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

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Abstract

We use a dynamic model to measure the impact of the entry of large stores on incumbents' productivity separate from demand while accounting for local markets and the endogeneity of entry. Using data on all retail food stores in Sweden, we find that incumbents' productivity increases after the entry of large stores and that the magnitude of the increase declines toward the upper part of the productivity distribution. Our findings highlight that large entrants drive productivity.

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

JEL Classification: C24, L11, L50, L81, O3.

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I. Introduction

A major structural change in retail markets during the last few decades has been the entry of large ("big-box") stores and the drastic decrease in the overall number of stores. This trend has been accompanied by intensive investment in information technologies and innovations to cut costs. The most striking example is the expansion of Walmart in the U.S.[1] Retail markets in Europe have also followed the "big-box" trend, although on a smaller scale. Some examples of big-box stores in European countries include Carrefour, Metro, Schwartz, and Tesco. Despite the significant structural shift toward big-box stores, the impact on productivity has received little attention.

This paper uses a dynamic structural model to estimate total factor productivity in retail markets and to quantify the effect of increased competition from the entry of large stores on incumbents' productivity and demand. Detailed data on all retail food stores in Sweden from 1996 to 2002 give us a unique opportunity to investigate the questions at hand.

Incumbent stores can respond strategically to big-box entry, and such responses are likely to be heterogeneous. For example, stores can lower their prices, increase their product offerings, or change their quality (Basker and Noel [2009], Matsa [2011], Basker *et al.* [2012]). Stores can also respond by investing in new technology and improving their management practices, logistics, and inventory management to increase productivity.

Productivity in the services and retail industries is not well understood. In fact, few studies go beyond measures such as sales and value-added per unit of input.[2] We present a first attempt to use a structural framework for estimating total factor productivity in retail markets and provide a general strategy to identify the effect of large store entrants on productivity separate from demand. We address several aspects of productivity in retail markets. First, we account for the fact that stores can substitute labor and capital

[1] Basker [2005], Basker [2007], Jia [2008], Haltiwanger *et al.* [2010], Ellickson and Grieco [2013], and Ellickson [2015].

[2] Some recent studies that focus on labor productivity include, e.g., Foster *et al.* [2006], Haltiwanger *et al.* [2010], Schivardi and Viviano [2011], Basker [2012], and Ellickson and Grieco [2013].

investments. This consideration is important because retail stores have invested heavily in new technologies such as scanner and barcode techniques to increase self-service, which has substantially decreased the cost of labor (Basker [2012]). Second, we recognize that productivity in service industries suffers from problems related to measuring output. When sales or value-added is used as an output, productivity might increase because stores with market power in local markets can set higher prices (Foster *et al.* [2008]). Third, we view large store entrants as part of the local market environment and thus recognize that they affect incumbents' productivity and exit.

The modeling framework takes into account that store productivity can be influenced by the external environment in which stores operate and by internal factors. Many questions remain open regarding external drivers of productivity (Syverson [2011]). The external environment can influence productivity in at least two ways. The first is through productivity gains within stores. Such gains can arise due to spillovers, where stores have an opportunity to learn best business practices related to, for example, management from a large store entrant in the local market. The second way that the external environment can influence productivity is through a selection effect among stores by inducing the exit of low-productivity stores. We model productivity changes as a result of a passive effect of entry, although we also recognize that it is plausible that stores engage in active efforts to increase their productivity. We quantify the overall effect of large store entrants on productivity rather than modeling all of the possible sources of productivity improvement.

Our dynamic structural model builds on recently developed methods of estimating production functions that have been almost exclusively applied to manufacturing industries (Olley and Pakes [1996]).[3] The objective of these methods is to understand productivity heterogeneity within industries (Ericson and Pakes [1995]). The modeling of the external environment in local markets is an addition to the scarce literature on how to measure and understand heterogeneity in productivity in retail markets.[4] A central feature of the

[3]Levinsohn and Petrin [2003], Ackerberg *et al.* [2007], De Loecker [2011], Doraszelski and Jaumandreu [2013], Gandhi *et al.* [2014], and Ackerberg *et al.* [2015].

[4]In a companion paper, we evaluate the effect of entry regulations on productivity in retail trade sectors other than food in Sweden (Maican and Orth [2015]). The paper also

proposed model is that stores are allowed to react differently to large store entry, thus allowing us to calculate a productivity response by each store in the data. We evaluate the effects of large store entrants on different parts of the distribution of local market productivity, aggregate weighted productivity in local markets, and exit.

To disentangle the effect of large store entrants on productivity from demand, we augment the production function with a simple horizontal product differentiation demand system, whereby exogenous demand shifters and large store entrants affect prices (Klette and Griliches [1996], De Loecker [2011]).[5] Our joint model of productivity and demand addresses four endogeneity concerns. The first two relate to endogeneity of large store entry and output in local markets. These concerns are addressed using political preferences, previous periods' output, and characteristics of neighboring markets as instruments. The last two concerns relate to standard problems of simultaneity of input usage with productivity and selection on exit in estimations of the service-generating function (Ackerberg *et al.* [2007]). Because retail markets are characterized by lumpy investments and difficulties in measuring product stocks, we recover productivity from the store labor demand function (Levinsohn and Petrin [2003], Doraszelski and Jaumandreu [2013]).

Food retail is an important industry because groceries account for a substantial share (15 percent) of private consumption (Statistics Sweden [2005]). The structural shift toward larger but fewer stores is striking in Sweden. The total number of stores decreased by 17 percent, whereas the share of large stores increased from 19 to 26 percent during our sample period from 1996-2002. Average sales space increased by as much as 33 percent, but the total sales space remained virtually constant. Our framework is particularly

relates to the vast literature on how competition affects productivity. Previous theoretical work has emphasized both positive and negative effects, while empirical work has often emphasized positive effects. Examples of recent contributions are Nickell [1996], Bertrand and Kramarz [2002], Djankov *et al.* [2002], Aghion and Griffith [2005], Greenstone *et al.* [2010], De Loecker [2011], and Buccirossi *et al.* [2013].

[5] A quantity-based production function, which has begun to be used in manufacturing, is not suited for services because physical output is unobserved and thus lacks a unit of measure. Our study touches on the more general question of how to measure productivity in services, especially because of the rapid expansion of service markets such as information technology, e.g., Google (Syverson [2011]).

attractive when applied to local markets that consist of many stores with independent pricing strategies and input decisions, as is the case in Sweden. Most stores operate as independent or franchise units affiliated with four major retail groups, of which only one operates as a cooperative.[6]

Our main results show that large store entrants force low-productivity stores to exit and surviving stores to increase their productivity. The median incumbent increases its productivity by 3.1 percent as a result of a large store entry. A key result is that productivity increases most among incumbents in the bottom part of the productivity distribution and declines with the productivity of incumbents. A large store entrant increases productivity by up to 1-2 percentage points more for a store in the 25th local market productivity percentile than for a store in the 75th percentile. Stores with low productivity are small; i.e., they have fewer employees, lower capital stock, and less value-added. Productivity gains from large store entrants are higher if stores are affiliated with more retail groups in a local market. The median increase in store productivity is 2.3 and 3 percent in markets with two and four groups, respectively. We document the robustness of the results when alternative modeling specifications are used.

