Industry Dynamics and Format Repositioning in Retail*

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Draft: August 27, 2012

Abstract

In differentiated product markets, when firms are affected by demand shocks, they may react by repositioning their products, which in turn affects market structure. This paper proposes a dynamic oligopoly model to estimate the costs of repositioning store formats together with sunk costs of entry and sell-off values of exit in the retail industry. The model gives important information about driving forces behind format changes and how such repositioning can be linked to entry and exit. Using data from Sweden, the results indicate that both repositioning and entry costs increase with market size, and their growth decreases when moving to larger markets. Small markets have higher sell-off values than repositioning costs, but large entry costs. The difference between higher entry and lower repositioning costs explains why the number of observed repositionings is higher than the number of entrants. Since entry is regulated in most of OECD countries, repositioning costs and their link to competition have important implications for competition policy.

Keywords: imperfect competition; dynamic oligopoly; dynamic estimation; industry dynamics; repositioning; retail.
JEL Classification: L1, L13, L81

*I would like to thank Jaap Abbring, Dan Ackerberg, Victor Aguirregabiria, Eric Bartelsman, Pierre Dubois, Amit Gandhi, Lapo Filistrucchi, Lennart Hjalmarsson, Matilda Orth, Catherine Schaumans, Che-Lin Su, Johan Stennek, and Andrew Sweeting for very useful comments and suggestions. In addition, I thank participants at EARIE (Toulouse), EARIE (Ljubliana), the 2008 Nordic Retail Conference (Stockholm), CEPR (Toulouse), Tilburg University, EEA-ESEM (Malaga), and the University of Gothenburg Industrial Organization seminars. Financial support from the Swedish Competition Authority is gratefully acknowledged.

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1 Introduction

There have been major structural changes in retail markets during the last decades, e.g., decreasing number of stores and the rise of the "big-box" format. Due to the increasing importance of information technology and distribution systems, large retail firms dominate, each operating a number of well-defined store formats, and continuously reconsidering store formats as well as possible entry of new stores, or exit. Recent investments in retail aim to increase product differentiation in store formats. However, each investment implies sunk costs. There are only a few studies that emphasize firms' strategies on format repositioning in local markets in response to strategies of rival firms (Sweeting, 2012; Gandhi et al., 2008). But, the retail industry has large scale-and-scope economies where format repositioning has key implications for competition.[1]

The aim here is to provide a model that estimates and links respositioning costs with sunk costs of entry and sell-off (exit) values. If rival firms enter with new stores, the reaction of the firm may be to change the formats of affected stores or to shut down some stores. Shifts in costs of entry and repositioning can then lead to markets with few stores, with little product differentiation and low competition. A retail market increasingly dominated by a small number of stores is bad for both consumers and suppliers. In Europe, there are countries where the top five firms made up 70 percent or more of the grocery market in 2005: Germany (70 percent), France (70 percent), Austria (79 percent), Estonia (79 percent), Ireland (81 percent), Slovenia (82 percent), Sweden (82 percent), and Finland (90 percent). Since entry is regulated in most of the OECD countries, sunk costs of entry and repositioning-format costs have important implications for policy analysis.[2]

This paper uses a fully dynamic oligopoly model to estimate the costs of format repositioning, sunk costs of entry, and sell-off values of exit in the Swedish

[1]Focusing on food prices in the EU, the European Commission published a report in December 2008, recommending among other things that, "regulations that restrict entry of new companies into the market need to be scrutinized and removed when appropriate, while keeping in mind their environmental and social goals" (European Commision 2008:321).

[2]Pilat (1997) surveys entry regulations in OECD countries.

retail food industry.[3] [4]During the period 2001-2006 the number of stores that changed format was substantially larger than the number of stores that entered. For example, over 80 percent more stores changed format than entered in 2006. Four important firms dominate the Swedish retail food market. The focus here is on the individual store, but the paper also accounts for firm's strategies.[5] This is important, since firms try to change the formats of their stores in response to local competition. The format of the store is chosen to maximize the store's expected future profits.[6] But these choices may affect the future format choices of other stores in the market.

In each period, I estimate a discrete choice demand model, that accounts for spatial differentiation, to recover unobserved store quality. Store quality is defined as the mean of unobserved store characteristics across consumers. It is unobserved by the researcher but known to the store. Section 3.1 provides a detailed discussion about what I measure by quality. By changing format, stores try to increase the their store quality (quality effect), but this changing cannot be done without any cost. First, though stores try to keep their old consumers while hoping to also gain new ones, there may be a fall in sales in the short-run until the customers adjust to the new format. But second, there may also be sunk costs of investment associated with format repositioning. Regulation and decisive factors for format repositioning that are observable and differ across markets, e.g., local demographic characteristics allow to estimate mean repositioning costs the for observed changes.

Returns from format repositioning are realized over future periods and, there-

[3]Maican (2008) uses a similar approach to estimate the sunk costs of store-type repositioning, i.e., switching from a grocery store to a convenience store. But due to the small number of observed changes in store type, an accurate estimation of sunk costs is hard to obtain. The present paper extends Maican (2008) by introducing spatial competition and uses store concept instead of store type to define store-format. This is important, since store type is more related to size, while store concept is related to the firm's business model. A firm can change store concept to adjust to market competition. A more detailed discussion about the store-format definition is given in Section 2.

[4]There are studies that estimate costs paid by individuals/households when moving between different cities offering different market opportunities (Kennan and Walker, 2006; Bayer and Falko, 2006; and Gemici, 2007).

[5]While the dynamic setting at firm level could be problematic, since techniques for estimating dynamic games with incomplete information assume stationarity, the growth of the retail industry may be a non-stationary process, since some firms never exit.

[6]Since the store format is based on the business model given by the firm, the model presented at the store level surprises also the firm effect.

fore, a dynamic model is best for estimating repositioning costs and benefits.[7] The dynamic approach used here is based on the two-step procedure proposed by Bajari et al. (2007) (BBL). In the first step, I estimate price adjusted quality of each store from a random-coefficients demand model (Berry et al., 1995; Nevo, 2001; Davis, 2006). Using assumptions on the timing of innovations in store-quality relative to store-format choices, this estimation allows for endogenous format choices. These timing assumptions are used in the production-function estimation literature (Olley and Pakes, 1996; Blundell and Bond, 2000; Levinsohn and Petrin, 2003; and Ackerberg et al., 2006). The estimated quality is then used to estimate the sales-generating function. In addition, the paper also estimates entry, exit, and format-attractiveness policies. In the second step, using an inequality estimator (Pakes et al., 2007b), the paper recovers the sunk costs of entry, sell-off (exit) value, and format-repositioning costs. An advantage of using inequality estimator is that it is robust to simulation errors in the value function. This estimation approach is also used by Ho (2007) and Ishii (2005) when estimating models in a static setting, and by Holmes (2008) in a dynamic study of Wal-Mart's store locations.

Recent literature on estimation of dynamic games with Markov perfect equilibria has developed alternative extensions to the Hotz and Miller (1993) and Hotz et al. (1994) approaches (Aguirregabiria and Mira, 2007; Bajari et al., 2007; Pakes et al., 2007a; and Pesendorfer and Schmidt-Dengler, 2003). Several recent papers have estimated dynamic oligopoly games using industry data. First, there are studies of entry and exit in homogenous product markets: Ryan (2012) analyzes the cement industry and Collard-Wexler (2010) studies the ready-mix concrete industry. Second, there are papers that allow for vertical product differentiation by using logit-demand models: Beresteanu and Ellickson (2006) and Macieira (2006) analyze the supermarket and supercomputer industries, respectively. Third, there are few studies of both horizontal and vertical product differentiation: Analyzing the U.S. radio industry, Sweeting (2012) uses a random coefficients demand model to measure the costs of product repositioning. Jeziorski (2012) investigates cost efficiencies from mergers after the 1996 deregulation of U.S. radio using a structural dynamic framework.

This paper is closely related to Sweeting (2012) and Ryan (2012). Both those papers use the BBL dynamic framework to estimate sunk costs. Sweeting (2012)

[7] When firms reposition their products quickly, static modeling can capture the essential aspects of repositioning (Draganaska et al., 2009).

does not model entry and exit. This paper explicitly model entry and exit since there is a close connection between entry, exit, and format repositioning in retail markets. To my knowledge, this is the first paper that models entry, exit as well as repositioning at the same time. The sunk costs of entry are backed out as in Ryan (2012). However, an important difference is that I also account for spatial competition. Location is a key factor for a store, and consumers have preferences over both geographic and store characteristics. Finally, this paper is first, to my knowledge, to estimate repositioning costs in the retail industry.

Another alternative is to model at the firm level (Aguirregabiria and Vicentini, 2006; Jia, 2008). Using a static setting, Jia (2008) provides an empirical model for measuring the impact of chain stores on other discount retailers and quantifying the scale-economies within a chain. Her model allows for flexible competition patterns among all players. However, it has some limitations, such as that it cannot be applied to oligopoly games with three or more chains. In this case the strategy of the firm is modeled choosing the number, format, and location of its stores. The researcher then explicitly models firm behaviour, but might miss important information at store level. The researcher assumes that stores in the same format are identical, the only difference between two stores in the same format being their location. By aggregating stores, the researcher loses important information, such that why a firm changed the format of one store but kept others in the same format, if all were in similar locations. In addition, the researcher can then only estimate the distribution of store quality. In my case, recovering the adjusted quality of individual store is important, since store adjusted quality influences demand, and therefore is an important decision-factor for the firm.

This paper uses detailed data on all retail food stores in Sweden during 2001 to 2006. This is the first model of the store format repositioning. Given the complexity of this industry (multiple ownership, spatial differentiation, and regulation), the estimated parameters are preliminary, i.e. they cannot be used as a direct guide for policies. This paper provides initial estimates of these costs while future research should consider robustness tests and consider the implications of the results. I assume that the estimated repositioning costs are the same for each store within each group market. The results indicate that the costs of format repositioning increase with market size. For three groups by market-size, the ratio between median sales and average repositioning costs is over 20. Format repositioning seems most profitable, however, in medium-sized markets, with a population between 20,000 and 60,000. I find higher entry costs per median sales in medium than in large markets. Sell-off values on exit are about twice as high in the large markets as in the small ones.

The findings show that stores are less likely to exit if they have high quality, if they are located in large markets, or if the firm operates many stores in the same format. Entry is more likely in large markets and if rivals have high quality, i.e., if there is room for product differentiation. Stores with high quality are more likely to be in large formats, and old stores are less likely to reposition themselves. Furthermore, distance is found to be a key factor when consumers choose a store. Store's adjusted quality is more persistent for non-repositioning stores.

The next section gives a brief overview of the Swedish retail food industry and relevant recent events, and also discusses the data sources and introduce the variables. Section 3 then presents the theoretical model, while Section 4 discusses the results whereas Section 5 summarises and draw conclusions.

2 Overview of the Swedish Retail Food Industry

Annual retail sales in Sweden in 2004 were around SEK 400 billion, one-third of private consumption, of which 52 percent was grocery sales and 48 percent is non-food. Four large firms dominate Swedish food retail: ICA, Coop, Axfood, and Bergendahls together had more than 90 percent of all food retail sales in 2004. ICA, the largest firm (with 44 percent), consists of independently owned stores but with a fairly high degree of centralized decision-making. Axfood is a mix of franchisees and fully-owned stores.[8] Coop, on the other hand, consists of centralized cooperatives where decisions are made at the cooperative level (national or local). Axfood and Coop together have market shares slightly over 20 percent each. Bergendahls (4 percent) operates mainly in the south/south-western parts of the country. In addition, international firms with well-defined discount formats (Netto and Lidl) entered the Swedish market in 2002 and 2003, respectively. So far, they have fairly modest market shares. Finally, independent stores have about 8 percent market share.

Data. The data-set comes from Delfi Marknadsparter AB (DELFI); details of its sources are given in Appendix A. A store defined by physical location is the unit of observation. The data contain yearly information on all retail food stores

[8] Axel Johnson and the D-group merged at the end of the 1990s, to create Axfood, again with fairly centralized decision-making and uniformly-designed stores.

in the Swedish market during 2001 to 2006, including format, age, owner/firm, sales, sales space, and location. Store format depends on firm/owner, sales space (size), parking, product assortment, etc. Since retail food demand is a function of the market's population but varies across income levels, I connected demographic information from Statistics Sweden(SCB), such as population by age-groups and average income, to the store data from DELFI.

Store format. The retail food industry consists of firms that operate stores in different sizes, where each store has a well defined business concept. The name of a store is usually affiliated with the owner/firm and its self-defined store-concept (such as "very large" or "near you"). The main purpose of the paper is to measure average repositioning costs from one concept to another. However, since the number of store concepts is large (over 30), to reduce the space-dimensionality I group them into 18 *formats* (Table 1), each format containing one or more close store concepts of the same firm. The most important store concepts of one firm are kept in one format, however.

I distinguish cases where, the firm decided to replace one format with another for all its stores in that format. These aggregate format changes, decided at the firm level, are not considered as format repositioning for purposes of this study. On the other hand, a store can change format within or across firms, limited to some extend by sales space available. For example, a hypermarket is not likely to switch to a convenience store (more below). Because of the restricted entry (regulations), the reserve is also unlikely.[9]

To define the possible repositioning alternatives, I re-group the stores in four size groups based on sales space: very large (i.e., hypermarkets), large (i.e., supermarkets), medium (i.e., convenience stores), and small. The four main firms have store concepts in all these four size-groups. I only allow stores to change to other formats within the current size-group or in the next larger or smaller size-group.

