# Entry and Store Type Differentiation in Retail Markets*

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**Abstract**

This paper investigates competition between retail food stores when introducing a new store format, namely hard discounters. I use a static entry model with endogenous store type choices and flexible competitive effects across types. Using data on retail food stores in Sweden, I find evidence of asymmetries in the competitive effects across types. Small and large stores have the most pronounced impact on profitability of hard discounters, but small stores reduce profits slightly more than large. Discount stores, on the contrary, do not decrease profits of small and large to the same extent. Furthermore, small and large stores compete more intense within type than hard discounters.

*Keywords*: Imperfect competition, Product differentiation, Retail markets, Hard discounters.
*JEL Classification*: L11, L13, L81.

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## 1 Introduction

Differentiation plays a central role in retail markets and its importance has increased over time. Retail markets in both the U.S. and Europe share two trends. First, a focus on uniformly designed store concepts operated by centralized chains. Second, entry of new store formats such as discount retailers. As an example, the market share for U.S. discount retailers such as Wal-Mart, K-Mart and Target has increased rapidly since the first store entered in the 1950s.[1] Over 70 percent of total retail food sales in U.S. was captured by discount stores in 1997 (Jia 2008). A difference between U.S. and Europe is however that the shape of the discount format is not alike. Apart from the national chains, offering low prices in large stores, so called "hard discounters" have expanded rapidly across Europe in recent years. That is, rather small stores with a core focus on low prices, limited product range and service level. The extent to which hard discounters influence competition between current players is still an open question and an evaluation requires taking store heterogeneity into account.

The goal of this paper is to investigate entry and store type differentiation in retail markets, and to assess the impact of hard discounters on competition and profitability of different store types. I use a static entry model that allows for asymmetric competitive effects across types. The empirical application relies on detailed data of all retail food stores in Sweden for a long period of time both pre- and post of hard discount entry.

To quantify the degree of competition within and between store types is of concern from both a regulation and business perspective. In particular, the study links to competition policy through entry regulations. That Europe has a much more restrictive regulation than the U.S. provides a direct link between entry of new players, such as hard discounters, and competition policy. Because Sweden has a representative market structure and regulation to many other European countries the findings are of interest to a broad audience.

The model builds on the framework by Seim (2006) and allows for heterogeneous players and for the possibility that the intensity of competition varies across store types. Heterogeneity in players' profit functions is especially important in retail markets as heterogeneous store types operate in the same local market. Specifically, I add the possibility of asymmetric competitive effects that just recently has been put forward in the literature (Berry and Tamer 2006, Ciliberto and Tamer 2009). This implies that the impact that each store type has on profits of rival types differ. The basic theoretical anticipation is that competition from own store types is more intense compared to competition from other store types. In other words, we expect stores to protect themselves

[1] See e.g. Basker (2005), Basker (2007), Jia (2008), and Holmes (2010) for studies about Wal-Mart.

from competition by differentiating as competition gets more intense (Mazzeo 2002, Berry and Tamer 2006). Using a static model requires that stores are in long-run equilibrium. This assumption is not restrictive in the current application because descriptive evidence shows that there are no major changes in store turnover as a result of entry of hard discounters (discussed in detail below). That is, exit by national chain stores seem not to be the main response to hard discount entry.

The present paper contributes to the literature on product differentiation in retail food markets. Players choose different store types and I allow the competitive effects between these store types to be flexible. In detail, players choose among small, large and hard discount types where the key is to identify competitive effects assigned to and from hard discounters. I thus abstract from explicitly investigating national chains and their expansion. Another contribution is that I explicitly investigate entry of the new hard discount format. Differentiation in retail markets has rarely been studied in a European context, and I explicitly deal with this new hard discount format. I am just aware of one paper on differentiation and entry of hard discounters (Cleeren et al. 2010). In contrast to prior work (which only analyze hard discounters and supermarkets), the current paper allows the choice of large store types to be endogenous. To consider more than one store type is central in the retail market where national chains operate both small and large types. To explicitly model large stores is moreover important as their share of the total number of stores increases steadily. Thus, the paper contributes to the understanding of competition between hard discounters and different store types, not just supermarkets.[2]

Already in 1960, the hard discount pioneer Aldi entered the German market, followed by Lidl and others. Lidl operates currently in 20 European countries, with particularly high market shares in Germany, France, Italy, Spain, UK and Belgium (AC Nielsen 2007). In Sweden, the first hard discount store entered in 2002. A completely new store format thus started to operate in a market dominated by traditional store concepts controlled by national chains. After an expansive entry strategy during the first years, the number of discount entrants flattens out after 2005 (Figures 1). For national chains, the trend is reverse, i.e., it has been a drastic fall in the total number of stores. During the period 1993-2008, the number of stores reduced by half. In addition, the share of large stores increased from 14 to 22 percent (Figures 2-3). The annual changes are surprisingly constant and seem not to change due to hard discount entry. At the local market level, average exit rates for national chains, i.e. excluding hard discounters, are rather similar in entry markets before and after discounters start to operate (Figure

[2]The trend of low cost firm entering into markets with large, well established, players is common also across other markets such as airlines and retail clothing.

4). Although there is a slight increase the year of entry, there are substantially higher exit rates several years ahead of discount entry.[3] Based on these descriptive patterns, I assume that stores are in long-run equilibrium in 2008. To estimate the model prior to hard discounters, I use data from 1995. This year is chosen because it is several years before introduction of hard discounters and avoids potential effects caused by a merger in 2000. Hence, I account for the rapid initial expansion of hard discounters and analyze a period prior to entry along with later years of the market in long-run equilibrium.[4]

Do hard discounters compete more intense with small stores than with large stores? To what extent do hard discount stores compete with each other? The answers to these questions connect closely to competition policy because entry is regulated in the majority of OECD countries. Entry regulations are much more restrictive in Europe compared to the U.S. and recently the European Parliament recently approved an investigation on supermarket dominance (European Parliament 2008). The main idea is that the pros and cons of a new entrant need careful evaluation by local authorities. I analyze how store types compete and, hence, whether it is central to consider the number of stores of different types and not just the total number of stores throughout the planning process. A central policy concern that connects to this paper is entry of new international chains. Thus, this study emphasizes the issue whether, and if so how much, new international chains that enter into the Swedish market impact profitability and competition.

The results show asymmetries in the competitive intensity across store types. Both large and small store types reduce payoffs of hard discounters, but small stores reduce profits of discounters more than large stores. The two greatest competitive effects are in fact the ones from small and large stores on discounters. The reverse effects, i.e. from hard discounters on small and large, are smaller. The results also show that small and large stores compete more intense within type than hard discounters. The findings suggest that it is important for local authorities that evaluate competitive effects of new entrants to consider not just the number of stores but also their type.

The rest of the paper is organized as follows. The next section summarizes the literature followed by the market and data in Section 3. Section 4 presents the model and estimation strategy, Section 5 shows the empirical results, while Section 5 summarizes and concludes.

[3]Municipalities (in total 290) are used as local markets. The low exit rate after five years is likely due to few entrants in 2003.

[4]This approach is in line with Greenstein and Mazzeo (2006), Jia (2008) and Berry and Jia (2010). To investigate the dynamic evolution of the new format and assess the changes over time require a model that is much more complex and computationally demanding, and is beyond the scope of this paper. A couple of papers studies supermarket competition using dynamic structural models (Beresteanu and Ellickson 2006, Aguirregabiria et al. 2007, Maican 2010). Contrary to the analysis of market structure over time in dynamic models, the aim of the present paper is to explain observed product differentiation in a static setting.

## 2 Related literature

The paper relates to the literature on static entry models (Berry and Tamer 2006) and general discrete choice models that analyze strategic interactions, for which Draganska et al. (2008) provide an excellent survey. The early literature on entry relies on homogenous firms (Bresnahan and Reiss 1990, Bresnahan and Reiss 1991, Asplund and Sandin (1999)), followed by extensions to differentiation (Berry 1992, Mazzeo 2002, Seim 2006, Dunn 2008) and more general forms of store heterogeneity (Ciliberto and Tamer 2009). Seim (2006) develops a static two-period model of entry and spatial differentiation, endogenizing location choices. Using data on video stores in U.S., she finds that the intensity of competition decreases with distance to competitors. Mazzeo (2002) studies U.S. motels and develops a static two-period model of endogenous entry and type decisions where firms differ in quality. The results show that competition is strongest between motels with similar quality. Similar approaches are taken by Dranove et al. (2003) and Greenstein and Mazzeo (2006). Toivonen and Waterson (2005) analyze competition between heterogeneous firm types in the U.K. fast food industry, taking players' identity into account. They find that variable profits are decreasing in the presence of rivals, but increasing in the number of own outlets. heterogeneous store types are also considered by Schaumans and Verboven (2008), Cleeren et al. (2010) and Vitorino (2010).[5]

More recently, models that allow for general forms of heterogeneity across players have been put forward. Ciliberto and Tamer (2009) use an application of the U.S. airline industry where the competitive effects differ across airlines in a flexible way. Another example is Ellickson et al. (2010) that account for players' identities in the U.S. retail food market.

An essential question in the retail literature is the presence of the so called chain effect. That is, multi-store retail chains that operate different store types across a large number of local markets. The few studies that touch upon this issue all rely on a limited number of players. Jia (2008) considers Wal-Mart, K-mart and small stores, Holmes (2010) analyzes economies of density of Wal-Mart, and Nishida (2010) studies a two player game in the convenience market in Japan.

