RESEARCH INSTITUTE OF
INDUSTRIAL ECONOMICS

IFN Working Paper No. 984, 2013

# Entry Regulations, Product Differentiation and Determinants of Market Structure

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# Entry Regulations, Product Differentiation and Determinants of Market Structure*

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July 23, 2014

**Abstract**

We use a dynamic oligopoly model of entry and exit with store-type differentiation to evaluate how entry regulations affect profitability and market structure in retail. Based on unique data for all retail food stores in Sweden, we find different cost structures and asymmetric competition across store types. Two additional small stores correspond to the same decrease in a small store's long-run profits as one large store. A number of counterfactual experiments that target the entry of different store types and markets with various degrees of regulation provide rich information for policymakers concerning the effect of regulations on market structure dynamics.

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

*We would like to thank John Asker, Christoph Bauner, Gregory Crawford, Uli Doraszelski, Igal Hendel, Ariel Pakes, Amil Petrin, Mark Roberts, Yuya Takahashi, Otto Toivanen, Frank Verboven and seminar participants at the Swedish National Conference in Economics 2011 (Uppsala), the thirteenth 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.

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# 1 Introduction

The effect of regulations on profitability and market structure is a topic of great concern for both economists and policymakers. 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] Total annual food expenditures in the US exceed USD 1,100 billion, and the average household purchases groceries every week and spends up to an hour per trip. Food consumption represents approximately 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 various policies are likely to be substantial. A careful analysis of regulations requires comprehensively modeling both the demand and supply side, which from an empirical perspective, 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 fixed costs of incumbents in local markets under different degrees of regulation. A unique data set containing 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.

A central contribution of this paper is that we quantify the impact of entry regulations on long-run profits and the evolution of market structure in retail using a dynamic oligopoly model. Our dynamic model builds on Pakes, Ostrovsky and Berry (2007) [POB] and explicitly incorporates demand, local markets, differentiation in store type, strategic interactions between stores, and the presence of regional entry regulations. As product differentiation and substantial simultaneous entry and exit characterize nearly all retail markets, this implies that we must model heterogeneous stores and the dynamics of market structure over time. The degree of differentiation depends on local demand, and it influences both competition and the cost structure of an industry, which in turn determine the market structure and its evolution over time. Strategic decisions and different reactions by heterogeneous stores to changes in policies determine long-run

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

profitability and the dynamics of the market structure. We use the model to perform counterfactual experiments that target the entry of different store types and capture asymmetries and indirect responses to changes in policies by store type over time. Policy changes in environments with heterogeneous stores are likely to have different impacts on and induce different responses by stores (Ericson and Pakes, 1995). The proposed model is quite general and can be applied to other regulated industries in which data on both prices and firm characteristics are available.

We apply the model to a unique combination of data on store characteristics for all retail food stores in Sweden during the period 2001-2008 and data on store-level prices and 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.[2] A dynamic approach is crucial in retail because the market has undergone a structural change toward larger but fewer stores (Figure 1). Store-type differentiation is essential, as large stores represent only 20 percent of the total number of stores but over 60 percent of aggregate sales and sales space (Table 1).

The Swedish 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 determine their own prices. Focusing on store types is appropriate for Sweden because, to a large extent, independent store owners operate the stores, thus reducing the influence by national firms, and all stores (not only large ones) are affected by entry regulations. Second, the entry and exit of stores are the main determinants of the market structure.[3] Third, the trend toward larger but fewer stores has not changed over the last few decades in

[2]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. 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.

[3]Entry and exit are often considered to play a greater role in 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).

most OECD countries. From the perspective of competition policy, it is important to obtain information on the sunk costs of entry and how these vary under different degrees of regulation. From a welfare perspective, 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.[4]

In addition to POB, our paper is most closely related to Dunne et al. (2013) who model identical firms using data on dentists and chiropractors.[5] They estimate an average firm profit function and sunk and fixed costs and then perform a counterfactual exercise in which a change in regulation shifts the entry cost. Furthermore, Suzuki (2013) models and empirically evaluates the impact of land-use regulations on the entry and exit of hotel chains. More generally, our paper is also related to other recent studies that employ dynamic structural models of entry and exit (Aguirregabiria and Mira, 2007; Bajari et al., 2007; Pesendorfer and Schmidt-Dengler, 2008; Ryan, 2012; Abbring et al., 2013; Collard-Wexler, 2013; Sweeting, 2013; Fowlie et al., 2014; Hünermund et al., 2014).[6]

Our analysis proceeds in four steps. First, we estimate a discrete choice model of static demand. Second, we use the demand estimates to calculate variable profits for each store and market. Third, we estimate parameters of the entry cost and fixed cost distributions for small and large stores and local markets that vary with respect to the stringency of entry regulations

[4]The evaluation of entry costs for different store types and the factors affecting these costs provide crucial information in markets in which the average travel distance for purchasing food increases. In Sweden, the average travel distance for purchasing food was approximately 9.83 kilometers during the 1995-2002 period (The Swedish Institute of Transport and Communication).

[5]For other recent applications of the POB framework, see Elejalde (2012) and Fan and Xiao (2013).

[6]See also Asplund and Nocke (2006) and Doraszelski and Satterthwaite (2010). Berry and Reiss (2007) survey the literature on two-period static entry games, and Berry and Tamer (2007) discuss identification in static entry games. For a contribution considering a static entry game with demand, see Gowrisankaran and Krainer (2011). 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 on retail chain expansion where exit is extremely rare (e.g., Toivanen and Waterson, 2011; Beresteanu et al., 2010; Holmes, 2011; Basker et al., 2012; Arcidiacono et al., 2013). There are studies that investigate store location in retail markets that primarily build on static models (e.g., Seim, 2006; Jia, 2008; Holmes, 2011; Orth, 2011; Ellickson et al., 2013; Nishida, 2014). In Appendix I, we extend our model to account for differentiation in location (Davis, 2006; Seim, 2006).

using a dynamic model. The assumptions required to estimate a dynamic game with heterogeneous stores, however, must be balanced against the computational burden and presence of multiple equilibria. An advantage of our model is that it allows for correlations in entry costs between store types, which is important when stores decide to enter a specific store type. In the proposed model, the actual equilibrium played is determined from the data. Having data on all Swedish retail food stores for a long period of time allows us to consistently estimate transition probabilities across the states for incumbents and entrants in the dynamic problem.[7] The structural parameters of the distributions of entry costs and fixed costs are estimated by matching the observed entry and exit rates in the data to those predicted by the model. Fourth, we perform various counterfactual experiments that reduce the entry costs of small and/or large store types in markets with restrictive regulations.

The results show that the entry costs for each store type are higher in local markets with restrictive, relative to liberal, regulation. We find differences in own- and cross-price elasticities and asymmetric competition across store types. Two additional small stores decrease a small store's long-run profits to the same extent as one additional large store. For small stores, competition from large stores intensifies after entry costs are reduced, especially in markets with a low-profit regime. A comparison of alternative counterfactual experiments shows, for example, that entry cost reductions that only apply to large stores impose substantial competitive pressures on small stores, which in turn induce the entry and exit of small stores despite their entry costs not being explicitly targeted by the policy. We conclude that, to accurately evaluate alternative entry regulation policies, it is important to consider that changes in the costs faced by one store type have implications for the endogenous entry, exit and long-run profits of the rival store type.

The next section presents the data and market. Section 3 presents the dynamic model. Section 4 discusses the empirical implementation of the model, Section 5 presents the empirical results, and Section 6 reports the

[7] Pakes et al. (2007) claim that the correct equilibrium will be selected in sufficiently large samples. 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 transition probabilities if the period is not sufficiently long.

results of several counterfactual exercises that highlight turnover, long-run profitability and trade-offs between different store types. Section 7 discusses robustness and Section 8 concludes the paper. In several instances, we refer to an online appendix containing various analyses that are not discussed in detail in the paper.

# 2 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 determine their own prices. This contrasts national pricing, which exists, for example, in the UK. The centralized decision making, and thus the concern regarding national strategies, in the Swedish retail food market is thus less pronounced than that in many other countries. Firms primarily act 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 combination of franchises and centrally owned stores, the latter of which are primarily located in the south and southwest of Sweden.[8] Coop, however, consists of centralized cooperatives, and decisions are made at the national or local level. In 2011, approximately 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 comprise the remaining 7 percent market share. International firms with hard discount formats entered the Swedish market in 2002 (Netto) and 2003 (Lidl).

**Data.** Three different data sets covering stores, demographics, and prices are incorporated in our empirical application. The first and primary data set includes all retail food stores in the Swedish market during the 2001-2008 period and is collected by Delfi Marknadsparter AB (DELFI). A unit of observation is a store based on its geographical location, i.e., its physi-

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

cal address. We access store's geographic location (geo-coordinates), store type, firm affiliation, sales, sales space (in square meters), wholesaler and the location (geo-coordinates). The store type classification (12 different) depends on size, location, product assortment, and so forth. Store types are similar for stores that are affiliated with different firms, and we jointly analyze several store types in the dynamic analysis. We define the five largest types (hypermarkets, department stores, large supermarkets, large grocery stores, and others) as "large" and four other types (small supermarkets, small grocery stores, convenience stores, and mini-markets) as "small."[9] We believe that these types are representative of small and large stores in the Swedish retail food market. Due to the complexity of defining output and the variety of product assortments across stores, as is common in studies on the retail food market, we do not have information on quantity sold for each product.

The second data set contains demographic information from Statistics Sweden (SCB), i.e., population, population density, average income, distribution of income across age groups, and political preferences. The third data set is collected by the Swedish National Organization of Pensioners (PRO) and contains annual price information for approximately 30 products in approximately 1,000 stores during the 2003-2008 period.[10] The data set is rich and covers stores of different sizes, formats and firms throughout the entire country. The surveyed products cover a wide range of frequently purchased items of well-defined brands and pack sizes.[11] 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 mar-

[9]Gas stations, seasonal stores, and stores under construction are excluded from the analysis. Stores classified as "other" stores are large and externally located.

[10]To accurately evaluate the role of regulations in the industry dynamics of local markets, it is crucial to use information on all stores. Ideally, we would thus prefer to have a price measure for each of the stores in the data. In our application to Swedish retail food, this requires one to annually measure prices in over 5,000 stores, which is a non-trivial task. We are unaware of any study relying on price information for all stores in a retail food market. For our purposes, as we face data limitations, we believe the PRO data have good coverage in terms of stores types, owners, regions, products and time for our purposes.

[11]PRO is divided into a number of geographic districts, approximately 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. Based on the names and addresses of the stores in DELFI, we identify the stores that are included in the PRO survey.

ket and year. In the empirical application, we consider a basket containing 11 products. Appendix B provides details about the components of the product basket and descriptive statistics of the price.

**Local markets.** Food products fulfill daily needs and are often relatively perishable. Thus, stores are generally located near to consumers. The travel distance for purchasing food is relatively short (except if prices are sufficiently low), and nearness to home or work is therefore a key concern for consumers in selecting where to shop, although travel distance likely increases with store size.[12] 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 only competitively interact 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 account for commuting patterns, which are important for the absolutely largest stores, such as hypermarkets and department stores, while municipalities appear more suitable for large supermarkets. As discussed below, municipalities are also where local government decisions regarding new entrants are made. We therefore use municipalities as local markets.

**Entry, exit and market shares.** 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 in year $t$ as a store that operates in year $t$ but not in $t-1$. We define an exit in year $t$ as a store that operates in year $t-1$ but not in $t$. The variables $e_{mt}$ and $x_{mt}$ measure the number of entrants and exits in market $m$ in year $t$. The total number of stores in the beginning of period $t+1$, $n'_{mt+1}$, is given by $n'_{mt+1} = n_{mt} + e_{mt} - x_{mt}$, where $n_{mt}$ is the number of incumbent stores in period $t$. We only consider physical entry and exit as these are the relevant considerations for estimating sunk and fixed costs. Thus, we do not include stores that change owners but continue to operate at the same address.

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

To construct market shares, we use a store's sales and the price of the large product basket to derive the quantity of product baskets a store sells in year $t$. The store's market share is defined as its quantity divided by the total quantity in each local market and year (Section 4.1).[13]

**Entry regulation.** The majority of OECD countries have entry regulations that empower 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) empowers the country's 290 municipalities to decide on applications for new entrants. All stores are regulated by the PBA in Sweden, contrasting, for example, with regulations in U.K., which explicitly focus on large stores. Each store seeking to enter the market is required to file a formal application with 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 addressed by the 21 county administrative boards. The PBA is considered 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.

Our study shares the common feature with previous work on entry regulations that it acknowledges that there is no single ideal measure of regulatory stringency in local markets. Drawing heavily on previous work on land-use and entry regulations, we collect data from several sources (Bertrand and Kramarz, 2002; Schivardi and Viviano, 2011; Suzuki, 2013; Turner et al., 2014). As our main measure of regulatory stringency, we access data on political preferences, i.e., the share of non-socialist seats in the local government (Bertrand and Kramarz, 2002; Schivardi and Viviano, 2011). The exogeneity of political preferences in measuring regu-

[13]The empirical findings remain robust when constructing market shares using sales instead of quantity (Section 7).

latory stringency relies on local economic issues' not determining future election outcomes. In Sweden, we believe it is reasonable to rely on the assumption that land-use issues do not determine the outcomes of local elections. Swedish municipalities have numerous responsibilities. Childcare, schooling and elderly care are the main spending areas likely to influence voter's decisions more heavily. For Sweden, we expect that non-socialist local governments are more liberal regarding new entry.[14] This is confirmed by simple reduced-form regressions. Overall, 117 of the 290 municipalities have had a non-socialist local government for at least one of the years in our study period. In 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).