Table 1 presents summary statistics for all formats grouped by firm. The largest is *ICA Maxi* (3,3378 m^2) followed by *Coop Large*, *ICA Kvantum*, and *Axfood Willys*, while the smallest is *Others*, i.e., gas station stores, small corner stores and the hard discounters Netto and Lidl. *ICA Maxi* has the highest average sales per square meter (SEK 88,000/m^2), followed by *Begendahls Vi* (SEK 81,000/m^2), while *Axfood Handlarń* has the lowest (SEK 36,000/m^2). *Axfood Vivo* and *ICA*

[9]The Swedish Plan and Building Act (PBA) authorizes the 290 municipalities to decide over applications for new entrants, while inter-municipality cases are handled by the 21 county administrative boards. Several reports have stressed the need to better analyze how regulation affects market outcomes (Pilat 1997; Swedish Competition Authority 2001:4, 2004:2, 2008:5).

Rimi disappeared from 2001 to 2006, while *Begendahls Vi* and *Coop Nära* appeared.

Figure 1 shows how the numbers of stores by format evolve during the study period. ICA increased the number of *ICA Maxi* hypermarkets, but reduced the number of *ICA Nära* small stores. Axfood increased the number of *Willys* supermarket, and of *Tempo* and *Handlarń* small stores, but reduced the number of *Hemköp* supermarket. During the study period, Coop tries to redefine its store formats towards well defined formats such as *Nära* and *Forum* (in different sizes). Finally, besides starting *Vi*, Bergendahls expanded the number of its *Other* stores.

Market definition. Food products fulfill basic needs and consumers typically travel relatively short distances when buying food (except if prices are sufficiently low). Consequently, nearness to work and home are key aspects for consumers when choosing a store, though the distance likely increases with store-size.[10]

Local markets must be isolated geographic units, such that stores competitively interact only with other stores in the same one. *Postal areas* (in total 1534) are not large enough for large stores, which leaves the 88 *local labor markets* defined by the 290 *municipalities*. The *local labor markets* take commuting patterns into account, which are important for largest stores. *Municipalities* are more appropriate for, while matching the local-government decisions. Therefore, I use municipalities as local markets.

Descriptives. Table 2 presents store characteristics during the study period. The total number of stores decreases from 6,524 in 2001 to 5,953 in 2006 (about 9%), which confirms the trend towards fewer retail stores discussed above. In all years, the number of exits exceed the number of entrants. The number of format repositionings vary between 589 (in 2005) and 243 (in 2006). Average annual sales increases around 25 percent during the period, but only 14 percent for industry as a whole, implies more larger stores at the end of the period. Median population at the local-market (municipality) level increased almost 6 percent, while the median number of families increases by almost 5 percent. The median sales of repositioning stores are lower than the average sales for the full sample, indicating that repositioning is most common among small stores.

The next step is to analyze the difference between repositioning markets (where at least one repositioning occurred during the study period) and non-repositioning

[10]According to surveys made by the Swedish Institute for Transport and Communication Analysis, the average travel distance for trips with the main purpose of buying retail food products was 9.83 kilometers (1995-2002).

markets. There are 52 markets where I observe repositioning every year (2001-2006); 41 with at least one during 4 years; 71 during 3 years; 63 during 2 years; 51 during only 1 year; and 12 markets where there are no format repositionings during the whole period.

Table 3 presents median characteristics for markets with and without repositioning. Repositioning markets have about twice the median population and twice the median number of stores throughout period. Repositioning markets are less concentrated, with C_4 only 0.19 in 2006 compared to 0.39 in non-repositioning markets. They also have more entrants and exits. There is persistent high correlation between the numbers of repositionings and of entries, increasing over time (0.63 in 2002 compared to 0.88 in 2006), as does the correlation between the numbers of repositionings and exits (0.50 in 2002 compared to 0.66 in 2005). These high correlations are why it is important to analyze entry, exit, and repositioning at the same time as done here.

Another important question is what characterizes markets where each format is present. Table 4 shows median characteristics of repositioning and non-repositioning markets by format. The formats present in most municipalities are *ICA Supermarket* (230 markets), *ICA Nära* (247 markets), and *Coop Medium* (219 markets). For all formats, markets with repositioning have larger median populations than markets without. Median market-share in repositioning markets is lower than in non-repositioning markets for all formats except *Coop OBS* and *Vi*. All formats expect *Rimi*, *OBS et al.*, *Axfood Others*, *Bergendahls Others*, and *Others* have median sales per square meter.

The total numbers of format repositionings from 2001 to 2006 for each firm are presented in Tables 5-8. For example, there are 8 repositionings from *ICA Kvantum* to *ICA Maxi*, and 2 repositionings from *ICA Maxi* to *ICA Kvantum* during the period (Table 5). The highest number of repositionings are from *ICA Nära* to *Others* (220). As mentioned earlier, the format *Rimi* disappeared with most of the stores switching to *ICA Supermarket* (100) and *ICA Nära* (30). There are also many repositionings from *ICA Nära* to Axfood's formats *Handlarń* and *Tempo*.

Table 6 presents repositionings from Axfood, including many from *Vivo* to *Hemköp et al.* and to *Vi*, as well as many from *Hemköp et al.* to *Willys et al.* and to *Tempo*, and from *Axfood Others* to *Handlarń* and to *Others*. The number of repositionings from Bergendahls' formats is small and mostly to other firms (Table 7). Finally, most Coop repositionings were from *Coop Medium* to *Coop Nära* or

Coop Large, and to other firms' formats such as *Handlarń* and *Bergendahs Others* (Table 8).

3 The Modeling Approach

Local markets in the retail industry are characterized by simultaneous entry, exit, and format repositioning. My model, built on the work of Ericson and Pakes (1995), provides a theoretical framework of industry dynamics to account for these features.

All economically important characteristics of stores are included in a vector of commonly-observed state variables. Stores receive state-dependent revenues from selling products and services in each period. Store format, local demand, and competition influence the evolution of the state-vector. Equilibrium is attained when stores follow strategies that maximize the discounted present value of their expected stream of payoffs given the expected strategies of their competitors. An important assumption is that stores are maximizing their individual payoffs even if they have the same owner/firm. However, since firms try to avoid cannibalization, and also benefit from economies of scope, common ownership may affect store formats. This effect of common ownership is not modeled explicitly. However I control, for the effect of common ownership on store payoffs and policy functions (as discussed in the Introduction).

Timing. There is an infinite sequence of periods, years in this case. The timing of the simultaneous game is as follows:

1. Incumbent stores observe their current store-quality, formats, and local market demographics.

2. Each potential entrant receives a draw from the distribution of entry costs, and then makes decisions.

3. Consumers choose to buy from a store based on its quality. Consumers and local market demographics generate the store's revenues. There is also a fixed cost for incumbent stores.

4. Each store receives a private shock υ to its payoffs from choosing a specific format for the following year. The private shocks are assumed i.i.d

over stores, formats, and years. After observing its private shock, the store decides its format for the year after that.

5. Stores choose their formats. State space variables quality and local market demographics evolve according to stochastic processes described below (section 3.3).

6. Incumbent stores that exit the market receive their sell-off values. Stores that enter pay an entry fee.

Stores that exit of course sell products and services in the year before leaving the market. Furthermore, stores change formats (or not) without knowing the decisions of their competitors. At the beginning of each year, they observe quality and the entry, exit, and repositioning decisions of their rivals in the previous period. Since private shocks are i.i.d., stores do not update their expectations of their rivals future behavior after observing their actions.

Equilibrium. The actions that a store takes in a given period (exit or repositioning) affect current profits and the state variables, and, therefore, future strategic interactions. In this way, the model captures dynamic competition via entry, exit, and repositioning decisions. There are N_m stores in market m, denoted $j = 1, \cdots, N_m$, that make decisions at times $t = 1, 2, \cdots, \infty$. Store characteristics in period t are summarized by the vector of state variables, *quality* $\boldsymbol{\omega}_t \in \mathbb{R}^{N_m}$. Given states $\boldsymbol{\omega}_t$, the stores choose entry, exit, and repositioning simultaneously. Each store j receives a private shock υ_{jt}, drawn independently across stores and over time from a distribution $Q_j(\cdot|\boldsymbol{\omega}_t)$. Differences in each store's productivity might be one explanation for the existence of private shocks. I denote $a_{jt} \in A_j$ the action of store j and $\boldsymbol{a}_t = (a_{1t}, \cdots, a_{Nt}) \in \boldsymbol{A}$ the vector of actions at time t. The vector of private shocks is $\boldsymbol{\upsilon}_t = (\upsilon_{1t}, \cdots, \upsilon_{Nt})$.

The profits of store j at time t, $\pi_j(\boldsymbol{a}_t, \boldsymbol{\omega}_t, \upsilon_{jt})$, depend on its quality (state) ω_{jt}, the actions of all the stores in the market $\mathbf{a}_t$, and the store's private shock υ_{jt}. Profits are net of fixed and sunk costs at time t, such as entry costs, and repositioning costs, as well as sell-off value. In addition, all stores are assumed to have a common discount factor $0 < \beta < 1$. Conditional on current quality $\boldsymbol{\omega}_t$, the expected future profit of store j, evaluated prior to realization of the private shock, is

$$\mathbb{E}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \pi_j(\boldsymbol{a}_\tau, \boldsymbol{\omega}_\tau, \upsilon_{j\tau}) | \boldsymbol{\omega}_t\right].$$

Finally, to define the transition between states, I assume that quality evolves as an AR(1) process, where the speed of quality-adjustment is estimated from a static-demand model. To be more precise, quality at $t+1$, $\boldsymbol{\omega}_{t+1}$, is drawn from a probability distribution $P(\boldsymbol{\omega}_{t+1}|\boldsymbol{a}_t, \boldsymbol{\omega}_t)$. This implies that entry, exit, or changing format might affect future competition.
I focus on pure strategy Markov perfect equilibria (MPE). As in Bajari et al. (2007), I assume that there is at least one MPE (Doraszelski and Satterthwaite, 2010) for details on existence and uniqueness). The existence of which implies that each store's behaviour depends on its current quality and its current private shock. If Ω is the quality space, a profile of vector strategies is $\sigma = (\sigma_1, \cdots, \sigma_N)$, where $\sigma : \Omega \times \Upsilon_1 \times \cdots \times \Upsilon_N \to A$, Υ_j is the space for the private shock υ_j and A is the space of actions. Assuming Markov behaviour implies that store j's expected profit, given state $\boldsymbol{\omega}$, can be written

$$V_j(\boldsymbol{\omega}|\sigma) = \mathbb{E}_{\upsilon}\left[\pi_j(\sigma(\boldsymbol{\omega}, \boldsymbol{\upsilon}), \boldsymbol{\omega}, \upsilon_j) + \beta \int V_j(\boldsymbol{\omega}|\sigma) dP(\boldsymbol{\omega}'|\sigma(\boldsymbol{\omega}, \boldsymbol{\upsilon}), \boldsymbol{\omega})|\boldsymbol{\omega}\right].$$

A strategy profile $\boldsymbol{\sigma}$ is a Markov perfect equilibrium given opponent profile σ_{-j} if each store j prefers strategy σ_j to all Markov strategies $\sigma_j^{'}$, so that

$$(1) \quad V_j(\boldsymbol{\omega}|\sigma_j, \sigma_{-j}) \geq V_j(\boldsymbol{\omega}|\sigma_j^{'}, \sigma_{-j})$$

for all j, $\boldsymbol{\omega}$, and $\sigma_j^{'}$.

4 Estimation

Store demand. The utility of consumer i from buying from store j in market m in period t is a function of observed and unobserved vector of store characteristics ($\mathbf{x}_{jmt}$,ω_{jmt}), a vector of observed consumer characteristics $\mathbf{z}_{imt}$, and a vector of unobserved consumer characteristics $\boldsymbol{\nu}_{imt}$. Unobserved store quality is difficult to quantify but is a determinant of demand. Stores may have the same format but differ in consumers' perceptions of their display, variety offered, advertising, and service, all elements of quality.

Each store's market-share also depends on its format, as well as other store characteristics such as owner, age, sales space, local demand, and competition. Since quality is not directly observed in the data, it is backed out through estimation of the demand model.

The utility of consumer i from buying from store j is then given by the scalar $u_{ijmt} = u(\mathbf{z}_{imt}, \mathbf{x}_{jmt}, \omega_{jmt}; \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of parameters to be estimated. Consumers with different characteristics ($\mathbf{z}_{imt}$, $\boldsymbol{\nu}_{imt}$) make different store choices. By integrating out the choice function over the distribution of $\mathbf{z}_{imt}$ and $\boldsymbol{\nu}_{imt}$, the aggregate demand of the store can be obtained. It is assumed that $\boldsymbol{\nu}_{imt}$ follows a normal distribution, so that its parameters can be estimated. The mean and standard deviation of $\boldsymbol{\nu}_{imt}$ appear in the utility function as part of the vector $\boldsymbol{\theta}$. Consumer i chooses store j if and only if

$$(2) \quad u(\mathbf{z}_{imt}, \boldsymbol{\nu}_{imt}, \mathbf{x}_{jmt}, \omega_{jmt}; \boldsymbol{\theta}) \geq u(\mathbf{z}_{imt}, \boldsymbol{\nu}_{imt}, \mathbf{x}_{rmt}, \omega_{rmt}; \boldsymbol{\theta}) \quad \text{for} \quad j \neq r$$

where the alternatives $r = 1, \cdots, N_m$ represent the competing stores in the market m.

