictive	-0.005	-0.159	-1.46E-9	-2.66E-7	0.092	-0.021	0.031	0.018
Sum of changes		-9.194	-2163.134	-1.26E-7	-2.342	120.055	228.471	2.544	2.735
B. Above median aggregated market index									
10th percentile	Restrictive	-0.003	-0.025	0.000	0.000	-0.001	-0.009	0.000	-8.95E-4
25th percentile	Restrictive	-6.95E-4	-0.003	0.000	0.000	0.001	-0.003	0.000	0.000
50th percentile	Restrictive	0.001	-0.003	0.000	0.000	0.011	0.006	0.000	0.000
75th percentile	Restrictive	0.014	0.002	0.000	0.000	0.075	0.097	0.002	0.005
90th percentile	Restrictive	0.061	0.023	0.000	0.000	0.346	0.336	0.106	0.129
Mean	Restrictive	0.010	-0.005	-2.67E-10	-3.18E-8	0.080	0.088	0.035	0.028
Sum of changes		26.139	-249.796	-3.58E-8	-1.851	120.961	844.110	4.068	3.680

NOTE: Profit generating specification $\mathcal{M}_4$ is used in the counterfactual. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Municipalities are defined to have restrictive regulations if the regulation index, defined in section 3, is below the median. The value of exit follows an exponential distribution. Entry cost follows a unimodal distribution that allows for type correlation.

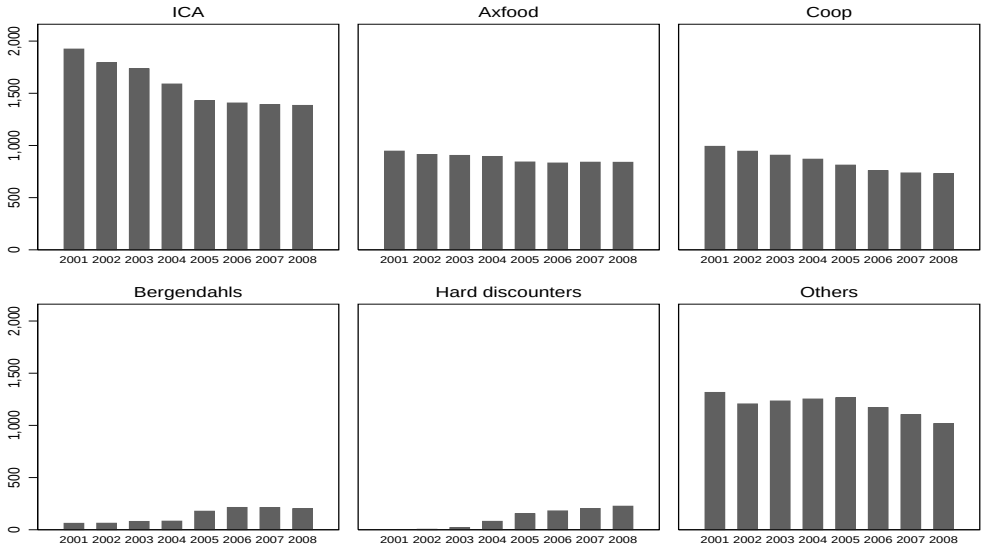

Figure 1: Total number of stores by firm affiliation 2001-2008.