In addition to political seats, we have data on the number of the applications approved (PBA) by local authorities for each municipality and year. This includes applications to change land-use plans and the total number of existing land-use plans.[15] The data are collected by the Swedish Mapping, Cadastral and Land Registration Authority (Lantmäteriet). Municipalities with a non-socialist majority approve more PBA applications. The correlation between non-socialist seats and the number of approved PBA applications in local markets is 0.596.

To measure local market regulation, we use the share of political seats alone and index variables constructed using the share of political seats and various measures of the number of approved PBA applications (Suzuki, 2013; Turner et al., 2014). By construction, the index variables are not sensitive to the size of the local market. In detail, we use an index in which

[14]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.

[15]In addition, we have data on the number of approved PBA applications permitting 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 performed 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.

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. The higher the index is, the more the 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 approximately 0.14. We define municipalities as having restrictive (liberal) regulations if the index is below (above) the median. To keep the exposition tractable, we report results using only one index definition. The robustness checks (Section 7) and Appendix H discuss results when only using political seats or alternative definitions of the regulation index to measure regulation.

**Descriptive statistics.** 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 increase by more than 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 nearly 22 percent in 2008. Large stores account for the majority of the sales and sales space. Their sales increase 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 experienced higher growth in sales than in sales space or the number of stores, indicating improvements in efficiency. The total number of entrants is fairly constant over time, with the number of exits being slightly less than twice the number of entrants. The majority of entrants and exits are small stores (Appendix B).

Figures 1 shows that the number of small stores decreases by approximately 20 percent to 3,215 in 2008, but the number of large stores is fairly constant. There is a decline in the total number of stores affiliated with three of the main firms: 28 percent for ICA, 26 percent for Coop, and 11 percent for Axfood. The opposite trend is observed 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 the number of stores affiliated with ICA, Coop, and Others, whereas the changes are smaller in magnitude for small stores that are affiliated with Axfood. Figure 2 shows that the total number of entrants increases until 2005 and then declines, while the number of stores that exit peaks in 2004. Figure 3 shows that the entry and exit rates are correlated over time.

Table 2 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 approximately 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. As entry and exit do not occur in all markets in a given year, we observe variation in the upper percentiles. For example, the entry rate for the 75th percentile varies substantially over time (0-0.06).

Exit occurs 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 the 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.

**Descriptive patterns that link to structural results.** In our sample, the median store size is approximately 215 square meters for small stores and approximately 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 sales, a median large store sells about ten times more than a median small store. The sales per square meter of a median large store are approximately 21 percent higher than those for a median small store. These figures emphasize the importance of estimating costs separately for small and large stores, as we do in this paper.

# 3 A dynamic oligopoly model

This paper employs a dynamic model to analyze the distributions of retail stores' entry and fixed costs to understand the dynamics of market structure.[16] We build on the framework developed by Pakes, Ostrovsky,

[16]The model can be used to estimate sell-off values or fixed costs, see Section 7 and Appendix C.

and Berry (2007) and account for differentiation in type/location, which is common in retail markets, and incorporate a discrete choice demand model. On the demand side, consumers have preferences over small and large stores, where lower prices in large stores can offset a longer travel distance. On the supply side, entry and exit are key in determining the degree of product differentiation and market supply in retail. This stands in contrast to industries in which the market structure is driven by the firm-margin. 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. To evaluate entry regulations, it is crucial to model both consumer preferences and other determinants of market supply such as entry and fixed costs because they affect stores' strategic interactions and the evolution of market outcomes.[17]

In the beginning of each period, a set of incumbents $\mathbf{J}^c$ and potential entrants $\mathbf{J}^e$ simultaneously decide their actions. Incumbents choose whether to continue to operate with store type (or in location) $z \in \mathcal{Z}$ or exit.[18] We follow the common assumption that fixed costs and sunk costs is private information that are known prior to players' decisions and i.i.d. from known distributions (Bajari et al., 2007; Pakes et al., 2007). Each incumbent $j^c$ of type $z$ receives a draw of the fixed cost $\phi^c_{jz}$ from the common distribution $F^{\phi_z}$, which is paid in the next period if they continue. Potential entrants decide whether to enter a store of type $z \in \mathcal{Z}$. The entry cost for each potential entrant $j^e$ of type $z$, denoted $\kappa^e_{jz}$, is a draw from the common distribution $F^{\kappa_z}$. Entrants' decisions are made one period ahead of when they start to operate, which implies that we can obtain continuation and entry values that do not depend on entry costs. All stores of type $z$ are identical up to the draw of the fixed cost and entry fee. For simplicity of

[17]To make the presentation of the model brief and tractable, we present the modeling assumptions throughout the text rather than specifying a succinct list of assumptions.

[18]The simplest version of the model only incorporates differentiation in store type. The model can be generalized to account for location and firm characteristics, but the computational burden will increase because of the large state space. In Sweden, individual stores determine 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 2 for details). An 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. Few studies recognize the issue of the chain effect across local markets, and they all consider a small number of players (Jia, 2008; Holmes, 2011; Nishida, 2014).

notation, we omit the store indexes $j^c$ and $j^e$ from the entry and fixed cost draws in what follows. All parameters of the distributions of fixed costs $F^{\phi_z}$ and sunk costs $F^{\kappa_z}$ are collected in $\boldsymbol{\theta}$.

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 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 $n_z$ is the number of incumbents and $e_z$ 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 $\mathbb{P}(\mathbf{y}'|\mathbf{y})$.

We do not allow stores to invest or change owners or formats. That store concepts in retail are rather uniform justifies this assumption. Nevertheless, the proposed dynamic model allows us to understand asymmetries in strategic interactions between small and large stores and how these influence the dynamics of the market structure on the supply side.

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

$$V_z(\mathbf{s}, \phi_z; \boldsymbol{\theta}) = \pi_z(\mathbf{s}; \boldsymbol{\theta}) + max\{\beta VC_z(\mathbf{s}; \boldsymbol{\theta}) - \beta\phi_z, 0\}, \tag{1}$$

where $\pi_z(\cdot)$ is the profit function; $VC_z(\cdot)$ is the continuation value; $\phi_z$ is the fixed cost; and $0 < \beta < 1$ is the discount factor. Incumbents know their fixed cost $\phi_z$ but not the number of entrants and exits, prior to making their decisions. The optimal policy for an incumbent is to exit if the draw of the fixed cost is larger than the expected future profits, which yields the probability of exit $p^x_z(\mathbf{s}) = Pr(\phi_z > VC_z(\mathbf{s}; \boldsymbol{\theta})) = 1 - F^{\phi_z}(VC_z(\mathbf{s}; \boldsymbol{\theta}))$. Incumbents that continue obtain the continuation value

$$\begin{aligned} VC_z(\mathbf{s}; \theta) = \; & E^c_{\mathbf{s}'}[\pi_z(\mathbf{s}'; \boldsymbol{\theta}) + E_{\phi'_z}[\max\{\beta VC_z(\mathbf{s}'; \boldsymbol{\theta}) - \beta\phi'_z, 0\}]] \\ = \; & E^c_{\mathbf{s}'}[\pi_z(\mathbf{s}'; \boldsymbol{\theta}) + \beta(1 - p^x_z(\mathbf{s}'))(VC_z(\mathbf{s}'; \boldsymbol{\theta}) \\ - \; & E[\phi'_z|\phi'_z \leq VC_z(\mathbf{s}'; \boldsymbol{\theta})])], \end{aligned} \tag{2}$$

where $\mathbf{s}' = (n'_z, n'_{-z}, \mathbf{y}')$. If we assume that $\phi_z$ follows an exponential distribution, we obtain $E[\phi'_z|\phi'_z < VC_z(\mathbf{s}';\boldsymbol{\theta})] = \sigma_z - VC_z(\mathbf{s}')[p^x_z(\mathbf{s}')/(1-p^x_z(\mathbf{s}'))]$. Substituting this into (2), we obtain

$$VC_z(\mathbf{s};\boldsymbol{\theta}) = E^c_{\mathbf{s}'}[\pi_z(\mathbf{s}';\boldsymbol{\theta}) + \beta VC_z(\mathbf{s}';\boldsymbol{\theta}) - \beta\sigma_z(1 - p^x_z(\mathbf{s}'))], \tag{3}$$

where $\sigma_z$ is a parameter in the exponential distribution that represents the inverse of the mean.

**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

$$VE_z(\mathbf{s};\boldsymbol{\theta}) = E^e_{\mathbf{s}'}[\pi_z(\mathbf{s}';\boldsymbol{\theta}) + \beta VC_z(\mathbf{s}';\boldsymbol{\theta}) - \beta\sigma_z(1 - p^x_z(\mathbf{s}'))], \tag{4}$$

where $p^x_z(\mathbf{s}')$ is a potential entrant's perceptions of the number of exits of each type conditional on entering the market and $E^e_{\mathbf{s}'}[\cdot]$ indicates the expectations of entrants. 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 $Pr(\kappa_z < VE_z(\mathbf{s};\boldsymbol{\theta})) = F^{\kappa_z}(VE_z(\mathbf{s};\boldsymbol{\theta}))$.

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. Thus, first, we have the condition that the entry value must be larger than the draw of the entry cost. Then, we have that the type decision must yield the highest expected discounted future profits among all type alternatives

$$\beta VE_z(\mathbf{s};\boldsymbol{\theta}) \geq \kappa_z \tag{5}$$

$$\beta VE_z(\mathbf{s};\boldsymbol{\theta}) \geq \beta VE_{-z}(\mathbf{s};\boldsymbol{\theta}). \tag{6}$$

Entry costs for small and large stores in a given local market are likely to depend on a set of similar characteristics. This can depend on the geographic location determining the cost of buildings, logistics, and the distribution of consumers relative to stores (population and store densities), for example. To formally operationalize this in the model, we allow for correlations in the draws of entry costs for large and small stores. We assume that entry costs follow a unimodal distribution with the general density function given by

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

for $\mu \in (1/a, \infty)$, where the parameter $a$ ($a > 0$) defines the boundary support for the entry cost $\kappa$. Because of the boundary support, there will be no entry if the number of incumbents is very large. The entry costs for small ($\kappa_{small}$) and large stores ($\kappa_{large}$) in a local market are thus correlated because they reflect differences in costs for a store in a given local market due to, e.g., the costs of buildings and logistics. We expect higher entry costs for large stores because they require more land, building permissions and influence the traffic and the environment, i.e., $\kappa_{large} > \kappa_{small}$. To allow for a correlation in entry costs, we assume that $\kappa_{large} = \kappa_{small} + \mu$, where $\kappa_{small}$ and $\mu$ follow unimodal distributions with parameters $a_1$ ($a_1 > 0$) and $a_2$ ($a_2 > 0$), respectively. The parameters $a_1$ and $a_2$ are estimated in the second stage together with $\sigma_z$.

We now define the continuation values, profits, and exit probabilities as vectors and define a matrix of transition probabilities $\boldsymbol{W}_z^c$ that indicates the transition from state $\mathbf{s}$ to state $\mathbf{s}' \neq \mathbf{s}$ for type $z$

$$\boldsymbol{VC}_z(\boldsymbol{\theta}) = \boldsymbol{W}_z^c[\boldsymbol{\pi}_z + \beta \boldsymbol{VC}_z(\boldsymbol{\theta}) - \beta\sigma_z(1 - \boldsymbol{p}_z^x)], \tag{7}$$

which implies that

$$\boldsymbol{VC}_z(\boldsymbol{\theta}) = [I - \beta \boldsymbol{W}_z^c]^{-1}\boldsymbol{W}_z^c[\boldsymbol{\pi}_z - \beta\sigma_z(1 - \boldsymbol{p}_z^x)], \tag{8}$$

where $I$ is the identity matrix. Using nonparametric estimates of $\boldsymbol{W}_z^c$ and $\boldsymbol{p}_z^x$ from the data, we can obtain an estimate of the value function at each state. There is no dependence over time in the transition probabilities.[19] For potential entrants, the value of entry is

$$\boldsymbol{VE}_z(\boldsymbol{\theta}) = \boldsymbol{W}_z^e[\boldsymbol{\pi}_z + \beta \boldsymbol{VC}_z(\boldsymbol{\theta}) - \beta\sigma_z(1 - \boldsymbol{p}_z^x)], \tag{9}$$

where $\boldsymbol{W}_z^e$ is the transition matrix that yields the probability that an entrant starts operating at $\mathbf{s}'$ conditional on entering in state $\mathbf{s}$.

[19] The presence of serially correlated unobservables is discussed in detail in Sections 4 and 7.