An outside alternative is the option of buying from stores with different formats. I set stores that never changed format during the study period as outside alternative for each local market. In my case the outside alternative is *Others* (Table 1). The presence of this outside alternative allows us to model changes in total sales as a function of store characteristics.

Consider

$$B_{jmt} = \{\boldsymbol{\nu} | u(\mathbf{z}_{imt}, \boldsymbol{\nu}_{imt}, \mathbf{x}_{jmt}, \omega_{jmt}; \boldsymbol{\theta}) \geq u(\mathbf{z}_{imt}, \boldsymbol{\nu}_{imt}, \mathbf{x}_{rmt}, \omega_{rmt}; \boldsymbol{\theta}), \quad j = 0, 1, \cdots, N_m\},$$

where B_{jmt} is the set of values for $\boldsymbol{\nu}_{imt}$ that induces the choice of store j rather than store r. Assuming that the $F_0(\boldsymbol{\nu})$ provides the density of $\boldsymbol{\nu}$ in the population of interest, the market-share of store j as a function of the characteristics of all stores in the market is

$$(3) \quad \mathbf{s}_{jmt}(\mathbf{x}_{jmt}, \omega_{jmt}; \boldsymbol{\theta}) = \int_{\boldsymbol{\nu} \in B_{jmt}} F_0(d\boldsymbol{\nu}).$$

Let $\mathbf{s}(\cdot)$ be the N_m-element vector of functions whose j^{th} component is given by (3)

$$\mathbf{s}(\mathbf{x}, \boldsymbol{\omega}; \boldsymbol{\theta}) = [s_1(\mathbf{x}_1, \omega_1; \boldsymbol{\theta}), \cdots, s_{N_m}(\mathbf{x}_{N_m}, \omega_{N_m}; \boldsymbol{\theta})]'.$$

Then, if *pop* is the number of consumers in market m, the vector of demand for the N_m stores is $pop \times \mathbf{s}(\mathbf{x}, \boldsymbol{\omega}; \boldsymbol{\theta})$. In the empirical application I set *pop* equal to the population in each market.

In the demand model, I allow for interaction between consumer and store characteristics. Following Berry et al. (1995), I also allow each individual to have different preferences for some observed store characteristics. The random-coefficients model generated is then

$$(4) \quad u_{ijmt} = \mathbf{D}_{jmt}\overline{\boldsymbol{\theta}}_1 + \mathbf{x}_{jmt}\boldsymbol{\theta}_1 + \mu_{ijmt} + \omega_{jmt} + \epsilon_{ijt}$$

where u_{ijmt} is the utility of consumer i from buying from store j in market m in period t; $\mathbf{D}_{jmt}$ is a row vector that contains 0 and 1, where 1 indicates the format of the store; the term μ_{ijmt} captures the interaction between the store's format and consumer characteristics; and $\mathbf{x}_{jmt}$ are store characteristics j, i.e., age and distance to center of zip code; ω_{jmt} is quality of store j; and ϵ_{ijt} represents unobserved sources of variation that are independent across consumers, given the store, and across stores, given the consumer. The term μ_{ijmt} contains two components: (i) interaction between observed consumer characteristics ($\mathbf{z}_{imt}$) and store format ($\mathbf{D}_{jmt}$), and (ii) interaction between unobserved consumer characteristics (the $\boldsymbol{\nu}_{imt}$) and store format, or

$$\mu_{ijmt} = \mathbf{z}_{imt}\mathbf{D}_{jmt}\boldsymbol{\theta}_2 + \boldsymbol{\nu}_{imt}\mathbf{D}_{jmt}\boldsymbol{\Psi}, \qquad \boldsymbol{\nu}_{imt} \sim N(0, \boldsymbol{\psi}^2),$$

where $\boldsymbol{\nu}_{imt}$ is assumed to have multivariate normal distribution.

In the demand specification, I also control for spatial differentiation between stores. Store location is one of the most important factors that generate sales. Consumers tend to shop closer to their home and work, and the choice of store also depends on store format, prices, and product assortment, etc. Location is defined by three digit postal-codes, with the assumption that consumers are located in the center of each one. One of the reasons for using postal-codes is that competition is more intense in smaller areas. With the geographical coordinates of each store and its postal-code, I compute the distance between the store and the center of the postal-code area using the Haversine formula.[11]

An alternative measure would be the distance to that store of the same size or

[11] The Haversine formula is based on latitude and longitude measures with R the radius of the earth, the distance between two points A and B is given by

$$d_{A,B} = 2R \arcsin\left[min\left\{\left((sin(0.5(lat_B - lat_A)))^2 + cos(lat_A)cos(lat_B)(sin(0.5(lon_B - lon_A)))^2\right)^{0.5}, 1\right\}\right].$$

format that is closest to the center of the postal-code area. First, the minimum distance for each size-groups (4 different) in the postal-code area is computed. Then, relative distance is computed as the difference between each store's distance and the minimum distance. To be more precise, I give an example. Assume a postal area where three stores operate with the following distances to the center: *ICA Nära* (300m), *Coop Nära* (600m), and *Tempo* (500m). The relative distances are then: *ICA Nära* (0m), *Coop Nära* (300m), and *Tempo* (200m). Consequently, *ICA Nära* has an advantage over *Coop Nära* (300m) of being closer to consumers. Choosing size-groups instead of formats to define relative distance allows consumers to shop from other firms that have a store of the same size. The advantage of relative distance is that it models consumer preference for size-groups, but it restricts consumer choices. In the empirical part, I use store's distance to the center of the postal area to account for spatial differentiation.

Demand estimation. The main objective of the demand estimation is to obtain a measure of the store's quality ω_{jmt}. To back out the quality, I use the same method used in the production function literature to back out the unobserved productivity. I assume that a store's quality evolves as an AR(1) process, and that all customers value it in the same way. The evolution of store quality is estimated using a standard approach for random-coefficient demand (Berry et al., 1995, Nevo, 2000, and Ackerberg et al., 2008).

A drawback of this approach is that it assumes that observed product characteristics is exogenous. In my case, ω_{jmt} measures price adjusted quality because the store prices are unobserved. It is a difficult task to construct an informative and consistent price index at the store level, e.g., different stores offer different product varieties. One strategy is to specify a price equilibrium equation and introduce it in the demand specification. However, this might be problematic due to the existence of multiple equilibria.

Innovations in the quality of format repositioning ξ^{re}_{jmt} and non-repositioning stores ξ^{nre}_{jmt} are unknown when stores make decisions for the following year, so that

$$(5) \quad \text{Repositioning:} \qquad \omega_{jmt} = \rho_1^{re}\omega_{jmt-1} + \rho_0^{re} + \xi^{re}_{jmt}$$

$$(6) \quad \text{Non-repositioning:} \qquad \omega_{jmt} = \rho_1^{nre}\omega_{jmt-1} + \rho_0^{nre} + \xi^{nre}_{jmt},$$

where $\xi^{re}_{jmt} \in N(0, \eta^{re})$ and $\xi^{nre}_{jmt} \in N(0, \eta^{nre})$. Moreover, innovations ξ^{re}_{jmt} and ξ^{nre}_{jmt} are assumed to evolve independently across markets.

I use these innovations to form a set of moment conditions used in the estimation (Berry et al., 1995; Sweeting, 2012). The mean utility provided by store j in market m at time t is then

$$(7) \quad \delta_{jmt} = \mathbf{D}_{jmt}\overline{\boldsymbol{\theta}}_1 + \mathbf{x}_j\boldsymbol{\theta}_1 + \omega_{jmt} = \mathbf{y}_{jmt}\tilde{\boldsymbol{\theta}}_1 + \omega_{jmt},$$

where $\tilde{\boldsymbol{\theta}}_1 = (\overline{\boldsymbol{\theta}}_1, \boldsymbol{\theta}_1)$. In the first step of the estimation, I obtain an estimate of quality $\omega_{jmt}(\cdot)$ as a function of $\boldsymbol{\theta}$. In the second step, an identification assumption that $\boldsymbol{\theta} = \boldsymbol{\theta}_0$ is needed, where $\boldsymbol{\theta}_0$ is the true value of $\boldsymbol{\theta}$. In the third step, I use method of moments to find $\boldsymbol{\theta}$.

An approximation of the market-shares conditional on ($\boldsymbol{\delta}$,$\boldsymbol{\theta}$) is given by

$$(8) \quad s_{jmt}(\boldsymbol{\theta}, \boldsymbol{\delta}) = \int \frac{\exp[\delta_{jmt} + \mu_{ijmt}]}{1 + \sum_r \exp[\delta_{rmt} + \mu_{irmt}]} f(\boldsymbol{\nu}) d(\boldsymbol{\nu}).$$

Pakes's (1986) simulation method is used to find this approximation, $s_{jmt}(\boldsymbol{\theta}, \boldsymbol{\delta}, P^{ns})$, where P^{ns} is the empirical distribution of the simulation draws.[12] For a given $\boldsymbol{\theta}$ and the set of simulation draws for $\boldsymbol{\nu}$, the unique values of $\boldsymbol{\delta}$ that predict the observed market-shares are found using contraction mapping (Berry et al., 1995). Equation (7) implies that

$$(9) \quad \omega_{jmt}(\boldsymbol{\theta}, P^{ns}) = \delta_{jmt} - \mathbf{D}_{jmt}\overline{\boldsymbol{\theta}}_1 - \mathbf{x}_j\boldsymbol{\theta}_1 = \delta_{jmt} - \mathbf{y}_{jmt}\tilde{\boldsymbol{\theta}}_1$$

i.e., that quality $\omega_j(\cdot)$ is a function of parameters, the data, and simulation draws.

Identification. An endogeneity problem arises because unobserved quality ω_{jmt} might be correlated with store-format. For each store, innovation in quality ξ_{jmt} is given by

$$(10) \quad \xi_{jmt} = \omega_{jmt} - \rho_1\omega_{jmt-1} - \rho_0(\delta_{jmt} - \rho_1\delta_{jmt-1}) - (y_{jmt} - y_{jmt-1})\tilde{\boldsymbol{\theta}}_1 - \rho_0$$

These innovations are uncorrelated with store-format at t and $t-1$, which allows us to form the following moment-conditions:

$$(11) \quad E[w_{jmt}\hat{\xi}_{jmt}(\boldsymbol{\theta})] = 0,$$

where $\boldsymbol{\theta}$ are all parameters of the demand-system and quality-transitions, and w_{jmt} is a set of instruments. y_{jmt}, y_{jmt-1}, and δ_{jmt-1} together with log of population

[12] When using simulation to compute the integral, a simulation error is introduced, the variance of which error decreases with the number of simulations used. Pakes (1996) and Berry et al. (1995) discuss this in detail.

plus competition variables interacted with store format, are used as instruments to estimate $\boldsymbol{\theta}$ by minimizing $\| G_{N,ns}(\boldsymbol{\theta}) \|$, where

$$(12) \quad G_{N,ns}(\boldsymbol{\theta}) = \sum_j \xi_{jmt}(\boldsymbol{\theta}, P^{ns}) \times w_j.$$

In addition, in order to identify ρ_1, I also include the log of market-share at $t-1$ interacted with an indicator of whether if the store changes format or not.

Payoffs, entry, and exit. A store's full period payoff function depends on whether it is an entrant, a continuing incumbent, a repositioning incumbent, or exits. Store payoff depends on store format, repositioning costs, and fixed costs.

The payoff for an incumbent store j in market m in period t is

(13)

$$\pi_{jmt}(\omega_{jmt}, \boldsymbol{\omega}_{-jmt}; \boldsymbol{\alpha}, \boldsymbol{\gamma}) = r(\boldsymbol{\omega}; \boldsymbol{\alpha}) - \gamma_1 I(f_{jmt+1} \neq f_{jmt}) - \gamma_2 I(f_{jmt} \neq 0) + \gamma_3 \upsilon_{jmt},$$

where $r(\cdot)$ is the revenue function, γ_1 are the sunk costs of repositioning format, and γ_2 are fixed costs paid every period the store operates. The coefficient γ_3 is scale of the i.i.d payoff shocks υ_{jmt}, which are assumed to be drawn from a Type I extreme-value distribution. The revenues of store j in market m in period t are:

$$(14) \quad r_{jmt}(\omega_{jmt}, \boldsymbol{\omega}_{-jmt}) = \boldsymbol{\alpha}_{mt}(1 + K_{jmt}\boldsymbol{\alpha}^K)(1 + H\boldsymbol{\alpha}^H) + \epsilon^r_{jmt},$$

where $\boldsymbol{\alpha}_{mt}$ are the set of year-market fixed-effects dummies. While additional store characteristics are collected in K, H contains variables that measure the competition from other formats in the local market, including estimated store-quality of competitors.