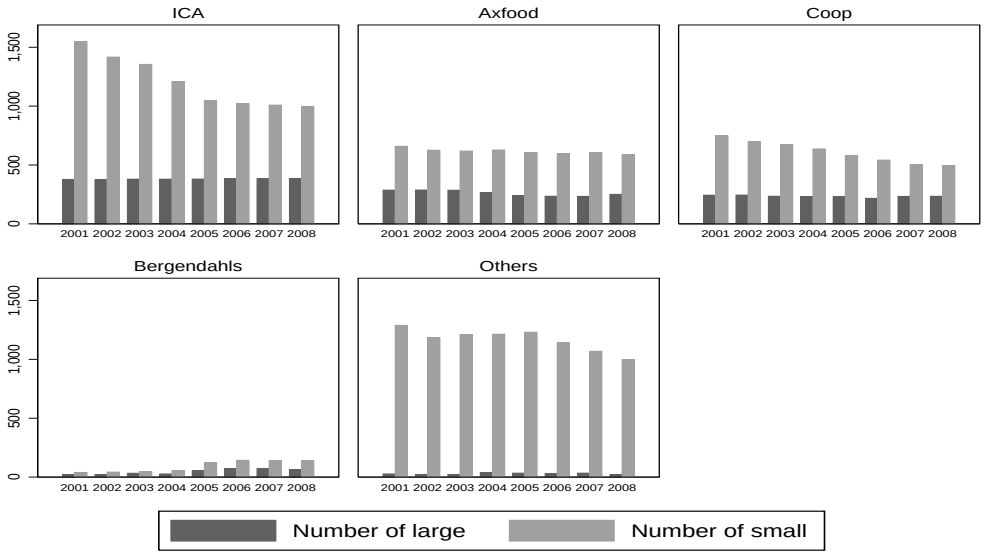

Figure 2: Number of large and small stores by firm affiliation 2001-2008.

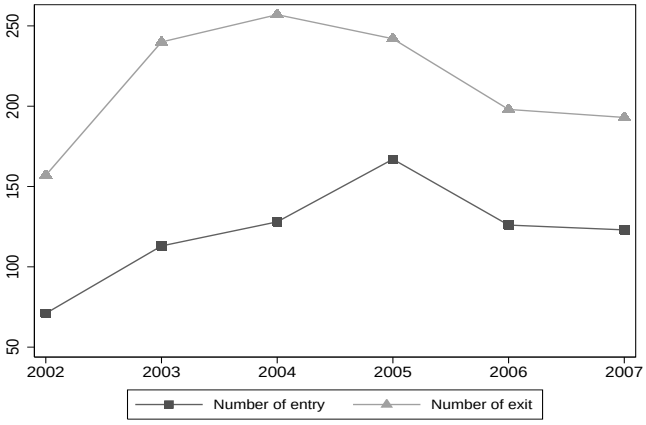

Figure 3: Total number of entries and exits in Sweden 2002-2007.

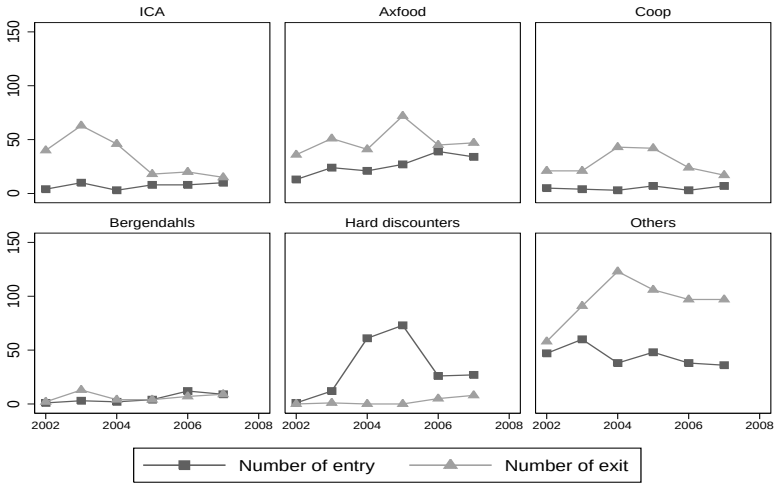

Figure 4: Total number of entries and exits by firm affiliation 2002-2007.