**Equilibrium.** Incumbents and potential entrants make simultaneous moves, and they both form perceptions of the entry and exit of their rivals. In equilibrium, these perceptions must be consistent with the stores' actual behavior. The incumbents' perceptions of rival incumbents' behaviors are identical for all rivals of the same type. Similarly, all potential entrants have the same probability of entering with a given type. The solution concept is a Markov Perfect Equilibrium. Yet, more than one equilibrium might exist. As in POB, the model guarantees that in the recurrent class, there is only one profile of equilibrium policies that is consistent with a given data-generating process.[20] The data will thus select the equilibrium that is played. As POB argue, the correct equilibrium will be selected if samples are sufficiently large. For this purpose, the present paper exploits the detailed data that we have access to, covering the total population of stores in Sweden for a long period of time. Appendix D provides details regarding the construction of the transition matrices.

**Comparisons to alternative approaches: static and dynamic.** The model rests on several assumptions that are already grounded in the POB-type models, e.g., cost draws are i.i.d., timing assumptions on entry. Our model differs from previous work based on the POB framework in the following ways: First, we account for heterogeneous stores. Second, we allow the cost draws of different store types to be correlated. Third, we use a demand system and data on store-level prices to recover variable profits.

We can compare our dynamic model with static, two-period models that allow for heterogeneous types. The static entry models with identical firms developed by Bresnahan and Reiss (1987) and Bresnahan and Reiss (1991) are extended to account for heterogeneous players by Mazzeo (2002) and Seim (2006) (Berry and Reiss (2007) survey this literature). A static analysis based on cross-sectional data cannot separately identify sunk costs from fixed costs, is unable to explain the descriptive patterns of entry and exit that we observe in our data, and requires the market structure to be in long-run equilibrium.[21] Our model differs from the static models of heterogeneous firms in the following ways: First, we distinguish short-run

[20] For details and explanations, see Pakes et al. (2007)

[21] Applying a static model to cross-sectional data from 2001 might thus yield substantially different results than using data from 2008, where there are 16 percent fewer stores and 3.5 percentage points more large stores.

profits from long-run profits (continuation and entry values). Second, we distinguish sunk costs from fixed costs. Third, we allow for transitions in the market structure over time and let the prior market structure and the number of stores to influence the future market structure. In summary, a dynamic model is necessary if one wishes to quantify how profitability and market structure change due to entry, exit and policy modifications.

There are previous works combining static entry models with a static demand system (Gowrisankaran and Krainer, 2011) and using dynamic models of demand (Gowrisankaran and Rysman, 2012). We contribute to this literature by jointly considering a dynamic entry and exit setting with a static demand framework.

# 4 Identification and estimation

The empirical implementation proceeds in four steps: First, we construct variable profit measures for each store by estimating a discrete choice demand model. Second, we estimate the parameters of the profit-generating function at the store-type level, which is used to compute the variable profits for small and large store types in different states. Third, we estimate the transition probabilities, which are used to compute the continuation and entry value functions. Fourth, we estimate the cost distributions (fixed and sunk) for each store type in liberal and restrictive markets.

## 4.1 Demand and profits

To estimate the dynamic model, we construct the average variable profits by store type for each market-year observation. Given the presence of heterogeneous stores, we must take care in calculating profits, as we must account for all systematic differences in profits between the store types. To do so, we rely on a demand model because understanding preferences that determine the incentives facing producers is key (Ackerberg et al., 2007). Generally, accounting (book-value) profits are viewed with skepticism (Scherer and Ross, 1990). For robustness, we check and find that the constructed profits are in line with the aggregated profits reported by

Statistics Sweden (SCB).[22]

**Demand estimation.** To construct variable profits, we rely on a static discrete choice demand model. We believe it is reasonable to assume a static demand system for retail food because consumers purchase food products, which are of limited durability, on a frequent basis. We adopt a nested logit specification with correlation $\tau$ across stores belonging to the same group of store type $z \in \mathcal{Z}$. The arguments for using store types as nests rely on the assumption that store type likely influences consumer choice. Consumers acknowledge that stores differ and perceive similar store types to be closer substitutes. This allows preferences to be correlated across stores of a certain type. Following Berry (1994), the utility of consumer $i$ of store $j$ in local market $m$ is given by

$$u_{ijmt} = \delta_{jmt} + \zeta_{izmt} + (1-\tau)\epsilon_{ijmt}, \tag{10}$$

where $\epsilon_{ijmt}$ is identically and independently distributed extreme value, $\zeta_{izmt}$ is common to all stores in group $z$ and has a distribution function such that if $\epsilon_{ijmt}$ 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.[23] Let $\delta_{jmt} = \mathbf{x}_{jmt}\beta - \alpha p_{jmt} + \eta_f + \eta_m + \xi_{jmt}$, where $\mathbf{x}_{jmt}$ are control variables such as the log of store size ($m^2$), average local market income, and income squared; $p_{jmt}$ is the price of the product basket; $\eta_f$ are dummies for the main firms (ICA, Axfood, Coop, and Bergendahls); and $\eta_m$ are fixed effects for local markets. The remaining demand shocks $\xi_{jmt}$ are not correlated across store types and markets and could include a store's local advertising, for example. Integrating out over the idiosyncratic preferences yields the estimable demand equation

$$ln(s_{jmt}) - ln(s_{0mt}) = \mathbf{x}_{jmt}\beta - \alpha p_{jmt} + \tau ln(s_{jmt|z}) + \eta_f + \eta_t + \xi_{jmt}, \tag{11}$$

[22]Section 7 and Appendix G provide additional information on profits and links to previous work on POB-type models, i.e., constructing profits from observed sales and using cost approximation (Holmes, 2011; Dunne et al., 2013).

[23]While the nested logit demand model relaxes the logit assumption of uncorrelated consumer preferences across stores by allowing preferences to be correlated across stores within a group (small or large), it nevertheless imposes restrictions on cross-price elasticities, which are symmetric within a group (Grigolon and Verboven, 2013). Berry et al. (1995) and Berry et al. (2004) provide rich discrete choice frameworks to model demand.

where $s_{jmt}$ is the market share of store $j$ constructed using the quantity of a product basket that a store sells in year $t$ in market $m$, i.e., $q_{jmt} = sales_{jmt}/p_{jmt}$ and $s_{jmt} = q_{jmt}/\sum_{k \in m, k \neq j} q_{kmt}$. $s_{jmt|z}$ is the within-group share of store $j$ in group $z$ in market $m$ and $s_{0mt}$ is the market share of the outside option defined as buying food from stores not affiliated with the four main firms. We form moment conditions on $\xi_{jmt}$ to identify $\alpha$, $\beta$ and $\tau$.

**Store profits.** The variable profits of store $j$ are given by

$$\pi_{jmt} = (p_{jmt} - mc_{jmt})q_{jmt}(\mathbf{p}, \mathbf{x}; \boldsymbol{\psi}), \tag{12}$$

where $mc_{jmt}$ is the marginal cost of store $j$ in market $m$; $q_{jmt}$ is the quantity of food product baskets sold by store $j$; $\mathbf{p}$ is the price vector; $\mathbf{x}$ is the store characteristics matrix; and $\boldsymbol{\psi} = (\alpha, \beta, \tau)$ represents parameters to be estimated.[24]

We assume that stores compete in prices, determining the basket price, and that $p_{jmt}$ is the result of a pure strategy Nash equilibrium. The fact that individual stores determine their own prices in Sweden supports this assumption.[25] In the standard nested logit specification, derived in Berry (1994), the price minus marginal cost takes a simple analytical form

$$p_{jmt} - mc_{jmt} = \left[ \frac{(1-\tau)}{\alpha} / [1 - \tau s_{jmt|z} - (1-\tau) s_{jmt}] \right]. \tag{13}$$

**Identification.** To estimate equation (11), we require instruments for the endogenous variables price $p_{jmt}$ and the within-group share $s_{jmt|z}$. There is variation in prices across store types, firms, markets and years. As instruments for $p_{jmt}$, we use the main cost shifters for retail food stores ($\mathbf{w}_{jmt}$), which are the labor and logistics costs. We proxy for these costs using average wages and the distance to the nearest distribution center for each store type, firm and market. These instruments are correlated with the store's price because of the service production costs, and they do not in-

[24] Using market share based on sales, the variable profits are computed as $\pi_{jmt} = (p_{jmt} - mc_{jmt}) M s_{jm}(\mathbf{p}, \mathbf{x}; \boldsymbol{\psi})$, $M$ is the total market size, i.e., the number of consumers that purchase the food product (our product basket).

[25] The first-order conditions then imply that $s_{jmt}(\mathbf{p}, \mathbf{x}; \boldsymbol{\psi}) + (p_{jmt} - mc_{jmt}) \frac{\partial s_{jmt}(\mathbf{p}, \mathbf{x}; \boldsymbol{\psi})}{\partial p_{jmt}} = 0$.

clude store-specific demand shocks.[26] As an instrument for $s_{jmt|z}$, we use the log of the number of stores of each type in the local market. In addition, we also use the average number of stores of each type in other local markets. Moreover, any function of these variables is a valid instrument. The parameters $\beta$ are identified using moment conditions on $\mathbf{x}_{jmt}$. Section 7 discusses robustness results using additional identification strategies for the demand equation.

**Store type profits.** We use the demand estimates to construct variable profits for each store type, market and year according to

$$\pi_{zmt} = \frac{1}{n_{zmt}} \sum_{r=1}^{n_{zmt}} (p_{rmt} - mc_{rmt}) q_{rmt}(\mathbf{p}, \mathbf{x}; \boldsymbol{\psi}), \tag{14}$$

where $n_{zmt}$ is the number of stores of type $z$ in market $m$. In addition, Section 7 and Appendix G discuss alternative approaches to constructing operating profits similar to Holmes (2011) and Dunne et al. (2013).

**Estimation of profit-generating function.** We employ a rich specification of the profit function. The profits of store type $z$ in market $m$ in year $t$ is a function of the state variables

$$\begin{aligned} \pi_{zmt} = \;& \gamma_0 + \mathbf{y}_{mt}\boldsymbol{\gamma}_y + \gamma_z n_{zmt} + n_{zmt}\mathbf{dm}_z\boldsymbol{\gamma}_{zd} + \gamma_{z,2}n_{zmt}^2 + \\ & \mathbf{n}_{-zmt}\boldsymbol{\gamma}_{-z} + \mathbf{n}_{-zmt}\mathbf{dm}_z\boldsymbol{\gamma}_{-zd} + \mathbf{n}_{-zmt}^2\boldsymbol{\gamma}_{-z,2} + \\ & \mathbf{dm}_z\boldsymbol{\gamma}_d + \epsilon_{zmt}, \end{aligned} \tag{15}$$

where $n_{zmt}$ is the number of stores of the own type; $\mathbf{dm}_z$ is a dummy matrix for types; $\mathbf{n}_{-zmt}$ is the number of rival type stores (it is a matrix if there are more than two types); $\mathbf{y}_{mt}$ includes exogenous state variables (profit shifters) and market-year fixed effects; $\epsilon_{zmt}$ is a type-market specific error term that is i.i.d.; and $\boldsymbol{\gamma}$ is the parameter vector to be estimated. Controlling for type implies different profit functions for types. We include all covariates in the demand function and marginal cost function. Income and population are key variables that shift retail demand. Distance to the

[26] The average prices of stores of the same type in other local markets can also be used as an instrument for $p_{jmt}$ (Hausman, 1997; Nevo, 2001; Hendel and Nevo, 2006). This instrument is correlated with the store's price because of the service production costs and is valid if there are no national demand shocks.

distribution center and wages shift costs.[27] We also control for local market regulation and for unobserved heterogeneity using market fixed effects.

To better control for unobserved market effects when estimating the cost parameters and to reduce the dimensionality of the state space, we use the index variable $y_{mt}$ as the third state variable in the dynamic model.[28] We construct $y_{mt}$ based on estimates from (15), i.e., $y_{mt} = \sum_{k=1}^{K}(x_{mt}^k)^2\hat{\gamma}_2 + \sum_{k=1}^{K} x_{mt}^k\hat{\gamma}_1 + \hat{f}_m$, where $x_{mt}^k$ is one of the observed local market or store characteristics (income, distance to the distribution center, population, and regulation) that affects stores' profits and $\hat{f}_m$ are estimated local markets fixed effects. We use the above specification. Our results are robust, however, to the inclusion of different combinations of variables in the index $y_{mt}$. Section 7 discusses robustness and presence of serially correlated unobservables.

## 4.2 Value functions and transitions between states

To compute the continuation values for incumbents ($\boldsymbol{VC}_z$) and entrants ($\boldsymbol{VE}_z$), we need to calculate the expected discounted future profits that the store would obtain from counterfactual future states. The transition probability matrices ($\boldsymbol{W}_z^c$) and ($\boldsymbol{W}_z^e$) are computed for each store type and local markets with different degrees of entry regulation using the observed states in the data, i.e., empirical transition probabilities. As explained in Section 2, we define municipalities as having a restrictive (liberal) implementation of the PBA if the regulation index is below (above) median. The grouping of local markets is considered exogenous to the stores, and we consequently do not attempt to model expected changes in regulations over time (Dunne et al., 2013).

