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Entry, Competition and Productivity in Retail

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To my mother and father

Abstract

This thesis deals with different aspects of competition in retail markets. It consists of four self-contained papers.

Paper I:

Productivity Dynamics and the Role of “Big-Box” Entrants in Retailing

Entry of large (“big-box”) stores along with a drastic fall in the total number of stores is a striking trend in retail markets. We use a dynamic structural model to estimate retail productivity in a local market setting. In particular, we provide a general strategy of how to measure the causal effect of entry of large stores on productivity separate from demand. To control for endogeneity of large entrants, we use political preferences. Using detailed data on all retail food stores in Sweden, we find that large entrants force low productivity stores to exit and surviving stores to increase their productivity. Productivity increases most among incumbents in the bottom part of the productivity distribution, and then declines with the productivity level of incumbents. When controlling for prices, the impact of large entrants on productivity increases substantially. Our findings suggest that large entrants play a crucial role for driving productivity growth.

Paper II:

A Dynamic Analysis of Retail Productivity

The retail sector has dramatically changed due to the adoption of information technology and the trend towards larger but fewer stores. In this paper, we use recently developed methods to decompose aggregate productivity growth in retail, i.e., we quantify the relative importance of entrants, exits, and incumbents. To estimate productivity, we use a dynamic structural model controlling for unobserved prices, subsector, and local market characteristics. Using data on all retail firms in Sweden and a dynamic decomposition framework, we find that incumbents and exit of low productive firms play an important role for retail productivity growth.

Paper III:**Entry and Spatial Differentiation in Retail Markets**

This paper investigates spatial competition between heterogeneous retail food stores using a static entry model with endogenous location choices and flexible competitive effects across store types. The model is applied to data on all retail food stores in Sweden and highlights strategic interaction between traditional stores and so-called hard discounters, i.e., small stores with a core focus on low prices and limited product assortment. The results show high returns to spatial differentiation and that the intensity of competition depends on store type. Competition between stores of the same type is strong for both discounters and traditional stores, but declines relatively fast with distance. Discounters reduce the profits of traditional stores located nearby. The reverse effect is smaller but more persistent as distance increases. Because entry is regulated and hard discount firms have expanded across many European countries, the findings link directly to competition policy.

Paper IV:**Store Dynamics, Differentiation and Determinants of Market Structure**

Substantial entry and exit and a trend toward larger but fewer stores constitute a major structural change in retail markets in the last few decades. To study the determinants of market structure in retail markets, this paper uses a dynamic structural oligopoly model of entry and exit that allows for store-level heterogeneity. Using a rich data set on all retail food stores in Sweden, we estimate entry cost of potential entrants and sell-off values for exit for small and large stores. We find empirical evidence of type competition. An additional large store in the market decreases the profits of large stores about seven percentage points more than for small stores. For small stores, the average entry cost is about two times larger than the sell-off value of exit. Using structural estimates, we evaluate the impact of different policies on the cost structure for each store type and market structure dynamics. Small stores are negatively affected by more efficient incumbents, whereas large stores incur higher entry costs due to other factors such as higher rent or cost of buildings. The findings have a direct link to competition policy because the majority of OECD countries have entry regulations, and the consequences of regulation in retail food are frequently debated among policy makers in the EU.

Contents

Acknowledgements iv-v

Paper I:

Productivity Dynamics and the Role of “Big-Box” Entrants in Retailing

1. Introduction	2
2. The retail food market and data	5
3. Productivity estimation	9
3.1 Static labor demand function	14
3.1.1 Identification using a nonparametric labor demand function	15
3.1.2 Identification using a parametric labor demand function	20
3.2 Dynamic input control function	22
3.3 Additional identification and estimation issues	23
4. Results	25
4.1 Value-added generating function estimates	25
4.2 The impact of large entrants on productivity	27
4.3 Specification tests and robustness	31
5. Conclusions	33
References	35
Appendix A	50
Appendix B	51
Appendix C	53
Appendix D	53
Appendix E	56

Paper II:

A Dynamic Analysis of Retail Productivity

1. Introduction	2
2. Data and the Swedish retail food sector	4
3. Modeling approach	7
4. Results productivity estimation	12
5. Productivity decomposition	14
6. Conclusions	18
References	20
Appendix A	33
Appendix B	33
Appendix C	34
Appendix D	35

Paper III:

Entry and Spatial Differentiation in Retail Markets

1. Introduction	2
2. Data and market	5
2.1 Descriptive statistics	8
2.2 Traditional stores' response to hard discount entry	10
3. Entry model	11
3.1 Identification	18
4. Empirical implementation and estimation	20
5. Results	23
5.1 Reduced-form estimates	23
5.2 Estimates of the structural model	25
6. Conclusions	27
References	29
Appendix A	45
Appendix B	48
Appendix C	50

Paper IV:	
Store Dynamics, Differentiation and Determinants of Market Structure	
1. Introduction	2
2. A dynamic model of entry and exit	5
3. Data and characteristics of the Swedish retail food market	11
4. Empirical implementation	16
5. Results	20
6. Counterfactuals	23
7. Conclusions	24
References	26
Appendix A	36

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Paper I

Productivity Dynamics and the Role of “Big-Box” Entrants in Retailing*

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Abstract

Entry of large (“big-box”) stores along with a drastic fall in the total number of stores is a striking trend in retail markets. We use a dynamic structural model to estimate retail productivity in a local market setting. In particular, we provide a general strategy of how to measure the causal effect of entry of large stores on productivity separate from demand. To control for endogeneity of large entrants, we use political preferences. Using detailed data on all retail food stores in Sweden, we find that large entrants force low productivity stores to exit and surviving stores to increase their productivity. Productivity increases most among incumbents in the bottom part of the productivity distribution, and then declines with the productivity level of incumbents. When controlling for prices, the impact of large entrants on productivity increases substantially. Our findings suggest that large entrants play a crucial role for driving productivity growth.

Keywords: Retail markets; imperfect competition; industry dynamics; productivity; dynamic structural model.

JEL Classification: C24, L11, O3.

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1 Introduction

Recent methods for structural estimation of production functions have almost only been applied to manufacturing industries.¹ There have been few attempts to estimate multi-factor productivity in retail markets, where entry and exit have been found to play a more crucial role for labor productivity growth than in manufacturing (Foster et al., 2006). The major structural change in retail markets during the last few decades is in fact the entry of large (“big-box”) stores, along with a drastic fall in the number of stores. The most striking example is the expansion of Wal-Mart, which has been found to greatly lower retail prices, and increase exit of retail stores in the U.S., the “Wal-Mart effect.”² For instance, the number of single-store retailers in the U.S. declined by 55 percent from 1963 to 2002 (Basker, 2007). Retail markets in Europe also follow the “big-box” trend, though on a smaller scale, with for example Carrefour, Metro, Schwartz, and Tesco. Although there is an emerging literature on retail markets, the impact of this structural change on productivity has not been given much attention.³ Our goal is to estimate productivity in retail markets and measure the causal effects of increased competition from large entrants on stores’ productivity shocks and demand shocks (shocks to prices).

The paper connects to the literature on dynamic models with heterogenous firms (Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995). In particular, we build on the growing literature on productivity heterogeneity within industries that use dynamic structural models (Olley and Pakes, 1996; Pavcnik, 2002; Levinsohn and Petrin, 2003; Buettner, 2004; Akerberg et al., 2006; De Loecker, 2011; Doraszelski and Jaumandreu, 2011). They found that increased competition from high productive entrants forces low productive firms to exit, increasing the market shares of more productive firms.⁴ The productivity distribution is thus truncated from below, increasing the mean and decreasing dispersion (Melitz, 2003; Syverson, 2004; Asplund and Nocke, 2006). Using a local market approach, Syverson (2004) emphasizes that demand density results in similar improvements in the productivity distribution.⁵

¹Olley and Pakes (1996), Pavcnik (2002), Levinsohn and Petrin (2003), Buettner (2004), Akerberg et al. (2006), De Loecker (2011), Doraszelski and Jaumandreu (2011).

²Basker (2005), Basker (2007), Basker and Noel (2009), Holmes (2011), and Jia (2008). Fishman (2006) and Hicks (2007) provide a general discussion on the Wal-Mart effect.

³Three European contributions are Bertrand and Kramarz (2002), who find that retail markets in France have lower labor growth and higher concentration as a consequence of regulation, and Sadun (2008) and Haskel and Sadun (2011), who find that the regulation in the U.K. reduces employment and productivity growth.

⁴Caves (1998), Bartelsman and Doms (2000), and Syverson (2011) provide surveys, mainly on manufacturing.

⁵The paper also relates to the vast literature on how competition affects productivity, emphasizing both positive and negative effects theoretically, and often positive effects empirically. Recent theoretical contributions are Nickell (1996), Schmidt (1997), Boone (2000), Melitz (2003), and Raith (2003), whereas

Our contribution is that we consider how to estimate productivity in retail markets, and provide a general strategy for how to identify the causal effect of large entrants on productivity separate from demand. Importantly, we add to the literature on structural productivity estimation examined at the industry level by analyzing local markets. Detailed data on all retail food stores in Sweden give us unique opportunities to analyze the questions at hand.

The model considers the following key features of retail markets. First, stores operate in local markets. Second, large entrants causally influence store productivity. Third, lack of data on prices and quantities at the firm/establishment level is common for many industries, and even more so in retail due to the problem of how to measure output (Griffith and Harmgart, 2005; Reynolds et al., 2005). Most studies of imperfectly competitive industries that use sales or value-added as a measure of output do not control for unobserved prices, although a few examples exist (Melitz, 2000; Katayama et al., 2003; Levinsohn and Melitz, 2006; De Loecker, 2011; Doraszelski and Jaumandreu, 2011). We augment the production function with a simple horizontal product differentiation demand system (CES) where exogenous demand shifters and large entrants affect prices, and thus obtain an industry markup (Klette and Griliches, 1996). As a consequence, we quantify the effect of large entrants on stores' productivity shocks cleaned from the effect on residual demand shocks. Fourth, a common characteristic of retail data is lumpy investments and lack of data on intermediate inputs such as the stock of products (materials). We discuss identification using both static and dynamic control functions for productivity, and highlight trade-offs between different sets of assumptions. To proxy for store productivity, we particularly focus on the labor demand function from stores' short-run optimization problem together with high-quality data on store-specific wages. The assumption of static labor is less restrictive in retail than in many other industries since part-time working is common, the share of skilled labor is low, and stores frequently adjust labor due to variation in customer flows.

The role of large entrants is directly linked to competition policy because the majority of OECD countries have entry regulations, though much more restrictive in Europe than in the U.S. The main rationale is that new entrants generate both positive and negative externalities which require careful evaluation by local authorities. Advantages, such as productivity gains, lower prices, and wider product assortments, stand in contrast to drawbacks, in terms of fewer stores, and environmental issues. Since we anticipate large entrants to have an extensive impact on market structure, they are carefully evaluated in the planning process. The consequences of regulation (e.g., supermarket dominance)

recent empirical contributions include Porter (1990), MacDonald (1994), Nickell (1996), Blundell et al. (1999), Sivadasan (2004), and Aghion et al. (2009).

are frequently debated among policy makers in Europe (European Parliament, 2008; European Competition Network, 2011). Our primary objective is not to quantify the magnitude of inter-firm reallocations over time, i.e., how (large) entrants, exits, and incumbents contribute to aggregate productivity growth.⁶ Instead we provide evidence for how large entrants influence exit and changes in the productivity distribution of incumbents in local markets.

We focus on food retailing because it accounts for a large (15 percent) share of consumers' budgets (Statistics Sweden, 2005) and thus constitutes a large share of retailing. Besides, many other service sectors follow similar trends as retail food. The Swedish market is appropriate to analyze because it follows two crucial trends common among nearly all OECD countries: There has been a structural change toward larger but fewer stores; in fact, the total number of stores in Sweden declined from 36,000 in the 1950s to below 6,000 in 2003 (Swedish National Board of Housing, Building, and Planning, 2005). And there is an entry regulation that gives municipalities power to decide over the land use and, consequently, whether or not a store is allowed to enter the market.

The empirical results show that it is important to allow for a general productivity process and to control for prices. Large entrants force low productive stores to exit and surviving stores to increase their productivity. Productivity increases most among incumbents in the bottom part of the productivity distribution, and then declines with the productivity level of incumbents. Controlling for prices results in a substantial increase in the impact of large entrants on productivity across the whole distribution. The average increase is about two times higher for 10th percentile productivity stores compared to 90th percentile ones. Controlling for endogeneity of large entrants reduces the marginal effects somewhat, especially for stores in the upper part of the productivity distribution. At the industry level, aggregate productivity growth was about 9 percent during 1997-2002. We conclude that large entrants spur reallocation of resources toward more productive stores. From a policy perspective, we claim that a more liberal design and application of entry regulations would support productivity growth in the Swedish retail food market.

The next section describes the retail food market and the data. Section 3 presents the modeling approach for estimating productivity, and Section 4 reports the empirical results. Section 5 summarizes and draws conclusions.

⁶We estimate the contribution of all entrants to aggregate productivity growth using various productivity decompositions (Griliches and Regev, 1995; Foster et al., 2001; Melitz and Polanec, 2009). Yet, due to data constraints, we cannot quantify the exact contribution of large entrants.

2 The retail food market and data

Historically, the Swedish retail food market consists of a mix of different firm organizations with a clear tendency toward independent and franchise stores where firms work as wholesale providers. Decisions over pricing, inputs, and exit are thus traditionally made by individual store owners in Sweden. However, the degree of centralized decision making has increased over time, with entry of large stores (henceforth referred as large entry) as one major driving force.⁷ For our purposes, we therefore focus on the rather recent implementation of firms' centralized decisions to enter large stores together with the historical network of incumbent stores that to a high extent operate as independent or franchise stores. The distinction between decisions made by firms (large entry) and stores (prices, inputs, and exit) is important for our identification strategy which is discussed in detail in Section 3.

Stores belong to four main firms. ICA consists of a group of independent store owners that started out collaborating on wholesale provision. Axfood contains a mix of independent and franchise stores.⁸ Bergendahls has a mix of franchises and centrally owned stores and operates mainly in the south and southwest of Sweden. COOP, on the contrary, consists of centralized cooperatives with decisions made at the local or national level. Despite its cooperative structure, independent store owners in COOP still have power to decide over, e.g., pricing and labor. Stores that are affiliated to these four firms together constitute about 92 percent of the market shares in 2002: ICA(44 percent), COOP(22 percent), Axfood(23 percent), and Bergendahls(3 percent). Various independent owners make up the remaining 8 percent market share.⁹

A majority of OECD countries have entry regulations that give power to local authorities. The regulations differ substantially across countries, however (Hoj et al., 1995; Boylaud and Nicoletti, 2001; Griffith and Harmgart, 2005; Pilat, 2005). While some countries strictly regulate large entrants, more flexible zoning laws exist, for instance in the U.S. (Pilat, 1997). The Swedish Plan and Building Act (PBA) gives power to the 290 municipalities to decide over applications for new entrants. In case of inter-municipality questions of entry, they are handled by the 21 county administrative boards. PBA is claimed to be one of the major barrier to entry, resulting in diverse outcomes, e.g., in price levels, across municipalities (Swedish Competition Authority, 2001:4). Several reports stress the need to better analyze how regulation affects market outcomes (Pilat,

⁷Although firms have been operating stores of different sizes for decades, they did not start to focus on uniform store concepts until the end of the study period (Maican, 2010a).

⁸In 2000, Axel Johnson and the D-group (D&D) merged to Axfood, initiating more centralized decision making and more uniformly designed store concepts from 2001 and onwards.

⁹International firms with hard discount formats entered the Swedish market after the study period: Netto in 2002 and Lidl in 2003 (Orth, 2011).

1997; Swedish Competition Authority, 2001:4, 2004:2). Large entrants are often newly built stores in external locations, making regulation highly important.¹⁰ Appendix A describes PBA in greater detail.

■ **Data.** In order to cover various store productivity measures and define large entrants, we use two micro-data sets. The first data set, collected by Delfi Marknadsparter AB (DELFI), defines a unit of observation as a store based on its geographical location, i.e., its physical address. This dataset, covering all retail food stores in the Swedish market during 1995-2002, includes store type, chain, revenue class, and sales space (in square meters). The store type classification (12 different) depends on size, location, product assortment etc. An advantage with DELFI is that it contains all stores and their physical locations; shortcomings are a lack of input/output measures and the fact that revenue information is collected by surveys and reported in classes. Therefore, we use DELFI only to define large entrants.

The most disaggregated level for which more accurate input and output measures exist is organization number (Statistics Sweden, SCB).¹¹ An organization number can consist of one store or several. SCB provides data at this level based on tax reporting. Financial Statistics (FS) provides input and output measures, and Regional Labor Statistics (RAMS) comprises data on wages for all organization numbers from 1996 to 2002 belonging to SNI code 52.1, “Retail sales in non-specialized stores,” which covers the four dominant firms (ICA, Coop, Axfood, and Bergendahls).¹² Anonymous codes in FS-RAMS imply that we do not know the exact identity of the organization number. It is therefore not possible to link exactly which stores in DELFI belong to each organization number in FS-RAMS.¹³ Based on the total number of stores and organization numbers, over 80 percent of the stores in DELFI each have their own organization number. Hence, less than 20 percent of the observations in FS-RAMS consist of two or more stores. If a firm consists of more than one store, we observe total, not average, inputs and outputs. Note that all stores are reported in both data sets. Finally, we connect demographic information (population, population density, average income, and political preferences)

¹⁰Possibly, firms can adopt similar strategies as their competitors and buy already established stores. As a result, more productive stores can enter without PBA involvement and, consequently, the regulation will not work as an entry barrier that potentially affects productivity. Of course, we cannot fully rule out that firms buy already established stores.

¹¹A so-called organization number specifies the identity of a corporate body. The Swedish Tax Authority (Skatteverket) has a register of all organization numbers used for tax reporting. The numbers are permanent and unique, i.e., one number follows the corporate body throughout its whole existence and two identical organization numbers do not exist. The register contains date of registration of the organization number and information regarding any exit/bankruptcy (Swedish Tax Authority, 2011).

¹²SNI (Swedish National Industry) classification codes build on the EU standard NACE.

¹³FS-RAMS do not rely on addresses like DELFI, so we could not do a more detailed investigation of productivity and geographical distance (location).

from SCB to FS-RAMS and DELFI. Appendix A gives more information about both data sets.

■ **Local markets.** Food products fulfill daily needs, are often of relatively short durability, and stores are thus located close to consumers. The travel distance when buying food is relatively short (except if prices are sufficiently low), and nearness to home and work are thus key aspects for consumers choosing where to shop, although distance likely increases with store size.¹⁴ The size of the local market for each store depends on its type. Large stores attract consumers from a wider area than do small stores, but the size of the local market also depends on the distance between stores. We assume that retail markets are isolated geographic units, with stores in one market competitively interacting only with other stores in the same local market. A complete definition of local markets requires information about the exact distance between stores. Without this information we must rely on already existing measures. The 21 counties in Sweden are clearly too large to be considered local markets for our purposes, and the 1,534 postal areas are probably too small, especially for large stores (on which we focus). Two intermediate choices are the 88 local labor markets and the 290 municipalities. Local labor markets take into account commuting patterns, which are important for the absolutely largest types such as hypermarkets and department stores, while municipalities seem more suitable for large supermarkets. As noted, municipalities are also the location of local government decisions regarding new entrants. We therefore use municipalities as local markets.

■ **Large entrants and endogeneity.** DELFI relies on geographical location (address) and classifies store types, making it appropriate for defining large entrants. Because of a limited number of large stores, we need to analyze several of the largest store types together. We define the five largest types (hypermarkets, department stores, large supermarkets, large grocery stores, and other¹⁵) as “large” and four other types (small supermarkets, small grocery stores, convenience stores, and mini markets) as “small.”¹⁶ Gas station stores, seasonal stores, and stores under construction are excluded due to these types not belonging in the SNI-code 52.1 in FS-RAMS. From the point of view of the Swedish market, we believe that these types are representative of being large.

A key problem when analyzing the link between large entrants and productivity

¹⁴The importance of these factors is confirmed by discussions with representatives from ICA, COOP, and Bergendahls. According to surveys conducted by the Swedish Institute for Transport and Communication Analysis, the average travel distance for trips with the *main* purpose of buying retail food products is 9.83 kilometers (1995-2002).

¹⁵Stores classified as other stores are large and externally located.

¹⁶Alternatively, we define observations in FS-RAMS with sales above the 5th percentile of large stores' sales in DELFI as large; otherwise as small. Even though the available data do not allow for a perfect match, the number of large entrants in FS-RAMS (so defined) follows a trend over time similar to that of the large entrants in DELFI. The empirical results (available from the authors upon request) are consistent with those reported here.

growth is the endogeneity of large entry. We hence need to bring exogenous variation in large entry using instruments. No major policy reforms changing the conditions for large entrants took place in Sweden during the study period (see Appendix A for details about PBA).¹⁷ Local authorities in Sweden decide however about entry of big-box stores. Following Bertrand and Kramarz (2002), Sadun (2008), and Schivardi and Viviano (2011), we use political preferences in municipalities as instruments for large entrants.¹⁸ We use variation in political preferences across local markets throughout the election periods 1994-1998, and 1999-2002 to add exogenous variation in the number of large entrants. We expect non-socialist local governments to have a more liberal view of large entrants.

■ **Descriptive statistics.** Table 1 presents descriptive statistics of the Swedish retail food industry from the two data sets DELFI and FS-RAMS for 1996-2002. As noted, over 80 percent of the observation units in FS-RAMS are identical to the stores in DELFI. The rest (20 percent in the beginning and 14 percent in the end) are multi-store units in FS-RAMS. The number of stores in DELFI decreases over the period from 4,664 to 3,585, i.e., a 23 percent reduction, indicating that many stores closed. In FS-RAMS, the number of observations decreases by about 17 percent (from 3,714 to 3,067).¹⁹ The share of large stores in DELFI increases from 19 percent to nearly 26 percent. While total sales space is virtually constant, mean sales space increases 33 percent. Thus, there has been a major structural change toward larger but fewer stores in the Swedish retail food market. Total wages (in FS-RAMS) increase over 22 percent (in real terms), while the number of employees increases only 9 percent.²⁰ Total sales increase about 26 percent (in FS-RAMS). Total sales in DELFI are lower and increase only 10 percent due to survey collection and interval reporting.

Table 2 shows the distribution of stores and firms across all local markets (municipalities) and years. The average number of stores is 23 and the standard deviation 35. A majority of markets consist of stores that belong to three firms whereas almost no markets consist of stores of a single firm.²¹ Most stores belong to ICA, about twice as many compared to COOP and Axfood in the upper part of the distribution. On average

¹⁷Studies based on U.K. data have used major policy reforms to handle endogeneity of entry (Sadun, 2008; Aghion et al., 2009).

¹⁸Data on the number of applications and rejections for each municipality is not available in Sweden. Even if this information would have been available, it is not completely exogenous since the number of applications is easily influenced by current local government policies. We believe that the share of seats taken by non-socialist parties is a valid instrument.

¹⁹This indicates that entry and exit based on changes in organization numbers in FS-RAMS in some cases differ from entry and exit based on addresses in DELFI due to, e.g., re-organizations.

²⁰The aggregate growth of real wages in Sweden was 24 percent during the period.

²¹ICA stores operate in almost all of the 290 markets. COOP decreases from 236 to 227 markets and Axfood from 276 to 266 during the study period. Bergendahls stores are in 21 markets in the beginning and 42 markets in the end.

as many as 7.25 stores belong to ICA and slightly below 4 to COOP and Axfood, respectively. That each local market consists of many stores, together with the fact that stores decide over their own prices in Sweden, support our choice of the demand system.

ICA, Axfood and COOP have strikingly similar store size distributions throughout the whole distribution (Table 3). Median store size is 316 square meters for ICA, 350 for Axfood, 400 for COOP, and 448 for Bergendahls. The averages of 540 for ICA and about 620 for Axfood and COOP confirm that most stores are small. Bergendahls focuses on larger stores (average size of 1,297 square meters) and operates only in a few markets.

Table 4 shows median characteristics of local markets with and without large entrants during 1997-2002. The median number of stores varies between 22 and 54 in large entry markets, compared to 13-15 in non-entry markets. The number of markets with at least one large entrant varies between 6 and 23. Among these, up to three large entrants established in the same market in the same year. As expected, median entry and exit are higher in large entry than in non-entry markets, and so are median population, population density, and income. Large entry markets also have a lower concentration; the median four store concentration ratio is about 0.5 in these markets, while it is over 0.7 in markets without large entrants.

3 Productivity estimation

This paper focuses on a general strategy of trying to measure causal effects of entry of large stores on stores' efficiency shocks (shocks to technology and to X-inefficiency) and on demand shocks. Our model of competition among retail stores is based on Ericson and Pakes' (1995) dynamic oligopoly framework. A store is described by a vector of state variables $\mathbf{s} \in \mathbb{S}$ consisting of productivity $\omega \in \Omega$, capital stock $k \in \mathbb{R}_+$, the number of large entrants $e^L \in \mathbb{Z}_+$, and other local market demand shifters $\mathbf{x} \in \mathbb{R}_+^x$.²² Because all stores decide over their own prices in Sweden and a majority of stores operate as independent or franchise units, we model each store as a separate unit that decides over prices, inputs, and exit.²³ Incumbent stores maximize the discounted expected value of

²²We follow the common notation of capital letters for levels and small letters for logs for all variables except e^L , which is in levels.

²³If we aggregate and analyze decisions of, e.g., pricing at the firm level (instead of the store level), we lose a lot of the dynamics crucial for our analysis of the Swedish retail food market. National pricing with market power to firms instead of stores is more common in other countries (e.g., U.K.). In order to analyze the relation between firms and stores in more detail, we would need data on the identity of (multi-) stores for which we observe inputs and outputs. The decision to exit or continue is made at the store level, although firms can influence the decision of each store through possible chain effects. Section 2 provides details about the organization of firms.

future net cash flows. Stores compete in the product market and collect their payoffs. At the beginning of each time period, incumbents decide whether to exit or continue to operate in the local market. Incumbent stores are assumed to know their scrap value received upon exit γ prior to making exit and investment decisions. If the store continues, it chooses optimal levels of labor l and investment i . We assume that capital is a dynamic input that accumulates according to $K_{t+1} = (1 - \delta)K_t + exp(i_t)$, where δ is the depreciation rate. Changes in stores' investment do not guarantee a more favorable state tomorrow, but do guarantee more favorable distributions over future states.

Large entry is an exogenous state variable that affects current and expected future profits of the stores and, therefore, the investment decisions. Given the structure of the Swedish retail food market discussed in Section 2, we assume that firms decide over entry of large stores and that individual stores cannot influence this decision. The distinction between decisions made by firms (large entry) and stores (prices, inputs, and exit) is important for our identification strategy. We assume that the process of large entry is completely static, i.e., that the current number of large entrants is a sufficient statistic for future values of large entrants and that stores do not form beliefs about future large entry when making strategic choices.²⁴

Our assumption on how large entrants affect productivity relies on the X-inefficiency hypothesis, i.e., increased competition forces stores to improve their productivity, which induces reallocation and exit. We distinguish between the impact of large entrants on productivity and that on prices. Large entrants immediately affect stores' residual demand and thus the local market equilibrium prices, but affect store productivity with a one year lag. The fact that stores can adjust their prices fast and consumers can easily switch stores validates the assumption that demand responds instantly to large entry. That it takes time for stores to adjust their productivity in response to increased competition justifies the assumption of a lagged effect of large entrants on productivity. Extending Olley and Pakes (1996)(hereafter OP), the transition probabilities of productivity follow a controlled first-order Markov process with $P(d\omega|\omega, e^L)$ where it is explicit that large entrants have a causal impact on productivity.

We denote $V(\mathbf{s}_{jt})$ to be the expected discounted value of all future net cash flows for store j in market m at period t , where $\mathbf{s}_{jt} = (\omega_{jt}, k_{jt}, e_{mt}^L, \mathbf{x}_{mt})$. $V(\mathbf{s}_{jt})$ is defined by the solution to the following Bellman equation with the discount factor $\beta < 1$:

$$V(\mathbf{s}_{jt}) = \max \left\{ \gamma, \sup_{i_{jt}, l_{jt}} [\pi(\mathbf{s}_{jt}) - c_i(i_{jt}, k_{jt}) - c_l(l_{jt}) + \beta E[V(\mathbf{s}_{j,t+1})|\mathcal{F}_{jt}]] \right\}, \quad (1)$$

²⁴A concern is that firms may decide to enter large stores in markets with certain characteristics. We control for this using political preferences at the local market as an instrument for large entrants when estimating store productivity (discussed in detail below).

where $\pi(\mathbf{s}_{jt})$ is the profit function, which is increasing in both ω_{jt} and k_{jt} ; $c_i(i_{jt}, k_{jt})$ is investment cost in new capital, which is increasing in investment choice i_{jt} and decreasing in capital stock k_{jt} ; $c_l(l_{jt})$ is the labor adjustment cost, which is increasing in labor l_{jt} ; and \mathcal{F}_{jt} represents information available at time t . The solution to the store's optimization problem (1) gives optimal policy functions for labor $l_{jt} = \tilde{l}_{jt}(\mathbf{s}_{jt})$, investment $i_{jt} = \tilde{i}_{jt}(\mathbf{s}_{jt})$, and exit $\chi_{jt+1} = \tilde{\chi}_{jt}(\mathbf{s}_{jt})$.²⁵ The exit rule χ_{jt+1} depends on the threshold productivity $\underline{\omega}_{mt}(k_{jt}, e_{mt}^L, \mathbf{x}_{mt})$.

■ **Value-added generating function and imperfect competition.** For simplicity of exposition, we assume Cobb–Douglas technology where stores sell a homogeneous product, and that the factors underlying profitability differences among stores are neutral efficiency differences. Cobb–Douglas is the most common specification in the empirical productivity literature. Importantly, the logarithmic form of the Cobb–Douglas function can be seen as a first-order Taylor approximation of a nonparametric function.²⁶ The production function can be specified as

$$q_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \omega_{jt} + u_{jt}^p, \quad (2)$$

where q_{jt} is the log of quantity sold by store j at time t ; l_{jt} is the log of labor input; and k_{jt} is the log of capital input. The unobserved ω_{jt} is productivity, and u_{jt}^p is either measurement error (which can be serially correlated) or a shock to productivity that is not predictable during the period in which inputs can be adjusted and stores make exit decisions. In other words, all endogeneity problems regarding inputs are concentrated in ω_{jt} . Since physical output is complex to measure in retail markets and therefore not observed, we use deflated value added as a proxy for output.

Equation (2) assumes that prices are constant across stores.²⁷ Foster et al. (2008) analyze the relation between physical output, revenues, and firm-level prices in the context of market selection. They find that productivity based on physical quantities is negatively correlated with establishment-level prices, whereas productivity based on revenues is positively correlated. When a store has some market power, like in retail food, its price influences its productivity. If a store cuts its price, then more inputs are needed to satisfy increasing demand. This negative correlation between inputs and prices leads to underestimation of the labor and capital parameters in the production function (Klette

²⁵This formulation of the model is consistent with labor having dynamic implications. If labor is a static input, it is a solution of a short-run optimization problem, i.e., stores do not need to solve the dynamic optimization problem to find optimal labor.

²⁶A translog production function is considered for robustness (Section 4.3).

²⁷Under perfect competition, productivity of the price-taking stores is not influenced by store-level prices.

and Griliches, 1996; Melitz, 2000; Levinsohn and Melitz, 2006; De Loecker, 2011).²⁸ Following this literature, we consider a standard horizontal product differentiation demand system (CES)

$$p_{jt} = p_{mt} + \frac{1}{\eta}q_{jt} - \frac{1}{\eta}q_{mt} - \frac{1}{\eta}u_{jt}^d, \quad (3)$$

where p_{jt} is output price, p_{mt} and q_{mt} are output price and quantity in local market m , and u_{jt}^d is demand shocks. The parameter η (< -1 and finite) captures the elasticity of substitution among stores.²⁹

Due to data constraints, the demand system is quite restrictive, implying a single elasticity of substitution for all stores. Thus, there are no differences in cross-price elasticities, i.e., we have a constant markup over marginal cost ($\frac{\eta}{1+\eta}$), and the Learner index is ($\frac{1}{|\eta|}$).³⁰ Access to data on store-level prices and product characteristics would allow us to consider heterogeneous products and consumers in a Berry et al. (1995) (BLP) framework. Constructing an index price at the store level for all stores is, however, difficult due to lack of data.

Although our CES demand model is restrictive because of data constraints, our application fulfills aggregation restrictions that make it consistent with a model of heterogeneous consumers in characteristics space (Anderson et al., 1989). The Swedish retail food market satisfies all restrictions, namely that the number of store characteristics is large enough compared to the number of store types in each local market, that stores operate in different geographical locations, i.e., are non-collinear, and that all consumers purchase products.

In terms of our empirical implementation, the Swedish retail food market has several features that make a simple CES approach less restrictive than in many other industries. Stores decide over their own prices and we do not expect a single store to influence the market price because local markets contain many stores as a result of our focus on large entrants.³¹ Furthermore, all stores offer a wide range of products, i.e., we assume that stores have the same basic function for consumers – to provide food.³² Despite this, it is well known that retail stores can differentiate in store size (format), geographic location,

²⁸If the products are perfect substitutes, then deflated sales are a perfect proxy for unobserved quality-adjusted output.

²⁹The vertical dimension is to some extent also captured since deflated output measures both quantity and quality, which is correlated with store type (size).

³⁰We can however allow the elasticity of substitution to differ across local market groups such as counties (21 in total). The Learner index for county g is then $\frac{1}{|\eta_g|}$. An alternative would be to estimate two elasticities, one for large stores and one for small. Yet this would require two price indices, and we have access to only one price index.

³¹On average, there are 30 stores in markets with large entrants and 15 in markets without (Table 4).

³²Large and small stores are found to compete as substitutes both within and across types in Sweden (Maican and Orth, 2011). This could be due to that we only consider stores with a full product range, but also the small size (total population) of the Swedish retail food market.

and quality. In Sweden, however, price differences are found to be small between firms and stores for a homogenous product basket (Asplund and Friberg, 2002).³³ Given our data constraints, we therefore focus on the key dimension of differentiation in location. Although the demand system implies fully symmetric price changes across stores in response to large entry in the local market, we relax the default assumption of perfect substitutability ($\eta = -\infty$) in the early productivity literature.

Since we have unobserved store prices and quantities, we use deflated value-added y_{jt} , defined as $q_{jt} + p_{jt} - p_{mt}$, as output in the estimation. However, if p_{mt} is unobserved, the consumer price index for food products p_{It} can be used as a proxy. Combining unobserved store price p_{jt} in (3) and the production function (2), we then have the value-added generating function

$$y_{jt} \equiv \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{mt} + \left(1 + \frac{1}{\eta}\right) \omega_{jt} - \frac{1}{\eta} u_{jt}^d + \left(1 + \frac{1}{\eta}\right) u_{jt}^p. \quad (4)$$

To estimate the value-added generating function, we have to control for both unobserved productivity (ω_{jt}) and demand shocks (u_{jt}^d). The unobserved prices (p_{jt}) are explained by variations in inputs and aggregate demand. However, other factors will also affect store prices. We use the number of large entrants (e_{mt}^L) and observed local market demand shifters (\mathbf{x}'_{mt}) to control for demand shocks at the local market level

$$u_{jt}^d = \beta_e e_{mt}^L + \mathbf{x}'_{mt} \boldsymbol{\beta}_x + v_{jt}, \quad (5)$$

where v_{jt} represents remaining i.i.d. store level shocks to demand that are not observed or predictable by stores before making their input and exit decisions. That is, they are not in the store's information set \mathcal{F}_{jt} and thus are uncorrelated with inputs, outputs or exit. Section 3.3 discusses identification when shocks v_{jt} are correlated over time. By substituting (5) into (4), the value-added generating function is

$$y_{jt} = \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{mt} - \frac{1}{\eta} \beta_e e_{mt}^L - \frac{1}{\eta} \mathbf{x}'_{mt} \boldsymbol{\beta}_x + \left(1 + \frac{1}{\eta}\right) \omega_{jt} - \frac{1}{\eta} v_{jt} + \left(1 + \frac{1}{\eta}\right) u_{jt}^p. \quad (6)$$

Equation (6) states clearly that prices respond instantly to large entrants.

■ **Productivity process.** The controlled Markov process assumption implies that actual productivity is the sum of expected productivity given the information set \mathcal{F}_{jt-1} ,

³³Based on a sample of stores, Asplund and Friberg (2002) found that large stores offer just slightly lower prices (about 3 percent) and have only a modest impact on prices in surrounding stores (less than 1 percent). Small differences in prices also indicate that stores tend to offer similar quality.

$E[\omega_{jt}|\mathcal{F}_{jt-1}]$, and the i.i.d. productivity shocks ξ_{jt} . The shocks ξ_{jt} may be thought of as the realization of uncertainties that are naturally linked to productivity, and they are mean independent of all information known at $t - 1$. Both previous productivity (ω_{jt-1}) and number of large entrants (e_{mt-1}^L), which are part of the information set \mathcal{F}_{jt-1} , affect current productivity as follows

$$\omega_{jt} = h(\omega_{jt-1}, e_{mt-1}^L) + \xi_{jt}, \quad (7)$$

where the function $h(\cdot)$ approximates the conditional expectation, $E[\omega_{jt}|\mathcal{F}_{jt-1}]$.³⁴ Hence, lagged large entry has a causal impact on current productivity.

3.1 Static labor demand function

The stock of products (materials), capital, and labor are main inputs for retail stores. Intermediate inputs would be an excellent choice to recover productivity in retail markets (Levinsohn and Petrin, 2003; Akerberg et al., 2006; De Loecker, 2011). Ideally we would thus like to have data on the stock of products, but such data are unfortunately not available.³⁵ The investment policy function is restrictive to use because retail stores make lumpy investments and we can only use stores with positive investment (Olley and Pakes, 1996). Instead we use the labor demand function from stores' static profit maximization problem as control function for productivity together with a good measure of store-specific wages (Doraszelski and Jaumandreu, 2011). That is, we assume that labor is a static and variable input chosen based on current productivity.

The static labor assumption has the advantages that we can include many stores with zero investment and abstract from assumptions about stores' dynamic programming problem. However, it does not allow for costs of training, hiring, and firing of employees.³⁶ For several reasons this is less restrictive in retail than in many other industries. Part-time workers are common. As much as 40 percent of the employees in retail food work part time, compared to 20 percent for the Swedish economy as a whole (Statistics Sweden). The share of skilled labor is low in retail. Only 15 percent of all retail employees

³⁴Population density might also affect store productivity through the X-inefficiency hypothesis. Stores located in dense markets face high competition that makes them improve their productivity (Syverson, 2004).

³⁵The complexity of food products and that stores have different product assortments make it difficult to collect data on the stock of products for all stores. If such data were available, it would open for interesting comparisons of results using different control functions of static inputs (labor versus materials).

³⁶When there are labor adjustment costs, labor has dynamic implications and enters as a state variable in the store's dynamic problem. For comparison and robustness, we consider labor having dynamic implications as well as identification using investment as a dynamic control function in Section 3.2.

had a university education in 2002, compared to 32 percent for the total Swedish labor force (Statistics Sweden). Stores have long opening hours and adjust their labor due to variations in customer flows over the day, week, month and year. Moreover, the training process might be shorter than in many other industries. The number of full-time adjusted employees is our measure of labor. Under the assumption of static labor, we consider identification using both nonparametric (Section 3.1.1) and parametric (Section 3.1.2) control functions.

3.1.1 Identification using a nonparametric control function

When labor is a static input, the general labor demand function that comes from stores' short-run maximization problem is

$$l_{jt} = \tilde{l}_t(\omega_{jt}, k_{jt}, w_{jt}, q_{mt}, e_{mt}^L, \mathbf{x}_{mt}), \quad (8)$$

where $\tilde{l}_t(\cdot)$ is an unknown function strictly increasing in ω_{jt} , and w_{jt} is the log of wage rate at the store level. The use of a nonparametric control function has the advantage that we can relax the assumption of Cobb-Douglas technology and rely on a general production function such as translog.

To back out productivity from a general labor demand function, we need the following key assumptions to hold. First, the labor demand function is strictly monotonic in productivity. Under our assumption that labor is a static input, the *invertibility condition* (*strict monotonicity*) of the labor demand function holds because of our constant markup assumption of the CES demand system. Under a CES demand system, the monotonicity condition for a static input holds when more productive stores do not have disproportionately higher markups than less productive stores (Levinsohn and Melitz, 2006).

Second, productivity ω_{jt} is the only unobservable entering the labor demand function. This rules out, e.g., measurement error, optimization error in labor, and a model in which exogenous productivity is not single dimensional. In absence of this *scalar unobservable* assumption, productivity ω_{jt} cannot be perfectly inverted out.

Third, we need helpful variation in store-specific wages.³⁷ Even if store wages change over time, we need additional variation at the store level if we also control for time effects in estimation of the value-added generating function. The idea is that store-level wages

³⁷The average wage contains both price of labor and its composition, e.g., ages, gender, and skill groups. Our measure of wage is a good reflection of exogenous changes in the price of labor because the 22 percent growth in total retail wages during the period (Table 1) is in line with the 24 percent growth in aggregate real wages in Sweden (Statistics Sweden).

only influence productivity but not demand.³⁸ Moreover, aggregate demand, current large entrants, and exogenous demand shifters (e.g., population, population density, and income) only influence store prices. High-quality data on store-specific wages and the fact that stores set wages, temporary job contracts, and part-time working ensure the existence of wage variation across stores.³⁹ The coefficient of variation for wages is about 18 percent across firms and 53 percent across municipalities. The variation in store wages over time accounts for 19 percent. Regressing time and market fixed effects on deflated wages, we find that time only accounts for about 0.6 percent and market dummies explain about 9 percent of the wage variation. In addition, only 2 percent of the variation in annual wage changes at the firm level is explained by year and market fixed effects.

Fourth, we need a set of *timing assumptions* of when in the productivity process inputs are chosen and firms decide over large entry. Our assumptions mentioned above state that capital is a dynamic input, labor is a static and variable input chosen based on current productivity, and large entrants influence demand instantly whereas it takes one year until they affect productivity.

Large entrants e_{mt}^L , local demand shifters \mathbf{x}_{mt} , and market quantity q_{mt} vary across markets and time whereas wages w_{jt} , labor l_{jt} , and capital k_{jt} also vary across stores. Although firms decide over large entry in a static manner without any influence from individual stores, firms can decide to enter markets with certain characteristics, which might induce a correlation between e_{mt}^L and remaining shocks to demand v_{jt} and shocks to production u_{jt}^p . We control for this endogeneity of large entrants in the first step of the OP/ACF framework by using the share of non-socialist seats in local governments to instrument for large entry (Bertrand and Kramarz, 2002; Sadun, 2008; Schivardi and Viviano, 2011). The basic idea is that we expect non-socialist local governments to be more positive toward large store entry than socialist ones.⁴⁰

Table A.1 shows first-stage regressions using political preferences as an explanatory variable for large entrants. Increasing the share of non-socialist seats at the municipality level has a positive impact on number of large entrants. This result is robust to year

³⁸In absence of store level wages, it may however be difficult to estimate the coefficients of static inputs in the Cobb-Douglas case (Bond and Söderbom, 2005).

³⁹Yet wages might pick up unobserved worker quality. Since workers' quality is unobserved by the econometrician but observed by stores, we have two unobservables to control for, which complicates estimation. However, this is not a big concern in the retail food market where quality of workers is expected to be fairly homogenous.

⁴⁰The Social Democratic Party is the largest party nationally with 40.6 percent of the seats on average. It collaborates with the Left Party (8 percent) and the Green Party (4.2 percent). The non-socialist group consists of the Moderate Party (18 percent), most often together with the Center Party (13.2 percent), Christian Democrats (5.9 percent), and the Liberal Party (5.6 percent). 22 percent of the municipalities had a non-socialist majority during 1996-1998, increasing to 32 percent during 1999-2002. The non-socialists had 8.6-85 percent, averaging 40.7 percent (1996-1998) and 44.1 percent (1999-2002).

or market fixed effects, emphasizing the relevance of our instrument. To be a good instrument for large entrants, political preferences should not be related to demand at the local market level. Since everybody buys food and population is more important than income for aggregate food demand, we do not expect that political preferences affect food demand at the municipality level. In the empirical part, we validate the instrument (Section 4.1). We believe it is reasonable to assume that local market demand does not change systematically with people's voting behavior. Food products are purchased frequently by almost everyone, so we expect the nature of food products to cause rather small differences in aggregate demand across municipalities with different political views. We moreover expect population to be more important than income for aggregate demand for retail food products.

■ **Estimation.** By inverting the labor demand function (8) to get productivity ω_{jt} and substitute into (6), the value-added generating function becomes

$$y_{jt} = \phi_t(l_{jt}, w_{jt}, k_{jt}, q_{mt}, e_{mt}^L, \mathbf{x}_{mt}) + \epsilon_{jt}, \quad (9)$$

where $\phi_t(\cdot) = \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{mt} - \frac{1}{\eta} \beta_e e_{mt}^L - \frac{1}{\eta} \mathbf{x}'_{mt} \beta_x + \left(1 + \frac{1}{\eta}\right) \omega_{jt}$, and $\epsilon_{jt} \equiv -\frac{1}{\eta} v_{jt} + \left(1 + \frac{1}{\eta}\right) u_{jt}^p$. The unknown function $\phi_t(\cdot)$ is approximated using a third-order polynomial expansion in its arguments.