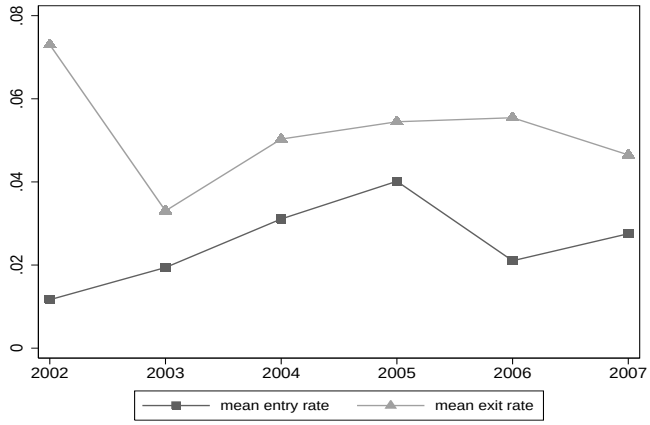

Figure 5: Mean entry and exit rates across local markets 2002-2007.

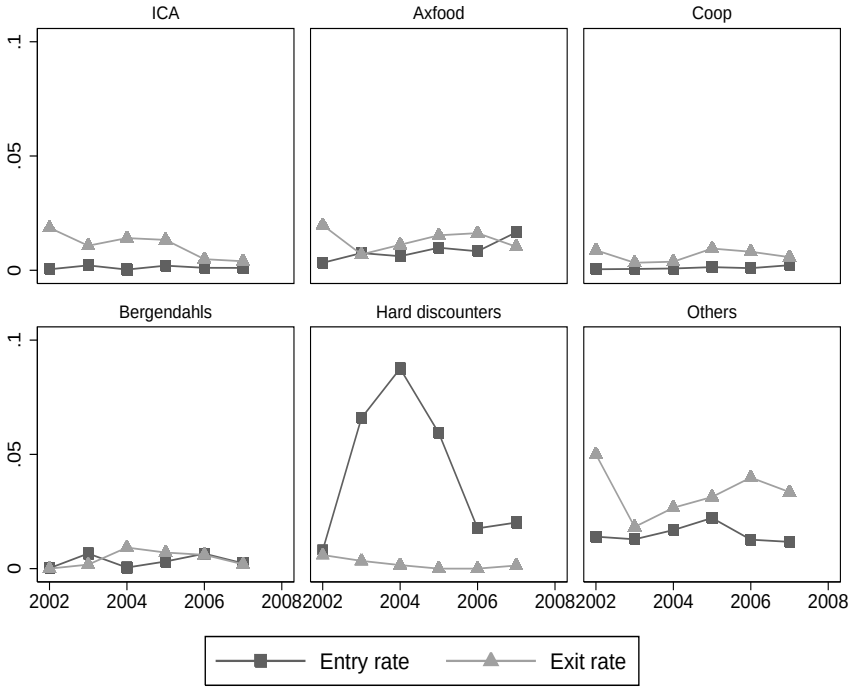

Figure 6: Mean entry and exit rates by firm affiliation and local markets 2002-2007.

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 for market entry become 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 made to the PBA. From April 1, 1992, to December 31, 1996, the PBA was slightly different, prohibiting the use of buildings from counteracting efficient competition. Since 1997, the PBA has been more or less the same as it was 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 policy changes seem small (Swedish Competition Authority, 2001:4). Nevertheless, the PBA is considered 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 PBA, 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 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 that is linked to its geographical location (address). The twelve store types, based on size, location, product assortment, and so forth, 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. Revenue (including VAT) is recorded in 19 classes. Owing 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 in a similar manner. In total, 698 observations from the sales and sales space data are missing.