We estimate the transition probabilities using all municipalities in Sweden with a population of fewer than 200,000, i.e., large cities, such as

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

[28] An alternative approach to reduce the dimensionality of the transition matrices is to classify geographic markets into smaller groups and exploit 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 us to better control for unobserved heterogeneity. The presence of serially correlated unobservables can induce a positive bias on competition parameters in the profit regression, i.e., we provide conservative estimates. The robustness section considers serially correlated unobservables in greater detail.

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. As the exogenous index variable $y_{mt}$ is continuous and part of the state space, we discretize the index in five groups based on quantiles to reduce dimensionality of the state space. We analyze 290 local markets over 8 years, and the different configurations of small stores, large stores and the market index yield a high dimensional state space. 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).[29]

Appendix D presents the technical details used to construct the empirical transition matrices. Pakes et al. (2007) provide a detailed discussion of the advantages of using empirical transition matrices over structural ones. For structural transitions, we need to impute entry and exit rates for states that are not observed in the data, which might affect the estimation of the cost parameters. However, the empirical transition matrices ($\boldsymbol{W}_z^c$) and ($\boldsymbol{W}_z^e$) are sparse because not all states are observed in the data, which can increase the variance in the estimates of $VC_z$ and $VE_z$. Following POB's suggestion ("smoothing" the value functions), we estimate continuation and entry values for the states observed in the data and then use b-splines to obtain $VC_z$ and $VE_z$ for the states that are not observed in the data (Appendix D).[30] Therefore, the "smoothed" $VC_z$ and $VE_z$ are used in the estimation of the cost parameters.

## 4.3 Estimation of entry and fixed costs

The final stage involves parameter estimation of sunk costs ($\kappa_z$) and fixed costs ($\phi_z$) for each store type in local markets with restrictive and liberal regulation. The continuation value is computed for each state and is known

[29]The dimensionality of the generated state space is determined according to all possible combinations of the number of small stores, the number of large stores and values of the market index. After the transition matrices are computed, they are retained in memory to increase computational efficiency. Calculating the inverses of the transition matrices is the most demanding computational task. 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 matrices necessary to evaluate the value functions on an ordinary laptop with a dual-core processor.

[30]The results are robust to using simple linear regressions instead of b-splines.

up to the parameter of the distribution of fixed costs $F^{\phi_z}$. The value of entering depends on the entry cost draw from the distribution $F^{\kappa_z}$. A minimum distance estimator or indirect inference estimator can be used to estimate the cost parameters. Both estimators yield similar estimates in our application, which is unsurprisingly because indirect inference is also a GMM estimator. In the case of indirect inference, we use ordinary least squares (OLS) to regress entry and exit probabilities from the data and the model, respectively, on the state variables, i.e., $\mathbf{p} = \mathbf{s}\boldsymbol{\rho}$, and save the estimated coefficients $\boldsymbol{\rho}$ (data) and $\boldsymbol{\rho}(\boldsymbol{\theta})$ (model). The criterion function minimizes the distance between the regression coefficients:

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} [\hat{\boldsymbol{\rho}} - \hat{\boldsymbol{\rho}}(\boldsymbol{\theta})]' \mathbf{A}_R [\hat{\boldsymbol{\rho}} - \hat{\boldsymbol{\rho}}(\boldsymbol{\theta})], \tag{16}$$

where $\mathbf{A}_R$ is the weighting matrix.[31] Appendix E describes details regarding the estimation.

# 5 Results

This section discusses the estimated results for the demand estimation, profit-generating function, cost parameters, and the implied continuation values and probabilities to enter and exit.

## 5.1 Demand estimates

Table 3 reports the estimates of the demand equation (11) 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 average local market income and income squared. The price coefficient ($\alpha$) is positive and significant in all specifications.[32] As expected, the coefficient is smaller

[31] A minimum distance estimator that minimizes the distance between theoretical and observed probabilities is employed to estimate the cost distribution parameters. Let $\hat{\mathbf{p}}_0$ 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 $\hat{\mathbf{p}}_1$ is obtained from the assumed cost distributions and computed value functions. The minimum distance estimator is defined as: $\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} [\hat{\mathbf{p}}_0 - \hat{\mathbf{p}}_1(\boldsymbol{\theta})]' \mathbf{A}_R [\hat{\mathbf{p}}_0 - \hat{\mathbf{p}}_1(\boldsymbol{\theta})]$

[32] Note that the price enters the demand equation (11) with a negative sign.

after we control for the endogeneity of price and local market characteristics that shift demand. In the OLS specifications, the coefficient of the within-store-type (group) share is approximately 0.90. It decreases to 0.637 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 obtained the demand estimates, we compute the implied price elasticities. We calculate unweighted average own- and cross-price elasticities for all markets. Table 4 presents the own- and cross-price elasticities for small and large stores, reporting cross elasticities both within and between store types. The average own-price elasticity is -3.871 for a small store and -3.001 for a large store. The average cross-price elasticity for the same store type is 0.125 for small stores and 0.221 for large stores. These findings indicate that asymmetric competition exists within store types, i.e., the own-price elasticities are larger (in absolute terms) than the cross-price elasticities. Among the cross-price elasticities for the rival store type, the impact of increasing the prices of small stores on the market shares of large stores (0.031) is smaller than that of increasing the prices of large stores on the market shares of small stores (0.221). Cross-price elasticities provide information on which store type gains the most market share if the rival type increases its price by 1 percent. Small stores gain more than large ones when the price of the rival store type increases. In other words, consumers prefer large stores if prices are sufficiently low to compensate for transportation costs.

We use the demand estimates to construct average variable profit for small and large stores according to equation (14). To evaluate how well our predicted variable profits correspond to stores' actual profits, we compare our profit measures using accounting information on reported profits from Statistics Sweden (SCB). We can obtain a measure of operating profits by subtracting the estimated average fixed cost from the second stage (results are reported in Section 5.3) from our variable profit estimates. Overall, our predicted operating profits are good approximations of the annual operating profits reported by SCB. Our findings show a median variable profits of SEK 1.5 million for small stores and SEK 14.3 million for large stores. The next step is to use these profits to estimate a profit-generating function and obtain an estimate of stores' profits for each value of the state space.

## 5.2 Estimation of profit function

Table 5 reports the estimates of the profit-generating function using a single-form specification for both types but accounting for type. The dependent variable is the log of mean variable profits for each store type and market. Using the OLS estimator, we consider four specifications. Specification $\mathcal{M}_1$ uses the number of small and large stores, the number of small and large stores squared, the store-type dummy, the store-type dummy interacted with the number of small and large stores, population, distance to the nearest distribution center and squared terms of these exogenous variables as covariates. $\mathcal{M}_2$ adds local market fixed effects, $\mathcal{M}_3$ adds income, and $\mathcal{M}_4$ also includes the local market regulation index. Specifications $\mathcal{M}_3$ and $\mathcal{M}_4$ include the covariates in the static demand estimation and are fully consistent with our model. The relative difference between the profits of small and large stores is more meaningful than our absolute estimation, which depends on our assumptions presented in Section 4.[33]

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 approximately 8 percent ($\mathcal{M}_1$).[34] The coefficients and marginal effects for the number of large stores 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 profits of small/large stores decrease by approximately three times more from an additional large store than from an additional small store. The marginal effects for both the number of small and 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 earn higher profits than small stores, which is what we observe in the data. The interactions of the number of small/large

[33]The reported results are averages of the estimated variable profits over markets. These estimates come from aggregate data at the type level that are based on our nested logit demand estimates. Section 7 and Appendix G discuss an alternative methodology to construct profits.

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

competitors and the dummy for large stores provide 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 nearly 7 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 distance to the nearest distribution center is negative and statistically significant at the 1 percent level in all specifications. That lower logistics and distribution costs increase profits is consistent with results obtained for Walmart (Basker and Noel, 2009, Holmes, 2011). The coefficients for income are positive and significant at conventional levels.

## 5.3 Structural parameter estimates

Table 6 presents parameter estimates for the distributions (Panel A) and the average (in millions of 2001 Swedish kronor) (Panel B) of fixed costs and entry costs for each store type (1 USD=9.39 SEK, 1 EUR=8.34 SEK). We estimate the entry cost parameters for markets with restrictive and liberal entry regulations (Section 2).

We present results for the four different profit function specifications. As expected, large stores have higher fixed costs and entry costs than small stores and entry costs are higher in restrictive markets. These results are robust across all specifications. For expositional simplicity, we focus on $\mathcal{M}_4$ which is fully consistent with our model. The average fixed cost is 10 times higher for large than for small stores. Small stores have entry costs of SEK 8.609 and SEK 11.746 million in liberal and restrictive markets, i.e., 20 percent lower in liberal than in restrictive markets. For large stores, the corresponding entry costs are SEK 86.760 and SEK 94.324 million, i.e., 8 percent lower in liberal than in restrictive markets.

To evaluate the extent to which our average entry cost estimates are reasonable, we compare them to publicly available investment costs for new stores. The reported cost, including land, buildings, and equipment, 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). Our estimates of sunk entry costs include other costs such as those related to the regulatory process. Nevertheless, the range of our cost estimates appears empirically reasonable when assessing the magnitude of our implied value functions.

**Value functions and store-type differentiation.** We use the estimated parameters to evaluate the continuation value of incumbents ($VC_z$), the value of entry for potential entrants ($VE_z$), and the probabilities of exit ($p_z^x$) and entry ($p_z^e$) for small and large stores.[35] The value functions are computed for each state (in millions of 2001 SEK). $VE_z$ does not depend on the estimated parameter of the entry cost distribution. However, lower entry rates imply higher entry costs. The slope of the profit function indicates the strength of short-run competition, and entry and exit have a long-run impact on store profits.

Table 7 reports the distribution of the value functions ($VC_z$, $VE_z$) for small and large incumbents and entrants in the observed markets with restrictive and liberal regulations. For both store types, the median $VC_z$ and $VE_z$ are lower in liberal than in restrictive markets.

**Long-run competition.** Based on our cost estimates, we obtain the continuation and entry values and entry and exit probabilities for each state in the state space. This information is extremely rich when considering two store types and having a high dimensional state space. To make the presentation tractable, we also estimate 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 $p_z^x$. The long-run marginal effects are functions of number of small stores, number of large stores, and the local market index that help to explain the observed heterogeneity in long-run profits, entry, and exit across markets.

Table 8 shows the average marginal effects of an additional store on $VC_z$, $VE_z$, $p_z^e$ and $p_z^x$ in liberal and restrictive markets. Long-run profits decrease when the number of stores increases. An additional large store decreases long-run profits for small stores to a greater degree than the long-run profits for large stores (-0.0352 vs. -0.0450). An additional small

[35] As noted, we assume that the fixed costs follow an exponential distribution and that the entry costs follow a unimodal distribution (see POB). We can assume other distributions. The computational burden substantially increases, however, using another distribution for fixed costs because we need to use contraction mapping to compute $VC_z$.

store decreases long-run profits for small stores to a greater extent than for large stores (-0.0180 vs. -0.0174). These results demonstrate persistence of asymmetric store-type competition in the long run. For small incumbents, approximately two additional small stores are needed to generate the same decrease in long-run profits as an additional large store. However, fewer small stores are needed to compensate for the reduction in long-run profits caused by an additional store in restrictive than in liberal markets. These findings are consistent with our profit-generating function estimates and emphasize asymmetric competition between store types. Small stores are more likely to exit and less likely to enter when an additional small or large store operates in the market. Large stores are more likely to exit and less likely to enter when an additional small or large store operates in a restrictive market. However, large stores are less likely to exit when an additional small operates in the liberal market. Thus, our model mimics the observed trend toward larger but fewer stores observed in the data. An additional large store decreases the value of entry of large stores by 2-3 percentage points more than for small stores. The decline in long-run profits ($VC_z$ and $VE_z$) due to an additional store in the market is larger in regulated than in liberal markets, i.e., there is a larger competitive effect in restricted markets, which have higher profits than liberal markets.

# 6 Counterfactual policy experiments

Policymakers face the challenge of deciding whether new small or large stores are allowed to enter a local market. It is therefore crucial to understand changes in long-run profitability and the entry and exit of own and rival store types when stimulating the entry of large and/or small stores. Our goal is to evaluate policies that target different store types and local markets with various degrees of regulation. The asymmetric and indirect effects of such policies remain an open empirical question, which is difficult to predict from a theoretical perspective. We use the estimated model to conduct counterfactual policy experiments and quantify 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.

We focus on local markets with restrictive regulation and compare three alternative policies (Dunne et al., 2013). In these markets, we replace the parameters of the entry cost distributions with those that we obtain in the liberal markets. First, we reduce the entry cost for both small and large stores in restrictive markets to be equal to those in liberal markets (CF-1). Second, we only reduce the entry cost for large stores in restrictive markets to be equal to those in liberal markets (CF-2). Third, we only reduce the entry cost for small stores in restrictive markets to be equal to those in liberal markets (CF-3). By only encouraging the entry of either large or small stores, we can evaluate the indirect effect on the dynamics of the rival store type. Even if the cost for different store types will be equal across all markets, we expect to observe changes in market structure dynamics in the long-run due to the existing market structure and the market characteristics.