Several papers use static entry models and apply different cross-sections of data throughout the empirical application. Greenstein and Mazzeo (2006) employ two dif-

[5] Several other applications use incomplete information games in static settings. As an example, Einav (2010) analyzes timing of movie releases and Ellickson and Misra (2008) examine pricing strategies across food retailers. Sweeting (2009) analyzes timing choices of radio broadcasts using both a two-step approach and the nested fixed point in estimation.

ferent cross-sections of data to investigate competition in telecommunication before and after a valuation crash. Jia (2008) and Berry and Jia (2010) also use a similar approach, as do the current application where I utilize data pre- and post of hard discount entry.

## 3 Market and data

The data set used in the empirical part of the paper contains all retail food stores active in the Swedish market during 1993-2008. The data is provided by DELFI Marknadspartner AB that uses an extensive number of channels to collect the information.[6] Each store has an identification number linked to its address. I have information on exact address, geo-coordinates (longitude and latitude), store type (12 different), owner, chain, sales space in square meters, revenues, year of entry, wholesale provider and the location (geo-coordinates) of the distribution centers for each wholesaler. For each store I hence observe the exact location.

I also use information on demand and cost shifters. Population, the age distribution of population, the number of families, average income, average wage and the share of seats taken by non-socialist parties in local governments are taken from Statistics Sweden (SCB).[7] Average price per square meter of houses sold, provided by Värderingsdata AB, are used to construct a measure of rent at the municipality level.

■ **Local market definition.** Competition in retail markets takes place at the local level and I therefore need to define a relevant local market. Of course, the size of the local market vary with store type and the distance across stores. The definition of local markets needs to fulfill the following requirements: First, the model requires that local markets are independent geographical areas, i.e., that stores only compete with other stores in the same local market. Second, I need to use markets where different store types operate. It is thus only relevant to put forward local markets that are large enough. On the other hand, markets that are too large will not be relevant because they most likely contain a number of sub-markets. Third, markets to select need to minimize the potential influence from any kind of spatial differentiation of stores. This because geographic location, apart from store type, is a crucial source of differentiation

[6] The sources are: (1) Public registers, trade press and daily press, (2) The Swedish retailers association (SSLF), (3) Kuponginlösen AB, (4) The chains' head quarters, (5) Matching customer registers from suppliers (customers) (6) Telephone interviews, (7) Yearly surveys, (8) The Swedish retail institute (HUI). In addition, controls of location, store type, owner and chain affiliation are made in the annual reports.

[7] Average income contains all sources of income including social insurances, pension, study allowances etc. SCB collects data on wages of retail-staff for Sweden as a whole, but not for individual municipalities. Wages for employees in municipalities (and the state) are available at the municipality level and are therefore used as a proxy.

in retail markets but it is not explicitly taken into account in the model. In other words, the sample markets need to be similar enough in order to at least bound the degree of spatial differentiation. A complication of the analysis of different store types is that the size of the local market differs across types. A careful investigation of market sizes for different store types is beyond the scope of the present paper.

Local labor markets (in total 88) consider commuting patterns and are most likely relevant for the absolutely largest stores whereas localities (in total 1,622) are more a plausible market definition for somewhat smaller stores. Municipalities (in total 290) are then the reasonable alternative that comprises the too wide versus too narrow local market definitions just mentioned.

The mean municipality population is almost 31,728 whereas the median is only 15,301 in 2008. Many municipalities are thus relatively small. Using store addresses as starting point, the goal is to select municipalities that fulfill our requirements of a local market definition above. Five municipalities that share boarder with Norway recognize a substantial share of demand from outside of Sweden and are therefore excluded.[8] I chose municipalities with a population between 9,500 and 100,000 which gives a total number of 209 local markets. Metropolitan municipalities with a population over 100,000 are excluded. These markets most likely consist of several sub-markets and are therefore not relevant to bring in the sample markets. Moreover, I drop rural and small municipalities below the 20th percentile of population, below 9,500, that plausibly are too small in terms of demand and/or geographical area to comprise differentiation in store type.

■ **Players and entry regulation.** The Swedish retail food market is representative to many of the OECD-countries. The market consists of hard discounters and national chains that operate different store concepts. The four national chains ICA, Axfood, COOP and Bergendahls cover a major part of the market.[9] Together they constitute for an industry market share of 88 percent in 2006. ICA is the largest chain with a market share of over 43 percent. Historically, ICA has been a network of independent stores collaborating on transport, marketing and purchasing. However, more centralized decision making and refined store concepts including definite product assortments have been developed during the last years. Axfood, constructed by a merger in 2000, has 18 percent of the market.[10] From having a wide range of store types Axfood has

[8]These municipalities are: Strömstad, Eda, Årgäng, Dals-Ed and Tanum.

[9]The store concepts are (2008): ICA Maxi, ICA Kvantum, ICA Supermarket, ICA Nära for ICA; Willys, Willys Hemma, Hemköp, Handlarn, Tempo for Axfood; COOP Forum, COOP Extra, COOP Konsum, COOP Nära for COOP; City Gross, Vi, Matöppet and Prisxtra for Bergendahls.

[10]The D-group started to restructure already in 1998. In 1999, the D-group and Dagab merged to D&D. In 2000, Axfood was created through a merge between D&D and Hemköp, and acquisitions of Spar Sverige, Spar Finland and Spar Inn Snabbgross.

gone towards fewer store concepts focusing on, for example, a large type with low price strategy. COOP consists of a mix of national and regional cooperatives and has almost 20 percent of total sales. Bergendahls is to a large extent established in the south and southwestern parts of Sweden and carries a fast growing market share around 7 percent. The remaining stores have 9 percent of the market and are mainly small stores with limited product assortment such as 7-Eleven and gas-station stores. In the empirical application I abstract from gas-station stores due to their limited product range and special geographical location (in total 1,298 stations). Note that the national chains and hard discounters capture over 90% of the market and therefore support almost the entire market.

The static model relies on the assumption that stores are in long-run equilibrium. The interest of this paper is thus to use a cross-section in a point in time when stores are in long-run equilibrium, and thus not to investigate the evolution of the market structure up to this point. As few as 4-5 percent of the markets experience entry and/or exit by national chains every year. Dynamics in the number of national chains across local markets is therefore not a concern, but rather choices of store type. Hard discounters have entered in recent years. Netto in 2002, followed by Lidl in 2003. Their overall strategy is to enter a new store type offering low prices together with limited product assortment and service level. Looking on the patterns over time (Figures 2-3), there is a decrease in the total number of stores. The expansion of hard discounters is most pronounced the years after they entered their first stores. The entry pattern flattens out over time (Figure 1). Based on this argument, it is reasonable to assume that stores are in long-run equilibrium in 2008 when Lidl 139 stores and Netto 87. To evaluate the competitive effects prior to hard discount entry, I use data from 1995. This year is chosen for two reasons: it is several years ahead of the first hard discount entrant and avoids the structural change that took place during 1998-2000 due to the Axfood merger.

As in the majority of retail food markets in OECD, entry is regulated by the plan and building act (PBA) in Sweden. PBA implies that each chain (owner) needs to send a formal application for each new entrant to the local authorities. Hence, the municipalities (290) should evaluate new entrants through the planning process. Aspects such as market concentration, prices, product assortment, environmental issues should be considered in the analysis (Swedish National Board of Housing, Building, and Planning 1999, Swedish Competition Authority 2001:4). In January 2008, it became explicit in PBA that municipalities must encourage competition when they investigate consequences of new entrants.

■ **Differentiation in type.** Our data provide a classification of 12 different store types such as convenience stores, mini markets, grocery stores and supermarkets.[11] The store types differ in aspects like product assortment, size, service level and location. In total, I construct three groups of store types namely hard discount stores, large stores, small stores. I consider hypermarkets, department stores, large supermarkets, large grocery stores and other stores as large. Our definition implies that large stores has a mean sales space of over 1,771 square meters. Consequently, the remaining store types (except hard discounters) are classified as small. Average sales space for the small store type is 304 square meters. Netto and Lidl operate hard discount stores that to a high extent are defined as small grocery stores with an average sales space of 542 square meters. In 2008, the minimum population for hard discount stores was 9,577 while the minimum population for large stores was 4,000. The traditional chains operate both large and small store types, respectively.

An alternative definition of large and small store types is to use a pure measure of square meter, which is done for robustness. A definition of the large type as stores with a sales space larger than 1000 square meters result in similar grouping as those based on the DELFI type definition.

■ **Descriptive statistics.** Figure 1 shows the expansion of hard discounters. After the first 5 entrants in 2002, there was a rapid increase to 154 stores in 2005. From 2006 and onwards the growth of hard discounters flattens out, reaching a total number of 226 stores in 2008. There has been a drastic fall in the number of stores operated by national chains. Figure 2 shows over 6,500 stores on aggregate in 1993 but only slightly over 4,000 in 2008. That is, a reduction by almost half. In contrast the share of large stores has a strong increasing trend, from only 14 percent in 1993 to as much as 22 percent in 2008. As shown in Figure 3, the decline in the number of stores by national chains has flattens off somewhat after 2005. Moreover, the number of stores owned by others than the national and discount chains is rather constant across time with a slight drop after 2005.

Table 1 shows aggregate summary statistics for number of stores, sales and sales space in 1995 and 2008. In 1995, there are 6,631 stores among which 14.4 percent are large and the remaining are small. In 2008, there are 4,398 stores among which 5.1 percent are hard discount stores. While the share of large stores is 14.4 percent in 1995, large stores constitute as much as 52.5 percent of total sales and 50.5 percent of the total number of square meters. In 2008, large stores constitute 21.8 of all stores but as much as 65.4 percent of total sales and 60.5 percent of total square meters. Although large stores only stand for about one fifth of the number of stores, they thus cover the

[11]The complete list of store types are: hypermarkets, department stores, large supermarkets, large grocery stores, small supermarkets, small grocery stores, convenience stores, mini markets, gas-station stores, seasonal stores, stores under construction and other stores.

majority of sales and sales space.