Appendix B: Price data

The data on prices are 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 2003-2008 period.[38] The sample thus covers roughly 20 percent of the total number of stores. Stores of different sizes, formats and firms are investigated across the entire country. We form a product basket by selecting eleven products that are available in all stores and do not change their characteristics and package size. These products are as follows: sugar (Strosocker Dansukker 2 kg); cereals (Havregryn fiber AXA 800 g); mashed potatoes (Potatismos Felix); macaroni (Snabbmakaroner Kungsornen 1 kg); coffee (Gevalia mellan brygg 500 g); chocolate milk (O'boy Kraft 500 g); bread (Husman Wasabrod 500 g); biscuits (Guldmarie Goteborgskex 200 g); breakfast cereals (Familjemusli orig Finax); margarine (Bregott 600 g); caviar (Kalle kaviar Abba 190 g). Table B.1 shows the summary statistics of the price of a basket that contains one package of each of these eleven products. Large stores offer a cheaper price than small ones for the basket. For both store types, the difference between the 75th and the 25th percentile is about 30 SEK. Table B.2 presents the distribution of the basket prices for small and large stores belonging to main firms. First, for all firms, large stores offer lower prices. Second, Bergendahls offers a lower median price for our selected basket than other firms. Third, the difference between the median price from a large store and from a small store is less than 10 SEK. Fourth, ICA offers the minimum prices among the main 4 firms. The figures show that we have price variation across store types and firms.

Table B.1: Descriptive statistics of the basket price by store type, 2001-2008

Store type	Minimum	Q25	Q50	Q75	Maximum
Small	98.50	192.72	211.90	222.83	327.30
Large	152.80	188.15	203.85	215.50	278.50

NOTE: The price is in 2001 SEK (1 USD=9.39 SEK, 1 EUR=8.34 SEK). The basket consists of eleven products.

[38]Because our store data cover the 2001-2008 period, we compute price predictions in 2001 and 2002. We model the price as an AR(1) process with exogenous controls such us local market demand shifters. This is not restrictive since we only need predicted prices for 2 years. In addition, our demand estimates are robust to the sample choice (2001-2008 or 2003-2008). We prefer to use the full sample (2001-2008) because we use this sample when computing transition matrices in the dynamic setting.

Table B.2: Descriptive statistics of the basket price by firm and store type, 2001-2008

Store type	Minimum	Q25	Q50	Q75	Maximum
Panel A: ICA					
Small	159.00	191.85	210.83	221.25	268.80
Large	152.80	187.37	203.90	215.05	266.90
Panel B: Axfood					
Small	170.20	192.53	213.18	224.03	304.10
Large	165.39	192.30	204.30	215.68	278.50
Panel C: Bergendahls					
Small	166.80	190.07	201.00	220.63	263.70
Large	164.23	186.25	196.39	210.62	262.90
Panel D: Coop					
Small	168.60	195.40	213.90	225.80	327.30
Large	164.23	188.06	204.49	216.39	266.90
Panel E: Others					
Small	98.50	192.72	213.05	222.37	275.30
Large	163.90	186.72	206.68	219.29	263.70

NOTE: The price is in 2001 SEK (1 USD=9.39 SEK, 1 EUR=8.34 SEK). The basket consists of eleven products.

Appendix C: Alternative approach to constructing 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 revenue 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), product stocks, machinery/equipment, and other costs, such as marketing and promotion costs. 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 store types and markets because they, apart from store size, depend on the geographic location of the store. The remaining costs might only vary across store types, and we therefore assume that they are proportional to store size (in square meters and sales).

Having the revenue and the variable costs for each type, we first construct the operating profits for each type and market (Holmes, 2011). Operating profits are defined as he difference between the gross profit margin and costs of rent and wages. In the estimation, we use 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 to account for the cost of running the distribution system, the fixed cost of running the central administration, and other costs. These costs are not considered variable costs.[39]

The average price per square meter for houses sold times the median number of square meters of each store type is a reasonable approximation for the cost of buildings. We assume 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 considered a measure of store size.[40] The total cost of labor is then calculated as wages times three employees for small stores and times five employees for large stores. Relying on these assumptions, we calculate a measure of operating profits $\tilde{\pi}_z$.

[39]The paper accounts for distribution costs in the main specification (Section 4). The minimum distance from each location to the nearest distribution center for each store type will be used as an approximation of distribution costs.