The possibility of documenting productivity gains arising from large store entrants has important policy implications. Entry regulations are in effect in the OECD, although such regulations are much more restrictive in Europe than in the U.S.[7] In Maican and Orth [2015], we find that more liberal entry regulations increase store productivity in the Swedish retail trade. Productivity is obviously an important object to study because it can be directly incorporated into a cost-benefit analysis of the entry of new large stores.

The next section describes the Swedish retail food market. Section III presents the

[6]While we recognize the importance of ownership in retail markets, we do not model ownership and only show descriptives from our single-agent model. There is a growing stream of literature that models entry while accounting for ownership in a dynamic oligopoly framework (Sweeting [2010], Sweeting [2013]).

[7]The consequences of retail regulations (e.g., supermarket dominance) are frequently debated among policymakers in Europe (European Parliament [2008], European Competition Network [2011], European Commission [2012]). See also Pilat [1997], Boylaud and Nicoletti [2001], and Griffith and Harmgart [2005].

model and discusses identification and estimation, whereas Section IV presents the data. Section V presents the empirical results and robustness checks, and Section VI summarizes and draws conclusions. In several places, we refer to an online appendix containing various analyses that are not discussed in detail in the paper.

II. The Swedish retail food market

This section provides information about the Swedish retail food market. Retail food stores in Sweden have independent pricing strategies and are affiliated with four major groups that historically collaborate on wholesale provision.[8] Stores tend to operate as independent or franchise units that are relatively independent of their group affiliation. ICA consists of a group of independent store owners that was started based on collaboration in wholesale provision. Axfood contains a mix of independent and franchise stores. Bergendahls has a mix of franchises and centrally owned stores and operates mainly in the south and southwest of Sweden. Coop, by contrast, consists of cooperatives, with decisions made at the local or national level. Despite its cooperative structure, independent store owners in Coop have the power to decide on, e.g., pricing and labor. The joint market share of the stores affiliated with these four groups constituted approximately 92 percent of total sales in 2002. Stores affiliated with ICA constituted 44 percent of total sales. The corresponding figures were 22 percent for stores affiliated with Coop, 23 percent for stores affiliated with Axfood and 3 percent for stores affiliated with Bergendahls. Various independent owners composed the remaining 8 percent of the market share (fifth group).[9] The store size distributions are similar across group affiliations. To reflect the fact that each store operates independently with its own pricing policy and to emphasize

[8]Previous research on Swedish food retailing uses the expressions group and wholesaler rather than firms (Asplund and Friberg [2002], Chamber Trade Sweden [2013]).

[9]Stores affiliated with ICA operated in almost all of the 290 markets. Coop decreased from 236 to 227 markets and Axfood from 276 to 266 during the study period. Bergendahls stores were in 21 markets at the beginning and 42 markets at the end. The median (mean) store sizes are 316 (540) square meters for stores affiliated with ICA, 350 (620) for Axfood, 400 (620) for Coop, and 448 (1,297) for Bergendahls. Hence, most stores are small.

store-level heterogeneity in productivity, we model each store as a separate unit.

Large stores. The big-box expansion in Sweden comprises the entry of large hypermarkets. These large stores differ from other stores in a number of respects. For example, they operate almost exclusively in out-of-town locations, and a separate and sufficiently large parking lot is provided to customers. In contrast, stores located closer to consumers' homes and work are often easier to reach by foot, bike, or public transport. Large stores deliver broad product assortments with a high degree of self-service. There has been a rapid expansion of self-scanning, which is widespread in large stores. In addition, large stores often offer different services than other stores, including independent cafés and bakeries, gaming services and full pharmacies.

Entry regulation. The Plan and Building Act (PBA) empowers the 290 municipalities in Sweden to make decisions regarding the applications of new entrants. The main rationale for entry regulations is that new entrants generate both positive and negative externalities that require careful evaluation by local authorities. Advantages, such as productivity gains, lower prices, and wider product assortment, contrast with disadvantages, notably, fewer stores and environmental effects. The PBA is viewed as a major barrier to entry, resulting in diverse outcomes, e.g., price levels, across municipalities (Swedish Competition Authority [2001]). Several reports emphasize the need to better analyze how regulation affects market outcomes (Swedish Competition Authority [2001, 2004]). Because large store entrants are expected to impact the market structure extensively, they are carefully evaluated by local governments. Online appendix A describes the PBA in greater detail.

Local markets. Food products fulfill daily needs and are often of relatively short durability. Thus, stores are located close to consumers. Travel distance when buying food is relatively short unless the prices are sufficiently low. Proximity to home and work are thus key considerations for consumers in choosing where to shop, although distance likely increases with store size. 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 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). The 88 local labor markets take into account commuting patterns, which are important for hypermarkets and department stores, while the 290 municipalities appear to be more suitable for large supermarkets.

An accurate definition of local markets reflects the fact that consumers think of all stores in the local market as their choice set. We believe municipalities are reasonable local markets in our setting for at least three reasons. The first is that survey evidence of shopping behavior shows that most consumers buy groceries in their municipality. According to surveys, more than 80 percent of Swedish consumers never or rarely buy groceries outside of their home municipality. More precisely, 17 percent never buy groceries outside of their municipality, 46 percent do so less than 1-2 times per month, and 23 percent do so 1-2 times per month (Swedish Trade Federation [2011]).[10] The second reason is that municipal governments evaluate new entrants and thus have to account for the responses of all incumbents in the municipality. The third reason is that distance measures show that the average distance for consumers to the nearest store in their municipality is 2.3 kilometers. The corresponding average distance to the second nearest store is 4 kilometers. In virtually all municipalities, the nearest store for over 80 percent of the population is within 15 kilometers.

Given the information derived from surveys, regulations, and descriptive distance measures, we believe that it is reasonable to use municipalities as local markets. Sweden is divided into 290 municipalities that cover the whole country and include all types of areas, ranging from rural to metropolitan. We exclude the three largest metropolitan municipalities (Stockholm, Göteborg, Malmö), which are likely to consist of submarkets. The

[10] Only 15 percent buy their groceries outside of the municipality more than 1-2 times per month. Moreover, 71 percent of consumers travel by car to buy groceries.

population in the remaining markets ranges from 3,244 to 192,496. The average market consists of 25,836 people, whereas the median market consists of 15,133 people.

A typical medium market has one major urban area and some smaller populated areas, e.g., the municipality of Vetlanda, with approximately 25,000 inhabitants. Typically, small markets only have one small urban area. For instance, the municipality of Perstorp has approximately 7,000 inhabitants and consists of one city and its surrounding villages. Large markets typically consist of a large city together with several other urban centers, e.g., the municipality of Karlstad, with approximately 80,000 inhabitants.

III. Empirical model

This paper measures the effect of the entry of large stores on incumbents' productivity shocks while controlling for local market characteristics and unobserved prices.