There are rather small differences across chains. While 27.8 percent of ICA's stores are large in 2008, the corresponding figure for the other players is 30-32 percent. Hence, ICA operates more small stores compared to other players. Large stores constitute about 65 percent of sales and sales space for ICA and COOP but over 70 percent for Axfood and Bergendahls. Among stores owned by others only 2 percent are large, covering about 20 percent of total sales space and almost 40 percent of sales by others. This quantifies the magnitude of the structural change towards larger but fewer stores that has taken place in the market during the period under study.

Turning to local markets, Figure 4 shows that average local market exit rates for national chains (excluding hard discounters) are rather similar in entry markets before and after discounters start to operate. Although there is a slight increase the year after entry, it is no systematic patterns in exit rates related to entry of hard discounters.[12] There is significantly higher average exit rates by national chains in markets before discount entry (0.054) than after (0.049). There is no statistical difference in average exit rates in markets with (0.05) and without (0.052) discount stores during the period 2003-2008. The average number of exist stores is however significantly higher in markets with discount entry (1.2) than in those without (0.57). This indicates that discounters enter large markets, and that there is a positive correlation between entry and exit (0.55).

Table 2 presents market configurations of the sample markets when at least one store of the various types is present. Since I select markets that are relatively homogenous, I expect somewhat similar market configurations. As anticipated, small store types exist in all markets. Since, in most cases, each player operates either one or zero large stores, the number of large stores to a large extent captures the number of chains present in the market. 10 out of the 209 sample markets consists only of small stores, 77 markets contain small and large types whereas all types i.e. small, large and discount operate together in 121 markets. Only one market has the configuration small and discount stores.

Panel 1 in Table 2 shows descriptive statistics of demand characteristics. The population is, as anticipated, lower in markets where only small stores operate (12,141) while it is higher in markets where all three store types operate jointly (33,799). Markets with both small, large and discount stores have a lower share of pensioners, and a higher share of young people. The share of women is lowest in markets with only small stores.

Panel 2 in Table 2 shows descriptive statistics for the average number of stores and chains across local markets with different type configurations. The average number of

[12] Municipalities (in total 290) are used as local markets. The low exit rate after five years is likely due to few entrants, and thus markets, in 2003.

small stores is slightly more than double the number of large stores. On average, the number of small stores ranges from 7.50 to 9.96. The average number of large stores is almost 4 in markets with discounters, but only 2.6 in markets without. In markets where discounters are present, 1.39 discount stores operate on average.

Table 3 presents a detailed view of the number of national chains and the number of discount chains across the sample markets in 2008. Hard discounters operate in 122 markets, out of which 89 contain one discount chain and 33 two. The most common configuration is three national chains but no discount chain (55 markets). This is followed by the configuration of three national chains and one hard discount chain (52 markets). Three markets are monopolies by a national chain.

Table 4 shows market configurations of the number of stores by national chains in all markets and markets with and without hard discounters in 2008. The cross tabulation of configurations of large and small store types show that the decision for large stores is mainly binary. For Axfood and COOP, over 80 percent of the markets are covered by the (0,1) alternatives for large stores, while the corresponding number for ICA is 70 percent. To operate a large store can therefore be seen as a binary choice for chains. Zero large stores characterize 40 percent of the markets for Axfood and COOP but 20 percent of the markets for ICA. Axfood and COOP have less than 4 small stores, whereas ICA has less than 5 small stores, in over 75 percent of the markets. Axfood and COOP have thus surprisingly similar configurations. Hence, national chains with similar market shares tend to have exceptionally similar store type structure. The difference between the main player, ICA, and Axfood and COOP, is that ICA operates both an additional large and small store. As the number of stores of different types as well as the number of chains vary across markets, Tables 2 and 4 indicate that not only market size can explain the variation in the presence and number of chains and types.

## 4 Entry model

The model is a static game of incomplete information.[13] In the first stage, a set of potential entrants $K$ simultaneously decide whether or not to enter a store in market $m = 1, ..., M$. If they enter they decide over store type $z = \{S, L, D\}$ in the second stage, where $S$ is small store, $L$ is large store, and $D$ is hard discount. Finally, stores interact and payoffs are realized. Decisions are made independently for each individual store. In

[13] As entry of hard discounters does not seem to cause a main structural shift in entry and exit, it is appropriate to use a static model.

other words, each store is seen as a separate unit over which decisions are made.[14] The payoff of the outside option to not enter is normalized to zero. Players' decisions are also assumed to be independent across local markets, i.e, a separate game is played in each local market.[15] Given entry, each player decides a type strategy. In the retail food market, chains operate a number of different store types across local markets. The set of potential entrants would thus consists of a set of chains that upon entry decide what store type to operate. Taking the identity of chains into account the profit of store type $z$ owned by chain $c$ is

$$\pi(a_{cz}^m) = \boldsymbol{\pi}(X_{cz}^m, a_{cz}^m, a_{-cz}^m; \theta) + \epsilon(a_{cz}^m) \tag{1}$$

where $\theta$ are parameters to be estimated. The profit function consists of a deterministic part $\boldsymbol{\pi}(X_{cz}^m, a_{cz}^m, a_{-cz}^m; \theta)$ and an idiosyncratic shock $\epsilon(a_{cz}^m)$ that is private information to the chain-type combination. I define $X_{cz}^m$ as a state vector that contains exogenous characteristics for each chain-type and market. The state vector is known to all players and the econometrician. It is important to emphasize that the profit function allows for chain-type specific information apart from market characteristics. Hence, stores differ in type and chain through observed characteristics and a payoff shock $\epsilon(a_{cz}^m)$. The deterministic part of profits contains: First, the state vector that captures market and chain-type specific information. Second, the expectation over competition from rival stores of each type. Players make their entry and store type choices simultaneously so that the action of one player depends on the actions taken by all other players in the local market. The profit function is reduced form in a sense that I do not model demand, pricing or cost explicitly. The profit function captures however the trade-off between demand, cost and competition. The profit function of chain $c$ operating store type $z$ in market $m$ is

$$\pi_{cz}^m = X_{cz}^m \beta + g(N_{cz}^m, N_{cz'}^m, N_{c'z}^m, N_{c'z'}^m; \lambda_{.cz}) + \psi^m + \epsilon_{cz}^m \tag{2}$$

where $X_{cz}^m$ captures exogenous demand and cost shifters, $\psi^m$ is an unobserved market effect, $N_{cz}^m$ is the number of stores of the same chain-type combination and $N_r^m$ is the number of stores of other chain-type combinations, where $r = (cz', c'z, c'z')$, $c \neq c'$ and $z \neq z'$. The competitive effects of store type competition are given by

[14] This implies that each player decides over individual stores, i.e., players do not make joint decisions over stores across different local markets. In Sweden, centralized decisions are made by Bergendahls, Lidl, Netto, and increasingly also within ICA, while national or local cooperatives decide in COOP, centralized and franchise stores within Axfood and several of the small chains e.g. gas-stations stores. See Section 2 for a detailed description.

[15] Most of the empirical entry literature relies on this assumption. As multi-store retail chains operate different store types across a large number of local markets, there is a concern of a chain-effect. This topic has just recently got attention in the literature and base on models with a few players (Jia 2008, Holmes 2010, Nishida 2010).

the matrix $\lambda_{.cz} = (\delta_{.cz}, \gamma_{r.cz})$. The on-diagonal elements $\delta_{cz,cz}$ give the own chain-type competitive effects whereas the off-diagonal elements $\gamma_{r.cz}$ give the rival chain-type competitive effects. If there are $C$ chains and a total of $Z$ types, the dimension of $\lambda_{.cz}$ is $(C^m * Z^m) \times (C^m * Z^m)$.[16]

■ **Identity of chains vs. differentiation in type.** Note that Equation (2) takes both the identity of chains and the differentiation choice of store type into account. By relaxing the symmetry assumption that all stores are identical and allow for flexible competition effects, my model is able to capture the nature of competition in retail markets in detail. The number of competitive parameters increases however rather fast. With 3 national chains operating 2 types, 2 hard discount chains and allow for asymmetric competitive effects, $\lambda_{.cz}$ is a $8 \times 8$ dimensional matrix. In this case there are 64 competitive parameters to be estimated.[17] Though retail markets are characterized by oligopoly structure with rather few (national) players, the dimension of the problem increases as the choice set of each player expands, i.e., the number of types. As one would like to analyze separate choices of store types for chains' stores, the complexity of the model increases drastically with the action space.

Since differentiation includes multiple dimensions and I need to reduce the number of competitive parameters, the alternatives are to either assume store type differentiation or heterogeneity in chain identity. I assume that all stores of the same type are identical, i.e., all national chains and hard discount chains (respectively) are identical. I validate this assumption by the following arguments. The national chains in Sweden operate well defined store formats that each targets a specific segment of demand. For example, ICA and COOP both has a small store format (ICA Nära and COOP Nära), a medium format (ICA Supermarket, COOP Konsum) and a large format (ICA Kvantum/Maxi and COOP Forum). The hard discount chains also operate similar and well-defined store formats. The hard discount type is about 550 square meters of sales space, with a similar location approach. Grouping national chains and hard discounters into types relies on the assumption that chains treat large and small stores strategically similar across the local markets under study. Table 4 justifies that the national chains Axfood and COOP have strikingly similar market configurations of small and large stores, while ICA differs slightly. From a policy perspective, a central issue is what type of stores

[16]Retail chains stand in front of the decision whether to enter a market or not, and if they enter what store types to choose and how many stores of each type. A possible extension of the present model is to let national chains choose not just whether to operate a certain store type or not but also how many stores of each type to operate (see Table 4). National chains would then have a discrete choice for large stores but an ordered choice for small stores. This would also allow for the possibility of a complementarity effect between the choice of small and large types (Augereau et al. 2006, McDevitt and Roberts 2010).