Estimation of the value-added generating function is done in two steps. The aim of the first step is to separate productivity (ω_{jt}) from shocks to production (u_{jt}^p) and demand (v_{jt}), i.e., ϵ_{jt} . The first step only gives an estimate of $\phi_t(\cdot)$, $\hat{\phi}_t(\cdot)$, which helps in recovering productivity as follows:

$$\omega_{jt}(\boldsymbol{\beta}) = \frac{\eta}{(1+\eta)} \left[\hat{\phi}_t(\cdot) - \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] + \frac{1}{\eta} q_{mt} + \frac{1}{\eta} \beta_e e_{mt}^L + \frac{1}{\eta} \mathbf{x}'_{mt} \boldsymbol{\beta}_x \right], \quad (10)$$

where $\boldsymbol{\beta} = (\beta_l, \beta_k, \eta, \beta_e, \boldsymbol{\beta}_x)$. To obtain an estimate of $\phi_t(\cdot)$ using the OLS estimator, we need the following moment conditions to hold:

$$E[\epsilon_{jt} | f(l_{jt}, w_{jt}, k_{jt}, q_{mt}, e_{mt}^L, \mathbf{x}_{mt})] = 0, \quad t = 1, \dots, T, \quad (11)$$

where f is vector valued instrument functions (Wooldridge, 2009).

Our assumption of using the labor demand function from stores' static optimization problem to back out productivity requires that wages are exogenous. If wages are uncorrelated with the i.i.d. shocks ($E[\epsilon_{jt} | w_{jt}] = 0$), then $\hat{\phi}_t(\cdot)$ can be estimated using OLS. If this assumption does not hold, corresponding moments based on w_{jt-1} ($E[\epsilon_{jt} | w_{jt-1}] = 0$)

can be used to estimate $\hat{\phi}_t(\cdot)$ by GMM.⁴¹

When firms decide to enter markets with certain demand characteristics that are unobserved to the econometrician, the moment condition $E[\epsilon_{jt}|e_{mt}^L] = 0$ is not fulfilled, i.e., the number of large entrants is not an exogenous demand shifter. An instrument for large entry is valid if it is correlated with the decision to enter large stores but uncorrelated with i.i.d. shocks ϵ_{jt} . That is, we require the instrument of e_{mt}^L to move around large entry independently of demand. Moments based on either lagged large entry $E[\epsilon_{jt}|e_{mt-1}^L] = 0$ or local market political preferences $E[\epsilon_{jt}|pol_{mt}] = 0$ can then be used in the first step. When controlling for endogeneity of wages and large entrants, the first step moments in (11) are replaced with

$$E[\epsilon_{jt}|f(l_{jt}, w_{jt-1}, k_{jt}, q_{mt}, e_{mt-1}^L, pol_{mt}, \mathbf{x}_{mt})] = 0, \quad t = 1, \dots, T. \quad (12)$$

Using GMM instead of OLS in the first step increases the computational burden.

In the second step, we nonparametrically regress $\omega_{jt}(\boldsymbol{\beta})$ on a polynomial expansion of order three in $\omega_{jt-1}(\boldsymbol{\beta})$ and e_{mt-1}^L to obtain an estimate of $\xi_{jt}(\boldsymbol{\beta})$. Identification of the parameters $\boldsymbol{\beta} = (\beta_l, \beta_k, \eta, \beta_e, \boldsymbol{\beta}_x)$ comes from the following moments

$$E \left\{ \xi_{jt}(\boldsymbol{\beta}) \middle| \begin{pmatrix} l_{jt-1} \\ k_{jt-1} \\ q_{mt-1} \\ e_{mt-1}^L \\ \mathbf{x}_{mt-1} \end{pmatrix} \right\} = 0. \quad (13)$$

The assumption that labor is a static and variable input implies that the choice of labor at $t - 1$ is uncorrelated with current productivity and hence with shocks in current productivity. The moment $E[\xi_{jt}(\boldsymbol{\beta})|l_{jt-1}] = 0$ then identifies β_l . If labor instead is a static and fixed input, i.e., labor is decided before the realization of the productivity shock ξ_{jt} , then β_l can be identified from $E[\xi_{jt}(\boldsymbol{\beta})|l_{jt}] = 0$. This moment condition, consistent with hiring, firing, and training costs of labor, is especially useful for short panels.

The assumption that stores decide investment in capital at $t - 1$ implies that the coefficient of capital β_k is identified from $E[\xi_{jt}(\boldsymbol{\beta})|k_{jt}] = 0$. If we do not require a timing assumption on stores' investment decision, actual shocks to productivity are uncorrelated with the previous capital and $E[\xi_{jt}(\boldsymbol{\beta})|k_{jt-1}] = 0$ can be used to identify β_k .

Given the assumptions of a static entry process and timing, e_{mt}^L is uncorrelated with

⁴¹In case of endogeneity, this identification strategy also applies to the observed variables used to control for demand shocks, e.g., income.

the innovation in productivity, $E[\xi_{jt}(\boldsymbol{\beta})|e_{mt}^L] = 0$. This moment condition is used to identify the coefficient of large entrants. There is no endogeneity problem of large entry through the productivity process in the second step. Instead, endogeneity might only arrive through correlations with shocks to demand and production (ϵ_{jt}) in the first step.

The parameters on aggregate market quantity and local market demand shifters are identified in a similar manner as labor. Previous periods' aggregate quantity and demand shifters are both uncorrelated with current productivity and thus with shocks in current productivity, i.e., $E[\xi_{jt}(\boldsymbol{\beta})|q_{mt-1}] = 0$ for η and $E[\xi_{jt}(\boldsymbol{\beta})|\mathbf{x}_{jt-1}] = 0$ for $\boldsymbol{\beta}_x$.

The parameters $\boldsymbol{\beta}$ are estimated by minimizing the sample analogue of the moment conditions (13). Since there are nonlinearities in the coefficients, we use the Nelder-Mead numerical optimization method to minimize the GMM objective function

$$\min_{\boldsymbol{\beta}} Q_N = \left[\frac{1}{N} W' \xi(\boldsymbol{\beta}) \right]' A \left[\frac{1}{N} W' \xi(\boldsymbol{\beta}) \right], \quad (14)$$

where A is the weighting matrix defined as $A = \left[\frac{1}{N} W' \xi(\boldsymbol{\beta}) \xi'(\boldsymbol{\beta}) W \right]^{-1}$ and W is the matrix of instruments. Estimation is done at the industry level, controlling for local market conditions.⁴²

■ **Standard errors.** Although bootstrap is used to compute standard errors in the two-step estimator in the literature (Akerberg et al., 2006), it might not be the best choice when the underlying model is more complicated. First, bootstrap requires additional computation time, for example when we compute competition measures in each market for each subsample. Moreover, optimization errors can appear when we estimate the parameters on various subsamples. Since the choice of stores in different samples gives a different impact of competition from the large entrants, we might need a large number of bootstraps.

This paper uses Akerberg et al. (2011) to compute the standard errors in the ACF framework. Akerberg et al. (2011) suggest methods that simplify semiparametric inference by deriving various numerical equivalence results. They show identical numerical variance of structural parameters between the estimates of the semiparametric variance (Newey, 1994; Ai and Chen, 2007) and the parametric asymptotic variance using two-step parametric results (Murphy and Topel, 1985; Newey and McFadden, 1994). Using an Akerberg et al. (2011) equivalence, we can obtain standard errors using formulas from the parametric literature. The first step in ACF requires computation of the finite

⁴²Estimation results at the county level (21 municipality groups) are available from the authors. The advantages of estimating at the county level are that counties are responsible for inter-municipality implementation of the entry regulation and that we obtain markups at the county level. The major disadvantage is that we lose efficiency in estimation in the small counties.

number of parameters when the inverse labor demand function is approximated using a polynomial sieve. It can be shown that the sieve estimator of the asymptotic variance of the structural parameters is numerically identical to Murphy and Topel's (1985) equation.

3.1.2 Identification using a parametric control function

Assuming Cobb-Douglas technology and that labor is a static and variable input chosen based on current productivity, a parametric expression for the labor demand function can be derived from the first-order conditions (Doraszelski and Jaumandreu, 2011):

$$l_{jt} = \frac{1}{1 - \beta_l} [\ln(\beta_l) + \alpha + \beta_k k_{jt} + \omega_{jt} - (w_{jt} - p_{jt})], \quad (15)$$

where $\alpha = \ln E[\exp(u_{jt}^p)]$. The assumptions under the nonparametric control function apply also in the parametric case (Cobb-Douglas), i.e., scalar unobservable, monotonicity, variation in wages, and timing assumptions. Consequently, we get a known functional form for the (inverse) labor demand function. That each store sets wages guarantees that we obtain a good proxy for unobserved store productivity. Solving for ω_{jt} in equation (15) yields the parametric inverse labor demand function

$$\omega_{jt} \equiv \tilde{l}_t^{-1}(\cdot) = \frac{\eta}{1+\eta} \left[\delta_1 + [(1 - \beta_l) - \frac{1}{\eta}\beta_l]l_{jt} + w_{jt} - p_{jt} - \left(1 + \frac{1}{\eta}\right)\beta_k k_{jt} + \frac{1}{\eta}q_{mt} + \frac{1}{\eta}\beta_e e_{mt}^L + \frac{1}{\eta}\mathbf{x}'_{mt}\boldsymbol{\beta}_x \right], \quad (16)$$

where $\delta_1 = -\ln(\beta_l) - \ln(1 + \frac{1}{\eta}) - \ln E[\exp(u_{jt}^p)] + \frac{1}{\eta} \ln E[\exp(v_{jt})]$. By substituting the controlled Markov process (7) into (15), we obtain

$$l_{jt} = \frac{1}{1 - \beta_l} [\ln(\beta_l) + \alpha + \beta_k k_{jt} + h(\omega_{jt-1}, e_{mt-1}^L) + \xi_{jt} - (w_{jt} - p_{jt})]. \quad (17)$$

Using (6) and (7), the value-added generating function becomes

$$y_{jt} = \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta}q_{mt} - \frac{1}{\eta}\beta_e e_{mt}^L - \frac{1}{\eta}\mathbf{x}'_{mt}\boldsymbol{\beta}_x + \left(1 + \frac{1}{\eta}\right) h(\omega_{jt-1}, e_{mt-1}^L) + \left(1 + \frac{1}{\eta}\right) \xi_{jt} - \frac{1}{\eta}v_{jt} + \left(1 + \frac{1}{\eta}\right) u_{jt}^p. \quad (18)$$

In both (17) and (18), ω_{jt-1} is given by (16). The condition for identification in (18) is that the variables in the parametric part of the model are not perfectly predictable (in the least square sense) by the variables in the nonparametric part (Robinson, 1988; Newey et al., 1999). The actual capital stock k_{jt} cannot be inferred from $\tilde{l}_{t-1}^{-1}(\cdot)$ and e_{mt-1}^L in the nonparametric part. The $\tilde{l}_{t-1}^{-1}(\cdot)$ is identical with ω_{jt-1} , but k_{jt} cannot be inferred

from $\tilde{l}_{t-1}^{-1}(\cdot)$, e.g., demand shifters \mathbf{x}_{mt-1} that are part of ω_{jt-1} guarantee identification in (18). For example, \mathbf{x}_{mt} cannot be perfectly predicted from ω_{jt} .

Equations (17) and (18) form a system of equations with y_{jt} and l_{jt} as endogenous variables. The reduced form equation taken to estimate can easily be derived. Assuming that wages and large entrants are exogenous, this system of equations is over-identified using a constant, k_{jt} , l_{jt-1} , w_{jt} , e_{mt}^L , and \mathbf{x}_{mt-1} as instruments. In case of endogenous wages and large entrants, we can use previous wages (w_{jt-1}) and local political preferences (pol_{mt}) instead of w_{jt} and e_{mt}^L .

The parametric approach is more transparent than the nonparametric in how real wages affect labor demand. Identification is heavily based on two different sources of variation in the data. First, we need variation in store wages (and prices if available) for the model to be identified. If there is not enough variation in wages across stores over time and markets, it is not possible to separately identify β_l . Second, we need enough variation in large entrants across markets and time since previous large entrants (e_{mt-1}^L) and its polynomial expansion are used to identify the nonparametric function and the current number of large entrants (e_{mt}^L) is used to identify β_e . The variation in wages and large entry have been explained in detail under the nonparametric control function (Section 3.1.1).

■ **Estimation.** We use the sieve minimum distance (SMD) procedure proposed by Ai and Chen (2003) and Newey and Powell (2003) for i.i.d. data (see Akerberg et al., 2011, for a discussion of semiparametric inference to IO models). The goal is to obtain an estimable expression for the unknown parameters β and h_H , where H indicates all parameters in $h(\cdot)$. We approximate $h(\cdot)$ by a third-order polynomial expansion in ω_{jt-1} , given by (16), and e_{mt-1}^L .⁴³ We use a tensor product polynomial series of capital (k_{jt}), labor (l_{jt-1}), wages (w_{jt}), the consumer price index for food products (p_{It}), actual and previous large entrants (e_{mt}^L , e_{mt-1}^L), and demand shifters (\mathbf{x}_{mt-1}). Lagged wages (w_{jt-1}) and political preferences (pol_{mt}) can be used to avoid possible endogeneity problems of wages and large entrants. This set of instruments is also used to estimate the optimal weighting matrix. A crucial difference from the nonparametric setup is that the moments used to identify the parameters in (18) are formed on the sum of i.i.d. shocks ($(1 + 1/\eta)\xi_{jt} + \epsilon_{jt}$) instead of ξ_{jt} (ACF estimator).⁴⁴

The parameters (β, h_H) are then jointly estimated using GMM by minimizing the

⁴³As a robustness check, we also expand $h(\cdot)$ using a fourth-order polynomial, and the results are similar.

⁴⁴The shocks ϵ_{jt} are defined as the sum of demand and production shocks, i.e., $\epsilon_{jt} \equiv -\frac{1}{\eta}v_{jt} + (1 + \frac{1}{\eta})u_{jt}^p$ (Section 3.1.1).

objective function.⁴⁵

$$\min_{\boldsymbol{\beta}, h_H} Q_N = \left[\frac{1}{N} W' \psi(\boldsymbol{\beta}, h_H) \right]' A \left[\frac{1}{N} W' \psi(\boldsymbol{\beta}, h_H) \right], \quad (19)$$

where A is the weighting matrix defined as $A = \left[\frac{1}{N} W' \psi(\boldsymbol{\beta}, h_H) \psi'(\boldsymbol{\beta}, h_H) W \right]^{-1}$ and W is the matrix of instruments, and $\psi_{jt}(\boldsymbol{\beta}, h_H) = \left[\left(1 + \frac{1}{\eta}\right) \xi_{jt} + \epsilon_{jt} \right]$. Estimation is done at the industry level while controlling for local conditions. Appendix B presents a detailed description of the parametric estimation procedure. The two-step approach moments might generate more precise estimates than the parametric approach because all variation from i.i.d. shocks ϵ_{jt} is taken out in the first step. We confirm this in the empirical part (Section 4.1).

3.2 Dynamic input control function

This subsection considers the case of recovering productivity from dynamic controls using investment or labor. Assuming labor is chosen before making investment decisions, stores' policy function of investment can be written as

$$i_{jt} = \tilde{i}_t(\omega_{jt}, l_{jt}, k_{jt}, q_{mt}, p_{jt}, e_{mt}^L, \mathbf{x}_{mt}). \quad (20)$$

This assumption is consistent with labor having dynamic implications and also solves the collinearity problems in the first step in OP discussed in Akerberg et al. (2006). We then need to rely only on stores with positive investment, which corresponds to a drop of 18 percent of the observations. Although wages are omitted from equation (20), it may be useful to include for identification (De Loecker and Warzynski, 2011). The estimation strategy is similar to the one in Section 3.1.1. First, we recover productivity for a given set of parameters $\omega_{jt}(\boldsymbol{\beta})$ but without estimating any parameter:

$$y_{jt} = \phi_t(l_{jt}, i_{jt}, k_{jt}, q_{mt}, e_{mt}^L, \mathbf{x}_{mt}) + \epsilon_{jt}, \quad (21)$$

where $\phi_t(\cdot) = \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{mt} - \frac{1}{\eta} \mathbf{x}'_{mt} \beta_x - \frac{1}{\eta} \beta_e e_{mt}^L + \left(1 + \frac{1}{\eta}\right) \omega_{jt}$ and $\epsilon_{jt} = -\frac{1}{\eta} v_{jt} + \left(1 + \frac{1}{\eta}\right) u_{jt}^p$. In the second step, we nonparametrically regress $\omega_{jt}(\boldsymbol{\beta})$ on a polynomial expansion of order three in $\omega_{jt-1}(\boldsymbol{\beta})$ and e_{mt-1}^L . If labor is fixed, current labor is used as instrument (ACF_i^{df}). If labor is variable, previous labor can be used instead

⁴⁵This simplex method (Nelder-Mead) converges quickly and is more robust to the starting values than quasi-Newton methods such as BFGS. Our parametric estimation procedure is written in R (<http://www.r-project.org>). The procedure is more computationally demanding than the two-step estimator (OP/ACF). In addition, controlling for selection increases computation time.

(ACF $_i^{dv}$). The other parameters β are identified using the moment conditions (13).

The general labor demand function (8) is consistent with labor having dynamic implications when l_{jt-1} is one of its arguments, i.e., labor is a dynamic input and part of the state space:

$$l_{jt} = \tilde{l}_t(\omega_{jt}, l_{jt-1}, k_{jt}, q_{mt}, p_{jt}, w_{jt}, e_{mt}^L, \mathbf{x}_{mt}). \quad (22)$$

We only observe a good measure of store-specific wages but no other good candidates for store-specific variables. When assuming that labor is a dynamic input, wage thus has to evolve as an exogenous state variable together with large entrants and demand shifters for the scalar unobservable assumption and the strict monotonicity condition to hold (Pakes, 1994). The presence of l_{jt-1} in the state space implies that estimation requires two lags in the data, i.e., we lose two years in the second stage in ACF. In rest, the identification and estimation strategy is identical to the one described in Section 3.1.1. When labor is a dynamic and variable (fixed) input, we can recover β_l using a moment condition based on l_{jt-1} (l_{jt}).

To invert productivity from a dynamic input such as i_{jt} or l_{jt} , the following conditions have to be satisfied. First, the demand functions $\tilde{l}_t(\cdot)$ and $\tilde{i}_t(\cdot)$ are strictly increasing in ω_{jt} . The functions $\tilde{l}_t(\cdot)$ and $\tilde{i}_t(\cdot)$ are solutions to the dynamic programming problem (1). That is, we need to model the evolution of additional state variables in stores' dynamic programming problem. The strict monotonicity of $\tilde{l}_t(\cdot)$ and $\tilde{i}_t(\cdot)$ in ω_{jt} holds if large entrants e_{mt}^L and \mathbf{x}_{mt} come from static and exogenous processes (Pakes, 1994; Maican, 2010b).⁴⁶ Another condition is that the store profit function is supermodular in ω_{jt} and e_{mt}^L . Second, we need the scalar unobservable assumption that ω_{jt} is the only unobservable in $\tilde{l}_t(\cdot)$ or $\tilde{i}_t(\cdot)$. Third, we need timing assumptions on inputs and large entry.

3.3 Additional identification and estimation issues

As the identification strategies discussed above involve a range of assumptions and a number of trade-offs, we now consider additional issues of importance for identification and estimation.

■ **Nonparametric one-step estimator.** Wooldridge (2009) and ACF (equation (27)) suggest a one-step estimator using GMM based on moment conditions $E[\epsilon_{jt}|\mathcal{F}_{jt}] = 0$ and $E[(1 + \frac{1}{\eta})\xi_{jt} + \epsilon_{jt}|\mathcal{F}_{jt-1}] = 0$. Even if this estimator is more efficient than the two-step estimator, it is very computationally demanding in our case due to a large number of

⁴⁶It is not restrictive to model local market demand shifters as exogenous processes. If the quality of labor is important, it is a strong assumption to model wages as an exogenous process. It is however not that strong for industries like retail food where education levels are low and training time is short. The dynamic assumption on labor is then motivated by hiring and firing costs.

parameters to be estimated.

■ **Correlated demand shocks.** In the case that v_{jt} captures persistent demand shocks, i.e., our initial i.i.d. assumption fails to hold, we have to make additional assumptions to ensure identification. Furthermore, when stores make exit decisions based on both ω_{jt} and v_{jt} , the scalar unobservable assumption does not hold. The actual demand shocks can be written as the sum of expected demand shocks given the store information set \mathcal{F}_{jt-1} , ($E[v_{jt}|\mathcal{F}_{jt-1}]$), and the i.i.d. shocks μ_{jt} that are not predictable by stores when they make input and exit decisions and are uncorrelated with demand shifters,

$$v_{jt} = E[v_{jt}|\mathcal{F}_{jt-1}] + \mu_{jt}. \quad (23)$$

Therefore, the value-added generating function becomes

$$\begin{aligned} y_{jt} = & \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{mt} - \frac{1}{\eta} \beta_e e_{mt}^L - \frac{1}{\eta} \mathbf{x}'_{mt} \boldsymbol{\beta}_x \\ & + \left(1 + \frac{1}{\eta}\right) E[\omega_{jt}|\mathcal{F}_{jt-1}] + \left(1 + \frac{1}{\eta}\right) \xi_{jt} - \frac{1}{\eta} E[v_{jt}|\mathcal{F}_{jt-1}] \\ & - \frac{1}{\eta} \mu_{jt} - \frac{1}{\eta} u_{jt}^d + \left(1 + \frac{1}{\eta}\right) u_{jt}^p. \end{aligned} \quad (24)$$

There is a trade-off between a flexible approximation of the ω_{jt} process and separation of remaining demand shocks v_{jt} from productivity.⁴⁷

First, if ω_{jt} and v_{jt} follow dependent Markov processes, then v_{jt-1} will enter as a separate variable in the conditional expectation $E[\omega_{jt}|\omega_{jt-1}, e_{mt-1}^L, v_{jt-1}]$. To solve the identification problem in (24), we need an estimate of v_{jt-1} . The Berry et al. (1995) (BLP) literature produces estimates of a set of “unobserved product characteristics” that might be used as v_{jt} , which we might interpret as unobserved store quality (Ackerberg et al., 2007 discuss this in detail). Yet in our case, it is impossible to back out v_{jt} using the BLP method because it requires more store-specific data such as prices and advertising.

Second, if ω_{jt} and v_{jt} follow independent Markov processes, then expected productivity at time t conditional on information set \mathcal{F}_{jt-1} does not depend on v_{jt-1} . However, in this case v_{jt} is an important determinant of optimal labor or investment, and thus affects actual productivity ω_{jt} . Since we have two unobservables (ω_{jt} and v_{jt}) and no other control variable for v_{jt} , identification in (24) requires an additional assumption that $\tilde{\omega}_{jt} \equiv (1 + \frac{1}{\eta})\omega_{jt} - \frac{1}{\eta}v_{jt}$. That is, quality-adjusted productivity $\tilde{\omega}_{jt}$ follows a first-order nonlinear Markov process: $\tilde{\omega}_{jt} = E[\tilde{\omega}_{jt}|\mathcal{F}_{jt-1}] + \tilde{\xi}_{jt} = \tilde{h}(\tilde{\omega}_{jt-1}, e_{mt-1}^L) + \tilde{\xi}_{jt}$, where $\tilde{h}(\cdot)$ is an approximation of the conditional expectation (Melitz, 2000; Levinsohn and Melitz, 2006). In other words, a positive shock in either productivity or demand makes stores

⁴⁷The alternative of not controlling for prices at all requires even stronger assumptions.

sell more, but the exact source of the shock does not matter. Appendix D discusses the identification when ω_{jt} and v_{jt} follow different $AR(1)$ processes (dynamic panel).

■ **Selection.** Stores decide to exit based on their productivity, and this creates a correlation between inputs and productivity that we have to account for. Selection can be essential in retail markets because large stores are more likely to survive larger shocks to productivity than are small stores. Even if stores have low productivity, there might be other reasons for stores to stay active such as expected changes in the market conditions, logistic support by the firm, and a good location. Stores' decisions to exit in period t depend directly on ω_{jt} , and therefore the decision is correlated with the productivity shock ξ_{jt} . If there are still unobserved demand shocks in productivity after controlling for price, controlling for selection eliminates the bias in the estimated input coefficients. The threshold productivity takes large entrants e_{mt}^L and local market characteristics \mathbf{x}_{mt} such as population, population density, and income into account. To estimate the value-added function while controlling for selection, we use predicted survival probabilities \mathcal{P}_{t-1} . Substituting the survival probabilities and the inverse labor demand function (10 or 16) into (18) yields the final value-added generating function that we estimate:

$$\begin{aligned}
y_{jt} = & \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{mt} - \frac{1}{\eta} \beta_e e_{mt}^L - \frac{1}{\eta} \mathbf{x}_{mt}' \beta_x \\
& + \left(1 + \frac{1}{\eta}\right) h(\mathcal{P}_{t-1}, \omega_{jt-1}, e_{mt-1}^L) + \left(1 + \frac{1}{\eta}\right) \xi_{jt} - \frac{1}{\eta} v_{jt} \\
& + \left(1 + \frac{1}{\eta}\right) u_{jt}^p.
\end{aligned} \tag{25}$$

Appendix C gives a detailed description of selection, and the results are briefly discussed in Section 4.3.

4 Results

The empirical results contain estimates of the value-added generating function and the impact of large entrants on store productivity and exit. Finally, we provide various specification and robustness tests.

4.1 Value-added generating function estimates

Table 5 shows estimates of the value-added generating function using OLS as well as different specifications of the nonparametric two-step estimator (ACF) and the parametric one-step estimator (EDJ). All semiparametric specifications use labor as a proxy for

productivity and include previous large entrants in the productivity process: ACF_l is the basic implementation of Akerberg et al. (2006) using labor demand as proxy; ACF_{lm} controls for prices using large entrants and local market characteristics (population, population density, and income) in ACF_l ; ACF_{lme} controls for endogeneity of large entry and wages in the first step in ACF_{lm} ; EDJ_{lm} is the implementation of Doraszelski and Jaumandreu (2011) that controls for prices and local market characteristics; and EDJ_{lme} controls for endogeneity of large entry and wages in EDJ_{lm} .

A major advantage of $ACF_{lm(e)}$ and $EDJ_{lm(e)}$ is that they control for unobserved prices, which otherwise might create a downward bias in the scale estimator (omitted price bias) (Klette and Griliches, 1996). Another advantage is that the correction for omitted prices also yields an estimate of market output, which makes it possible to compute the implied demand elasticity (η) and an average industry markup controlling for local market competition.

As theory suggests, the estimate of returns to scale ($\beta_l + \beta_k$) in the $ACF_{lm(e)}$ and $EDJ_{lm(e)}$ regressions is greater than in OLS (1.121) and ACF_l (1.005). It varies between 1.504 (ACF_{lme}) and 1.621 (EDJ_{lme}) in the specifications that control for price.⁴⁸ The minimum point estimate of labor is 0.671 (ACF_{lme}) and the maximum is 0.948 (OLS). By controlling for possible endogeneity of wages in the first step, the coefficient of labor decreases slightly, from 0.674 to 0.671 in $ACF_{lm(e)}$ and from 0.748 to 0.716 in $EDJ_{lm(e)}$. The minimum point estimate of capital is 0.162 (ACF_l) and the maximum is 0.307 (ACF_{lme}). We use a moment based on k_{jt-1} to identify capital in all specifications. If capital follows the standard assumption of being fixed and dynamic in ACF_l , the coefficient of capital is 0.120 and the one of labor is 0.894 (not reported). After controlling for local market competition, the capital coefficient increases, which is in the direction of controlling for selection bias.

The smallest estimate of the implied elasticity of demand is (in absolute terms) 2.256 (EDJ_{lme}), followed by 2.758 (EDJ_{lm}), 2.858 (ACF_{lm}), and 2.864 (ACF_{lme}). Thus, the implicit assumption $\eta = -\infty$, often used in empirical studies, does not hold. The markup, defined as price over marginal cost, ranges between 1.504 (ACF_{lme}) and 1.796 (EDJ_{lme}). Our estimates are consistent with previous findings based on retail data (Hall, 1988).

The coefficient of large entrants is positive and statistically significant, but small. The impact of a large entrant on residual demand, and hence prices, is on average about 2 percent in ACF_{lm} , just slightly lower when controlling for endogeneity of large entrants in ACF_{lme} , and about 6 percent in EDJ_{lm} .⁴⁹ The positive effect of large entrants might

⁴⁸If we do not control for unobserved demand shocks we expect the coefficients of labor and capital to be upward biased. The reason is the positive correlation between inputs and demand shocks.

⁴⁹Our results indicate acceptance of the null that political preferences are uncorrelated with the remaining demand shocks in the value-added generating function by regressing political preferences on the

be due to that our simple demand system, which is a consequence of data constraints, only allows us to estimate an average impact and does not consider any distributional effects. Large entrants may for example reduce prices in nearby stores. Our finding that large stores have a modest impact on prices is consistent with previous studies on the Swedish retail food market (Asplund and Friberg, 2002).

Apart from large entrants, prices can change through observed market characteristics in the remaining demand shocks (u_{jt}^d). Almost all demand shifters have the expected sign in all specifications. The coefficient of population is positive and statistically significant. Furthermore, the effect of demand shocks on price is smaller in more dense markets. The coefficient of population density is -0.145 in EDJ_{lm} and -0.114 in EDJ_{lme} . The corresponding coefficient is close to zero for the $ACF_{lm(e)}$ specifications. It is negative but not statistically significant in ACF_{lm} , but positive and significant in ACF_{lme} .

Importantly, the coefficient of population in EDJ_{lm} (0.251) and the one of large entrants in EDJ_{lme} (0.368) are both larger than using the ACF estimator. Since EDJ uses the sum of shocks in productivity, production, and demand to form moment conditions, it is not possible to sort out demand and production shocks from productivity similar to the first step in ACF, which might cause simultaneity bias in the demand shifter coefficients. Summarizing, our findings suggest the importance of controlling for simultaneity, omitted price bias, and unobserved demand shocks when estimating productivity in different local markets.

4.2 The impact of large entrants on productivity

The next step is to investigate whether large entrants influence the productivity of stores. Focusing on local markets, we evaluate whether large entrants have a greater impact on one part of the productivity distribution than another using productivity estimated by ACF and EDJ.

The paper recovers productivity from both labor demand and value-added generating functions. To have a measure that is comparable across different methods, productivity can be recovered from the value added generating function in both ACF and EDJ

$$\omega_{jt} = \frac{\eta}{1+\eta}[y_{jt} - (1 + \frac{1}{\eta})[\beta_l l_{jt} + \beta_k k_{jt}] + \frac{1}{\eta}q_{mt}] + \frac{1}{\eta}\beta_e e_{mt}^L + \frac{1}{\eta}\mathbf{x}'_{mt}\boldsymbol{\beta}_x. \quad (26)$$

This productivity measure contains i.i.d. demand and production shocks. To recover productivity without i.i.d. shocks, we use the inverse labor demand function that is given by

sum of remaining shocks.

equations (10) and (16) for ACF and EDJ, respectively.

Figure 1 presents histograms for productivity recovered from labor demand and value-added functions estimated by ACF_{lm} . The average productivities from both measures (output and proxy) are close, but there are distributional differences and, as expected, higher variance when using the value-added function. The ratio of interquartile range over median is about 0.07 and 0.09 for productivity recovered from labor demand and the value-added function, respectively.

Figure 2 shows kernel density estimates of productivity (estimated by EDJ_{lm}) in markets the year of, and the year after, large entry.⁵⁰ Except for the below 25th percentile, productivity is greater after large entry for all parts of the productivity distribution.

■ **Transitions in the productivity distribution.** To explore changes in productivity distributions in local markets, we classify incumbents into six percentile bins (p10, p10-25, p25-50, p50-75, p75-90, p90) each year, based on their productivity. Then we follow movements between percentile bins or exit over time.

High productive incumbents stay high productive in large-entry markets but decrease their productivity in non-entry markets (Table 6). Low productive incumbents in markets without large entry decrease their productivity or stay low productive without being forced to exit. The share of incumbents that stay in p10 is 5 percentage points higher in markets without large entry (Panel A). The total share of stores that exit is higher in markets with large entry than in markets without and the most pronounced differences are in the tails. Over 20 percent of the stores in p10 exit in entry markets but only 16 percent in non-entry markets. Regardless of large entry, more stores increase their productivity in the bottom part of the distribution (Panels A and B). Finally, entry markets have less movements between extreme percentiles. Only 2 percent move from p90 to p10 in markets with large entry and about 4 percent in markets without.

■ **Productivity process.** In our model, equation (7) gives a nonparametric estimate of the conditional expectation of productivity given previous productivity and number of large entrants, $\hat{h}(\omega_{jt-1}, e_{mt-1}^L)$, i.e., it states how large store entry influences store's future productivity. A central contribution of our model is that it considers local markets, in contrast to previous studies on structural estimation of production functions (Olley and Pakes, 1996; Akerberg et al., 2006; De Loecker, 2011; Doraszelski and Jaumandreu, 2011). Our focus is therefore on whether large entrants have a greater impact on one part of the local market productivity distribution than another. We focus on incumbent stores and exclude stores that enter or exit (see next subsection for exit).

Table 7 shows a simple linear specification estimated by OLS using productivity, large

⁵⁰We primarily focus on changes after large entry because several permanent reasons might explain differences between markets with and without large entrants.

entrants, and the interaction term between large entry and productivity.⁵¹ This specification might not be entirely consistent with our model but gives us basic information about how large entrants influence productivity. The results suggest that large entrants increase productivity, yet the impact decreases with the productivity of incumbents.

Table 8 shows the specification entirely consistent with our model, i.e., equation (7). We approximate $h(\omega_{jt-1}, e_{mt-1}^L)$ using a third-order polynomial expansion in its arguments. To emphasize local markets, we evaluate the marginal effects of large entrants for different productivity percentiles at the local market level (10th, 25th, 50th, 75th, and 90th). For expositional reasons, Table 8 presents means and standard deviations of the marginal effects of large entrants across all local markets for different percentiles. We show results, including the support, for ACF_l , $ACF_{lm(e)}$, and $EDJ_{lm(e)}$ backing out productivity from the value-added generating function.

The support is positive for all specifications that control for prices, i.e., the average impact is positive for all local market productivity percentiles. Large entrants thus result in within-store productivity improvements among incumbents. The marginal effect decreases when moving toward the upper parts of the productivity distribution, i.e., large entrants force low productive incumbents to improve their productivity more than high productive ones.⁵²

Without controlling for prices (ACF_l), the marginal effects of large entry are substantially smaller. In fact, the lower bound of the support and the average effects for above median percentiles are negative. The adjusted R^2 for the productivity process is, moreover, 2-3 times lower in ACF_l than in $ACF_{lm(e)}$ and $EDJ_{lm(e)}$. Not controlling for imperfect competition and for large entrants influencing prices separate from productivity leads to underestimation of the marginal effects of large entrants on productivity.

For high productive incumbents, the average marginal effect is similar for $ACF_{lm(e)}$ and EDJ_{lm} . In the 90th percentile, all are about 0.06-0.07. For low productive incumbents, the average marginal effect is larger for $ACF_{lm(e)}$ than for EDJ_{lm} . In the 10th percentile, it is 0.135 (0.132) compared to 0.095. For $ACF_{lm(e)}$, the productivity increase in a 10th percentile store is about two times that in a 90th percentile store. The corresponding increase in a 75th percentile store is about 50 percent larger than that in a 25th percentile store. For EDJ_{lm} , these differences in marginal effects across the distribution are smaller.

⁵¹Note that there is no endogeneity problem of large entrants because e_{mt-1}^L is uncorrelated with current innovation in productivity ξ_{jt} by our static entry process assumption (discussed in detail in Section 3).

⁵²Estimation results based only on small incumbents, i.e., excluding stores of the five largest store types in DELFI, show similar positive effects of large entrants on productivity. The results are available from the authors upon request.

If we do not control for large entrants' impact on prices separate from productivity, 10th percentile stores increase productivity as much as three times more than a 90th percentile store. A larger dispersion, based on averages across markets, is thus due to that part of the increase in productivity is a response in prices.

Controlling for endogeneity of large entrants in ACF_{lme} reduces the average marginal effect of large entrants. The magnitude of the drop is largest for high productivity incumbents, i.e., 10 percent in the 90th percentile but only 2 percent in the 10th. The marginal effects in EDJ_{lme} are substantially larger than for all other estimators.

■ **Exit** Over 20 percent and 13 percent of the stores in the two lowest percentile bins exit in entry markets, but only 16 percent and 11 percent in non-entry markets (Table 6). Large entrants thus result in more exit among low productive stores. While exit mainly occurs from the bottom part of the distribution, entrants are found across the whole distribution (not reported) as in previous findings in retail markets (Foster et al., 2006).

According to our model, stores decide whether to exit or continue in the beginning of period t based on their information set consisting of the previous or current state variables productivity, capital, large entrants, and demand shifters (Section 3). We control for demand shocks (u_{jt}^d) by observable demand shifters ($e_{mt}^L, \mathbf{x}_{mt}$) such that the remaining shocks to demand (v_{jt}) are i.i.d. We assume that these shocks are not predictable by stores when exit decisions are made. If stores can observe or predict the remaining demand shocks (v_{jt}) after we control for observable demand shifters, it is not possible to estimate the exit regression as below.

Table 9 shows regression results for the probability of exit. The first specification (columns 1 and 3) relies on the pure stopping rule and does not consider stores' position in the local market productivity distribution. In line with both theory and previous empirical studies (Olley and Pakes, 1996; Pavcnik, 2002), exit is less likely if productivity and the capital stock are high but more likely if the market size is large. The coefficient of large entry has the expected positive sign but is not significant at conventional significance levels.

The expanded specification (columns 2 and 4) includes interaction terms of large entrants with the six local market productivity dummies, using the middle group (p50-75) as reference. The coefficient of the interaction term is positive and jointly significant with the coefficient of large entry for p10 and p25 (ACF_{lm}), but negative for p90 (EDJ_{lm}). The probability to exit is about 0.02 (ACF_{lm}) higher after large entry for stores in the bottom part of the productivity distribution than for those in the middle. Correspondingly, the probability to exit is about 0.001 (EDJ_{lm}) lower for stores in the top part of the productivity distribution than for those in the middle.

■ **Decomposition of aggregate productivity growth.** Finally, we decompose aggregate productivity growth of all entrants, exits, and incumbents (due to data constraints we cannot measure the contribution of large entrants to aggregate productivity growth). We use three recent decompositions – the ones by Foster et al. (2001) (FHK), Griliches and Regev (1995) (GR), and Melitz and Polanec (2009) (MP), which is a dynamic version of the static decomposition by Olley and Pakes (1996). All decompositions are discussed in detail in Appendix E, along with results for MP.

Aggregate productivity growth was about 9 percent from 1997 to 2002 (Table 10). While overall industry growth is the same in all decompositions, the relative contributions of incumbents, entrants, and exits differ. In both GR and FHK, incumbent stores that increase their productivity at initial sales contribute about 8 percent and net entry 2-4 percent. Incumbent stores that increase productivity and market shares stand for 3.7 percent of the growth in FHK. The decomposition results confirm our findings based on large entrants, i.e., incumbents that increase their productivity and low productive stores that exit foster productivity growth in retail.

4.3 Specification tests and robustness

This section presents a number of different specifications and tests in order to evaluate how robust our findings are to the assumptions made. For the nonparametric case $ACF_{l(m(e))}$, we allow for a dynamic input control function, relax the timing assumption of labor, and consider a more general production function such as translog. For the parametric case $EDJ_{lm(e)}$, we test the assumption of static labor. Finally, we comment on results when controlling for selection.

■ **Dynamic input control.** Table 11 (columns 4 and 5) shows estimation results for ACF specifications using investment as a dynamic control for productivity. We present results assuming that labor is a dynamic (d) and fixed (f) or variable (v) input. The support of large entrants is presented for each specification.

First, the labor coefficient is 0.694 when l_{jt} is used to identify labor (ACF_i^{df}), and 0.761 when l_{jt-1} is used (ACF_i^{dv}). Second, the coefficient of capital increases when current labor is used as instrument (0.248 versus 0.219). Third, the support for the marginal effect of large entrants is [-0.025, 0.017] for ACF_i^{df} and [-0.023, 0.017] for ACF_i^{dv} . The support is thus not affected by the choice of moment condition for labor. Furthermore, the support is similar to when using labor as a static control function, i.e., ACF_l in Table 8. We conclude that our results are not sensitive to the control function used under perfect competition. The estimation results under imperfect competition are not reported

due to high values of the elasticity of substitution. This might be caused by the selection problem induced by investment as proxy for productivity, i.e., only stores with positive investment are used. Results using labor as a dynamic input control function are not reported due to that we lose two years of data in the second step in ACF.

■ **Relaxing the timing assumption on labor.** If there are hiring and firing costs of labor, we can use current labor (l_{jt}) as instrument when using a static nonparametric control function of labor. Table 11 (columns 2 and 3) shows the results under the assumption that labor is a static and fixed input ($ACF_{l(m)}^{sf}$). The results are directly comparable with those when labor is static and variable, i.e., $ACF_{l(m)}$ in Tables 5 and 8. Under perfect competition, the coefficient of labor decreases from 0.843 to 0.647 and the coefficient of capital increases from 0.162 to 0.240 (ACF_l^{sf} versus ACF_l in Table 5). This timing assumption gives similar support of the marginal effect of large entrants when productivity is recovered from the value-added function, i.e., [-0.041, 0.029] for ACF_l^{sf} and [-0.041, 0.036] for ACF_l in Table 8. Controlling for imperfect competition, the labor coefficient decreases to 0.634, capital to 0.215, and demand elasticity increases to -1.77 (ACF_{lm}^{sf} versus ACF_{lm} in Table 5). The support for large entrants is [0.371, 0.663], which is larger than using a moment based on l_{jt-1} to identify the labor coefficient.

■ **Test of static labor.** In the parametric specification EDJ_{lm} , we test the validity of our assumption that labor is static. If the inverse labor demand function is misspecified, the labor coefficient in the value-added generating function differs from the one in the inverse labor demand function. We estimate the restricted and unrestricted models. Then we compute the GMM distance statistic, $D_N = N * [Q_N(\beta_{restricted}) - Q_N(\beta_{unrestricted})]$, to test the null of equal labor coefficients. Note that we could estimate only the unrestricted model and test the equality of the labor coefficients directly by a Wald test. The two statistics are however asymptotically equivalent under the null hypothesis (Newey and West, 1987). The null of equal coefficients is accepted for EDJ_{lm} , i.e., our assumption of static labor is valid.

■ **Alternative production technology.** Recovering productivity from a parametric labor demand function requires Cobb-Douglas technology for the value-added generating function ($EDJ_{lm(e)}$ in Section 3.1.2). However our two-step estimator based on the nonparametric labor demand function does not require the Cobb-Douglas assumption ($ACF_{lm(e)}$ in Section 3.1.1). Therefore, we also estimate the impact of large entrants on productivity using a translog production function and the ACF_{lm} estimator (De Loecker and Warzynski, 2011). Instead of the Cobb-Douglas production function in equation (2), we use the translog function

$$q_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{lk} l_{jt} k_{jt} + \omega_{jt} + u_{jt}^p, \quad (27)$$

which requires three additional parameters to be estimated. Those are the ones on labor squared (β_{ll}), capital squared (β_{kk}), and the interaction between labor and capital (β_{lk}). The results, not reported but available from the authors upon request, are consistent with our previous findings. Large entrants have a greater impact on low productive incumbents than on high productive ones. An additional large entrant increases productivity by about 4 percent for a 10th percentile productivity store, by about 2 percent for a median store, and by about 0.1 percent for 90th percentile store.

■ **Selection.** We also control for selection in the ACF and EDJ specifications. Theory and empirical investigations predict lower labor and higher capital coefficients after controlling for selection (Akerberg et al., 2007).⁵³ Controlling for imperfect competition, we find that selection has a small impact on the estimated coefficients using moments based on ξ_{jt} (productivity shocks), i.e., the ACF estimator. Being somewhat more sensitive to the specification used, selection affects, e.g., the demand elasticity in the parametric estimator (EDJ) that uses moments based on $\left[\left(1 + \frac{1}{\eta}\right) \xi_{jt} + \epsilon_{jt}\right]$ (sum of all shocks).⁵⁴

5 Conclusions

The present study gives new insights into competition and productivity differences among retail stores. Net entry is found to foster almost all labor productivity growth in the U.S. retail sector (Foster et al., 2006). However, multi-factor productivity in retail markets has rarely been studied, contrary to manufacturing. We provide a first attempt to use recent advances in structural estimation of production functions to estimate productivity in retail markets and to investigate how entry of large (“big-box”) stores influences stores’ efficiency shocks and demand shocks. On both sides of the Atlantic, the pros and cons of the big-box format have been widely debated (the Wal-Mart effect). Based on recent extensions of the Olley and Pakes’ (1996) framework, we provide a model that takes key features of retail markets into account. Apart from large entrants, we emphasize the importance of local markets, imperfect competition, lumpy investments, and limited access to quantity data on products purchased and sold by each store.

We analyze whether large entrants force low productive stores out of the market and increase productivity among surviving stores with different positions in the productivity distribution. We use political preferences in local markets to control for endogeneity of large entrants. Our empirical application relies on detailed data on all retail food stores

⁵³Since stores with large capital stock might survive even if they have low productivity, we expect selection to induce a negative correlation between capital and the disturbance term in the selected sample.

⁵⁴The unreported results are available from the authors upon request.

in Sweden, a sector that is representative to many European markets in terms of market structure and regulation.

The results show that when estimating retail productivity, it is central to control for imperfect competition and to allow for a general productivity process. We recognize that large entrants drive reallocation of resources toward more productive stores. After large entry, low productive stores are more likely to exit. In addition, large entrants increase future productivity of incumbent stores. The magnitude of the effect varies however with an incumbent's position in the productivity distribution. The productivity increase declines when moving toward the upper part of the distribution, implying that productivity increases relatively more among low productive incumbents than among high productive ones. Controlling for prices reduces the increase in productivity following large entry for all parts of the productivity distribution. In addition, the impact on productivity becomes slightly smaller when controlling for endogeneity of large entry. Industry productivity growth was about 9 percent from 1997 to 2002 in the Swedish retail food market. We conclude that entry of big-box stores spurs reallocation of resources toward more productive stores, and thus works as a catalyst for retail productivity growth.