Incumbent stores that choose to exit have the payoff

$$(15) \quad \pi_{jmt}(\omega_{jmt}, \boldsymbol{\omega}_{-jmt}) = \tilde{r}_{jmt} + \gamma_4,$$

where γ_4 is the sell-off value associated with closing down the store and exiting the market. Finally, the payoff for an entrant is a simple function of the fixed cost of entry $(entry_f)$:

$$\pi_{jmt}(\boldsymbol{\omega}_{-jmt}) = -sunk_{jmt},$$

where $sunk_{jmt}$ is the sunk cost of entry.

Evolution of state space. The probability of moving to another state is given by the combinations of all paths that lead to that state. To obtain a new state, an incumbent has two options: (i) it stays in the market and moves to a new state; or (ii) it exits and is replaced by a new entrant in the new state. For any change in the state vector, I have to account for the entry, exit, and repositioning decisions of incumbents and potential entrants. I model entry is a restricted way because in my data entry is based on the address. Therefore, in the forward simulations, potential entrants can enter only in locations where stores exit. The probability of entry and exit can be written in terms of optimal entry and exit strategies:

$$(16)\quad Pr(entry|\omega_j) = \int \Theta(\omega_j, sunk_j) dG(sunk_j)$$

$$(17)\quad Pr(exit|\omega_j) = \Phi(\omega_j).$$

There are a few further assumptions required. First, because in many cases, entry and exit strategies take the form of simple cutoff rules in dynamic oligopoly models (Beresteanu and Ellickson, 2006), I assume that both conditional probabilities (16) and (17) can be approximated using probit models. Second, from the demand-estimation assumption we have that quality evolves stochastically according to the AR(1) processes described by (5) and (6). Third, since each market m is defined by its characteristics, e.g., the total number of formats and population groups, I assume that the growth rates for population groups evolve according to the following AR(1) processes

$$(18)\quad pop^g_{mt} = \delta^{pop}_{1,g} pop^g_{mt-1} + \delta^{pop}_{0,g} + \upsilon^{pop}_{mt},$$

where g is one of population groups and $\upsilon^{pop}_{mt} \sim N(0, \eta^{pop})$.

Value functions. Given the policy functions and the evolution of the state space, the value functions for incumbents and entrants can be computed, giving the expected discounted present value of the store of a given quality. The value function has two components: the per period payoff function (profit of incumbents, or sunk costs of entry for entrants), and the expected value of next period. Stores use the value function to choose their optimal format, entry, or exit. When a store considers changing format, it compares the marginal benefit of having a new quality against the cost of achieving it. Similarly sell-off value at exit is compared with its continuation value.

A potential entrant compares its draw from the distribution of sunk entry-costs against its expected value if it enters. Since private shocks on profits are assumed to be i.i.d, I integrate out all private information in the store's per-period payoff function when computing these value functions. In other words, stores choose their optimal strategy on given the ex-ante value function of next period's potential store qualities.

I assume that the potential entrant only lives one year, so that there is no reason to solve for an optimal stopping rule. If it has a higher sunk-costs draw in the current period, it may postpone entering until it receives a more favorable draw. Given current quality and its sunk-costs of entry draw, $sunk_j$, the value function of the potential entrant that decides to enter is

$$(19)\quad V_j^e(\boldsymbol{\omega}, sunk_j) = max_{f_j^e} \left\{ -sunk_j + \beta \int V_j(\boldsymbol{\omega}') dP(\boldsymbol{\omega}'|\boldsymbol{\omega}, \boldsymbol{\upsilon}) \right\}.$$

This value function includes the optimal choice of store-format. Since the potential entrant is forward-looking and rational, its expected value of entering accounts for the chosen formats of other stores and their entry and exit decisions. The choice of store-format does not depend on $sunk_j$, i.e., stores choose format f_j^e conditional on entering. In other words, for a given quality there is a draw from the distribution of sunk-costs of entry such that a store would be indifferent between entering or not,

$$(20)\quad \overline{sunk}_j = \beta \int V_j(\boldsymbol{\omega}') dP(\boldsymbol{\omega}'|\boldsymbol{\omega}, \boldsymbol{\upsilon}).$$

The entry function is denoted $\Theta(\omega_j, sunk_j)$. In equilibrium, a store enters the market if it receives a sunk-costs of entry draw less than this value.

If a store decides to leave the market, it obtains profit $\pi_j(\boldsymbol{\omega})$ and sell-off value $scrap_j$. On the other hand, if it stays in the market it receives the following payoff, which depends on the cost of repositioning if it changes format

(21)

$$V_j^{stay}(\boldsymbol{\omega}) = max_{f_j} \left\{ -\gamma_1 I(f_{jt+1} \neq f_{jt}) - \gamma_2 I(f_j \neq 0) + \beta \int V_j(\boldsymbol{\omega}') dP(\boldsymbol{\omega}'|\boldsymbol{\omega}, \boldsymbol{\upsilon}) \right\}.$$

Summarizing, then the value function of an incumbent is a combination of its expected payoffs if it stays in the market and if it exits,

$$(22)\quad V_j(\boldsymbol{\omega}) = \int V_j(\boldsymbol{\omega}')dP(\boldsymbol{\omega}'|\boldsymbol{\omega}, \boldsymbol{\upsilon}) + (1 - \Phi(\omega_j))V_j^{stay}(\boldsymbol{\omega}) + \Phi(\omega_j)\gamma_4.$$

Distribution of sunk entry-costs. The estimated policy functions describe how a store will behave at each point. In addition, given the primitives of the model, which quantify the benefits and costs of those actions, it is possible to find the distribution of sunk entry-costs (Bajari et al., 2007; Ryan, 2012). Knowledge about store behaviour whether it enters, exits, or repositions, and the revenues associated with those behaviours, allows computation of the expected value of entry. If that value is positive yet the store did not enter, the store must have received a large entry-costs drawn that made it unprofitable to enter. The distribution of sunk entry-costs can be recovered by matching its cumulative distribution to the predicted probability of entry. A store enters when the value of doing so, $EV^e(\boldsymbol{\omega})$, is larger than $sunk_j$. By simulating many forward paths of possible outcomes given that the firm entered, and averaging over those paths, I obtain the expected value of entry, which I then match against observed rates of entry at different quality states. Therefore, the probability that a store enters is given by

$$(23)\quad Pr(sunk_j \leq EV^e(\boldsymbol{\omega})) = F^e(EV^e(\boldsymbol{\omega}); \mu_F, \sigma_F^2),$$

where $F^e(\cdot)$ is the cumulative distribution of sunk entry-costs. The entry probability estimated, by probit, gives us $Pr(entry|\boldsymbol{\omega})$. If ns is the number of quality states from which I simulate EV^e, I recover the parameters of the distribution by market-size from the following optimization problem:

$$(24)\quad min_{\mu_F, \sigma_F} \frac{1}{ns} \sum_{k}^{ns} [Pr(entry|\boldsymbol{\omega}) - F^e(EV^e(\boldsymbol{\omega})]^2; \mu_F, \sigma_F^2).$$

Estimation of sunk repositioning costs. The next step is estimation of average sunk repositioning costs (γ_1), fixed costs of operation (γ_2), the scaling parameter for heterogeneity of sunk costs (γ_3), and the scrap value (γ_4). The estimation is done using Pakes et al. (2007b)'s (PPHI) moment-inequality estimator. The inequalities are formed from the condition that the payoffs obtained using stores' actual strategies must have been higher than those from any alternative strategy (equation 1): $V_j(\boldsymbol{\omega}|\sigma_j, \sigma_{-j}) - V_j(\boldsymbol{\omega}|\sigma_j', \sigma_{-j}) \geq 0$. By construction, the value function

$$
(25) \quad \begin{aligned} V_j(\boldsymbol{\omega}|\sigma_j, \sigma_{-j}) \quad &= \mathbb{E}_{\sigma_j,\sigma_{-j}} \textstyle\sum_{t=0}^{\infty} \beta^t r(\cdot; \hat{\boldsymbol{\alpha}}) - \gamma_1 \mathbb{E}_{\sigma_j,\sigma_{-j}} \sum_{t=0}^{\infty} \beta^t I(f_{jt} \neq f_{jt+1}) \\ &-\gamma_2 \mathbb{E}_{\sigma_j,\sigma_{-j}} \textstyle\sum_{t=0}^{\infty} \beta^t I(f_{jt} \neq 0) + \gamma_3 \mathbb{E}_{\sigma_j,\sigma_{-j}} \sum_{t=0}^{\infty} \beta^t \upsilon_{jt}(f_{jt+1}), \\ &+\gamma_4 \mathbb{E}_{\sigma_j,\sigma_{-j}} \textstyle\sum_{t=0}^{\infty} \beta^t I(\chi_{jt+1=1}), \end{aligned}
$$

where $\mathbb{E}_{\sigma_j,\sigma_{-j}}$ is the expectation operator over future states conditional on strategies, is linear in $\boldsymbol{\gamma}$. Having an estimator for the value function, I use the PPHI estimator, which allows for simulation error in the estimated value function.[13] While the simulation error can also be reduced by increasing the number of forward simulations, this would be expensive here and, therefore, it is more efficient to use the PPHI estimator.[14]

Since we are not able to measure profits $\pi(\cdot)$ exactly, we can calculate an approximation, denoted $\tilde{\pi}(\cdot; \boldsymbol{\gamma})$, which is known up to the parameter-vector $\boldsymbol{\gamma}$. This approximation has the arguments: strategies σ_j and σ_{-j} ; the observed vector of determinants of profits, $\boldsymbol{y}$; and the parameter vector $\boldsymbol{\gamma}$. An approximation to the difference in profits that the store would have earned if it had chosen $\sigma_j^{'}$ instead of σ_j is denoted $\Delta\tilde{\pi}(\sigma_j, \sigma_j^{'}, \cdot)$. The change in true profits can be written as

$$
(26) \quad \Delta\pi(\sigma_j, \sigma_j^{'}, \boldsymbol{\sigma}_{-j}, \boldsymbol{y}, \boldsymbol{\gamma}) = \Delta\tilde{\pi}(\sigma_j, \sigma_j^{'}, \boldsymbol{\sigma}_{-j}, \boldsymbol{y}; \boldsymbol{\gamma}) + \nu_{1,j,\sigma_j,\sigma_j^{'}} + \nu_{2,j,\sigma_j,\sigma_j^{'}},
$$

where ν_1 and ν_2 are unobserved determinants of true profits, differing in what the store knows about them. The store knows ν_2 before it chooses its strategy for the next period, so ν_2 is part of its information set $\mathcal{I}_j$. I assume that the store-decision does not depend on ν_1, so $\mathbb{E}[\nu_{1,j,\sigma_j,\sigma_j^{'}}|\mathcal{I}_j] = 0$ by construction and profits are observable up to the parameter-vector $\boldsymbol{\gamma}$ plus an error which is mean-conditional on the store's information set (ν_1), i.e., I assume that $\nu_{2,j,\sigma_j,\sigma_j^{'}}$ is identically zero for all σ_j and $\sigma_j^{'}$.

The PPHI estimator requires that expected profits using the actual strategy σ_j be higher than under alternative $\sigma_j^{'}$

$$
(27) \quad \mathbb{E}[\Delta\pi(\sigma_j, \sigma_j^{'}, \boldsymbol{\sigma}_{-j}, \boldsymbol{y})|\mathcal{I}_j] \geq 0.
$$

[13] Sweeting (2012) and Holmes (2008) also use the PPHI estimator in their dynamic framework.

[14] Simulation error appears since store-quality and format-decisions, as well as market demographics, can evolve in so many ways.