For the alternative values of the entry costs, we solve the incumbent and entrant stores' optimization problems for $VC_z$ and $VE_z$ at each grid point. We 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 re-compute transition matrices for incumbents and entrants of each store type in markets with different regulations. We assume that the potential small and large store entrants follow different Poisson distributions (Section 7 provides additional details on potential entrants).[36]

**Industry dynamics and store-type differentiation**. For each store type, we compute the difference (in percent) between the predicted long-run profits, values of entry, and probabilities of entry and exit, based on the new entry costs (from liberal markets) and our long-run profits obtained from the estimated entry costs in restrictive markets. Table 9 reports the

[36]The parameters of these Poisson distributions are selected to match the Swedish local markets, where the expected number of potential entrants for both small and large stores is 9. The procedure automatically performs different tests to check whether we obtain reasonable transition probabilities that are consistent with the behavior observed in the local markets. A large value for the expected number of potential entrants substantially increases the 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 discussions with market participants and as that the number of stores decreases over time, it is unreasonable to assume that there are an infinite (or very large) number of potential entrants in the retail food industry.

average and sum of these differences by store type and market with high-profit and low-profit regimes. Although all stores are regulated in Sweden, we primarily focus on policies reducing entry costs for large stores, i.e., CF-1 and CF-2. The probability of entry increases after reducing the entry costs, i.e., total and average changes in entry probabilities are positive for both store types. More intense competition due to lower entry costs increases the probability of exit for both small and large stores, i.e., the total and average changes in exit probabilities are positive. In addition, the continuation value of incumbents decreases for both small and large stores after reducing entry costs, which also indicates an increase in competition.

The policy experiments CF-1 and CF-2 help us to understand the asymmetric changes in store type competition in the long run in markets with high and low profit regimes. Overall, there is heterogeneity across store types and local markets. First, both policy experiments show more intense competition for stores in markets with a low-profit regime, i.e., $VC_z$ decreases more in markets with a low-profit than a high-profit regime.[37] The $VC_{small}$ in CF-2 decreases by approximately 2-3 percentage points more than under CF-1 in low-profit regime markets (-0.051 vs. -0.028). In other words, on average, the competitive pressure on small stores in low-profit markets is larger when only incentives are provided for the entry of large stores instead of both store types. Under both CF-1 and CF-2, long-run profits for large stores ($VC_{large}$) decrease by approximately 3 percent in both market types. Policy experiment CF-2 provides an example of increasing competitive pressure from large stores on small stores without explicitly encouraging the entry of small stores. The findings under CF-2 show that the drop in long-run profits of small stores in low-profit markets is approximately 4 percentage points larger than in high-profit markets.

Second, when reducing entry costs for small and large stores (CF-1), the probability of a small store entering is 2 percentage points higher in low-profit markets than in high-profit markets or when only reducing entry costs for large stores (CF-2), i.e., 0.063 vs 0.048 or 0.039. Furthermore, the entry of large stores is 0.5 percentage points more likely when only reducing entry costs for large stores rather than for both store types. Lower entry costs for both store types thus increase the likelihood of entry for

[37]A market is denoted as having a low-profit regime if the local market index $y_{mt}$ is below the median.

small stores to a greater extent than for large ones. Therefore, a reduction in small stores' entry costs has an important impact on the entry of small stores, especially in low-profit markets. The aggregate summary statistics on the long-run profits for potential entrants show large dispersion in changes (due to large positive changes in certain markets). Because of the increased competition due to the decline in entry costs, the median decline in the $VE_z$ of large stores is approximately 2 percent.

**Changes in long-run competition**. Using our cost estimates, we evaluate the marginal effects concerning how long-run profits and the probabilities of entry and exit change with the state variables (the number of small and large stores). To assess whether the intensity of long-run competition changes when we reduce entry costs, we re-compute these marginal effects after imposing the counterfactuals (CF-1 – CF-3). Table 10 shows the average marginal effects of $VC_z$, $VE_z$, $p_z^x$, and $p_z^e$ with respect to the number of small and large stores before and after the counterfactual policy experiments. This allows us to understand changes in asymmetric competition between small and large stores due to modified entry policies, which is crucial when considering the trade-offs of entry between small and large store types.

For small stores, competition from large stores intensifies after entry costs are reduced, i.e., an additional large store results in more substantial declines in the continuation values for small stores. An additional small store, on the contrary, results in smaller reductions in the continuation values for both store types. We compute how many small stores are needed to obtain the same decrease in long-run profits as one large store before and after changes in entry costs, i.e., the ratio $r_z = (\partial f_z/\partial n_{large})/(\partial f_z/\partial n_{small})$, where $f_z = \{VC_z, VE_z, p_z^x, p_z^e\}$. Before the counterfactuals, $r_{small}^{before-cf} = 1.92$ and $r_{large}^{before-cf} = 2.58$. After the policy experiments, we have $r_{small}^{cf-1,2,3} = \{2.06, 2.07, 2.05\}$ and $r_{large}^{cf-1,2,3} = \{2.47, 2.46, 2.44\}$. The reduction in entry costs increases the competitive effect on continuation values of large on small stores relative to small on small. Only reducing the entry cost for large stores (CF-2) yields the largest number of small stores needed to compensate for the reduction in the long-run profits of small stores caused by a large store. Reducing only the entry cost for small stores (CF-3) gives the lowest number of small stores needed to obtain the same reduction in long-run profits of large stores caused by another large store.

After reducing entry costs in the policy experiments, the increase in the exit probability of small stores does not change if there is an additional store (small or large) in the market. Furthermore, the exit of large incumbents is even less likely if an additional small or large store operates in the market. A reduction in entry costs causes the entry probability to decrease to an even greater extent with each additional store in the market, which suggests increasing in competition.

In summary, our comparison of alternative policies for small and large stores show that lower entry costs increase entry and exit while also decreasing the long-run profitability of incumbents through fiercer competition. A policy that only targets the entry of large stores has substantial implications for the entry, exit and profitability of small stores. The presence of such an indirect policy spillover effects across store types cannot be captured using either a static model or a dynamic model of homogeneous stores - both of which were previously used in the literature. A policy that only encourages the entry of small stores (CF-3) is more effective at increasing the competitive pressure on both small and large stores in the long run, i.e., it induces a larger decrease in $VC$ and $VE$ for both small and large stores with an additional store in the market. Exogenous features of local markets will play a role in determining the long-run profits and market structure resulting from policy changes.

Our counterfactuals show that in markets with store-type differentiation, we need to evaluate the heterogeneity in stores' responses to policy changes, as stores of one type indirectly influence rival types through short-run competition, which in turn determines the endogenous evolution of the market structure over time.

# 7 Robustness analysis

In this section, we discuss the robustness of our main results. Our main findings are not affected by alternative measures of regulation and profits, different demand and profit function specifications, or changes in the number of potential entrants. Finally, we also highlight possible extensions of the dynamic model.

**Regulation measures.** We perform the following robustness checks of our regulation measures. First, we present results concerning profit function estimation and cost estimates using the share of non-socialist seats as measure of the stringency of regulation (Appendix H). Liberal markets are defined as those with a non-socialist majority in local governments, whereas restrictive markets are those with a socialist majority. Second, our empirical findings are robust to different definitions and cut-off points of the regulation index. Third, we consider different weights of the variables included in the index.[38]

**Alternative profit measures.** Constructing profits using a discrete choice demand model provides the advantage of improved control for heterogeneity at the store level. To address skepticism regarding using price information for a product basket, we present results using accounting profit information for robustness (Dunne et al., 2013). 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 G.1 in Appendix G).

**Number of potential entrants.** To re-compute the new transition probabilities in the counterfactual policy experiments, we require the number of potential entrants of each store type. The new transition probabilities for incumbents and entrants are computed using the structural formulas in POB (pp.383). Because we employ two different GMM estimators and empirical transition probabilities that use the difference between observed and predicted entry and exit rates from the model, we do not need to have the number of potential entrants when estimating fixed and entry costs.[39] Assuming a fixed number of potential entrants from an internal or external pool might be overly restrictive for retailing, as it is difficult to define an external pool, and the internal pool is sensitive to changes in local conditions and store type combinations. To relax these restrictions, we assume that the number of potential entrants of each store type comes from a Poisson distribution and that the mean of this distribution is not influenced by

[38]The results of the latter two robustness checks are available from the authors upon request.

[39]However, the use of a pseudo-log-likelihood estimator requires knowing the number of potential entrants (see pp.386 in POB).

changes in the degree of regulation.

A proper model of the endogeneity of potential entrants with respect to regulation is left to future research because it substantially complicates the modeling framework and computations and requires additional assumptions. Changes in regulation might affect entry by changing the number of potential entrants. We do not believe that this is as pronounced in our application to the Swedish retail food market as in many other industries for at least two reasons. First, there was no structural shift in regulation during the study period. Second, we observe multiple entries of large stores in local markets in two or more consecutive years in the data. Based on discussion with market participants and given that the number of stores decreases over time, it is unreasonable to assume that there are an infinite (or very large) number of potential entrants in the Swedish retail food industry. We observe a constant trend toward larger but fewer stores over time, and the aggregate demand for food products is not likely to change drastically over time.

**Demand specification.** In the demand analysis, we consider a product basket containing 11 products (Appendix B). Our main results are robust to using a small product basket with only three products. The results only indicate changes in the size of profits and costs, but the cost ratio for small and large stores remains the same. The profit estimates are robust to the method for constructing the market shares used in the demand estimation, i.e., if we use sales instead of quantify (Section 4.1 and footnote 24). The demand estimates using market shares based on sales are available from authors upon request.

In addition to the cost shifters, for robustness, the paper also uses additional instruments to identify the price coefficient: (i) the average prices of stores of the same type in other local markets (Hausman, 1997; Nevo, 2001; Hendel and Nevo, 2006); (ii) sum of the sales space of other stores with the same owner and the sum of the sales space of other stores of the same type but with a different owner (BLP instruments) (Berry et al., 1995). Our main findings are robust to the use of these additional instruments. It is important to note that using these instruments requires us to make additional assumptions. The average price in other markets is a valid instrument when there are no national demand shocks. The advantages and disadvantages of different types of instruments in identifying the demand equation are discussed in detail in Nevo (2000).

**Serially correlated unobservables.** Our structural estimation results are robust to different combinations of variables in the local market index $y_{mt}$. Even if a rich profit function specification including local market fixed effects is used (equation (15) and Table 5), there might nevertheless be persistent differences in profits across markets due to unobserved factors. The presence of serially correlated unobservables can induce positive bias in the competition parameters in the profit regression. Thus, the expected negative effect of competition on profits might be underestimated due to unobserved heterogeneity, e.g., persistent demand shocks. In other words, the paper provides conservative estimates of the competition effects.

**Quantifying changes in long-run competition.** Table 9 reports the average and total marginal effects from changes in continuation and entry values and the probabilities of entry and exit when an additional small or large store operates in the market. To assess the sensitivity of the results, we also compute the entire distribution of the marginal effects. Our main results remain robust throughout the distribution of marginal effects (results are available from authors upon request). While analyzing the entire distribution provides rich information on competition effects, the averages and sums of marginal effects provide a consistent summary of these effects.

**Cost estimates and counterfactuals using sell-off values.** The model can be used to estimate sell-off values instead of fixed costs. For robustness, we consider cost estimates and counterfactual results using sell-off values rather than fixed costs in Appendix F. Table F.1 in Appendix F indicates that the average sell-off value is approximately 10 times higher for large than for small stores. The average entry costs for large stores are 18 percent lower in markets with liberal than with restrictive regulations (SEK 110.9 vs. 136.5 million). The corresponding difference is 10 percent for small stores (SEK 12.11 vs. 13.56 million). For both store types, the average $VC_z$ and $VE_z$ are lower in liberal than in restrictive markets (Table F.2). The decrease in long-run profits from an additional large store is approximately 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 (Tables F.3-F.4). Counterfactual simulations show that decreasing the entry costs of small and large stores in restrictive markets to the levels observed in liberal markets results in higher entry rates and lower long-run profits for incumbents (Table F.5).

**Modeling firm.** Because of computational complexity, this paper only controls for firm/owner in the static component of the model (the discrete choice demand). Using the framework to understand store dynamics on the basis of 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 an application to the Swedish retail food market, modeling store type differentiation is more interesting because it provides information concerning the trade-offs between small and large stores in a market in which all stores are regulated, which is important for both consumers and firms.

**Spatial differentiation.** Based on the descriptive patterns of the market trending toward larger but fewer stores, the current version of the paper presents an implementation that captures differentiation in store type. We capture the net competitive effects across store types given their geographic locations. It is straightforward to extend the model to also include differentiation in both type and location (Appendix I). The major constraints are the dimensionality of the state space and computational complexity.