Service-generating function. Stores sell products and services according to Cobb-Douglas technology:

$$Q_{jt} = L_{jt}^{\beta_l} K_{jt}^{\beta_k} exp(\omega_{jt} + u_{jt}^{p}), \tag{1}$$

where Q_{jt} is the service output by store j at time t; L_{jt} is the labor input; K_{jt} is capital stock; ω_{jt} is store productivity;[11] and u_{jt}^{p} are the service output shocks.[12] The service output Q_{jt} does not include items that are purchased from a wholesaler and sold in the store, i.e., intermediate inputs.

Stores know their productivity ω_{jt} when they make their input and exit decisions. Store productivity is correlated over time, and it is unobserved by the researcher. We assume that store productivity follows a controlled first-order Markov process, i.e., $P(\omega_{jt}| \omega_{jt-1}, e_{mt-1}^{L})$, where e_{mt-1}^{L} is the number of large store entrants in market m in year $t-1$. Accounting for the external environment in the productivity process allows for heteroge-

[11] Cobb-Douglas technology is the first-order Taylor approximation of a general production technology. Other technology functions, such as translog, can also be used (see robustness section).

[12] In the case of value-added, u_{jt}^{p} may be associated with measurement error when there is the same measurement error in intermediate inputs and output (Gandhi *et al.* [2014]).

neous store responses to large store entry. The model allows for a flexible relationship between store productivity and large store entrants, which is discussed in detail below.[13] The previous number of large store entrants affects not only the ω_{jt} but also after the period t through ω_{jt}, i.e., the effect of large store entrants in each period accumulates into productivity.[14]

The external environment in which stores operate can influence productivity in at least two ways. The first is through productivity gains within stores. Such productivity gains can arise due to spillovers, where incumbent stores have a one-time opportunity to learn best business practices from a large store entrant in the local market. The second is through a selection effect among stores by inducing the exit of low-productivity stores.

We measure the overall effect of large entrants on store productivity. An additional large store entrant in the market decreases the service output. To compensate for the decrease in service output, stores try to increase their productivity to continue to operate. The fact that it takes time for stores to adjust their productivity in response to increased competition justifies a lagged effect of large store entrants on productivity.

Because service output is difficult to measure in retail markets and is therefore unobserved in many data sets, deflated value-added is often used as a proxy for service output. In this case, store prices are included in the output measure, and they affect the productivity measure. In other words, the productivity measure includes price and demand variations (Foster *et al.* [2008]). Thus, the relationship between measured productivity and large store entrants is affected by the impact of large store entrants on prices and demand. To isolate the effect of large store entrants on productivity, we consider a standard

[13] We follow the common notation of capital letters for levels and small letters for logs for all variables except for the number of large store entrants e^L, which is in levels.

[14] The way that we model the relationship between store productivity and large store entrants is complementary to previous work on retail productivity (e.g., Foster *et al.* [2006], Schivardi and Viviano [2011], Basker *et al.* [2012], Ellickson and Grieco [2013]). For example, Ellickson and Grieco [2013] use detailed spatial and panel data to quantify changes in growth rates every year before and after entry. None of these papers focus on a structural approach of modeling total factor productivity and large store entry.

horizontal product differentiation demand system (CES):

$$Q_{jt} = Q_{mt} \left(\frac{P_{jt}}{P_{mt}} \right)^{\eta} exp(\mu_{jt}), \tag{2}$$

where Q_{mt} is the aggregated service output in local market m; P_{jt} is the service output price of store j; P_{mt} is the average price in the market; and μ_{jt} represents store-level shocks to demand (Klette and Griliches [1996], De Loecker [2011]). The parameter η (< -1 and finite) captures the elasticity of substitution among stores. The demand system implies 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 Lerner index is ($\frac{1}{|\eta|}$). This simple demand system is suitable for retail markets where stores have independent pricing strategies and the local markets consist of many stores, such that a single store does not influence the market price.

Combining the service output (1) and demand equation (2), we obtain an expression for the log of deflated value-added (y_{jt}) as a function of inputs and local market output:

$$\begin{aligned} y_{jt} \equiv \quad & q_{jt} + p_{jt} - p_{mt} = \left(1 + \tfrac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \tfrac{1}{\eta} q_{mt} \\ & + \left(1 + \tfrac{1}{\eta}\right) \omega_{jt} - \tfrac{1}{\eta} \mu_{jt} + (1 + \tfrac{1}{\eta}) u^p_{jt}, \end{aligned} \tag{3}$$

where p_{jt} and p_{mt} are logs of the service output prices at the store and market levels, respectively.

Estimation of the service-generating function (3) involves controls for both unobserved productivity ω_{jt} and unobserved demand shocks μ_{jt}. In the retail industry, other local market characteristics can explain store price variation in addition to the log of store output q_{jt} and the log of market output q_{mt}. For example, differences in the number of large store entrants across local markets over time likely affect unobserved demand shocks μ_{jt} and, therefore, store prices. We decompose demand shocks μ_{jt} into observed local market characteristics $\mathbf{x}_{mt}$ and the number of large stores that enter a local market in period t, e^L_{mt}:

$$\mu_{jt} = \beta_e e^L_{mt} + \mathbf{x'}_{mt} \boldsymbol{\beta}_x + u^d_{jt}, \tag{4}$$

where u^d_{jt} are remaining unobserved demand shocks.[15] Controlling for demand shocks μ_{jt} in the service-generating function (3) yields the specification taken to the estimation

$$\begin{aligned} y_{jt} = & \left(1+\tfrac{1}{\eta}\right)[\beta_l l_{jt} + \beta_k k_{jt}] - \tfrac{1}{\eta} q_{mt} - \tfrac{1}{\eta}\beta_e e^L_{mt} - \tfrac{1}{\eta}\mathbf{x'}_{mt}\boldsymbol{\beta}_x \\ & + \left(1+\tfrac{1}{\eta}\right)\omega_{jt} - \tfrac{1}{\eta} u^d_{jt} + (1+\tfrac{1}{\eta})u^p_{jt}. \end{aligned} \tag{5}$$

The remaining shocks in (5) are grouped into ϵ_{jt}, where $\epsilon_{jt} = -\frac{1}{\eta}u^d_{jt} + (1+\frac{1}{\eta})u^p_{jt}$.