But assumption $\mathbb{E}[\nu_{1,j,\sigma_j,\sigma_j^{'}}|\mathcal{I}_j]=0$, yields the inequality in approximated profits

(28) $\mathbb{E}[\Delta\tilde{\pi}(\sigma_j,\sigma_j^{'},\boldsymbol{\sigma}_{-j},\boldsymbol{y},\boldsymbol{\gamma})|\mathbf{w}_j]\geq 0,$

where $\mathbf{w}_j\in\mathcal{I}_j$. Taking sample averages across observations yields the following moment-inequalities

(29) $$\frac{1}{N}\sum_{j=1}^{N}\Big[\Delta\pi(\sigma_j,\sigma_j^{'},\boldsymbol{\sigma}_{-j},\boldsymbol{y},\boldsymbol{\gamma})\otimes h(\mathbf{w}_j)\Big]\geq 0,$$

where $h(\mathbf{w}_j)$ is a set of instrument functions. The number of moment-inequalities can be increased by increasing the number of alternative strategies or by expanding the number of instruments. The moment-inequalities here are

(30) $$\begin{aligned}\tfrac{1}{N}\textstyle\sum_{j=1}^{N}\big[\quad & (T_{1,\sigma_j,\sigma_{-j}}-T_{1,\sigma_j^{'},\sigma_{-j}})-\gamma_1(T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}})\\ & -\gamma_2(T_{3,\sigma_j,\sigma_{-j}}-T_{3,\sigma_j^{'},\sigma_{-j}})+\gamma_3(T_{4,\sigma_j,\sigma_{-j}}-T_{4,\sigma_j^{'},\sigma_{-j}})\\ & +\gamma_4(T_{5,\sigma_j,\sigma_{-j}}-T_{5,\sigma_j^{'},\sigma_{-j}})\Big]\geq 0,\end{aligned}$$

for five alternatives of $\sigma_j^{'}$, where T_k is the sample average of the term k in equation (25). Using inequality (30), the lower bound for the sunk cost of repositioning from the following inequality:

(31) $$\begin{aligned}\gamma_1\geq\quad & \tfrac{T_{1,\sigma_j,\sigma_{-j}}-T_{1,\sigma_j^{'},\sigma_{-j}}}{T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}}}-\gamma_2\tfrac{T_{3,\sigma_j,\sigma_{-j}}-T_{3,\sigma_j^{'},\sigma_{-j}}}{T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}}}+\gamma_3\tfrac{T_{4,\sigma_j,\sigma_{-j}}-T_{4,\sigma_j^{'},\sigma_{-j}}}{T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}}}\\ & +\gamma_4\tfrac{T_{5,\sigma_j,\sigma_{-j}}-T_{5,\sigma_j^{'},\sigma_{-j}}}{T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}}}\end{aligned}$$

(if $T_{2,\sigma_j,\sigma_{-j}}<T_{2,\sigma_j^{'},\sigma_{-j}}$). By increasing the number of format repositioning both the revenues and cost of repositioning increase. Thus, this policy that is not preferred by stores gives us the lower bound for the repositioning cost. The upper bound is obtained using a strategy that decreases the number of repositionings, which implies a decrease in revenues:

(32) $$\begin{aligned}\gamma_1\leq\quad & \tfrac{T_{1,\sigma_j,\sigma_{-j}}-T_{1,\sigma_j^{'},\sigma_{-j}}}{T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}}}-\gamma_2\tfrac{T_{3,\sigma_j,\sigma_{-j}}-T_{3,\sigma_j^{'},\sigma_{-j}}}{T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}}}+\gamma_3\tfrac{T_{4,\sigma_j,\sigma_{-j}}-T_{4,\sigma_j^{'},\sigma_{-j}}}{T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}}}\\ & +\gamma_4\tfrac{T_{5,\sigma_j,\sigma_{-j}}-T_{5,\sigma_j^{'},\sigma_{-j}}}{T_{2,\sigma_j,\sigma_{-j}}-T_{2,\sigma_j^{'},\sigma_{-j}}}\end{aligned}$$

(if $T_{2,\sigma_j,\sigma_{-j}} > T_{2,\sigma'_j,\sigma_{-j}}$).

The lower bound for the fixed cost is zero. The upper bound of the fixed cost is obtained implementing a strategy that reduces the number of format repositioning:

$$\begin{aligned} \gamma_2 \leq \quad & \frac{T_{1,\sigma_j,\sigma_{-j}} - T_{1,\sigma'_j,\sigma_{-j}}}{T_{3,\sigma_j,\sigma_{-j}} - T_{3,\sigma'_j,\sigma_{-j}}} - \gamma_1 \frac{T_{2,\sigma_j,\sigma_{-j}} - T_{2,\sigma'_j,\sigma_{-j}}}{T_{3,\sigma_j,\sigma_{-j}} - T_{3,\sigma'_j,\sigma_{-j}}} + \gamma_3 \frac{T_{4,\sigma_j,\sigma_{-j}} - T_{4,\sigma'_j,\sigma_{-j}}}{T_{3,\sigma_j,\sigma_{-j}} - T_{3,\sigma'_j,\sigma_{-j}}} \\ & + \gamma_4 \frac{T_{5,\sigma_j,\sigma_{-j}} - T_{5,\sigma'_j,\sigma_{-j}}}{T_{3,\sigma_j,\sigma_{-j}} - T_{3,\sigma'_j,\sigma_{-j}}} \end{aligned} \tag{33}$$

(if $T_{3,\sigma_j,\sigma_{-j}} > T_{3,\sigma'_j,\sigma_{-j}}$). In the empirical section, this strategy is implemented by reducing by 0.05 the probability to repositioning in every state. Another alternative strategy is not allowing repositioning.

A store that changes the format receives a large draw of ν. Large repositioning costs can explain why some stores never change their format even if they receive favorable draws of ν. The upper bound of the scale parameter γ_3 is obtained using an alternative strategy that increases ν, reduce the revenues, and makes repositioning a constant strategy, i.e., format choices are made equal. I implement this strategy by equalizing the choice probabilities for other formats and leaving unchanged the choice of the current format.

$$\begin{aligned} \gamma_3 \leq \quad & \frac{T_{1,\sigma_j,\sigma_{-j}} - T_{1,\sigma'_j,\sigma_{-j}}}{T_{4,\sigma_j,\sigma_{-j}} - T_{4,\sigma'_j,\sigma_{-j}}} + \gamma_1 \frac{T_{2,\sigma_j,\sigma_{-j}} - T_{2,\sigma'_j,\sigma_{-j}}}{T_{4,\sigma_j,\sigma_{-j}} - T_{4,\sigma'_j,\sigma_{-j}}} + \gamma_2 \frac{T_{3,\sigma_j,\sigma_{-j}} - T_{3,\sigma'_j,\sigma_{-j}}}{T_{4,\sigma_j,\sigma_{-j}} - T_{4,\sigma'_j,\sigma_{-j}}} \\ & + \gamma_4 \frac{T_{5,\sigma_j,\sigma_{-j}} - T_{5,\sigma'_j,\sigma_{-j}}}{T_{4,\sigma_j,\sigma_{-j}} - T_{4,\sigma'_j,\sigma_{-j}}} \end{aligned} \tag{34}$$

(if $T_{4,\sigma_j,\sigma_{-j}} < T_{4,\sigma'_j,\sigma_{-j}}$). The drawback of this strategy is that the store can also choose to exit.

The next step is to propose an alternative strategy to estimate the upper bound of the sell-off value (scrap value), γ_4. This bound is obtained by increasing the likelihood to exit. In the empirical implementation, I increase exit probability by 0.05.

$$\begin{aligned} \gamma_4 \leq \quad & -\frac{T_{1,\sigma_j,\sigma_{-j}} - T_{1,\sigma'_j,\sigma_{-j}}}{T_{5,\sigma_j,\sigma_{-j}} - T_{5,\sigma'_j,\sigma_{-j}}} + \gamma_1 \frac{T_{2,\sigma_j,\sigma_{-j}} - T_{2,\sigma'_j,\sigma_{-j}}}{T_{5,\sigma_j,\sigma_{-j}} - T_{5,\sigma'_j,\sigma_{-j}}} + \gamma_2 \frac{T_{3,\sigma_j,\sigma_{-j}} - T_{3,\sigma'_j,\sigma_{-j}}}{T_{5,\sigma_j,\sigma_{-j}} - T_{5,\sigma'_j,\sigma_{-j}}} \\ & - \gamma_3 \frac{T_{4,\sigma_j,\sigma_{-j}} - T_{4,\sigma'_j,\sigma_{-j}}}{T_{5,\sigma_j,\sigma_{-j}} - T_{5,\sigma'_j,\sigma_{-j}}} \end{aligned} \tag{35}$$

(if $T_{5,\sigma_j,\sigma_{-j}} < T_{5,\sigma'_j,\sigma_{-j}}$). Due to heterogeneity across Swedish local markets, I estimate the cost-parameters for a groups of markets.[15]

5 Results

This section presents the results from: demand estimation; revenue generating function estimation; entry, exit, and repositioning policies; and repositioning and entry costs.

Demand. Table 9 shows the estimates from the demand model presented in Section 3.1. The demographic format-taste parameters show to some extent expected patterns. Stores in markets with a large proportion of children (population 0-14) tend to have large and very large formats (Table 9). *ICA Supermarket* is the most preferred format in these markets. The very large formats *ICA Maxi* (1.03) and *Coop Large* (0.88) are are preferred in these markets. *ICA Kvantum*, also a large format, is found to be less preferred in markets with a high proportion of children, however. Perhaps the effect of demographics is captured by other demographics. Axfood's large format *Willys et al.*, which is promoted as "Sweden's cheapest bag of groceries", is the one preferred in markets with the most kids (1.25), however. Young adults (15-34) prefer small formats such as *ICA Nära* (0.69), *Tempo* (0.80), and *Coop Nära* (1.99). *ICA Maxi* (0.68) is the most preferred very large format in markets with large share of young adults. The medium format *ICA Supermarket* (0.82), and small formats such as *Tempo* (1.98) are preferred in markets with large share of older people (over 65). As with young adults, *ICA Maxi* is the most preferred very large format in markets with large share of older people.

As discussed earlier, distance to the center of postal-code (three digit postal-code area) is used to control for spatial differentiation in the demand estimation, allowing us to explore the benefits of a store being closer to consumers. The estimated coefficients of distance represents the travel costs. *ICA Supermarket*, *Vi*, and *Coop Nära* are the formats that are close to the consumers. However, they are found to have relatively large travel cost. Consumers are less likely to choose these formats based on distance, i.e., there are other factors that affect consumers choices.

The age of the store is positive (0.65) and significant at traditional levels.

[15] Appendix C presents an alternative estimator for repositioning costs.

Perhaps indicating that older stores might have better location. Sales space is also positive and significant, because large stores usually provide a wider range of products and lower prices.

The standard deviations of the random components format-tests are small and mostly are insignificantly different from zero. Demographics, therefore, seems to capture most of the systematic differences in tastes for formats within markets. Given the small standard deviation of the random coefficient on *Others*, there is an acceptable degree of substitution with the outside good.

As explained earlier, unobserved adjusted quality is backed out from the demand estimation. The AR(1) parameters for repositioning and non-repositioning are both less than one. This implies that the processes that describe quality are stationary, through quality is more persistent for the non-repositioning stores ($\rho_{nre} = 0.62$), as one might expect.

Repositioning stores have higher quality than non-repositioning stores in the upper tail of the distribution, but lower in the lower tail. The median quality of a repositioning store is larger that of a non-repositioning store, however.

Sales generating function estimation. Table 10 shows estimates of four sales-generating function specifications, each including market demographics and store characteristics such as age and quality. I allow for nonlinearity in quality by including quality and quality square, i.e., the marginal effect of quality on sales depends on quality.

Model 2 adds repositioning, while Model 3 also controls for format competition. Model 4 also controls for the effect of current on future sales (non-linear sales-effects) by including a dummy that specifies whether the store's market-share is less than the market-average. A marginal increase in sales due to an increase in store's quality decreases with quality in all four models.

Increasing the proportion of kids has a positive impact on sales, while the effect of young adults is negative, perhaps because a higher proportion of this group might imply a lower income-level relative to the control group (35-65). While the store's age has a positive effect on sales (Model 4), the distance has a negative impact. As might be expected, both the number of stores in the same format and the number of stores owned by other firms have negative effects on sales. The direct effect of repositioning is positive, but not significant, which is not surprising since it might take time for consumers to adjust to the new format. Low previous market-share has a negative impact on sales.

To estimate sunk costs of entry and repositioning, I use Model 4 since it provides the highest correlation between observed and predicted sales for both repositioning and non-repositioning stores.

Policy functions. Table 11 reports the multinomial logit estimates of incumbent stores' format strategies. The first part of the table reports the market-demographic variables that affect the prevalence of each format, i.e., the proportion of the population in by age group and changes in those groups. In markets with a large proportion of children, stores are more likely to choose large formats such as *ICA Maxi* (345), *ICA Kvantum* (334), *Coop Large* (336), and *Bergendahls Others* (341). In markets with a large proportion of young adults or with increasing proportion of young adults, large formats such as *ICA Maxi* (72), *Coop Large* (49), and *Willys et al.* (16) are more likely. In markets with a large proportion of adults, *Coop Nära* is the most preferred format.

Stores with high quality are more likely to be in large formats (*ICA Maxi*, *Coop Large*). Axfood's small formats, *Tempo* and *Handlarń*, are also associated to have high quality (Axfood increased the number of stores in these formats during the period).

In markets where rivals have high quality, ICA focuses most on *ICA Kvantum* (0.098), *ICA Supermarket* (0.018), and *ICA Nära* (0.020); Axfood on *Handlarń* (0.039) and Coop on *COOP Medium* (0.026). Thus, three of ICA's formats are more likely in markets where rivals have high quality (product differentiation). All formats are less likely the more other stores there were the same format. The positive parameters on other formats show that stores try to differentiate in format.

The right part of Table 11 reports the coefficients on age, distance from other stores in rival format, and market-share. I allow the coefficients to differ depending on whether a store remains in the same format or changes format. Old stores in large formats are less likely to change format. Old stores that change are less likely to be in one of ICA's formats. On the other hand, old stores that change are more likely to become *Coop Nära*, *Axfood Others*, or *Hemköp et al.*. Stores far from others that changed format are more likely to become *Bergendahls Others*, *Handlarń*, or *OBS et al.*.

Table 12 reports estimates of entry and exit policies, aggregated for all formats, but accounting for market and format fixed-effects. Stores with high quality are less likely to exit. Exit is also less likely in large markets, and if the firm has many stores of the same format in the same market, which might indicate economies of density (Holmes 2008). On the other hand, stores are more likely to exit if they are old or if rivals have high quality.

Entry is more likely if rivals have high quality, and in markets with large population. Entry is less likely if the firm already operates many stores in that format in the same market, or if there are many other-firm rivals.