[17]In total, 4 national chains operate in Sweden. However, abstracting from the smallest chain (Bergendahls) it is still possible to capture almost 90 percent of the market shares.

that compete with each other. Hence, the interesting question is not the exact identity of competitors but the type of competitors a store face. Based on these arguments, I assume differentiation in store type and thus assume that all stores of a certain type are identical independent of chain affiliation. In other words, stores are grouped such that all stores of the same type are assumed to be homogenous. The decision whether to operate a small or large type is however likely to be correlated.[18] For simplicity the model in the current version of the paper abstracts from the joint decision to operate small and large types.

Another possibility is to assume that all stores belonging to the same chain are identical, i.e., no differentiation in store type. This assumption would be more appropriate for industries where firms are similar to the extent that they operate only one uniform concept, and where the players' identity is of particular interest for the research question at hand. Studies that incorporate identity of firms are Toivonen and Waterson (2005) analyzing McDonalds and Burger King, and a recent application by Ciliberto and Tamer (2009) who analyze the U.S. airline industry. Using 3 national chains and 2 hard discount chains, I would estimate $5 \times 5 = 25$ competitive parameters. As mentioned above, there are minor dynamics over time in the number of chains across markets. Chain differentiation while abstracting from type differentiation captures the fact that the identity of chains matters for competition. The drawback is however the similarity assumption of store types, which is not reasonable for the retail food market.

■ **Payoffs with type differentiation.** Abstract from the identity of entrants but take type differentiation into account gives the following payoff function.

$$\pi_z^m = X_z^m \beta + g(N_z^m, N_{z'}^m; \lambda_{.z}) + \psi_m + \epsilon_z^m \tag{3}$$

where $\lambda_{.z}$ is a $Z^m \times Z^m$ dimensional matrix of competitive effects with $\delta_{zz}$ capturing own-type competitive effects and $\gamma_{zz'}$ capturing rival-type competitive effects. $N_z^m$ and $N_{z'}^m$ are the number of stores of the same type and rival types, and $\epsilon_z^m$ is a private shock to profitability. I assume that $g(.)$ is linear so that the presence of rivals enters the profit function linearly, a shared feature with e.g. Berry (1992) and Seim (2006). An alternative would be to allow for more flexible competitive effects (e.g. Bresnahan and Reiss 1991), but at the cost of an increase in the computational burden. Using a linear

[18] That the decision to operate small and large store types are correlated calls for a model in line with Augereau et al. (2006). In their model of technology adoption, each firm choose between two technologies. A firm can adopt either one or both technologies, or not adopt at all. The choice of both technologies has a complementarity effect. It is however difficult to separate the impact of complementarities from correlation in unobservables. Augereau et al. (2006) restrict the estimation to one of these, and interpret that the effect can be either due to complementarities or correlation - but not the separate effect. In other words, it is not possible to distinguish between technologies being complements from unobservables.

specification of $g(.)$, the payoff function becomes

$$\pi_z^m = X_z^m \beta + \delta_{zz} N_z + \sum_{\substack{z' \\ z' \neq z}} \gamma_{zz'} N_{z'} + \psi^m + \epsilon_z^m \tag{4}$$

The central feature of the model is the competitive parameters that are allowed to be flexible and vary both in magnitude and sign depending on store type. Using differentiation in type, I estimate $3 \times 3 = 9$ competitive parameters.

Retail food demand tightly links to population which is therefore included as a demand shifter. To capture that demand varies by the demographic distribution of the population, I also use the share of kids (0-9 years old) and pensioners (above 65 years old) as demand shifters. The costs of retail stores include logistics, products, rent, labor, and other costs e.g. advertisement. Average price per square meter of buildings captures rent. To cover labor costs, I use average monthly wage in the municipality. Costs of logistics is measured by the minimum distance to the nearest distribution center.[19] To proxy for differences in regulation across local markets, I use the share of non-socialist seats in the municipality.

If there are unobserved market characteristics that players condition their entry and type decisions on, I would not capture the true competitive effects. Examples of these kind of variables are unobserved demand, decisions over highways or information about restrictions due to the entry regulation. Therefore, $\psi^m$ is market characteristics unobserved to the researcher but known by all chains (e.g. how local authorities apply the entry regulation). The unobserved market effect is assumed to be normally distributed with mean 0 and variance $\sigma^2$.

■ **Strategies and equilibrium.** Players take the decision to operate a specific store type if it can cover sunk costs, or profits are positive and higher than all other type choices. The random component $\epsilon_z^m$ captures shocks to profitability that are only observed by the store but not by its competitors. Its distribution is however known to all other players and to the econometrician. Consequently, other players do not observe the realization of a player's private shock. Because $\epsilon_z^m$ is private information to each type choice, players form expectations about post-entry profits, i.e., actions taken by a player rely on expectations (conjectures) of competitors' responses. Players decide to choose type subject to their expectations of competitors optimal choices and their own profitability shock. Given that all stores of the same type are identical, the expected

[19] See the Identification section for details.

profits to operate store type $z$ is given by

$$E[\pi_z^m] = X_z^m \beta + \delta_{zz} E[N_z^m] + \sum_{z'} \gamma_{zz'} E[N_{z'}^m] + \psi^m + \epsilon_z^m \tag{5}$$

Players maximize their expected profits, choosing the type that gives the highest payoff relative all other types. The probability $p_z^m$ to choose type $z$ thus satisfies

$$p_z^m = Pr(E[\tilde{\pi}_z^m] + \epsilon_z^m \geq E[\tilde{\pi}_{z'}^m] + \epsilon_{z'}^m; z' \neq z) \tag{6}$$

where $\tilde{\pi}_z^m = X_z^m \beta + \delta_{zz} E[N_z^m] + \sum_{z'} \gamma_{zz'} E[N_{z'}^m] + \psi^m$. All stores of the same type are identical and thus have the same conjectures about rivals' strategies. For a total number of entrants $N^m$ in market $m$, the expected number of stores of the own type $z$ and rival types $z'$ are

$$E[N_z^m] = (N^m - 1) p_z^m \tag{7}$$

$$E[N_{z'}^m] = \sum_{\substack{z' \\ z' \neq z}} (N^m - 1) p_{z'}^m \tag{8}$$

I assume that the private information $\epsilon_z^m$ is independently and identically distributed across chains and types with a type I extreme value distribution. The distributional assumption implies multinomial logit probabilities for players' beliefs, conditional on the number of entrants in the market. Note the assumption of symmetry across types, i.e., each store of the same type has the same equilibrium conjecture of its competitors' actions.

$$\begin{aligned} p_z^{m*} &= \frac{exp(X_z^m \beta + \delta_{zz}[(N^m-1)p_z^m] + \sum_{z'} \gamma_{zz'}[(N^m-1)p_{z'}^m] + \psi^m)}{\sum_t exp(X_t^m \beta + \delta_{tt}[(N^m-1)p_t^m] + \sum_{t'} \gamma_{tt'}[(N^m-1)p_{t'}^m] + \psi^m)} \\ &= \frac{exp(\pi_z(\mathbf{X}, \mathbf{p}^*, N^m, \theta))}{\sum_t exp(\pi_t(\mathbf{X}, \mathbf{p}^*, N^m, \theta))} \end{aligned} \tag{9}$$

The solution to the game is a Bayesian Nash Equilibrium (Seim 2006, Bajari et al. 2009) that gives a set of type probabilities that solve the system of equations in (9). That is, the optimal strategy for each player conditional on its beliefs about competing players' best responses as well as competitors beliefs about the player's choice. In contrast to the single agent multinomial model, the choice probabilities of each player is a function of the choice probabilites of other players. According to Brouwer's fixed point theorem it exist at least one equilibrium for any finite $X_z^m$.

The choice probability of each store type is for a given number of entrants in the market $N^m$, so I now turn to the first stage of the game. Following Seim (2006), the probability to enter a market relates the type probabilities, the market effect $\psi^m$ and the outside option of not entering. As mentioned earlier, the payoff not to enter is normalized to zero. Since all stores of a certain type are identical, they have the same probability of entering the market. The expected number of entrants is then given by the number of potential entrants ($K^m$) times the probability to enter, where the probability to enter is

$$Pr(entry) = \frac{exp(\psi^m)\sum_t exp(\pi_t(\mathbf{X}, \mathbf{p}^*, N^m, \theta))}{1 + exp(\psi^m)\sum_t exp(\pi_t(\mathbf{X}, \mathbf{p}^*, N^m, \theta))} \tag{10}$$

Note that the market effect does not influence the choice of a specific store type but instead the total number of entrants in the market. Combining the system of probabilities in (9) with the probability to enter (10) and the number of potential entrants ($K^m$), the market effect can be adjusted such that the expected number of entrants in the model equals the observed number of entrants in the data.

$$\psi^m = ln(N^m) - ln(K^m - N^m) - ln(\sum_t exp(\pi_t(\mathbf{X}, \mathbf{p}^*, N^m, \theta)) \tag{11}$$

This gives a joint equilibrium prediction of the type probabilities and the number of entrants.