Our findings contribute with knowledge to competition policy since entry regulation issues are a great concern to policy makers in Europe, where such regulations are generally much more restrictive than in the U.S. As an example, the European Parliament recently highlighted an investigation of supermarket dominance (European Parliament, 2008). We argue that a more restrictive design and application of entry regulations can hinder reallocation toward more productive units and thus hinder aggregate productivity growth. Besides productivity, entry regulations compound a wide range of other aspects. How to balance potential productivity growth against increased traffic and broader environmental issues is an interesting topic for future research. It would also be interesting to apply our extended Olley and Pakes (1996) framework to other service markets such as banking and health care services. Future work would also benefit from using fully dynamic models (Aguirregabiria et al., 2007; Beresteanu et al., 2010; Dunne et al., 2011; Holmes, 2011) that more carefully consider the importance of sunk costs, chain effects, and market adjustments.

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Table 1: Characteristics of the Swedish Retail Food Market

A. DELFI						
Year	No. of stores	Large stores	Large entry	Mean sales space (m^2)	Total sales space (m^2)	Total sales
1996	4,664	905	21	538	2,510,028	129,326,000
1997	4,518	925	8	550	2,483,248	126,732,397
1998	4,351	926	9	587	2,552,794	130,109,604
1999	4,196	936	18	604	2,514,367	133,156,023
2000	3,994	948	23	654	2,587,952	138,314,044
2001	3,656	942	28	689	2,471,510	139,352,920
2002	3,585	932	5	718	2,525,084	142,532,944
B. FS-RAMS						
Year	No. of "multi-stores"	No. of employees	Total wages	Value added	Total sales	
1996	3,714	74,100	9,882,234	18,319,407	141,743,876	
1997	3,592	73,636	10,322,136	18,838,130	142,840,611	
1998	3,482	74,696	10,766,043	19,185,120	147,726,647	
1999	3,398	74,758	11,110,785	19,570,472	152,160,949	
2000	3,287	77,180	11,536,063	20,389,492	154,106,865	
2001	3,094	76,905	11,522,482	20,748,902	158,512,132	
2002	3,067	80,931	12,081,931	22,473,696	179,335,162	

NOTE: DELFI is provided by Delfi Marknadspartner AB and contains all retail food stores based on their geographical location (address). FS-RAMS is provided by Statistics Sweden and consists of all organization numbers in SNI code 52.1, i.e., "multi-store" units that contain one store or several (e.g., due to the same owner). Sales (incl. 12% VAT), value-added, and wages are measured in thousands of 1996 SEK (1USD=6.71SEK, 1EUR=8.63 SEK). Sales in DELFI are collected by surveys and reported in classes, while sales are based on tax reporting in FS-RAMS. Therefore, total sales are lower in DELFI than in FS-RAMS. From 1996 to 2002, the total population in Sweden increased from 8,844,499 to 8,940,788.

Table 2: Distribution of stores and firms across local markets and years

	No. of stores					Total no. of stores	No. of firms	Share of pop with nearest store < 2km
	ICA	Axfood	COOP	Bergendahls	Others			
Minimum	0	0	0	0	0	3	1	0.45
10th percentile	2	0	1	0	2	7	2	0.59
25th percentile	3	1	1	0	3	9	3	0.66
50th percentile	5	2	2	0	5	15	3	0.75
75th percentile	9	4	5	0	8	25	3	0.82
90th percentile	15	8	8	1	16	44	3	0.91
Maximum	86	93	88	12	218	460	4	1.00
Mean	7.25	3.66	3.91	0.22	8.25	23.29	2.86	0.74
Std. deviation	7.74	6.76	5.81	0.89	16.87	35.34	0.55	0.12

NOTE: This table shows the distribution of the number of stores and firms across local markets as well as the share of population with less than 2 kilometers to the nearest store. ICA, Axfood, COOP and Bergendahls are defined as firms. Municipalities, considered as local markets, increase from 288 to 290 due to three municipality break-ups during the period, which gives a total of 2,021 market-year observations. Distance to the nearest store is calculated based on 800x800 meter grids and is only available for 2002 (290 observations).

Table 3: Distribution of store characteristics by firm

	ICA		Axfood		COOP		Bergdahl's	
	Space (m^2)	Sales	Space (m^2)	Sales	Space (m^2)	Sales	Space (m^2)	Sales
Minimum	20	250	15	250	14	750	70	1,500
10th percentile	90	3,500	90	3,500	120	7,000	130	5,500
25th percentile	150	7,000	149	5,500	228	12,500	210	9,000
50th percentile	316	17,500	350	17,500	400	17,500	448	17,500
75th percentile	650	35,000	875	45,000	710	35,000	1,750	67,500
90th percentile	1,150	67,500	1,500	87,500	1,410	67,500	2,800	140,000
Maximum	10,000	510,000	11,400	470,000	7,700	580,000	13,000	700,000
Mean	540	31,442	622	33,751	620	33,239	1,297	54,126
Std. deviation	673	47,025	761	45,056	673	44,657	1,944	93,069
No. of obs.	14,649		7,403		7,905		450	

NOTE: This table shows the distribution of number of square meters and sales of stores that belong to different firms during the period 1996-2002. Sales (incl. 12% VAT) is measured in thousands of 1996 SEK.

Table 4: Medians of local market characteristics

Year	1997	1998	1999	2000	2001	2002
A. Markets with large entrants						
No. of stores	37.00	54.00	29.00	32.00	33.00	22.00
No. of all entrants	2.00	2.00	3.00	2.00	1.00	2.00
No. of all exits	3.00	2.00	2.00	3.00	1.00	--
Population	57,441.00	60,429.00	37,195.00	48,250.00	58,361.00	22,907.00
Population density	80.88	57,92.00	68.03	79.38	77.29	52.77
Per capita income	149.10	157.60	161.60	170.30	179.10	177.60
Store concentration (C_4)	0.53	0.49	0.62	0.60	0.53	0.70
Total no. of markets	10	9	20	20	23	6
B. Markets without large entrants						
No. of stores	15.00	15.00	15.00	14.00	13.00	14.00
No. of all entrants	0.00	0.00	1.00	0.00	0.00	0.00
No. of all exits	0.00	1.00	1.00	1.00	0.00	--
Population	14,827.00	15,133.00	14,322.00	14,154.00	14,068.00	15,207.00
Population density	25.80	25.78	25.22	25.60	24.75	26.20
Per capita income	143.30	149.10	155.90	162.50	168.40	175.90
Store concentration (C_4)	0.71	0.71	0.72	0.73	0.75	0.76
Total no. of markets	278	279	269	269	266	284

NOTE: 1996 is left out because entrants are not observed. Municipalities, considered as local markets, increase from 288 to 290 due to three municipality break-ups during the period. Stores, entrants and exits come from DELFI. Population density is defined as total population per square kilometer in the municipality. Concentration (C_4) shows the market share captured by the top four stores.

Table 5: Value-added generating function estimates

	OLS	Nonparametric			Parametric	
		ACF_l	ACF_{lm}	ACF_{lme}	EDJ_{lm}	EDJ_{lme}
Log no. of labor	0.948 (0.006)	0.843 (0.006)	0.674 (0.005)	0.671 (0.005)	0.748 (0.001)	0.716 (0.001)
Log of capital	0.167 (0.004)	0.162 (0.004)	0.304 (0.004)	0.307 (0.003)	0.233 (0.001)	0.187 (0.001)
Market output $\left(-\frac{1}{\eta}\right)$			0.350 (0.013)	0.349 (0.013)	0.362 (0.001)	0.443 (0.001)
Number of large entrants			0.022 (0.002)	0.018 (0.002)	0.064 (0.001)	0.368 (0.001)
Log of population			0.018 (0.003)	0.016 (0.003)	0.251 (0.001)	0.056 (0.001)
Log of population density			-0.003 (0.004)	0.016 (0.005)	-0.145 (0.001)	-0.114 (0.001)
Scale $(\beta_l + \beta_k)$	1.121	1.005	1.505	1.504	1.540	1.621
Demand elasticity (η)			-2.858	-2.864	-2.758	-2.256
Markup $\left(\frac{\eta}{1+\eta}\right)$			1.530	1.504	1.568	1.796
Sargan (p-value)					0.000	0.000
No. of obs.	23,521	17,747	17,747	17,747	17,747	17,747

NOTE: The dependent variable is log of deflated value added. Labor is measured as number of full-time adjusted employees. All regressions include year dummies. In all specifications that control for imperfect competition, reported parameters include elasticity, i.e., $(1 + \frac{1}{\eta})\beta_l$ for labor, $(1 + \frac{1}{\eta})\beta_k$ for capital, $-\frac{1}{\eta}\beta_x$ for exogenous demand shifters, and $-\frac{1}{\eta}\beta_e$ for large entry (see equations (6) and (18)). *OLS* is ordinary least square regression. All *ACF* and *EDJ* specifications include previous large entrants in the productivity process. *ACF_l* is Akerberg, Caves, and Fraser's (2006) two-step estimation method using labor as proxy for productivity; *ACF_{lm}* is two-step estimation using a nonparametric labor demand function as proxy for productivity and controlling for imperfect competition, but wages and large entrants are exogenous; *ACF_{lme}* is two-step estimation using a nonparametric labor demand function and controlling for imperfect competition and endogeneity of wages and large entrants (Section 3.1.1); *EDJ_{lm}* is one-step estimation using a parametric labor demand function and controlling for imperfect competition. *EDJ_{lme}* is one-step estimation using a parametric labor demand function and controlling for imperfect competition and endogeneity of wages and large entrants (Section 3.1.2). Reported standard errors (in parentheses) are robust to heteroscedasticity. All *ACF* and *EDJ* specifications use previous capital stock and labor as instruments. *ACF_{lme}* and *EDJ_{lme}* use the share of non-socialist seats in the local government as instrument for current large entry. In *ACF*, standard errors are computed using Akerberg et al. (2011). In *EDJ*, two-step GMM is used for estimation. Market output is measured as the market share weighted output in the municipality. Mark-up is defined as price over marginal cost.

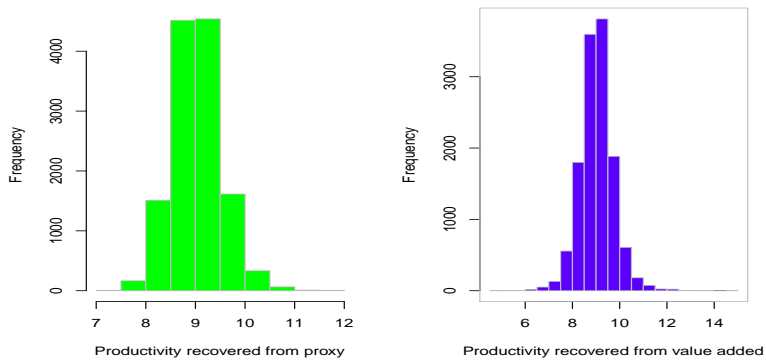


Figure 1: Histogram of estimated productivity from ACF_{lm} using labor demand and value-added functions.

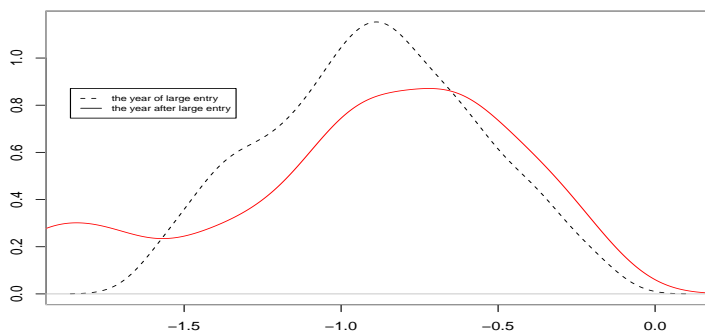


Figure 2: Productivity kernel density estimates, incumbent stores in markets the year of, and the year after, large entry

Table 6: Transition matrix from t-1 (column) to t (row) in percentage

Percentile	<p10	p10-p25	p25-p50	p50-p75	p75-p90	>p90
Panel A. Productivity from ACF_{lm}						
Markets with large entrants in t-1						
<p10	22.09	12.14	8.75	5.65	3.83	2.50
p10-p25	22.09	26.43	10.83	9.68	7.10	5.83
p25-p50	18.60	22.86	34.58	26.21	13.11	4.17
p50-p75	6.98	15.71	24.58	29.84	30.60	7.50
p75-p90	5.81	7.14	7.08	13.71	20.22	23.33
>p90	3.49	2.14	2.92	3.63	12.02	30.00
Exit	20.93	13.57	11.25	11.29	13.11	26.67
Markets without large entrants in t-1						
<p10	27.29	14.91	8.16	3.93	3.93	4.31
p10-p25	22.66	24.02	15.33	8.25	8.25	3.56
p25-p50	18.23	30.61	32.24	22.39	22.39	6.26
p50-p75	8.68	11.51	22.46	32.21	32.21	13.59
p75-p90	3.09	4.70	8.07	15.50	23.98	23.30
>p90	3.76	2.97	3.76	7.68	17.19	27.29
Exit	16.30	11.29	9.99	10.04	11.16	21.68
Panel B. Productivity from EDJ_{lm}						
Markets with large entrants in t-1						
<p10	15.83	9.87	7.50	4.55	4.51	2.22
p10-p25	18.33	21.05	13.57	6.20	9.02	2.22
p25-p50	24.17	23.68	27.14	19.83	17.29	7.78
p50-p75	10.83	21.05	29.29	28.51	18.80	7.78
p75-p90	7.50	5.92	11.43	20.25	23.31	18.89
>p90	3.33	5.26	1.43	6.61	13.53	33.33
Exit	20.00	13.16	9.64	14.05	13.53	27.78
Markets without large entrants in t-1						
<p10	18.43	15.59	10.53	7.04	5.85	5.78
p10-p25	20.49	15.88	16.49	12.45	9.21	5.88
p25-p50	23.24	27.72	25.94	22.00	18.27	10.24
p50-p75	13.04	18.38	21.37	25.91	23.32	14.71
p75-p90	4.71	6.62	9.57	15.31	19.52	18.86
>p90	3.73	3.90	5.05	8.32	13.45	23.33
Exit	16.37	11.91	11.05	8.97	10.38	21.20

NOTE: Productivity is estimated using the ACF_{lm} and EDJ_{lm} described in Section 3. Productivity is backed out from the value-added generating function. Municipalities are considered as local markets. Large entrants in period t-1 are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores).

Table 7: Linear productivity process: Impact of large entrants on future productivity

	Nonparametric			Parametric	
	ACF_l	ACF_{lm}	ACF_{lme}	EDJ_{lm}	EDJ_{lme}
Productivity _{t-1}	0.486 (0.012)	0.541 (0.008)	0.555 (0.008)	0.542 (0.011)	0.568 (0.010)
Productivity _{t-1} * Large entrants _{t-1}	-0.057 (0.024)	-0.068 (0.018)	-0.068 (0.017)	-0.065 (0.024)	-0.049 (0.024)
Large entrants _{t-1}	0.250 (0.115)	0.596 (0.158)	0.816 (0.216)	0.024 (0.014)	-0.055 (0.029)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.996	0.986	0.998	0.729	0.914
No. of obs.	12,540	12,540	12,540	12,540	12,540

NOTE: ACF_l is Akerberg, Caves and Frazier's (2006) two-step approach controlling for imperfect competition, where wages and large entrants are exogenous. ACF_{lm} is Akerberg, Caves and Frazier's (2006) two-step approach controlling for imperfect competition, where wages and large entrants are exogenous. ACF_{lme} uses previous wages and political preferences to control for endogeneity of wages and large entrants in the first step in ACF_{lm} . This table presents OLS regressions using productivity recovered from the value-added generating function: $\omega_{jt} = (\eta/(1 + \eta)) [y_{jt} - (1 + 1/\eta)[\beta_l l_{jt} + \beta_k k_{jt}] + (1/\eta)q_{mt} + (1/\eta)\mathbf{x}'_{mt}\boldsymbol{\beta}_x + (1/\eta)\beta_e e_{mt}^L]$. Standard errors reported in parentheses. Large entrants in period $t - 1$ are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). We use six percentile bins for productivity in each market and year, with p50-75 used as reference group.

Table 8: Nonlinear productivity process: Summary statistics of marginal effects of large entrants on future productivity

	ACF_t		ACF_{Im}		ACF_{Ime}		EDJ_{Im}		EDJ_{Ime}	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
10th percentile productivity $_{t-1}$	0.010	0.015	0.135	0.034	0.132	0.037	0.095	0.019	0.391	0.017
25th percentile productivity $_{t-1}$	0.003	0.013	0.122	0.033	0.119	0.036	0.089	0.017	0.396	0.013
50th percentile productivity $_{t-1}$	-0.005	0.012	0.104	0.034	0.101	0.038	0.083	0.016	0.401	0.010
75th percentile productivity $_{t-1}$	-0.013	0.012	0.085	0.036	0.080	0.041	0.076	0.015	0.404	0.004
90th percentile productivity $_{t-1}$	-0.020	0.014	0.070	0.040	0.063	0.045	0.071	0.015	0.406	0.007
Support	[-0.041, 0.036]		[0.018, 0.180]		[0.003, 0.177]		[0.053, 0.130]		[0.357, 0.412]	
Adjusted R^2	0.130		0.279		0.314		0.311		0.219	
No. of obs.	7,467		7,467		7,467		7,457		7,457	

NOTE: Marginal effects are computed using percentile of previous productivity in each market and year. ACF_t is Akerberg, Caves, and Frazier's (2006) two-step approach using labor demand as a proxy for productivity. ACF_{Im} is Akerberg, Caves, and Frazier's (2006) two-step approach controlling for imperfect competition, where wages and large entrants are exogenous. ACF_{Ime} uses previous wages and political preferences to control for endogeneity of wages and large entrants in the first step in ACF_{Im} . EDJ_{Im} is one-step estimation using a parametric labor demand function and controlling for imperfect competition (Section 3.1.2). EDJ_{Ime} is one-step estimation using a parametric labor demand function and controlling for imperfect competition and endogeneity of wages and large entrants. Productivity is recovered from the value-added generating function: $\omega_{jt} = (\eta/(1+\eta)) [\eta y_{jt} - (1+1/\eta) \beta_l l_{jt} + \beta_k k_{jt}] + (1/\eta) q_{mt} + (1/\eta) \beta_x e_{mt}$. Large entrants in period $t-1$ are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores).

Table 9: Regression results: Exit

	Nonparametric (ACF_{lm})		Parametric (EDJ_{lm})	
	(1)	(2)	(3)	(4)
Log of productivity _t	-0.124 (0.027)		-0.182 (0.042)	
Large entrants _{t-1}	0.043 (0.043)	-0.115 (0.092)	0.026 (0.042)	-0.068 (0.069)
p10*Large entrants _{t-1}		0.336 (0.132)		0.136 (0.122)
p10-p25*Large entrants _{t-1}		0.263 (0.131)		0.104 (0.121)
p25-p50*Large entrants _{t-1}		0.193 (0.118)		-0.123 (0.113)
p75-p90*Large entrants _{t-1}		0.080 (0.143)		-0.214 (0.141)
p90*Large entrants _{t-1}		0.189 (0.145)		-0.319 (0.150)
Log of capital _t	-0.090 (0.014)	-0.082 (0.013)	-0.083 (0.013)	-0.079 (0.013)
Log of population _t	0.054 (0.023)	0.066 (0.022)	0.033 (0.025)	0.078 (0.023)
Log of population density _t	-0.004 (0.017)	0.001 (0.017)	0.005 (0.016)	-0.012 (0.015)
Log of income _t	-0.054 (0.224)	-0.196 (0.221)		
Year dummies	Yes	Yes	Yes	Yes
No. of obs.	11,132	11,132	7,376	7,376

NOTE: This table shows probit regressions on exit. Productivity is estimated using the ACF_{lm} and EDJ_{lm} methods described in Section 3. Reported standard errors (in parentheses) are robust to heteroscedasticity. Large entrants in period t-1 are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). We use six percentile bins for productivity in each local market and year, with p50-75 used as reference group.

Table 10: Decomposition of retail food productivity growth, 1997 to 2002

Overall industry growth	Percentage of growth from					Net entry (4) - (5)
	Within stores (1)	Between stores (2)	Cross stores (3)	Entry (4)	Exit (5)	
A. Baily et al. (1992) / Foster et al. (2001)						
0.088	0.079	-0.029	0.037	0.065	0.063	0.002
B. Griliches and Regev (1995)						
0.088	0.097	-0.013		0.043	0.038	0.004

NOTE: Appendix E describes the decompositions in detail. This decomposition uses Equation (33) in Appendix E. Productivity is estimated using the semi-parametric estimation (ACF_{lm}) described in Section 3. Shares of local market sales are used as weights.

Table 11: Two-step estimation results using different timing assumptions for inputs and proxies

	OLS	Static control: labor		Dynamic control: investment	
		ACF_l^{sJ}	ACF_{lm}^{sJ}	ACF_i^{dJ}	ACF_i^{dv}
Log no. of labor	0.948 (0.006)	0.647 (0.002)	0.634 (0.001)	0.694 (0.001)	0.761 (0.003)
Log of capital	0.167 (0.004)	0.240 (0.001)	0.215 (0.001)	0.248 (0.001)	0.219 (0.002)
Market output $\left(-\frac{1}{\eta}\right)$			0.564 (0.012)		
Number of large entrants			0.049 (0.001)		
Log of population			-0.030 (0.002)		
Log of population density			0.015 (0.003)		
Scale ($\beta_l + \beta_k$)	1.121	0.887	1.951	0.942	0.980
Demand elasticity (η)			-1.771		
Markup $\left(\frac{\eta}{1+\eta}\right)$			2.295		
Support large entrants (output)		[-0.041, 0.028]	[0.371, 0.663]	[-0.025, 0.017]	[-0.023, 0.017]
No. of obs.	23,521	17,747	17,747	17,747	17,747

NOTE: The dependent variable is log of deflated value added. Labor is measured as number of full-time adjusted employees. All regressions include year dummies. For ACF_{lm}^{sJ} reported parameters include elasticity, i.e., $(1 + \frac{1}{\eta})\beta_l$ for labor, $(1 + \frac{1}{\eta})\beta_k$ for capital, $-\frac{1}{\eta}\beta_x$ for exogenous demand shifters, and $-\frac{1}{\eta}\beta_e$ for large entry (see equations (6) and (18)). *OLS* is ordinary least square regression. ACF_l^{sJ} is Akerberg, Caves, and Fraser's (2006) two-step estimation method using labor as proxy for productivity, and labor is static and fixed. ACF_{lm}^{sJ} is two-step estimation using a nonparametric labor demand function as proxy for productivity, labor is static and fixed, and controlling for imperfect competition but wages and large entrants are exogenous. ACF_i^{dJ} is Akerberg, Caves, and Fraser's (2006) two-step estimation method using investment as proxy for productivity and labor is dynamic and fixed. ACF_i^{dv} is Akerberg, Caves, and Fraser's (2006) two-step estimation method using investment as proxy for productivity, and labor is dynamic and variable. Standard errors in parentheses. In *ACF*, standard errors are computed using Akerberg et al. (2011). Market output is measured as the market share weighted output in the municipality. Markup is defined as price over marginal cost.

Appendix A: PBA and data sources

■ **Entry regulation (PBA).** On July 1, 1987, a new regulation was imposed in Sweden, the Plan and Building Act (PBA). Compared to the previous legislation, the decision process was decentralized, giving local governments power over entry in their municipality and citizens a right to appeal the decisions. Since 1987, only minor changes have been implemented in PBA. From April 1, 1992 to December 31, 1996, the regulation was slightly different, making explicit that the use of buildings should not counteract efficient competition. Since 1997, PBA has been more or less the same as prior to 1992. Long time lags in the planning process make it impossible to directly evaluate the impact of decisions. In practice, differences because of the policy change seem small (Swedish Competition Authority 2001:4). Nevertheless, PBA is claimed to be one of the major entry barriers, resulting in different outcomes, e.g., price levels, across municipalities (Swedish Competition Authority 2001:4, Swedish Competition Authority 2004:2). Municipalities might then be able to put pressure on prices through the regulation. Those that constrain entry have less sales per capita, while those where large and discount stores have a higher market share also have lower prices.

■ **The DELFI data.** DELFI Marknadspartner AB collects daily data on retail food stores from a variety of channels: (1) public registers, the trade press, and daily press; (2) the Swedish retailers association (SSLF); (3) Kuponginlösen AB (which deals with rebate coupons collected by local stores); (4) the chains' headquarters; (5) matching customer registers from suppliers; (6) telephone interviews; (7) yearly surveys; and (8) the Swedish Retail Institute (HUI). Location, store type, owner, and chain affiliation are double-checked in corporate annual reports.

Each store has an identification number linked to its geographical location (address). The twelve store types, based on size, location, product assortment, etc., are hypermarkets, department stores, large supermarkets, large grocery stores, other stores, small supermarkets, small grocery stores, convenience stores, gas-station stores, mini markets, seasonal stores, and stores under construction.

Sales and sales space are collected via yearly surveys. Revenues (including VAT) are recorded in 19 classes. Due to the survey collection, a number of missing values are substituted with the median of other stores of the same type in the same local market. In total, 702 stores have missing sales: 508 in 1996, and 194 in later years. For sales space, all 5,013 values are missing for 1996, and are therefore replaced with the mean of each store's 1995 and 1997 values. In addition, 2,810 missing sales space values for later years are replaced similarly. In total, 698 observations are missing both sales and sales space.

■ **The FS-RAMS data.** FS-RAMS contains all registered organization numbers in the

different Swedish industries from 1996 to 2002. *Value added* is defined as total shipments, adjusted for inventory changes, minus costs of materials. *Labor* is the total number of employees. We deflated sales, value added, wages, and investment by the consumer price index (CPI) from IMF-CDROM 2005.

Capital is constructed using a perpetual inventory method, $K_{t+1} = (1-\delta)K_t + \exp(i_t)$. Since the data distinguishes between buildings and equipment, all calculations of the capital stock are done separately for buildings and equipment. In the paper, we include equipment in the capital stock. Including both equipment and buildings in the capital stock does not change the results, however. As suggested by Hulten and Wykoff (1981), buildings are depreciated at a rate of 0.0361, and equipment at 0.1179. In order to construct capital series using the perpetual inventory method, an initial capital stock is needed. We set initial capital stock to its first occurrence in FS-RAMS, defining entry as the first year in FS (some of the stores have been in FS since 1973).

Table A.1: The relation between large entrants and political preferences

	(1)	(2)	(3)	(4)
Local political preferences	0.272	0.251	0.508	0.586
	(0.054)	(0.051)	(0.223)	(0.315)
Log of population				0.169
				(0.668)
Log of population density				0.176
				(0.497)
Log of income				-0.033
				(0.148)
Year dummies	No	Yes	No	No
Market dummies	No	No	Yes	Yes
Root of mean squared errors	0.319	0.317	0.270	0.271
Number of observations	1,848	1,848	1,848	1,848

NOTE: The dependent variable is the number of large entrants. OLS estimator is used. Robust standard errors to heteroscedasticity are in parentheses.

Appendix B: Estimation strategy in the parametric case

The semi-parametric regression (25) is estimated using the sieve minimum distance (SMD) procedure proposed in Newey and Powell (2003) and Ai and Chen (2003) for i.i.d. data.⁵⁵ The goal is to obtain an estimable expression for the unknown parameter of interest, $\alpha = (\beta, h)'$. We denote the true value of the parameters with the subscript a ,

⁵⁵Chen and Ludvigson (2007) show that the SMD procedure and its large sample properties can be extended to stationary ergodic time series data.

so that $\alpha_a = (\beta_a, h_a)'$. The moment conditions could then be written more compactly as

$$E[\psi_{jt}(\mathbf{X}_{jt}, \beta_a, h_a) | \mathcal{F}_t^*] = 0 \quad j = 1, \dots, N \quad t = 1, \dots, T \quad (28)$$

where N is the total number of stores, \mathcal{F}_t^* is the information set at time t , and $\psi_{jt}(\cdot)$ is defined as

$$\begin{aligned} \psi_{jt}(\mathbf{X}_{jt}, \beta_a, h_a) &\equiv \left[\left(1 + \frac{1}{\eta}\right) \xi_{jt} - \frac{1}{\eta} v_{jt} + \left(1 + \frac{1}{\eta}\right) u_{jt}^p \right] \\ &= y_{jt} - \left(1 + \frac{1}{\eta}\right) [\beta_0 + \beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{mt} - \frac{1}{\eta} \beta_e e_{mt}^L \\ &\quad - \frac{1}{\eta} \mathbf{x}'_{mt} \beta_x - h(\omega_{jt-1}, e_{mt-1}^L). \end{aligned}$$

Let \mathcal{F}_t be an observable subset of \mathcal{F}_t^* . Then equation (28) implies

$$E[\psi_{jt}(\mathbf{X}_{jt}, \beta_a, h_a) | \mathcal{F}_t] = 0 \quad j = 1, \dots, N \quad t = 1, \dots, T. \quad (29)$$

If the information set \mathcal{F}_t is informative enough, such that $E[\psi_{jt}(\mathbf{X}_{jt}, \beta, h) | \mathcal{F}_t] = 0$ for all j and for any $0 \leq \beta < 1$, then $(\beta, h)' = (\beta_a, h_a)'$. The true parameter values must satisfy the minimum distance relation

$$\alpha_a = (\beta_a, h_a)' = \arg \min_{\alpha} E[m(\mathcal{F}_t, \alpha)' m(\mathcal{F}_t, \alpha)],$$

where $m(\mathcal{F}_t, \alpha) = E[\psi(\mathbf{X}_t, \alpha) | \mathcal{F}_t]$, $\psi(\mathbf{X}_t, \alpha) = (\psi_1(\mathbf{X}_t, \alpha), \dots, \psi_N(\mathbf{X}_t, \alpha))'$ for any candidate values $\alpha = (\beta, h)'$. The moment conditions are used to describe the SMD estimation of $\alpha_a = (\beta_a, h_a)'$. The SMD procedure has three parts. First, we can estimate the function $h(\cdot)$, which has an infinite dimension of unknown parameters, by a sequence of finite-dimensional unknown parameters (sieves) denoted h_H . Approximation error decreases as the dimension H increases with sample size N . Second, the unknown conditional mean $m(\mathcal{F}_t, \alpha) = E[\psi(\mathbf{X}_t, \alpha) | \mathcal{F}_t]$ is replaced with a consistent nonparametric estimator $\hat{m}(\mathcal{F}_t, \alpha)$ for any candidate parameter values $\alpha = (\beta, h)'$. Finally, the function h_H is estimated jointly with the finite dimensional parameters β by minimizing a quadratic norm of estimated expectation functions,

$$\hat{\alpha} = \arg \min_{\beta, h_H} \frac{1}{T} \sum_{t=1}^T \hat{m}(\mathcal{F}_t, \beta, h_H)' \hat{m}(\mathcal{F}_t, \beta, h_H). \quad (30)$$

We approximate $h(\cdot)$ by a third-order polynomial and substitute it in (29) as if it were the true model. Since the errors $\psi_t(\cdot)$ are orthogonal to the regressors $\mathcal{F}_t = (1, l_{jt-1}, k_{jt}, q_{mt-1}, e_{mt-1}^L, \mathbf{x}_{mt-1})$, we use a third-order power series of \mathcal{F}_t , denoted \mathbf{P} , as instruments. We estimate $m(\mathcal{F}, \alpha)$ as the predicted values from regressing the errors $\psi_t(\cdot)$

on the instruments. Using \mathbf{P} , we specify the weighting matrix as $\mathbf{A} = I_N \otimes (\mathbf{P}'\mathbf{P})^{-1}$, making the estimation a GMM case. The weighting matrix \mathbf{A} gives greater weight to moments that are highly correlated with the instruments. Using the specified GMM implementation, the parameter values $(\boldsymbol{\beta}, h_H)$ are jointly estimated.

Appendix C: Selection

A store's decision to exit in period t depends directly on productivity ω_{jt} , so that the decision will be correlated with the productivity shock ξ_{jt} . To identify the value-added generating function coefficients, we use estimates of survival probabilities, given by

$$\begin{aligned}
 Pr(\chi_t = 1 | \underline{\omega}_t(k_{jt}, e_{mt-1}^L, \mathbf{x}_{mt-1}), \mathcal{F}_{t-1}) &= Pr(\omega_{jt} \geq \underline{\omega}_t(k_{jt}, e_{mt-1}^L, \mathbf{x}_{mt-1}) | \\
 &\quad \underline{\omega}_t(k_{jt}, e_{mt-1}^L, \mathbf{x}_{mt-1}), \omega_{jt-1}) \\
 &= P_{t-1}(i_{jt-1}, l_{jt-1}, k_{jt-1}, w_{jt-1}, \\
 &\quad p_{mt-1}, q_{mt-1}, e_{mt-1}^L, \mathbf{x}_{mt-1}) \\
 &\equiv \mathcal{P}_{t-1},
 \end{aligned} \tag{31}$$

where the second equality follows from (16). We can omit i_{jt} when using labor demand to back-out productivity. Controlling for selection, we can express the nonparametric function $h(\cdot)$ (the approximation of the conditional expectation $E[\omega_{jt} | \mathcal{F}_{t-1}]$) as a function of threshold market productivity $\underline{\omega}_t$ and the information set \mathcal{F}_{t-1} . As a result, threshold market productivity can be written as a function of \mathcal{P}_{t-1} and \mathcal{F}_{t-1} . Substituting equations (16) and (31) into (2) yields

$$\begin{aligned}
 y_{jt} &= \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{mt} - \frac{1}{\eta} \beta_e e_{mt}^L - \frac{1}{\eta} \mathbf{x}'_{mt} \boldsymbol{\beta}_x \\
 &\quad + \left(1 + \frac{1}{\eta}\right) h(\mathcal{P}_{t-1}, \omega_{jt-1}, e_{mt-1}^L) + \left(1 + \frac{1}{\eta}\right) \xi_{jt} - \frac{1}{\eta} v_{jt} \\
 &\quad + \left(1 + \frac{1}{\eta}\right) u_{jt}^p.
 \end{aligned} \tag{32}$$

Appendix D: Dynamic panel approach

■ Another estimator that can be used is dynamic panel (DP).⁵⁶ We denote the sum of the remaining shocks (productivity and demand) ψ_{jt} , i.e., $\psi_{jt} \equiv (1 + 1/\eta)\omega_{jt} - (1/\eta)v_{jt} + (1 + 1/\eta)u_{jt}^p$ (equation (6)). To estimate equation (6) using DP, we need assumptions on: (i) evolution of the error components ω_{jt} , v_{jt} , and u_{jt}^p , and (ii) possible correlations between these errors and k_{jt} , l_{jt} , e_{mt}^L , and \mathbf{x}'_{mt} . The aim is to construct functions of aggregate

⁵⁶See the dynamic panel model of Blundell and Bond (2000).

errors (ψ_{jt}) that are not correlated with past, present, and future values of explanatory variables (Akerberg et al., 2006). In case of DP, we observe ψ_{jt} but not its components. The assumptions on the error components are as follows: (a) u_{jt}^p are i.i.d. over time and uncorrelated with l_{jt} , k_{jt} , e_{mt}^L , and \mathbf{x}_{mt} , i.e, they are measurement errors or unanticipated shocks to output; (b) ω_{jt} follows an $AR(1)$ process where l_{jt} , k_{jt} , e_{mt}^L , and \mathbf{x}'_{mt} can be correlated with ω_{jt} ; and (c) ξ_{jt} (innovations in productivity) are uncorrelated with $l_{j\tau}$, $k_{j\tau}$, $e_{m\tau}^L$, and $\mathbf{x}'_{m\tau}$ prior to time t ($\tau < t$). This is also an assumption on the information sets of stores, i.e., stores cannot predict or observe the innovation in productivity shocks (ξ_{jt}).

There are major differences between DP and our ACF and EDJ specifications. In DP, we cannot compute individual ω_{jt} and only the sum $[(1+1/\eta)\omega_{jt} - (1/\eta)v_{jt} + (1+1/\eta)u_{jt}^p]$. ACF and EDJ allow for an arbitrary first order controlled Markov process, while DP allows for a linear and parametric Markov process. Regarding the relative efficiency of DP and ACF estimators, ACF is more efficient than DP because it is based on moment conditions with lower variance, i.e., ACF uses moments based on ξ_{jt} and DP uses moments based on $(\psi_{jt} - \rho\psi_{jt-1})$. Considering $\omega_{jt} = \rho\omega_{jt-1} + \xi_{jt}$, we use the moments

$$E \left[\psi_{jt} - \rho\psi_{jt-1} \left| \left\{ \begin{array}{c} l_{j\tau} \\ k_{j\tau} \\ q_{m\tau} \\ e_{m\tau}^L \\ \mathbf{x}'_{m\tau} \end{array} \right\}_{\tau=1}^{t-1} \right. \right] = 0$$

to identify the parameters in the value-added generating function using DP (Akerberg et al., 2006). We assume that current innovations in productivity ξ_{jt} are not correlated with $[(1+1/\eta)\omega_{jt-1} - (1/\eta)v_{jt-1} + (1+1/\eta)u_{jt-1}^p]$ and use the moment $E[\xi_{jt}|(1+1/\eta)\omega_{jt-1} - (1/\eta)v_{jt-1} + (1+1/\eta)u_{jt-1}^p] = 0$ to identify ρ . When productivity follows a controlled Markov process $\omega_{jt} = \rho\omega_{jt-1} + \rho e_{mt-1}^L + \xi_{jt}$, we cannot use $(\psi_{jt} - \rho\psi_{jt-1})$ to form moment conditions. We then need an additional differentiation to eliminate the effect of large entrants from $(\psi_{jt} - \rho\psi_{jt-1})$, which is data demanding.

There are advantages of DP over our ACF and EDJ specifications: (a) ACF and EDJ require estimation of a nonparametric function that can have an impact on the sample distribution of these estimators; (b) DP can allow for store level fixed effects in contrast to ACF and EDJ; and (c) DP requires weaker assumptions on u_{jt}^p and v_{jt} : (i) strict exogeneity – u_{jt}^p and v_{jt} are not correlated with inputs and market variables for all t , and (ii) weaker strict exogeneity – u_{jt}^p and v_{jt} are not correlated with inputs prior to t . Our main ACF and EDJ specifications require strict exogeneity assumptions on u_{jt}^p and v_{jt} .

In case of sequential exogeneity assumption, u_{jt}^p and v_{jt} affect future input choices and might affect future entry decisions, which violates the scalar unobservable assumption necessary for the OP/ACF framework. In general, the OP/ACF framework only uses the latest dated valid observation for each input and market variables as instruments. In contrast, DP uses orthogonality between differentiated residuals ($\psi_{jt} - \rho\psi_{jt-1}$) and all inputs and market variables suitably lagged. ξ_{jt} and ξ_{jt-1} are assumed uncorrelated with inputs and market variables. While more moments might add efficiency, they also might generate small sample bias.

■ **Correlated demand shocks.** In this case, we assume that ω_{jt} and v_{jt} follow different $AR(1)$ processes. To be more precise, we assume that $\omega_{jt} = \rho_1\omega_{jt-1} + \xi_{jt}$ and $v_{jt} = \rho_2v_{jt-1} + \mu_{jt}$, where ξ_{jt} and v_{jt} are i.i.d. and uncorrelated with the inputs. One way to eliminate the unobserved demand shocks from the value-added generating function (24) is to take the first difference $\tilde{y}_{jt} = y_{jt} - \rho_1y_{jt-1}$. If $\rho_1 = \rho_2$, this is sufficient for identification. If $\rho_1 \neq \rho_2$, the unobserved demand shocks v_{jt} is completely removed if we apply the difference $\tilde{y}_{jt} - \rho_2\tilde{y}_{jt-1}$ in (24). Note that $\tilde{y}_{jt} - \rho_2\tilde{y}_{jt-1}$ is stationary if $\rho_1 > \rho_2$, i.e., if productivity is more persistent than the demand shocks (the roots of $\tilde{y}_{jt} - \rho_2\tilde{y}_{jt-1}$ are $\rho_2 - \rho_1$ and $-\rho_2$).

The advantage of the control function approach is that it allows for nonlinearities in the productivity process and the possibility of controlling for selection. The drawbacks of the control function approach are that we observe quality-adjusted productivity when there are remaining correlated demand shocks and that we need more assumptions to back out productivity and to identify the parameters. The advantages of dynamic panel are that we can sort out persistent demand shocks from productivity and that no more proxy assumptions are needed for identification. A drawback of allowing for two different $AR(1)$ processes in the dynamic panel approach is that it is more data demanding, because we need two lags and thus drop two years of data to make sure that we have removed the persistent unobserved demand shocks. Since a store needs to be present in the data for at least three years, this severely restricts the dynamics. Most importantly, controlling for large entrants in the productivity process requires additional assumptions and is more data demanding.

Table D.1 shows estimation results for the value-added generating function using two different dynamic panel specifications. The first specification (DP1) allows productivity and persistent demand shocks to follow the same $AR(1)$ process, i.e., an updated version of the Blundell and Bond (2000) estimator. The second specification (DP2) allows productivity and persistent demand shocks to follow different $AR(1)$ processes.

The estimates of capital are over three times larger in DP1 and DP2 than in EDJ. In ACF and EDJ, productivity follows a nonlinear Markov process. As noted, comparing

with DP, the capital coefficients are smaller and the labor coefficients larger. The estimated productivity transition (ρ_1) is about 0.4 in both DP1 and DP2, i.e., a rather low persistency in productivity over time. Furthermore, the estimated demand elasticity in DP1 (-5.674) seems unreasonably high in absolute value for retail food (Hall 1988). To test the assumption of linearity in productivity, we regress current productivity, recovered from DP1 and DP2, on a third-order polynomial extension of previous productivity. The coefficients of ω_{jt-1}^2 and ω_{jt-1}^3 are statistically different from zero, indicating that productivity does not follow an AR(1) process. This might be one of the reasons for the large values of capital (over 0.4) in the DP specifications. We therefore recognize that it is important to allow for a nonlinear Markov process in productivity.

Table D.1: Value-added generation function estimates using dynamic panel

	DP1		DP2	
	(1)	(2)	(1)	(2)
Log no. of labor	0.754 (0.001)	0.916	0.686 (0.004)	0.900
Log of capital	0.400 (0.001)	0.485	0.426 (0.003)	0.400
Market output	0.176 (0.002)		0.313 (0.001)	
Number of large entrants	-0.945 (0.002)	-5.371	-0.031 (0.001)	-0.098
Population density	-0.103 (0.002)	-0.421	-0.166 (0.001)	-0.529
Productivity transition (ρ_1)	0.417 (0.002)		0.449 (0.007)	
Productivity transition (ρ_2)			0.353 (0.106)	
Scale ($\beta_l + \beta_k$)	1.402		1.426	
Demand elasticity (η)	-5.574		-3.198	
Markup ($\frac{\eta}{1+\eta}$)	1.214		1.089	
No. of obs.	15,640		15,640	

NOTE: The dependent variable is log of deflated value added. Labor is measured as number of full-time adjusted employees. All regressions include year dummies. Columns (1) show estimated coefficients including elasticity; Columns (2) show estimated coefficients without elasticity. DP1 is linear estimation of equation (6) when ω_{jt} and v_{jt} follow the same AR(1) process. DP2 is linear estimation of equation (6) when ω_{jt} and v_{jt} follow two different AR(1) process. Market output is measured as the market share weighted output in the municipality. Markup is defined as price over marginal cost.

Appendix E: Productivity decompositions

Because we cannot determine the exact contribution of large entrants, our data allow us to decompose aggregate productivity growth due to entrants, exits, and incumbents. Industry-level productivity (Ω_t) can then be expressed as the weighted average produc-

tivity $\Omega_t \equiv \sum_{j \in N} ms_{jt} \omega_{mt}$, where N is the number of stores and $ms_{jt} = sales_{jt}/sales_t$.

The change in retail food productivity from year t to year t' can be written as

$$\begin{aligned} \Delta\Omega_{t,t'} &= \sum_{j \in C_{t,t'}} ms_{jt} \Delta\omega_{jt,t'} + \sum_{j \in C_{t,t'}} \Delta ms_{jt,t'} (\omega_{jt} - \Omega_t) \\ &\quad + \sum_{j \in C_{t,t'}} \Delta ms_{jt,t'} \Delta\omega_{jt,t'} + \sum_{j \in E_{t,t'}} ms_{jt'} (\omega_{jt'} - \Omega_t) \\ &\quad - \sum_{j \in X_{t,t'}} ms_{jt} (\omega_{jt} - \Omega_t), \end{aligned} \quad (33)$$

where Δ is the difference operator ($\Delta\Omega_{t,t'} = \Omega_{t'} - \Omega_t$); $C_{t,t'}$ is the set of continuing stores, i.e., operating in both t and t' ; $E_{t,t'}$ is the set of entering stores, i.e., that operated in t' but not in t ; and $X_{t,t'}$ is the set of exiting stores, i.e., that operated in t but not in t' . This decomposition, derived by Foster et al. (2001)(FHK), is a modified version of the decomposition by Baily et al. (1992).

The decomposition (33) thus consists of five terms. The first term (Within) is the increase in productivity when the continuing stores increase their productivity at initial sales. The second term (Between) is the increase in productivity when continuing stores with above-average productivity expand their share of sales relative to stores with below-average productivity. The third term (Cross) captures the increase in productivity when continuing stores increase their market shares, while the fourth and fifth terms (Entry and Exit) are productivity increases due to entry and exit, respectively.

The second productivity decomposition used is given by Griliches and Regev (1995) (GR) and modified by FHK to allow for entry and exit:

$$\begin{aligned} \Delta\Omega_{t,t'} &= \sum_{j \in C_{t,t'}} \bar{ms}_j \Delta\omega_{jt,t'} + \sum_{j \in C_{t,t'}} \Delta ms_{jt,t'} (\bar{\omega}_j - \bar{\Omega}) \\ &\quad + \sum_{j \in E_{t,t'}} ms_{jt'} (\omega_{jt'} - \bar{\Omega}) \\ &\quad - \sum_{j \in X_{t,t'}} ms_{jt} (\omega_{jt} - \bar{\Omega}), \end{aligned} \quad (34)$$

where a bar over a variable indicates the average of the variable across t and t' . The within term in the GR decomposition consists of the growth rates of continuing stores' productivity weighted by the average of their shares across t and t' . Both decompositions compare aggregate productivity of entering and existing stores, either to the aggregate productivity of all stores (FHK) or to the unweighted average of aggregate productivity of all stores (GR).