How to recover productivity and assess the relationship between store productivity and the number of large store entrants in a market is complex, especially because it relates to how competition from large store entrants affects productivity. In our setting, 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. The shocks u^p_{jt} and u^d_{jt} are not predictable during the period in which inputs can be adjusted and stores make exit decisions.[16] Stores are assumed to know their scrap value received upon exit γ prior to making exit and investment decisions. If the store continues, it chooses optimal levels of investment i and labor l. Store j maximizes the discounted expected value of future net cash flows using the Bellman equation (Olley and Pakes [1996]):

$$V(\mathbf{s}_{jt}) = max\left\{\gamma, \sup_{i_{jt}}[\pi(\mathbf{s}_{jt}) - c_i(i_{jt}, k_{jt}) + \beta E[V(\mathbf{s}_{jt+1})|\mathcal{F}_{jt}]\right\}, \tag{6}$$

where $\mathbf{s}_{jt} = (\omega_{jt}, k_{jt}, w_{jt}, q_{mt}, p_{mt}, e^L_{mt}, \mathbf{x}_{mt})$; w_{jt} is the log of the wage rate at the store level; β is a store's discount factor; $\pi(\mathbf{s}_{jt})$ is the profit function, which is increasing in both ω_{jt} and k_{jt}; $c_i(i_{jt}, k_{jt})$ is the investment cost of new capital (equipment), which is

[15]The assumption that the marginal impact of large store entrants on demand shocks does not depend on the number of large entrants is not restrictive in our setting because we control for aggregate local market demand, and the markets only have three large store entrants per year at the most. However, this assumption can be relaxed by adding $(e^L_{mt})^2$ in (4) at the cost of an additional parameter to be estimated.

[16]The assumption on remaining demand shocks u^d_{jt} is restrictive, but it substantially simplifies the estimation of the model. It implies that all of the variation in market share in a local market for the same prices is uncorrelated with labor, capital, and exit decisions. This assumption can be avoided if we have access to store prices (online appendix B.3).

increasing in investment choice i_{jt} and decreasing in current capital stock k_{jt} for each fixed i_{jt} (Pakes [1991]); and $\mathcal{F}_{jt}$ represents the information available at time t. We assume that capital is a dynamic input that accumulates according to $K_{t+1} = (1-\delta)K_t + exp(i_t)$, where δ is the depreciation rate. In our setting, groups decide about the entry of large stores, and individual stores cannot influence this decision. Local market shifters and wages follow exogenous processes.

The solution to a store's dynamic maximization problem (6) yields optimal policy functions for investment $i_{jt} = \tilde{i}_{jt}(\mathbf{s}_{jt})$ and exit $\chi_{jt+1} = \tilde{\chi}_{jt}(\mathbf{s}_{jt})$. The exit rule χ_{jt} depends on the threshold productivity $\underline{\omega}_{mt}$, which is a function of all state variables except store productivity (Olley and Pakes [1996]). A store continues ($\chi_{jt} = 1$) if its productivity is larger than the local market threshold ($\omega_{jt} > \underline{\omega}_{mt}$). We assume that labor $l_{jt} = \tilde{l}_{jt}(\mathbf{s}_{jt})$, which is part of profits $\pi(\cdot)$, is chosen to maximize short-run profits (Levinsohn and Petrin [2003], Doraszelski and Jaumandreu [2013]).[17]

Productivity for stores that continue to operate in period t follows a Markov process

$$\omega_{jt} = h(\omega_{jt-1}, e^L_{mt-1}, \mathscr{P}_{jt}) + \xi_{jt}, \tag{7}$$

where $h(\cdot)$ is an approximation of the conditional expectation, and ξ_{jt} are shocks to productivity that are mean-independent of all information known at $t-1$. $\mathscr{P}_{jt}$ are predicted survival probabilities of being in the data in period t, conditional on the information in $t-1$, $\mathscr{P}_{jt} = Pr(\chi_{jt} = 1|\mathcal{F}_{t-1})$ (Olley and Pakes [1996]). Two stores with the same productivity and capital have different distributions of future productivities if they operate in local markets with a different number of large store entrants. The Markov process (7) implies that store productivity should shift, and stores that cannot improve productivity have to exit.

A timing assumption distinguishes an incumbent's response to large store entrants on demand from productivity. Large store entrants immediately affect stores' residual

[17] If labor has dynamic implications (e.g., in the case of labor adjustment costs), then labor in the previous period is part of the state space, and the optimal policy function for labor $l_{jt} = \tilde{l}_{jt}(\mathbf{s}_{jt})$ is derived from solving the dynamic optimization problem (6).

demand and thus local market equilibrium prices, but they affect store productivity with a one-year lag. The plausibility of this timing assumption for service industries ultimately depends on the empirical application at hand. More generally, several aspects could validate this assumption for retailing. First, intensive investments in information technology, such as scanners, have enabled stores to quickly adjust prices at a low cost (Basker [2015]). Consumers can also easily switch stores. Second, it is likely that it takes time for stores to adopt new technologies and take advantage of improvements in, for instance, management and logistics.[18] De Loecker [2011] uses a similar timing assumption when analyzing productivity effects from trade liberalization in the textile industry. Indeed, this timing assumption is particularly appealing in local retail markets that consist of many stores and where stores apply independent pricing strategies. It is important to control for demand because the presence of demand shocks related to large store entrants produces a downward bias in the effect of the large store entrants on productivity. Subsection 5.4 and online appendix B.1-B.2 discuss additional remarks on the timing assumption of the entry of large stores.

The relevant question from a policy perspective is to model entry rather than the number of large stores, i.e., entry is regulated, and policymakers need to evaluate entrants' impact on consumers and the market structure. We also focus on the fact that new stores come with new technology and innovations. The productivity process (7) implies that the effect of an entrant on productivity dissipates over time, which is in line with the literature that follows Ericson and Pakes [1995] studying the impacts of innovation, exports, and competition on productivity (e.g., Aw *et al.* [2011], De Loecker [2011], Doraszelski and Jaumandreu [2013]). To include the stock of large entrants (i.e., the number of large stores) in the productivity process (7) yields a persistent effect of large entry on productivity. Because a large store entrant in $t-1$ will affect both productivity

[18]This assumption directly follows the assumptions in recent work on dynamic structural models of R&D and productivity, where investment in R&D affects productivity with a one-year lag (e.g., Ericson and Pakes [1995], Doraszelski and Jaumandreu [2013]). A major difference is that we consider the role of the external environment (large store entry) rather than a firm's choices of R&D.

and demand, it is questionable whether we can separately identify the effect on demand from that on productivity without additional modeling assumptions (De Loecker [2011], online appendix B.2-3).

We base our empirical strategy on stores' static decisions on labor to disentangle the relationship between current productivity, the entry of large stores, and future productivity (Doraszelski and Jaumandreu [2013]). Three major concerns are addressed when estimating the service-generating function (5). The first concern relates to the standard problems of simultaneity of input usage on productivity, i.e., labor and capital are correlated with store productivity. All endogeneity problems regarding inputs are concentrated in ω_{jt}. The labor demand function $l_{jt} = \tilde{l}_{jt}(\mathbf{s}_{jt})$ allows us to recover the unobserved productivity ω_{jt}, to control for it in the service-generating function (5) and to use it in the productivity process (7). The second concern addresses selection on exit due to productivity. The third concern addresses the endogeneity of local market quantity q_{mt} and entry of large stores e^L_{mt} due to their possible correlation with remaining demand shocks u^d_{jt} in ϵ_{jt}.

