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

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IFN Working Paper No. 898, 2012

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

Florin Maican and Matilda Orth

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

Florin Maican<sup>†</sup> and Matilda Orth<sup>‡</sup>

January 9, 2012

## 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:* O3, C24, L11.

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# 1 Introduction

Recent methods for structural estimation of production functions have almost only been applied to manufacturing industries.<sup>1</sup> 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.”<sup>2</sup> 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.<sup>3</sup> 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 heterogeneous 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.<sup>4</sup> 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.<sup>5</sup>

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

<sup>2</sup>Basker (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.

<sup>3</sup>Three 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.

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

<sup>5</sup>The 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)

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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.<sup>6</sup> 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.

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<sup>6</sup>We 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.<sup>7</sup> 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.<sup>8</sup> 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.<sup>9</sup>

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,

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<sup>7</sup>Although 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).

<sup>8</sup>In 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.

<sup>9</sup>International 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.<sup>10</sup> 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).<sup>11</sup> 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).<sup>12</sup> 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.<sup>13</sup> 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)

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<sup>10</sup>Possibly, 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.

<sup>11</sup>A 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).

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

<sup>13</sup>FS-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.<sup>14</sup> 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 other<sup>15</sup>) as “large” and four other types (small supermarkets, small grocery stores, convenience stores, and mini markets) as “small.”<sup>16</sup> 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

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<sup>14</sup>The 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).

<sup>15</sup>Stores classified as other stores are large and externally located.

<sup>16</sup>Alternatively, 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).<sup>17</sup> 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.<sup>18</sup> 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).<sup>19</sup> 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.<sup>20</sup> 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.<sup>21</sup> Most stores belong to ICA, about twice as many compared to COOP and Axfood in the upper part of the distribution. On average

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

<sup>18</sup>Data 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.

<sup>19</sup>This 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.

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

<sup>21</sup>ICA 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  $\mathbf{x} \in \mathbb{R}_+^x$ .<sup>22</sup> 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.<sup>23</sup> Incumbent stores maximize the discounted expected value of

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

<sup>23</sup>If 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  $\gamma$  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  $\delta$  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.<sup>24</sup>

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  $\beta < 1$ :

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

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<sup>24</sup>A 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  $\omega_{jt}$  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  $\chi_{jt+1} = \tilde{\chi}_{jt}(\mathbf{s}_{jt})$ .<sup>25</sup> The exit rule  $\chi_{jt+1}$  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.<sup>26</sup> 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  $\omega_{jt}$  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  $\omega_{jt}$ . 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.<sup>27</sup> 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

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<sup>25</sup>This 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.

<sup>26</sup>A translog production function is considered for robustness (Section 4.3).

<sup>27</sup>Under 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).<sup>28</sup> 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  $\eta$  ( $< -1$  and finite) captures the elasticity of substitution among stores.<sup>29</sup>

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 ( $\frac{1}{|\eta|}$ ).<sup>30</sup> Access to data on store-level prices and product characteristics would allow us to consider heterogenous 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.<sup>31</sup> 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.<sup>32</sup> Despite this, it is well known that retail stores can differentiate in store size (format), geographic location,

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

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

<sup>30</sup>We 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.

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

<sup>32</sup>Large 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).<sup>33</sup> 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 ( $\omega_{jt}$ ) 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  $\mathcal{F}_{jt-1}$ ,

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<sup>33</sup>Based 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  $\xi_{jt}$ . The shocks  $\xi_{jt}$  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 ( $\omega_{jt-1}$ ) 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,  $E[\omega_{jt}|\mathcal{F}_{jt-1}]$ .<sup>34</sup> 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.<sup>35</sup> 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.<sup>36</sup> 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

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<sup>34</sup>Population 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).

<sup>35</sup>The 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).

<sup>36</sup>When 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  $\omega_{jt}$ , 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  $\omega_{jt}$  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  $\omega_{jt}$  cannot be perfectly inverted out.

Third, we need helpful variation in store-specific wages.<sup>37</sup> 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

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<sup>37</sup>The 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.<sup>38</sup> 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.<sup>39</sup> 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.<sup>40</sup>

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

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<sup>38</sup>In 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).