Olley and Pakes (1996) (OP) propose a static decomposition of aggregate productivity, in which the weighted productivity of continuing stores, Ω_t , has two components: (1) contribution of productivity improvements, $\bar{\Omega}_t$; and (2) market share reallocations for the continuing stores $cov(ms_{jt}, \omega_{jt}) \equiv \sum_j (ms_{jt} - \bar{ms}_t)(\omega_{jt} - \bar{\Omega}_t)$. The difference in

productivity index, $\Delta\Omega_{t,t'}$, can be written as

$$\Delta\Omega_{t,t'} = \Delta\bar{\Omega}_{t,t'} + \Delta cov_{t,t'}. \quad (35)$$

The OP decomposition ignores entry and exit. However, Melitz and Polanec (2009) (MP) suggest a dynamic OP decomposition where there is a positive contribution for entering and exiting stores only when the aggregate productivity of these stores is larger than that of continuing stores in corresponding periods. The aggregate productivity in periods t and t' can be decomposed as

$$\begin{aligned} \Omega_t &= ms_{C_t}\Omega_{C_t} + ms_{X_t}\Omega_{X_t} \\ \Omega_{t'} &= ms_{C_{t'}}\Omega_{C_{t'}} + ms_{E_{t'}}\Omega_{E_{t'}}, \end{aligned} \quad (36)$$

where ms_{C_t} , $ms_{C_{t'}}$, $ms_{E_{t'}}$, and ms_{X_t} are the aggregate market shares of incumbents (in period t and t'), entrants and exits, respectively. The change in aggregate productivity can be written as

$$\Delta\Omega_{t,t'} = \Delta\bar{\Omega}_{C_{t,t'}} + \Delta cov_{C_{t,t'}} + ms_{E_{t'}}(\Omega_{E_{t'}} - \Omega_{C_{t'}}) + ms_{X_t}(\Omega_{C_t} - \Omega_{X_t}), \quad (37)$$

where the contribution of continuing firms is divided into within-firm productivity improvements ($\Delta\bar{\Omega}_{C_{t,t'}}$) and market share reallocations ($\Delta cov_{C_{t,t'}}$) as in OP. The contribution of entrants and exits contains two parts, unweighted average productivity (direct effect) and the covariance term (indirect effect). For entrants: $ms_{E_{t'}}(\bar{\Omega}_{E_{t'}} - \bar{\Omega}_{C_{t'}})$, and $ms_{E_{t'}}(cov(\Omega_{E_{t'}}) - cov(\Omega_{C_{t'}}))$. For exits: $ms_{X_t}(\bar{\Omega}_{C_t} - \bar{\Omega}_{X_t})$, and $ms_{X_t}(cov(\Omega_{C_t}) - cov(\Omega_{X_t}))$.

In the results using MP, entrants and exits only have a positive contribution when their aggregate productivity is larger than that of continuing stores in the same period (Table E.1). Incumbent stores are more productive than both entrants (-5.3 percent) and exits (-7.2 percent). Among incumbents, stores that obtain productivity improvements are central (19.2 percent), whereas reallocation of market shares among them is not (-8.5 percent). The direct effect of exits is about 4 percent showing that exits with lower productivity than incumbents play a key role for growth. The indirect effects show that the covariance between market shares and productivity is greater for entrants and exits than for incumbents.

Table E.1: Dynamic Olley and Pakes decomposition of productivity growth 1997-2002

	Percentage of growth from						
	Surviving		Entrants		Exits		
	Unweigh.	Cov	Unweigh.	Weigh.	Unweigh.	Weigh.	
Overall Industry Growth	0.088	0.192	-0.085	0.043	-0.053	-0.146	-0.072

NOTE: Appendix E describes the decomposition in detail. Melitz and Polanec (2009) provide a comprehensive discussion about productivity decomposition. Productivity is estimated using the semi-parametric estimation ACF_{lm} described in Section 3. Shares of local market sales are used as weights.

Paper II

A Dynamic Analysis of Retail Productivity*

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Abstract

The retail sector has dramatically changed due to the adoption of information technology and the trend towards larger but fewer stores. In this paper, we use recently developed methods to decompose aggregate productivity growth in retail, i.e., we quantify the relative importance of entrants, exits, and incumbents. To estimate productivity, we use a dynamic structural model controlling for unobserved prices, subsector, and local market characteristics. Using data on all retail firms in Sweden and a dynamic decomposition framework, we find that incumbents and exit of low productive firms play an important role for retail productivity growth.

Keywords: Retail, imperfect competition, dynamic structural model, productivity decomposition

JEL Classification: L11, L81, L88, O30.

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1 Introduction

The retail sector has changed dramatically due to the adoption of information technology such as scanners, barcodes and credit card processing machines. In parallel, there has been a substantial trend towards larger but fewer stores along with an expansion of multi-store chains. Walmart is the most striking example and its consequences on market structure have received considerable attention in both research and popular media.¹ Theory emphasizes that entry, exit and reallocation are central for productivity growth if new technology enters via new stores, but not if technological change is evenly distributed across firms (Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995; Foster et al., 2006). Entry and exit have been found to explain almost all labor productivity growth in the U.S. retail sector. This stands in contrast to the manufacturing sector, where entry and exit are found to only stand for about 30 percent of total growth (Bartelsman and Doms, 2000; Foster et al., 2006).² Productivity in European retail markets has rarely been investigated in comparison to those in the U.S.³ This is particularly remarkable due to the frequently debated productivity gap between the U.S. and Europe.⁴ A fundamental understanding of drivers of productivity growth in retail markets is needed, especially in the light of entry regulations, which are common in Europe.

In this paper, we estimate productivity and quantify the contribution of incumbents, entrants and exits to aggregate productivity growth in the Swedish retail sector. Using detailed data on all retail firms in Sweden, we apply recently developed methods both to decompose aggregate productivity growth in retail (Griliches and Regev, 1995; Foster et al., 2001; Melitz and Polanec, 2009) and to estimate multi-factor productivity (Ackerberg et al., 2007). We add two central features to the literature: First, we use recent decomposition methods, previously applied on manufacturing industries, to decompose productivity growth in retail

¹Walmart has been found to increase exit (Jia, 2008), reduce retail prices, and affect job creation (Basker, 2005; Basker, 2007; Basker and Noel, 2009), as well as improve logistic efficiencies (Holmes, 2011). Fishman (2006) and Hicks (2007) provide a general discussion about the Walmart effect.

²Syverson (2011) surveys recent productivity literature.

³Among European countries, the U.K. has been the major focus, finding a slowdown in productivity after 1996 (Haskel and Khawaja, 2003), and that regulation matters for market outcome (Pilat, 2005; Reynolds et al., 2005).

⁴The retail sector stands for a continuously growing share of economic activity. In most countries, the sector contributes to about 3-6 percent of GDP and 5-10 percent of total employment (McKinsey&Company, 2006; McKinsey&Company, 2010).

(Griliches and Regev, 1995; Melitz and Polanec, 2009). We also apply the method by Foster et al. (2001) and Foster et al. (2006), who analyze labor productivity growth in U.S. retail, to European retail data. Second, we consider multi-factor productivity and not just labor productivity, which has been commonly used in previous retail studies (Bertrand and Kramarz, 2002; Foster et al., 2006; Sadun, 2008). Importantly, we use recent advances in structural estimation of production functions and provide a dynamic structural model based on the Olley and Pakes (1996)'s framework (hereafter OP) to estimate productivity in retail markets. A key advantage of our model is that it allows us to compute mark-up estimates for each sub-sector. We treat subsectors separately, while also taking the retail sector as a whole into account. In this sense we take a somewhat broader perspective of the use of dynamic models, as compared with many other industry studies. The results from the current analysis are interesting for competition policy as it relates closely to governmental subsidies as well as entry and planning regulations that decide over new entrants.

Our model for retail markets builds on the growing literature on heterogeneity in productivity within industries that use dynamic structural models (Olley and Pakes, 1996; Pavcnik, 2002; Levinsohn and Petrin, 2003; Akerberg et al., 2006). First, we implement a simple demand system to control for unobserved prices, and thus to handle that retail markets are imperfectly competitive. We follow recent extensions of the OP framework that emphasize the importance of controlling for price and demand shocks when estimating productivity (Melitz, 2000; Katayama et al., 2003; Levinsohn and Melitz, 2006; Maican and Orth, 2009; De Loecker, 2011; De Loecker and Warzynski, 2011; Doraszelski and Jaumandreu, 2011). This approach has the additional advantage of yielding mark-up estimates at the sector level. Second, we analyze a number of independent local markets, since retail competition mainly takes place in nearby surrounding geographical areas. Hence, we account for the fact that demand differs across both different sectors and local markets. Third, a key feature is that retail stores make lumpy investments, and we consider this as we back out unobserved productivity from the labor demand function. The assumption that labor is a static input ignores training, hiring, and firing costs. We argue that this assumption is reasonable for the current application. Part-time work is common in retail, the share of skilled labor is low, and stores frequently adjust labor due to variation in customer flows. Due to the complexity of measuring output in retail markets (Griffith and Har-

mgart, 2005; Reynolds et al., 2005), we use labor productivity in comparison to estimated multi-factor productivity.

Our results show sector mark-ups (price over marginal cost) between 1.03 and 1.92. These findings are in line with previous results based on U.S. data (Hall, 1988).⁵ The most productive firms have a large capital stock and relatively low labor, while the opposite is true for the least productive firms. Productivity is highest in firms located in markets with a relatively large population, although not in metropolitan areas, and lowest in firms located in markets characterized by a small population but high population density. We find differences in productivity growth across sectors, and that the relative importance of entrants, exits, and incumbents varies with the decomposition method. Using the approach by Griliches and Regev (1995) and Foster et al. (2001), we find that net exit plays a crucial role for growth, together with incumbent firms. Applying a dynamic Olley and Pakes decomposition (Melitz and Polanec, 2009), surviving firms contribute relatively more to productivity growth. To obtain high aggregate growth in a sector, it is crucial that exiting firms have lower average productivity than incumbent firms.

Section 2 presents the retail industry and data. Section 3 describes the modeling approach of estimating productivity, followed by results in Section 4. Section 5 reports the decomposition of productivity growth, and Section 6 concludes the paper.

2 Data and the Swedish retail sector

■ **Data.** We use detailed data from Statistics Sweden (SCB) that contains all retail establishments from 1996 to 2002. The unit of observation is a firm based on organization number for tax reporting. Each firm consists of one establishment or several due to, e.g., joint ownership. The data contain two parts. First, Financial Statistics (FS) at the firm level, which contain input and output measures such

⁵De Loecker and Warzynski (2011) use a framework based on translog production function that accommodates various price setting models to estimate mark-ups using firm level data. In the estimation, our model is more restrictive (average mark-up) because it requires assumption of Cobb-Douglas technology to recover productivity in one step (increase in efficiency). However, Maican and Orth (2009) show how our model can be transformed to accommodate translog production function using a nonparametric labor demand function to proxy for productivity. As in De Loecker and Warzynski (2011) case, the cost is an increase in number of parameters to be estimated.

as sales, value added, investments etc. Second, Regional Labor Market Statistics (RAMS) at the establishment level, which include number of employees and wages. Anonymity hinders us from identifying owners and connecting individual establishments with firms (see Appendix A for a detailed description of the data). We use all establishments that belong to SNI-code 52, “Retail trade, except of motor vehicles and motorcycles; repair of personal household goods.” Since we have access to detailed information, it is possible to use the five-digit industry codes (for retail 74 in total). To simplify the presentation and to analyze similar product groups together, we use the following 16 subsectors (discussed in detail in Appendix B) in the empirical application: Food, Specialized Food, Tobacco, Textile, Clothing, Footwear, Furniture, Electronics, Hardware, Books, Mail Order, Sports, Watches, Toys, Computers and Others.

Sales, value added, investments and capital are deflated by sub-groups of the Consumer Price Index (CPI). We can thus control for subsector prices, which is important since subsectors are heterogenous. Retail food prices are used for Food, Specialized Food and Tobacco. Separate and individual sub-groups are also used for Textile, Clothing, Footwear, Furniture, Hardware, Books and Telecommunications and Computers. For the remaining groups we use CPI.

■ **Entry regulation.** Retail markets in Europe are connected to policy issues of both government entry subsidies and planning regulation. Labor growth in France is for example found to be lower because of the regulation (Bertrand and Kramarz, 2002).⁶ The majority of OECD countries have entry regulations giving power to local authorities. The restrictions, however, differ substantially across countries. While some countries strictly regulate large entrants, more flexible zoning laws exist for instance in the U.S. (Hoj et al., 1995; Pilat, 1997; Boylaud and Nicoletti, 2001; Griffith and Harmgart, 2005; Pilat, 2005). The Swedish Plan and Building Act (PBA) gives power to the 290 municipalities to decide over applications for new entrants. Inter-municipality questions of entry are handled by the 21 county administrative boards.⁷ The PBA is claimed to be one of the major barriers to entry, resulting in diverse outcomes, e.g., in price levels, across local markets (the Swedish Competition Authority, 2001:4). Several reports stress the need to better analyze how regulations affect market outcomes (Pilat, 1997; the Swedish Compe-

⁶Data on number of formal applications for entry and of rejections are not available in Sweden, which constrains us to evaluate the entry regulation indirectly.

⁷Opening hours are also regulated in some countries, but not in Sweden.

tition Authority, 2001:4; the Swedish Competition Authority, 2004:2)⁸ Appendix C describes the PBA in greater detail.

Our modeling approach takes local competition into account, and market size is determined by subsector, store size, and distance to competitors. We expect the local market to be narrower the shorter the durability of goods. The 290 municipalities that decide over entry are most likely too small for durable goods. We use the 21 counties as market definition. From a regulation perspective, counties are appropriate because they have power over inter-municipality entry decisions.

■ **Descriptive statistics.** Table 1 shows summary statistics for the Swedish retail sector during the period 1996-2002. The general trend is that total sales, value added, and the number of employees increase over time, while the number of firms decreases. There is a slowdown in sales and a fall in investments in 2001, which then recovers in 2002. Total sales increases 34 percent to 326 billion SEK in 2002. Value added is 63 billion SEK in 2002, implying an increase of 37 percent since 1996, which is somewhat lower than for sales. Investments increase rapidly until 2000 and then drop. Over the whole period, investments increase by 47 percent to a total of 5 billion SEK. The number of employees (full-time adjusted yearly average) increases from 144,000 to 159,000, i.e. by 10 percent. The opposite trend is found for number of firms. Except for the year 2000, Table 1 shows a monotonic fall in number of firms. There is a total drop of 10 percent during the period. These industry level descriptives show a pronounced trend of restructuring towards larger but fewer firms. Food is the largest subsector, with almost half of total sales and 20 percent of all establishments in 2002, followed by Clothing, Others, and Furniture.

Table 2 shows median and dispersion measures of key variables from 1996 to 2002. Dispersion is defined as the difference between the 75th percentile and 25th percentile firms divided by the median. This measure, which shows the spread of the distribution, is chosen to avoid measurement problems and outliers. The median firm increases sales by 15 percent over the period. The corresponding increase in value added is 22 percent, while investments increase 9 percent. The median firm has three employees (full-time adjusted) over the whole period, most

⁸Possibly, firms can adopt similar strategies as their competitors and buy already established stores. As a result, more productive stores can enter without involvement of the PBA and, consequently, the regulation will not work as an entry barrier that potentially affects productivity. Large entrants, however, are often newly built stores in external locations, making the regulation highly important. Of course, we cannot fully rule out the opportunity that firms buy already established stores.

likely because firms that change size are the ones in the tails of the distribution. For all variables, dispersion increases over time. A comparison across variables shows that investment has the highest values, i.e., investment is the variable that differs the most across firms. Dispersion is about three times larger for investment than for sales, value added, and number of employees.

Table 3 shows entry and exit rates by subsector and size. Entry and exit rates among small stores are highest in Tobacco and Specialized Food. Large entrants are common in Food, Toys, Hardware, Furniture, and Sports. Hardware and Sports are the only subsectors with net entry; all others have net exit with the highest outflow of establishments in Textile and Books.

Table 4 reports descriptive statistics of annual growth in value added, number of employees, wages, and capital over the study period. The share of small establishments is highest in Tobacco and Textile but lowest in Food. Mean value added increases the most in Sports and Toys as also in large establishments in Specialized Food but the least in Textile, Footwear, Books, and small Food establishments. Employment growth is highest in Toys and Specialized Food but lowest in Food, Electronics and Watches. Large Tobacco establishments and small Sport establishments also have high employment growth. Capital growth is high in Electronics and Sports but low in Tobacco, Textile and Watches. The mean values are high also for large establishments in Furniture whereas corresponding low values are found in Books and Toys. Small establishments have high capital growth also in Furniture.

3 Modeling approach

Our model follows the approach by Olley and Pakes' (1996) (hereafter OP), but adopted for key characteristics of the retail sector. We assume the following production function with Cobb-Douglas technology:

$$q_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \omega_{jt} + \xi_{jt}, \quad (1)$$

where q_{jt} is the log of quantity sold by store j at time t ; l_{jt} is log of labor input; and k_{jt} is logs of capital input.⁹ The unobserved ω_{jt} is productivity, and ξ_{jt} is either

⁹The algorithm is easy to apply to a general specification; for example, translog with neutral efficiency across stores would do equally well.

measurement error (which can be serially correlated) or a shock to productivity. Standard estimators of (1) such as OLS, fixed effects, and instrumental variables are inconsistent due to simultaneity and selection biases (Olley and Pakes, 1996; Akerberg et al., 2006).

Incumbent stores maximize the expected discounted value of future net cash flows. After they collect their payoffs in the product market, incumbents decide whether to exit or to continue to operate in the beginning of each time period. The state variables are productivity $\omega \in \Omega$, capital stock $k \in \mathbb{R}_+$, and local market characteristics $z \in Z$, while the decision variables are investment $i \geq 0$ and/or labor l . If the store exits, scrap value ϕ is received. If the store continues, it chooses optimal levels of investment and labor. Labor is chosen based on current productivity, while capital accumulates according to $K_{t+1} = (1 - \delta)K_t + exp(i_t)$, where δ is the depreciation rate. As in OP, the transition probabilities of productivity follow a first order Markov process with $P(d\omega|\omega)$ and takes the following form:

$$\omega_{jt} = E[\omega_{jt}|\mathcal{F}_{t-1}] + v_{jt}. \quad (2)$$

Thus the store's actual productivity ω_{jt} can be decomposed into expected productivity $E[\omega_{jt}|\mathcal{F}_{t-1}]$ and a random shock v_{jt} . The shock v_{jt} may be thought of as the realization of uncertainties that are naturally linked to productivity. The conditional expectation function $E[\omega_{jt}|\mathcal{F}_{t-1}]$ is unobserved by the econometrician (though known to the store).

To estimate productivity in retail, we consider the following key features of retail markets in our model: (i) imperfect competition and hence central to control for prices, (ii) local market competition, (iii) labor and capital are key inputs while we often have weak measures of intermediate inputs such as products purchased, and (iv) large stores are more likely than small stores to survive larger shocks in productivity, so it is important to control for selection. A similar approach is taken by Maican and Orth (2009), who analyze entry of big-box stores and productivity in retail food.

■ **Imperfect competition.** The best proxy for output is sales or value added, which implies that prices set by stores that operate in imperfect competitive markets will enter into productivity when we estimate the production function in (1). Thus, a negative correlation appears between inputs and prices as more inputs are necessary to capture the increase in demand when stores reduce prices. As a result, we will underestimate the labor and capital parameters in (1) without

controlling for prices (Klette and Griliches, 1996; Melitz, 2000; Foster et al., 2008; De Loecker, 2011).¹⁰ We assume a demand function with a negative slope and that stores operate in a market with horizontal product differentiation, where η (< -1 and finite) captures the elasticity of substitution among products.¹¹

$$p_{jt} = p_{smt} + \frac{1}{\eta}q_{jt} - \frac{1}{\eta}q_{smt} - \frac{1}{\eta}u_{jt}^d, \quad (3)$$

where p_{jt} is output price, p_{smt} and q_{smt} are output price and quantity in subsector s , and u_{jt}^d is shocks to demand. We split demand shocks into one observed and one unobserved part, $u_{jt}^d = z'_{mt}\beta_z + \varepsilon_{jt}$ where ε_{jt} is shocks to demand that are not predicted or anticipated by firms when they make input and exit decisions. We use population, population density, and income in the local market as observed demand shifters z'_{mt} . This simple demand system assumes one elasticity of substitution for all stores within each subsector, i.e., no differences in cross-price elasticities. However, implementing a demand system for each subsector makes it possible to control for the fact that the demand conditions vary across subsectors. We observe deflated value added (sales) $y_{jt} = q_{jt} - p_{jt}$, so if firm level prices are observed we directly substitute (1) into (3).¹² Firm level prices are difficult to measure in retail markets and due to this data constraint, we deflate value added with the subsector consumer price index, which is constant across local markets, i.e., $p_{smt} = p_{st}$. Note that we use one consumer price index for each subsector. By substituting (2) into (1), and using (3) to control for prices, we get

$$y_{jt} = \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta}q_{smt} - \frac{1}{\eta}z'_{mt}\beta_z + \left(1 + \frac{1}{\eta}\right) E[\omega_{jt} | \mathcal{F}_{t-1}] + \left(1 + \frac{1}{\eta}\right) v_{jt} - \frac{1}{\eta}\varepsilon_{jt} + \left(1 + \frac{1}{\eta}\right) \xi_{jt}. \quad (4)$$

¹⁰If the products are perfect substitutes, deflated sales are a perfect proxy for unobserved quality adjusted output. Foster et al. (2008) analyze the relation between physical output, revenues, and firm-level prices in the context of market selection, finding that productivity based on physical quantities is negatively correlated with establishment-level prices while productivity based upon revenues is positively correlated with those prices.

¹¹The vertical dimension is to some extent also captured since q_{jt} measures both quantity and quality, which is correlated with stores type (size).

¹²We use deflated value added and not deflated sales. The advantage of using value added is that we control for the impact of materials i.e. the stock of products bought from the wholesaler. This is important since we have (as common in retail) a weak measure of intermediate inputs. A drawback of using value added is however that the elasticity of demand is theoretically defined for sales and not for value added.

The final production function allows us to estimate the elasticity of demand η and hence to compute mark-ups for each subsector. We approximate the conditional expectation $E[\omega_{jt}|\mathcal{F}_{t-1}]$ by the nonparametric function $g(\cdot)$. Our goal is to back out unobserved productivity $\omega_{jt} = g(\omega_{jt-1}) + v_{jt}$. The assumptions on the productivity process and the estimation strategy depend on whether or not the demand shocks ε_{jt} are persistent over time. Unobserved prices result in that we need to consider persistent demand shocks that will enter into productivity.

If ε_{jt} is correlated over time, we need additional assumptions for identification since the scalar unobservable assumption in OP is violated. We can allow ω_{jt} and ε_{jt} to follow either Markov processes or AR(1) processes. If ω_{jt} and ε_{jt} follow dependent Markov processes, the demand shock will enter into the information set that forms expected productivity $E[\omega_{jt}|\omega_{jt-1}, \varepsilon_{jt-1}]$. We can use an estimate of ε_{jt} in line with Berry et al. (1995), but this is not feasible due to data limitations (we would need additional store specific information). If ω_{jt} and ε_{jt} follow independent Markov processes, the demand shock will determine the optimal choices of labor and/or investment throughout which it affects productivity. We then need to either accept a quality-adjusted productivity that includes actual productivity and a demand shock or assume that ω_{jt} and ε_{jt} follow AR(1) processes, which allow us to sort out persistent demand shocks from productivity. We assume first that ω_{jt} and ε_{jt} follow the same AR(1) process so that the exact source of the shock is irrelevant (Melitz, 2000; Levinsohn and Melitz, 2006). We then assume that ω_{jt} and ε_{jt} follow two different AR(1) processes, i.e., we are less restrictive in the source of the shock. Note however that this is very data demanding since we can only use firms that are present in the data for at least three years in a row. This consequently abstracts from a substantial part of the dynamics, that might be central for productivity growth. Under the assumption of AR(1) processes (same or different), identification follows immediately and no additional assumptions are needed for estimation.

If ε_{jt} is i.i.d., we can use a flexible approximation of the productivity process and control for selection. We now turn to how to back out unobserved productivity in this case. In the empirical application we focus on productivity following a Markov process.

■ **Labor demand.** To estimate (4), we need to recover information about unobserved productivity ω_{jt-1} . We use labor demand in line with Doraszelski and Jaumandreu (2011), which stands in contrast to OP and Akerberg et al. (2006)

(ACF), who use the unknown policy function of investment in capital and labor/materials. For the retail sector, this assumption is less restrictive compared to many other industries. Part-time work is common, the share of skilled labor is relatively low, and stores frequently adjust their labor due to variation in customer flows across time. Thus, we consider that retail stores do lumpy investments, i.e., invest one year followed by several years without investment, and thereby consider also the years of zero investments. In year t , stores choose current labor l_{jt} based on current productivity ω_{jt} , which gives demand for labor as

$$l_{jt} = \frac{1}{1 - \beta_l} \left[\ln(\beta_l) + \beta_k k_{jt} + \omega_{jt} - (s_{jt} - p_{jt}) + \ln\left(1 + \frac{1}{\eta}\right) \right],$$

where s_{jt} is total wages paid by firm j in period t . Solving for ω_{jt} yields the inverse labor demand function

$$\omega_{jt} = \frac{\eta}{1+\eta} \left[\lambda_0 + \left[(1 - \beta_l) - \frac{1}{\eta} \beta_l \right] l_{jt} + s_{jt} - p_{st} - \left(1 + \frac{1}{\eta} \right) \beta_k k_{jt} + \frac{1}{\eta} q_{smt} + \frac{1}{\eta} z'_{mt} \beta_z \right], \quad (5)$$

where p_{st} is used as a proxy for p_{smt} and $\lambda_0 = -\ln(\beta_l) - \ln(1 + 1/\eta) - \ln E[\exp(\xi_{jt})] + \frac{1}{\eta} \ln E[\exp(\varepsilon_{jt})]$.¹³

■ **Selection.** As large retail firms are more likely to survive larger shocks in productivity than small firms, we control for selection. The decision to exit is correlated with ε_{jt} because it relies on current productivity. We therefore control for selection by estimating survival probabilities as

$$\begin{aligned} Pr(\chi_t = 1 | \underline{\omega}_t(k_t, z_{mt-1}), \mathbf{F}_{t-1}) &= Pr(\omega_t \geq \underline{\omega}_t(k_t, z_{mt-1}) | \underline{\omega}_t(k_t, z_{mt-1}), \omega_{t-1}) \\ &= P_{t-1}(i_{t-1}, l_{t-1}, k_{t-1}, s_{t-1}, p_{st-1}, q_{smt-1}, z_{mt-1}) \\ &\equiv \mathcal{P}_{t-1}, \end{aligned} \quad (6)$$

where the threshold market productivity $\underline{\omega}_t$ and the information set \mathbf{F}_{t-1} will enter the function $g(\cdot)$. As a result, threshold market productivity can be written as a function of \mathcal{P}_t and \mathbf{F}_t . Substituting (5) and (6) into (4) yields the final

¹³The condition for identification is that the variables in the parametric part of the model are not perfectly predictable (in the least square sense) by the variables in the non-parametric part (Robinson, 1988). Hence there cannot be a functional relationship between the variables in the parametric and non-parametric parts (Newey et al., 1999).

production function that we estimate:

$$\begin{aligned}
y_{jt} = & \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{smt} - \frac{1}{\eta} z'_{mt} \beta_z + g(\mathcal{P}_{t-1}, \lambda_0 + [(1 - \beta_l) - \frac{1}{\eta} \beta_l] l_{jt-1} \\
& - \left(1 + \frac{1}{\eta}\right) \beta_k k_{jt-1} + s_{jt-1} - p_{st-1} + \frac{1}{\eta} q_{smt-1} + \frac{1}{\eta} z'_{mt} \beta_z) + \left(1 + \frac{1}{\eta}\right) v_{jt} - \frac{1}{\eta} \varepsilon_{jt} \\
& + \left(1 + \frac{1}{\eta}\right) \xi_{jt}.
\end{aligned} \tag{7}$$

■ **Estimation.** The estimation of our semi-parametric model adjusted for retailers (EOP) proceeds as follows. We first use a probit model with a third order polynomial to estimate survival probabilities and then substitute the predicted survival probabilities into (4). Thereafter, we estimate (7) using the sieve minimum distance (SMD) procedure proposed by Newey and Powell (2003) and Ai and Chen (2003) for independent and identically distributed (i.i.d.) data. The goal is to obtain an estimable expression for the unknown parameters β and g_{K_T} , where K_T indicates all parameters in $g(\cdot)$. We approximate $g(\cdot)$ by a third order polynomial expansion in \mathcal{P}_{t-1} and ω_{jt-1} , given by (5).¹⁴ We use a tensor product polynomial series of labor (l_{jt-1}), capital (k_{jt-1}), total wages (s_{jt-1}), consumer price index in the sector (p_{st}) and local market conditions (z_{mt-1}) as instruments, where the local market conditions include population, population density, and income. The same set of instruments is used to estimate the optimal weighting matrix. Using the specified GMM implementation, the parameter values (β, g_{K_T}) are jointly estimated. Since there are non-linearities in the coefficients, we use the Nelder-Mead numerical optimization method to minimize the GMM objective function. We control for local market characteristics in all estimations. Appendix D presents a detailed description of the estimation procedure.

4 Results productivity estimation

Table 5 shows the value added production function coefficients from our extended Olley and Pakes estimation (EOP) and from OLS. We present results for each subsector. EOP yields a lower elasticity of scale than OLS. We control for unobserved prices in EOP, which otherwise might create a downward bias in the scale estimator (Klette and Griliches, 1996). The results in EOP show that the

¹⁴For robustness, we also expand $g(\cdot)$ using a fourth order polynomial, yet the results are similar.

elasticity of scale is around one for all subsectors, though some interesting differences occur across subsectors. The labor coefficient varies between 0.316 (Toys) and 0.896 (Food) whereas the capital coefficient varies between 0.073 (Specialized Food) and 0.309 (Mail Order).

Our EOP estimator also controls for selection. Since firms with a large capital stock can survive even if they have low productivity, we expect selection to induce a negative correlation between capital and the disturbance term in the selected sample. Theory and empirical investigations then predict a lower labor coefficient and a higher capital coefficient (Akerberg et al., 2007). The point estimate of labor is lower using EOP than OLS in all sectors, except Food. The point estimate of capital is higher using EOP than OLS in about half of the sectors.

An advantage of EOP is that the correction for omitted prices also yields an estimate of market output, which makes it possible to compute the elasticity of demand and the mark-up defined as price over marginal cost. We find an elasticity of demand between -2.09 (Tobacco) and -3.62 (Toys).¹⁵ The mark-up (price over marginal cost) ranges from 1.03 (Mail Order) to 1.92 (Tobacco). Our findings on mark-ups are in line with previous results based on U.S. data (Hall, 1988).

■ **Policy functions.** Figure 1 illustrates the labor policy function, i.e., the link between productivity, labor, and capital for the whole retail sector during the whole period. The firms with the highest productivity have high capital stock and relatively low labor, while the opposite is true for firms with low productivity. For a given number of employees, the marginal effect of capital is larger for firms with a capital stock above median compared to those below. The marginal increase in productivity caused by a cut in labor diminishes with firm size (number of employees).

Figure 2 shows the investment policy function, i.e., the link between productivity, investment, and capital. Firms characterized by the highest productivity consist of two groups: firms with low capital and high investments and firms with high capital and low investments. That is, the most productive firms either invest heavily (enter) or have a high capital stock but do not invest so much (large incumbents). The marginal increase in productivity is substantially higher for firms with above-median investments than for those with below-median investments. Large investments are thus necessary to get a considerable increase in productivity.

¹⁵Here we leave out five sectors with unreasonable values of the elasticity of demand (Specialized Food, Books, Mail Order, Sports, Others).

Figure 3 illustrates the link between productivity, population, and population density. Firms with the lowest productivity are located in markets characterized by low population and high population density. Productivity is highest for firms located in markets with relatively high population, although not metropolitan areas. For a given population, however, productivity is higher among firms in less dense markets. Consequently, differentiation in location is central for productivity.

■ **Descriptives: Estimated productivity.** Table 6 shows descriptive statistics for multi-factor productivity (estimated by EOP) and labor productivity. We define labor productivity as value added per employee. Median productivity increases until the year 2000 and then decreases, which connects closely to the investment pattern over time. Over the whole period, median productivity increases by 5 percent while dispersion in productivity decreases by 6 percent. For labor productivity, the corresponding figures are 3 percent and 1 percent, respectively. Thus, the magnitude of the changes over time are larger for productivity than for labor productivity.

5 Productivity decompositions

Our goal is to decompose aggregate productivity growth in the Swedish retail sector using firm productivity estimated by our semiparametric method in Section 3. We thus quantify the relative contributions of incumbents, entrants, and exits to overall growth in each sector. A number of decomposition methods have been used in the literature, among which we assess three of the most recent contributions. We first consider the decompositions by Foster et al. (2001)(FHK) and Griliches and Regev (1995) (GR), both of which modify the method by Baily et al. (1992). We then consider a recent decomposition of Melitz and Polanec (2009) (MP), which extends the static decomposition by OP to a dynamic approach that takes entry and exit into account.

All decomposition methods rely on that sector level productivity (Ω_t) is expressed as a weighted average productivity $\Omega_t \equiv \sum_{j \in N} ms_{jt} \omega_{jt}$, where N is the number of firms and $ms_{jt} = sales_{jt}/sales_t$ is the firm's market share in the sector. Note that the changes in aggregated productivity are common across all methods and that only the relative contributions of incumbents, entrants, and exit vary across methods. All decompositions have been applied on manufacturing indus-

tries, except FHK which analyzes labor productivity growth in U.S. retail.

First, we present the decomposition derived by Foster et al. (2001)(FHK). The change in retail productivity from year t to year t' can be written as

$$\begin{aligned}\Delta\Omega_{t,t'} &= \sum_{j \in C_{t,t'}} ms_{jt} \Delta\omega_{jt,t'} + \sum_{j \in C_{t,t'}} \Delta ms_{jt,t'} (\omega_{jt} - \Omega_t) \\ &+ \sum_{j \in C_{t,t'}} \Delta ms_{jt,t'} \Delta\omega_{jt,t'} + \sum_{j \in E_{t,t'}} ms_{jt'} (\omega_{jt'} - \Omega_t) \\ &- \sum_{j \in X_{m,t,t'}} ms_{jt} (\omega_{jt} - \Omega_t),\end{aligned}\quad (8)$$

where Δ is the difference operator ($\Delta\Omega_{t,t'} = \Omega_{t'} - \Omega_t$); $C_{t,t'}$ is the set of continuing firms, i.e., operating both in t and t' ; $E_{t,t'}$ is the set of entering firms, i.e., that operated in t' but not in t ; and $X_{t,t'}$ is the set of exiting firms, i.e., that operated in t but not in t' . The decomposition (8) thus consists of five terms. The first term (Within) is the increase in productivity when the continuing firms increase their productivity at initial sales. The second term (Between) is the increase in productivity when continuing firms with above-average productivity expand their share of sales relative to firms with below-average productivity. The third term (Cross) captures the increase in productivity when continuing firms increase their market shares, while the fourth and fifth terms (Entry and Exit) are productivity increases due to entry and exit, respectively.

The second productivity decomposition used is given by Griliches and Regev (1995) (GR).

$$\begin{aligned}\Delta\Omega_{t,t'} &= \sum_{j \in C_{t,t'}} \overline{ms}_j \Delta\omega_{jt,t'} + \sum_{j \in C_{t,t'}} \Delta ms_{jt,t'} (\overline{\omega}_j - \overline{\Omega}) \\ &+ \sum_{j \in E_{t,t'}} ms_{jt'} (\omega_{jt'} - \overline{\Omega}) - \sum_{j \in X_{t,t'}} ms_{jt} (\omega_{jt} - \overline{\Omega}),\end{aligned}\quad (9)$$

where a bar over a variable indicate the average of the variable across t and t' . The within term in the GR decomposition is the growth rates of continuing firms' productivity weighted by the average of the shares across t and t' . The reallocation of market share term compares the average firm productivity with average aggregate productivity. The contribution of entrants is positive if aggregate productivity of entrants (in period t') is larger than average aggregate productivity. The contribution of exits is positive if aggregate productivity of exits (in period t) is larger than average aggregate productivity.

Both FHK and GR compare aggregate productivity of entering and existing firms to either aggregate productivity of all firms (FHK) or the unweighted average of aggregate productivity of all firms (GR). Both methods also use fixed

weights (market shares) for continuing firms when splitting between within-firm improvements and reallocation of market shares. Initial period weights are used in FHK whereas time averages are used in GR.

Third, we show a recent decomposition by Melitz and Polanec (2009) (MP), which is an extension of the static decomposition by Olley and Pakes (1996). OP proposes a decomposition of aggregate productivity that abstracts from entry and exit. The weighted productivity for continuing firms, Ω_t , has two components: (1) contribution of productivity improvements, $\bar{\Omega}_t$ and (2) market share reallocations for the continuing firms, $cov(ms_{jt}, \omega_{jt}) \equiv \sum_j (ms_{jt} - \bar{ms}_t)(\omega_{jt} - \bar{\Omega}_t)$. The difference in productivity index, $\Delta\Omega_{t,t'}$, can be written as

$$\Delta\Omega_{t,t'} = \Delta\bar{\Omega}_{t,t'} + \Delta cov_{t,t'}. \quad (10)$$

MP suggest a dynamic OP decomposition with entry and exit. There is a positive contribution for entering and exiting firms only when the aggregate productivity of these firms is larger than that of continuing firms in corresponding periods. The aggregate productivity in period t and t' , respectively, can be decomposed as

$$\begin{aligned} \Omega_t &= ms_{C_t}\Omega_{C_t} + ms_{X_t}\Omega_{X_t} \\ \Omega_{t'} &= ms_{C_{t'}}\Omega_{C_{t'}} + ms_{E_{t'}}\Omega_{E_{t'}}, \end{aligned} \quad (11)$$

where ms_{C_t} , $ms_{C_{t'}}$, $ms_{E_{t'}}$, and ms_{X_t} are the aggregate market shares of incumbents (in period t and t'), entrants, and exits, respectively. The change in aggregate productivity can be written as

$$\Delta\Omega_{t,t'} = \Delta\bar{\Omega}_{C_{t,t'}} + \Delta cov_{C_{t,t'}} + ms_{E_{t'}}(\Omega_{E_{t'}} - \Omega_{C_{t'}}) + ms_{X_t}(\Omega_{C_t} - \Omega_{X_t}), \quad (12)$$

where the contribution of continuing firms is divided into within-firm productivity improvements ($\Delta\bar{\Omega}_{C_{t,t'}}$) and market share reallocations ($\Delta cov_{C_{t,t'}}$) as in OP. The contribution of continuing firms is positive if their aggregate productivity increases over time. Entrants have a positive contribution if their aggregate productivity is larger than the aggregate productivity of continuing firms in the coming period. Productivity of exits is positive if the aggregate productivity of exiting firms is lower than that of continuing firms.

There are some key differences between the different decomposition methods. In MP, entrants and exits will have a positive contribution only if their aggregate productivity is larger than that of continuing firms. The other two methods com-

pare the aggregate productivity of entrants and exists to aggregate productivity of all firms in the initial period (FHK) and the unweighted time average productivity of all firms (GR), respectively. Moreover, FHK and GR use fixed weights for continuing firms whereas MP (and OP) define reallocation as a change in the unweighted covariance between market shares and productivity.

■ **Results: Productivity decompositions.** We decompose sector productivity growth in Swedish retailing between the base year $t = 1996$ and $t' = \{1997, \dots, 2002\}$. Table 7 presents the FHK and GR decompositions of industry productivity growth from 1997 to 2001 for estimated productivity (EOP). Table 8 shows the results using the dynamic Olley and Pakes decomposition MP.

Overall industry growth in productivity is positive for most sectors. Using FHK and GR, we find that net exit contributes substantially to growth. In Toys and Tobacco, almost all productivity growth comes from net entry. In Food, Clothing and Computers, about half of the growth is due to net entry. The other half comes from incumbent firms that continue throughout the whole period. Sectors that exhibit low productivity growth have a small contribution of net entry. Instead, incumbents that increase both productivity and market shares contribute the most.

Using the MP decomposition, incumbents contribute more to aggregate productivity growth than using FHK or GR. This is exactly what we expect. In fact, surviving firms that improve their productivity constitute the most important source of productivity growth in, e.g., Food, Clothing, and Computers. For sectors with somewhat lower growth (Footwear, Furniture, Electronics), incumbents that increase both their productivity and market shares are important.

Comparing entrants and exits, the magnitude of the contribution from the latter is larger than the contribution from the former. One exception, however, is Toys, where productivity improvements from entrants are the most crucial factor. Entry of so called category killers in Toys might explain this result. The direct contribution from entrants has mixed signs. A positive sign implies that entrants have higher average productivity than surviving firms. This is true for, e.g., Toys, Food, Tobacco, and Computers. The indirect contribution from entrants is negative for all sectors. Hence, the covariance between productivity and market shares is greater for entrants than for incumbents. The direct impact from exit has mixed signs. Sectors with high growth have a positive sign while sectors with low growth have a negative. To achieve high aggregate productivity growth in a sector, it

thus seems important that firms that exit have lower average productivity than incumbents. In sectors with low growth, exitors tend to have higher productivity than incumbents. The market mechanism of pushing the least efficient stores out from the market seems thus very central for obtaining a high growth. The exit process thus plays a key role for aggregate growth in productivity. The indirect contribution of exit is positive for all sectors except Mail Order. Hence, surviving firms exhibit a higher covariance between productivity and market shares than exiting firms.

To summarize, there are differences in aggregate productivity growth between sectors. The channels that contribute to productivity growth vary across decomposition methods. Using FHK or GR, our results show that net exit plays a key role together with more productive incumbents. These findings are in line with previous studies on labor productivity in retail (Foster et al., 2006). Using MP, incumbents and low productive exits play a central role to increase aggregate growth.

6 Conclusions

This paper examines driving forces of productivity growth in retail and decomposes the contribution of entry, exit, and incumbents. The addressed issue is particularly interesting since retail markets have undergone a dramatic shift connected to the increased use of technology in terms of scanners, barcodes and online credit card processes. In addition, there has been a structural change towards larger but fewer stores. The combination of improved information technology and economies of scale, density, and scope has dramatically changed the retail sector and its importance for overall economic activity is increasing steadily. Despite these striking trends, rather few studies have investigated multi-factor productivity in the retail sector as a whole, and the U.S. market has got more attention than the European.

We use recent productivity decomposition methods to quantify the relative importance of entrants, exits, and incumbents for aggregate growth in retail. We also provide a dynamic structural model, by using recent extensions of the Olley and Pakes' (1996) framework, to estimate multi-factor productivity. In detail, we control for unobserved prices by introduction of a simple demand system, back out productivity from the labor demand function, and control for subsector and local market characteristics. A key advantage of our model is that it provides mark-ups

at the subsector level.

The empirical application relies on detailed data on all retail establishments in Sweden 1996-2002, which is representative to many retail markets in OECD. The results show that there are non-trivial differences in productivity across retailers. First, we find that high productive firms have, as expected, high capital but relatively low labor. Second, firms located in large local markets are found to have higher productivity. Third, estimated mark-ups, defined as price over marginal cost, vary between 1.03 and 1.92.

Aggregate productivity growth also differs between sectors, and the channels of improvements in productivity vary with the applied decomposition method. Using static decomposition methods, results show that entry of high productive firms and exit of low productive ones play a crucial role for aggregate multi-factor productivity growth (Griliches and Regev, 1995; Foster et al., 2001). This result confirms previous findings on labor productivity in the U.S. retail sector (Foster et al., 2001). The present paper finds that net exit is important in sectors with high aggregate growth whereas expanding incumbents that survive contribute most in sectors with lower aggregate growth. Using a dynamic decomposition, we find that exit of low productive firms and incumbents contribute to growth (Melitz and Polanec, 2009). While the relative contribution of entrants and incumbents differ across decomposition methods, they both show that the exit process of low productive firms is crucial for productivity growth.

Our findings relate to competition policy through governmental subsidies and the presence of entry regulations in Europe. We find that restrictive design or use of entry regulations may hinder productivity growth. Yet, these gains need to be balanced against drawbacks in terms of the environment, traffic, and accessibility for target consumers such as pensioners. Lastly, our results show that it is particularly important for regulatory policies to highlight a clear understanding of the exit process of low productive stores.

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Table 1: Descriptive statistics, Swedish retail 1996-2002

	1996	1997	1998	1999	2000	2001	2002	Δ (%)
Sales	244.0	250.0	264.0	278.0	295.0	302.0	326.0	34.0
Value added	43.1	44.7	47.8	50.0	54.8	54.9	59.2	37.0
Investment	3.4	3.4	3.6	4.5	5.3	4.8	5.0	47.0
Capital stock	10.0	11.0	12.0	15.0	17.0	19.0	20.0	100.0
No. of employees	144.0	144.0	151.0	149.0	155.0	158.0	159.0	10.0
No. of firms	21,464.0	20,787.0	20,318.0	20,085.0	20,169.0	19,618.0	19,233.0	-10.0

NOTE: Sales (excl. VAT), value added, investment and capital stock are measured in billions of 1996 SEK (1 USD=6.71SEK, 1 EUR=8.63 SEK). Number of employees is measured in thousands.

Table 2: Median and dispersion, Swedish retail 1996-2002

	Sales		Value Added		Investment		Labor	
	Median	Dispersion	Median	Dispersion	Median	Dispersion	Median	Dispersion
1996	2,855	1.77	628	1.58	13.0	4.92	3	1.33
1997	2,854	1.83	633	1.70	15.7	4.44	3	1.33
1998	3,086	1.80	696	1.68	15.5	4.25	3	1.00
1999	3,254	1.84	744	1.69	17.4	4.33	3	1.00
2000	3,453	1.84	783	1.71	19.1	4.55	3	1.00
2001	3,466	1.85	789	1.73	16.7	4.44	3	1.00
2002	3,607	1.88	824	1.77	15.5	4.59	3	1.00

NOTE: Sales, value added, investment and capital stock are measured in thousands of 1996 SEK (1 USD=6.71SEK, 1 EUR=8.63 SEK). Number of employees is measured in thousands. Dispersion=interquartile range/median.