# 8 Conclusions

This paper examines store dynamics and cost structures in the retail food market using a structural model of demand, entry and exit. The framework, which builds on Pakes et al. (2007), allows for differentiation in store type. We highlight the role of asymmetries between heterogeneous players in industry dynamics, an aspect that is is difficult to assess in theory, two-period static entry models or through dynamic models with the entry and exit of homogeneous stores. We estimate the sunk entry costs and fixed costs for small and large stores in markets with different degrees of regulation to evaluate the role of regulations in determining industry dynamics. Based on the structural estimates, we perform 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, short- and long-run profits, and fixed and entry costs show asymmetries between store types. The decrease in a small store's long-run profits from an additional large store is approximately twice that from an additional small store. Reduced entry costs lead to more intense competition among incumbents in markets with a low-profit regime, i.e., long-run profits decrease relatively more than in high-profit markets. Entry cost reductions exacerbate the trend that we observe in the data, by which competition becomes stronger from large stores and small stores exit. Policies that encourage the entry of only one store type significantly influence the endogenous entry, exit and continuation values of the rival store type. A comparison of alternative policies demonstrates, for example, that only providing entry cost reductions for large stores imposes substantial competitive pressure on small stores, which in turn induces the entry and exit of small stores despite that their entry costs are not explicitly targeted by the policy.

Future research could assess the importance of spatial differentiation and ownership in determining the observed differences in the cost structure. These two features have yet to be implemented into the dynamic section 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.

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**Table 1:** Characteristics of the Swedish retail food market

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

NOTE: DELFI is provided by Delfi Marknadspartner AB and contains all retail food stores based on their geographical location (address). Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Sales (incl. 12% VAT) are measured in thousands of 2001 SEK (1 USD=9.39 SEK, 1 EUR=8.34 SEK).

**Table 2:** Entry and exit rates across local markets and years

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

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

**Table 3:** Estimated parameters of the demand equation: Nested logit

| | 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 | 0.282 | 0.002 | 0.401 | 0.132 |
| Log of income | | | | | -1.106 | 0.006 | 1.298 | 0.300 |
| Log of income squared | | | | | 0.055 | 0.0004 | -0.110 | 0.010 |
| ICA | 0.129 | 0.010 | 0.152 | 0.012 | 0.094 | 0.007 | 1.881 | 0.234 |
| Axfood | 0.136 | 0.010 | 0.150 | 0.011 | 0.045 | 0.007 | 1.624 | 0.129 |
| Coop | 0.218 | 0.011 | 0.241 | 0.013 | 0.086 | 0.008 | 1.806 | 0.223 |
| Bergendahls | -0.061 | 0.020 | -0.047 | 0.020 | -0.121 | 0.014 | 1.266 | 0.215 |
| Price | 0.016 | 0.0001 | 0.017 | 0.0002 | 0.0006 | 0.0001 | 0.019 | 0.004 |
| Market share (grp) | 0.971 | 0.0015 | 0.959 | 0.0040 | 0.898 | 0.0014 | 0.637 | 0.169 |

NOTE: The average price of a type in the other local markets and average wages are used as instruments for prices. The log of the average market share in its own group in the other local markets is used as instrument for market share within the group.

**Table 4:** Average estimated own and cross price elasticities by store type

| | Small ($i$) | Small($j$) | Large ($k$) | Large ($m$) |
|---|---|---|---|---|
| Small ($i$) | -3.871 | 0.125 | 0.221 | 0.221 |
| Small($j$) | 0.125 | -3.871 | 0.221 | 0.221 |
| Large ($k$) | 0.031 | 0.031 | -3.001 | 0.841 |
| Large ($m$) | 0.031 | 0.031 | 0.841 | -3.001 |

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 5:** Profit-generating function estimates

| | Model specification | | | |
|---|---|---|---|---|
| | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ |
| Number of small stores | -0.068 | -0.110 | -0.103 | -0.100 |
| | (0.005) | (0.009) | (0.009) | (0.008) |
| Number of small stores × Large type | 0.018 | 0.018 | 0.018 | 0.018 |
| | (0.005) | (0.004) | (0.004) | (0.004) |
| Number of small stores squared | 0.0006 | 0.001 | 0.0009 | 0.0009 |
| | (0.0001) | (0.0002) | (0.0002) | (0.0002) |
| Number of large stores | -0.318 | -0.366 | -0.370 | -0.366 |
| | (0.029) | (0.043) | (0.043) | (0.043) |
| Number of large stores × Large type | -0.069 | -0.071 | -0.071 | -0.071 |
| | (0.019) | (0.014) | (0.014) | (0.014) |
| Number of large stores squared | 0.012 | 0.015 | 0.016 | 0.016 |
| | (0.001) | (0.002) | (0.002) | (0.002) |
| Log of population | -5.553 | -22.322 | -21.280 | -21.145 |
| | (0.582) | (4.776) | (6.117) | (6.110) |
| Log of population squared | 0.314 | 1.146 | 1.125 | 1.115 |
| | (0.029) | (0.224) | (0.287) | (0.287) |
| Log of distance to DC | -0.854 | -1.181 | -1.181 | -1.181 |
| | (0.221) | (0.259) | (0.259) | (0.259) |
| Log of distance to DC squared | 0.040 | 0.056 | 0.056 | 0.056 |
| | (0.010) | (0.012) | (0.012) | (0.012) |
| Log of income | | | 0.794 | 0.795 |
| | | | (0.470) | (0.470) |
| Log of income squared | | | -0.054 | -0.054 |
| | | | (0.029) | (0.029) |
| Large type | 2.356 | 2.350 | 2.350 | 2.350 |
| | (0.053) | (0.040) | (0.040) | (0.040) |
| Regulation | | | | -1.181 |
| | | | | (0.259) |
| Market fixed effects | No | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.683 | 0.802 | 0.802 | 0.802 |
| Root of mean squared errors | 0.806 | 0.618 | 0.617 | 0.617 |
| Absolute mean errors | 0.651 | 0.382 | 0.381 | 0.381 |
| 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. The OLS estimator is used. Robust standard errors are presented 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 2 is used to measure the degree of regulation in each local market.

**Table 6:** Estimation results for 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 | | | | | | | | |
| Entry cost restrictive markets ($a$) | 0.247 | 0.272 | 0.259 | 0.255 | 0.033 | 0.034 | 0.033 | 0.036 |
| | (0.023) | (0.023) | (0.024) | (0.027) | (0.008) | (0.007) | (0.007) | (0.007) |
| Entry cost liberal markets ($a$) | 0.317 | 0.358 | 0.351 | 0.348 | 0.033 | 0.056 | 0.043 | 0.038 |
| | (0.033) | (0.040) | (0.041) | (0.041) | (0.010) | (0.011) | (0.011) | (0.011) |
| B. Mean of fixed cost and entry cost | | | | | | | | |
| Fixed cost ($\phi$) | 0.436 | 0.271 | 0.349 | 0.346 | 2.380 | 2.716 | 3.432 | 3.368 |
| Entry cost restrictive markets ($\kappa$) | 12.123 | 11.001 | 11.577 | 11.746 | 101.556 | 98.458 | 103.823 | 94.324 |
| Entry cost liberal markets ($\kappa$) | 9.460 | 8.378 | 8.544 | 8.609 | 98.186 | 61.720 | 76.816 | 86.760 |

NOTE: Standard errors are presented in parentheses. $\mathcal{M}_1 - \mathcal{M}_4$ are different specification of the profit generating function (see Table 5). 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 as having restrictive (liberal) regulations if the regulation index, defined in Section 2, is below (above) the median. Fixed cost follows an exponential distribution. The entry cost for small stores ($\kappa_{small}$) follows a unimodal distribution with parameter $a_1$. For large stores, the entry cost is $k_{large}$=$k_{small}$ + $\mu$, where $\mu$ follows a unimodal distribution with parameter $a_2$. The mean values in panel B are in millions of 2001 SEK (1 USD=9.39 SEK, 1 EUR=8.34 SEK).

**Table 7:** 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 ($VC_z$) | | | | |
| Minimum | 0.106 | 0.201 | 0.690 | 0.910 |
| 10th percentile | 2.100 | 2.013 | 22.421 | 15.464 |
| 25th percentile | 10.139 | 4.969 | 92.654 | 41.883 |
| 50th percentile | 16.283 | 13.053 | 156.602 | 101.561 |
| 75th percentile | 30.290 | 27.063 | 316.336 | 207.544 |
| 90th percentile | 52.875 | 57.167 | 492.502 | 630.681 |
| Maximum | 263.544 | 171.098 | 2805.376 | 1614.500 |
| Mean | 23.755 | 26.949 | 243.806 | 210.694 |
| B. Value function of entrants ($VE_z$) | | | | |
| Minimum | -0.041 | -5.510 | -1.401 | -0.026 |
| 10th percentile | 1.119 | 0.583 | 10.363 | 13.460 |
| 25th percentile | 2.755 | 1.913 | 27.360 | 25.612 |
| 50th percentile | 7.268 | 4.901 | 72.093 | 51.489 |
| 75th percentile | 17.179 | 12.435 | 165.164 | 124.437 |
| 90th percentile | 33.964 | 36.472 | 331.092 | 384.888 |
| Maximum | 131.772 | 109.891 | 1402.688 | 1237.556 |
| Mean | 13.903 | 12.178 | 144.477 | 131.386 |

NOTE: Value functions are computed using the estimated parameters for the exit and entry distributions and the most complex profit-generating function specification ($\mathcal{M}_4$). Only observed local market configurations are included. Municipalities are defined as having restrictive (liberal) regulations if the regulation index, defined in Section 2, is below (above) the median. Numbers are reported in millions of 2001 SEK.

**Table 8:** Estimation of the long-run competition effects on $VC$, $p^x$, $VE$, and $p^e$

| | $VC$ | | $p^x$ | | $VE$ | | $p^e$ | |
|---|---|---|---|---|---|---|---|---|
| | #Small | #Large | #Small | #Large | #Small | #Large | #Small | #Large |
| Restrictive: Small stores | -0.0180 | -0.0352 | 0.0011 | 0.0011 | -0.0196 | -0.0324 | -0.0019 | -0.0045 |
| Liberal: Small stores | -0.0109 | -0.0282 | 1.29E-4 | 1.11E-4 | -0.0091 | -0.0219 | -0.0013 | -0.0039 |
| Restrictive: Large stores | -0.0174 | -0.0450 | 0.0012 | 0.0028 | -0.0194 | -0.0444 | -0.0018 | -0.0046 |
| Liberal: Large stores | -0.0090 | -0.0366 | -1.80E-4 | 0.0014 | -0.0065 | -0.0315 | -0.0015 | -0.0042 |

NOTE: Averages of marginal effects are reported. The profit-generating specification $\mathcal{M}_4$ is used. 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 as having restrictive regulations if the regulation index, defined in Section 2, is below the median. The fixed cost follows an exponential distribution. Entry cost follows a unimodal distribution that allows for type correlation.

**Table 9:** Counterfactuals: Changes in $VC$, $p^x$, $VE$, and $p^e$ when entry costs in liberal and regulated markets are identical

| Statistic | Growth $VC$ | | Change $p^x$ | | Growth $VE$ | | Change $p^e$ | |
|---|---|---|---|---|---|---|---|---|
| | #Small | #Large | #Small | #Large | #Small | #Large | #Small | #Large |
| A1. CF-1: Low profit regime markets | | | | | | | | |
| Median | -0.028 | -0.036 | 1.31E-4 | 1.89E-4 | 0.050 | -0.017 | 0.063 | 0.016 |
| Sum of changes | -15.962 | -702.521 | 0.010 | 0.014 | 70.9683 | 346.439 | 3.974 | 1.187 |
| A2. CF-1: High profit regime markets | | | | | | | | |
| Median | -0.011 | -0.022 | -4.82E-4 | 1.25E-4 | -8.93E-4 | -0.016 | 0.048 | 0.015 |
| Sum of changes | -47.842 | -958.883 | -0.073 | 0.019 | 111.140 | -38.166 | 5.465 | 2.222 |
| B1. CF-2: Low profit regime markets | | | | | | | | |
| Median | -0.051 | -0.022 | 1.31E-4 | 1.86E-4 | -0.014 | -0.016 | 0.039 | 0.018 |
| Sum of changes | -82.909 | -418.053 | 0.010 | 0.014 | 78.653 | 168.703 | 2.823 | 1.368 |
| B2. CF-2: High profit regime markets | | | | | | | | |
| Median | -0.010 | -0.029 | -4.71E-4 | 1.22E-4 | 0.001 | -0.020 | 0.039 | 0.019 |
| Sum of changes | -53.619 | -941.829 | -0.071 | 0.018 | 119.307 | 58.85 | 5.840 | 3.288 |

NOTE: The profit-generating specification $\mathcal{M}_4$ is used in the counterfactuals. Counterfactual CF-1 decreases entry costs for both small and large stores in restrictive markets to be equal to those in liberal markets. Counterfactual CF-2 only decreases entry costs for large stores in restrictive markets to be equal to those in liberal markets. 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 as having restrictive regulations if the regulation index, defined in Section 2, is below the median. The fixed cost follows an exponential distribution. Entry cost follows a unimodal distribution that allows for type correlation.