<sup>39</sup>Yet 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.

<sup>40</sup>The 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  $\omega_{jt}$  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 ( $\omega_{jt}$ ) from shocks to production ( $u_{jt}^p$ ) and demand ( $v_{jt}$ ), i.e.,  $\epsilon_{jt}$ . 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.<sup>41</sup>

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  $\epsilon_{jt}$ . 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

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

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  $\beta_l$ . If labor instead is a static and fixed input, i.e., labor is decided before the realization of the productivity shock  $\xi_{jt}$ , then  $\beta_l$  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  $\beta_k$  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  $\beta_k$ .

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

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<sup>41</sup>In 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 ( $\epsilon_{jt}$ ) 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  $\eta$  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.<sup>42</sup>

■ **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

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<sup>42</sup>Estimation 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  $\omega_{jt}$  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),  $\omega_{jt-1}$  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  $\omega_{jt-1}$ , 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  $\omega_{jt-1}$  guarantee identification in (18). For example,  $\mathbf{x}_{mt}$  cannot be perfectly predicted from  $\omega_{jt}$ .

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  $\beta_l$ . 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  $\beta_e$ . 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  $\beta$  and  $h_H$ , where  $H$  indicates all parameters in  $h(\cdot)$ . We approximate  $h(\cdot)$  by a third-order polynomial expansion in  $\omega_{jt-1}$ , given by (16), and  $e_{mt-1}^L$ .<sup>43</sup> 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  $\xi_{jt}$  (ACF estimator).<sup>44</sup>

The parameters  $(\beta, h_H)$  are then jointly estimated using GMM by minimizing the

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

<sup>44</sup>The shocks  $\epsilon_{jt}$  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.<sup>45</sup>

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

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  $\epsilon_{jt}$  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 ( $\text{ACF}_i^{df}$ ). If labor is variable, previous labor can be used instead

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<sup>45</sup>This 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.

( $\text{ACF}_i^{dv}$ ). The other parameters  $\beta$  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  $\beta_l$  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  $\tilde{i}_t(\cdot)$  and  $\tilde{l}_t(\cdot)$  are strictly increasing in  $\omega_{jt}$ . 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  $\omega_{jt}$  holds if large entrants  $e_{mt}^L$  and  $\mathbf{x}_{mt}$  come from static and exogenous processes (Pakes, 1994; Maican, 2010b).<sup>46</sup> Another condition is that the store profit function is supermodular in  $\omega_{jt}$  and  $e_{mt}^L$ . Second, we need the scalar unobservable assumption that  $\omega_{jt}$  is the only unobservable in  $\tilde{l}(\cdot)$  or  $\tilde{i}(\cdot)$ . 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

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<sup>46</sup>It 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  $\omega_{jt}$  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  $\mu_{jt}$  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  $\omega_{jt}$  process and separation of remaining demand shocks  $v_{jt}$  from productivity.<sup>47</sup>

First, if  $\omega_{jt}$  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 (Akerberg 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  $\omega_{jt}$  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  $\omega_{jt}$ . Since we have two unobservables ( $\omega_{jt}$  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

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<sup>47</sup>The 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  $\omega_{jt}$  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  $\omega_{jt}$ , and therefore the decision is correlated with the productivity shock  $\xi_{jt}$ . 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:

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

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 ( $\eta$ ) 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.<sup>48</sup> 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  $EDJ_{lm}$ .<sup>49</sup> The positive effect of large entrants might

<sup>48</sup>If 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.

<sup>49</sup>Our 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

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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 interquantile 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.<sup>50</sup> 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

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<sup>50</sup>We 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.<sup>51</sup> 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.<sup>52</sup>

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.

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

<sup>52</sup>Estimation 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 ( $\beta_{ll}$ ), capital squared ( $\beta_{kk}$ ), and the interaction between labor and capital ( $\beta_{lk}$ ). 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).<sup>53</sup> Controlling for imperfect competition, we find that selection has a small impact on the estimated coefficients using moments based on  $\xi_{jt}$  (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).<sup>54</sup>

## 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

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<sup>53</sup>Since 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.

<sup>54</sup>The 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.