Table 3: Entry and exit by sub-sector in Swedish retail 1996-2002

Sector	Entry rate			Exit rate			Net entry	Estab.	Obs
	Small	Large	Total	Small	Large	Total			
Food	0.063 (0.012)	0.046 (0.010)	0.109 (0.015)	0.091 (0.008)	0.051 (0.018)	0.142 (0.024)	-0.031 (0.016)	3,376.28 (243.43)	23,634
Specialized Food	0.103 (0.018)	0.011 (0.004)	0.113 (0.019)	0.138 (0.014)	0.019 (0.005)	0.157 (0.015)	-0.040 (0.022)	1,399.28 (117.87)	9,795
Tobacco	0.136 (0.026)	0.003 (0.002)	0.140 (0.025)	0.159 (0.013)	0.004 (0.003)	0.164 (0.014)	-0.021 (0.018)	668.57 (36.62)	4,680
Textile	0.071 (0.021)	0.007 (0.003)	0.078 (0.021)	0.129 (0.027)	0.007 (0.003)	0.136 (0.026)	-0.055 (0.047)	355.14 (41.36)	2,486
Clothing	0.082 (0.014)	0.011 (0.001)	0.094 (0.016)	0.097 (0.014)	0.013 (0.003)	0.110 (0.015)	-0.015 (0.021)	2,467.57 (72.83)	17,273
Footwear	0.063 (0.008)	0.008 (0.003)	0.071 (0.008)	0.093 (0.011)	0.011 (0.004)	0.104 (0.011)	-0.033 (0.018)	591.71 (41.49)	4,142
Furniture	0.094 (0.016)	0.012 (0.003)	0.106 (0.015)	0.097 (0.018)	0.014 (0.005)	0.111 (0.020)	-0.003 (0.019)	1,603.86 (23.12)	11,227
Electronics	0.066 (0.020)	0.007 (0.002)	0.073 (0.020)	0.087 (0.015)	0.009 (0.002)	0.096 (0.017)	-0.023 (0.024)	1,291.00 (62.15)	9,037
Hardware	0.080 (0.013)	0.018 (0.003)	0.099 (0.013)	0.073 (0.013)	0.019 (0.006)	0.092 (0.016)	0.008 (0.020)	1,313.29 (22.66)	9,193
Books	0.062 (0.014)	0.009 (0.002)	0.071 (0.012)	0.100 (0.012)	0.016 (0.008)	0.116 (0.012)	-0.044 (0.019)	561.29 (50.06)	3,929
Mail Order	0.174 (0.076)	0.066 (0.068)	0.239 (0.139)	0.154 (0.046)	0.049 (0.027)	0.204 (0.052)	0.042 (0.163)	138.57 (23.68)	970
Sports	0.096 (0.026)	0.011 (0.002)	0.107 (0.025)	0.095 (0.009)	0.013 (0.004)	0.108 (0.010)	0.001 (0.014)	1,101.00 (10.94)	7,707
Watches	0.054 (0.019)	0.004 (0.004)	0.058 (0.019)	0.075 (0.016)	0.006 (0.004)	0.081 (0.015)	-0.021 (0.019)	594.29 (26.72)	4,160
Toys	0.078 (0.018)	0.025 (0.011)	0.103 (0.024)	0.112 (0.028)	0.025 (0.009)	0.137 (0.023)	-0.027 (0.047)	228.43 (13.23)	1,599
Others	0.070 (0.011)	0.010 (0.001)	0.081 (0.011)	0.085 (0.011)	0.010 (0.005)	0.095 (0.014)	-0.013 (0.022)	1,976.00 (53.51)	13,832

NOTE: Small represents establishments with less than five employees; Large otherwise.

Table 4: Descriptive statistics of growth 1996-2002

Sector	Value Added		Employees		Capital		Wages		Share Small	Estab.
	Small	All	Small	All	Small	All	Small	All		
Food	0.036 (0.298)	0.059 (0.238)	0.013 (0.334)	0.032 (0.201)	0.141 (0.418)	0.182 (0.428)	0.017 (0.310)	0.047 (0.194)	0.448 (0.027)	3376.285 (243.428)
Specialized Food	0.075 (0.293)	0.084 (0.281)	0.061 (0.359)	0.079 (0.348)	0.153 (0.439)	0.159 (0.427)	0.086 (0.351)	0.101 (0.325)	0.845 (0.016)	1399.285 (117.879)
Tobacco	0.057 (0.284)	0.060 (0.277)	0.042 (0.341)	0.053 (0.339)	0.112 (0.397)	0.115 (0.396)	0.063 (0.302)	0.072 (0.296)	0.937 (0.003)	668.571 (36.619)
Textile	0.046 (0.275)	0.056 (0.274)	0.037 (0.329)	0.044 (0.316)	0.109 (0.423)	0.120 (0.421)	0.051 (0.284)	0.059 (0.270)	0.893 (0.012)	355.142 (41.357)
Clothing	0.087 (0.340)	0.089 (0.318)	0.045 (0.336)	0.060 (0.318)	0.163 (0.507)	0.176 (0.495)	0.059 (0.279)	0.073 (0.254)	0.772 (0.022)	2467.571 (72.828)
Footwear	0.050 (0.246)	0.054 (0.228)	0.029 (0.314)	0.040 (0.294)	0.127 (0.436)	0.150 (0.459)	0.037 (0.235)	0.049 (0.210)	0.777 (0.008)	591.714 (41.495)
Furniture	0.102 (0.337)	0.098 (0.300)	0.045 (0.330)	0.063 (0.309)	0.198 (0.544)	0.222 (0.549)	0.069 (0.278)	0.080 (0.239)	0.748 (0.019)	1603.857 (23.118)
Electronics	0.064 (0.274)	0.069 (0.260)	0.036 (0.291)	0.032 (0.190)	0.193 (0.477)	0.201 (0.458)	0.048 (0.223)	0.061 (0.206)	0.793 (0.019)	1291.000 (62.150)
Hardware	0.076 (0.284)	0.073 (0.243)	0.032 (0.302)	0.034 (0.188)	0.185 (0.441)	0.185 (0.402)	0.051 (0.245)	0.061 (0.200)	0.686 (0.010)	1313.285 (22.654)
Books	0.052 (0.255)	0.051 (0.218)	0.024 (0.323)	0.044 (0.297)	0.129 (0.412)	0.136 (0.397)	0.039 (0.256)	0.051 (0.214)	0.716 (0.027)	561.285 (50.062)
Mail Order	0.154 (0.450)	0.170 (0.462)	- 0.017 (0.352)	0.054 (0.284)	0.304 (0.650)	0.255 (0.505)	0.034 (0.381)	0.091 (0.268)	0.544 (0.035)	138.571 (23.677)
Others	0.074 (0.245)	0.077 (0.223)	0.040 (0.318)	0.080 (0.287)	0.161 (0.437)	0.163 (0.418)	0.058 (0.252)	0.071 (0.225)	0.776 (0.029)	1976.000 (53.510)
Sports	0.100 (0.333)	0.106 (0.312)	0.060 (0.347)	0.075 (0.331)	0.186 (0.450)	0.197 (0.451)	0.079 (0.293)	0.091 (0.268)	0.798 (0.021)	1101.000 (10.939)
Watches	0.031 (0.208)	0.036 (0.202)	0.031 (0.299)	0.024 (0.198)	0.107 (0.393)	0.132 (0.418)	0.033 (0.211)	0.043 (0.196)	0.829 (0.013)	594.285 (26.719)
Toys	0.097 (0.351)	0.104 (0.320)	0.061 (0.359)	0.082 (0.336)	0.153 (0.433)	0.155 (0.427)	0.064 (0.302)	0.084 (0.271)	0.698 (0.036)	228.428 (13.227)

NOTE: Small represents establishments with less than five employees. Value added, capital and wages are measured in thousands of 1996 SEK (1USD=6.71SEK, 1EUR=8.63 SEK).

Table 5: Production function estimates

	OLS		EOP						No. of obs.
	Labor	Capital	Labor	Capital	Scale	Demand	Markup	Selection	
Food	0.871 (0.005)	0.161 (0.003)	0.896 (0.0001)	0.158 (0.0001)	1.51	-2.20	1.83	no	15,329
Specialized Food	0.808 (0.008)	0.122 (0.004)	0.473 (0.00002)	0.073 (0.000005)	0.64	-10.43	1.11	no	10,056
Tobacco	0.760 (0.02)	0.077 (0.008)	0.677 (0.0003)	0.039 (0.0005)	1.19	-2.09	1.92	no	2,737
Textile	0.900 (0.021)	0.140 (0.01)	0.607 (0.001)	0.118 (0.0006)	1.06	-2.97	1.51	yes	1,273
Clothing	0.945 (0.008)	0.118 (0.004)	0.843 (0.0002)	0.103 (0.0006)	1.29	-2.94	1.52	no	11,488
Footwear	0.918 (0.01)	0.110 (0.007)	0.519 (0.0003)	0.003 (0.0002)	0.82	-3.36	1.42	no	2,879
Furniture	0.962 (0.009)	0.114 (0.005)	0.417 (0.0001)	0.140 (0.00003)	1.02	-2.15	1.87	no	7,508
Electronics	0.951 (0.010)	0.136 (0.005)	0.426 (0.0002)	0.253 (0.0001)	1.05	-2.68	1.60	no	6,302
Hardware	0.924 (0.008)	0.153 (0.005)	0.495 (0.00001)	0.188 (0.00001)	0.97	-3.55	1.39	no	6,591
Books	0.889 (0.01)	0.137 (0.008)	0.663 (0.006)	0.157 (0.003)	0.89	-15.5	1.07	yes	2,773
Mail Order	0.880 (0.04)	0.168 (0.04)	0.431 (0.0007)	0.309 (0.0002)	1.03	-30.9	1.03	yes	563
Sports	0.896 (0.01)	0.119 (0.006)	0.687 (0.0006)	0.092 (0.0006)	0.96	-5.58	1.22	yes	5,302
Watches	0.937 (0.01)	0.106 (0.007)	0.682 (0.002)	0.093 (0.003)	1.48	-3.08	1.48	yes	2,943
Toys	0.802 (0.03)	0.211 (0.02)	0.316 (0.003)	0.251 (0.001)	0.84	-3.62	1.38	no	1,093
Others	0.877 (0.009)	0.161 (0.004)	0.826 (0.0007)	0.141 (0.00008)	1.18	-4.79	1.26	yes	1,444
Computers	0.955 (0.009)	0.133 (0.006)	0.779 (0.002)	0.086 (0.003)	1.16	-3.41	1.41	yes	6,998

NOTE: Productivity (in logs) is estimated using the semi-parametric estimation EOP described in Sections 3 and 4.

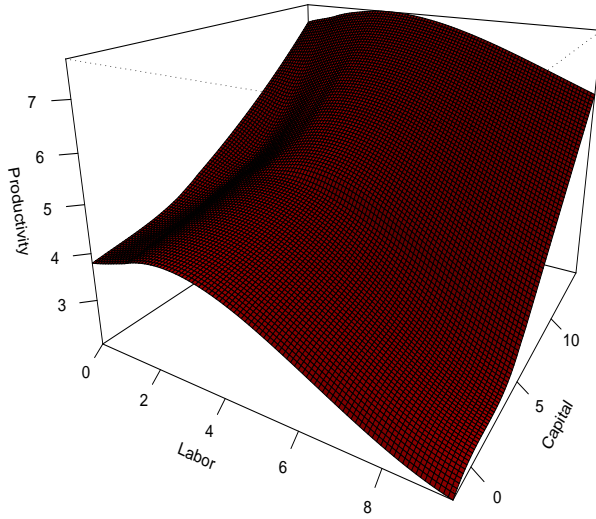


Figure 1: The relation between productivity, optimal labor, and capital 1996-2002

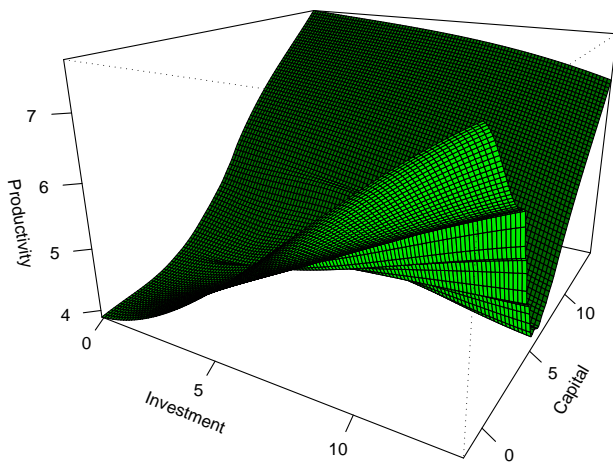


Figure 2: The relation between productivity, optimal investment, and capital 1996-2002

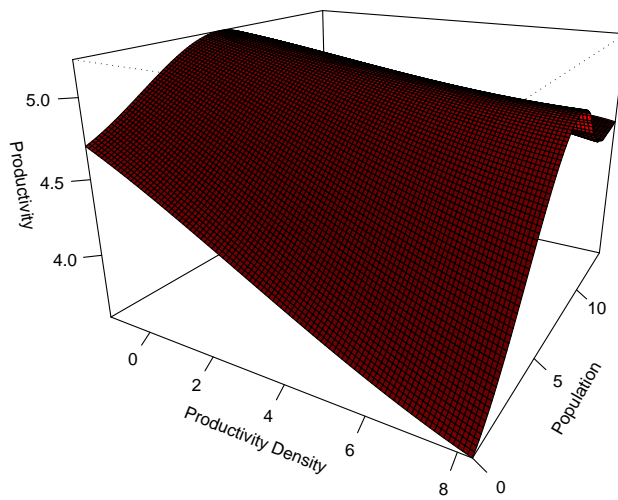


Figure 3: The relation between productivity, population, and population density 1996-2002

Table 6: Summary statistics productivity and labor productivity

Year	Productivity		Labor productivity	
	Median	Dispersion	Median	Dispersion
1996	4.382	0.568	5.516	0.103
1997	4.651	0.556	5.548	0.101
1998	4.666	0.556	5.576	0.107
1999	4.670	0.545	5.637	0.101
2000	4.676	0.538	5.675	0.101
2001	4.634	0.544	5.667	0.104
2002	4.623	0.535	5.689	0.102

NOTE: Multi-factor productivity and labor productivity in logs. Multi-factor productivity is estimated using the semi-parametric estimation EOP described in Sections 3 and 4. Labor productivity is defined as log of value added per employee.

Table 7: Decomposition of retail productivity growth, 1996-2002: Foster et al. (2001) and Griliches and Regev (1995)

Sector	Decomp.	Overall industry growth	Percentage of growth from					Net Entry (4) - (5)
			Within firms (1)	Between firms (2)	Cross firms (3)	Entry (4)	Exit (5)	
Food	FHK	0.4160	0.186	0.005	0.038	0.181	0.007	0.187
	GR		0.205	0.007		0.098	0.106	0.203
Specialized Food	FHK	0.3057	0.044	0.060	0.061	0.106	0.036	0.142
	GR		0.074	0.088		0.042	0.101	0.143
Tobacco	FHK	0.5610	0.174	-0.078	0.025	0.333	0.107	0.440
	GR		0.186	-0.064		0.191	0.247	0.438
Textile	FHK	-0.3008	-0.209	-0.025	0.035	-0.090	-0.013	-0.103
	GR		0.125	0.007		-0.002	0.048	0.046
Clothing	FHK	0.3119	0.147	-0.012	-0.008	0.113	0.072	0.185
	GR		0.143	-0.008		0.056	0.121	0.177
Footwear	FHK	0.0344	0.084	-0.081	0.133	-0.122	0.021	-0.101
	GR		0.150	-0.019		-0.125	0.028	-0.097
Furniture	FHK	0.0905	0.017	0.057	0.081	-0.085	0.020	-0.065
	GR		0.058	0.097		-0.099	0.034	-0.065
Electronics	FHK	0.194	0.030	-0.028	0.128	0.031	0.034	0.065
	GR		0.093	0.023		0.001	0.077	0.078
Hardware	FHK	-0.0018	-0.039	-0.009	0.050	0.020	-0.024	-0.004
	GR		-0.014	0.016		0.021	-0.025	-0.004
Books	FHK	0.3650	0.202	0.005	0.106	0.083	-0.031	0.052
	GR		0.255	0.023		0.028	0.059	0.087
Mail Order	FHK	-0.0743	-0.053	-0.008	0.021	-0.004	-0.031	-0.034
	GR		-0.043	0.003		0.013	-0.048	-0.035
Sports	FHK	-0.0233	-0.032	-0.020	0.049	0.007	-0.027	-0.020
	GR		-0.008	0.005		0.011	-0.031	-0.020
Watches	FHK	-0.6573	-0.612	-0.020	0.075	-0.094	-0.007	-0.101
	GR		-0.574	-0.007		-0.014	-0.068	-0.083
Toys	FHK	1.3699	-0.026	-0.053	0.102	1.434	-0.087	1.346
	GR		0.025	-0.022		1.086	0.281	1.367
Others	FHK	0.1577	0.071	-0.007	0.046	0.039	0.009	0.048
	GR		0.094	0.016		0.014	0.034	0.047
Computers	FHK	0.2190	0.128	-0.036	0.003	0.120	0.004	0.124
	GR		0.130	-0.032		0.072	0.049	0.121

NOTE: The decomposition is done using equation (8) in Section 5. Productivity is estimated using the semi-parametric estimation EOP described in Sections 3 and 4. Stores' shares of local market sales are used as weights.

Table 8: Dynamic Olley and Pakes decomposition of retail productivity growth 1996-2002: Melitz and Polanec (2009)

Sector	Total Growth	Surviving		Entrants		Exits	
		Unweigh.	Cov	Unweigh.	Weigh.	Unweigh.	Weigh.
Food	0.4160	0.381	-0.001	0.024	-0.055	0.013	0.147
Specialized Food	0.3057	0.057	0.223	-0.036	-0.097	0.062	0.134
Tobacco	0.5610	0.356	-0.109	0.100	-0.219	0.214	0.233
Textile	-0.3008	-0.395	0.127	-0.011	0.011	-0.022	0.034
Clothing	0.3119	0.363	-0.155	-0.002	-0.089	0.105	0.125
Footwear	0.0344	0.134	0.021	-0.156	-0.102	0.035	0.266
Furniture	0.0905	0.085	0.140	-0.162	-0.164	0.029	0.171
Electronics	0.1942	0.071	0.103	-0.040	-0.106	0.061	0.240
Hardware	-0.0018	-0.019	0.022	0.036	-0.132	-0.041	0.104
Books	0.3650	0.406	0.057	-0.038	-0.064	-0.060	0.131
MailOrder	-0.0743	-0.150	0.079	0.055	-0.006	-0.058	-0.080
Sports	-0.0233	-0.034	0.029	0.021	-0.069	-0.040	0.089
Watches	-0.0978	-0.077	-0.020	-0.007	-0.022	0.007	0.013
Toys	1.3699	0.037	0.022	1.499	-0.104	-0.189	0.268
Others	0.1577	0.149	0.012	-0.017	-0.052	0.013	0.079
Computers	0.2190	0.123	0.048	0.042	-0.052	0.007	0.107

Decomposition of retail productivity growth. The decomposition is done using equation (8) in Section 5. Productivity is estimated using the semi-parametric estimation EOP described in Sections 3 and 4. Stores' shares of local market sales are used as weights.

Appendix A: The FS-RAMS data

FS-RAMS contains all firms, based on organization number, in different Swedish industries from 1996 to 2002. *Value added* is defined as total shipments, adjusted for inventory changes, minus costs of materials. *Labor* is the full-time adjusted average number of employees during the year. We deflated sales, value added, wages, and investment by the consumer price index (CPI).

Capital is constructed using a perpetual inventory method, $K_{t+1} = (1 - \delta)K_t + I_t$. Since the data distinguishes between buildings and equipment, all calculations of the capital stock are done separately for buildings and equipment. In the paper, we include equipment in the capital stock. Including both equipment and buildings in the capital stock does not change our results, however. As suggested by Hulten and Wykoff (1981), buildings are depreciated at a rate of 0.0361, and equipment at 0.1179. In order to construct capital series using the perpetual inventory method, an initial capital stock is needed. We set initial capital stock to the first occurrence in FS-RAMS, defining entry as the first year in FS (some of the stores are in FS since 1973).

Appendix B: Retail subsectors (SNI codes)

We take all establishments that belong to SNI code 52 (Retail trade, except motor vehicles and motorcycles; repair of personal household goods), and exclude monopolies, SNI 52250 - Retail sale of alcoholic and other beverages, SNI 52310 and 52320 - Dispensing chemists and Retail sale of Medical and orthopaedic goods, SNI 5262 and 5263 - Retail sales via stalls and markets, other non-store retail sale “Food” represents Retail sale in non-specialized stores with food, beverages, or tobacco predominating (52111-52129); “Specialized food” is Retail sale of food, beverages in specialized stores (52210-52242, 52271-52279, 52330); “Tobacco” Retail sale of tobacco in specialized stores (52260); “Textile” Retail sale of textiles (52410); “Clothing” Retail sale of clothing (52421-52425); “Footwear” Retail sale of footwear and leather goods” (52431-52432); “Furniture” Retail sale of furniture, lighting equipment, and household articles n.e.c. (52441-52444); “Electronics” Retail sale of electrical household appliances and radio and television goods (52451-52454); “Hardware” Retail sale of hardware, paints and glass (52461-52462); “Books” Retail sale of books, newspapers and stationery (52471-

52472); “Watches” Retail sale of watches and clocks, jewelery, gold wares, and silverware (52483-52484); “Sports” Retail sale of sports and leisure goods (52485); “Toys” Retail sale of games and toys (52486); “Others” Retail sale in specialized store, including spectacles and other optical goods, photographic equipment and related services, flowers and other plants, pet animals, second-hand goods, art, art gallery activities, coins and stamps, computers, office machinery and computer programmes, telecommunication equipment, wallpaper, carpets, rugs and floor coverings, boats and boating accessories, office furniture, specialized stores n.e.c. (52488, 52491-52499, 52501-52509, 52710-52740); “Mail order” Retail sale vial mail order houses (52611-52619); “Computer and telecommunication” Retail sale of computers, software and telecommunication (52493-52494).

Appendix C: Entry regulation

On July 1, 1987, a new regulation was imposed in Sweden, the Plan and Building Act (PBA).¹⁶ Compared to the previous legislation, the decision process was decentralized, giving local governments power over entry in their municipality, and citizens could now appeal these decisions. Since 1987, only minor changes have been implemented in PBA. From April 1, 1992 to January 1, 1997, the regulation was slightly different, making explicit that the use of buildings should not counteract efficient competition. Since 1997, PBA has been more or less the same as prior to 1992. Long time lags in the planning process make it impossible to directly evaluate the impact of decisions. In practice, differences due to the policy change seem small (the Swedish Competition Authority, 2001:4). The PBA is claimed to be one of the major entry barriers, resulting in different outcomes, e.g., price levels, across municipalities (the Swedish Competition Authority, 2001:4; and the Swedish Competition Authority, 2004:2). Municipalities are then, through the regulation, able to put pressure on prices. In detail, they find that square meters of sales space per capita is lower in municipalities that constrain entry, while municipalities with a higher market share of large and discount stores have lower prices.

¹⁶The the Swedish Competition Authority (2001:4) provides a detailed description.

Appendix D: Estimation strategy

We first use a probit model with a third order polynomial to estimate the survival probabilities in (6). The predicted survival probabilities are then substituted into (7), which is estimated in the second step. We now turn to details about the estimation procedure of the latter step. The semi-parametric regression (7) is estimated using the sieve minimum distance (SMD) procedure proposed in Newey and Powell (2003) and Ai and Chen (2003) for independent and identically distributed (i.i.d.) data.¹⁷ The goal is to obtain an estimable expression for the unknown parameter of interest, $\boldsymbol{\alpha} = (\boldsymbol{\beta}, g)'$. We denote the true value of the parameters with the subscript "a": $\boldsymbol{\alpha}_a = (\boldsymbol{\beta}_a, g_a)'$. The moment conditions could then be written more compactly as

$$E[\rho_j(\mathbf{x}_t, \boldsymbol{\beta}_a, g_a) | \mathbf{F}_t^*] = 0, \quad j = 1, \dots, N \quad (13)$$

where N is the total number of stores, \mathbf{F}_t^* is the information set at time t , and $\rho_j(\cdot)$ is defined as

$$\begin{aligned} \rho_j(\mathbf{x}_t, \boldsymbol{\beta}_a, g_a) \equiv \epsilon_{jt} + \zeta_{jt} = & y_{jt} - \left(1 + \frac{1}{\eta}\right) [\beta_0 + \beta_l l_{jt} + \beta_k k_{jt}] + \frac{1}{\eta} q_{mt} + \frac{1}{\eta} z'_{mt} \beta_z \\ & - g(\omega_{jt-1}). \end{aligned}$$

Let \mathbf{F}_t be an observable subset of \mathbf{F}_t^* , then equation (13) implies

$$E[\rho_j(\mathbf{x}_t, \boldsymbol{\beta}_a, g_a) | \mathbf{F}_t] = 0 \quad j = 1, \dots, N. \quad (14)$$

If the information set \mathbf{F}_t is informative enough, such that $E[\rho_j(\mathbf{x}_t, \boldsymbol{\beta}, g) | \mathbf{F}_t] = 0$ for all j and for any $0 \leq \beta < 1$, then $(\boldsymbol{\beta}, g)' = (\boldsymbol{\beta}_a, g_a)'$. The true parameter values must satisfy the minimum distance relation

$$\boldsymbol{\alpha}_a = (\boldsymbol{\beta}_a, g_a)' = \arg \min_{\boldsymbol{\alpha}} E[m(\mathbf{F}_t, \boldsymbol{\alpha})' m(\mathbf{F}_t, \boldsymbol{\alpha})],$$

where $m(\mathbf{F}_t, \boldsymbol{\alpha}) = E[\rho(\mathbf{x}_t, \boldsymbol{\alpha}) | \mathbf{F}_t]$, $\rho(\mathbf{x}_t, \boldsymbol{\alpha}) = (\rho_1(\mathbf{x}_t, \boldsymbol{\alpha}), \dots, \rho_N(\mathbf{x}_t, \boldsymbol{\alpha}))'$ for any candidate values $\boldsymbol{\alpha} = (\boldsymbol{\beta}, g)'$. The moment conditions are used to describe the SMD estimation of $\boldsymbol{\alpha}_a = (\boldsymbol{\beta}_a, g_a)'$. The SMD procedure has three parts. First, we can estimate the function $g(\cdot)$, which has an infinite dimension of unknown

¹⁷Chen and Ludvigson (2007) show that the SMD procedure and its large sample properties can be extended to stationary ergodic time series data.

parameters, by a sequence of finite-dimensional unknown parameters (sieves) denoted g_{K_T} . The approximation error decreases as the dimension K_T increases with sample size N . Second, the unknown conditional mean $m(\mathbf{F}_t, \boldsymbol{\alpha}) = E[\rho(\mathbf{x}_t, \boldsymbol{\alpha})|\mathbf{F}_t]$ is replaced with a consistent nonparametric estimator $\hat{m}(\mathbf{F}_t, \boldsymbol{\alpha})$ for any candidate parameter values $\boldsymbol{\alpha} = (\boldsymbol{\beta}, g)'$. Finally, the function g_{K_T} is estimated jointly with the finite dimensional parameters $\boldsymbol{\beta}$ by minimizing a quadratic norm of estimated expectation functions:

$$\hat{\boldsymbol{\alpha}} = \arg \min_{\boldsymbol{\beta}, g_{K_T}} \frac{1}{T} \sum_{t=1}^T \hat{m}(\mathbf{F}_t, \boldsymbol{\beta}, g_{K_T})' \hat{m}(\mathbf{F}_t, \boldsymbol{\beta}, g_{K_T}). \quad (15)$$

We approximate $g(\cdot)$ by a third order polynomial and substitute it into (14) as if it were the true model. Since the errors $\rho_j(\cdot)$ are orthogonal to the regressors $\mathbf{F}_t = (1, l_{t-1}, k_t, e_{t-1}^L, z_{t-1})$, we use a third order power series of \mathbf{F}_t , denoted \mathbf{P} , as instruments. We estimate $m(\mathbf{F}, \boldsymbol{\alpha})$ as the predicted values from regressing the errors $\rho_j(\cdot)$ on the instruments. Using \mathbf{P} , we specify the weighting matrix as $\mathbf{W} = I_N \otimes (\mathbf{P}'\mathbf{P})^{-1}$, making the estimation a GMM case. The weighting matrix \mathbf{W} gives greater weight to moments that are highly correlated with the instruments. Using the specified GMM implementation, the parameter values $(\boldsymbol{\beta}, g_{K_T})$ are jointly estimated.

Paper III

Entry and Spatial Differentiation in Retail Markets*

Matilda Orth[†]

January 24, 2012

Abstract

This paper investigates spatial competition between heterogeneous retail food stores using a static entry model with endogenous location choices and flexible competitive effects across store types. The model is applied to data on retail food stores in Sweden and highlights strategic interaction between traditional stores and so-called hard discounters, i.e., small stores with a core focus on low prices and limited product assortment. The results show high returns to spatial differentiation and that the intensity of competition depends on store type. Competition between stores of the same type is strong for both discounters and traditional stores, but declines relatively fast with distance. Discounters reduce the profits of traditional stores located nearby. The reverse effect is smaller but more persistent as distance increases. Because entry is regulated and hard discount firms have expanded across many European countries, the findings link directly to competition policy.

Keywords: Imperfect competition, spatial differentiation, retail markets, hard discounters.

JEL Classification: L11, L13, L81.

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1 Introduction

Differentiation in both geographic location and store type plays a central role in retail markets and its importance has increased over time. U.S. and European retail markets share two trends. First, stores operate uniformly designed store concepts. 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 Today these three firms account for 75 percent of total discount retail sales in the U.S. (Ellickson et al., 2010). A difference between the U.S. and Europe is however that the shape of the discount format is not the same. So-called “hard discounters”, which are rather small stores with a core focus on low prices, a limited product range and a low service level, have expanded rapidly in Europe. Already in 1960, the hard discount pioneer Aldi entered the German market, followed by Lidl and others. In more recent years, these international players have entered mature markets, which consist of well-established traditional retail food stores, using geographic location as the key strategic variable.² In light of their entry and because entry regulations exist in most European countries, there is a need to evaluate the nature of competition and differentiation.

The goal of this paper is to investigate entry and spatial differentiation among heterogeneous stores in retail markets, and to assess the competitive intensity between hard discounters and traditional stores. I use a static entry model that allows for asymmetric competitive effects across both store identity and geographic locations. The empirical application relies on rich data on all retail food stores in Sweden, including their exact geographic location, before and after hard discount entry.

The paper relates to the empirical literature on entry games (Berry and Reiss, 2006; Berry and Tamer, 2006). The early papers on entry study homogenous firms, followed by extensions to differentiation and more general forms of heterogeneity (Bresnahan and Reiss, 1990; Bresnahan and Reiss, 1991; Berry, 1992; Asplund and Sandin, 1999; Mazzeo, 2002; Toivonen and Waterson, 2005; Ciliberto and Tamer, 2009). The geographic location of players is often crucial for market outcomes. A main challenge is however that strategic location decisions are complex high-dimensional problems. Several papers that analyze entry and spatial competition use static entry games (Seim, 2006; Jia, 2008; Zhu and Singh, 2009; Ellickson et al., 2010; Datta and Sudhir, 2011).³ There are a few studies

¹See, e.g., Basker (2005), Basker (2007), Jia (2008), and Holmes (2011) for studies on Wal-Mart.

²Lidl currently operates in 20 European countries, with particularly high market shares in Germany, France, Italy, Spain, U.K., and Belgium (AC Nielsen, 2007).

³In the discrete choice demand literature, models similar to Berry (1994), Berry et al. (1995), and Berry et al. (2004) have been applied in spatial settings (Thomadsen, 2005; Davis, 2006; Ho and Ishii, 2010). Estimating underlying primitives of demand and supply makes it possible to quantify welfare

of multi-market contact in retail markets using a limited number of firms, recently generalized by Ellickson et al. (2010) using a bounds approach (Jia, 2008; Nishida, 2010). In addition, Holmes (2011) develops a dynamic model of the expansion of Wal-Mart without strategic interaction.⁴

Optimal differentiation by new players entering a market depends on a trade-off between demand and competition, existing product differentiation, the geographic scope of the market, and regulation. My model builds on the spatial differentiation framework by Seim (2006) but allows for heterogenous players, i.e., that the competitive intensity between own and rival stores of different identities varies across geographic locations. The basic theoretical anticipation when stores are substitutes is that competitive intensity diminishes with distance and that stores of a similar type compete more intense than rival types (Mazzeo, 2002; Seim, 2006).⁵ The extent to which store type matters relative to distance is however an open empirical question. The present paper relates most closely to Zhu and Singh (2009), Datta and Sudhir (2011), and Vitorino (2011) who use U.S. supermarket data. In addition to previous work, the current paper has the possibility to utilize data before and after hard discount entry. It is moreover one of the very first studies of spatial competition and hard discount entry in European retail markets (Cleeren et al., 2010).

Evaluation of new entrants in retail is crucial since entry is regulated in most OECD countries, being much more restrictive in Europe than in the U.S. In fact, regulation in retail markets is frequently debated among European policy makers (European Parliament, 2008; European Competition Network, 2011). The Swedish regulation gives power to local authorities to decide over entry and location of stores. Does it matter for competition what type of store is allowed to enter, and what is the role of geographic location? Since hard discounters are the first entrants in Sweden that deviate from traditional stores, answers to these question are certainly of interest. The issue can also have implications for public policy more broadly, e.g., for transportation. Since hard discounters have started to operate in several European markets, the findings are of interest to a broad policy audience.

In Sweden, many stores operate as independent or franchise units that offer a wide range of products and decide their own prices. Hard discounters are homogenous with effects of new product launches (Petrin, 2002; Goolsbee and Petrin, 2004; Economides et al., 2008). Retail food prices are however complex to measure and difficult to obtain because of the multi-product/multi-format nature of the market.

⁴Only a few papers study supermarket competition using dynamic games (Aguirregabiria et al., 2007; Beresteanu et al., 2010; Maican, 2010). Smith (2004), Smith (2006), Ellickson (2006), and Ellickson (2007) constitute other important studies of retail markets.

⁵The opposite would be true if agglomeration matters and stores operate as strategic complements (e.g., Schaumans and Verboven, 2008; Datta and Sudhir, 2011).

a sales space of about 500 square meters and similar service levels and location strategies. Traditional stores also operate well-defined store formats (e.g., hypermarkets and convenience stores).⁶ I take large stores as exogenous and focus on the small formats for three reasons. First, the decision to enter a large store often involves large sunk costs, investments in the planning process, and firm coordination (e.g., Akerberg and Gowrisankaran, 2006; Grieco, 2011). Second, large stores have a considerably larger market size. Third, there has been a recent focus on developing small store formats by, e.g., Wal-Mart. The model allows for general forms of heterogeneity but for simplicity and to reduce the computational burden, I group traditional stores of different firms and hard discount stores as two separate store types.⁷

When a new player enters a market, the dynamics of consumers, firms, and products are all central for welfare (Dubé et al., 2005; Akerberg et al., 2007). Aspects like store turnover, sunk costs, timing of entry, preemption, learning, economies of density, and search and switching costs are crucial in a dynamic perspective. A complete analysis of hard discount entry would therefore require the use of a structural dynamic model which is both complex and computationally demanding and requires price data. The latter is particularly difficult to obtain in retail markets due to the multi-format and multi-product nature of the market. It is clearly beyond the scope of the current analysis to investigate the dynamic evolution of hard discounters and assess the changes over time. Instead I quantify the degree of competition between hard discounters and traditional stores in a static spatial setting, while showing descriptive evidence of adjustments toward a long-run equilibrium following entry by discounters. The paper should therefore be seen as a first step toward a better understanding of how entry by new international players, such as hard discounters, affects the profitability of traditional stores.

The results show that there are asymmetries in the competitive intensity across store types. I find high returns to spatial differentiation and that competitive intensity diminishes with distance between stores. Own-type competition is strong but declines faster with distance than rival-type competition. Traditional stores have a more persistent impact on discounters payoffs in the spatial dimension than vice versa. 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 location and store type.

The rest of the paper is organized as follows. The next section presents data and market, Section 3 explains the model. Section 4 presents the empirical implementation

⁶In countries like the U.K. and U.S. there exist specialized store concepts focusing on for example frozen food. The reason these do not exist in Sweden might be the limited size of the overall Swedish retail food market.

⁷To abstract from firm identity might be restrictive if stores behave strategically different. I rely on descriptive evidence to highlight this concern (see Section 3 for details).

and estimation, and Section 5 shows the empirical results. Finally, Section 6 summarizes and concludes the paper.

2 Data and market

The data set contains all retail food stores in Sweden 1993-2008. The data is provided by DELFI Marknadspartner AB, which uses an extensive number of channels to collect information.⁸ 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), format, firm, sales space (square meters), sales, year of entry (after 2001) and exact date of entry (before 2001), age, wholesale provider and the location (geo-coordinates) of all distribution centers for each wholesaler. One advantage of the data is that it contains details about exact location of all stores and wholesalers as well as the date of entry.

I also use information on observed demand and cost shifters. Data on population, age distribution of the population, number of families, average income, average wage, and the share of seats held by non-socialist parties in local governments are taken from Statistics Sweden (SCB). I define children as individuals under 10 years of age and pensioners as those over 65 years of age. 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. Average price per square meter of houses sold, provided by Värderingsdata AB, is used to construct a measure of rent and cost of buildings at the municipality level.

■ **Players and entry regulation.** The Swedish retail food market consists of traditional stores that mainly operate as independent or franchise units, and decide over their own prices and inputs. The hard discounters Netto and Lidl entered in 2002 and 2003, respectively. Netto was introduced as a joint venture between Dansk Supermarked and the incumbent firm ICA. It lasted until the end of 2006 when ICA reduced its stake from 50 to 5 percent. Unfortunately, the DELFI data does not contain sales for Lidl and Netto. However, approximated measures from DELFI show that Lidl's share of total sales increased from 1.1 to 3 percent, and Netto's from 0.8 to 2 percent, during the period 2004-2008.

Stores that belong to the four national firms ICA, Axfood, COOP, and Bergendahls

⁸The sources are: (1) public registers, trade press and daily press, (2) the Swedish Retailers Association (SSLF), (3) Kupongiölsen AB, (4) the chains' head quarters, (5) matching customer registers from suppliers (customers) (6) telephone interviews, (7) yearly surveys, and (8) the Swedish Retail Institute (HUI). In addition, location, store type, owner, and chain affiliation are checked in the annual reports.

had about 90 percent of the market in 2008. Stores operating under ICA has a joint market share of 45 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 in recent years. Stores that belong to Axfood, constructed by a merger in 2000, have 18 percent of the market.⁹ Axfood has moved from a wide range of store types to fewer store concepts focusing on, for example, a soft discount format. COOP has a market share of almost 20 percent and deviates from the other players as it consists of a mix of national and regional cooperatives and Bergendahls is largely concentrated to the southern and southwestern parts of Sweden and carries a fast-growing market share of around 7 percent. The remaining stores are mainly small stores with limited product assortment, such as 7-Eleven and gas station stores. During the period 2004-2008, total sales of traditional stores grew about 13 percent. A major part of this increase was due to increased sales of large store formats. Among smaller store formats, aggregate sales increased slightly for stores owned by ICA. Interestingly, total sales decreased slightly for small stores owned by Axfood and COOP.

As in the majority of retail food markets in OECD, entry is regulated by the plan and building act (PBA) in Sweden. PBA provides that each store (owner) must submit a formal application to the local authorities for each new entrant. The municipalities (290) are to evaluate applicants based on aspects such as market concentration, prices, product assortment, and environmental issues (Swedish National Board of Housing, Building, and Planning, 1999; Swedish Competition Authority, 2001:4). Importantly, PBA states explicitly that municipalities must promote competition when considering new entrants.

■ **Store types.** Stores operate well-defined store formats that all offer a rather complete product range and targets a specific segment of demand. The data provide a classification of 12 different store types such as convenience stores, mini markets, grocery stores, and supermarkets.¹⁰ Hard discounters operate as a well-defined format with similar location strategies. Both Netto and Lidl operate stores with an average sales space of about 500 square meters. Stores that belong to the national firms also operate in well-defined formats. For example, ICA and COOP both have a small store format (ICA Nära and COOP Nära), a medium format (ICA Supermarket, and COOP Konsum), and a large

⁹The D-group started to restructure already in 1998. In 1999, the D-group and Dagab merged to form D&D. In 2000, Axfood was formally created through a merge between D&D and Hemköp and acquisitions of Spar Sverige, Spar Finland, and Spar Inn Snabbgross.

¹⁰The 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.

format (ICA Kvantum/Maxi and COOP Forum).¹¹ The store types differ in aspects like product assortment, size, service level, and location. I classify hypermarkets, department stores, large supermarkets, large grocery stores, and other stores as large, which implies that large stores have a mean sales space of over 1,771 square meters. Consequently, the remaining store types, except hard discounters, are classified as traditional stores. The average sales space for the traditional store type is 304 square meters.

■ **Local market definition.** Food products are purchased on a frequent basis by everyone, and stores are therefore located close to consumers. The size of local markets varies with store type and distance between stores. The definition of local markets needs to consider independent geographic areas, make sense for spatial differentiation and division into smaller geographic units (locations), and cover different store types (in particular hard discounters).

Local labor markets (in total 88) consider commuting patterns and are most likely relevant for the absolutely largest stores. Municipalities (in total 290) are more likely to be appropriate for large Supermarkets but not for somewhat smaller stores. Therefore, I use localities (in total 1,622) as a baseline for the market definition. Most localities are relatively small. In 2008, the minimum population for hard discount stores was 10,500, while the minimum population for large stores was 11,400. I follow Zhu and Singh (2009) and use two different market definitions. First, localities with a population between 20,000 and 300,000 which gives a total of 164 local markets (henceforth locality markets).¹² Second, areas that constitute the major cities in Sweden which gives a sample of 31 local markets (henceforth regional markets). Regional markets are defined based on so-called zip codes which will be explained next.

■ **Differentiation in location.** I divide each market into locations using small geographical areas defined for mail delivery (zip codes). Similar to census tracts in the U.S., zip codes vary in size and share borders. An advantage is that they consider geographic characteristics such as big roads and water and forest areas. Zip code areas exist at different levels of aggregation.¹³ Since I need to calculate distances between stores, I define locations using zip codes at levels of aggregation that have geo-coordinates, i.e., the three- and five-digit levels. The regional markets mentioned above are defined at the

¹¹The store formats are (2008): ICA Maxi, ICA Kvantum, ICA Supermarket, and ICA Nära for ICA; Willys, Willys Hemma, Hemköp, Handlarn, and Tempo for Axfood; COOP Forum, COOP Extra, COOP Konsum, and COOP Nära for COOP; City Gross, Vi, Matöppet, and Prisxtra for Bergendahls.

¹²Three metropolitan areas with a population of over 300,000 are excluded since these markets most likely consist of several sub-markets (Stockholm, Göteborg, Malmö). Moreover, I drop rural and small localities that plausibly are too small in terms of demand and/or geographic area to comprise differentiation in location and/or type.

¹³The total number of zip codes at different levels of aggregations are: 9,500 (five-digit), 2,000 (four-digit), 570 (three-digit), and 89 (two-digit).

two-digit level.

In order to calculate the distances across locations, I place all stores at the population-weighted midpoint of the zip code. Based on distance bands, I calculate a radius from the midpoint of each zip code, which gives a distance band within a certain distance from each cell. The splitting of markets into locations (cells) is illustrated in Figure 6. The general idea of spatial differentiation, with homogenous firms, is that stores located in the closest geographic area (cell 1) compete most intensely with competitors in the same cell. The intensity of competition declines for competitors in the second band (cells 2, 5, and 4), followed by even lower intensity in the third band (cells 3, 6, 9, 8, and 7).¹⁴

■ **Sample markets and distance measures.** When taking the model to the data, several features need to be taken into account: (i) the geographic scope of cities/locations and the large variation in population density across Sweden, (ii) the choice of distance bands, and (iii) the limited total number of discount stores, which may induce few discounters per location. As noted, I use two definitions of local markets. First, the 164 locality markets with 4,657 locations (five-digit zip codes). Second, the 31 regional markets with 185 locations (three-digit zip codes).¹⁵ For robustness, I also consider municipalities (290 in total) and a sample of locality markets from 2006 in Appendices A-B.

Because of a limited number of hard discounters, I use two distance bands. Based on descriptive statistics of distances between all zip codes in the sample markets, I define the first radius to be the 25th percentile and the second the 75th percentile. For locality markets, this implies a radius of 1 kilometer for the first distance band and 9 kilometers for the second. The corresponding radiuses are 2 and 10 kilometers for the regional markets.

2.1 Descriptive statistics

Table 1 and Figure 1 show the expansion of hard discounters. After the first five entrants in 2002, there is 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 is a drastic fall in the number of stores operated by traditional stores. Figure 2 shows a drop from over 6,500 stores in 1993 to only slightly over 4,000 in 2008. In contrast the share of large stores grew substantially, from only 14 percent in 1993 to 21.8 percent in 2008.

¹⁴Distances between zip codes are computed using the Haversine formula. Based on latitude-longitude coordinate data, the distance d between two points A and B is given by

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

where $R = 6373$ kilometers denotes the radius to the earth, and x_A is longitude and x_B latitude.

¹⁵Localities cannot be used as local markets for the three-digit zip codes because a three-digit zip code can be part of several localities.

Moreover, the number of stores owned by others than the national and discount firms is rather constant across time with a slight drop after 2005 (Figure 3).