Repositioning costs and sell-off values. Using estimated quality, sales estimates, and policy functions, I can recover the cost parameters. Table 13 presents repositioning-cost estimates (identified sets) for markets with population below 20,000, population 20,000-60,000, and over 60,000, as well as median sales of repositioning stores, and the median number of repositioning stores per year during the period.

The confidence intervals for the estimated parameters are simulated (see Pakes et al., 2007b). To apply bootstrap is very time consuming because of the forward simulations. In addition to PPHI, there are different approaches for inferences with moment inequalities (Imbens and Manski, 2004; Chernozhukov et al., 2007; and Andrews and Soares, 2010). In this case, the confidence intervals are the extreme points of identified set. PPHI suggests a simulation method to construct the "inner" and "outer" confidence intervals. These intervals are asymptotically the true confidence intervals for the estimated bounds. I only report the "outer" threshold, i.e., the conservative values. The "outer" confidence intervals are obtained using 100 simulations.[16] The small number of simulations is due to computation burden, i.e., 100 programming problems have to be solved.[17]

Average repositioning costs depend on the size of the market, being about 63 percent higher in markets with population 20,000-60,000 than in smaller markets, and another 16 percent higher in the largest.[18] Median sales are more than 20 times higher than average repositioning costs, especially high for markets of 20,000-60,000. By far most repositioning are in large markets, though repositioning seems to be most profitable in middle size-group ones. Sell-off values on exit are twice as high in the large markets as in the small ones. Due to store heterogeneity, there is a large spread in sell-off values in large markets.

For robustness, Table 15 (Appendix C) shows the point estimates of the repositioning and sell-off values using the minimum distance estimator. The values of

[16] In Pakes et al. (2007b), Section 3.1.2 presents the estimation details of the confidence intervals.

[17] IPOPT optimizer is used (https://projects.coin-or.org/Ipopt). Ipopt is an optimizer for large scale nonlinear problems. In case that absolute norm is used, it is computationally efficient to used linear programming solvers. For example, the GLPK (http://www.gnu.org/software/glpk/), which is a package for solving large-scale linear programming.

[18] To get a conservative estimate, I used the upper bound to measure the changes in costs.

estimated parameters belong to the identified sets estimated using PPHI.

Entry costs. Table 14 shows estimated sunk costs of entry, again for markets grouped by size. It is far more expensive to enter a market than to reposition. This might explain why the number of repositioning is larger than the number of entrants. Mean entry costs increases substantially with market size. Entry costs are more than twice median sales in small markets, over four times median sales in medium markets, and a bit less in large markets. Thus, there is higher entry costs per median sales in medium than in large markets. The large estimation of entry costs in large markets may be due to big entrants that shift the mean.

6 Conclusions

While there have been important contributions in modelling both static and dynamic consumer demand for differentiated products, there have been few attempts at modelling their supply. The fact the products are differentiated means that shocks might cause firms to change their product assortment.

A dynamic oligopoly model is estimated in Swedish retail food industry to measure the costs associated with repositioning by changing store formats, which also often includes major changes in product assortment. The estimation gives important information about driving forces behind repositioning, associated costs, and how it can be linked to entry and exit.

There are high correlations between entry, exit, and repositioning. More generally, the paper provides a framework for studying repositioning in any industry where entry and exit are important. Understanding the potential role of repositioning in the trade-off between repositioning, entry, and exit is one of the aims of this paper. Since entry is regulated in most OECD countries, knowledge about repositioning and entry costs has important implications for policy.

In the Swedish retail food industry, repositioning costs increase with the size of the market, though at a decreasing rate. Stores are less likely to exit if they have high quality, are in large markets, or if there are many same-format stores in the same market. Entry is more likely in large markets or if rivals have high quality, so that there is room for product differentiation. Stores with high quality are more likely to be in large formats. Old stores are less likely to reposition. Distance is an important factor for consumers choosing a store. Finally, store's quality is more persistent for non-repositioning stores.

In future work, cost estimates of the four different size groups (see Section 2) of stores will provide valuable information about repositioning. Having the estimated structural parameters, different policy experiments can be implemented. My interest is to evaluate how the cost of repositioning could be affected by lowering the cost of entry, and how sunk cost of entry could be affected by lowering the cost of repositioning. I modelled multi-product ownership, i.e., the fact that each firm operates many stores, in a limited way. Since I only control for owners in stores' policies, I did not explicitly model the dynamics of their product selection. Selection of products in multi-product firms is an important topic for future research. Understanding it will give us more information about market power, business cannibalization, and economies of scope.

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Table 1: Store formats by firm

Format	Firm	Store concepts into the defined format	Sales space m^2	Average sales per m^2(SEK)	Number of stores 2001	2002	2003	2004	2005	2006
1	ICA	ICA Maxi	3,378	88	31	32	34	35	41	49
2	ICA	ICA Kvantum	2,205	75	119	121	124	126	127	122
3	ICA	ICA Supermarket	875	66	450	437	534	524	496	484
4	ICA	ICA Nära	263	52	1,226	1,134	1,152	1,044	937	930
5	Axfood	Willys et al.	1,559	69	56	76	111	135	146	150
6	Axfood	Vivo	745	70	253	121	91	88	0	0
7	Axfood	Hemköp et al.	1,214	56	180	269	251	224	174	161
8	Axfood	Handlarn	167	36	117	172	187	208	217	221
9	Axfood	Tempo	286	43	89	103	103	111	147	151
10	ICA	Rimi	801	63	134	135	0	0	0	0
11	Axfood	Axfood Others	281	61	281	172	162	129	158	157
12	COOP	Coop Nära	302	68	0	0	0	0	97	114
13	COOP	Coop Large	2,349	59	63	60	61	88	99	112
14	COOP	Coop Medium	535	54	801	815	786	725	576	508
15	COOP	OBS et al.	1,382	65	122	61	60	56	40	25
16	Bergendahls	Vi	867	81	0	0	0	0	86	98
17	Bergendahls	Bergendahls Others	1,290	47	62	73	80	83	92	108
18	Others	Others	134	45	2,540	2,447	2,440 2	638	2,679	2,563

NOTES: Data from DELFI. Average sales per square meter are in 2001 thousand SEK (1 EUR=9 SEK, 1 USD= 8 SEK). Each format contains one or more store concepts. *ICA Nära* includes also ICA Express stores; *Willys et al.* includes Willys and Willys Hemma; *Hemköp et al.* includes Exet, Spar, Matex, Axfood Storlivs, and Billhälls; *Axfood Others* (format number 11) includes Jour Livs, Matnära, Axfood Närlivs Rätt Pris, Axfood Lågpris, and Östenssons; *Coop Large* (format number 13) includes COOP Forum level 2 and 3, B & W, Gröna Konsum, COOP Extra, and Konsum Extra; *Coop Medium* includes stores Coop Konsum level 1 and 4; *OBS et al.* includes OBS, Robin Hood, Domus, Prix, and Fakta; *Bergendahls Others* (format number 17) includes Favör, Matöppet, Prisxtra, City Gross, and Ekohallen, Eko, and AG-Favör; *Others* includes Statoil, OKQ8, Nära Dej, Matbutiken, Fri Mat, 7-Eleven, Pressbyrån Närlivs, Shell, Preem, Bilisten, Lidl, Netto, Norsk Hydro, Din-X, Uno-X, Pump, Samuelsons Servicehandeln, Pressbyrån Franchise, Q Star, and yet others.

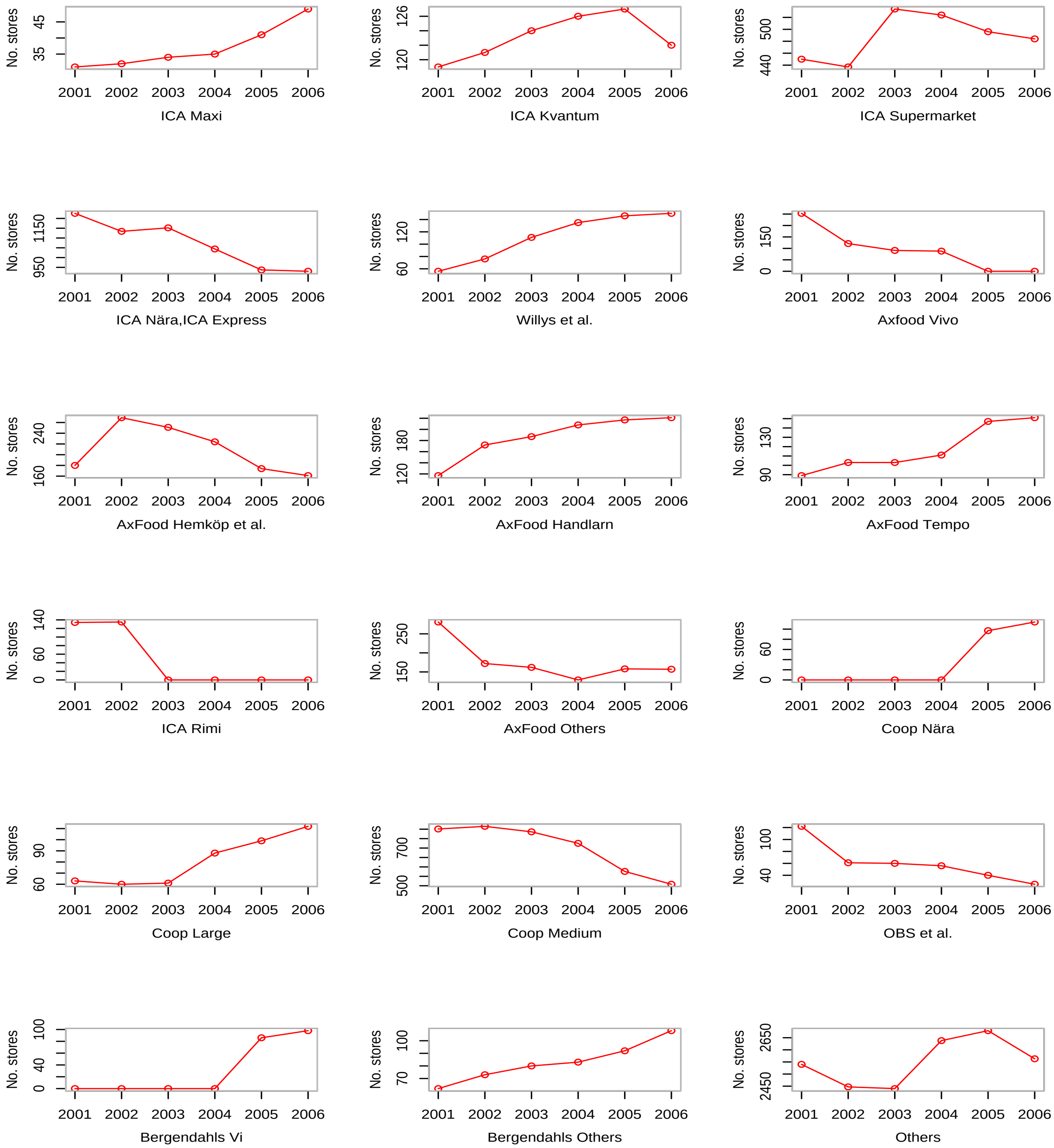

Figure 1: Evolution of the number of stores by format (see Table 1) during 2001-2006.

Table 2: Store characteristics, 2001-2006

Year	# of Stores	# of Repos. Format	# of Entries	# of Exits	Average Sales	Total Sales	Format repositioning sales 25%	Format repositioning sales 50%	Format repositioning sales 75%	Median pop.	Median families
2001	6,524	-	-	339	23,594	153,927,750	-	-	-	38,706	19,852
2002	6,228	481	94	167	25,368	157,993,250	5,500	17,500	45,000	38,706	19,852
2003	6,176	321	134	239	27,080	167,247,500	12,500	35,000	55,000	38,706	19,852
2004	6,214	300	311	261	27,386	170,178,020	3,500	9,000	35,000	39,145	20,410
2005	6,112	589	171	293	28,242	172,613,250	4,500	12,500	27,500	39,477	20,554
2006	5,953	243	134	-	29,463	175,395,290	4,500	9,000	31,250	40,873	20,770

NOTES: Sales are reported in thousands of 2001 SEK. Population and numbers of families are at municipality level (290).

Table 3: Median characteristics of repositioning and non-repositioning markets

Year	Population		# of Stores		# of Entries (E)		# of Exits (X)		C_4		$Cor(R,E)$	$Cor(R,X)$
	Repos.	Non-Repos.	Repos.	Non-Repos.	Repos.	Non-Repos.	Repos.	Non-Repos.	Repos.	Non-Repos		
2002	21,450	10,549	33.5	15.5	2.5	1.0	3.5	1.0	0.236	0.365	0.63	0.50
2003	26,355	11,014	32.5	17.0	3.0	1.0	3.5	1.0	0.168	0.370	0.72	0.53
2004	22,319	12,615	32.0	18.5	5.0	2.0	4.5	2.0	0.165	0.358	0.78	0.80
2005	23,104	11,270	31.0	13.0	3.5	1.0	4.0	1.0	0.221	0.450	0.76	0.66
2006	27,120	11,804	31.0	17.0	2.5	2.5	-	-	0.186	0.394	0.88	-

NOTE: *Repositioning* markets are those where at least one repositioning occurred during the year. *Non-Repositioning* markets are all others. $Cor(R,E)$ and $Cor(R,X)$ are correlations between the numbers of repositionings (R) and entries (E), and (R) or exit (X) across markets where repositioning occurred.