## References

- ACKERBERG, D., L. BENKARD, S. BERRY, AND A. PAKES (2007): “Econometric Tools for Analyzing Market Outcomes,” *Handbook of Econometrics*, 6, 4171–4276.
- ACKERBERG, D., K. CAVES, AND G. FRASER (2006): “Structural Identification of Production Functions,” Mimeo, UCLA.
- ACKERBERG, D., X. CHEN, AND J. HAHN (2011): “A Practical Asymptotic Variance Estimator for Two-Step Semiparametric Estimators,” Discussion Paper 1803, Cowles Foundation Discussion Paper.
- AGHION, P., R. BLUNDELL, R. GRIFFITH, P. HOWITT, AND S. PRANTL (2009): “The Effects of Entry on Incumbent Innovation and Productivity,” *Review of Economics and Statistics*, 91(1), 20–32.
- AGUIRREGABIRIA, V., R. MIRA, AND H. ROMAN (2007): “An Estimable Dynamic Model of Entry, Exit and Growth in Oligopoly Retail Markets,” *American Economic Review*, 97(2), 449–454.
- AI, C., AND X. CHEN (2003): “Efficient Estimation of Models with Conditional Moment Restrictions Containing Unknown Functions,” *Econometrica*, 71(6), 1795–1843.
- (2007): “Estimation of Possibly Misspecified Semiparametric Conditional Moment Restriction Models with Different Conditioning Variables,” *Journal of Econometrics*, 141, 5–43.
- ANDERSON, S. P., A. DE PALMA, AND J.-F. THISSE (1989): “Demand for Differentiated Products, Discrete Choice Models, and the Characteristics Approach,” *The Review of Economic Studies*, 56(1), 21–35.
- ASPLUND, M., AND R. FRIBERG (2002): “Food Prices and Market Structure in Sweden,” *Scandinavian Journal of Economics*, 104(4), 547–567.
- ASPLUND, M., AND V. NOCKE (2006): “Firm Turnover in Imperfectly Competitive Markets,” *Review of Economic Studies*, 73(2), 295–327.
- BAILY, M., C. HULTEN, AND D. CAMPBELL (1992): “Productivity Dynamics in Manufacturing Establishments,” *Brookings Papers on Economic Activity*, pp. 187–249.
- BARTELSMAN, E., AND M. DOMS (2000): “Understanding Productivity: Lessons from Longitudinal Microdata,” *Journal of Economic Literature*, 38(3), 569–594.
- BASKER, E. (2005): “Job Creation or Destruction? Labor-Market Effects of Wal-Mart Expansion,” *Review of Economics and Statistics*, 87(1), 174–183.
- (2007): “The Causes and Consequences of Wal-Mart’s Growth,” *Journal of Economic Perspectives*, 21(3), 177–198.

- BASKER, E., AND M. NOEL (2009): “The Evolving Food Chain: Competitive Effects of Wal-Mart’s Entry into the Supermarket Industry,” *Journal of Economics and Management Strategy*, 18(4), 177–198.
- BERESTEANU, A., P. ELLICKSON, AND S. MISRA (2010): “The Dynamics of Retail Oligopoly,” Mimeo, University of Rochester.
- BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): “Automobile Prices in Market Equilibrium,” *Econometrica*, 63(4), 841–890.
- BERTRAND, M., AND F. KRAMARZ (2002): “Does Entry Regulation Hinder Job Creation? Evidence from the French retail industry,” *Quarterly Journal of Economics*, 117(4), 1369–1413.
- BLUNDELL, R., AND S. BOND (2000): “GMM Estimation with Persistent Panel Data: An Application to Production Functions,” *Econometric Reviews*, 31(3), 549–569.
- BLUNDELL, R., R. GRIFFITH, AND J. VAN REENEN (1999): “Market Share, Market Value, and Innovation in a Panel of British Manufacturing Firms,” *Review of Economic Studies*, 66(3), 529–554.
- BOND, S., AND M. SÖDERBOM (2005): “Adjustment Costs and the Identification of Cobb-Douglas Production Functions,” Working Paper 05/04, Institute of Fiscal Studies.
- BOONE, J. (2000): “Competitive Pressure: The Effects on Investments in Product and Process Innovation,” *RAND Journal of Economics*, 31(3), 549–569.
- BOYLAUD, O., AND G. NICOLETTI (2001): “Regulatory reform in retail distribution,” OECD Working Paper 32.
- BUETTNER, T. (2004): “R&D and the Dynamics of Productivity,” Mimeo, London School of Economics.
- CAVES, R. (1998): “Industrial Organization and New Findings on the Turnover and Mobility of Firms,” *Journal of Economic Literature*, 36(4), 1947–1982.
- CHEN, X., AND S. LUDVIGSON (2007): “Land of Addicts? An Empirical Investigation of Habit-Based Asset Pricing Models,” Mimeo, New York University.
- DE LOECKER, J. (2011): “Product Differentiation, Multi-Product Firms and Estimating the Impact of Trade Liberalization on Productivity,” *Econometrica*, 79(5), 1407–1451.
- DE LOECKER, J., AND F. WARZYNSKI (2011): “Markups and Firm-Level Export Status,” *Forthcoming American Economic Review*.
- DORASZELSKI, U., AND J. JAUMANDREU (2011): “R&D and Productivity: Estimating Endogenous Productivity,” Mimeo, University of Pennsylvania.
- DUNNE, T., S. KLIMEK, M. ROBERTS, AND Y. XU (2011): “Entry, Exit and the Determinants of Market Structure,” NBER Working Paper 15313.