III(i). Identification and estimation

This subsection discusses the identification and estimation of the service-generating function (5). We use a store's labor demand function to recover productivity and discuss both nonparametric and parametric approaches (Olley and Pakes [1996] (OP), Doraszelski and Jaumandreu [2013]). The nonparametric approach uses a two-step estimator, and the parametric approach uses a one-step estimator. While the parametric approach is more efficient because it uses a single equation in the estimation, it is dependent on the Cobb-Douglas technology assumption. We show the empirical results using both approaches but focus on the nonparametric approach in the main text because we also estimate the model using a more general technology (e.g., translog) in addition to Cobb-Douglas. Most importantly, both approaches can be applied.

Recovering productivity. We use the labor demand function from the stores' static profit maximization problem to recover productivity together with a good measure of store-specific wages (Doraszelski and Jaumandreu [2013]).[19] Using labor demand to recover productivity has the advantage that we can include stores with zero investment. The number of full-time adjusted employees is our measure of labor. Labor is a static and variable input chosen based on current productivity. For several reasons, this assumption is less restrictive in retail than in many other industries. First, part-time workers are common. As many as 40 percent of employees in food retail work part time, compared with 20 percent in the Swedish economy as a whole (Statistics Sweden). In addition, the share of skilled labor is low in retail. Only 15 percent of all retail employees had a university education in 2002, compared with 32 percent in the total Swedish labor force (Statistics Sweden). Moreover, we find no systematic differences in hiring educated workers between small and large stores in our data. Stores have long and similar opening hours and adjust their labor due to variations in customer flows over the day, week, month, and year. The training process might also be shorter than in many other industries.[20] We relax the static labor assumption in the robustness section.

The general labor demand function that arises from the stores' optimization problem (6) is

$$l_{jt} = \tilde{l}_t(\omega_{jt}, k_{jt}, w_{jt}, q_{mt}, p_{mt}, e^L_{mt}, \mathbf{x}_{mt}).$$

To back out productivity, the following key assumptions must hold. First, the labor demand function $\tilde{l}_t(\cdot)$ must be strictly monotonic in productivity, which holds when labor is a static input and more productive stores do not have disproportionately higher markups than less productive stores. By adding mild regularity conditions on a general technology in equation (1) instead of Cobb-Douglas technology, we show that static labor demand is strictly increasing in productivity under imperfect competition (online appendix D.1

[19]Intermediate inputs would be an excellent choice of proxy for productivity in retail markets (Levinsohn and Petrin [2003]). Ideally, we would like to have data on the stock of products (materials), but such data are unfortunately not available in many data sets on service industries. The investment policy function is restrictive because retail stores make lumpy investments, and we can only use stores with positive investment (Olley and Pakes [1996]).

[20]We assume that the labor market is efficient, so there are no training, hiring or firing costs, no labor supply constraints for stores (they can hire when they want), and no labor market rigidities.

provides the proof). One important condition is that labor's marginal product is increasing in productivity, which is fully consistent with store profit-maximization behavior. In particular, the nonparametric approach is suitable for complex models with a large state space where it is difficult to use a parametric form for the labor demand function. Second, ω_{jt} is the only unobservable entering the labor demand function, which rules out, e.g., measurement error, optimization error in labor, and a model in which exogenous productivity is not single dimensional. Our detailed register data of wages for all employees in Swedish retail are less subject to measurement errors due to reporting. Third, we require variation in store-specific wages. Even if store wages change over time, we need additional variation at the store level if we are to control for time effects in the estimation.[21] The variation in store wages in our data is discussed in detail in Section IV (data) and online appendix C.

In the first step in the nonparametric approach, we obtain an estimate of the service output without remaining shocks ϵ_{jt}. Inverting the labor demand function $\tilde{l}_t(\cdot)$ to obtain productivity ω_{jt} (i.e., $\tilde{l}_t^{-1}(\cdot)$) and substituting it into (5), the service-generating function becomes

$$y_{jt} = \phi_t(l_{jt}, w_{jt}, k_{jt}, q_{mt}, p_{mt}, e^L_{mt}, \mathbf{x}_{mt}) + \epsilon_{jt}, \tag{8}$$

where $\phi_t(\cdot) = \left(1+\frac{1}{\eta}\right)[\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta}q_{mt} - \frac{1}{\eta}\beta_e e^L_{mt} - \frac{1}{\eta}\mathbf{x}'_{mt}\boldsymbol{\beta}_x + \left(1+\frac{1}{\eta}\right)\tilde{l}_t^{-1}(\cdot)$. The estimation of (8) yields an estimate of service output without demand and service output shocks ϵ_{jt} , i.e. $\hat{\phi}_t$, that is used to obtain productivity as a function of the parameters $\boldsymbol{\beta} = (\beta_l, \beta_k, \eta, \beta_e, \boldsymbol{\beta}_x)$:

$$\begin{aligned} \omega_{jt}(\boldsymbol{\beta}) = \; & \tfrac{\eta}{(1+\eta)}\Big[\hat{\phi}_t - \left(1+\tfrac{1}{\eta}\right)[\beta_l l_{jt} + \beta_k k_{jt}] + \tfrac{1}{\eta}q_{mt} + \tfrac{1}{\eta}\beta_e e^L_{mt} \\ & + \tfrac{1}{\eta}\mathbf{x}'_{mt}\boldsymbol{\beta}_x\Big]. \end{aligned} \tag{9}$$

The presence of the demand shocks u^d_{jt} in ϵ_{jt} adds possible endogeneity concerns re-

[21] In the absence of store-level wages, however, it may be difficult to estimate the coefficients of static inputs in the Cobb-Douglas case (Bond and Söderbom [2005]). The proposed estimation strategy assumes that the first-order condition for labor does not include the derivative of the wage rate with respect to labor.

garding large store entrants, local market output, and wages (i.e., the moments $E[\epsilon_{jt}|e^L_{mt}, q_{mt}, w_{jt}] = 0$ do not hold) when estimating equation (8). To obtain the estimate $\hat{\phi}_t$ from (8), we use polynomial series, the Two-Stage Least Squares (2SLS) estimator and the moment conditions

$$E[\epsilon_{jt}|f(l_{jt}, w_{jt-1}, k_{jt}, q_{mt-1}, \sum_{o\neq m} q_{ot}, e^L_{mt-1}, \sum_{o\neq m} e^L_{ot}, pol_{mt}, \mathbf{x}_{mt})] = 0,$$

where $t = 1, \cdots, T$, f is vector-valued instrument functions (Wooldridge [2009]), $\sum_{o\neq m} q_{ot}$ is the aggregate quantity in the neighborhood's local markets, and $\sum_{o\neq m} e^L_{ot}$ is the number of large entrants in the neighborhood's local markets.