■ **Asymmetric Competitive Effects.** As mentioned above, a source of high dimensionality is the number of competitive effects, i.e., $\delta$ and $\gamma$. Using the profit specification (4) with a total number of 3 types ($z = S, L, D$), requires a total of $3 \times 3 = 9$ competitive parameters are estimated. The on-diagonal elements in $\lambda_{.z}$ capture the own type competitive parameters $\delta_{zz}$, where $z = S, L, D$. That is, the impact on profitability of each store type from other stores of the same type. These own type competitive parameters are flexible in a sense that $\delta_{SS} \neq \delta_{LL} \neq \delta_{DD}$. The off-diagonal elements in $\lambda_{.z}$ contain the rival type competitive parameters $\gamma_{zz'}$, where $z \neq z'$. Hence, the effect of stores of other types $z'$ on the profitability of a stores of type $z$. Importantly, I allow $\gamma_{z'z} \neq \gamma_{zz'}$, i.e., the competitive effects between two different types to be asymmetric. The parameters are flexible in both magnitude and sign. In other words, the competitive impact from large stores on hard discounters ($\gamma_{LD}$) can differ from the competitive impact from hard discounters on large stores ($\gamma_{DL}$) so that $\gamma_{LD} \neq \gamma_{DL}$.

■ **Identification.** The identification strategy relies on three assumptions. First, the normalization that the payoff of not entering equals zero. This imposes the standard outside option assumption necessary for identification mentioned above. Second, the assumption that the $\epsilon_z^m$s are distributed i.i.d. across types with a known distribution function. It is necessary to have variation across equations in the system for identification. In case that every type is identical, two stores of the same type have equivalent conjectures over expected competition from rivals, demand and cost. The model will suffer from collinearity as there is no additional information that can trace out the difference between players' decisions. The private information structure of the model implies that the payoff shocks to one type only connect to choices of that type and do not impact other types' choices. Although the entry decisions are closely linked, I do not expect the payoff shocks to be related. In addition, I also assume that the error terms are uncorrelated across local markets. As mentioned above, I rely on the assumption that the error term has a type 1 extreme value distribution which gives the 'logit' form of choice probabilities. The parameters will be identified through variation in the number of stores or various types across local markets. The underlying assumption of independence of irrelevant alternatives is what identifies the parameters as the choice probabilities of two choices will not be affected by introduction of a third alternative.

Finally, I add type specific variables in the payoff function to constitute additional exclusion restrictions for identification.[20] Without further exclusion restrictions than the private information of payoff shocks, there is a need of rich data to parametrically identify the parameters under the specified assumption (Augereau et al. 2006, Sweeting 2009). Especially, this relates to the case of heterogeneous profit functions where the aim is to separately identify different competitive effects. For two stores of different types, the distance to the nearest distribution center will determine a difference between types' decisions. The store with a shorter distance to the distribution center will have stronger preferences for entering comparing with the store with a longer distance (Zhu et al. 2009, Nishida 2010). Using data on the distance to distribution centers give a natural exclusion restriction.

When taking the model to the data, I use the minimum distance from the center of the market to the nearest distribution center for national chains and hard discounters, respectively. Using type specific cost shifters as exclusion restriction helps identifying the competitive effects assigned to and from hard discounters, which is the main focus of the paper. It is however trickier to pin down the strategic effects related to large and small types, which implies that I need to impose either symmetry assumptions or rely on set identification. Despite the cost of logistics captured by the distance to the distribution center, most cost variables are similar across types (size) and markets.[21]

■ **Multiple equilibria.** Multiplicity is a well-known problem in entry games with incomplete information and simultaneous moves. In particular, this refers to models that allow for heterogeneous players. A generalization of the standard static entry model with identical firms is thus not straight forward, especially when introducing firm spe-

[20]In case of differentiation across chains, it is also possible to introduce private information to each chain which is unobserved to researchers and other chains. This approach is taken by Ellickson and Misra (2008). The realization of the random variable is private information to the chain but its distribution is common knowledge. Hence, introducing asymmetric information between chains can help to trace out the competitive parameters.

[21]The main costs for a retail store include stock of products, logistics, rent, machinery/equipment, wages and other costs such as advertising. These costs often correlates highly with store type (square meter of sales space) together with characteristics of the local market. Future versions of the paper will include more cost information at the local market level e.g. average price per square meter for buildings.

cific observables in the profit functions. As the complexity of the model increases and brings us closer to reality, the possibility of multiple equilibria becomes apparent. With respect to the model in the current paper, the concern of multiple equilibria raises as the number of types increases. Consequently, multiple equilibria might exist and I cannot guarantee that I select the correct one (Pakes 2010, Bajari et al. 2009, Aradillas-Lopez 2009, Ciliberto and Tamer 2009, Bajari et al. 2010).

The existing literature has provided several strategies for how to deal with this problem. One can add additional structure to the game by imposing a sequential structure (e.g. Mazzeo 2002, Einav 2010).[22] Furthermore, one can impose a selection mechanism on which equilibrium to select (e.g. Sweeting 2009). Jia (2008) and Nishida (2010) choose the equilibrium that is most reasonable a priori in their complete information settings. Bajari et al. (2010) proposes to compute all possible equilibria, both pure and mixed, estimating both profits and an equilibrium selection mechanism. Another alternative is to use a bounds approach (Tamer 2003 , Ciliberto and Tamer 2009, Andrews et al. 2006, Pakes et al. 2006, Pakes 2010), discussed in more detail below.

Different approaches have thus be applied to solve the problem of multiple equilibria. Multiple equilibria should be more likely in large markets that contain a rich variety of stores and a complex market structure. The use of small and medium sized markets can therefore reduce the concern of multiplicity (Augereau et al. 2006, Jia 2008). Moreover, well-defined profit functions that take the key source of differentiation into account can possibly mitigate the problem.

■ **Ex-post regret.** The static model implies that I investigate a long-run equilibrium outcome. A limitation of static games with incomplete information is the possibility of ex-post regret which might influence the possibility that I observe a long-run outcome. In the current application, this is of less of a concern, especially for large stores and hard discounters. These two store types rarely exit. They also constitute the main part of entry during the period. Entry of either of these two types are associated with large sunk costs. Most often they enter in new geographical locations which require investments in new buildings and equipment as well as administration related to the planning process. For small stores, on the contrary, ex-post regret will be more restrictive since they account for the majority of exists.

Data throughout introduction and expansion of hard discounters allow me to compare different cross-sections of data. Similar approaches are taken by e.g. Greenstein and Mazzeo (2006), Jia (2008) and Berry and Jia (2010). The first hard discounter entered the Swedish market in 2002. Using annual data for 15 years, I follow the entry

[22] Bresnahan and Reiss 1991, Berry 1992 use characteristics common across equilibria in complete information settings.

patterns which show that they expand rapidly in the beginning while then flattening off. I use a cross-section of markets several years before (1995) and after (2008) hard discounters started to enter to analyze stores in long-run equilibrium.

## 4.1 Estimation

Since the model is flexible in defining asymmetric competition effect among types and chains, the estimation depends on the specification. I assume differentiation only in type. The parameters to be estimated are: $\beta$ that captures store type characteristics and exogenous market conditions, $\delta_{zz}$ which includes the competitive effects between same types, $\gamma_{zz'}$ which contains the competitive effects between stores of different types, and $\sigma$ which is the random market component. To simplify the notation, I group all these parameters in $\theta = (\beta, \delta, \gamma, \sigma)$.

The starting point for estimation is the Nested Fixed Point method (Rust 1987, Seim 2006). For each market and a given set of parameters, the probability equilibrium for each market is found by numerically solving the system of equations (9) for its fixed point. The nested fixed point algorithm implies that the system of equations needs to be solved for its fixed point for every possible parameter vector of $\beta$, $\delta$, $\gamma$ and market unobservable $\psi^m$. Assuming that players move simultaneously I thus need to solve for the fixed point in each market, for all possible values of the equilibrium probabilities. A way to solve this has been to use a rich variety of different starting values and to investigate whether all possible starting values converge to the same parameter estimates (Augereau et al. 2006, Seim 2006, Ellickson and Misra 2008). Finding the fixed point solution to the set of equations for the equilibrium is however time consuming since the equations are nonlinear. In addition, the rich structure of the asymmetric competitive effects leaves further concerns of the computational time. As the model here allows for flexible competitive effects, the computational burden increases as I need to solve for the fixed point for every possible value of the parameters.

Several alternatives to the nested fixed point method for estimating discrete choice models with strategic interactions have developed. Recent approaches aim not only to reduce the computational burden, but also to handle problems of, e.g., multiple equilibria and common unobservables (discussed in detail below).

One alternative approach, used in the current version of the paper, is constraint optimization (Su and Judd 2008, Vitorino 2010). Using constraint optimization, I maximize the likelihood function subject to the constraint that the system of equations in (9) holds. It is thus possible to do the estimation only in one step. In other words, I maximize the likelihood function by adding Lagrange multipliers to each of the equations in (9). Constraint optimization allows me to solve the problem once, adding Lagrange multipliers for each constraint. The likelihood function consists of both the type choice probabilities conditional on the market effect and the probability of entry. Hence, the multinomial logit probabilities are multiplied by the probability that the market effect is such that the predicted number of entrants are equal to the observed number of entrants in the data. This stand in contrast to Vitorino (2010) who uses constraint optimization in a framework where store types are known ex-ante. The constrained likelihood function taken to estimate is:

$$L(\theta) = \prod_{m=1}^{M} \prod_{z=1}^{Z} p_\theta(.|X_z^m, N^m, \psi^m) g_\lambda(\psi^m | X_z^m, N^m, K^m) \tag{12}$$

s.t.

$$p_z^{m*} = \frac{exp(\pi_z(\mathbf{X}, \mathbf{p}^*, N^m, \theta))}{\sum_t exp(\pi_t(\mathbf{X}, \mathbf{p}^*, N^m, \theta))}$$

Based on an assumption on the number of potential entrants ($K$), the market effect is a result of the condition that the expected number of entrants equals the actual number of entrants. The market effect follows from the adjustment of the market effect between potential and actual number of entrants. In this respect, the approach taken here follows the one in Seim (2006).[23] The number of potential entrants is assumed to be 2 times the actual number of entrants in each local market.