The average store size is 733 square meters for Axfood, 862 for ICA, and 946 for COOP (Table 2). The median store is smallest for Axfood (305), followed by ICA (550) and COOP (595). Overall, the store size distribution is fairly similar across firms, with the exception of Other owners, which mainly consists of small stores and gas stations. The market configurations of large and small stores by firm show that Axfood and COOP have surprisingly similar configurations (Table 3). Hence, national firms with similar market shares tend to have exceptionally similar store type structures. The difference between the main player, i.e., ICA, and Axfood and COOP at the municipality level is that ICA operates both an additional large and an additional small store.

Table 4 shows an average of 13.5 traditional stores in each locality market. The corresponding figures for discounters and large are 1.43 and 5.48, respectively. Average population is 57,540 with a standard deviation of 44,142. Regional markets are larger with 53 traditional, 3 discounters and 12 large stores on average. At most, 9 discount stores operate in regional markets. All regional markets consist of a population of at least 47,749 people. The number of locations is much lower in regional markets, it varies between 2 and 10 compared to between 8 and 102 in the locality markets.

At the location level, it is evident that stores differentiate in the spatial dimension (Table 5). Discounters operate in only 155 out of the total 4,657 locations for the locality markets. Most locations consist of zero or one store, and at most six traditional stores and two discounters operate in a given location. In regional markets, there is substantially more variation in the number of traditional stores per location. Up to 30 stores operate in the same location. Few discounters operate however in the same location, i.e., spatial differentiation seems crucial.

Since the goal is to assess type and location differentiation, Table 6 presents summary statistics over the number of stores across locations and distance bands for locality markets. The number of stores increases when moving from location to distance band 1 and 2, respectively. The mean number of traditional stores varies from 0.39 to 4.19. The average number of hard discounters is 1.15 and 1.63. The number of traditional stores is larger than the number of discounters for locations and for both bands. Note that the detailed level of analysis becomes evident as there is not too much variation across distance bands. Nevertheless, the number of stores increases when moving from the first to the second band for both store types, i.e., spatial differentiation matters for all store types.

2.2 Traditional stores' response to hard discount entry

It is important to acknowledge incumbents' response to hard discount entry, especially since hard discounters have expanded quite rapidly by entering a completely new store format into mature markets. To do this, and to verify whether the static approach is supported by the data, I illustrate changes in market structure before and after discount entry using localities as local markets. I consider all discount entrants as independent events, though results are similar also when distinguishing between the first and second discount entrant.

As mentioned above, the total number of stores declines at a constant rate and does not change due to entry of the new international players. The average market with hard discount entry contains about 13 stores by national firms, 7 formats, and 3 firms at the time of entry (Figure 4). The averages and the mean of the distribution measures across local markets are similar before and after discount entry. Kernel density estimates of the sales space of traditional stores, using grouped data on markets before and after hard discount entry, show almost identical distributions. Thus, sales space does not change drastically in response to discount entry. These findings suggest modest variation across local markets in response to discount entry.

■ **Exit.** To evaluate exit in relation to discount entry, I compute exit rates for traditional stores excluding hard discounters. A median exit rate of zero indicates that most local markets do not experience exit in a given year. Local market averages are about 4.5 percent for all stores and slightly lower for the three big firms ICA, Axfood, and COOP (Figure 5). The standard deviations are constant over the event period. Following discount entry, the average exit rate declines somewhat for stores that belong to the three main firms but increases slightly for all stores. The changes are as small as 1 percentage point. It is thus stores owned by others that tend to exit in response to hard discount competition. Two years following discount entry, the exit rates for all stores become lower than prior to the discount entry.¹⁶ This implies that overall, hard discount entry does not seem to be followed by substantial increases in exit by incumbent stores. That many of these variables are stable despite hard discount entry might suggest that incumbents instead respond through changes in pricing, quality, and product characteristics such as introduction of private labels. Keeping this in mind, I will now turn to the static entry model.

¹⁶Modest changes in exit rates are also found at the municipality level (Appendix A).

3 Entry model

The model is a static two-stage game of incomplete information. The static approach is justified by the fact that discounters have entered a mature market with stable players who have been operating for decades, and descriptive evidence shows modest changes in overall market structure as a result of the new entry.¹⁷ In the first stage, potential entrants (stores) K^m simultaneously decide whether or not to enter in market $m \in \{1, \dots, M\}$. Stores are assumed to make their entry decision independently, such that each store is seen as a separate unit for which decisions are made. This implies that each player is an individual store and that firms do not make joint decisions over stores across different local markets. This assumption is supported by the fact that most retail food stores in Sweden operate as independent or franchise units that decide their own prices and that stores in Sweden have a higher level of independence compared to many other countries, e.g., the U.K. and the U.S.¹⁸ As most of the static entry literature, I assume independent decisions across markets.¹⁹ In the second stage, stores that entered decide which firm or type $z \in \{1, \dots, Z\}$ to belong to and in what location $l \in \{1, 2, \dots, L^m\}$ to operate. That is, given entry into the market, stores simultaneously decide a firm and location strategy so that the action of one store depends on the actions taken by all other stores in the local market. That the entry decision is made before the firm and location decisions is driven by the following arguments. First, I only focus on small stores, who frequently change their firm identity in given locations. During the period 2001-2008, for example, twice as many small stores changed owner or format than entered. Second, about 15 percent of the discounters started to operate by taking over existing stores. That Netto was partly owned by ICA when they opened in Sweden implied, for example, that several ICA stores were transformed to Netto. This makes it important to consider that the firm choice is made together with the location decision.²⁰ Finally, stores compete in local markets and

¹⁷Since hard discounters are still expanding in Sweden one could still question whether a static approach is supported by the data.

¹⁸As mentioned in Section 2, there is some heterogeneity in decision making across firms. The decision making is partly centralized within Lidl and Netto. The focus on small stores alleviates some of the concerns that firms fully control the entry decision. Since traditional stores have been operating for decades and there is substantial exit over time, the decision that traditional stores make is more of whether to continue to operate rather than whether to enter.

¹⁹Most of the empirical entry literature relies on this assumption. Jia (2008), Ellickson et al. (2010), Nishida (2010), and Holmes (2011) are examples of studies that consider multi-market contact.

²⁰The alternative is to assume that stores belong to a known firm *ex ante* and only decide whether to enter and in what location to operate (Datta and Sudhir, 2011; Vitorino, 2011). Stores can also be assumed to enter sequentially. Traditional stores would then make their entry decisions before hard discounters, using the solution concept of Perfect Bayesian Nash Equilibrium. This assumption could possibly be validated by traditional stores' modest response to hard discount entry in number and characteristics of stores. Data on the exact date of entry could moreover be used. See Schaumans (2009) and Einav (2010) for examples of static games of incomplete information with sequential moves.

payoffs are realized. The nature of competition in the product market is assumed to be known to all players. The structure of the game is shown in Figure 7. The profit function of store i is specified as

$$\pi_{izl}^m = \mathbf{X}_{zl}^m \alpha_z + g_z(\Delta_{.l}^z, \mathbf{N}_z^m) + g_{z'}(\Delta_{.l}^{z'}, \mathbf{N}_{z'}^m) + \psi^m + \epsilon_{izl}^m, \quad \forall \quad z' \neq z, \quad (1)$$

where \mathbf{X}_{zl}^m contains exogenous variables of demand and cost; $g_z(\cdot)$ and $g_{z'}(\cdot)$ are functions of competition where \mathbf{N}_z^m and $\mathbf{N}_{z'}^m$ are vectors of the number of stores of own and rival firms in each location; ψ^m is an unobserved market effect, assumed to be normally distributed with mean μ and variance σ^2 and known to all stores but not to the econometrician; ϵ_{izl}^m is an idiosyncratic shock assumed to be independently and identically distributed across stores, firms, locations and markets; and $\alpha_z, \Delta_{.l}^z, \Delta_{.l}^{z'}, \mu, \sigma$ are parameters to be estimated. The competitive effects across locations are given by $\Delta_{.l}^z$ and $\Delta_{.l}^{z'}$. In a given location, there are a total of Z^2 firm-to-firm competitive parameters. If there are L^m locations and a total of Z firms, there are a total of $L^m \times L^m \times Z^2$ competitive effects.

I make three key assumptions that are central for the identification strategy. First, the payoff of the outside option to not enter is normalized to zero. Second, the random component ϵ_{izl}^m is assumed to be private information to the store, but its distribution is however known to all other players and to the econometrician. Examples of factors included in the private information shock are management and customer support. Third, the exogenous profit shifters are known to all players and the econometrician, and capture market, location and firm-specific information. The last two assumptions imply that stores differ in firm identity and location through observed characteristics and a payoff shock ϵ_{izl}^m .

For expositional simplicity, I ignore the local market index in what follows. I assume that $g_z(\cdot)$ and $g_{z'}(\cdot)$ are linear so that competition from an additional store of each firm influences profits at a constant rate. An alternative would be to allow for more flexible competitive effects (e.g., Bresnahan and Reiss, 1991), but only at the cost of an increase in the computational burden.²¹ Using a linear specification for competition, the payoff function becomes

$$\pi_{izl} = \mathbf{X}_{zl} \alpha_z + \sum_{h=1}^L \delta_{hl}^{zz} N_h^z + \sum_{h=1}^L \sum_{\substack{z' \\ z' \neq z}} \delta_{hl}^{z'z'} N_h^{z'} + \psi + \epsilon_{izl}, \quad (2)$$

²¹The most natural extension would be to allow for the first and second hard discount entrant explicitly (Cleeren et al., 2010).

where h is an index for location. The profit function does not allow the number of stores to influence variable profits or fixed costs differently, which is in line with, e.g., Berry (1992), Mazzeo (2002), and Seim (2006), but stand in contrast to Bresnahan and Reiss (1991). The main advantage of using a single reduced-form profit function is that variable profits do not necessarily increase in proportion to market size, especially in the case of product differentiation. Moreover, it may be difficult to find separate measures of variable profits and fixed costs.²²

■ **Distance bands.** The specification of profits in equation (2) includes a rich structure of competitive effects across locations. To reduce the dimensionality, I group locations in distance bands (Seim, 2006; Zhu and Singh, 2009; Datta and Sudhir, 2011). I assume that each store faces competition based on distance between locations rather than on the exact identity of the location. In other words, the competitive intensity is assumed to be identical for stores of the same firm in locations within the same distance band. This simplifies the profit function to

$$\pi_{izl} = \mathbf{X}_{zl}\alpha_z + \sum_{b=1}^B \delta_b^{zz} N_b^z + \sum_{b=1}^B \sum_{\substack{z' \\ z' \neq z}} \delta_b^{zz'} N_b^{z'} + \psi + \epsilon_{izl}, \quad (3)$$

where b is the distance band of location l . The sum of the number of stores of type z across locations that belong to distance band b of location l is thus given by N_b^z , and correspondingly $N_b^{z'}$ for z' . In the case of two distance bands ($B=2$), δ_1^{zz} represents the competitive effect from stores of the same firm in the first distance band, and δ_2^{zz} correspondingly in the second. The rival-firm coefficients are given by $\delta_1^{zz'}$ and $\delta_2^{zz'}$.

■ **Firm identity and store types.** The model includes many dimensions: stores i , firms z , and distance bands b . Since the dimensionality of the problem, the number of competitive parameters, and the computational burden increase as the number of firms and the choice set of players expand, I make simplifying assumptions. In Sweden, there is a total of two hard discount firms and four traditional firms working as wholesale providers (see Section 2 for a detailed description). Using the profit specification (3) with six firms ($Z = 6$) and two distance bands ($B = 2$) implies estimation of a total of $(Z \times Z \times B) = (6 \times 6 \times 2) = 72$ competitive parameters. I therefore assume that all stores that belong to traditional firms (ICA, COOP, Axfood, Others), and that all stores that belong to the discount firms (Lidl, Netto), are identical, respectively. The assumption

²²A possible extension of the present model is to let traditional stores choose not just whether to operate a certain store type or not but also how many stores of each type to operate (see Table 3). Traditional stores would then have a binary choice for large stores but an ordered choice for small stores, and one would have to control for correlation between the choices (Augereau et al., 2006; McDevitt and Roberts, 2010).

that all stores of the same type are homogenous is valid if traditional (hard discount) stores of different firms do not differ systematically in size and they act strategically similar across the local markets under study. If this assumption does not hold, market power by the firm identity will be important. Although it cannot fully be ruled out, I put forward the following arguments for why the grouping of stores into homogenous types may not be too restrictive in the current application. First, store characteristics (square meters, sales) are similar across stores that belong to the three main firms (Table 2). Second, market configurations of small and large stores are similar across firms (Table 3). Third, traditional stores' formats are well-defined, so their overall entry strategies tend to be similar, e.g., convenience stores operate close to consumers. The interesting question to put forward, given the high dimensionality of the problem, is not what the exact identity of the competitors is but rather whether they are hard discounters or traditional stores and where they are located.

■ **Asymmetric competitive effects.** Under the assumption of homogenous store types, the own and rival-type competitive effects are given by δ_b^{zz} , and $\delta_b^{zz'}$. Ideally, I want to allow the competitive effects between two different types to be asymmetric, i.e., $\delta_b^{z'z} \neq \delta_b^{zz'}$. In its most general form, the model allows the parameters to be flexible in both magnitude and sign across both types and distance bands.

■ **Strategies and equilibrium.** Stores decide to operate in a specific type-location combination if it can cover sunk costs or the expected profits are positive. Because ϵ_{izl} is private information to each type-location choice, stores form expectations about post-entry profits. That is, actions taken by a store rely on expectations (conjectures) regarding competitors' responses. Players thus decide to choose a type-location combination subject to their expectations of competitors' optimal choices and their own profitability shock. Given that all hard discounters and all traditional stores of the same type are identical, respectively, the expected profit for store i of type z operating in location l is given by

$$E[\pi_{izl}] = \mathbf{X}_{z,l} \alpha_z + \sum_{b=1}^B \delta_b^{zz} E[N_b^z] + \sum_{b=1}^B \sum_{\substack{z' \\ z' \neq z}} \delta_b^{zz'} E[N_b^{z'}] + \psi + \epsilon_{izl}, \quad (4)$$

where the expected numbers of competitors of own and rival types across distance bands are given by $E[N_b^z]$ and $E[N_b^{z'}]$. Players maximize their expected profits, choosing the type-location combination that gives the highest payoff relative to all other type-location choices. The probability that a rival store j chooses type z and location l is

$$p_{jzl} = Pr(E[\bar{\pi}_{jzl}] + \epsilon_{jzl} \geq E[\bar{\pi}_{jz'l'}] + \epsilon_{jz'l'}; \quad \forall j \neq i, \quad \forall z'l' \neq zl), \quad (5)$$

where $E[\bar{\pi}_{jzl}] = \mathbf{X}_{zl}\alpha_z + \sum_{b=1}^B \delta_b^{zz} E[N_b^z] + \sum_{b=1}^B \sum_{z' \neq z} \delta_b^{zz'} E[N_b^{z'}] + \psi$. All stores of the same type in the same location are identical and thus have the same conjectures about rivals' strategies. For a total number of entrants in the market, S , the expected numbers of stores of the own type z and of the rival types z' that store i faces in location l are

$$E[N_b^z] = (S-1) \sum_{k \in b} p_{zk} + I_{b=1}, \quad (6)$$

$$E[N_b^{z'}] = (S-1) \sum_{k \in b} p_{z'k}, \quad \forall \quad z' \neq z, \quad (7)$$

where k indicates location in distance band b of location l , p_{zk} and $p_{z'k}$ follow from (5) and the assumption that all stores of the same type and location are identical, and $I_{b=1}$ is equal to one for the own store type in the first distance band. The expected number of entrants of each type in distance band b of location l is given by the total number of competitors in the market $(S-1)$ times the sum over the probabilities that they operate as type z or z' in locations k that belong to band b . For the own store type, I need to consider that the store itself operates in the first distance band conditional on entry, as indicated by $I_{b=1}$.

The i.i.d. type 1 extreme value distributional assumption on the private information ϵ_{izl} implies multinomial logit probabilities for players' beliefs, conditional on the number of entrants in the market. Note the assumption of symmetry across types and locations, i.e., each store of the same type-location has the same equilibrium conjecture of its competitors' type-location actions. This implies

$$p_{zl}^* = \frac{\exp(\mathbf{X}_{zl}\alpha_z + (S-1) \sum_{b,k \in b} \delta_b^{zz} p_{zk}^* + \delta_b^{zz} I_{b=1} + (S-1) \sum_{z'} \sum_{b,k \in b} \delta_b^{zz'} p_{z'k}^* + \psi)}{\sum_t \sum_h \exp(\mathbf{X}_{th}\alpha_t + (S-1) \sum_{\bar{b},k \in \bar{b}} \delta_{\bar{b}}^{tt} p_{tk}^* + \delta_{\bar{b}}^{tt} I_{\bar{b}=1} + (S-1) \sum_{t'} \sum_{\bar{b},k \in \bar{b}} \delta_{\bar{b}}^{tt'} p_{t'k}^* + \psi)}, \quad (8)$$

where t is store type, k and h are locations in market m , and $b, \bar{b} \in \{1, \dots, B\}$ are distance bands for locations l and h . In contrast to the single-agent multinomial model, the choice probabilities of each player are a function of the choice probabilities of other players. To simplify notation

$$p_{zl}^* = \frac{\exp(\bar{\pi}_{zl}(\mathbf{X}, \mathbf{P}^*, S, \theta_p))}{\sum_t \sum_h \exp(\bar{\pi}_{th}(\mathbf{X}, \mathbf{P}^*, S, \theta_p))}, \quad \forall \quad z = 1, \dots, Z, \quad \forall \quad l = 1, \dots, L, \quad (9)$$

where $\theta_p = (\alpha_z, \delta_b^{zz}, \delta_b^{zz'})$. The solution to the game is a Bayesian Nash equilibrium (Seim, 2006; Bajari et al., 2010a) that gives a set of type-location probabilities that solve the

system of equations (9), i.e., the optimal strategy for each player conditional on its beliefs about competitors' best responses as well as competitors' beliefs about the player's choice.

I only consider pure strategy equilibria. According to Brouwer's fixed point theorem, it exist at least one equilibrium for any finite \mathbf{X} , i.e., existence of equilibrium is guaranteed (Seim, 2006; Vitorino, 2011). However, there may exist more than one equilibrium. The underlying assumption is that the same equilibria is played in markets that are observationally the same such that a different equilibrium is not played in similar markets. I leave the discussion about uniqueness of equilibrium until in the end of this section.

■ **First stage.** When stores make their type and location choices in the second stage it is for a given number of entrants in the market. In the first stage, stores decide whether to enter the market irrespective of the type configuration and location possibilities in the market. The equilibrium condition is that all stores make positive expected profits. This assumption implies that the equilibrium number of stores at the market level is given by the market effect and does not depend on the types and locations chosen by stores.

Following Seim (2006) and Datta and Sudhir (2011), the probability to enter a market depends on the type-location probabilities, the market effect ψ , and the outside option to not enter. As mentioned earlier, the payoff from not entering is normalized to zero. Systematic differences across store types and locations do not influence the probability to enter the market but only the type-location choices. That discounters and traditional stores (excluding large) are of similar size makes it less restrictive to assume that the identity of stores does not matter for the total number of stores in the market. The expected number of entrants is then given by the number of potential entrants K times the probability to enter, where the probability to enter is given by

$$Pr(entry) = \frac{\exp(\psi) \sum_t \sum_h \exp(\bar{\pi}_{th}(\mathbf{X}, \mathbf{p}^*, S, \theta_p))}{1 + \exp(\psi) \sum_t \sum_h \exp(\bar{\pi}_{th}(\mathbf{X}, \mathbf{p}^*, S, \theta_p))}. \quad (10)$$

Note that the market effect does not influence the choice of a specific location or store type but instead the total number of entrants in the market. Combining the system of probabilities (9) with the probability to enter (10) and the number of potential entrants (K), 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

$$\psi = \ln(S) - \ln(K - S) - \ln \left(\sum_t \sum_h \exp(\bar{\pi}_{th}(\mathbf{X}, \mathbf{p}^*, S, \theta_p)) \right). \quad (11)$$

Hence, the market effect is adjusted in relation to the number of potential entrants and the outside option to not enter. This gives a joint equilibrium prediction of the type-location probabilities and the number of entrants. It is important to note that the market

unobservable is for a given number of stores. That is, the unobserved market effect does not influence any of the store type-locations differently. The equilibrium does not have a closed form solution, instead it needs to be solved numerically (Seim, 2006).

■ **Multiple equilibria.** Multiplicity is a well-known problem in entry games with simultaneous moves. 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).²³ Furthermore, one can impose a selection mechanism for 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. (2010b) propose computation of all possible equilibria, both pure and mixed, estimating both profits and an equilibrium selection mechanism. Another alternative is to use a bounds approach, discussed in more detail below (Tamer, 2003; Andrews et al., 2006; Ciliberto and Tamer, 2009; Pakes, 2010; Pakes et al., 2011).

Seim (2006) shows that her model has a unique equilibrium using two distance bands and a market with four locations, assuming that competitive intensity decreases with distance. For a larger number of locations and bands, she proves uniqueness by simulations ex post, relying on exogenous variation across locations. That is, her numerical fixed-point algorithm converges to a single solution given exogenous variation across locations (or declining competitive effects).

The multiplicity problem refers closely to models that bring us closer to reality allowing for heterogeneous players. In particular, it relates to when introducing type/firm-specific observables in the profit function. In my model, multiple equilibria might exist and I cannot guarantee that the correct one is selected (Ciliberto and Tamer, 2009; Aradillas-Lopez, 2010; Bajari et al., 2010a; Bajari et al., 2010b; Pakes, 2010). I follow previous studies on entry and store heterogeneity in static games and let the data pick the equilibrium selected (Zhu and Singh, 2009; Datta and Sudhir, 2011; Vitorino, 2011). 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 we in fact observe a long-run outcome. In the current application, this is of less concern since for hard discounters

²³Bresnahan and Reiss (1991) and Berry (1992) use characteristics common across equilibria in complete information settings.

because they rarely exit. Of course, the outflow of small stores from the market raises concerns of ex-post regret for traditional stores. However, taking the number of traditional stores prior to hard discount entry as exogenous and instead considering a change from one period to another could alleviate this concern. Relatedly, data during both introduction and expansion of hard discounters allow me to compare different cross-sections of data, an approach taken by, e.g., Greenstein and Mazzeo (2006), Jia (2008), and Berry and Jia (2010).

3.1 Identification

The identification strategy relies on three assumptions. First, the assumption that ϵ_{iz}^m is private information to the store and is distributed i.i.d. across types, locations, and markets. Yet, its distribution is known to all players and to the econometrician. Second, the normalization that the payoff of not entering equals zero. This imposes the standard outside option assumption necessary for identification. Third, the exogenous variation in observed characteristics across store types, locations/bands, and markets is assumed to be common information to all players and the econometrician.

It is necessary to have variation across equations in the system of equations (9) for identification. In case every type-location is identical, two stores of the same type and location 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 the choices made by other types. Although the entry decisions are closely linked, I do not expect the payoff shocks to be related, e.g., a store only observes its own but not its rivals' management skills. 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 of various types across locations and 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.

In case of symmetric competitive effects and no type and location specific observables, it is possible to rely on exogenous variation in demand shifters across locations for identification of the strategic effects (Seim, 2006). Without further exclusion restrictions than the private information of payoff shocks, there is a need for rich data in order to

identify the competitive parameters (Augereau et al., 2006; Sweeting 2009; Bajari et al., 2010a). In my model, the third step in the identification strategy is to add type-location specific variables in the payoff function (Bajari et al., 2010a; Bajari et al., 2010b). It is crucial to highlight that the number of competitive parameters increases exponentially in the number of types. For example, there are 4 competitive effects across bounds for 2 types and 9 competitive effects across bounds for 3 types. For this reasons, previous studies have added symmetry assumptions (Datta and Sudhir, 2011).

I divide exogenous profit shifters into three groups: those that vary across (i) store types and locations, (ii) locations/bands, and (iii) markets. Type-location specific variables constitute additional exclusion restrictions for identification, and create variation in probabilities across types and locations. Candidate variables are those that are anticipated to shift payoffs of one store type-location but reasonably not the other. For this aim, I rely on cost shifters. Importantly, the distribution network is suggested to be crucial for location of retail stores (Holmes, 2011). For two stores of a different type-location, the distance to the nearest distribution center will determine a difference between type-location decisions and give a natural exclusion restriction. The store with a shorter distance to its distribution center will have stronger preferences for entering compared to the store with a longer distance (Zhu and Singh, 2009; Nishida, 2010; Vitorino, 2011). The geographic location of distribution centers is taken as exogenous and known to all players and the econometrician. I believe this is a reasonable assumption in the current application since the distribution centers of traditional stores have been known for a long time and that the discounters have a limited number of publicly known distribution centers.²⁴ The key is not that the number of exclusion restrictions needs to be large, but rather that there is variation in the variable across types and locations (Bajari et al., 2010b). Despite relying on exclusion restrictions, there is still a need for rich variation in the the type-configurations across distance bands to separately identify the asymmetric effects.

■ **Discussion.** Grouping stores of different firms into two types has the advantage that it reduces the dimensionality of the problem. Using a more disaggregated level of the analysis and considering each firm separately, and imposing symmetry assumptions on the competitive effects, would however add additional identifying variation across equations in the system of equations (9). In my case, cost shifters such as the distance to the nearest distribution center can then be used for each firm (Vitorino, 2011). Furthermore, for a store that belongs to a given firm, variation in the number of large stores owned by

²⁴Most previous studies use exogenous distribution center locations, e.g., Zhu and Singh (2009), Ellickson et al. (2010), Nishida (2010), and Holmes (2011). In fact, few studies have considered the endogenous location decision of distribution centers jointly with store location decisions.

the same or rival firm can add additional variation across stores of different firm identity. To be clear, the number of large rivals would vary across both firms and bands instead of only across bands. Possibly, the trade-off between competition and business-stealing across stores of traditional firms could be investigated using this set-up (Dunn, 2008).

Considering firm identity also enables introduction of private information to each firm that is unobservable by the researcher and other firms but has a distribution that is common knowledge. In this vein, Ellickson and Misra (2008) introduce chain-specific shocks when analyzing pricing strategies of retail stores. Similarly, Orhun (2005) adds location-specific unobservables.

4 Empirical implementation and estimation

When taking the model to the data I use two store types: traditional stores and hard discounters. I group the exogenous profit shifters of demand and cost into those that vary across store types, and or locations/bands, and markets. Retail food products are consumed on a frequent basis by everyone, and location is a major determinant of the consumers that a store will have. Using location level data on population, I include population across distance bands. In addition, I use share of children and pensioners to capture demographic differences at the market level, as well as average income.

The main costs for retail stores include logistics, cost of building/rent, wages, stock of products, machinery/equipment and other costs such as advertising. To control for costs of logistics, I use the distance to the nearest distribution center for each zip code. As the empirical implementation suppresses firm identity in store types, I use the minimum distance from the center of the location to the nearest distribution center for traditional stores and hard discounters, respectively. To measure costs of buildings, I use the median prices for houses sold in the municipality. Remaining costs are assumed constant, motivated by the fact that they correlate highly with square meters of sales space and homogenous grouping of stores of different firm identity.

Estimation is done using the nested fixed point method (Rust, 1987; Seim, 2006). The following parameters are to be estimated: α_z , which captures store type and location characteristics, and exogenous market conditions; δ_b^{zz} , which includes the competitive effects between same types; $\delta_b^{zz'}$, which contains the competitive effects between rival types; and the random market components μ and σ . To simplify the notation, I group the parameters into $\theta_p = (\alpha_z, \delta_b^{zz}, \delta_b^{zz'})$, and $\theta_f = (\mu, \sigma)$. For each type, location and 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, which gives a representation of the

probability of each type and location being chosen by stores. The likelihood function is given by

$$L(\theta_p, \theta_f) = \prod_{m=1}^M P_{\theta_p}(\mathbf{d}^m | \mathbf{X}^m, S^m, \psi^m) f_{\theta_f}(\psi^m | \mathbf{X}^m, S^m, K^m), \quad (12)$$

where the vector \mathbf{d}^m indicates the type-location choices of potential entrants in market m . The first part of the likelihood $P_{\theta_p}(\mathbf{d}^m | \mathbf{X}^m, S^m, \psi^m)$ contains the probability that a certain type-location combination is chosen by stores conditional on the market effect. The second part of the likelihood $f_{\theta_f}(\psi^m | \mathbf{X}^m, S^m, K^m)$ contains the probability of observing a particular realization of ψ^m where the actual number of entrants S^m is equal to the predicted number of entrants. The approach is similar to the one used in the demand literature (Berry, 1994; Berry et al., 1995). Based on an assumption on the number of potential entrants (K^m), the market effect is a result of the condition that the expected number of entrants equals the actual number of entrants. The market effect thus follows from the adjustment of the market effect between potential and actual number of entrants. I assume that the number of potential entrants equals two times the actual number of entrants.²⁵

Assuming that players move simultaneously, I need to solve for the fixed point, i.e., the equilibrium probabilities in each market. 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). Because of the possible existence of multiple equilibria, I use a global optimization algorithm (differential evolution algorithm) to maximize the likelihood function.²⁶ 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. Because stores are of similar size and offer a wide range of products and large stores are taken as exogenous, I expect stores to be substitutes and thus the negative competitive parameters to be negative.²⁷ Therefore, I restrict the competitive parameters to be negative in the estimation. I will now turn to discuss alternative estimation approaches.

■ **Alternative Approaches.** Several alternatives to the nested fixed point method for estimating discrete choice models with strategic interactions have developed. Recent

²⁵Since the pool of entrants is fixed exogenously, it is crucial to consider different numbers of potential entrants for robustness.

²⁶Standard errors are computed using a numerical approximation to the Hessian matrix at the optimal parameter values.

²⁷It is more likely that large and small stores operate as complements, i.e., consumers engage in two-stop shopping (Smith, 2004).

approaches aim not only to reduce the computational burden, but also to handle problems of, e.g., multiple equilibria and common unobservables. Below I present all of the following alternative approaches and in the Appendix I show preliminary estimation results for the first: a) maximum simulated likelihood; b) constraint optimization (Su and Judd, 2011); c) nested pseudo likelihood (Aguirregabiria and Mira, 2007); d) a two-step approach (Bajari et al., 2007; Bajari et al., 2010a); and e) set identification and bounds (Pakes et al., 2011).

Maximum simulated likelihood is straightforward to use. Potential entrants do not matter but instead the market effect is simulated and averaged over in the estimation. More details and results similar to Zhu and Singh (2009), i.e., using differentiation in store type and location, without considering own-type effects, are presented in Appendix B.

Constraint optimization is an alternative where estimation takes place in only one step (Su and Judd, 2011; Vitorino, 2011). The likelihood function is maximized subject to the constraint that the system of equations in (9) holds. That is, one maximizes the likelihood function by adding Lagrange multipliers to each of the equations in (9), which allows for solving the problem once. The drawback of this approach becomes evident when there are many constraints, i.e., a high number of types and locations. This approach is therefore ill-suited for the current application. Some additional details of constraint optimization are presented in Appendix C.

In the two-step approach by Bajari et al. (2010a), the first step involves consistent estimates of the type-location probabilities, and these are taken to the likelihood function in the second step. This is based on the assumption that the same equilibrium is played in each local market. Having a long panel of data, or (additional) exclusion restrictions in order to estimate consistent probabilities in the first step, makes it possible to use the two-step estimation method (Bajari et al., 2007; Bajari et al., 2010a).

The basic idea of the nested pseudo likelihood method proposed by Aguirregabiria and Mira (2007) is to solve the system recursively and not solve for the fixed point for all possible parameter values of α_z , δ_b^{zz} , $\delta_b^{zz'}$, and ψ^m . First, one starts with arbitrary probabilities and plugs them into the likelihood function, and states a distributional assumption for and integrate over the market unobservables. Second, one finds the parameter values of α_z , δ_b^{zz} , $\delta_b^{zz'}$, given the probabilities. In the next step, one uses these parameters to evaluate the system of equations again. This will yield new probabilities to plug into the likelihood function. This recursive approach continues until convergence. The consistency of this method in more complicated set-ups has however recently been questioned (Pesendorfer and Schmidt-Dengler, 2010).

A last alternative is to rely on set identification and bound approaches that use in-

equality restrictions (Tamer, 2003; Andrews et al., 2006; Ciliberto and Tamer, 2009; Ellickson et al., 2010; Pakes, 2010; Pakes et al., 2011). In the complete information game by Ciliberto and Tamer (2009), firms have heterogeneous profit functions and markets are allowed to have different selection mechanisms. Allowing for multiple equilibria, they restrict the parameter estimates to a set and rely on partial identification. Pakes et al. (2011) put forward an approach that is directly based on profit inequalities from players' optimal behavior. Ellickson et al. (2010) and Holmes (2011) present applications to retail markets.²⁸

5 Results

The empirical results contain estimates from reduced-form regressions and the structural model in Section 3. I consider all stores together (homogenous stores) and hard discounters and traditional stores separately (heterogenous stores). The results rely on cross-sectional data from 2008 and variables explained in Section 4.

The most simple point of departure for the reduced-form analysis is to consider identical potential entrants that decide whether or not to operate in a location along with the assumption that this occurs if expected profits are positive or larger than the sunk costs. Following the entry literature, and using the sample of locality markets where most locations consist of at most one store (Table 5), I estimate simple probit regressions similar to Berry (1992) and Reiss (1996), assuming that stores face the decision of whether or not to enter a location. In addition, I consider entry decisions for exogenously given store types as in Toivonen and Waterson (2005). Both specifications are modified versions of equation (3) where ϵ_{izl} captures events unobserved to the econometrician. Note that none of these regressions take the nested structure of stores' entry, type, and location choices into account. Although they are not directly comparable with the structural model, nor handle endogeneity or unobserved heterogeneity, they do constitute simple benchmarks.

5.1 Reduced-form estimates

Table 7 shows reduced-form regression results for all stores, hard discounters, and traditional stores. For homogenous stores, I first only include exogenous profit shifters (Column 2). If stores do not strategically interact at all, this specification would capture

²⁸The current version of the paper does not incorporate any of these concepts, but future versions might deal with these approaches in more detail.

the true decision of stores to enter a location. Second, I add the number of competitors in the second distance band (Column 1). For the type-specific specifications, I first include rival-type competitors in both bands (Columns 3 and 5), and then add the number of own-type competitors in the second band (Columns 4 and 6). The underlying assumption in this analysis is that the number of competitors is uncorrelated with ϵ_{izl} . To try to instrument would require exogenous instruments that only move around the number of competitors (across locations and bands) but not the observed exogenous profit shifters.²⁹

For homogenous stores, the coefficient of the number of rivals in the second distance band is positive, though not statistically significant (Column 1). Indeed, a regression with the number of competitors as the only covariate, and some specifications using other sets of controls, give a positive and significant coefficient. That profits would increase in the number of competitors is obviously not according to the theoretical anticipation, given that we believe that hard discounters and traditional stores operate as substitutes. For discounters, the coefficient of traditional competitors is negative and statistically significant in both distance bands (-0.076 and -0.057). Hence, a traditional store reduces profits more if it is located in the first instead of in the second band. An additional hard discounter in the second distance band (-0.495) reduces profits as much as five times more than an additional traditional store in either of the bands. These findings suggest large differences in marginal effects and that discounters engage in fierce competition.

For traditional stores, the coefficient on discount rivals in the first band is negative and statistically significant (-0.212). The corresponding coefficient is positive but not significant in the second distance band (0.067). Adding own-type rivals in the second band does not result in a significant coefficient or any noteworthy changes in the other parameters.

Among the coefficients of the exogenous profits shifters, the one on distance to the nearest distribution center is negative and statistically significant in all specifications. This emphasizes that it is crucial to be close to the distribution center and highlights the importance of logistic costs and economies of density for store location (Holmes, 2011). In the first band, large stores reduce profits of traditional stores but not discounters. However, in the second band, the corresponding coefficient is negative and significant for both types. Cost of buildings appears crucial for the location of discounters, whereas population in the first distance band matters more for traditional stores. The coefficient on income is significant and negative, which perhaps capture that discounters and small

²⁹Political preferences and the number of applications and rejections to local authorities have previously been used to instrument for new entrants in retail applications (e.g., Bertrand and Kramarz, 2002; Sadun, 2008). In the current setting, we would expect a more liberal design and application of the local market regulation to influence both store types. Datta and Sudhir (2011) consider detailed information about zoning regulation.

stores tend to focus on areas characterized by lower purchasing power. Although the reduced-form analysis does not take causality or endogeneity into account, it provides a baseline for comparison.

5.2 Estimates of the structural model

Table 8 shows results of the structural entry model with differentiation using hard discounters and traditional stores. I only present results for the regional markets due to problems of getting the algorithm to converge when using the locality markets. Potential explanations to this might be that the locality markets consist of a large number of locations, which makes it difficult to solve for the fixed-point, and that there is too little variation in the data across locations and bands (Tables 5 and 6). For the results using regional markets, I want to emphasize that they need to be interpreted with caution due to potential problems of multiple equilibria. As noted in Section 4, I restrict the competitive parameters to be negative.

The results show that the intensity of competition and returns to differentiation vary across store types, in line with expectations. To interpret the competition parameters, I compare store types and/or distance bands. In the first distance band, the strongest competitive effect is the own-type effect of traditional stores (-3.950), followed by the own-type effect of discounters (-3.684). Competition between similar store types thus seems central where there is intense competition among traditional stores and discounters, respectively. The strongest rival-type effect is the one of discounters on traditional stores. In absolute terms, it is slightly smaller than the own-type effects (-3.333). The corresponding decrease in profits caused by the reversed interaction, i.e., the effect of traditional stores on discounters, constitutes the weakest effect among all competitive parameters in the first distance band (-1.907). Hence, it is about half that of the own-type effect for traditional stores.

While competition between same-type stores dwindles fast with distance, competition between rival-types is more persistent. The own-type effects in the second band are only about one-fifth of those in the first, i.e., -0.782 versus -3.950 and -0.613 versus -3.684. Interestingly, the reduction in discounters' payoffs caused by a traditional store is largest among all second band parameters (-1.623). Taken together, the results show that there are high returns to spatial differentiation, especially for stores of the same type.³⁰

³⁰A brief comparison of the structural and reduced-form estimates shows a number of conflicting findings. First, that rival-types reduce profits of discounters more than own-types in the second band is opposite to the reduced-form results (Column 4 in Table 7). Second, high persistency in the rival-type coefficient for traditional stores stands in contrast to the insignificant rival-type coefficient in the second

The coefficient on the distance to the distribution center has an expected negative sign in all specifications, suggesting the importance of lowering logistics costs for profitability. The coefficient of population for discounters is substantially lower in the second band (0.412) than in the first (4.631). Presence of large stores decreases profits for both traditional stores and discounters. While large stores reduce the payoffs for traditional stores more if they are located in the first band than in the second, the opposite holds for large stores with respect to discounters. Since the specification abstracts from the exact identity of stores, the competition effect from large stores on small measures the net effect of competition and business-stealing within and across stores operating under the same firm.

It is important to emphasize that the results presented above rely on relatively large regional markets. Preliminary results using the full sample of locality markets show somewhat weaker competitive effects within discount stores. Moreover, preliminary estimates using a sub-sample of large locality markets (above 30,000 people) confirm the findings that discounters compete intensively in the nearby area, i.e., in line with the results for the regional markets in Table 8.

■ **Robustness.** In order to check to what extent the results from the model depend on some of the assumptions I made, I plan to consider a number of robustness tests. First, and most important, I would like to estimate the structural model using homogenous stores. This would give a point of comparison to what extent store type heterogeneity matters. Second, I would like to change the number of potential entrants. Finally, it would be important to re-define distance measures and store types, and to evaluate whether the results change when excluding stores of some of the major firms. Some preliminary robustness results using data from 2006 are presented in Appendix B.

■ **Counterfactual simulations.** As mentioned in the introduction, a key question for competition policy is to what extent store identity and geography matter for profitability. Although the structural framework allows for using the model for counterfactual analysis, it is complicated by the presence of multiple equilibria in the current application. Despite this, I will highlight a couple of policy questions that I would like to address by using my model for counterfactual simulations. First, I would like to quantify the change in profits of traditional stores caused by hard discount entry. To do that, I could estimate the model prior to hard discount entry, e.g., in 2001 (or prior to that). Together with 2008 information on exogenous variables and store configurations, but excluding the discount stores that entered the market, these estimates could be used to compute the new equi-

band found in the reduced-form (Column 6 in Table 7). Although models are not directly comparable and different samples are used, these findings nevertheless suggest that endogeneity concerns need to be taken seriously.

librium market structure, i.e., the market structure as if there were no hard discounters. It basically means that the market effect ψ would be adjusted until the new equilibrium market structure is found. This exercise is attractive since it allows me to quantify the change in profits of traditional stores that is caused by hard discounters. Second, it would also be interesting to analyze markets with growing demand, both in terms of density and geographic scope of consumers (Seim, 2006; Zhu and Singh, 2009). This relates closely to the fact that the travel distance for consumers to the nearest store has increased over time and to the discussion of where new stores are or should be allowed to enter.

6 Conclusions

Retail food stores with a clear focus on low prices and limited product assortment, 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 well established large and small stores connected to mature firms. How do hard discounters influence profitability and to what extent does differentiation matter? And what is the role of the main strategic variable in food retail - geographic location? Previous research has not yet found an answer to these questions, and the current paper therefore aims to fill this gap.

A static entry game of incomplete information that accounts for store heterogeneity is used, and the two store types hard discounters and traditional stores are put forward in detail. Data on retail food stores in Sweden during the introduction and expansion of hard discounters are used in the empirical application. Besides modeling spatial differentiation among heterogeneous firms (store types) and allowing 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. 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, i.e., it is key to consider the identity of entrants. Both discounters and traditional stores engage in relatively strong competition with stores of the same type. Competition decreases however relatively fast with distance. For rival-types, discounters reduce profits of traditional stores located nearby. Although the reverse effect, i.e., of traditional stores on hard discounters, is smaller, it is more persistent as distance increases. I conclude that there are high returns to spatial differentiation and that the intensity of competition

depends crucially on store type. The static approach is justified by descriptive evidence that exit and changes in firms, formats and the distribution of sales space among incumbents are not main responses to hard discount entry. Since the results are sensitive to the specification used, and that convergence of the algorithm used is not always guaranteed, future work is needed to further explore and investigate the robustness of these results in more detail (Pesendorfer and Schmidt-Dengler, 2010).

The results contribute with knowledge to both policy makers and the retail business. Since many OECD countries have similar market structures and entry regulation as in Sweden, the results are interesting in a broad context. The findings suggest that it is important for local authorities to consider both store types and locations when evaluating competitive effects of new entrants.

One would ideally want to use the model for counterfactual simulations, which would make it possible to quantify the changes in profits of traditional stores caused by hard discount entry. A natural extension for future research would be to do a complete welfare analysis of the introduction of hard discounters. Since hard discount stores are still expanding in many countries, it would also be interesting to examine to what extent the findings in the present paper hold in a dynamic setting.

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Table 1: Number of stores by type and firm 2001-2008

Hard Discount			Traditional stores						
All	By firm		All	By firm					
	Lidl	Netto		ICA	COOP	Axfood	Others		
2001			5,240 (18.3)	1,924 (19.6)	946 (30.3)	992 (24.6)	1,378 (3.6)		
2002	5		4,926 (19.3)	1,793 (21.0)	914 (31.5)	945 (25.9)	1,269 (3.4)		
2003	21		4,882 (19.6)	1,735 (21.9)	905 (31.6)	907 (25.9)	1,314 (4.3)		
2004	81	51	4,770 (19.8)	1,589 (23.9)	895 (29.8)	869 (26.7)	1,336 (4.9)		
2005	154	86	4,680 (20.0)	1,429 (26.7)	842 (28.7)	812 (28.3)	1,443 (6.1)		
2006	181	104	4,564 (20.5)	1,407 (27.4)	832 (28.3)	759 (28.6)	1,385 (7.2)		
2007	204	120	4,489 (21.3)	1,392 (27.5)	840 (27.9)	737 (31.8)	1,316 (8.1)		
2008	226	139	4,398 (21.8)	1,384 (27.9)	839 (29.9)	730 (32.2)	1,219 (6.9)		

NOTE: The share of large stores (percent) in parentheses for traditional stores. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Gas stations are excluded.

Table 2: Distribution of store characteristics by firm in 2008

	ICA		Axfood		COOP		Others	
	Space (m^2)	Sales	Space (m^2)	Sales	Space (m^2)	Sales	Space (m^2)	Sales
Minimum	50	750	10	250	40	2,500	10	40
10th percentile	190	9,000	90	2,500	233	12,500	50	1,500
25th percentile	300	17,500	150	4,500	360	17,500	80	2,500
50th percentile	550	35,000	305	12,500	595	35,000	110	5,500
75th percentile	1000	67,500	1050	55,000	1050	55,000	160	9,000
90th percentile	2,115	140,000	2,000	110,000	2,376	125,000	325	17,500
Maximum	7,500	580,000	5,000	450,000	10,000	530,000	13,000	750,000
Mean	862	60,536	733	39,546	946	54,932	244	12,501
Std. deviation	908	80,388	868	58,189	995	66,091	741	38,237
No. of obs.	1,384		839		730		2,517	

NOTE: This table shows the distribution of number of square meters and sales of stores that belong to different firms in 2008. Gas stations are included in Others. Sales (incl. 12% VAT) is measured in thousands of SEK (1USD=6.62SEK, 1EUR=9.66SEK).

Table 3: Local markets and store type configurations by firm in 2008

	All markets			Without Discount			With Discount		
	Large			Large		Small	Large		
	0	1	2+	0	1	2+	0	1	2+
Firm 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
Firm 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
Firm 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
Firm 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: Local markets are defined as municipalities with a population of 9,500-100,000 but excluding municipalities bordering Norway (209 in total). Note that this differs from the locality markets and regional markets in Table 4. Lidl and Netto are defined as hard discounters. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores).