- ERICSON, R., AND A. PAKES (1995): "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62(1), 53–83.
- EUROPEAN COMPETITION NETWORK (2011): "ECN Brief Extended Issue," ECN Brief 05/2011, European Competition Network.
- EUROPEAN PARLIAMENT (2008): "On Investigating and Remedying the Abuse of Power by Large Supermarkets Operating in the European Union," Written Declaration 0088, European Parliament.
- FISHMAN, C. (2006): *The Wal-Mart Effect*. The Penguin Group.
- FOSTER, L., J. HALTIWANGER, AND C. KRIZAN (2001): "The Link Between Aggregate and Micro Productivity Growth: Evidence from Retail Trade," NBER Working Paper 13783.
- (2006): "Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s," *Review of Economics and Statistics*, 88(4), 748–758.
- FOSTER, L., J. HALTIWANGER, AND C. SYVERSON (2008): "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?," *American Economic Review*, 98(1), 394–425.
- GRIFFITH, R., AND H. HARMGART (2005): "Retail Productivity," *International Review of Retail, Distribution and Consumer Services*, 15(3), 281–290.
- GRILICHES, Z., AND H. REGEV (1995): "Productivity and Firm Turnover in Israeli Industry: 1979-1988," *Journal of Econometrics*, 65, 175–203.
- HALL, R. (1988): "The Relation between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy*, 96(5), 921–947.
- HASKEL, J., AND R. SADUN (2011): "Regulation and UK Retailing Productivity: Evidence from Microdata," *Economica*, pp. 1–24.
- HICKS, M. J. (2007): *The Local Economic Impact of Wal-Mart*. Cambria Press, Youngstown, New York.
- HOJ, J., T. KATO, AND D. PILAT (1995): "Deregulation and Privatisation in the Service Sector," OECD Working Paper 25.
- HOLMES, T. (2011): "The Diffusion of Wal-Mart and Economies of Density," *Econometrica*, 79(1), 253–302.
- HOPENHAYN, H. (1992): "Entry, Exit and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 60(5), 1127–1160.
- HULTEN, C., AND F. WYKOFF (1981): chap. The Measurement of Economic Depreciation, in C. Hulten (ed.), *Depreciation, Inflation, and Taxation of Income from Capital*, Urban Institute Press, Washington, D.C.