Table 4: Median characteristics of markets where formats are present, 2001-2006

Format (see Table 1)	Number of Markets						Population		Market Share		Sales per m^2	
	2001	2002	2003	2004	2005	2006	Repos.	Non-Repos.	Repos.	Non-Repos.	Repos.	Non-Repos.
ICA Maxi	31	32	33	34	39	45	69,741	45,266	0.233	0.284	89.10	83.05
ICA Kvantum	93	95	101	102	104	99	37,057	26,270	0.193	0.290	72.29	68.77
ICA Supermarket	211	209	234	233	233	230	23,922	13,324	0.056	0.145	61.87	61.51
ICA Nära	261	257	259	258	248	247	24,935	13,725	0.014	0.024	46.79	43.75
Willys et al.	31	47	73	89	93	99	49,863	30,532	0.086	0.136	59.21	56.94
Vivo	122	49	26	20	0	0	54,357	32,269	0.023	0.036	76.24	53.25
Hemköp et al.	111	138	135	125	108	100	33,234	20,116	0.051	0.131	53.57	52.76
Handlarń	80	104	111	124	128	126	27,120	15,453	0.006	0.012	30.77	30.22
Tempo	56	61	63	68	81	90	36,690	21,715	0.011	0.021	40.12	39.56
Rimi	88	90	0	0	0	0	37,448	30,229	0.047	0.064	57.41	61.11
Axfood Others	135	94	87	73	84	82	37,052	20,017	0.003	0.013	40.34	42.86
Coop Nära	0	0	0	0	41	52	53,302	24,953	0.013	0.021	64.10	53.52
Coop Large	50	51	52	70	79	89	49,918	25,764	0.122	0.147	60.24	47.60
Coop Medium	240	255	254	244	232	219	23,947	12,820	0.026	0.056	49.64	46.36
OBS et al.	94	45	45	45	35	24	26,300	26,131	0.151	0.149	54.69	55.63
Vi	0	0	0	0	21	33	56,467	29,475	0.023	0.022	70.00	50.00
Bergendahls Others	33	37	42	47	52	55	33,494	19,868	0.020	0.055	41.20	45.00
Others	285	284	286	287	289	287	22,328	13,000	0.006	0.011	32.25	31.34

NOTES: *Repositionig* markets are those where at least one repositioning occurred during the year. *Non-Repositioning* markets are all others.

Table 5: Format repositioning from ICA, 2001-2006

New Format (see Table 1)	from ICA Maxi	Kvantum	Supermarket	Nära	Rimi
ICA Maxi	-	8	0	0	0
ICA Kvantum	2	-	7	0	2
ICA Supermarket	0	8	-	7	100
ICA Nära	0	0	48	-	30
Willys et al.	0	0	0	2	0
Vivo	0	0	1	0	1
Handlarń	0	0	0	31	0
Tempo	0	0	0	21	0
Rimi	0	1	5	2	-
Axfood others	0	0	0	9	0
Vi	0	0	0	2	0
Bergendahls others	0	0	1	16	0
Others	0	2	1	220	1

NOTE: The figures represent the number of stores that switched format (see Table 1).

Table 6: Format repositioning from Axfood, 2001-2006

New Format (see Table 1)	Willys et al.	Vivo	Hemköp et al.	Handlarń	Tempo	AxFood Others
ICA Kvantum	0	2	0	0	0	0
ICA Supermarket	0	0	1	0	0	0
ICA Nära	0	1	4	0	1	1
Willys et al.	-	9	60	0	1	7
Vivo	0	-	0	0	1	1
Hemköp et al.	0	113	-	0	0	7
Handlarń	0	3	0	-	12	68
Tempo	1	19	45	3	-	14
Rimi	0	1	0	0	0	0
Axfood Others	0	5	4	8	4	-
COOP Medium	0	0	2	0	0	0
Vi	0	78	1	0	2	0
Bergendahls Others	0	4	3	0	6	4
Others	3	20	8	40	8	93

NOTES: The figures represent the number of stores that switched format (see Table 1).

Table 7: Format repositioning from Bergendahls, 2001-2006

Old Format (see Table 1)	ICA Supermarket	ICA Nära	Willys et al.	Hemköp et al.	Handlarń	Tempo	Axfood Others	COOP Medium	Vi	Others
Vi	0	0	1	3	1	2	0	0	0	1
Bergendahls Others	1	1	0	0	0	1	2	1	1	19

NOTES: The figures represent the number of stores that switch their format. One format contains one or more store concepts.

Table 8: Format repositioning from Coop, 2001-2006

Old Format (see Table 1)	ICA Nära	Willys et al.	Vivo	Handlarn	Tempo	Axfood Others	Coop Nära	Coop Large	Coop Medium	OBS et al.	Vi	Bergendahls Others	Others
Coop Large	0	1	0	0	0	0	0	0	43	0	0	0	0
Coop Medium	1	1	5	24	14	1	115	39	0	3	3	12	25
OBS et al.	0	0	0	0	0	0	0	53	38	0	0	0	1
Others	0	0	0	0	0	0	0	0	0	0	0	1	0

NOTES: The figures represent the number of stores that switched format.

Table 9: Demand model estimates

Format (see Table 1)	Std. Dev.	Distance	Pop. 0-14	Pop. 15-34	Pop. 65-100
ICA Maxi	0.1336	-0.6704	1.0289	0.6838	0.6420
	(1.0002)	(0.0274)	(0.0012)	(0.0358)	(0.0321)
ICA Kvantum	0.0272	-0.7171	-0.9031	0.4654	0.2201
	(2.0435)	(0.0902)	(0.0631)	(0.0002)	(0.0106)
ICA Supermarket	0.1822	-1.6194	2.4134	0.1637	0.8203
	(4.0305)	(0.0335)	(0.2648)	(0.0312)	(0.4253)
ICA Nära	0.7535	-0.4094	-0.2264	0.6900	0.2715
	(2.1431)	(0.2003)	(0.1231)	(0.0243)	(0.0155)
Willys et al.	0.6057	-0.8821	1.2520	0.3079	0.2587
	(3.0246)	(0.0548)	(0.324)	(0.1260)	(0.0332)
Vivo	0.3944	-0.9255	0.9616	0.7370	0.1189
	(3.257)	(0.1005)	(0.1946)	(0.0004)	(0.0282)
Hemköp et al.	0.9085	-0.7188	0.4967	0.4152	0.4151
	(0.0303)	(0.0332)	(0.0340)	(0.2112)	(0.0553)
Handlarń	0.1837	-0.0559	0.0886	0.2558	0.3278
	(4.566)	(0.0012)	(0.0394)	(0.0122)	(0.0134)
Tempo	0.1504	-0.4019	0.2046	0.7964	1.9868
	(0.0201)	(0.0141)	(0.0244)	(0.0432)	(0.0043)
Rimi	0.1333	-0.2393	0.1031	0.7484	-0.9531
	(0.0223)	(0.0030)	(0.1506)	(0.0003)	(0.0245)
Axfood Others	0.9813	-0.5016	0.5548	0.7413	0.4577
	(1.0033)	(0.0302)	(0.0232)	(0.0191)	(0.0126)
Coop Nära	0.6035	-1.0515	0.5386	1.9743	0.1485
	(5.0130)	(0.0004)	(0.0930)	(0.0023)	(0.0165)
Coop Large	0.2385	-0.6393	0.8863	0.4163	0.1556
	(3.0201)	(0.0221)	(0.0562)	(0.0646)	(0.0427)
Coop Medium	0.8516	-0.1116	0.2041	0.4366	0.1325
	(10.2374)	(0.0047)	(0.1041)	(0.0406)	(0.0256)
OBS et al.	0.3486	-0.6849	0.4394	0.3244	0.3012
	(4.0504)	(0.0257)	(0.0452)	(0.0757)	(0.0432)
Vi	0.9622	-1.0666	0.5819	0.6543	0.3114
	(8.0250)	(0.0303)	(0.0940)	(0.0043)	(0.0165)
Bergendahls Others	0.2408	-0.9030	0.0820	0.2175	0.3407
	(9.0031)	(0.0221)	(0.0322)	(0.0046)	(0.0047)
Age	0.6561				
	(0.0135)				
Sales space	0.0828				
	(0.0409)				
Quality transition	0.1718				
Repositioning	(0.0042)				
Quality transition	0.6232				
Non-repositioning	(0.0023)				
Number of observations	18,519				
GMM objective	28647				
Sargan p-value	0.184				

NOTES: Standard errors are in parentheses. Population is in logs at municipality level. Coefficients on market-format and year dummies are not reported.

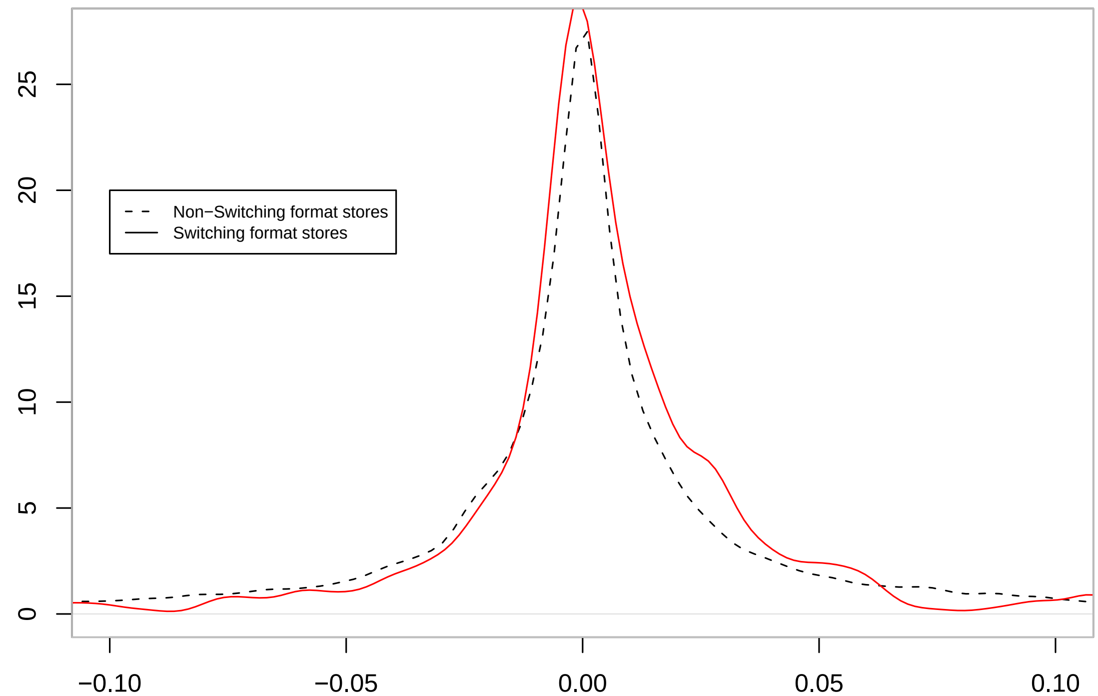

Figure 2: Quality kernel density estimates, repositioning and non-repositioning stores

Table 10: Sales function estimates

	Model 1	Model 2	Model 3	Model 4
Demographics				
Population (0-14 years)	0.0008	0.0007	0.0002	0.0009
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Population (15-34 years)	-0.0006	-0.0006	-0.0005	-0.0007
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Population (over 65 years)	0.0014	0.0014	0.0014	0.0017
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Store characteristics and competition				
Age	-0.0209	-0.0202	-0.0115	0.0002
	(0.0021)	(0.0021)	(0.0009)	(0.001)
Distance	-0.0282	-0.0282	-0.0165	-0.0011
	(0.0031)	(0.0031)	(0.0014)	(0.0006)
Store quality	0.0073	0.0074	0.0041	0.0004
	(0.0007)	(0.0007)	(0.0003)	(0.0001)
Store quality squared	-0.00005	-0.00005	-0.00003	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.000001)
Number of stores commonly owned in format			-0.0076	-0.0053
			(0.0007)	(0.0006)
Number of stores owned by other firms			-0.0065	-0.0043
			(0.0007)	(0.0005)
Format repositioning		0.0205	0.0594	0.0047
		(0.0069)	(0.0438)	(0.0023)
Revenue effects				
Store market share less than market average				-0.2174
				(0.1399)
Number of observations	18,519	18,519	18,519	18,519
Sales for non-repositioning				
actual mean	32,817	32,817	32,817	32,817
predicted mean	28,033	30,297	30,281	31,902
correlation of actual, predicted	0.10	0.42	0.42	0.45
Sales for repositioning				
actual mean	35,120	35,120	35,120	35,120
predicted mean	30,118	33,428	33,715	34,717
correlation of actual, predicted	0.16	0.44	0.44	0.46

NOTES: Estimation by non-linear least squares. Standard errors in parentheses. Specifications include market-year fixed effects. Sales are reported in thousands of 2001 SEK. Population is in logs at municipality level.