■ **Alternative estimation approaches.** Apart from constraint optimization the two-step method or a bounds approach are alternative estimation approaches. Starting with the two-step method by Bajari et al. (2009). The first step involves consistent estimates of the type probabilities, that are taken to the likelihood function in the second step. An advantage is that I can assume one equilibria in each local market instead of one equilibria in all markets, and thereby guarantee uniqueness. Having a long panel of data, or (additional) exclusion restrictions in order to estimate consistent probabilities in the first step give possibilities to use the two-step estimation method.

Second, a bounds approach that use inequality restrictions has been put forward (Tamer 2003, Andrews et al. 2006, Pakes et al. 2006, Ciliberto and Tamer 2009, Pakes 2010). In the complete information game by Ciliberto and Tamer (2009), firms have heterogeneous profit functions and markets are allowed to have different selection mech-

[23]Zhu and Singh (2009) use simulated maximum likelihood. They simulate $R$ draws with standard normal distribution $\psi = (\psi^1, \psi^2, \cdots, \psi^R)$ for the unobserved market effect. For each draw $\psi^r$, they obtain the Bayesian Nash equilibrium probabilities by solving the system of equations.

anisms. Allowing for multiple equilibria, they restrict the parameter estimates to a set and rely on partial identification.[24] Pakes et al. (2006) put forward an approach that base directly on profit inequalities from players' optimal behavior.[25]

# 5 Empirical Results

The estimation results of the entry model with differentiation in type is shown in Tables 5 and 6. The first table shows results after introduction of hard discounters (2008), i.e., the model incorporates three store types (small, large and discount). The second table shows results before introduction of hard discounters (1995), i.e., the model incorporates two store types (small and large).

The strategic competitive parameters are all negative which is consistent with the theoretical prediction, i.e., an increase in competition reduces payoffs. The magnitude of the intensity of competition and returns to differentiation vary across store types, also in line with expectations. The main focus is the competitive parameters from and to hard discounters along with the own type competitive effects.[26] To interpret the competition parameters, I compare store types.

Both large and small stores reduce profits of discounters (Table 5). The largest competitive effects are in fact those from small (-1.127) and large (-1.088) on hard discounters. On average, an additional small store reduces profits of discounters about 4 percent more than an additional large store reduces discounters' profits. The opposite competitive parameters, i.e. the ones from discount stores on large and small types, are substantially smaller. The competitive effects from discounters on small and large are of similar magnitude (about -1.03 on average). The results indicate that asymmetries in the competitive effects from and to hard discount stores are central. Hence, small and large stores have different impacts on payoffs of discount stores than vice versa.

Hard discounters have the weakest own-type competitive effect (-0.801), followed by

[24] The current version of the paper does not incorporate any of these concepts but future versions of the paper aim to deal with these approaches in more detail.

[25] An additional estimation approach is the Nested Pseudo Likelihood method proposed by Aguirregabiria and Mira (2007). The basic idea is to solve the system recursively and not solve for the fixed point for all possible parameter values of $\beta$, $\delta$ and $\psi^m$. First, to start with arbitrary probabilities and plug them into the likelihood function. Assuming a normal distribution with mean $\mu$ and variance $\sigma^2$ for the market unobservables enables the econometrician to integrate over these. Second, find the parameter values of $\beta$ and $\delta$, given the probabilities. The next step is to use these parameters and evaluate the system of equations again. This will give new probabilities to plug into the likelihood function. This recursive approach continues until convergence. The consistency of the method has however recently been questioned (Pesendorfer and Schmidt-Dengler 2010).

[26] Although the coefficients of small on large and vice versa are negative their magnitude should be interpreted with care due to identification problems (see Section 4 for details).

large stores (-0.864) and small stores (-0.942). For small, the own-type effect is almost 15 percent higher than for discount but only 8 percent higher than for large. Hard discounters have a relatively modest impact on payoffs of other hard discounters and do not compete intense within type. Small stores, on the other hand, compete more intense with other small.

Comparing the asymmetric competitive effects to and from hard discounters with the own-type effects, large stores reduce payoffs of discount stores about 20 percent more than they reduce profits of other large stores. The corresponding figure for small stores is 16 percent. The difference (4 percent) constitutes the fact that small stores reduce payoffs of discounters more than large stores and that discounters cause a similar reduction in profits for small and large. Discount stores reduce payoffs of small and large by 22 percent more than they reduce payoffs of other discounters, confirming the modest competitive effect among discounters.

As mentioned above, the own-type competitive effect for small is about 8 percent higher than for large. In 1995, i.e., before introduction of hard discounters (Table 6), small stores also reduce profits of other small stores (-0.842) more than large stores reduce profits of other large (-0.742). The difference in own-type effects is however 12 percent, i.e., 4 percentage points larger than in 2008. That is, the difference in own-type competitive effects for small and large become more similar after entry of hard discounters than before. The reason can either be less intense competition among small (compared to large), more intense competition among large (compared to small), or both. It is important to emphasize that there can be many reasons why the intensity of competition changes between 1995 and 2008. Apart from hard discounters, the main candidate is the structural change towards larger but fewer stores. To separate the relative magnitude of these factors, and to pin down individual changes in competitive effects, one would need a dynamic model. Nevertheless, the results using two different cross-sections indicate a change in relative magnitude of the competitive parameters for small and large store types.

All results base on the assumption of a given market size (local market definition) and abstracts from spatial differentiation, which most likely also influences the intensity of competition. In other words, the magnitude of the competitive effect from and to hard discounters might differ depending on geographical location. Preliminary results using differentiation in both location and store type (not reported) show that the degree of competition decreases with distance from rivals and that the competitive intensity from small and discount stores decline relatively fast with distance.

Retail demand is closely tied to population and the structure of the population. The income elasticity is moreover relatively low. I use population (in logs) together with share of kids and share of pensioners to measure demand.[27] All parameter estimates of demand characteristics are positive and significant at the 1 percent level. Profitability is thus, on average, higher in markets with larger population. Higher shares of kids and pensioners imply higher average payoffs, especially for large types. The coefficient on political preferences of a non-socialist local government is positive for all store types. In particular, this seems important for hard discounters. The parameters on wages and house prices are both positive, which might be explained by that they are closely tied to income and therefore measure the purchasing power in the market rather than cost. The coefficients on distance to the distribution center are also positive and significant at conventional levels.

## 6 Conclusions

Retail food stores with a clear focus on low prices, limited product assortment and prices, i.e. so called "hard discounters", have expanded rapidly across Europe in recent years. A completely new store format has thus entered markets previously dominated by large and small stores operated by well established national chains. How do hard discounters influence competition and market outcomes? There is not yet an answer to this question and the current paper therefore aims to fill this gap.

I use a static entry game of incomplete information that accounts for store heterogeneity. In particular, I consider the three store types large, small and hard discounters. Data on retail food stores in Sweden during introduction and expansion of hard discounters are used in the empirical application. Besides to model heterogeneous firms (store types) and allow for asymmetric competitive effects, the paper has the novelty of being one of the very first to highlight hard discounters. To investigate the competitive impact of new players in the retail food market is especially important because entry is regulated through zoning laws. That Europe has a much more restrictive regulation than the U.S. provides a direct link between entry of new players, such as hard discounters, and competition policy.

The results show that the intensity of competition depends crucially on store type. Small stores have the most pronounced impact on the profitability of hard discount stores together with large stores. Discount stores, on the contrary, do not reduce profits of small and large to the same extent. Furthermore, small and large stores compete more intense within type than hard discounters. The findings thus suggest asymmetries

[27]Future versions will consider more demographic characteristics, e.g. average distance for consumers to the nearest store calculated by GIS using a grid of 800x800 meter squares of land.

in the strategic interactions across store types.

Descriptive evidence shows that exit of incumbents is not a main response to hard discount entry. However, own-type competitive effects for small and large types become more similar after entry of discounters than before. To tell the magnitude to which this difference is due to entry of discounters or the overall change towards larger but fewer stores requires a dynamic model. Nevertheless, national chains impose competitive pressure on discounters and both small and large stores are hard competitors to hard discounters.

The results contribute with knowledge to both policy makers and the retail business. Since many OECD countries have a similar market structure and entry regulation as in Sweden, the results are interesting in a broad context. The findings suggest that it is important for local authorities that evaluate competitive effects of new entrants to consider not just the number of stores but also their store types. I conclude that it is central to consider heterogeneous store types when analyzing competition in retail food markets.

The presented results highlight an average effect by store type for a given market definition and geographical location. Preliminary results incorporating differentiation in both location and store type show that the competitive impact decreases with distance between rivals and that the competitive intensity from discount stores declines relatively fast with distance.

One would ideally want to use the model for counterfactual analysis and do policy experiments. Due to that the model accounts for store heterogeneity, which induces multiple equilibria, the current paper is limited in this respect. Ongoing research touches upon several ways to deal with the multiplicity problem, which is also an interesting area for future research. To what extent the findings in the present paper hold in a dynamic setting is another topic for future research. A dynamic approach would give a more detailed analysis of the competitive interactions over time, sunk costs of entry and sell-off values of exit.