- JIA, P. (2008): “What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry,” *Econometrica*, 76(6), 1263–1316.
- JOVANOVIC, B. (1982): “Selection and the Evolution of Industry,” *Econometrica*, 50(5), 649–670.
- KATAYAMA, H., S. LU, AND J. TYBOUT (2003): “Why Plant-Level Productivity Studies are Often Misleading, and an Alternative Approach to Inference,” NBER Working Paper 9617.
- KLETTE, T., AND Z. GRILICHES (1996): “The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous,” *Journal of Applied Econometrics*, 11(4), 343–361.
- LEVINSOHN, J., AND M. MELITZ (2006): “Productivity in a Differentiated Products Market Equilibrium,” Mimeo, Harvard University.
- LEVINSOHN, J., AND A. PETRIN (2003): “Estimating Production Functions Using Inputs to Control for Unobservables,” *Review of Economic Studies*, 70(2), 317–341.
- MACDONALD, J. (1994): “Does Import Competition Force Efficient Production?,” *Review of Economics and Statistics*, 76(4), 721–727.
- MAICAN, F. (2010a): “Industry Dynamics and Format Repositioning in Retail,” Mimeo, Department of Economics, University of Gothenburg.
- (2010b): “Productivity Dynamics, R&D, and Competitive Pressure,” Mimeo, Department of Economics, University of Gothenburg.
- MAICAN, F., AND M. ORTH (2011): “Store Dynamics, Differentiation and Determinants of Market Structure,” Mimeo, Reserach Institute of Industrial Economics (IFN) and University of Gothenburg.
- MELITZ, M. (2000): “Estimating Firm Level Productivity in Differentiated Product Industries,” Mimeo, Harvard University.
- (2003): “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity,” *Econometrica*, 71(6), 1695–1725.
- MELITZ, M., AND S. POLANEC (2009): “Dynamic Olley-Pakes Decomposition with Entry and Exit,” Mimeo, Princeton University.
- MURPHY, K. M., AND R. H. TOPEL (1985): “Estimation and Inference in Two-Step Econometric Models,” *Journal of Business and Economic Statistics*, 3(4), 370–379.
- NEWBY, W. (1994): “The Asymptotic Variance of Semiparametric Estimators,” *Econometrica*, 62(6), 1349–1382.
- NEWBY, W., AND D. F. MCFADDEN (1994): *The Handbook of Econometrics* chap. Large sample estimation and hypothesis testing. North-Holland, Amsterdam.

- NEWHEY, W., AND J. POWELL (2003): “Instrumental Variables Estimation of Nonparametric Models,” *Econometrica*, 71(3), 1557–1569.
- NEWHEY, W., J. POWELL, AND F. VELLA (1999): “Nonparametric Estimation of Triangular Simultaneous Equations Models,” *Econometrica*, 67(3), 565–603.
- NEWHEY, W., AND K. WEST (1987): “A Simple, Positive Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, 55(3), 1201–1228.
- NICKELL, S. (1996): “Competition and Corporate Performance,” *Journal of Political Economy*, 104(4), 724–746.
- OLLEY, S., AND A. PAKES (1996): “The Dynamics of Productivity in the Telecommunications Equipment Industry,” *Econometrica*, 64(6), 1263–1297.
- ORTH, M. (2011): “Entry and Differentiation in Retail Markets,” Mimeo, Reserch Institute of Industrial Economics (IFN), Stockholm.
- PAKES, A. (1994): chap. The Estimation of Dynamic Structural Models: Problems and Prospects Part II. Mixed Continuous-Discrete Control Models and Market Interactions, Laffont, J. J. and Sims, C. eds, *Advances in Econometrics: Proceedings of the 6th World Congress of the Econometric Society*, Chapter 5.
- PAVCNIK, N. (2002): “Trade Liberalization Exit and Productivity Improvements: Evidence from Chilean Plants,” *Review of Economic Studies*, 69(1), 245–276.
- PILAT, D. (1997): “Regulation and Performance in the Distribution Sector,” OECD Working Papers 180.
- (2005): “Assessing the Productivity of the UK Retail Sector: Some Further Reflections,” *The International Review of Retail, Distribution and Consumer Research*, 15(3), 291–296.
- PORTER, M. (1990): *The Competitive Advantage of Nations*. Macmillan Press.
- RAITH, M. (2003): “Competition, Risk, and Managerial Incentives,” *American Economic Review*, 93, 1425–1436.
- REYNOLDS, J., E. HOWARD, D. DRAGUN, B. ROSEWELL, AND P. ORMEROD (2005): “Assessing the Productivity of the UK Retail Sector,” *International Review of Retail, Distribution and Consumer Research*, 15(3), 237–280.
- ROBINSON, P. (1988): “Root-N-Consistent Semiparametric Regression,” *Econometrica*, 56(4), 931–954.
- SADUN, R. (2008): “Does Planning Regulation Protect Independent Retailers?,” Center for Economic Performance Discussion Paper No 888, London School of Economics.
- SCHIVARDI, F., AND E. VIVIANO (2011): “Entry Barriers in Retail Trade,” *Economic Journal*, 121(155), 145–170.