Table 11: Policy parameter estimates: repositioning format strategies

Format (see Table 1)	Pop. 0-14	Δ Pop. 0-14	Pop. 15-34	Δ Pop. 15-34	Pop. 65-100	Δ Pop. 65-100	Own quality	Rivals quality	No. own Formats	No. rivals	Stay ×Age	Switch ×Age	Stay ×Dist.	Switch ×Dist.	Stay × Market share	Switch × Market share
ICA Maxi	345.30	-204.735	72.082	165.369	-271.604	430.359	0.100	0.003	-4.336	0.179	-0.358	-0.422	-0.670	-3.355	70.376	40.907
	(0.045)	(0.072)	(0.042)	(0.069)	(0.009)	(0.016)	(0.016)	(0.005)	(0.604)	(0.005)	(0.055)	(0.067)	(0.148)	(0.060)	(0.780)	(0.067)
ICA Kvantum	334.62	-135.473	-8.922	175.906	-248.186	363.985	-0.077	0.008	-1.334	0.167	0.269	0.225	-1.251	-14.282	70.164	42.078
	(0.028)	(0.040)	(0.023)	(0.052)	(0.008)	(0.013)	(0.010)	(0.003)	(0.057)	(0.004)	(0.035)	(0.039)	(0.228)	(0.007)	(0.539)	(0.156)
ICA Supermarket	191.30	-86.721	-16.503	110.571	-219.378	251.676	0.006	0.018	-0.472	0.139	0.018	-0.054	-0.057	0.021	59.126	21.203
	(0.030)	(0.035)	(0.086)	(0.122)	(0.029)	(0.040)	(0.006)	(0.002)	(0.012)	(0.004)	(0.021)	(0.023)	(0.032)	(0.058)	(0.463)	(0.013)
ICA Nära	188.20	-47.723	-11.604	85.374	-28.716	167.076	-0.022	0.020	-0.285	0.121	0.118	0.061	0.128	0.062	30.160	11.760
	(0.094)	(0.139)	(0.601)	(0.814)	(0.178)	(0.228)	(0.005)	(0.001)	(0.008)	(0.004)	(0.017)	(0.018)	(0.023)	(0.053)	(1.034)	(0.070)
Willys et al.	262.32	-79.790	16.858	150.910	-163.264	326.505	0.046	0.001	-0.660	0.155	-0.178	-0.180	-0.344	-0.449	59.507	36.648
	(0.034)	(0.036)	(0.051)	(0.089)	(0.024)	(0.033)	(0.009)	(0.003)	(0.022)	(0.004)	(0.030)	(0.031)	(0.064)	(0.142)	(0.722)	(0.709)
Vivo	307.40	-137.283	-146.102	188.723	-310.258	235.689	-0.016	0.017	-0.344	0.126	0.089	0.044	-0.050	-0.345	57.083	16.709
	(0.034)	(0.048)	(0.010)	(0.026)	(0.004)	(0.008)	(0.009)	(0.004)	(0.011)	(0.004)	(0.032)	(0.035)	(0.085)	(0.675)	(0.193)	(0.005)
Hemköp et al.	273.91	-94.412	9.804	112.722	-299.879	396.696	-0.028	0.014	-0.693	0.155	0.120	0.110	0.016	0.131	58.467	31.218
	(0.027)	(0.036)	(0.020)	(0.035)	(0.009)	(0.014)	(0.007)	(0.002)	(0.020)	(0.004)	(0.026)	(0.027)	(0.047)	(0.061)	(0.626)	(0.166)
Handlarń	52.60	-36.425	-83.106	99.222	-276.976	249.792	0.030	0.037	-1.094	0.161	-0.072	-0.094	-0.145	-0.166	-106.767	-95.908
	(0.021)	(0.037)	(0.020)	(0.034)	(0.006)	(0.014)	(0.008)	(0.002)	(0.030)	(0.004)	(0.027)	(0.028)	(0.039)	(0.062)	(0.017)	(0.006)
Tempo	105.18	-1.073	-68.863	143.067	-124.473	237.636	0.037	0.024	-1.037	0.164	-0.097	-0.125	-0.269	-0.297	-43.008	-8.110
	(0.024)	(0.041)	(0.015)	(0.028)	(0.005)	(0.013)	(0.009)	(0.003)	(0.032)	(0.004)	(0.031)	(0.031)	(0.053)	(0.076)	(0.024)	(0.022)
Axfood Others	139.22	-87.366	-204.179	164.845	-453.006	249.841	-0.300	0.036	-0.885	0.149	1.028	0.997	1.269	1.172	58.009	35.261
	(0.019)	(0.037)	(0.013)	(0.027)	(0.007)	(0.017)	(0.008)	(0.002)	(0.025)	(0.004)	(0.029)	(0.029)	(0.043)	(0.120)	(0.164)	(0.030)
Coop Nära	303.41	79.893	-154.035	105.144	-143.469	-157.724	-0.056	0.004	-0.742	0.153	-1.715	0.204	-0.432	0.207	-112.152	-3.120
	(0.046)	(0.083)	(0.011)	(0.034)	(0.011)	(0.028)	(0.017)	(0.009)	(0.033)	(0.004)	(0.335)	(0.058)	(0.072)	(0.099)	(0.000)	(0.104)
Coop Large	336.05	-165.777	49.670	116.421	-231.398	372.340	0.044	0.007	-1.702	0.173	-0.114	-0.123	-0.754	-0.851	61.088	39.154
	(0.037)	(0.044)	(0.041)	(0.070)	(0.019)	(0.026)	(0.011)	(0.003)	(0.094)	(0.004)	(0.037)	(0.037)	(0.145)	(0.277)	(0.734)	(0.765)
Coop Medium	176.85	-22.874	-27.587	105.563	31.821	118.183	-0.096	0.026	-0.294	0.126	0.366	0.312	0.431	-1.746	55.942	24.581
	(0.034)	(0.084)	(0.403)	(0.551)	(0.115)	(0.142)	(0.006)	(0.001)	(0.008)	(0.004)	(0.020)	(0.023)	(0.027)	(0.931)	(0.651)	(0.018)
OBS et al.	127.11	-94.328	-13.593	127.303	-117.759	211.679	-0.154	0.032	-1.040	0.148	0.553	0.484	0.573	0.742	66.521	38.113
	(0.023)	(0.053)	(0.014)	(0.048)	(0.016)	(0.036)	(0.015)	(0.003)	(0.069)	(0.005)	(0.051)	(0.055)	(0.087)	(0.100)	(0.845)	(0.087)
Vi	42.37	-20.972	-152.186	160.744	61.124	-114.585	0.223	-0.006	-0.426	0.141	-3.788	-0.737	-8.365	-0.989	1.324	3.136
	(0.051)	(0.082)	(0.029)	(0.047)	(0.006)	(0.018)	(0.024)	(0.011)	(0.047)	(0.006)	(0.575)	(0.081)	(0.065)	(0.148)	(0.000)	(0.121)
Bergendahls Others	341.73	-150.366	-26.270	151.784	51.350	218.054	-0.136	0.002	-0.697	0.142	0.480	0.479	0.531	0.599	60.461	26.389
	(0.046)	(0.055)	(0.029)	(0.056)	(0.015)	(0.021)	(0.012)	(0.004)	(0.029)	(0.004)	(0.041)	(0.041)	(0.067)	(0.086)	(1.100)	(0.121)
Number of observations	18,519															
Log-Likelihood	-70771.77															

NOTES: Estimated multinomial logit model for conditional choice probabilities. Standard errors are in parentheses. Population is percent.

Table 12: Policy parameter estimates: entry and exit

	Entry probit $P(entry\|X)$	Exit probit $P(exit\|X)$
Quality		-0.049
		(0.006)
Competitors's quality in the same format	0.028	0.002
	(0.014)	(0.001)
Age		0.163
		(0.026)
Distance	0.025	0.021
	(0.012)	(0.002)
Population	1.904	-0.199
	(0.903)	(0.046)
Number of stores commonly owned in format	-0.061	-0.002
	(0.017)	(0.001)
Number of stores owned by other firms	-0.049	-0.0001
	(0.023)	(0.0001)

NOTES: Standard errors are in parentheses. Specifications include format market-year fixed effects. Population is in logs at municipality level.

Table 13: Parameter estimates: sunk repositioning costs and sell-off values

Parameter	Market Size		
	Population $< 20,000$	Population 20,000-60,000	Population $> 60,000$
Repositioning costs (γ_1)	[78.73 390.41]	[403.00 637.13]	[490.02 738.35]
PPHI outer - 95%	[62.41 416.23]	[384.45 701.92]	[481.52 793.32]
Sell-off values (γ_4)	[680.34 990.98]	[736.02 1203.92]	[920.97 1890.37]
PPHI outer - 95%	[603.72 1010.39]	[701.83 1308.62]	[839.82 1983.08]
Median sales of repositioning stores	8,000	17,500	17,500
Median sales/upper bound of repositioning costs	21	27	24
Mean no. of repositionings per year-market	1	2	11

NOTES: Repositioning costs are in thousands of 2001 SEK. The Pakes et al. (2007b) estimator is used. 100 simulations are used to construct the outer intervals.

Table 14: Sunk entry costs distribution results

Parameter	Market Size		
	Population $< 20,000$	Population 20,000-60,000	Population $> 60,000$
Mean	5,405	20,357	37,985
Variance	5E4	7E4	10E4
Median Sales of Entrants	2,500	4,500	10,750

NOTES: Median sales and costs are in thousands of 2001 SEK. The parameters were estimated by matching the cumulative distribution function of a normal distribution to the empirical probability of entry. The expected value of entry was computed using 100 replications of each state.

Appendix A. Sources of DELFI's data. DELFI Marknadspartner AB includes daily covers data on retail food stores from: (1) public registers, trade press, and daily press; (2) the Swedish Retailers Association (SSLF); (3) Kuponginlösen AB (a firm that deals with customers coupons); (4) each chains' headquarters; (5) matching customer registers from suppliers (customers); (6) telephone interviews, (7) annual surveys; and (8) The Swedish Retail Institute (HUI). In addition, DELFI verifies location, store-type, owner, and chain affiliation in annual reports.

Each firm has an identification number linked to it address. There are 11 store-types, based on size, location, product assortment, etc.: hypermarkets, department stores, large supermarkets, large grocery stores, other stores, small supermarkets, small grocery stores, convenience stores, gas-station stores, mini markets and seasonal stores.

Appendix B. Forward simulation steps that used to compute expected payoffs. The steps each year are :

1. Given store characteristics and market demographics, estimate the store quality from the random-coefficients demand model. I use 20 Halton draws for each unobserved characteristics.

2. Using the estimated sales generating function, compute discounted revenues for each store. I assume that the store are independently owned.

3. Compute the competition and demographics variables, which change every year and affect the multinomial (nested) logit format choice. Again, I assume that the stores are independently owned.

4. Simulate a choice for each store, i.e., compute the multinomial (nested) logit choice probabilities and compare then with a random random draw from a uniform distribution. If the store repositions I count how many times it does.

5. Conditional on current and previous, simulate the evolution of store-quality using draws from the empirical distribution of observed quality-innovations for the random components. In addition, simulate the evolution of demographics.

6. Update store formats.

Appendix C. Alternative estimators of sunk repositioning costs. An alternative estimator for the second step is the minimum-distance estimator, constructed using the set of inequalities below. Due to linearity in the cost function, the optimality conditions (1) can be re-written as

$$(36) \quad [W_j(\boldsymbol{\omega}, \sigma_j, \sigma_{-j}) - W_j(\boldsymbol{\omega}, \sigma_j^{'}, \sigma_{-j})]\boldsymbol{\gamma} \geq 0$$

This can be written in terms of profitable deviations from optimal policy,

$$(37) \quad g(\sigma_j^{'}; \boldsymbol{\gamma}, \boldsymbol{\alpha}) = [W_j(\boldsymbol{\omega}, \sigma_j, \sigma_{-j}) - W_j(\boldsymbol{\omega}, \sigma_j^{'}, \sigma_{-j})]\boldsymbol{\gamma}$$

where $\boldsymbol{\alpha}$ represents parameterization of the policy functions. More specifically, alternative policies can be drawn to generate a set of inequalities indexed by x. The estimates of W_j, denoted $\tilde{W}_j$, are obtained using forward simulation, and I use them in the sample analog of the objective function

$$(38) \quad Q_n(\boldsymbol{\gamma}, \boldsymbol{\alpha}) = \frac{1}{n_I} \sum_{x=1}^{n_I} (min\{\tilde{g}(x, \boldsymbol{\gamma}, \boldsymbol{\alpha}), 0\})^2$$

I use the Nelder-Mead method to obtain the starting values. Then I plug the estimated parameters as started values in the Uncmin optimization routine.[19] The later gives me the final estimates and the standard errors. Another alternative is to use the Laplace-type estimator (Chernozhukov and Hong, 2003).

Table 15: Alternative parameter estimates: sunk repositioning costs

Parameter	Market Size		
	Population $< 20{,}000$	Population 20,000-60,000	Population $> 60{,}000$
Repositioning costs (γ_1)	353	637	718
Std.	(102.34)	(223.26)	(287.03)
Median sales of repositioning stores	8,000	17,500	17,500
Median sales/repositioning costs	22	27	24
Mean no. of repositioning per year	1	2	11

NOTES: Median sales and repositioning costs are in thousands of 2001 SEK. Standard errors are in parentheses. The standard errors are not corrected for first-stage estimation errors.

[19]Uncmin performs unconstrained nonlinear optimizations (http://www1.fpl.fs.fed.us/optimization.html).