Table 4: Local market characteristics in 2008

	Mean	Std. dev.	Min	Max
A. Locality markets				
No. of traditional	13.53	17.02	2.00	96.00
No. of discounters	1.43	1.40	0.00	6.00
No. of large	5.48	3.96	0.00	23.00
Children (%)	11.40	1.50	8.66	17.64
Pensioners (%)	17.45	2.86	10.97	24.24
Population	57,540.54	44,142.85	20,018.00	252,078.00
Per capital income	268.59	37.91	211.40	504.20
Cost of buildings	16,751.26	8,870.83	322.00	43,846.00
No. of locations	28.31	19.70	8.00	102.00
B. Regional markets				
No. of traditional	53.58	38.49	22.00	166.00
No. of discounters	3.03	1.92	0.00	9.00
No. of large	12.65	5.81	0.00	25.00
Children (%)	11.72	1.40	10.02	15.92
Pensioners (%)	15.74	1.92	12.15	19.14
Population	137,629.10	78,313.55	47,749.00	294,434.00
Per capital income	264.48	36.25	211.40	418.60
Cost of buildings	20,269.74	8,742.12	9,890.00	43,846.00
No. of locations	5.97	2.37	2.00	10.00

NOTE: Locality markets are defined as localities with a population of 20,000-300,000 (164 in total). Regional markets are defined as the two-digit zip codes that constitute main city areas (31 in total). Children are defined as the population aged below 10 years of age and pensioners as those over 65. Price of houses sold is the median price per square meter of houses sold in the municipality (1USD=6.62SEK, 1EUR=9.66SEK). Population is calculated based on five-digit zip code information.

Table 5: Store configurations in locations

Traditional	Hard Discount		
	0	1	>1
A: Locality markets			
0	3,093	82	2
1	1,162	49	2
2	205	15	0
3	37	5	0
4	4	0	0
5	0	0	0
6	1	0	0
No. of locations	4,502	151	4
B: Regional markets			
0	10	0	0
1	9	0	0
2	8	1	0
3	13	4	0
4	9	6	0
5	11	2	0
6	11	4	0
7	5	2	0
8	3	3	0
9	5	4	1
10	4	6	0
11-15	10	16	4
16-20	9	4	4
21-25	3	7	3
26-30	0	3	1
No. of locations	110	62	13

NOTE: This tables shows store configurations of the number of traditional stores (excluding large) and hard discounters across locations in 2008. Five-digit zip codes are defined as locations in locality markets (4,657 in total). Three-digit zip codes are used as locations in regional markets (185 in total).

Table 6: Characteristics of locations and distance bands in locality markets

	Mean			Std. dev.			Min			Max		
	<i>loc</i>	<i>b</i> ₁	<i>b</i> ₂	<i>loc</i>	<i>b</i> ₁	<i>b</i> ₂	<i>loc</i>	<i>b</i> ₁	<i>b</i> ₂	<i>loc</i>	<i>b</i> ₁	<i>b</i> ₂
Traditional	0.39	2.21	4.19	0.63	1.24	2.03	0	1	1	6	8	11
Discounter	0.03	1.15	1.63	0.19	0.36	0.54	0	1	1	2	4	4
Large	0.03	1.13	1.80	0.19	0.35	0.84	0	1	1	3	4	5
Population	1,050	5,370	33,963	582	4,888	25,909	1	2	10	4,471	34,759	116,418

NOTE: This table shows summary statistics of number of stores by type and population across locations and distance bands in 2008. Locality markets are defined as localities with a population of 20,000-300,000 (164 in total) and five-digit zip codes are defined as locations (4,657 in total). Distances are calculated from the mid-point of the zip code. The radius measure is based on the 25th percentile and the 75th percentile measures of distances across all locations in the sample markets. A radius of 1 kilometer is used for band 1 (b_1), and 9 kilometers is used for band 2 (b_2).

Table 7: Reduced form probit estimates

	Heterogenous stores					
	Homogenous stores		Hard discounters		Traditional stores	
	(1)	(2)	(3)	(4)	(5)	(6)
Rivals b_1	0.011 (0.012)					
Hard discount rivals b_1					-0.212 (0.060)	-0.211 (0.060)
Hard discount rivals b_2				-0.495 (0.103)	0.067 (0.044)	0.066 (0.044)
Traditional rivals b_1			-0.076 (0.043)	-0.088 (0.043)		
Traditional rivals b_2			-0.057 (0.027)	-0.062 (0.029)		0.004 (0.013)
Large rivals b_1	-0.173 (0.063)	-0.172 (0.063)	0.091 (0.109)	0.056 (0.110)	-0.178 (0.063)	-0.178 (0.063)
Large rivals b_2	-0.037 (0.029)	-0.039 (0.029)	-0.141 (0.072)	-0.144 (0.074)	-0.056 (0.029)	-0.057 (0.029)
Distance to DC	-0.489 (0.279)	-0.452 (0.281)	-0.408 (0.028)	-0.412 (0.029)	-0.251 (0.008)	-0.251 (0.008)
Cost of buildings	-0.045 (0.059)	-0.044 (0.059)	-0.262 (0.101)	-0.248 (0.102)	0.070 (0.059)	0.070 (0.059)
Population b_1	0.045 (0.017)	0.044 (0.017)	0.067 (0.047)	0.081 (0.050)	0.063 (0.017)	0.063 (0.017)
Population b_2	-0.012 (0.017)	-0.020 (0.020)	0.082 (0.060)	0.205 (0.082)	-0.0.27 (0.018)	-0.030 (0.020)
Children	-0.013 (0.030)	-0.011 (0.030)	0.072 (0.069)	0.120 (0.070)	0.027 (0.030)	0.029 (0.030)
Pensioners	-0.013 (0.017)	-0.013 (0.017)	0.048 (0.037)	0.081 (0.038)	0.019 (0.017)	0.020 (0.017)
Income	-0.489 (0.279)	-0.452 (0.280)	-1.920 (0.604)	-2.701 (0.635)	-0.515 (0.279)	-0.508 (0.280)
Constant	9.092 (1.355)	9.316 (1.334)	14.33 (3.399)	4.835 (1.302)	17.085 (3.471)	4.773 (1.313)
Pseudo- R^2	0.256	0.257	0.325	0.343	0.207	0.207
No. of obs.	4,657	4,657	4,657	4,657	4,657	4,657

NOTE: This table shows probit estimates where the dependent variable takes the value one if a stores operates in a location and zero otherwise. Coefficients reported and standard errors in parentheses. Data from 2008. Samples markets are defined as localities with a population of 20,000-300,000 (164 in total) and five-digit zip codes are defined as locations (4,657 in total). Distance band 1 (b_1) refers to the surrounding area within 2 kilometer, and band 2 (b_2) to the distance band within 2-10 kilometers from the location. The number of potential entrants is assumed to be two times the observed number of entrants of each store type. Large stores are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Distance to DC measures the minimum distance to the nearest distribution center for all stores, hard discounters and traditional stores, respectively. Price per square meter of houses sold is used as a proxy for cost of buildings. Population, average income, and distance to DC are measured in logs.

Table 8: Results from the structural model with heterogenous stores

	Potential entrants $K = 2 \times$ total entrants	
	Hard discount	Traditional stores
Hard discount rivals b_1	-3.684 (0.230)	-3.332 (0.145)
Hard discount rivals b_2	-0.613 (0.132)	-1.052 (0.101)
Traditional rivals b_1	-1.907 (0.282)	-3.950 (0.166)
Traditional rivals b_2	-1.623 (0.230)	-0.782 (0.295)
Large rivals b_1	-1.690 (0.204)	-6.731 (0.139)
Large rivals b_2	-4.267 (0.109)	-2.882 (0.183)
Distance to DC	-2.788 (0.221)	-4.551 (0.134)
Cost of buildings	-5.928 (0.111)	-5.368 (0.248)
Population b_1	4.631 (0.125)	6.280 (0.124)
Population b_2	0.412 (0.118)	8.409 (0.101)
Children	-3.458 (0.164)	-1.760 (0.116)
Pensioners	-0.917 (0.127)	-3.138 (0.174)
Income	7.188 (0.106)	6.197 (0.169)
μ	-77.259	
σ	24.260	
Log-Likelihood	-15950.221	
No. of obs.	370	

NOTE: This table shows estimation results of the full structural entry model in Section 3. Data from 2008. Regional markets are defined as the two-digit zip codes that constitute main city areas (31 in total) and three-digit zip codes are used as locations (185 in total). The standard errors (reported in parentheses) are computed using a numerical approximation to the Hessian matrix at the optimal parameter values. Distance band 1 (b_1) refers to the surrounding area within 2 kilometer, and band 2 (b_2) to the distance band within 2-10 kilometers from the location. The number of potential entrants is assumed to be two times the observed number of entrants of each store type. Large stores are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Distance to DC measures the minimum distance to the nearest distribution center for hard discounters and traditional stores, respectively. Price per square meter of houses sold is used as a proxy for cost of buildings. Population, average income, and distance to DC are measured in logs.

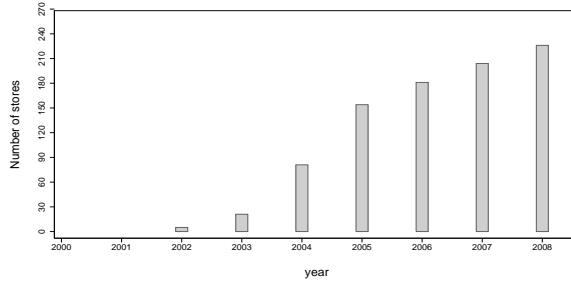


Figure 1: Number of hard discount stores in Sweden 2000-2008.

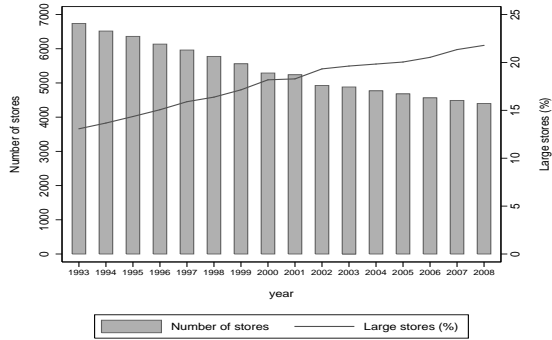


Figure 2: Total number of stores and share of large stores in Sweden 1993-2008.

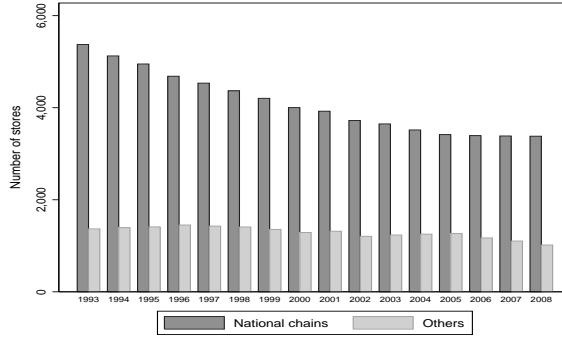


Figure 3: Total number of stores by national firms and other owners (excluding hard discounters) 1993-2008.

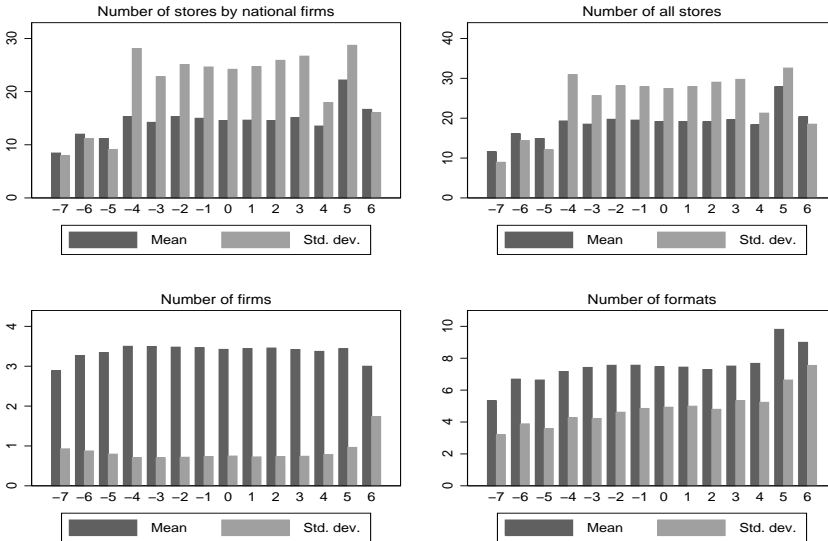


Figure 4: Number of stores, firms, and formats in local markets before and after hard discount entry.

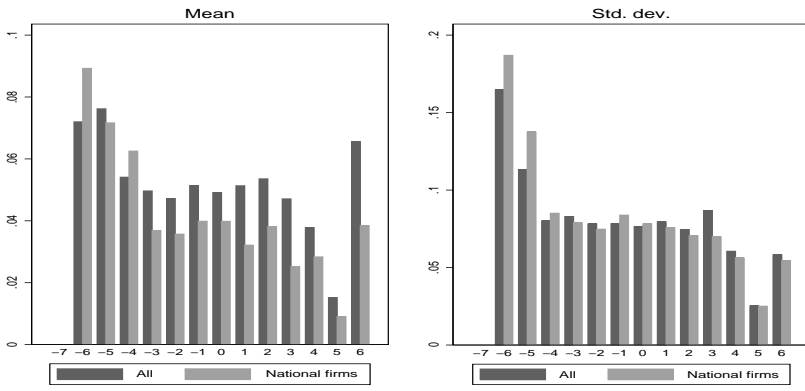


Figure 5: Local market exit rates of incumbent stores before and after hard discount entry.

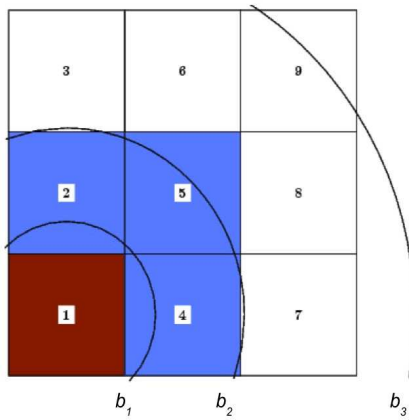


Figure 6: Impact on profits of competitors' location

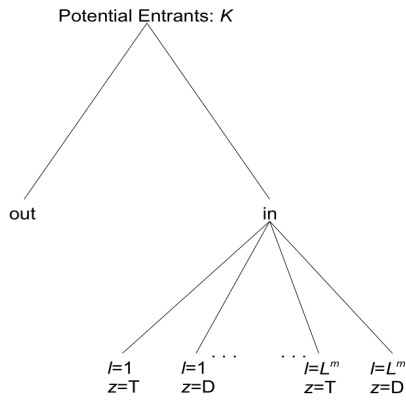


Figure 7: Entry, store type, and location choices

Appendix A: Data description and robustness

■ **Data.** Each year, the owners provide information on all stores they are operating. Each store has an identification number linked to its address. Sales are presented in 19 classes. There are 12 different store types defined based on size, geographic location, product assortment etc: 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. Firms include ICA, Axfood, COOP, Bergendahls and Others. The group Others include owners such as 7-eleven, Pressbyrån, Statoil, Preem, and OK.

■ **Alternative definition of local markets.** For robustness, I use municipalities as local markets (290 in total). Figure A.1 shows average exit rates at the municipality level before and after hard discount entry. There are significantly higher average exit rates by national firms 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 exit 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). In addition, I chose markets with a population from 9,500 to 100,000 but excluding municipalities bordering Norway (209 in total). Descriptive statistics using this sample is shown in Table 3.

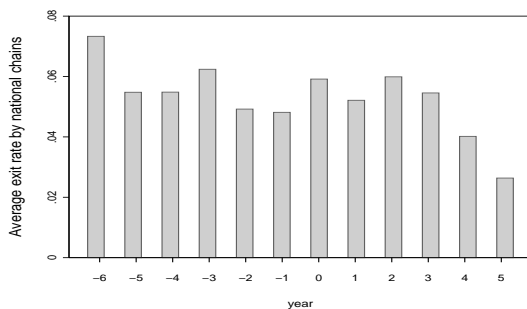


Figure A.1: Mean local market exit rate by traditional stores before and after hard discount entry (municipalities used as local markets).

■ **Sample markets from DELFI in 2006.** For robustness, I present descriptive statistics using a sample of markets from DELFI in 2006 with a population from 15,000 to 100,000, which gives 89 markets. Preliminary estimates of the structural model using this sample of markets are shown in Appendix B. Locations are defined as five-digit zip codes from DELFI, i.e., those that contain at least one store, which gives a total of 1,310 locations. Tables A.1, A.2, A.3 show descriptive statistics using data from 2006. Table A.1 shows market configurations of the number of traditional, large, and discount stores. Table A.2 presents characteristics of local markets and locations. Summary statistics of the number of stores in locations and distance bands are shown in Table A.3.

Table A.1: Market configurations 2006

Store Types	Number of Markets	Mean Population
(T,0,0)	14	20,948
(T,L,0)	21	30,867
(T,L,D)	54	33,644
All	89	30,992

NOTE: T = Traditional store type, L = Large store type, D = Discount store type. Localities in DELFI with a population of 15,000-100,000 in 2006 are used as local markets. The configuration presents markets with at least one store type present in the market. No markets have the remaining configurations (0,L,0); (0,0,D); (T,0,D); (0,L,D).

Table A.2: Local markets and locations 2006

A. Local Markets	Mean	Std.	Min	Max
No. Trad	16.6	8.82	3	54
No. Large	4.32	1.84	0	16
No. Discount	0.92	0.51	0	4
Population	30,992	13,261	15,005	98,326
No. locations	23.2	11.6	1	48
B. Locations (cells)				
No. Trad	1.12	0.78	0	6
No. Large	0.29	0.59	0	4
No. Discount	0.06	0.24	0	2
Population	1,354	741	1	6,656

NOTE: In total, 89 markets defined as localities in DELFI with a population of 15,000-100,000 in 2006. Five-digit zip codes in DELFI are used as locations (1,310 in total). Trad = Traditional store type, Large = Large store type, Discount = Discount store type.

Table A.3: Location and store types in 2006

Store type	Mean			Std. dev.			Min			Max		
	b_0	b_1	b_2	b_0	b_1	b_2	b_0	b_1	b_2	b_0	b_1	b_2
Trad	2.02	9.61	11.66	1.64	7.19	9.39	0	0	0	11	35	45
Large	0.51	2.53	3.26	0.79	2.20	3.11	0	0	0	5	11	16
Discount	0.10	0.55	0.60	0.30	0.77	0.87	0	0	0	2	4	4
All stores	2.63	12.7	15.5	1.89	8.94	12.4	1	0	0	13	44	63

NOTE: Localities in DELFI with a population of 15,000-100,000 in 2006 are used as local markets. Five-digit zip codes in DELFI are used as locations (1,310 in total). b_0 is the surrounding area within a radius of 0.5 kilometers from the mid-point of the current location, b_1 is the second band defined as the distance band between 0.5 and 2 kilometers, and b_2 is the third band and is specified by the distance band between 2 and 8 kilometers. Trad = Traditional store type, Large = Large store type, Discount = Discount store type.

Appendix B: Maximum simulated likelihood

This appendix briefly explains and shows estimation results of the entry model by maximum simulated likelihood using differentiation in location with 3 distance bands ($B = 3$) and differentiation in store type where $z = T, L, D$, where T =traditional, L =large, D =discount. For identification, I ignore own-type competitive effects by assuming $\delta^{zz} = 0$. Let the probability equilibrium realization that is consistent with market outcomes be $P(q_m) = \Pi_z P(q_{zm})$, where $q_{zm} = (q_{Tm}, q_{Lm}, q_{Dm})$. The likelihood function is given by

$$L(q, X, \psi; \theta) = \prod_{m=1}^M P(q_m | X_m, \psi_m; \delta). \quad (13)$$

Since I assume that the unobserved market effect ψ_m is normally distributed with mean μ and variance σ^2 , the unconditional maximum likelihood can be written as

$$L(q, X, \psi; \theta) = \prod_{m=1}^M \int P(q_m | X_m, \psi_m; \delta) dF(\psi_m | \sigma^2). \quad (14)$$

Following Zhu and Singh (2009), I use simulated maximum likelihood and simulate R draws with standard normal distribution $\psi = (\psi^1, \psi^2, \dots, \psi^R)$ for the unobserved market effect. For each draw ψ^r , the Bayesian Nash equilibrium probabilities P_m^r are obtained by solving the system of equations in (9). Repeating the procedure R times, the predicted probability of the observed outcome for market m is

$$\int P(q_m | X_m, \psi_m; \delta) dF(\psi_m | \sigma^2) = \frac{1}{R} \sum_{r=1}^R P_m^r(q_m). \quad (15)$$

Therefore, the log-likelihood taken to estimate is

$$\hat{\theta} = \arg \max_{\theta} \text{Log} L(q, x; \theta) = \sum_{m=1}^M \sum_{l=1}^{L_m} \sum_{z=1}^Z n_{zlm} \ln \left[\frac{1}{R} \sum_{r=1}^R P_{zlm}^r(q_{zlm}) \right], \quad (16)$$

where n_{zlm} is the number of stores of type z in location l in market m . The parameters are estimated using the Nelder-Mead optimization procedure.

■ **Results.** Table B.1 shows estimates of the structural model using sample markets from DELFI in 2006. Appendix A describes these sample of markets in more detail. The findings confirm that the competitive intensity declines faster for hard discounters than for traditional stores. Preliminary estimates using homogenous stores in 2006 show that the competitive intensity reduces mostly when moving from the second to the third distance band (Table B.2).

Table B.1: Results from type and location choice model in 2006

	Traditional		Large		Discount	
	Param.	Std Err	Param.	Std Err	Param.	Std Err
Traditional rivals b_0			-3.710	0.011	-4.000	0.002
Traditional rivals b_1			-3.147	0.010	-3.245	0.013
Traditional rivals b_2			-2.770	0.038	-2.650	0.031
Large rivals b_0	-4.060	0.007			-4.724	0.156
Large rivals b_1	-3.570	0.015			-4.420	0.342
Large rivals b_2	-2.790	0.012			-3.200	0.261
Discount rivals b_0	-3.249	0.019	-2.301	0.012		
Discount rivals b_1	-2.680	0.002	-1.562	0.011		
Discount rivals b_2	-0.329	0.013	-0.022	0.003		
Population b_0	0.768	0.025	0.940	0.034	1.240	0.029
Population b_1	0.465	0.037	0.639	0.002	0.635	0.120
Population b_2	0.091	0.001	0.440	0.019	0.330	0.001
No. of firms	-1.990	0.003	-0.981	0.004	-0.740	0.003
Log-Likelihood	-2123					
No. of obs.	3,930					

NOTE: Preliminary estimates using 89 locality markets from DELFI with a population of 15,000-100,000 in 2006. Five-digit zip codes in DELFI are used as locations (1,310 in total). Number of potential entrants is equal to 1.5 times actual number of entrants. b_0 is the first band with a radius of 0.5 kilometers from the mid-point of the current location, b_1 is the second band defined as the distance band between 0.5 and 2 kilometers, and b_2 is the third band and is specified by the distance band between 2 and 8 kilometers.

Table B.2: Results from location choice model in 2006

	Param.	Std Err
Rivals b_0	-1.584	0.081
Rivals b_1	-1.264	0.030
Rivals b_2	-0.415	0.014
Population, location	0.627	0.012
Number of families	0.763	0.033
No. of obs.	1,310	

NOTE: Preliminary estimates using 89 locality markets from DELFI with a population of 15,000-100,000 in 2006. Five-digit zip codes in DELFI are used as locations (1,310 in total). Number of potential entrants is equal to 1.5 times actual number of entrants. b_0 is the first band with a radius of 0.5 kilometers from the mid-point of the current location, b_1 is the second band defined as the distance band between 0.5 and 2 kilometers, and b_2 is the third band and is specified by the distance band between 2 and 8 kilometers.

Appendix C: Constraint optimization

This appendix contains a short description of constraint optimization (Su and Judd, 2011). 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, the likelihood function is maximized by adding Lagrange multipliers to each of the equations in (9). The likelihood function consists of both the type-location 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 stands in contrast to Vitorino (2011), who uses constraint optimization in a framework where store types are known ex-ante. The constrained likelihood function taken to estimate is then given by:

$$L(\theta) = \prod_{m=1}^M \prod_{z=1}^Z \prod_{l=1}^L p_{\theta_p}(\cdot | X_{zl}^m, S^m, \psi^m) f_{\theta_f}(\psi^m | X_{zl}^m, S^m, K^m) \quad (17)$$

s.t.

$$p_{zl}^{m*} = \frac{\exp(\pi_{zl}(X_{zl}^m, p^*, S^m, \theta))}{\sum_t \sum_h \exp(\pi_{th}(X_{zl}^m, p^*, S^m, \theta))}.$$

Paper IV

Store Dynamics, Differentiation and Determinants of Market Structure*

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and

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January 22, 2012

Abstract

Substantial entry and exit and a trend toward larger but fewer stores constitute a major structural change in retail markets in the last few decades. To study the determinants of market structure in retail markets, this paper uses a dynamic structural oligopoly model of entry and exit that allows for store-level heterogeneity. Using a rich data set on all retail food stores in Sweden, we estimate entry cost of potential entrants and sell-off values for exit for small and large stores. We find empirical evidence of type competition. An additional large store in the market decreases the profits of large stores about seven percentage points more than for small stores. For small stores, the average entry cost is about two times larger than the sell-off value of exit. Using structural estimates, we evaluate the impact of different policies on the cost structure for each store type and market structure dynamics. Small stores are negatively affected by more efficient incumbents, whereas large stores incur higher entry costs due to other factors such as higher rent or cost of buildings. The findings have a direct link to competition policy because the majority of OECD countries have entry regulations, and the consequences of regulation in retail food are frequently debated among policy makers in the EU.

Keywords: Retail markets; imperfect competition; product differentiation; entry; exit; sunk costs.

JEL Classification: L11, L13, L81.

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1 Introduction

Firm turnover and the cost structure of an industry are key determinants of market structure and its evolution over time. Markets are characterized by substantial simultaneous entry and exit that affect the market structure. In addition, product differentiation is central in many markets. One example is retail food, where store type and location are key dimensions. The degree of differentiation influences both competition and the cost structure of an industry, which in turn determine market structure. We present a dynamic model of entry and exit with product differentiation, recovering both entry cost of potential entrants and sell-off values of exit.

A central feature of our model is that it generalizes two-period static models of differentiation into a dynamic context.¹ The model builds on Pakes et al. (2007) (POB) but allows for differentiation in store type. We apply the model to a panel data set covering detailed information of all retail food stores in Sweden during 2001-2008. A dynamic approach is central because the market has undergone a structural change towards larger but fewer stores (Figures 1-2). Store type differentiation is essential as large stores cover only 20 percent of the total number of stores but over 60 percent of aggregate sales and sales space (Table 1). The retail food market has a number of characteristics that are appropriate for an application of our theoretical model: First, stores operate well-defined store types. Second, entry and exit of stores are main determinants of market structure.² Third, demand is closely tied to population. Fourth, the trend towards larger but fewer stores did not change during the last few decades.³

The present paper contributes with information on the dynamics of store type competition and asymmetries between store types. The evaluation of entry costs for different store types and understanding the factors affecting entry cost provide crucial information in markets where the average travel distance with the main purpose of buying food increases.⁴ The retail food market is important not only because food products constitute a high share of private consumption, but also because entry is regulated. Regulations are in effect in most OECD countries, and Europe

¹Berry and Reiss (2007) survey static entry literature, and Berry and Tamer (2007) discuss identification in static entry games.

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

³The model requires construction of consistent transition probabilities only once based on what is observed in the data. In markets with various structural changes over time we might not obtain consistent transition probabilities if the period is not sufficiently long.

⁴In Sweden, average travel distance with the main purpose of buying food was about 9.83 kilometers during 1995-2002 (The Swedish Institute of Transport and Communication).

has more restrictive regulations than the U.S., and the consequences of regulation in retail food are frequently debated among policy makers in the EU (European Parliament, 2008; European Competition Network, 2011). From the perspective of competition policy, it is therefore central to obtain information on the sunk costs of entry (and potentially on how these vary with different degrees of regulation). Because our model allows for counterfactuals using estimated structural parameters, it can be used to design policies to encourage entry of small stores that is beneficial to consumers. From a welfare point of view, it is key to understand players' incentives and the subsequent market outcomes, and hence to secure that various consumer groups have access to a wide range of products and store types.⁵

The model connects to two areas of literature: The first comprises recent studies using dynamic structural models of entry and exit (Aguirregabiria and Mira, 2007; Bajari et al., 2007 [BBL]; Pakes et al., 2007; Pesendorfer and Schmidt-Dengler, 2008).⁶ However estimating demand and cost, and then recovering the structural parameters is demanding from both a data and a computational perspective. This is certainly true for complex markets such as retailing.⁷ To use an approach based on POB, which instead requires a good measure of profits, is then a valid alternative. The second strand of literature concerns two-period static entry models with differentiation. These models ignore the presence of sunk costs as they cannot be separately identified from fixed costs (Bresnahan and Reiss, 1987; Bresnahan and Reiss, 1990; Berry, 1992; Mazzeo, 2002; Toivonen and Waterson, 2005; Seim, 2006; Jia, 2008).⁸

We model the long-run equilibrium using a model that allows for store heterogeneity. The model relies on a reduced form (observed) profit function. Dunne et al. (2011) apply a similar approach to data on dentists and chiropractors. They estimate an average firm profit function along with sunk costs and sell-off values. As the baseline model in POB, they abstract from any differentiation. We fol-

⁵Our approach (as POB) does not allow for a complete welfare analysis. A common constraint for the use of fully dynamic models is data limitations. We do not have access to household and price data to estimate demand.

⁶Akerberg et al. (2007) survey recent econometric methods in Industrial Organization including dynamic games.

⁷Maican (2010) uses a dynamic framework to analyze store format repositioning in the Swedish retail food market. There is a growing literature that analyzes retail chain expansion (e.g., Holmes, 2011; Toivonen and Waterson, 2005). Most of this literature investigates industries where exit is extremely rare. Holmes (2011) analyzes the diffusion of Walmart in the U.S. Toivonen and Waterson (2011) study the spread of McDonalds in the U.K.

⁸There are studies that investigate store location in retail markets (e.g., Seim, 2006; Jia, 2008; Ellickson et al., 2010; Nishida, 2010; Holmes, 2011; Orth, 2011). In future versions of the paper, we aim to account explicitly for location differentiation in our dynamic framework (Berry et al., 1995; Davis, 2006; Seim, 2006).

low POB but relax the assumption of identical firms, and recognize differentiation in store type. Many markets, like retail food, are characterized by heterogenous players, which calls for models with less restrictive assumptions. However, these assumptions need to be balanced against the computational burden and presence of multiple equilibria. In the proposed model, data pick up the equilibrium played. Separating large stores from small stores is important in our application because large stores stand for the majority of sales and sales space but only for a minor share of all stores. We are only aware of a few empirical applications of POB with heterogenous players. Elejalde (2011) investigates U.S. banks and finds that single-market banks have higher sunk costs of entry than multi-market banks. Fan and Xiao (2011) also find differences in cost structure across heterogenous firms using data on the telephone market in the U.S.

An advantage of our model is that it is based on the actions that actually take place in the market. This comes at the cost that we need information on profits. We cannot obtain accurate policy experiments if there are multiple equilibria in the data. Pakes et al. (2007) claim that the correct equilibrium will be picked for large enough samples. To address this issue, we take advantage of our data, which have the advantage of containing all stores active in the Swedish retail food market for a long period of time. The structural parameters of the distribution of entry costs and sell-off values are estimated by matching the observed entry and exit rates in the data to the ones predicted by the model.

Our empirical results are based on differentiation in type. We find empirical evidence of type competition and significant differences in the cost structure for small and large types. The estimates indicate that entry of an additional large store decreases the profits of small stores by about 11 percent and profits of large stores by about 18 percent. These findings are in line with the results from the static entry literature (Mazzeo, 2002). The average entry cost is about two times larger than the sell-off value for small stores. This result is reasonable due to the drastic fall in small stores and that most small entrants belong to other firms than the national ones. Asymmetries between store types are present. More efficient incumbents increase costs for small stores whereas higher cost of buildings (rent) increase the costs for large stores. Entry cost increases less than the sell-off value for small stores when the number of potential entrants increases.

The next section presents the model, followed by the data and market information. Section 4 discusses the empirical implementation of the model, Section 5 presents the empirical results, and Section 6 reports the results of several counterfactual exercises that highlight the importance of factors in generating turnover and

the level of long-run profitability. Section 7 conclude the paper.

2 A dynamic model of entry and exit

This paper uses a dynamic model to learn about the distribution of retail stores' entry and exit costs. The framework is based on Pakes et al. (2007) (POB) and accounts for differentiation in type/location, which is common in retail markets. Importantly, we exploit the fact that store concepts in retail food are well-defined and differ from POB in that store types are known.

In the beginning of each period, a set of incumbents $\mathbf{J} = (J_z, J_{-z})$ and potential entrants $\mathcal{E} = (\mathcal{E}_z, \mathcal{E}_{-z})$ simultaneously decide their actions. Incumbents choose whether to continue to operate with type (or in location) $z \in \mathcal{Z}$ or exit.⁹ Incumbents of type $z \in \mathcal{Z}$ receive a draw of the sell-off value ϕ_z from the distribution $F^{\phi_z}(\cdot|\boldsymbol{\theta})$ upon exit, where $\boldsymbol{\theta}$ is a parameter to be estimated. We follow the common assumption that exit draws are i.i.d. across markets and time. Stores only observe their own draws of the sell-off value but not their rivals' draws, which induces asymmetric information across stores. The distribution is, however, known to all players. The draw of the exit fee depends on the store type (location) of the store, i.e., stores of different types receive sell-off values from different distributions. This stands in contrast to POB, where all incumbents are ex-ante identical and receive draws of their sell-off values from the same distribution.

Potential entrants decide whether to enter their store type $z \in \mathcal{Z}$ or stay out. Entrants' decisions are made one period ahead of the period in which they start to operate. The entry cost for potential entrants of store type z , κ_z , is a draw from the distribution $F^{\kappa_z}(\cdot|\boldsymbol{\theta})$. Sunk costs are private information known prior to players' decisions and are i.i.d. distributed from a known distribution (Bajari et al., 2007; Pakes et al., 2007). We thus have two different pools of potential entrants (one for each type), that receive sunk cost draws from different distributions, upon deciding whether to enter or not. The entry costs might be higher the larger the store type. In POB, all potential entrants receive draws from the same distribution. The entry assumption, that entrants decide to enter a period ahead of the period in which they start to operate, allows us to obtain continuation and entry values that are

⁹In Sweden, individual stores decide over their own prices and a majority of stores operate as independent or franchise units. The degree to which firms are part of individual stores' strategic decisions varies somewhat among firms. COOP is the only firm that operates as a cooperation at the local or national level.

independent of entry costs.

A store is described by a vector of state variables $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$ that consists of the number of stores of each type active in a local market, (n_z, n_{-z}) and exogenous profit shifters specific to each type, \mathbf{y} . The index $-z$ includes other types except z . Furthermore, we assume independent local markets, i.e., a separate game is played in each local market. For notational simplicity, the presentation omits from the market index m .¹⁰ The number of stores of type z , n_z , evolves endogenously over time according to $n'_z = n_z + e_z - x_z$, where e_z and x_z are the number of entrants and exiters. The exogenous profit shifters that cover both demand and cost are public information to firms and evolve exogenously according to a first-order Markov process $\mathbb{P}(\mathbf{y}'|\mathbf{y})$.

All stores of type z are identical up to the draw of the sell-off value and entry fee. Profits of firms of the same type are therefore identical. We do not allow firms to invest or change owner or format. The fact that store concepts are rather uniform in the retail food market justifies this assumption. The model requires having observed profits in contrast to the literature on static entry and dynamic games that estimates the underlying primitives of demand and cost. Since it is difficult to collect data on prices and because store types are well-defined, we believe this approach is appropriate for our application to the Swedish retail food market.

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

$$V_z(n_z, n_{-z}, \mathbf{y}, \phi; \boldsymbol{\theta}) = \max\{\pi_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) + \beta\phi_z, \pi_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) + \beta VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})\}, \quad (1)$$

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

¹⁰Since stores decide over their own prices in Sweden and a majority of stores operate as independent or franchise units, multi-market contact is not as crucial as in many other countries. To relax the independence assumption across markets would severely increase the complexity and computational burden of the model. There are only a few attempts that recognize the issue of the chain effect across local markets, and they all use a small number of players (Jia, 2008; Holmes, 2011; Nishida, 2010).

of entrants, exits, and possible values of the profit shifters

$$VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) = \sum_{e_z, e_{-z}, x_z, x_{-z}, \mathbf{y}} \int_{\phi'_z} V_z(n_z + e_z - x_z, n_{-z} + e_{-z} - x_{-z}, \mathbf{y}, \phi'_z; \boldsymbol{\theta}) p_z^c(e_z, e_{-z}, x_z, x_{-z} | n_z, n_{-z}, \mathbf{y}, \lambda_z^c = 1) p(\mathbf{y}' | \mathbf{y}) p(d\phi'_z), \quad (2)$$

where $p_z^c(\cdot)$ is a z - incumbent's perception of rivals' type decisions $(e_z, e_{-z}, x_z, x_{-z})$ conditional on itself continuing, i.e., that $\lambda_z^c = 1$. The optimal policy for an incumbent is to exit if the draw of the sell-off value is larger than the value of continuing, which gives the probability to exit $Pr(\phi_z > VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})) = 1 - F^{\phi_z}(VC_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}))$.

□ **Entrants.** Potential entrants maximize the expected discounted future profits and enter if they can cover sunk costs. They start to operate in the next period. The value of entry is

$$VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}) = \sum_{e_z, e_{-z}, x_z, x_{-z}, \mathbf{y}} \int_{\kappa'_z} V_z(n_z + e_z - x_z, n_{-z} + e_{-z} - x_{-z}, \mathbf{y}, \phi'_z; \boldsymbol{\theta}) p_z^c(e_z, e_{-z}, x_z, x_{-z} | n_z, n_{-z}, \mathbf{y}, \lambda_z^c = 1) p(\mathbf{y}' | \mathbf{y}) p(d\kappa'_z), \quad (3)$$

where $p_z^e(\cdot)$ is a potential entrant's perceptions of the number of entrants and exits of each type conditional on entering. Entry occurs if the draw from the distribution of sunk costs is smaller than the value of entry, which results in the probability of entry being $Pr(\kappa_z < VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta})) = F^{\kappa_z}(VE_z(n_z, n_{-z}, \mathbf{y}; \boldsymbol{\theta}))$. Potential entrants choose to operate a store of type z if the expected profits are higher than for all other types and the outside option. Hence, we have first the condition that the entry value needs to be larger than the draw of the entry cost. Then we have that the type (location) choice needs to give the highest expected discounted future profits among all type alternatives:

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

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

■ **Equilibrium.** Incumbents and potential entrants make simultaneous moves and they both form perceptions of entry and exit among rivals. In equilibrium, these perceptions need to be consistent with actual behavior. The incumbents' percep-

tion of rival incumbents' behavior needs to be the same for all rivals of the same type. That is, all incumbents of a given type have the same probability of exit and this probability is indicated by the probability that the draw of the exit fee is larger than the value of continuing. Similarly, all potential entrants have the same probability to enter with a given type, i.e., they have the same probability that the draw of the entry cost is smaller than the value of entry. So again perceptions are the same for all rivals of the same store type.

For incumbents we need to construct the perceptions of p_z^c in equation (2). Conditional on that a z -incumbent continues, we have to compute the perceived probabilities of facing a particular number of entrants and exits of each type $p_z^c(e_z, e_{-z}, x_z, x_{-z} | n_z, n_{-z}, \mathbf{y}, \lambda_z^c = 1)$. That is, the probability that the exit draw is larger than the type-location continuation value, $\phi_z > VC_z(n_z, n_{-z}, \mathbf{y}, \phi_z; \boldsymbol{\theta})$ is

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

The perceptions of entry conditional on that they enter $p_z^c(\cdot)$ and the perceptions of exit of the same type $g_z^c(\cdot)$ and of the rival type $g_{-z}^c(\cdot)$ all need to be consistent with equilibrium behavior. The assumption of identical type competitors implies that incumbents' perceptions of competitors' exit from each type is given by the multinomial logit probabilities in case of more than two choices, and by the binomial distribution in case of two choices.

Potential entrants of each type are identical up to the draw of the sunk cost, so in equilibrium all potential entrants of each type need to have the same probability to enter. The perceptions are given by

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

where $p_z^e(\cdot)$ are the perceptions of the entry distribution conditional on that they enter, while $g_z^e(\cdot)$ and $g_{-z}^e(\cdot)$ are perceptions of exit of the same and rival types.

The solution concept is a Markov Perfect Equilibrium. Yet there might exist more than one equilibrium. As in POB, it is guaranteed that in the recurrent class there is not more than one profile of equilibrium policies that are consistent with a given data-generating process. The data will thus select the equilibrium to be played. As POB argue, the correct equilibrium will be picked if samples are large

enough. For this purpose, the present paper takes advantage of the detailed data we have access to, covering the total population of stores in Sweden for a long period of time.

■ **Transition probabilities: Incumbents.** An incumbent that continues will get the continuation value

$$VC_z(\mathbf{s}; \theta) = E_{\mathbf{s}'}^c[\pi_z(\mathbf{s}'; \theta) + \beta E_{\phi'_z}(\max\{VC_z(\mathbf{s}'; \theta), \phi'_z\} | \mathbf{s}')], \quad (8)$$

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

$$E_{\phi'_z}(\max\{VC_z(\mathbf{s}'; \theta), \phi'_z\} | \mathbf{s}') = (1 - p_z^x)VC_z(\mathbf{s}'; \theta) + p_z^x E[\phi'_z | \phi'_z > VC_z(\mathbf{s}'; \theta)]. \quad (9)$$

If we assume that ϕ_z has an exponential distribution, we get $E[\phi'_z | \phi'_z > VC_z(\mathbf{s}'; \theta)] = VC_z(\mathbf{s}') + \sigma_z$, which we substitute into (9). Using (8) we then get

$$VC_z(\mathbf{s}; \theta) = E_{\mathbf{s}'}^c[\pi_z(\mathbf{s}'; \theta) + \beta E_{\phi'_z}(\max\{(1 - p_z^x)VC_z(\mathbf{s}'; \theta) + p_z^x(VC_z(\mathbf{s}'; \theta) + \sigma_z)\})], \quad (10)$$

where σ_z is a parameter in the exponential distribution representing the inverse of the mean.

We now define the continuation values, profits, and exit probabilities as vectors, i.e., $\mathbf{VC}_z(\cdot)$, $\boldsymbol{\pi}_z$, and \mathbf{p}_z^x . Furthermore, let the perceptions be a matrix of transition probabilities \mathbf{W}_z^c that indicates the transition from state $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$ to state $\mathbf{s}' \neq \mathbf{s}$ for type z

$$\mathbf{VC}_z(\cdot) = \mathbf{W}_z^c[\boldsymbol{\pi}_z + \beta \mathbf{VC}_z(\cdot) + \beta \sigma_z \mathbf{p}_z^x]. \quad (11)$$

There is no dependence over time in the transition probabilities.¹¹

To compute the continuation value we need to calculate the expected discounted future profits that the store would gain in alternative future states. We then take weighted averages for those stores that actually continued from state \mathbf{s} . The idea is to use average discounted profits actually earned by stores that continue from state \mathbf{s} , i.e., to plug consistent estimates of \mathbf{W}_z^c and \mathbf{p}_z^x into (11) in order to get consistent estimates of $\mathbf{VC}_z(\cdot)$.

We average over the states in the recurrent class. Let R be the set of periods in

¹¹The presence of serially correlated unobservables is discussed in detail in the empirical implementation in Section 4.

state $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$:

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

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

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

Let $W_{\mathbf{s},\mathbf{s}'}^c$ be the probability that an incumbent transits to $\mathbf{s}' = (n'_z, n'_{-z}, \mathbf{y}')$ conditional on continuing in $\mathbf{s} = (n_z, n_{-z}, \mathbf{y})$. Consistent estimates for incumbents' transition probability from state \mathbf{s} to \mathbf{s}' are given by

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

Both $\tilde{p}_z^x(\mathbf{s})$ and $\tilde{W}_{\mathbf{s},\mathbf{s}'}^c$ will converge in probability to $p_z^x(\mathbf{s})$ and $W_{\mathbf{s},\mathbf{s}'}^c$ as $R(\mathbf{s}) \rightarrow \infty$. The transitions are weighted by the number of incumbents that continue in order to capture that incumbents do their calculations conditional on continuing. Now we use (11) to get estimates of $\mathbf{V}\mathbf{C}_z(\cdot)$ as a function of $\boldsymbol{\pi}_z$, $\tilde{\mathbf{p}}_z^x$ and $\tilde{\mathbf{W}}_z^c$:

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

where I is the identity matrix. Calculation of the continuation values includes inversion of the transition matrix. $\widehat{\mathbf{V}\mathbf{C}}_z(\cdot)$ is the mean of discounted values of the actual returns by players, creating a direct link to the data. Since \mathbf{W}_z^c and \mathbf{p}_z^x are independent of the parameters (for a known β), they only need to be constructed once. The computational burden decreases because the transitions are only constructed in the beginning of the estimation routine. The burden increases, on the other hand, in the number of states, mainly due to the inversion of the transition matrix.¹²

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

$$\tilde{W}_{\mathbf{s},\mathbf{s}'}^e = \frac{1}{\#R(\mathbf{s})} \frac{\sum_{r \in R(\mathbf{s})} (e_{r,z}) \mathbf{1}_{\mathbf{s}_{r+1}=\mathbf{s}'}}{\sum_{r \in R(\mathbf{s})} (e_{r,z})}. \quad (14)$$

¹²The number of states depends directly on the number of types/locations and on the way in which we discretize the exogenous demand and cost shifters.