- SCHMIDT, K. (1997): “Managerial Incentives and Product Market Competition,” *Review of Economic Studies*, 64(2), 191–213.
- SIVADASAN, J. (2004): “Barriers to Entry and Productivity: Micro-Evidence from Indian Manufacturing Sector Reforms,” Mimeo, University of Chicago.
- STATISTICS SWEDEN (2005): “Hushållens ekonomi - vem lånar, vem konsumerar? (The Economy of Households: Who lends, who consumes?),” Mimeo, Stockholm.
- SWEDISH COMPETITION AUTHORITY (2001:4): “Kan Kommunerna Pressa Matpriserna? (Can the Municipalities Put Pressure on Prices?),” Technical Report 4, Stockholm.
- (2004:2): “Konsumenterna, Matpriserna och Konkurrenterna (Consumers, Retail Food Prices, and Competition),” Technical Report 2, Stockholm.
- SWEDISH NATIONAL BOARD OF HOUSING, BUILDING, AND PLANNING (2005): “Shopping Matters! Retailing and Sustainable Urban Development,” Technical Report.
- SYVERSON, C. (2004): “Market Structure and Productivity: A Concrete Example,” *Journal of Political Economy*, 112(2), 1181–1222.
- (2011): “What Determines Productivity?,” *Journal of Economic Literature*, 49(2), 326–365.
- WOOLDRIDGE, J. M. (2009): “On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables,” *Economics Letters*, 104(3), 112–114.

**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		Bergendahls	
	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

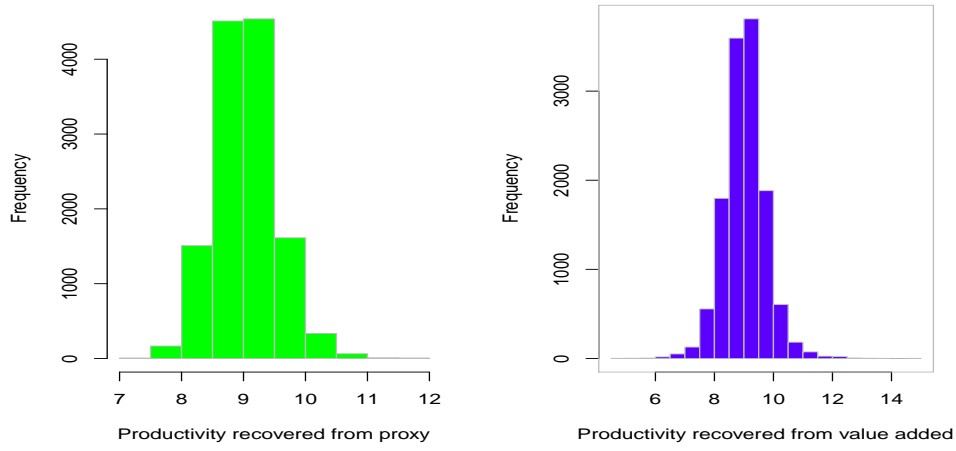
Year	1997	1998	1999	2000	2001	2002
A. Markets with large entrants						
No. of stores	37.00	54.00	29.00	32.00	33.00	22.00
No. of all entrants	2.00	2.00	3.00	2.00	1.00	2.00
No. of all exits	3.00	2.00	2.00	3.00	1.00	--
Population	57,441.00	60,429.00	37,195.00	48,250.00	58,361.00	22,907.00
Population density	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.