**Table 10:** Estimation of the long-run competition effects on $VC$, $p^x$, $VE$, and $p^e$

| | $VC$ | | $p^x$ | | $VE$ | | $p^e$ | |
|---|---|---|---|---|---|---|---|---|
| | #Small | #Large | #Small | #Large | #Small | #Large | #Small | #Large |
| A. Small stores | | | | | | | | |
| Before counterf. | -0.0180 | -0.0352 | 0.0011 | 0.0011 | -0.0196 | -0.0324 | -0.0019 | -0.0045 |
| After CF-1 | -0.0172 | -0.0355 | 0.0010 | 0.0011 | -0.0179 | -0.0335 | -0.0023 | -0.0060 |
| After CF-2 | -0.0171 | -0.0354 | 0.0010 | 0.0011 | -0.0174 | -0.0326 | -0.0021 | -0.0054 |
| After CF-3 | -0.0174 | -0.0357 | 0.0010 | 0.0011 | -0.0182 | -0.0336 | -0.0023 | -0.0059 |
| B. Large stores | | | | | | | | |
| Before counterf. | -0.0174 | -0.0450 | 0.0012 | 0.0028 | -0.0194 | -0.0444 | -0.0018 | -0.0046 |
| After CF-1 | -0.0173 | -0.0428 | 0.0012 | 0.0025 | -0.0172 | -0.0405 | -0.0019 | -0.0050 |
| After CF-2 | -0.0174 | -0.0429 | 0.0011 | 0.0025 | -0.0170 | -0.0403 | -0.0020 | -0.0053 |
| After CF-3 | -0.0176 | -0.0431 | 0.0011 | 0.0025 | -0.0177 | -0.0410 | -0.0020 | -0.0051 |

NOTE: Averages of marginal effects are reported. The profit-generating specification $\mathcal{M}_4$ is used in the counterfactuals. All counterfactuals decrease the entry costs in restrictive markets to be equal to those in liberal markets. Counterfactual 1 (CF-1) decreases entry costs for both small and large stores. Counterfactual 2 (CF-2) only decreases entry costs for large stores. Counterfactual 3 (CF-3) only decreases entry costs for small stores. 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 as having restrictive regulations if the regulation index, defined in Section 2, is below the median. The fixed cost follows an exponential distribution. Entry cost follows a unimodal distribution that allows for type correlation.

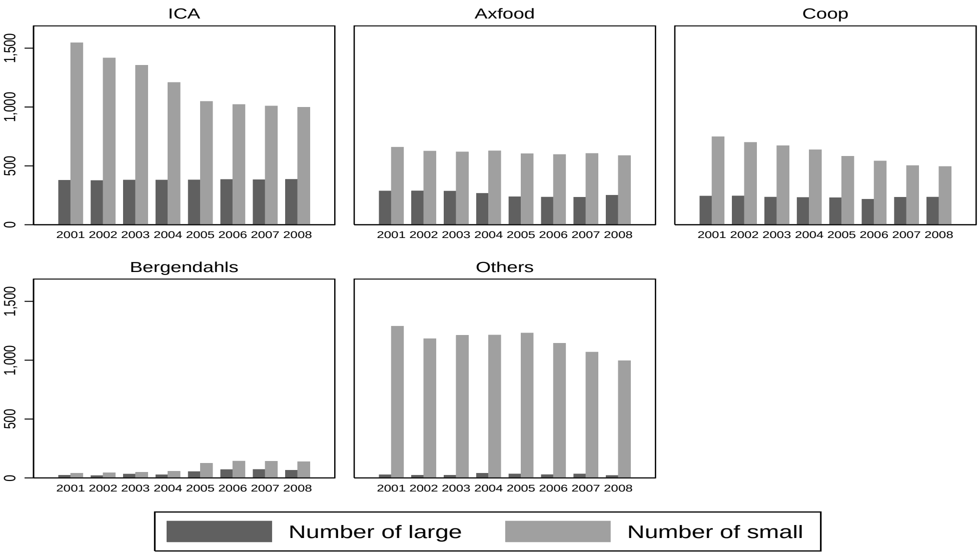


**Figure 1:** Number of large and small stores by firm affiliation 2001-2008.

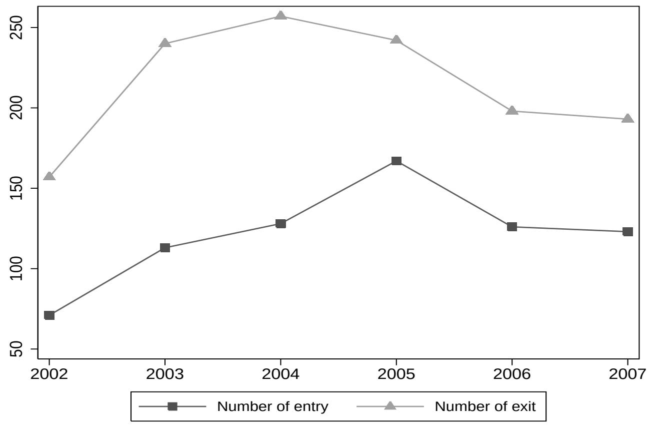


**Figure 2:** Total number of entries and exits in Sweden 2002-2007.

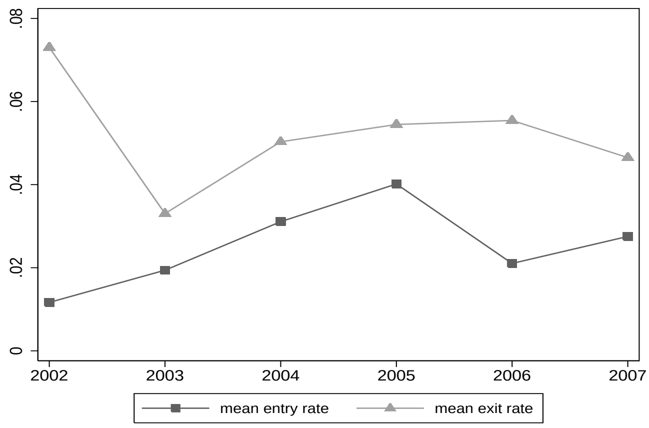


**Figure 3:** Mean entry and exit rates across local markets 2002-2007.

# ONLINE APPENDIX
# Entry Regulations, Product Differentiation and Determinants of Market Structure

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July 23, 2014

The online appendix consists of nine sections. Appendix A provides additional information about entry regulation in Sweden. Appendix B presents additional information about data sources. Appendix C provides additional details about the model. Appendix D provides details about the construction of the transition probabilities. Appendix E provides details about the estimation. Appendix F reports additional results based on sell-off values and the counterfactuals. Appendix G provides an alternative approach to constructing operating profits. Appendix H reports results using alternative measures of regulation. Appendix I extends the dynamic model to include spatial product differentiation.

## Appendix A: 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

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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.

## Appendix B: Data sources

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

Advantages of the data are that they are collected yearly and include the total population of stores. Sales (including VAT) and sales space are collected via yearly surveys. 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.

**Additional descriptive statistics.** Table B.1 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.

The majority of entrants and exits are small stores (Table B.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. Sales space and sales are surprisingly similar across stores that belong to different firms.

Figure 1 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).

Figures 2 and 3 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.

**Table B.1:** 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 B.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.

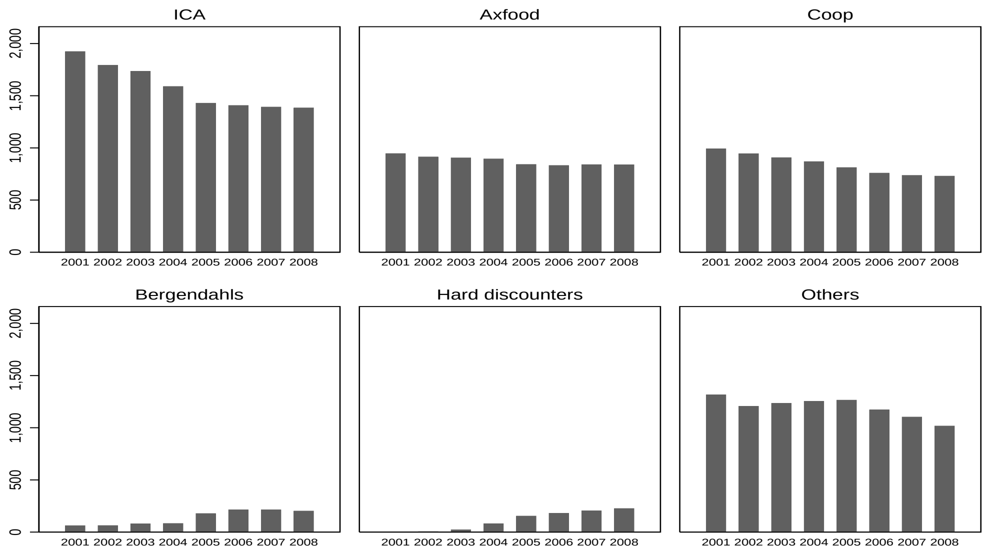


**Figure 1:** Total number of stores by firm affiliation 2001-2008.

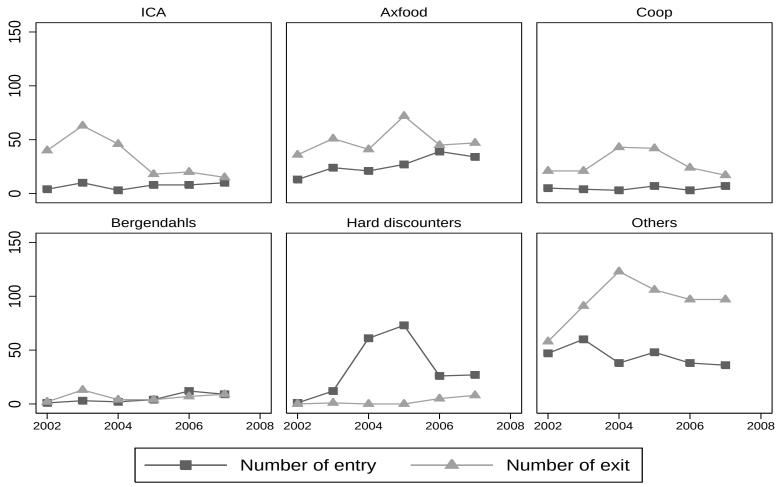


**Figure 2:** Total number of entries and exits by firm affiliation 2002-2007.

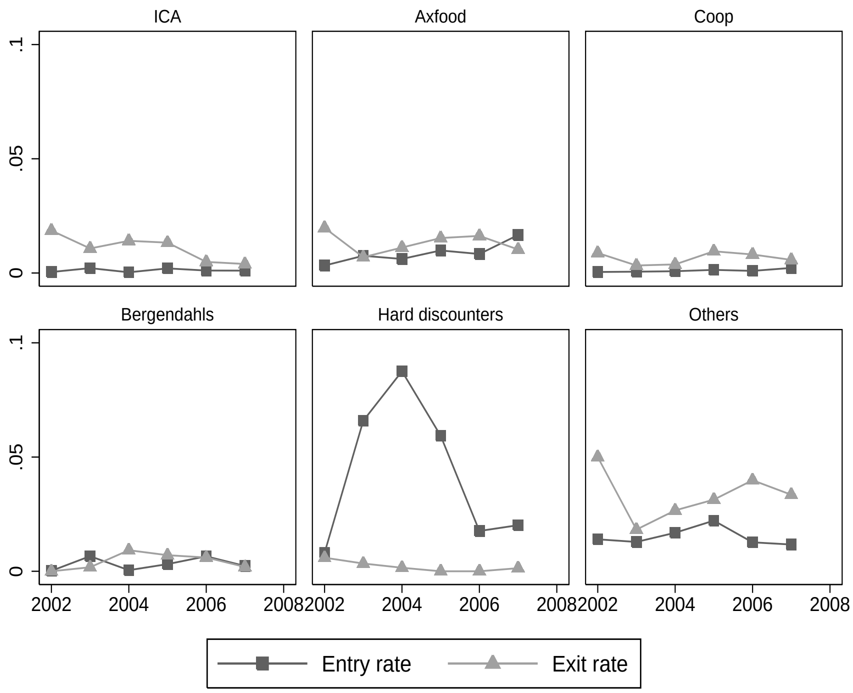


**Figure 3:** Mean entry and exit rates by firm affiliation and local markets 2002-2007.

**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.[1] 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. 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. 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.3 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.4 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

[1]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.

firms.

**Table B.3:** 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.

**Table B.4:** 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: Model: Continuation values, entry values and equilibrium

**Incumbents and sell-off value.** Section 3 in the paper presents the model using fixed-costs. The model can be rewritten to estimate sell-off values instead of fixed costs. The value function of an incumbent store of type $z$ is given by the Bellman equation

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

where $\pi_z(\cdot)$ is the profit function; $VC_z(\cdot)$ is the continuation value; $\phi_z$ is the sell-off value; and $0 < \beta < 1$ is the discount factor. Incumbents know their scrap value $\phi_z$ but not the number of entrants and exits, prior to making their decision.