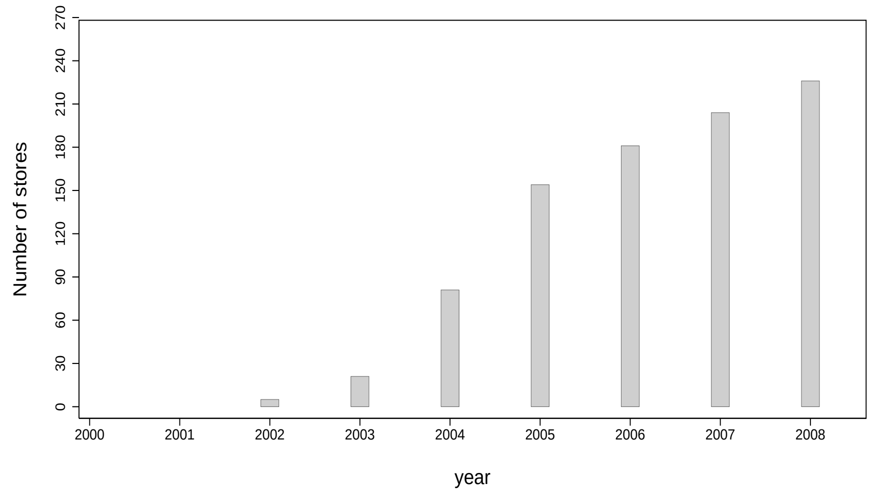


**Figure 1:** Number of hard discount stores in Sweden 2000-2008.

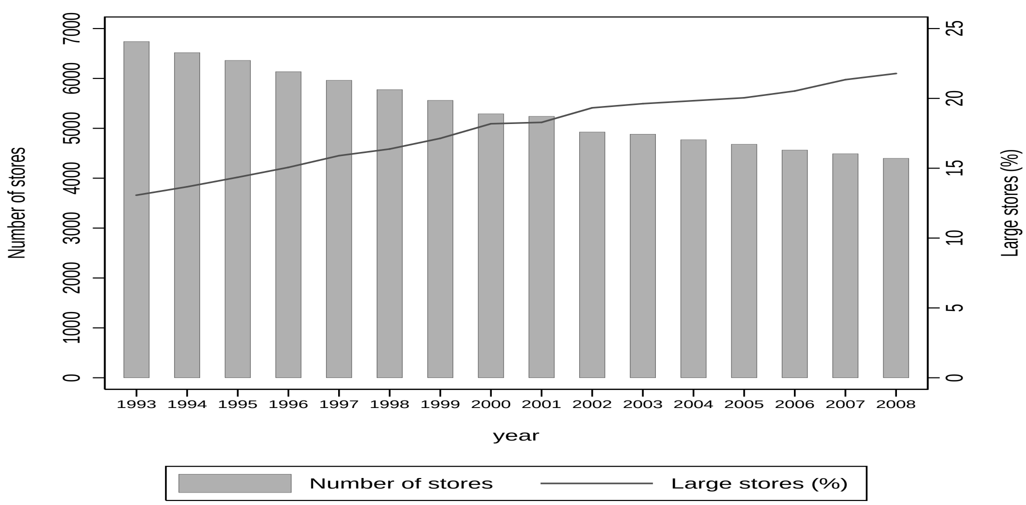


**Figure 2:** Total number of stores and share of large stores in Sweden 1993-2008.

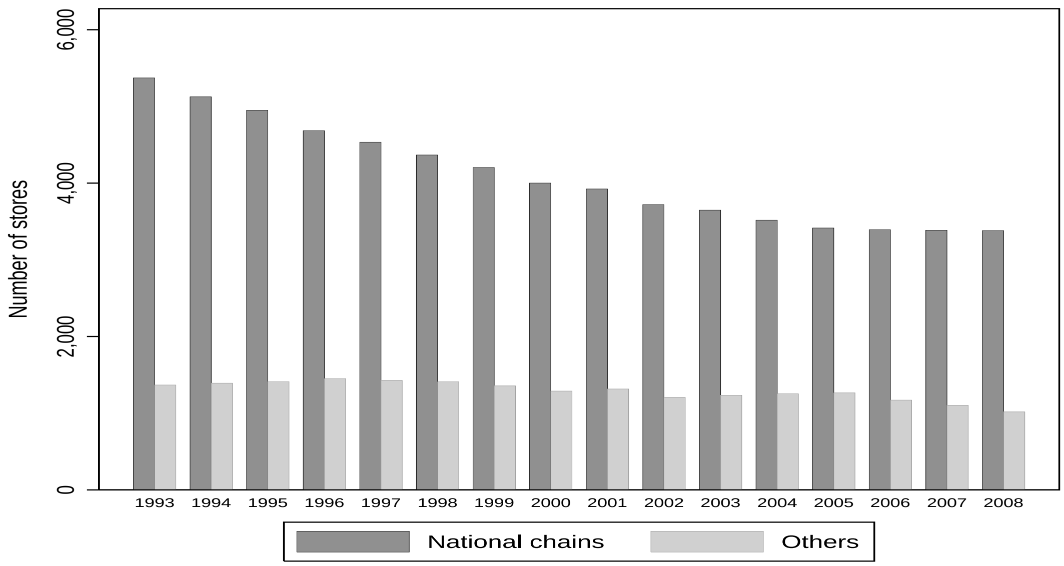


**Figure 3:** Total number of stores by national chains and other owners (excluding hard discounters) 1993-2008.

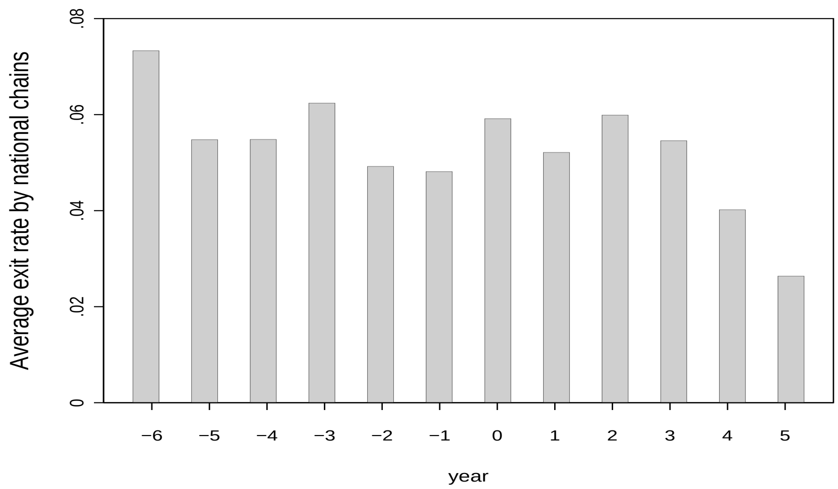


**Figure 4:** Average local market exit rate by national chains before and after hard discount entry.

**Table 1:** Summary statistics before and after hard discount entry

| | Stores | | Sales | | Sales space ($m^2$) | |
|---|---|---|---|---|---|---|
| | number | share of large | number | share of large | number | share of large |
| A. Before hard discounters (1995) | | | | | | |
| Chain 1 (ICA) | 2,517 | 0.136 | 60,570,248 | 0.481 | 1,105,276 | 0.474 |
| Chain 2 (Axfood) | 1,172 | 0.224 | 30,221,500 | 0.617 | 604,746 | 0.607 |
| Chain 3 (COOP) | 1,194 | 0.218 | 34,527,248 | 0.558 | 732,106 | 0.542 |
| Chain 4 (BERG) | 67 | 0.358 | 2,454,000 | 0.798 | 54,079 | 0.786 |
| Others | 1,411 | 0.018 | 6,017,430 | 0.198 | 203,496 | 0.162 |
| Total | 6,631 | 0.144 | 133,881,432 | 0.525 | 2,699,703 | 0.505 |
| A. After hard discounters (2008) | | | | | | |
| Chain 1 (ICA) | 1,384 | 0.278 | 75,479,728 | 0.649 | 1,195,292 | 0.605 |
| Chain 2 (Axfood) | 839 | 0.299 | 29,888,964 | 0.787 | 614,377 | 0.737 |
| Chain 3 (COOP) | 730 | 0.322 | 36,134,460 | 0.650 | 691,974 | 0.640 |
| Chain 4 (BERG) | 202 | 0.317 | 12,350,000 | 0.708 | 284,569 | 0.745 |
| Others | 1,017 | 0.020 | 6,560,622 | 0.398 | 169,594 | 0.203 |
| Hard disc. 1 (Lidl) | 139 | | | | 77,993 | |
| Hard disc. 2 (Netto) | 87 | | | | 48,498 | |
| Total | 4,398 | 0.218 | 164,477,296 | 0.654 | 3,082,295 | 0.605 |

NOTE: This table shows aggregate statistics for the total number of stores, sales and sales space. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Sales is measured in thousands of 1995 SEK and are not reported for Lidl and Netto. Sales space is the area used for selling and displaying goods in the store, measured in square meters.