Retail groups can decide to enter large stores in markets with favorable characteristics, such as a short distance to a distribution center or good logistics. In other words, the moment condition $E[\epsilon_{jt}|e^L_{mt}] = 0$ does not hold when ϵ_{jt} includes shocks due to advertising, sales promotion activities related to large store entrants, and distribution. To account for the endogeneity of large store entrants, we use the share of non-socialist seats in local governments (Bertrand and Kramarz [2002], Schivardi and Viviano [2011], Maican and Orth [2015]), the number of large store entrants in other markets (Hausman-type instruments), and the previous number of large store entrants as instruments.[22]

The remaining demand shocks in ϵ_{jt} affect stores differently and might also impact the aggregate service output, making the moment $E[\epsilon_{jt}|q_{mt}] = 0$ not hold. To control for possible endogeneity of market output, i.e., correlation between q_{mt} and u^d_{jt}, previous market output or market output in other local markets can be used as instruments for q_{mt}. When ϵ_{jt} include demand shocks related to wages, then $E[\epsilon_{jt}|w_{jt}] = 0$ does not hold and the moment $E[\epsilon_{jt}|w_{jt-1}] = 0$ can be used in the estimation.[23] We discuss the instru-

[22]Data on the number of applications and rejections for each municipality are not available in Sweden. Even if this information were available, it would not be completely exogenous because the number of applications is easily influenced by current local government policies. No major policy reforms changing the conditions for large store entrants occurred in Sweden during the study period. Hausman-type instruments are widely used, as they are always available, but their use is controversial (Hausman [1997]).

[23]An alternative solution to solve the possible endogeneity problems of wages is to use average local market wages instead of store wages. Our results in Section V remain robust

ments in detail below and present specification tests in the results section. The robustness section shows the estimates without controlling for endogeneity using the Ordinary Least Squares (OLS) estimator, as in the OP framework.

Selection. Store decisions to exit in period t depend directly on ω_{jt}; therefore, the decision is correlated with the productivity shock ξ_{jt} (Olley and Pakes [1996]). Selection can affect retail markets because large stores (large k_{jt}) are more likely to survive larger negative productivity shocks than are small stores. Even if stores have low productivity, there might be other reasons for stores to stay active, such as favorable market conditions, logistics support by the firm, and a good location. To control for selection when estimating the service-generating function, we use predicted survival probabilities $\mathscr{P}_{jt}$ (Olley and Pakes [1996]). The probability of being in the data in period t conditional on the information in $t-1$ is given by $Pr(\chi_{jt} = 1|\underline{\omega}_{mt}, \mathcal{F}_{t-1}) = Pr(\omega_{jt} \geq \underline{\omega}_{mt}|\underline{\omega}_{mt}, \mathcal{F}_{t-1}) = P_{jt}(l_{jt-1}, k_{jt-1}, w_{jt-1}, p_{mt-1}, q_{mt-1}, e^L_{mt-1}, \mathbf{x}_{mt-1}) \equiv \mathscr{P}_{jt}$, where the second equality follows from the inverse of the labor demand function. In the estimation, selection affects only the productivity process, i.e., $\omega_{jt} = h(\omega_{jt-1}, e^L_{mt-1}, \mathscr{P}_{jt}) + \xi_{jt}$.

Estimation of service-generating function parameters. In the second step, we use the productivity process in (7) to estimate the parameters of the service-generating function using the Generalized Method of Moments (GMM) estimator. We nonparametrically regress $\omega_{jt}(\boldsymbol{\beta})$ in (9) on a polynomial expansion of order three in $\omega_{jt-1}(\boldsymbol{\beta})$, e^L_{mt-1}, and $\mathscr{P}_{jt}$.

To identify $\boldsymbol{\beta}$, the following moment conditions based on productivity shocks ξ_{jt} can be used, i.e., $E[\xi_{jt}|l_{jt-1}, k_{jt-1}, e^L_{mt}, q_{mt-1}, \mathbf{x}_{mt-1}] = 0$ (i.e., the just-identified specification). This set of moments uses the timing assumption that large store entrants influence productivity with a one-year lag, and only current large entrants influence prices, which implies that we can use the moment $E[\xi_{jt}|e^L_{mt}] = 0$. Adding pol_{mt-1} and $\sum_{o \neq m} e^L_{ot-1}$ as instruments gives us an overidentified specification. We use this overidentified specification to obtain the main results in Section V. The robustness of our results when using

when using average local market wages. If the observed variation in store wages is due to differences in exogenous market conditions, the moment condition $E[\epsilon_{jt}|w_{jt}] = 0$ can be used in the estimation (Ackerberg *et al.* [2007]).

alternative moment conditions is discussed in Section V(v)[24]

The parameters $\boldsymbol{\beta}$ are estimated by minimizing the GMM objective function

$$\min_{\boldsymbol{\beta}} Q_N = \left[\frac{1}{N}W'\xi(\boldsymbol{\beta})\right]' A \left[\frac{1}{N}W'\xi(\boldsymbol{\beta})\right], \tag{10}$$

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.[25] The estimation is performed at the industry level, controlling for local market conditions. Standard errors are computed according to Ackerberg *et al.* [2012].[26]

Parametric approach. Using the Cobb-Douglas technology, we can derive a parametric form for the labor demand function under imperfect competition from a store's static optimization problem, i.e.,

$$\begin{aligned} \tilde{l}_t(\cdot) = \; & \tfrac{1}{[(1-\beta_l)-\frac{1}{\eta}\beta_l]}[-\delta_1 + (1+\tfrac{1}{\eta})\omega_{jt} - w_{jt} + p_{mt} + (1+\tfrac{1}{\eta})\beta_k k_{jt} \\ & -\tfrac{1}{\eta}q_{mt} - \tfrac{1}{\eta}\beta_e e^L_{mt} - \tfrac{1}{\eta}\mathbf{x}'_{mt}\boldsymbol{\beta}_x], \end{aligned} \tag{11}$$

where $\delta_1 = -ln(\beta_l) - ln(1+\frac{1}{\eta}) - \ln E[\epsilon_{jt}]$ (Doraszelski and Jaumandreu [2013]).

In this case, we can take advantage of the parametric form of the service-generating function without making auxiliary assumptions (e.g., strict monotonicity holds) and use

[24] When the moment $E[\xi_{jt}|e^L_{mt}] = 0$ does not hold, an overidentified specification based on the set of moments $E[\xi_{jt}|l_{jt-1}, k_{jt-1}, pol_{mt-1}, \sum_{o\neq m} e^L_{ot-1}, q_{mt-1}, \mathbf{x}_{mt-1}] = 0$ can be used to identify $\boldsymbol{\beta}$ (see Section V(v)). As Ackerberg *et al.* [2015] discuss in Section IV(i), there are many ways to estimate an Olley and Pakes' framework based on second step moments. For example, one can also use the moment conditions based on $\xi_{jt}+\epsilon_{jt}$ (see also the discussion in Gandhi *et al.* [2014]). It is also important to emphasize that stronger assumptions can lead to more precise estimates.

[25] Wooldridge [2009] and Ackerberg *et al.* [2015] [ACF] (equation (31)) 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 the large number of parameters to be estimated.