The expected value of entry is then

$$\widehat{\mathbf{V}}\mathbf{E}_z(\cdot) = \begin{bmatrix} \tilde{\mathbf{W}}_z^e + \beta\tilde{\mathbf{W}}_z^e[I - \beta\tilde{\mathbf{W}}_z^c]^{-1}\tilde{\mathbf{W}}_z^e \\ \beta\tilde{\mathbf{W}}_z^e\beta\tilde{\mathbf{W}}_z^c[I - \beta\tilde{\mathbf{W}}_z^c]^{-1}\tilde{\mathbf{p}}_z^x + \beta\tilde{\mathbf{W}}_z^e\tilde{\mathbf{p}}_z^x \end{bmatrix} \begin{bmatrix} \pi_z \\ \sigma_z \end{bmatrix} \quad (15)$$

■ **Unobservables.** The model requires the use of observed profits. Correlated unobserved variables such as persistent demand shocks would bias the estimates. Theory predicts an expected negative effect of the number of incumbents on profit. The presence of the serially correlated unobservables implies a positive bias in the estimated parameters. Therefore, a stronger competitive impact is anticipated in the presence of correlated unobservables. Although presence of serially correlated unobservables cannot be ruled out, this paper provides conservative estimates.

3 Data and characteristics of the Swedish retail food market

The retail food markets in the OECD countries are fairly similar, consisting of firms operating uniformly designed store types. In Sweden, the food market consists of stores that to a large extent operate as independent or franchise units. Individual stores decide over prices and inputs. Firms work mainly as wholesale providers and the degree of centralization varies somewhat across firms. In 2002, over 90% of all stores were connected to one of four firms: ICA(44%), Coop(22%), Axfood(23%), and Bergendahls(3%). Various independent owners make up the remaining 8% market share. International firms with hard discount formats entered the Swedish market in 2002 (Netto) and 2003 (Lidl). ICA consists mainly of independently owned stores with centralized decision making. Coop, on the other hand, consists of centralized cooperatives with decisions made at the national or local level. Axfood and Bergendahls each have a mix of franchises and centrally owned stores, the latter located mainly in the south and southwest of Sweden.¹³

A majority of OECD countries have entry regulations that give power to local authorities. However, the regulations differ substantially across countries (Hoj et al., 1995; Boylaud and Nicoletti, 2001; Griffith and Harmgart, 2005; Pilat, 2005). While some countries strictly regulate large entrants, more flexible zoning laws exist

¹³In 1997, Axel Johnson and the D-group merged, initiating more centralized decision making and more uniformly designed store concepts.

for instance, in the U.S. (Pilat, 1997). The Swedish Plan and Building Act (PBA) gives power to the 290 municipalities to decide over applications for new entrants. Inter-municipality questions of entry are handled by the 21 county administrative boards. The PBA is claimed to be one of the major barriers to entry, resulting in diverse outcomes, e.g., in price levels, across municipalities (Swedish Competition Authority, 2001:4). Several reports stress the need to better analyze how regulation affects market outcomes (Pilat, 1997; Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2). Large entrants are often newly built stores in external locations, making regulation highly important.¹⁴ Appendix A describes the PBA in greater detail.

■ **Data.** The store data is collected by Delfi Marknadsparter AB (DELFI) and defines a unit of observation as a store based on its geographical location, i.e., its physical address. The data set includes all retail food stores in the Swedish market during 2001-2008 and contains the geographic location (geo-coordinates) of each store, store type, chain affiliation, revenue class, sales space (in square meters), wholesaler and the location (geo-coordinates) of the wholesaler. The store type classification (12 different) depends on size, location, product assortment, etc. We drop gas station stores since that these are located at special places and offer a limited product assortment of groceries and a different product bundle than ordinary stores.¹⁵

We also merge demographic information (population, population density, average income, and political preferences) from Statistics Sweden (SCB) to DELFI. We consider information on the demographic distribution of population (e.g., share of children and pensioners), and the distribution of income across age groups. We also use average wages for municipality workers in the municipality.¹⁶ Finally, we use data provided by Värderingsdata AB on average and median price per square meter for houses sold for each municipality and year. In future versions of this paper, we will also use accounting data on store profits.

■ **Entry and exit.** As we have annual data on all Swedish retail stores based on address, we observe the physical entry and exit of stores. We define an entrant e_{mt} in market m in year t as a store that operates in year t but not in $t - 1$. We define

¹⁴Possibly, firms can adopt similar strategies as their competitors and buy already established stores. As a result, more productive stores can enter without PBA involvement and, consequently, the regulation will not work as an entry barrier that potentially affects productivity. Of course, we cannot fully rule out the opportunity that firms buy already established stores.

¹⁵There are about 1,300 gas stations in the data every year; 1,317 (2001) and 1,298 (2008).

¹⁶Statistics Sweden collects information on wages for employees in the retail sector using surveys. The sample is not large enough to provide data at the municipality level. We therefore use wages for municipality workers as a proxy for retail sector wages.

a store that exits, x_{mt} , from market m in year t as a store that operates in year $t - 1$ but not in t . The total number of stores n_{mt} is given by $n_{mt} = i_{mt} + e_{mt} - x_{mt}$, where i_{mt} is the number of incumbent stores.

We only consider physical entry and exit since this is what matters for estimation of sunk cost and fixed cost. This implies that we do not include stores that switch owners but continue to operate at the same address.¹⁷

Table 1 shows aggregate statistics for the period 2001-2008. The total number of stores decreases by 16 percent to 5,240 in the end of the period. While total sales increases by over 24 percent, the total number of square meters increases by only about 10 percent. The share of large stores increases by 3.5 percentage points to almost 22 percent in 2008. Large stores constitute for the majority of sales and sales space. Their sales increases by 3.8 percentage points to 61.8 percent in 2008, whereas their sales space increases by 2.7 percentage points to 60.5 percent. Thus, large stores had higher growth in sales than in sales space and number of stores, indicating efficiency improvements. The total number of entrants is rather constant over time with the number of exiters being slightly less than double the number of entrants.

The majority of entrants and exiters are small stores (Table 2). Among small entrants, many are owned by Others. For example, as many as 78 percent of the small entrants were owned by Others in 2002. In comparison, the share of large entrants that are not owned by national chains is substantially smaller. For exiters, about half of the small ones do not belong to a national chain, whereas a much lower share is found for large. Note that “other” owners exit a higher share of large stores than they enter.

Figures 1 and 2 show how the number of stores evolves for different players across time. The number of small stores decreases by about 20 percent to 3,215 in 2008, but the number of large stores is fairly constant. There is a fall in the total number of stores for the three main players: 28 percent for ICA, 26 percent for COOP, and 11 percent for Axfood. The reverse trend is found for Bergendahls and hard discounters. Large stores increase for ICA and Bergendahls and are fairly constant for COOP, while they decrease for Axfood and Others. Mainly national chains operate large stores, while almost all stores owned by Others are small. Small stores decline substantially for ICA, COOP, and Others, whereas the changes are smaller in magnitude for small stores owned by Axfood.

Figure 3 shows that the total number of entrants increases until 2005 and then declines, while the number of stores that exit peaks in 2004. Figure 4 shows that

¹⁷See Maican (2010) for an analysis of stores switching format.

the substantial outflow of stores are mainly owned by ICA, Axfood, Coop, and Others, i.e., well established players in the market. Hard discounters and small stores owned by Others dominate entry, together with Axfood. Note however that these observations concern only number of stores and not capacity (size/type of store).

Table 3 presents entry and exit rates across markets and owners for the period 2002-2007. On average, the exit rate is two to three times higher than the entry rate, but the standard deviations are about the same. The mean exit rate varies between 0.03 and 0.07 with a standard deviation of 0.05-0.08. The mean entry rate ranges between 0.01 and 0.04 and the standard deviation is somewhat lower than for exit. Since entry and exit do not occur in all markets, we observe a variation in the upper percentiles. For example, the 75th percentile entry rate varies substantially over time (0-0.06).

Figures 5-6 show that the average entry and exit rates share common trends for national chains, whereas the entry rate is remarkably high for hard discounters and the mean exit rate is high for Others.

Exit takes place in 9-40 percent of the markets in a given year, while the corresponding number for entrants is 15-30 percent. The overall correlation between entry and exit rates is 0.04 whereas the correlation between number of entrants and exits is 0.43. If we exclude the three metropolitan areas (Stockholm, Gothenburg, and Malmö), the correlation is weaker, 0.17. There is, as we expected, a positive correlation between entry and exit, which supports our approach of using a dynamic model.

■ **Local markets.** Food products fulfill daily needs and are often of relatively short durability. Thus stores are generally located close to consumers. The travel distance when buying food is relatively short (except if prices are sufficiently low), and nearness to home and work are therefore key aspects for consumers when choosing where to shop, though distance likely increases with store size.¹⁸ The size of the local market for each store depends on its type. Large stores attract consumers from a wider area than do small stores, but the size of the local market also depends on the distance between stores. We assume that retail markets are isolated geographic units, with stores in one market competitively interacting only with other stores in the same local market. A complete definition of local markets requires information about the exact distance between stores. Without this information we must rely on already existing measures. The 21 counties in Sweden are clearly too

¹⁸The importance of these factors is confirmed by discussions with representatives from ICA, COOP, and Bergendahls. According to surveys made by the Swedish Institute for Transport and Communication Analysis, the average travel distance for trips with the *main* purpose of buying retail food products is 9.83 kilometers (1995-2002).

large to be considered local markets for our purposes, while the 1,534 postal areas are probably too small, especially for large stores. Two intermediate choices are the 88 local labor markets or the 290 municipalities. Local labor markets take into account commuting patterns, which are important for the absolutely largest types such as hypermarkets and department stores, while municipalities seem more suitable for large supermarkets. As noted, municipalities are also the location of local government decisions regarding new entrants. We therefore use municipalities as local markets.

■ **Store types.** DELFI relies on geographical location (address) and classifies store types, making it appropriate for defining store types. Because of a limited number of large stores, we need to analyze several of the largest store types together. We define the five largest types (hypermarkets, department stores, large supermarkets, large grocery stores, and other¹⁹) as “large” and four other types (small supermarkets, small grocery stores, convenience stores, and mini markets) as “small.” Gas stations, seasonal stores, and stores under construction are excluded. From the point of view of the Swedish market, we believe that these types are representative of being small and large.

■ **Locations.** We divide each market using five-digit zip codes that provide us with a number of locations that share borders in line with Seim (2006), who uses census tracts. The zip codes are irregular areas that vary in size. The advantage of use zip codes is that they are constructed for mail delivery and therefore consider geographical characteristics such as big roads, water, and forest areas. Hence, we believe zip codes are an appropriate way of dividing markets. In order to calculate distances between cells, we place all stores at the population-weighted midpoint of the zip code. Based on the idea of distance bands in Seim (2006), we calculate a radius from the midpoint of each zip code, which gives us distance bands within a certain distance from each cell. The splitting of markets into locations (cells) is illustrated in Figure 7. The general idea of spatial differentiation is that stores located in the first neighboring (cell 1) compete most intensely with competitors in the same cell. The intensity of competition declines for competitors in the second neighboring (cells 2, 5, and 4), followed by even lower intensity in the third (cells 3, 6, 9, 8, and 7).²⁰ Thus, we expect the competition intensity to be strongest in the first neighboring and then to decrease as we move to further away from the actual

¹⁹Stores classified as “other” stores are large and externally located.

²⁰Following Seim (2006), distances between zip codes are computed using the Haversine formula. The distance d between two points A and B is given by $d_{A,B} = 2R \arcsin(\min((\sin(0.5(x_B - x_A)))^2 + \cos(x_A)\cos(x_B)(\sin(0.5(y_B - y_A)))^2)))^{0.5}, 1)$ where x is longitude and y latitude.

location.

4 Empirical implementation

This section presents the empirical strategy for recovering the cost parameters. The cost distributions of entry and exit are functions of the value of entry and continuation value. To compute the value functions for each market configuration, we need an estimation of the profit function for small and large types in those markets. Estimation of the value functions for a given set of parameters requires consistent estimation of the transition probabilities for continuing incumbents and entrants. The structural parameters of the distribution of entry costs and sell-off values are estimated by matching the observed entry and exit rates in the data to the ones predicted by the model. The current version of the paper presents only the implementation that captures differentiation in type. Future versions will include differentiation in both type and location.

■ **Estimation of profit generating function.** Our structural framework requires a good measure of profits. Although this paper uses a rich store-level data set, a direct measure of profits is not provided. However, detailed data on a wide range of variables for each store provide good opportunities to construct a profit measure. First, the data include revenues at the store level. Second, we assume that stores of the same type have identical costs. Third, a wide range of cost measures at the store level helps us to construct the total costs for each type. In future versions, accounting data on observed profits will be used as well.

The parameters of the profit function can be estimated statically and be a primitive in the second part of the estimation when the parameters of the cost distributions are estimated. The profit function is estimated as a function of state variables. For each state that is part of the transition probability matrices, a profit measure for each type can be obtained. The advantage of a static profit estimation approach is that it facilitates a better control for unobserved heterogeneity. The presence of serially correlated unobservables might induce a positive bias on competition parameters in the profit regression. Thus, the expected negative effect of competition on profit might be underestimated due to unobserved heterogeneity, e.g., persistent demand shocks. In other words, the paper provides conservative estimates for the competition effects.

The primary costs of retail chains include rent (cost of buildings), wages (cost of labor), distribution (logistics), stock of products, machinery/equipment, and other

costs such as marketing and costs of promotion. Most of these costs enter as variable costs in the profit function and we divide them into two groups: (i) costs that vary across both store types and markets, and (ii) costs that only vary across store types and are constant across markets. Rent, wages, and distribution costs all vary across both types and markets because they, apart from store size, depend on the geographic location of the store. The remaining costs might only vary across types and we therefore assume that they are proportional to store size (in square meters and sales).

Having the revenues and the variable costs for each type, the first step is to construct the operating profits for each type and market (Holmes, 2011). The difference between the gross profit margin and costs of rent and wages defines operating profits. In the estimation, this paper uses a gross profit margin of 17 percent. Constructing Walmart's operating profits, Holmes (2011) uses a gross profit margin of 24 percent from which he takes out 7 percent, which accounts for the cost of running the distribution system, the fixed cost of running central administration, and other costs. These costs are not considered variable costs.²¹

The average price per square meter for houses sold times the median the number of square meters of each store type is a reasonable approximation for the cost of buildings. The paper assumes that stores pay a rent of 12 percent of the total cost of buildings. The cost of labor is measured as average wages in the municipality times the size of the store. Number of employees, rather than number of square meters, is taken as a measure of store size.²² The total cost of labor is then calculated as wages times three employees for small store types and five employees for large types. Relying on these assumptions, we calculate a measure of operating profits $\tilde{\pi}_z$. This paper estimates a reduced form per-period profit-generating function as a function of the state variables using operating profits. In other words, we regress operating profits on the number of competitors of different types, all exogenous state variables, and local market fixed effects. Profits for stores of type z in market m in year t are

$$\begin{aligned} \tilde{\pi}_{ztm} = & \gamma_0 + \gamma_z n_{ztm} + n_{ztm} \mathbf{d}\mathbf{m}_z \gamma_{zd} + \gamma_{z,2} n_{ztm}^2 + \\ & \mathbf{n}_{-ztm} \gamma_{-z} + \mathbf{n}_{-ztm} \mathbf{d}\mathbf{m}_z \gamma_{-zd} + \mathbf{n}_{-ztm}^2 \gamma_{-z,2} + \\ & \mathbf{d}\mathbf{m}_z \gamma_d + \mathbf{y}_{tm} \gamma_y + \xi_m + \tau_t + \epsilon_{ztm}, \end{aligned} \quad (16)$$

²¹Future versions of this paper will also include distribution costs. The minimum distance from each location to the nearest distribution center for each store type will be used as an approximation of distribution costs.

²²The number of employees is from Statistics Sweden.

where n_{tm}^z is the number of stores of the own type; \mathbf{dm}_z is a dummy matrix for types; \mathbf{n}_{-zlm} is the number of rival type stores (it is a matrix if there are more than two types); \mathbf{y}_{tm} is exogenous state variables; ξ_m and τ_t are fixed effects for markets and years; and ϵ_{zlm} is a type-market specific error term that is i.i.d. distributed. Controlling for type implies different profit functions for types, and the goal is to estimate the parameter vector of the profit function γ . Population is our exogenous variable that is part of the state space. The numbers of stores of each type are the endogenous state variables. Section 5 discusses the estimation results for the profit-generating function.

■ **Extension: differentiation in location.** The present model can be extended by including differentiation in location. This new model has three main dimensions: store, location, and type. To account for spatial differentiation in detail, we use a large number of locations. Grouping locations based on distance reduces the dimensionality of the competition parameters. Adding the following assumption reduces the competition parameter space: a store faces competition not from the stores in each location of the market but from neighboring locations, which are defined by the distance between locations (Seim, 2006). For example, three distance bands specification is the most commonly used in the empirical literature (Figure 7). In this case, the profit function can then be specified as

$$\begin{aligned} \tilde{\pi}_{zlt} = & \gamma_0 + \gamma_{zl}n_{zlt} + n_{zlt}\mathbf{dm}_{zl}\gamma_{zl} + \sum_{k \in L} n_{zkt}\gamma_{zk} + \\ & \mathbf{n}_{-zlt}\gamma_{-zl} + \mathbf{n}_{-zlt}\mathbf{dm}_{zl}\gamma_{-zld} + \sum_{k \in L} \mathbf{n}_{-zkt}\gamma_{-zk} + \\ & \mathbf{dm}_{zl}\gamma_d + \mathbf{y}_{lt}\gamma_y + \xi_l + \tau_t + \epsilon_{zlt}, \end{aligned} \quad (17)$$

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

■ **Estimation of transition matrices and value functions.** The next step is to compute continuation and entry values for each store type at each state in the state space. We estimate the transition probabilities using all municipalities in Sweden with a population of less than 200,000, i.e., large cities like Stockholm, Gothenburg, and Malmö are excluded. The number of small store types in each market varies between 3 and 55, and there are between 2 and 18 large stores in each market. Since population is a continuous variable and part of the state space, the paper discretizes population in five groups based on quantiles to reduce the

state space dimensionality.²³ The dimensionality of the generated state space is 3,604 states. The transition probabilities matrices (\mathbf{W}_z^c) and (\mathbf{W}_z^e) are computed for each store type using the observed states in the data and (12) and (14). After the transition matrices are computed, they are kept in memory to increase the computation efficiency. The inverses of the transition matrices are the most demanding computational task.²⁴ For stores that continue from state \mathbf{s} , we compute the expected discounted future profits for alternative future states $\mathbf{s}' \neq \mathbf{s}$. For each state and type, we hence construct the actual $\mathbf{VC}_{z,m}(\cdot)$ and $\mathbf{VE}_{z,m}(\cdot)$ using (13) and (15). The exogenous state variable \mathbf{y}_{tm} evolves as a Markov process that is independent of n_{ztm} and \mathbf{n}_{-ztm} . Since there is a constant trend over time in our data, the estimated transition probabilities matrices are consistent.

■ **Structural parameters.** The second and final stage of estimation deals with parameter estimation for the distributions of sunk costs and sell-off values of exit. We assume that the sell-off values and entry costs follow an exponential and a logistic distribution, respectively. The parameters of the distributions are estimated for each type z . The continuation value is computed for each state and are known up to the parameter of the distribution of sell-off values $F^{\phi_z}(\cdot|\boldsymbol{\theta})$. The value of entering depends on the entry cost draw from the distribution $F^{\kappa_z}(\cdot|\boldsymbol{\theta})$. The potential entrants in each market can be defined in two ways: (i) the maximum number of stores in each market observed during the study period; (ii) the observed number of stores in each market multiplied by a constant, e.g., 2 for both types or 3 for small and 2 for large. However, the estimated results, presented in Section 5, are robust to the choices of number of potential entrants of each type. A minimum distance estimator that minimizes the distance between theoretical and observed probabilities is used to estimate the cost distribution parameters. Let $\hat{\mathbf{p}}$ be the vector of exit and entry probabilities observed in the data for each type and, therefore, used to estimate the transition matrices. The vector of theoretical probabilities $\hat{\mathbf{q}}$ is obtained from the assumed cost distributions and computed value functions. The minimum distance estimator is defined as

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

²³For robustness, we also consider regrouping population in 10 and 20 groups. However, increasing the number of states has the disadvantage of decreasing the number of visited states.

²⁴Our code, which is written in Java uses sparse matrices and parallel computing. For two types and 3,604 states, it takes less than one minute to compute all the matrices needed to evaluate the value functions on an ordinary laptop with a dual-core processor.

where \mathbf{A}_R is the weighting matrix defined by the following blocks

$$\mathbf{A}_R(j, j) = \begin{bmatrix} \frac{\#R(\mathbf{s}_1)^2}{R^2} & \frac{2\#R(\mathbf{s}_1)\#R(\mathbf{s}_2)}{R^2} & \dots & \frac{2\#R(\mathbf{s}_1)\#R(\mathbf{s}_S)}{R^2} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\#R(\mathbf{s}_S)\#R(\mathbf{s}_1)}{R^2} & \frac{2\#R(\mathbf{s}_S)\#R(\mathbf{s}_2)}{R^2} & \dots & \frac{\#R(\mathbf{s}_S)^2}{R^2} \end{bmatrix}$$

where $\#R(\mathbf{s})$ is the number of observations in state \mathbf{s} and R is the total number of observations. The matrix \mathbf{A}_R reduces the fine bias, yet is not the asymptotic optimal matrix.

5 Results

This section discusses the estimated results for the profit-generating function and the cost parameters. In our sample, a median small store has about 215 square meters and a median large store has about 1,725 square meters, i.e., a median large store is about eight times larger than a small store. In terms of revenues, a median large store sells about ten times more than a median small store. The revenues per square meter of a median large store are about 21 percent higher than for a median small store. In addition, the estimated profits per square meter of a median large store are about 34 percent higher than for a median small store. These figures emphasize the importance of estimating costs separately for small and large types, as done in this paper.

■ **Estimation of profit function.** Table 4 shows the estimates of the profit-generating function, without (1) and with (2) market fixed effects. We use a single form specification for both types but account for type. In this specification, the effect of competition depends on the actual market structure and store type. The dependent variable is the logarithm of mean operating profits for each store type in different geographical markets. The covariates are the number of small stores, number of large stores, number of small and large stores squared, store type dummy, store type dummy interacted with the number of small and large stores, population, population interacted with store type, and year-market fixed effects.

The OLS estimator with robust standard errors is used to estimate this specification. It is important to point out the following remarks. First, these estimates come from aggregate data at the type level. Second, the findings are the average of the mean of estimated operating profits over markets. Third, the relative difference between profits of small and large stores is more valuable than our absolute

estimation, which depends on our assumptions made in the previous section.

The coefficient of the number of small stores is negative and statistically significant at the 1 percent level in both specifications. Hence, on average, an additional small competitor decreases profits of a small store by about 2 percent (Column (1)). When we control for market heterogeneity (Column (2)), the non-linearity in the number of small stores becomes important. In this specification, the marginal effect of the number of small stores on the profits of small stores becomes positive (under 1 percent) for an average market.²⁵ However, the effect is still negative for small markets. In other words, the competition effect of an additional small store is smaller in large markets (high number of small stores). One possible explanation to this result is that stores might choose their location to avoid competition (spatial differentiation effect) in large markets.

Like for small stores, the coefficient of the number of large stores and the marginal effect of the number of large stores on profits are negative. Large stores make higher profits than small ones as indicated by the positive and significant coefficient on the dummy for large. The coefficient of the number of large stores squared is statistically significant at conventional levels in Specification (1) but not in (2). This might be due to high persistency in the number of large stores over time, which in fact corresponds to local market fixed effects. An additional large store decreases the profits of small stores by about 11 percent. Turning to the interactions of the number of small/large competitors and the dummy for large types, we find clear evidence of store type competition. The profits of a large store decrease by about 18 percent due to entry of an additional large store. That is, large competitors decrease the payoffs of large stores more than they induce a fall in profits for small ones. These findings are in line with the results from the static entry literature (Mazzeo, 2002) and hold for both specifications.

The coefficient of population is positive and significant at the 1 percent level in (1), but negative when controlling for market fixed effects in (2). This might be due to small changes in population over time, i.e., population is absorbed in the local market fixed effects. Furthermore, population does not seem to influence the profits of large and small stores significantly differently. Apart from market fixed effects, lack of controlling for spatial differentiation and differences in market size by store type are possible explanations for this unexpected finding.

■ **Structural parameter estimates.** Table 5 presents parameter estimates for the distributions of sell-off value and entry cost for each type. The estimates are

²⁵Note that the net effect is small but positive in (1), i.e., $(-0.017+0.021=0.004)$, which might be due to that we do not control for market heterogeneity.

obtained using a minimum distance estimator presented in the previous section and the Nelder-Mead optimization algorithm. The estimates indicate that the average entry cost is about two times larger than the sell-off value for small stores (Specification 1). For large stores, the average sell-off value is about 17 percent higher than the average entry cost. Furthermore, the average entry cost for small stores is about 30 percent larger than for large stores. This result might be unexpected at first sight. We observe, however, a fall in the number of small stores over time, while the number of large stores increases. In addition, there are few exits of large stores and a majority of exiting stores are not owned by the national chains. These figures might also explain why entry costs are higher for small stores than for large stores. In other words, small stores have low continuation values on average and, therefore, we observe more exits for small stores. Moreover, strong incumbents that are large can continue to operate.

■ **Store values, probability of exit, and probability of entry.** We use the estimated parameters to evaluate the value of an incumbent store continuing in operation (VC_z), the value of a potential entrant (VE_z), and the probabilities of exit (p_z^x) and entry (p_z^e) for small and large stores. The value functions are expressed in millions of 2001 SEK. The estimated structural parameters are the cost of operating over a one year period. Table 6 presents a sample of the results for small and large stores, respectively.

The discounted sum of expected future net profits of small and large stores varies with the state variables. The slopes of the profit function show the toughness of short-run competition, and entry and exit have a long-run impact on stores' pay-offs. An increase in the number of stores results in less store turnover, and more exit in the industry. An increasing population and holding the number of small and large stores fixed results in a substantial increase in the continuation values and a decrease in the probability to exit for both small and large stores. Therefore, differences across markets in population create significant differences in the long-run store values. These differences can be more important than the differences in the number of stores. In markets with 4-5 small stores, an additional large entrant decreases the long-run profits by about 2 percent for small stores and by about 3 percent for large stores. In markets with many stores, there is a small increase in the marginal effect of an additional large store on the long-run profits for large stores. For both small and large stores, the probability to exit increases when an additional store enters the market. Using the estimated structural parameters, the probability to exit is computed assuming that the sell-off value follows an exponential distribution for both types.

Assuming that entry costs are logistic distributed and the pool of entrants is two times the number of observed stores, we compute the values of entry (VE_z) for each state. VE_z does not depend on the estimated parameter of entry cost distribution. However, lower entry rates imply larger entry costs. The implications of the entry cost differences are explored in the counterfactual analysis. For both store types, the findings suggest that the probability of entry raises as population increases, and the value of entry decreases with the number of stores. For small stores, the reduction in the value of entry is higher in markets with many small stores. The mean entry cost for stores that choose to enter can be computed easily when the entry cost follows an exponential distribution, i.e., $E[\kappa_z < \beta VE_z(\cdot)] = \theta_z - \beta VE_z(\cdot)(1 - p_z^e)/p_z^e$, where θ_z is the estimated parameter of entry cost for type z .²⁶

6 Counterfactuals

Table 7 shows how the estimated results change when the initial assumptions are modified. As we change the profit measure, this exercise is supposed to be interpreted as “semi-counterfactuals.”

■ **Semi-counterfactuals.** An increase in the number of potential entrants results in a higher entry cost and sell-off value for small stores, but the gap between them decreases (Specification 1). In other words, the entry cost increases less than the sell-off value for small stores when the number of potential entrants increases. In contrast, increasing the number of potential entrants does not affect the costs for large types. A large number of potential entrants implies an increase in competition from the new entrants that decide to enter after the first period. This increase in competition seems to affect small types more than large.

In Specification 2, we increase the gross profit margin for all observed stores by 3 percentage points, i.e., we increase the efficiency of the observed stores in the data. Again, the small stores are affected, e.g., both sell-off value and entry cost increase. This artificial increase in efficiency also implies an increase in the sell-off value for large stores, but it does not affect the entry cost for large stores. These results might suggest that large types enter strategically, e.g., they might have better locations.

Another strategy is to decrease the rent for all stores, e.g., a decrease by 5 percentage points in Specification (3). Large types benefit the most from decreasing the rent. The sell-off value increases and the entry cost decreases for large types.

²⁶The results are not reported, and they are available from authors upon request.

These findings suggest that the cost related to buildings might be an entry barrier.

■ **Decrease in entry cost for small stores.** We evaluate how changes in the entry costs affect the long-run profits, i.e., the value of stores (VC_z) and the value of entry (VE_z), and the probabilities of entry and exit. Because the traveling distance for customers to buy food has increased, the main Swedish retail firms started focusing on reinventing small store formats in 2011. Using the structural estimates, we can evaluate the impact of a 30 percent decrease in the entry cost for small stores on long-run profits for small and large stores in various market configurations. For the alternative values of the entry costs, we need to solve the incumbent and entrant stores' optimization problems for VC_z and VE_z at each grid point. We have to compute the equilibrium values of small and large stores' perceptions of the number of entrants and exits for survivors and entrants (Pakes et al., 2007). The results indicate a decrease in the values of incumbent stores (VC_z). Preliminary estimates suggest that due to the increasing competition, the long-run profits decrease on average by about 11 percent for small stores and by about 16 percent for large stores in medium markets. Decreasing entry costs lead to an increase in the exit rate for small stores in large markets. The average entry values (VE_z) for new small stores decrease by about 6 percent. The complexity of market configurations in case of differentiated products calls for additional investigations of these findings.²⁷

7 Conclusions

This paper deals with store dynamics and cost structure in the retail food market using a structural model of entry and exit. The framework, which builds on Pakes et al. (2007), allows for differentiation in store type. The present paper contributes to the bridge between the literature on static entry models of differentiation and the literature on dynamic games, as well as to studies on retail markets. We estimate sunk costs of entry and sell-off values of exit for small and large store types.

Using data on all retail food stores in Sweden from 2001 to 2008, we find strong store type competition and different cost structures for small and large types. An additional large store decreases the profits of large types by about 7 percentage

²⁷Our theoretical framework relies on a good measure of profits. The otherwise detailed data from DELFI has the limitation that it lacks a measure of profits. It is therefore central to recognize potential changes in results when using observed profits. Accounting data on store profits will therefore be considered in future work.

points more than for small types. The average entry cost is about two times larger than the sell-off value of exit for small stores. This result can be explained by the drastic fall in the number of small stores along with the fact that most small entrants do not belong to national chains.

Increasing pressure from potential entrants implies a smaller increase in entry cost than in the sell-off value of exit for small types. Semi-counterfactual simulations of changing the operating profits show that small stores are negatively affected by more efficient incumbents. The corresponding results for large stores show unchanged cost of entry but an increase in sell-off values. This indicates that large stores may have good strategic locations. Large stores incur higher entry costs due to other factors such as higher rent or cost of buildings, which thus potentially act as a barrier to entry.

Future research needs to assess the importance of spatial differentiation and ownership for the observed differences in the cost structure. These two features are not part of the current analysis and could provide additional information about the nature of competition and differences in cost structures. Another key aspect is to understand how the cost of labor and new technology affect the market structure and, therefore, market dynamics.

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Table 1: Characteristics of the Swedish retail food market

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

NOTE: DELFI is provided by Delfi Marknadspartner AB and contains all retail food stores based on their geographical location (address). Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Sales (incl. 12% VAT) is measured in thousands of 2001 SEK (1USD=6.71SEK, 1EUR=8.63 SEK).

Table 2: Entry and exit by store type and owner

	All	Small stores		Large stores	
		number	share owned by others	number	share owned by others
A. Entrants					
2001					
2002	71	60	0.783	11	0.000
2003	113	93	0.612	20	0.150
2004	128	118	0.305	10	0.200
2005	167	153	0.301	14	0.143
2006	126	96	0.344	30	0.167
2007	123	95	0.316	28	0.214
2008	102	80	0.250	22	0.000
B. Exits					
2001	385	366	0.511	19	0.053
2002	157	142	0.387	15	0.200
2003	240	218	0.408	22	0.091
2004	257	240	0.500	17	0.176
2005	242	209	0.478	33	0.181
2006	198	181	0.530	17	0.059
2007	193	171	0.544	22	0.181
2008					

NOTE: Large entrants and exiters are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). *Others* are stores not owned by the national chains ICA, Coop, Axfood, and Bergendahls.

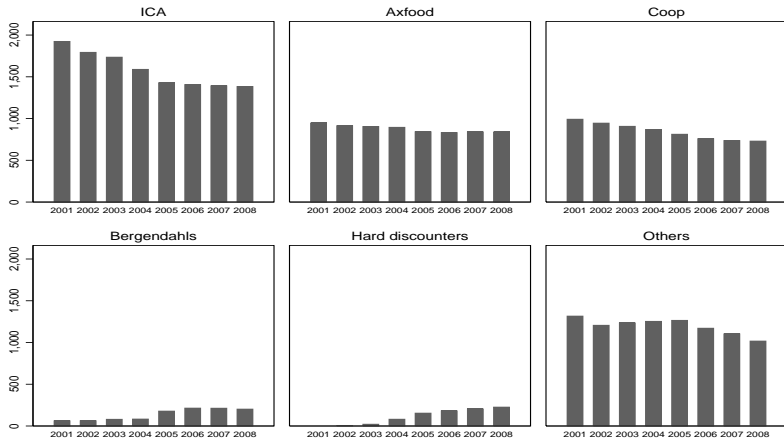


Figure 1: Total number of stores by owner 2001-2008.

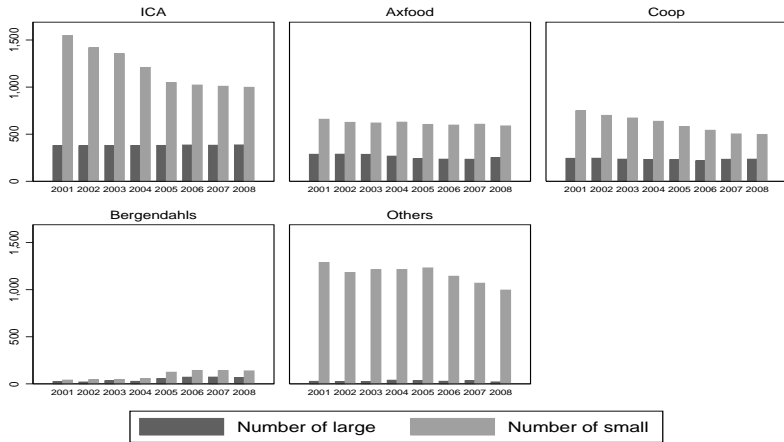


Figure 2: Number of large and small stores by national chains 2001-2008.

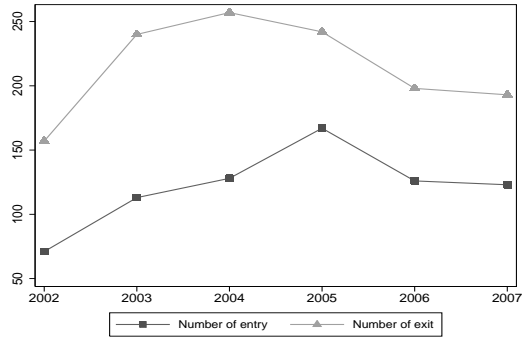


Figure 3: Total number of entries and exits in Sweden 2002-2007.

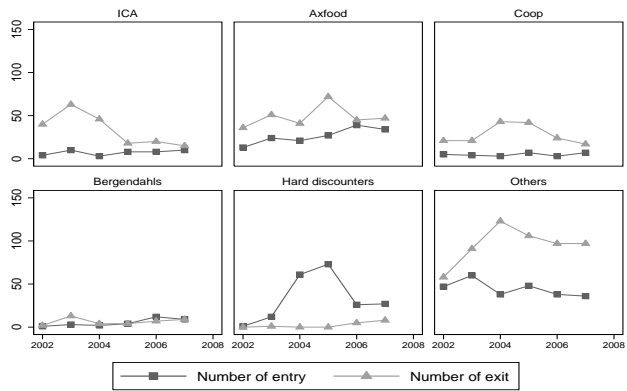
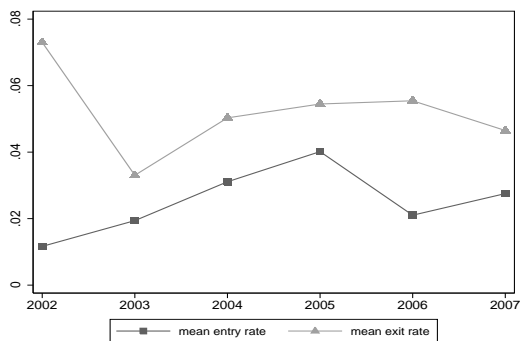


Figure 4: Total number of entries and exits by owner 2002-2007.

Table 3: Entry and exit rates across local markets and years

	p10	p25	Median	p75	p90	mean	sd
A. Entry rate							
2002	0	0	0.0	0.0	0.039	0.012	0.041
2003	0	0	0.0	0.013	0.071	0.019	0.045
2004	0	0	0.0	0.046	0.091	0.031	0.031
2005	0	0	0.0	0.064	0.125	0.040	0.073
2006	0	0	0.0	0.0	0.083	0.021	0.047
2007	0	0	0.0	0.026	0.095	0.027	0.065
B. Exit rate							
2002	0	0	0.062	0.111	0.182	0.073	0.083
2003	0	0	0.0	0.059	0.286	0.033	0.053
2004	0	0	0.0	0.091	0.333	0.050	0.050
2005	0	0	0.0	0.097	0.156	0.054	0.073
2006	0	0	0.0	0.100	0.153	0.055	0.078
2007	0	0	0.0	0.076	0.143	0.046	0.075

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

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

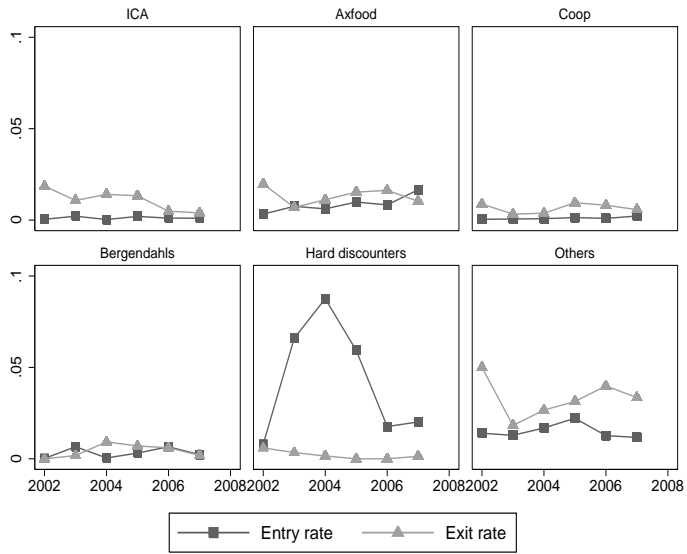


Figure 6: Mean entry and exit rates across owners and local markets 2002-2007.

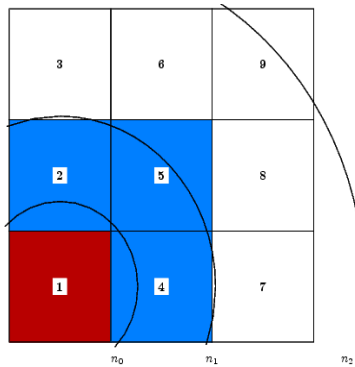


Figure 7: Illustration of distance bands

Table 4: Profit-generating function estimates

	(1)	(2)
Number of small stores	-0.017 (0.008)	-0.060 (0.021)
Number of small stores \times Large type	0.021 (0.005)	0.021 (0.004)
Number of small stores squared	-0.0001 (0.0001)	0.0007 (0.0003)
Number of large stores	-0.189 (0.034)	-0.118 (0.103)
Number of large stores \times Large type	-0.062 (0.023)	-0.062 (0.015)
Number of large stores squared	0.009 (0.001)	0.006 (0.006)
Population	0.533 (0.099)	-2.355 (0.985)
Population \times Large type	-0.041 (0.125)	-0.041 (0.084)
Large type	2.941 (1.170)	2.941 (0.794)
Intercept	2.476 (0.888)	32.85 (10.26)
Year fixed effects	yes	yes
Market fixed effects	no	yes
Adjusted R^2	0.832	0.896
Root of mean squared errors	0.559	0.443
Absolute mean errors	0.312	0.196
Number of observations	1,240	1,240

NOTE: The dependent variable is the log of estimated profits. Standard errors in parentheses. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). *Large type* is a dummy variable indicating whether the store type is large.

Table 5: Estimation results of structural parameters

	Mean sell-off value ϕ	Mean entry cost κ
Small stores	2.576 (1.287)	4.873 (0.957)
Large stores	4.178 (1.837)	3.543 (1.496)

NOTE: Standard errors in parentheses. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). Sell-off value of exit follows an exponential distribution. Entry cost follows a logistic distribution. The number of potential entrants is two times the number of actual stores (Section 4).

Table 6: Predicted value of dynamic benefits (VC , VE) and probabilities of exit and entry (p^x , p^e)

No. small stores	No. large stores	Market size Population	VC for incumbents	Probability of exit	VE for potential entrants	Probability of entry
Small type						
4	4	Small	18.86	2.44E-5	20.35	2.99E-7
4	3	Medium	31.36	1.02E-6	31.09	0.6833
4	4	Medium	30.69	1.75E-6	30.42	0.5340
5	3	Medium	31.18	1.18E-6	29.47	8.63E-4
5	4	Medium	30.65	1.82E-6	29.84	1.23E-4
6	4	Medium	25.82	8.96E-5	29.68	1.06E-4
22	5	Large	26.19	6.65E-5	28.06	7.84E-4
22	6	Large	25.61	1.05E-4	27.53	1.03E-5
22	7	Large	25.39	1.26E-4	25.38	9.50E-5
Large type						
4	4	Small	21.50	4.17E-3	26.96	0.0178
4	3	Medium	44.57	1.22E-5	43.43	0.4657
4	4	Medium	43.22	1.71E-5	42.38	0.4410
5	3	Medium	43.71	1.48E-5	49.27	0.0219
5	4	Medium	43.08	1.80E-5	54.36	0.0230
6	4	Medium	30.83	3.91E-4	44.14	0.0209
22	5	Large	46.15	8.22E-6	33.02	0.1114
22	6	Large	40.96	3.02E-5	23.65	0.0489
22	7	Large	31.82	2.40E-5	10.48	0.0391

NOTE: The sell-off value follows an exponential distribution. Entry cost follows a logistic distribution. The value functions are expressed in millions of 2001 SEK. The number of potential entrants is two times the number of actual stores.

Table 7: The impact of various policies on entry cost and sell-off value of exit

Specification	Small type		Large type	
	Sell-off value ϕ	Entry cost κ	Sell-off value ϕ	Entry cost κ
1	4.938 (2.031)	5.711 (1.355)	4.141 (1.951)	3.446 (1.572)
2	7.891 (1.456)	9.245 (2.466)	6.497 (2.941)	3.280 (1.340)
3	5.594 (2.046)	6.497 (1.245)	4.665 (1.715)	2.520 (1.182)

NOTE: The mean values are reported for entry cost and sell-off value of exit. Standard errors in parentheses. Large stores are defined as the five largest store types in DELFI (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). The value of exit follows an exponential distribution. Entry cost follows a logistic distribution. The number of potential entrants is two times the number of actual stores. Specification 1: increase in number of potential entrants, i.e., number of potential entrants is three times the number of actual stores. Specification 2: increase in sales efficiency, i.e., the gross profit margin increases by 3 percent. Specification 3: change in the local market cost, e.g., the rent of buildings decreases by 3 percent.

Appendix A: PBA and data sources

■ **Entry regulation (PBA).** On July 1, 1987, a new regulation was imposed in Sweden, the Plan and Building Act (PBA). Compared to the previous legislation, the decision process was decentralized, giving local governments power over entry in their municipality and citizens a right to appeal the decisions. Since 1987, only minor changes have been implemented in the PBA. From April 1, 1992 to December 31, 1996, the regulation was slightly different, making explicit that the use of buildings should not counteract efficient competition. Since 1997, the PBA has been more or less the same as prior to 1992. Long time lags in the planning process make it impossible to directly evaluate the impact of decisions. In practice, differences due to the policy change seem small (Swedish Competition Authority, 2001:4). Nevertheless, the PBA is claimed to be one of the major entry barriers, resulting in different outcomes, e.g., price levels, across municipalities (Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2). Municipalities are then, through the regulation, able to put pressure on prices. Those that constrain entry have less sales per capita, while those where large and discount stores have a higher market share also have lower prices.

■ **The DELFI data.** DELFI Marknadspartner AB collects daily data on retail food stores from a variety of channels: (1) public registers, the trade press, and daily press; (2) the Swedish retailers association (SSLF); (3) Kuponginlösen AB (which handles with rebate coupons collected by local stores); (4) the chains' headquarters; (5) matching customer registers from suppliers; (6) telephone interviews; (7) yearly surveys; and (8) the Swedish Retail Institute (HUI). Location, store type, owner, and chain affiliation are double-checked in corporate annual reports.

Each store has an identification number linked to its geographical location (address). The twelve store types, based on size, location, product assortment, etc., are hypermarkets, department stores, large supermarkets, large grocery stores, other stores, small supermarkets, small grocery stores, convenience stores, gas station stores, mini markets, seasonal stores, and stores under construction.

Sales and sales space are collected via yearly surveys. Revenues (including VAT) are recorded in 19 classes. Due to the survey collection, a number of missing values are substituted with the median of other stores of the same type in the same local market. In total, 702 stores have missing sales figures: 508 in 1996 and 194 in later years. For sales space, all 5,013 values are missing for 1996, and are therefore replaced with the mean of each store's 1995 and 1997 values. In addition, 2,810 missing sales space values for later years are replaced similarly. In total, 698 obser-

vations are missing both sales and sales space data.

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