**Incumbents perceptions.** 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

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

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 fixed-cost (or 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 perceptions.** 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

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

where $p^e_z(\cdot)$ is a potential entrant's perceptions of the number of entrants and exits of each type conditional on entering 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:

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

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

**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

(C-2). 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 $p_z^c(e_z, e_{-z}, x_z,\ x_{-z}|n_z, n_{-z}, \mathbf{y}, \lambda_z^c = 1)$. That is, the probability that the exit draw is larger than the type-location continuation value $\phi_z > VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})$ is

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

The perceptions of entry conditional on that they enter $p_z^c(\cdot)$ and the perceptions of exit of the same type $g_z^c(\cdot)$ and of the rival type $g_{-z}^c(\cdot)$ all need to be consistent with 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

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

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.

## Appendix D: Transition probabilities

**Incumbents and sell-off value.** An incumbent that continues will get the continuation value

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

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

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

If we assume that $\phi_z$ 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 (D-9). Using (D-8), we then get

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

where $\sigma_z$ 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 $z$

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

There is no dependence over time in the transition probabilities.[2]

**Incumbents: Empirical transition probabilities.** 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 $\boldsymbol{W}_z^c$ and $\boldsymbol{p}_z^x$ into (D-11) in order to get consistent estimates of $\boldsymbol{VC}_z(\cdot)$.

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

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

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

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

Let $W_{\mathbf{s},\mathbf{s}'}^c$ be the probability that an incumbent 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

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

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

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

of $\boldsymbol{VC}_z(\cdot)$ as a function of $\boldsymbol{\pi}_z$, $\tilde{\boldsymbol{p}}_z^x$ and $\tilde{\boldsymbol{W}}_z^c$ when modeling sell-off value:

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

where $I$ is the identity matrix. Modeling fixed-costs, we have (see Section 3)

$$\widehat{\boldsymbol{VC}}_z(\cdot) = [I - \beta\tilde{\boldsymbol{W}}_z^c]^{-1}\tilde{\boldsymbol{W}}_z^c[\boldsymbol{\pi}_z - \beta\sigma_z(1 - \tilde{\boldsymbol{p}}_z^x)]. \tag{D-14}$$

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 $\tilde{\boldsymbol{W}}_z^c$ and $\tilde{\boldsymbol{p}}_z^x$ are independent of the parameters (for a known $\beta$), 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.[3]

**Entrants: Empirical transition probabilities.** 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 $\mathbf{s}$:

$$\tilde{W}_{\mathbf{s},\mathbf{s}'}^e = \frac{1}{\#R(\mathbf{s})}\frac{\sum_{r\in R(\mathbf{s})}(e_{r,z})\mathbf{1}_{\mathbf{s}_{r+1}=\mathbf{s}'}}{\sum_{r\in R(\mathbf{s})}(e_{r,z})}. \tag{D-15}$$

The expected value of entry is then

$$\begin{aligned}\widehat{\boldsymbol{VE}}_z(\cdot) = \;& \left[\tilde{\boldsymbol{W}}_z^e + \beta\tilde{\boldsymbol{W}}_z^e[I - \beta\tilde{\boldsymbol{W}}_z^c]^{-1}\tilde{\boldsymbol{W}}_z^c\right]\boldsymbol{\pi}_z \\ & + \left[\beta\tilde{\boldsymbol{W}}_z^e\beta\tilde{\boldsymbol{W}}_z^c[I - \beta\tilde{\boldsymbol{W}}_z^c]^{-1}\tilde{\mathbf{p}}_z^x + \beta\tilde{\boldsymbol{W}}_z^e\tilde{\mathbf{p}}_z^x\right]\sigma_z.\end{aligned} \tag{D-16}$$

[3]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.

# Appendix E: Details on estimation

The empirical transition probability matrices used in the estimation are sparse. To compute the value functions for the states that are not observed in the data, we use a "smoothing" technique as suggested by Pakes et al. (2007). POB use kernel estimator. This paper uses b-splines and ordinary least square estimator. To estimate cost parameters, we use two different GMM estimators, i.e., an indirect inference estimator and an minimum distance estimator. The cost estimates are robust to the estimator choice.

**Indirect inference:** In case of indirect inference, we run ordinary least square regression on entry and exit probabilities from the data and from the model, i.e. $\mathbf{p} = \mathbf{s}\boldsymbol{\rho}$, and save the estimated coefficients $\boldsymbol{\rho}$ (data) and $\boldsymbol{\rho}(\boldsymbol{\theta})$ (model). The criterion function minimizes the distance between the regression coefficients:

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} [\hat{\boldsymbol{\rho}} - \hat{\boldsymbol{\rho}}(\boldsymbol{\theta})]' \mathbf{A}_R [\hat{\boldsymbol{\rho}} - \hat{\boldsymbol{\rho}}(\boldsymbol{\theta})], \tag{E-17}$$

where $\mathbf{A}_R$ is the weighting matrix, i.e., identity matrix or $Var[\boldsymbol{\rho}]^{-1}$.

**Minimum distance estimator:** 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

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

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.

## Appendix F: Cost estimates and counterfactuals using sell-off values

Table F.1 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).[4] We estimate the entry cost parameters for markets 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. 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.

**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

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

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 F.2 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 F.3 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 $VC_z$, $VE_z$, $p^e_z$ and $p^x_z$. Table F.4 shows the average marginal effects of an additional store.[5] 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 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 ($VE$)

[5]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.

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.

**Counterfactual results**. 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 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 F.5 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 H.2).

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.[6] 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

[6] 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.

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 ($VC_{large}$) 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.[7] 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.[8] 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

[7]These marginal effects are computed by regressing $VC_{small}$ on a linear combination of the state variables (see Table F.4).

[8]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.

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.

**Table F.1:** 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 ($\sigma$) | 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 ($\phi$) | 0.610 | 0.021 | 0.042 | 0.026 | 6.000 | 0.207 | 0.206 | 0.362 |
| Entry cost restrictive markets ($\kappa$) | 14.00 | 13.48 | 13.43 | 13.56 | 158.0 | 135.82 | 135.46 | 136.51 |
| Entry cost liberal markets ($\kappa$) | 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 H.1). 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 ($\kappa_{small}$) follows a unimodal distribution with parameter $a_{small}$. For large stores, we estimate the parameter of $\mu$ where $k_{large}$=$k_{small}$ + $\mu$, where $\mu$ 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 F.2:** 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 F.3:** 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 F.4:** 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 | -0.0 |
| | (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) | (0.0 |
| $R^2$ | 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 | -0.0 |
| | (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) | (0.0 |
| $R^2$ | 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 marke (column). Standard errors are in parentheses. The estimated marginal effects are obtained using average number of observed stores and the following regression specificatio ln(y)=$\beta_0 + \beta_1 n_{small} + \beta_2 n_{large} + \beta_3$MarketIndex $+ \beta_4$Regulation $+ \beta_5 n_{small} \times$ Regulation $+ \beta_6 n_{large} \times$ Regulation $+ \beta_7 n_{small} \times n_{large} + u$, where $y = \{VC, p^x, VE, p^e\}$, $n_{sm}$ 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 restrictive.

**Table F.5:** 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.

# Appendix G: 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 sales 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 sales 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.[9]

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

**Results: estimation of the alternative profit function.** Table G.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

[9]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.

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

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 G.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.

# Appendix H: Results using alternative measures of regulation

**Table H.1:** Profit-generating function estimates

| | Model specification | | | |
|---|---|---|---|---|
| | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_3$ | $\mathcal{M}_4$ |
| Number of small stores | -0.068 | -0.110 | -0.103 | -0.102 |
| | (0.005) | (0.009) | (0.009) | (0.009) |
| Number of small stores × Large type | 0.018 | 0.018 | 0.018 | 0.018 |
| | (0.005) | (0.004) | (0.004) | (0.004) |
| Number of small stores squared | 0.0006 | 0.001 | 0.0009 | 0.0009 |
| | (0.0001) | (0.0002) | (0.0002) | (0.0002) |
| Number of large stores | -0.318 | -0.366 | -0.370 | -0.373 |
| | (0.029) | (0.043) | (0.043) | (0.043) |
| Number of large stores × Large type | -0.069 | -0.071 | -0.071 | -0.071 |
| | (0.019) | (0.014) | (0.014) | (0.014) |
| Number of large stores squared | 0.012 | 0.015 | 0.016 | 0.016 |
| | (0.001) | (0.002) | (0.002) | (0.002) |
| Log of population | -5.553 | -22.322 | -21.280 | -20.808 |
| | (0.582) | (4.776) | (6.117) | (6.107) |
| Log of population squared | 0.314 | 1.146 | 1.125 | 1.100 |
| | (0.029) | (0.224) | (0.287) | (0.287) |
| Log of distance to DC | -0.854 | -1.181 | -1.181 | -1.181 |
| | (0.221) | (0.259) | (0.259) | (0.259) |
| Log of distance to DC squared | 0.040 | 0.056 | 0.056 | 0.056 |
| | (0.010) | (0.012) | (0.012) | (0.012) |
| Log of income | | | 0.794 | 0.791 |
| | | | (0.470) | (0.470) |
| Log of income squared | | | -0.054 | -0.054 |
| | No | No | (0.029) | (0.029) |
| Large type | 2.356 | 2.350 | 2.350 | 2.350 |
| | (0.053) | (0.040) | (0.040) | (0.040) |
| Regulation | | | | 0.358 |
| | | | | (0.322) |
| Market fixed effects | No | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.683 | 0.802 | 0.802 | 0.802 |
| Root of mean squared errors | 0.806 | 0.618 | 0.617 | 0.617 |
| Absolute mean errors | 0.651 | 0.382 | 0.381 | 0.381 |
| 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 H.2:** 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 | | | | | | | | |
| Entry cost restrictive markets ($a$) | 0.224 | 0.253 | 0.238 | 0.237 | 0.024 | 0.031 | 0.029 | 0.029 |
| | (0.023) | (0.023) | (0.024) | (0.027) | (0.008) | (0.007) | (0.007) | (0.007) |
| Entry cost liberal markets ($a$) | 0.305 | 0.345 | 0.336 | 0.340 | 0.030 | 0.036 | 0.035 | 0.036 |
| | (0.033) | (0.040) | (0.041) | (0.041) | (0.010) | (0.011) | (0.011) | (0.011) |
| B. Mean of fixed cost and entry cost | | | | | | | | |
| Fixed cost ($\phi$) | 0.072 | 0.008 | 0.009 | 0.009 | 0.651 | 0.076 | 0.084 | 0.079 |
| Entry cost restrictive markets ($\kappa$) | 13.37 | 11.83 | 12.56 | 12.61 | 133.99 | 106.77 | 113.25 | 113.14 |
| Entry cost liberal markets ($\kappa$) | 9.83 | 8.69 | 8.92 | 8.81 | 109.19 | 90.99 | 92.40 | 91.53 |

NOTE: Standard errors in parentheses. $\mathcal{M}_1 - \mathcal{M}_4$ are different specification of the profit generating function (see Table H.1). 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 they have a socialist (non-socialist) local government, defined in section 3. Fixed cost follows an exponential distribution. Entry cost for small stores ($\kappa_{small}$) follows a unimodal distribution with parameter $a_{small}$. For large stores, we estimate the parameter of $\mu$ where $k_{large}$=$k_{small}$ + $\mu$, where $\mu$ 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).

# Appendix I: 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).[11] 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.[12]

**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 differ-

[11]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.

[12]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.

entiation in detail, we use a large number of locations. Grouping locations based on distance reduces the dimensionality of the competition parameters. Adding the following assumption reduces the competition parameter space: a store faces competition not from the stores in each location of the market but from neighboring locations, which are defined by the distance between locations (Seim, 2006). For example, three distance bands specification is the most commonly used in the empirical literature (Figure 7). In this case, the profit function can then be specified as

$$\begin{aligned}\tilde{\pi}_{zlt} = \quad & \gamma_0 + \gamma_{zl} n_{zlt} + n_{zlt}\mathbf{dm}_{zl}\boldsymbol{\gamma}_{zl} + \textstyle\sum_{k\in L} n_{zkt}\gamma_{zk} + \\ & \mathbf{n}_{-zlt}\boldsymbol{\gamma}_{-zl} + \mathbf{n}_{-zlt}\mathbf{dm}_{zl}\boldsymbol{\gamma}_{-zld} + \textstyle\sum_{k\in L} \mathbf{n}_{-zkt}\boldsymbol{\gamma}_{-zk} + \\ & \mathbf{dm}_{zl}\boldsymbol{\gamma}_d + \mathbf{y}_{lt}\boldsymbol{\gamma}_y + \xi_l + \tau_t + \epsilon_{zlt},\end{aligned} \tag{I-19}$$

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

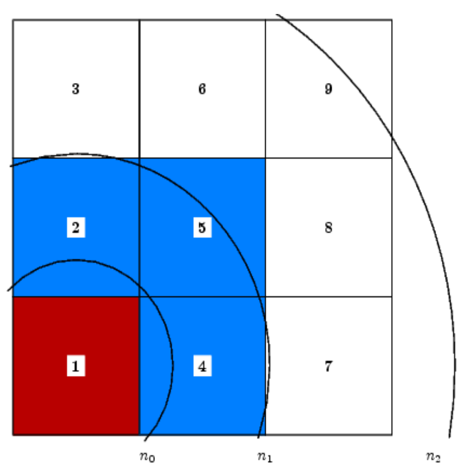


**Figure 4:** Illustration of distance bands

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