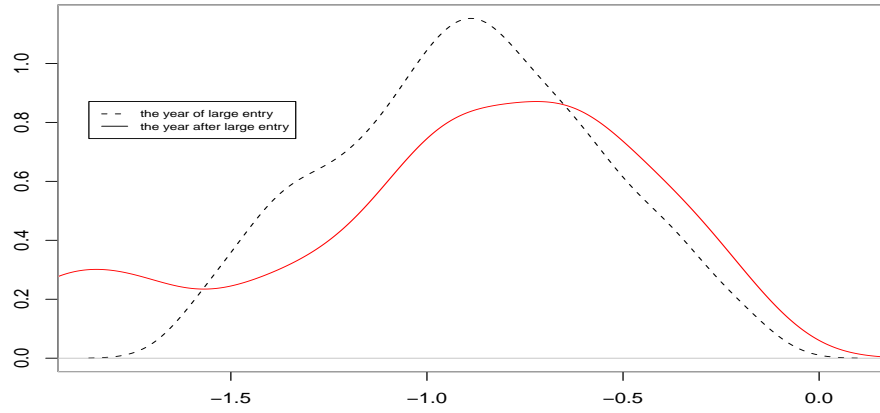
**Table 5:** Value-added generating function estimates

	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 $(\eta)$			-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<sub>l</sub>* is Akerberg, Caves, and Fraser's (2006) two-step estimation method using labor as proxy for productivity; *ACF<sub>lm</sub>* 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<sub>lme</sub>* 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<sub>lm</sub>* is one-step estimation using a parametric labor demand function and controlling for imperfect competition. *EDJ<sub>lme</sub>* 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<sub>lme</sub>* and *EDJ<sub>lme</sub>* 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 <sub>t-1</sub>	0.486 (0.012)	0.541 (0.008)	0.555 (0.008)	0.542 (0.011)	0.568 (0.010)
Productivity <sub>t-1</sub> * Large entrants <sub>t-1</sub>	-0.057 (0.024)	-0.068 (0.018)	-0.068 (0.017)	-0.065 (0.024)	-0.049 (0.024)
Large entrants <sub>t-1</sub>	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

	$ACF_l$		$ACF_{lm}$		$ACF_{lme}$		$EDJ_{lm}$		$EDJ_{lme}$	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
10th percentile productivity <sub>t-1</sub>	0.010	0.015	0.135	0.034	0.132	0.037	0.095	0.019	0.391	0.017
25th percentile productivity <sub>t-1</sub>	0.003	0.013	0.122	0.033	0.119	0.036	0.089	0.017	0.396	0.013
50th percentile productivity <sub>t-1</sub>	-0.005	0.012	0.104	0.034	0.101	0.038	0.083	0.016	0.401	0.010
75th percentile productivity <sub>t-1</sub>	-0.013	0.012	0.085	0.036	0.080	0.041	0.076	0.015	0.404	0.004
90th percentile productivity <sub>t-1</sub>	-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.  $ACF_l$  is Akerberg, Caves, and Frazier's (2006) two-step approach using labor demand as a proxy for productivity.  $ACF_{lm}$  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  $ACF_{lm}$ .  $EDJ_{lm}$  is one-step estimation using a parametric labor demand function and controlling for imperfect competition (Section 3.1.2).  $EDJ_{lme}$  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:  $\omega_{jt} = (\eta/(1 + \eta)) [y_{jt} - (1 + 1/\eta)[\beta_l l_{jt} + \beta_k k_{jt}] + (1/\eta)q_{mt} + (1/\eta)\mathbf{x}'_{mt}\beta_x + (1/\eta)\beta_e e_{mt}^L]$ . 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 <sub>t</sub>	-0.124 (0.027)		-0.182 (0.042)	
Large entrants <sub>t-1</sub>	0.043 (0.043)	-0.115 (0.092)	0.026 (0.042)	-0.068 (0.069)
p10*Large entrants <sub>t-1</sub>		0.336 (0.132)		0.136 (0.122)
p10-p25*Large entrants <sub>t-1</sub>		0.263 (0.131)		0.104 (0.121)
p25-p50*Large entrants <sub>t-1</sub>		0.193 (0.118)		-0.123 (0.113)
p75-p90*Large entrants <sub>t-1</sub>		0.080 (0.143)		-0.214 (0.141)
p90*Large entrants <sub>t-1</sub>		0.189 (0.145)		-0.319 (0.150)
Log of capital <sub>t</sub>	-0.090 (0.014)	-0.082 (0.013)	-0.083 (0.013)	-0.079 (0.013)
Log of population <sub>t</sub>	0.054 (0.023)	0.066 (0.022)	0.033 (0.025)	0.078 (0.023)
Log of population density <sub>t</sub>	-0.004 (0.017)	0.001 (0.017)	0.005 (0.016)	-0.012 (0.015)
Log of income <sub>t</sub>	-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
	Within stores	Between stores	Cross stores	Entry	Exit	
	(1)	(2)	(3)	(4)	(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	
		$ACF_l^{sf}$	$ACF_{lm}^{sf}$	$ACF_i^{df}$	$ACF_i^{dv}$
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 $(\eta)$			-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  $ACF_{lm}^{sf}$  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.  $ACF_l^{sf}$  is Akerberg, Caves, and Fraser's (2006) two-step estimation method using labor as proxy for productivity, and labor is static and fixed.  $ACF_{lm}^{sf}$  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.  $ACF_i^{df}$  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 Wyckoff (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.<sup>55</sup> 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  $a$ ,