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

Results: estimation of the alternative profit function. Table C.1 shows the estimates of our alternative profit-generating function, without Specification (1) and with Specification (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, the number of large stores, the number of small and large stores squared, a store type dummy, the store type dummy interacted with the number of small and large stores, the population, the population interacted with store type, and year-market fixed effects. The estimation is done using OLS with robust standard errors.

The coefficient for 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 the 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 (with a high number of small stores). One possible explanation for this result is that stores might choose their location to avoid competition (spatial differentiation effect) in large markets.

As for small stores, the coefficients for the number of large stores and the marginal effect of the number of large stores on profits are negative. Large stores have higher profits than small stores, as indicated by the positive and significant coefficient for the dummy for large stores. The coefficient for the number of large stores squared is statistically significant at conventional levels in Specification (1) but not in Specification (2). This result might be observed because of the high prevalence 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 stores, we find clear evidence of store type competition. The profits of a large store decrease by about 9 percent due to entry of an additional large store. That is, large competitors decrease profits to a greater extent for large stores than for small ones. These findings are consistent with results reported in the static entry literature (Mazzeo, 2002) and hold for both specifications.

The coefficient for population is positive and significant at the 1 percent level in Specification (1) but negative when we control for market fixed effects in Specification (2). Small changes in population over time may have led to this result, i.e., the population is absorbed in the local market fixed effects. Furthermore, the population does not seem to influence the profits of large and small stores differently. Apart from market fixed effects, the lack of controls for spatial differentiation and differences in market size by store type is a possible

explanation for this unexpected finding.

Table C.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 are presented 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 C.2: The impact of various policies on entry costs 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 costs and the sell-off value of exit. Standard errors are presented 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 costs follow a logistic distribution. The number of potential entrants is two times the number of actual stores. Specification 1: increase in the number of potential entrants, i.e., the 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 costs, e.g., the rent of buildings decreases by 3 percent.

Appendix D: 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 those used with Seim (2006), who uses census tracts. The zip codes are irregular areas that vary in size. The advantage of using zip codes is that they are constructed for mail delivery and therefore consider geographical characteristics such as main roads, waterways, and forested areas. Hence, we believe that zip codes are an appropriate way to divide 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 that are located in the first neighboring cell (cell 1) compete most intensely with competitors in the same cell. The intensity of competition declines for competitors in the second neighboring cells (cells 2, 5, and 4), followed by even lower intensity in the third (cells 3, 6, 9, 8, and 7).[41] Thus, we expect the competition intensity to be strongest in the first neighboring cell and then to decrease as we move to further away from the actual location.[42]

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

[41] Following Seim (2006), distances between zip codes are computed using the Haversine formula. Based on latitude-longitude coordinate data, the distance d between two points A and B is given by
$d_{A,B} = 2\text{Rarcsin}\left[\min\left((\sin(0.5(x_B - x_A)))^2 + \cos(x_A)\cos(x_B)(\sin(0.5(y_B - y_A)))^2\right)^{0.5}, 1\right]$
where R = 6,373 kilometers denotes the radius of the earth, x_A is longitude and x_B latitude.

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

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

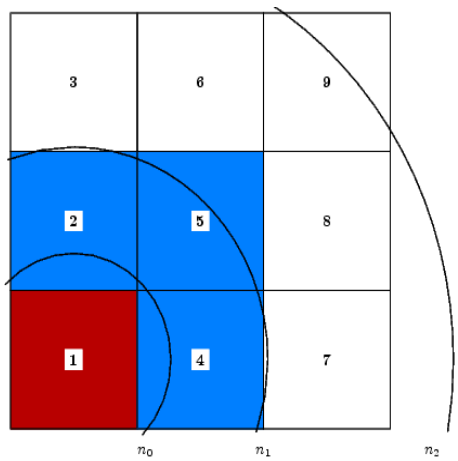

Figure 7: Illustration of distance bands