**Table 2:** Characteristics of local markets in 2008

| | Market configuration | | | | | |
|---|---|---|---|---|---|---|
| | (S,0,0) | | (S,L,0) | | (S,L,D) | |
| | Mean | Std. | Mean | Std. | Mean | Std. |
| A1. Demand | | | | | | |
| Population | 12,141 | 1,864 | 21,206 | 17,547 | 33,799 | 21,305 |
| Share of kids | 0.117 | 0.023 | 0.105 | 0.019 | 0.111 | 0.017 |
| Share of retired | 0.186 | 0.024 | 0.204 | 0.034 | 0.193 | 0.031 |
| Share of young | 0.085 | 0.007 | 0.093 | 0.015 | 0.105 | 0.019 |
| Share of women | 0.494 | 0.007 | 0.498 | 0.010 | 0.503 | 0.007 |
| A2. Market structure | | | | | | |
| Total | 7.50 | 2.72 | 11.29 | 7.28 | 15.29 | 8.99 |
| Small stores | 7.50 | 2.72 | 8.68 | 6.01 | 9.96 | 6.78 |
| Large stores | | | 2.61 | 2.09 | 3.94 | 2.53 |
| Discount stores | | | | | 1.39 | 0.61 |
| No. of markets | 10 | | 77 | | 121 | |

NOTE: This table shows characteristics of local markets defined as municipalities (in total 209). One market (not reported) has the configuration (S,0,D). Large stores (L) are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Small stores (S) are defined as the remaining seven store types in the DELFI data. Hard discount stores (HD) are owned by the hard discount chains Lidl and Netto.

**Table 3:** Market Configuration: chains in 2008

| Number of | Number of discount chains | | |
|---|---|---|---|
| national chains | 0 | 1 | 2 |
| 1 | 3 | 0 | 0 |
| 2 | 17 | 10 | 3 |
| 3 | 55 | 52 | 16 |
| 4 | 12 | 27 | 14 |
| All | 87 | 89 | 33 |

NOTE: S = Small store type, L = Large store type, D = Discount store type. The configuration presents markets with at least one store type present in the market. Municipalities with a population between 9,500 and 100,000 but excluding neighboring municipalities to Norway are used as local markets (209 in total).

**Table 4:** Local markets and store type configurations in 2008

| | All markets | | | Without Discount | | | With Discount | | |
|---|---|---|---|---|---|---|---|---|---|
| Small | Large | | | Large | | | Large | | |
| | 0 | 1 | 2+ | 0 | 1 | 2+ | 0 | 1 | 2+ |
| Chain 1 (ICA) | | | | | | | | | |
| 0 | 0 | 11 | 6 | 0 | 5 | 1 | 0 | 6 | 5 |
| 1 | 3 | 29 | 9 | 3 | 14 | 1 | 0 | 15 | 8 |
| 2 | 11 | 22 | 12 | 8 | 8 | 2 | 3 | 14 | 10 |
| 3 | 7 | 14 | 13 | 5 | 5 | 3 | 2 | 9 | 10 |
| 4 | 8 | 11 | 3 | 7 | 3 | 0 | 1 | 8 | 3 |
| 5 | 2 | 8 | 9 | 2 | 1 | 4 | 0 | 7 | 5 |
| 6+ | 7 | 8 | 16 | 6 | 5 | 4 | 1 | 3 | 12 |
| Chain 2 (AXFOOD) | | | | | | | | | |
| 0 | 25 | 13 | 10 | 14 | 6 | 2 | 11 | 7 | 8 |
| 1 | 38 | 23 | 5 | 19 | 10 | 3 | 19 | 13 | 2 |
| 2 | 22 | 18 | 6 | 12 | 4 | 1 | 10 | 14 | 5 |
| 3 | 6 | 11 | 1 | 4 | 4 | 0 | 2 | 7 | 1 |
| 4 | 2 | 4 | 8 | 2 | 1 | 3 | 0 | 3 | 5 |
| 5 | 0 | 2 | 5 | 0 | 0 | 1 | 0 | 2 | 4 |
| 6+ | 1 | 2 | 7 | 0 | 0 | 1 | 1 | 2 | 6 |
| Chain 3 (COOP) | | | | | | | | | |
| 0 | 32 | 38 | 5 | 15 | 10 | 4 | 17 | 28 | 1 |
| 1 | 28 | 22 | 6 | 15 | 7 | 2 | 13 | 15 | 4 |
| 2 | 10 | 20 | 6 | 6 | 11 | 0 | 4 | 9 | 6 |
| 3 | 8 | 9 | 7 | 5 | 4 | 1 | 3 | 5 | 6 |
| 4 | 3 | 3 | 1 | 1 | 1 | 0 | 2 | 2 | 1 |
| 5 | 0 | 2 | 2 | 0 | 0 | 1 | 0 | 2 | 1 |
| 6+ | 0 | 4 | 3 | 0 | 3 | 1 | 0 | 1 | 2 |
| Chain 4 (BERG) | | | | | | | | | |
| 0 | 135 | 15 | 0 | 69 | 3 | 0 | 66 | 12 | 0 |
| 1 | 27 | 8 | 2 | 8 | 2 | 1 | 19 | 6 | 1 |
| 2 | 9 | 2 | 1 | 2 | 0 | 0 | 7 | 2 | 1 |
| 3 | 2 | 3 | 1 | 0 | 1 | 0 | 2 | 2 | 1 |
| 4 | 0 | 2 | 1 | 0 | 0 | 1 | 0 | 2 | 0 |
| 5 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 6+ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Number of markets | 209 | | | 87 | | | 122 | | |

NOTE: Municipalities with a population between 9,500 and 100,000 but excluding neighboring municipalities to Norway are used as local markets (209 in total). Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores).

**Table 5:** Estimation results: After hard discount entry, 2008

| A. Strategic competitive effects | | | |
|---|---|---|---|
| | Large | Small | Discount |
| Large | -0.864 | -0.984 | -1.088 |
| | (0.000005) | (0.0001) | (0.0003) |
| Small | -1.105 | -0.942 | -1.127 |
| | (0.0003) | (0.0006) | (0.0001) |
| Discount | -0.033 | -1.032 | -0.801 |
| | (0.00000003) | (0.00006) | (0.00006) |
| **B. Market and store type characteristics** | | | |
| Population | 1.102 | 1.330 | 1.008 |
| | (0.00007) | (0.005) | (0.000006) |
| Share of kids | 1.016 | 1.009 | 0.964 |
| | (0.00005) | (0.0003) | (0.00006) |
| Share of pensioners | 1.052 | 0.935 | 0.894 |
| | (0.0003) | (0.0006) | (0.0006) |
| Local gov. | 0.921 | 0.979 | 1.227 |
| | (0.002) | (0.00002) | (0.002) |
| Rent | 1.058 | 0.854 | 1.079 |
| | (0.000001) | (0.006) | (0.00008) |
| Wages | 1.112 | 1.186 | 1.042 |
| | (0.001) | (0.001) | (0.00007) |
| Distance to DC | 1.042 | 1.087 | 1.068 |
| | (0.000001) | (0.0004) | (0.0009) |
| $\mu$ | 0.021 | | |
| $\sigma$ | -0.00000001 | | |
| log-Likelihood | -1413.686 | | |
| No. of obs. | 627 | | |

NOTE: Estimation results from estimation of the entry model in Section 4. Municipalities with a population between 9,500 and 100,000 but excluding neighboring municipalities to Norway are used as local markets (209 in total). Standard errors, computed using bootstrap, are reported in parenthesis. The number of potential entrants is assumed to be two times the actual number of entrants. Due to identification problems, the competitive parameters of large on small and vice versa should be interpreted with care. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Discount stores are hard discount stores owned by Netto and Lidl. Distance to distribution center (DC) is defined as the minimum distance from the mid-point of the local market to the nearest distribution center for Discount (Netto and Lidl) and small-large (ICA, Axfood, COOP, Bergendahls), respectively.

**Table 6:** Estimation results: Before hard discount entry, 1995

| A. Strategic competitive effects | | |
|---|---|---|
| | Large | Small |
| Large | -0.842 | -0.751 |
| | (0.0007) | (0.0004) |
| Small | -1.021 | -0.742 |
| | (0.001) | (0.00002) |

| B. Market and store type characteristics | | |
|---|---|---|
| Population | 1.102 | 0.764 |
| | (0.0004) | (0.008) |
| Share of kids | 1.007 | 0.817 |
| | (0.0006) | (0.001) |
| Share of pensioners | 1.255 | 0.868 |
| | (0.003) | (0.0006) |
| Local gov. | 1.011 | 0.865 |
| | (0.0001) | (0.0004) |
| Wages | 0.953 | 1.184 |
| | (0.001) | (0.007) |
| Rent | 1.030 | 1.266 |
| | (0.0001) | (0.0009) |
| Distance to DC | 1.056 | 1.127 |
| | (0.0008) | (0.008) |
| $\mu$ | 0.0001 | |
| $\sigma$ | -0.00000002 | |
| log-Likelihood | -1692.344 | |
| No. of obs. | 418 | |

NOTE: Estimation results from estimation of the entry model in Section 4. Municipalities with a population between 9,500 and 100,000 but excluding neighboring municipalities to Norway are used as local markets (209 in total). Standard errors, computed using bootstrap, are reported in parenthesis. The number of potential entrants is assumed to be two times the actual number of entrants. Due to identification problems, the competitive parameters of large on small and vice versa should be interpreted with care. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Discount stores are hard discount stores owned by Netto and Lidl. Distance to distribution center (DC) is defined as the minimum distance from the mid-point of the local market to the nearest distribution center for small and large, respectively.

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## Appendix A: Data description

Each year, the owners (chains) report information regarding all stores they are operating. Each store has an identification number linked to it´s address. Revenues are presented in 19 classes. There are 12 different store types defined based on size, geographical location, product assortment etc. hypermarket, department store, supermarket, grocery store, other store, small supermarket, small grocery store, convenience store, gas-station store, mini market and seasonal store. Owners (chains) include ICA, Axfood, COOP, Bergendahls and Others. The following owners belong to the group Others: Seven-eleven, Pressbyrån, Statoil, Preem, OK etc.