[26] Bootstrapping might not be the best choice when the underlying model is more complicated. For this reason, the one-step estimator proposed by Doraszelski and Jaumandreu [2013] is more efficient and preferable because the standard errors obtained from GMM do not need additional corrections.

a one-step estimator. An advantage of this approach is that it is more efficient. The one-step estimation uses the parametric labor demand function from Cobb-Douglas technology (11) to obtain productivity and controls for it in estimating the parameters of the service-generating function in equation (5) and the law of motion for productivity in equation (7) (Doraszelski and Jaumandreu [2013]). This approach yields a single equation to estimate, and only the conditional expectation function $h(\cdot)$ is unknown and must be estimated nonparametrically.[27] The identification in the parametric case uses moment conditions based on $(1 + 1/\eta)\xi_{jt} + \epsilon_{jt}$ (online appendix E). We refer the reader to Doraszelski and Jaumandreu [2013] and Ackerberg *et al.* [2015] for additional discussions of the one-step and two-step estimators and the efficient use of moment conditions in the estimation of production functions.

Instruments for large entrants. Local authorities make decisions regarding entry, and we expect non-socialist local governments to have more liberal views regarding large store entrants.[28] To be an effective instrument for large store entrants, political preferences (i.e., the share of non-socialist seats) should not be related to local market demand or

[27] One can derive the parametric form for the inverse labor demand function, i.e., $\omega_{jt} = \frac{\eta}{1+\eta}[\delta_1 + [(1-\beta_l) - \frac{1}{\eta}\beta_l]l_{jt} + w_{jt} - p_{mt} - \left(1+\frac{1}{\eta}\right)\beta_k k_{jt} + \frac{1}{\eta}q_{mt} + \frac{1}{\eta}\beta_e e^L_{mt} + \frac{1}{\eta}\mathbf{x}'_{mt}\boldsymbol{\beta}_x]$, which is the same as equation (9) when $\hat{\phi}_t = -ln(\beta_l) - ln(1+\frac{1}{\eta}) - lnE[\epsilon_{jt}] + l_{jt} + w_{jt} - p_{mt}$. Substituting productivity into the service-generating function gives $\phi_t(\cdot) = -ln(\beta_l) - ln(1+\frac{1}{\eta}) + l_{jt} + w_{jt} - p_{mt}$. In the case of the two-step estimator, we can obtain an estimate of store output without shocks ϵ_{jt}, i.e., $\hat{\phi}_t$, in the first step using a simple OLS regression with a constant and year dummies. The form of $\phi_t(\cdot)$ under the parametric approach also shows that moment conditions based on ϵ_{jt} and k_{jt}, $\mathbf{x}_{mt}$, and e^L_{mt} are not informative to identify β_k, β_e, and $\boldsymbol{\beta}_x$ (Ackerberg *et al.* [2015]). For this reason, the one-step estimator uses moments of $(1 + 1/\eta)\xi_{jt} + \epsilon_{jt}$, and the two-step estimator uses moments of ξ_{jt} or $(1 + 1/\eta)\xi_{jt} + \epsilon_{jt}$ to identify $\boldsymbol{\beta}$.

[28] The Social Democratic Party is the largest party nationally, with 40.6 percent of 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), which is most often aligned with the Center Party (13.2 percent), the Christian Democratic Party (5.9 percent), and the Liberal Party (5.6 percent). Twenty-two percent of municipalities had a non-socialist majority during the period from 1996-1998, increasing to 32 percent from 1999-2002. The non-socialists had 8.6-85 percent and averaged 40.7 percent from 1996-1998 and 44.1 percent from 1999-2002.

reflect characteristics of the population that favors shopping at big-box stores but can boost productivity at other stores. This approach raises the following concerns. First, the outcomes of elections might be influenced by economic conditions. Political business cycles can only affect our results if there is a substantial ability to predict future demand shocks when politicians are elected. We also investigate median local market characteristics for socialist markets with large store entrants and non-socialist markets without large store entrants. There are 1-6 socialist markets with large store entrants and 82-147 non-socialist markets without large store entrants during the study period. Socialist markets with large store entrants are larger markets (population) and have lower population density than non-socialist markets without large store entrants. In addition, these two groups of markets do not significantly differ in income per capita. Importantly, we control for local market characteristics (income growth, population growth, population density) when estimating productivity.

The second concern is that political preferences might capture local policies other than entry regulations. In Sweden, the PBA is rather exceptional because it enables local politicians to play a key role. Furthermore, in our context, the number of large store entrants in other markets is an appropriate instrument if the number of large store entrants in other markets reflects common trends or demand shocks that are only specific to large store entrants, e.g., unobserved advertising.

Although the proposed instruments are not perfect when there are correlated unobservables across markets, we believe that they are the best instruments, given the available data and modeling framework, and they have been used extensively in the empirical literature. Online appendix B.1 provides more details, and Section V(i) presents the statistical specification tests on the instruments.

IV. Data

The estimation of our service-generating function requires store-level data on output, inputs, wages, entry and exit. It also requires municipality-level data on aggregate output and local market characteristics.

The main data set is a yearly panel of all registered companies in Sweden from 1996 to 2002 provided by Statistics Sweden (SCB). We focus on SNI code 52.1, "Retail sales in non-specialized stores".[29] The data contain sales, value-added, investment, capital, the number of employees, and wages. Value-added is defined as sales minus costs for purchased goods and services used as inputs in sales production and is provided by the SCB. We observe the number of full-time adjusted employees and average full-time adjusted wages. Investment measures the difference between the real gross expenditures on capital and the real gross retirement of capital. We deflate sales, value-added, wages, and investment by the consumer price index. Because we access register data, a unit of observation is an organization number. In a few cases, an organization number can consist of more than one store (a "multi-store") in the same municipality, for which we observe total, not average, inputs and outputs.[30] The SCB also provides municipality demographics such as population, population density, and average income. In addition, it contains political preferences in municipalities throughout the election periods from 1994-1998 and 1999-2002.

To define large store entrants, we use another panel data set that contains detailed information about store type, square meters, and ownership for all retail food stores in Sweden from 1996 to 2002. This data set is provided by Delfi Marknadspartner (DELFI). A unit of observation is a store based on its geographic location (i.e., only its address). A store is assumed to enter if it is observed in the data in year t but not $t-1$, and a store is assumed to exit if it is observed in year t but not $t+1$. The DELFI is used to define large store entrants based on physical entry, detailed store type definitions and ownership. It is also used to calculate the number of retail groups that operate in each local market. Readers interested in how we address the different units of observation in the SCB and the DELFI as well as other details about the data are referred to online appendix A.

[29] Swedish National Industry (SNI) classification codes build on the EU standard NACE.

[30] In the SCB data, we observe the municipality in which each organization number is physically located. Further, entry and exit are defined only on the basis of organization numbers. We remove large store entrants from the SCB when estimating productivity.

Large store entrants. We define the five largest types of stores (hypermarkets, department stores, large supermarkets, large grocery stores, and other as "large" and four other types of stores (small supermarkets, small grocery stores, convenience stores, and mini markets) as "small." This classification accords with the Swedish Competition Authority (see, e.g., Swedish Competition Authority [2002]). In terms of the Swedish market, we believe that these types are representative of being "large."[31] In light of the entry regulation, we only consider the physical entry of large stores (defined only based on address). A store that is re-classified into one of the large store types during the period is thus not counted as a large store entry. Gas station stores, seasonal stores, and stores under construction are excluded, as they do not belong to SNI code 52.1 in the SCB.