<sup>55</sup>Chen 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  $\beta$  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  $\omega_{jt}$ , so that the decision will be correlated with the productivity shock  $\xi_{jt}$ . To identify the value-added generating function coefficients, we use estimates of survival probabilities, given by

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

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

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

## Appendix D: Dynamic panel approach

■ Another estimator that can be used is dynamic panel (DP).<sup>56</sup> We denote the sum of the remaining shocks (productivity and demand)  $\psi_{jt}$ , 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  $\omega_{jt}$ ,  $v_{jt}$ , 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

<sup>56</sup>See the dynamic panel model of Blundell and Bond (2000).

errors ( $\psi_{jt}$ ) that are not correlated with past, present, and future values of explanatory variables (Akerberg et al., 2006). In case of DP, we observe  $\psi_{jt}$  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)  $\omega_{jt}$  follows an  $AR(1)$  process where  $l_{jt}$ ,  $k_{jt}$ ,  $e_{mt}^L$ , and  $\mathbf{x}_{mt}'$  can be correlated with  $\omega_{jt}$ ; and (c)  $\xi_{jt}$  (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 ( $\xi_{jt}$ ).

There are major differences between DP and our ACF and EDJ specifications. In DP, we cannot compute individual  $\omega_{jt}$  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  $\xi_{jt}$  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

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

to identify the parameters in the value-added generating function using DP (Akerberg et al., 2006). We assume that current innovations in productivity  $\xi_{jt}$  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  $\rho$ . 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.  $\xi_{jt}$  and  $\xi_{jt-1}$  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  $\omega_{jt}$  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  $\xi_{jt}$  and  $\mu_{jt}$  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 ( $\rho_1$ ) 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  $\omega_{jt-1}^2$  and  $\omega_{jt-1}^3$  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 ( $\rho_1$ )	0.417 (0.002)		0.449 (0.007)	
Productivity transition ( $\rho_2$ )			0.353 (0.106)	
Scale ( $\beta_l + \beta_k$ )	1.402		1.426	
Demand elasticity ( $\eta$ )	-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  $\omega_{jt}$  and  $v_{jt}$  follow the same AR(1) process. DP2 is linear estimation of equation (6) when  $\omega_{jt}$  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 ( $\Omega_t$ ) can then be expressed as the weighted average produc-

tivity  $\Omega_t \equiv \sum_{j \in N} ms_{jt} \omega_{jt}$ , 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

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

where  $\Delta$  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:

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

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,  $\Omega_t$ , has two components: (1) contribution of productivity improvements,  $\overline{\Omega}_t$ ; and (2) market share reallocations for the continuing stores  $cov(ms_{jt}, \omega_{jt}) \equiv \sum_j (ms_{jt} - \overline{ms}_t)(\omega_{jt} - \overline{\Omega}_t)$ . 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						
Overall Industry Growth	Surviving		Entrants		Exits	
	Unweigh.	Cov	Unweigh.	Weigh.	Unweigh.	Weigh.
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.