Descriptive statistics. Table I presents descriptive statistics of the Swedish retail food industry from the two data sets, the DELFI and the SCB, for the period from 1996-2002. In the SCB, the number of observations decreases by approximately 17 percent (from 3,714 to 3,067). The share of large stores increases from 19 percent to nearly 26 percent during the sample period. While total sales space remains virtually constant, mean sales space increases by 33 percent. This result suggests that there has been a major structural change toward larger but fewer stores. The wage bill increases by over 22 percent (in real terms), while the number of employees increases by only 9 percent. Total sales increase by approximately 26 percent. Aggregate value-added per employee increases from SEK 247,220 to SEK 277,690 during the period (12 percent). The corresponding increase in value-added per sales space is from SEK 7,290 to SEK 8,720 (19 percent).

Place TABLE I about here

Figure 1 shows kernel density estimates of labor productivity, defined as value-added per worker, for surviving incumbents in the year of and the year after large entry (i.e., exiters in the year of and the year after large entry are excluded). Labor productivity is greater after large entry for all parts of the productivity distribution. These findings are striking

[31] Stores classified as other stores are large and located out-of-town. Sales, sales space, and other store characteristics suggest that it is reasonable to group, e.g., hypermarkets and large grocery stores together and to separate large and small supermarkets (online appendix A).

and provide the first evidence of how large store entrants influence productivity.

Place FIGURE 1 about here

Table II shows the distribution of stores and groups across all local markets and years. The average number of stores is 23, with a standard deviation of 35. A majority of markets consist of stores that belong to three groups, whereas almost no markets consist of stores that belong to a single group. In the upper part of the distribution, most stores belong to ICA, approximately twice as many as belong to Coop and Axfood. On average, as many as 7.25 stores belong to ICA, and slightly less than 4 each belong to Coop and Axfood.

Place TABLE II about here

Table III shows the median characteristics of local markets with and without large store entrants during the period from 1997-2002. Based on all stores, average value-added per employee increases from SEK 249,330 to SEK 266,280 (7 percent) during the study period, whereas average value-added per sales space (m^2) increases from SEK 4,850 to SEK 5,550 (14 percent). The median number of stores varies from 22 to 54 in markets with large store entry, compared with 13 to 15 in non-entry markets. The number of markets with at least one large store entrant varies from 6 to 23. Among these, up to three large store entrants become established in the same market in the same year. As expected, median entry and exit are higher in large store entry markets than in non-entry markets, as are median population and population density.

Place TABLE III about here

Wage variation. Variation in store-specific wages is required when using labor demand to recover store productivity. Our measure of wages is a good reflection of exogenous changes in the price of labor because the 22 percent growth in the retail wage bill during the period (Table I) is consistent with the 24 percent growth in aggregate real wages in Sweden (Statistics Sweden).[32] High-quality data on store-specific wages, the fact that

[32]The average wage contains both the price of labor and its composition, e.g., age, gender, and skill groups. In Sweden, we do not expect compositional effects due to

stores set wages, and the prevalence of temporary job contracts and part-time work ensure the existence of wage variation across stores. The coefficient of variation for wages is approximately 18 percent across stores and 53 percent across municipalities.

Using data for the year 2000, market dummy variables alone explain only 9.7 percent of the variation in store wages. By adding capital and a dummy for large stores and local market controls, we explain 14.2 percent of the wage variation. By including the number of employees as an additional measure of store size, the variation in wages explained by the covariates increases to 15.7 percent.

V. Results

This section presents the main empirical results from the model presented in Section III using the nonparametric approach. First, we discuss the estimation of the service-generating function that allows us to recover store productivity. Then, we discuss how large store entrants affect store productivity, aggregated weighed productivity in local markets, and exit.

Our main specification is the most general one that (i) controls for simultaneity and selection biases; (ii) allows the external environment of stores to affect productivity, i.e., the previous number of large store entrants affects the productivity process; (iii) allows for imperfect competition, where current large store entrants and other local market characteristics affect demand; and (iv) controls for endogeneity of large store entrants, aggregate market demand and wages (see Section III). Section V(v) considers alternative modeling

some employees working overtime or differences in opening hours across stores. The one-sided t-test results show that we cannot reject the null of equal means of the share of educated employees (0.064) for both small and large stores. However, wages might pick up unobserved worker quality. Because worker quality is unobserved by the econometrician but observed by stores, we have two unobservables to control for, which complicates the estimation. Instead, the unobserved quality will enter into our productivity measure. However, this concern is not significant in the retail food market, where the quality of workers is expected to be fairly homogeneous. Online appendix C also provides a detailed discussion of wage variation.

specifications, including the parametric (one-step) estimator, and discusses several robustness checks.

V(i). Service-generating function estimates

Table IV presents estimates of the service-generating function. We show the results from the OLS estimator under perfect competition (column 1) and the two-step estimator presented in Section III. Column (2) shows the estimates that include elasticity, and column (3) shows the estimates without elasticity (i.e., structural parameters).[33]

Place TABLE IV about here

The estimate for the labor coefficient augmented by demand elasticity is 0.406 and that for capital is 0.188 (column (2)). The corresponding structural parameters (without elasticity, i.e., β_l and β_k) are 0.797 for labor and 0.368 for capital. As theory suggests, the estimate of returns to scale ($\beta_l + \beta_k$) in our estimator that controls for imperfect competition is greater (1.165) than that under perfect competition given by the OLS results (0.929). Few studies that use a production function framework emphasize the returns to scale in service industries. Retail stores can take advantage of economies of scale in distribution, logistics and purchasing. The nature of the cost structure in retail indicates, for instance, that a store that serves fewer customers faces increasing costs as the distribution lines become longer and thinner. In addition, increasing returns to scale are expected in industries with high consumer participation, geographic dispersion, and multi-market contacts (economies of density). The scale is likely to increase with the degree of self-service, thus decreasing the amount of services actually performed by the store, and is found to be higher in retail food than in other retail sectors (Ofer [1973]).[34]

[33] Physical quantity cannot be measured in service industries; therefore, we report the coefficients of the service-generating function augmented by demand elasticity in column (2), i.e., $(1+1/\eta)\beta_k$ and $(1+1/\eta)\beta_l$. This reporting approach also allows for easy reading across different reduced-form estimators, for example, OLS.

[34] For food retailing in Israel, Ofer [1973] estimates returns to scale at 1.42 and at 1.31 when controlling for supermarkets. Bairam [1994] estimates returns to scale at

The Sargan test shows that the overidentifying restrictions used to estimate $\boldsymbol{\beta}$ are valid, i.e., the test fails to reject the null hypothesis that the instruments are uncorrelated with the productivity shocks ξ_{jt} (p-value=0.985).

The estimate of the implied elasticity of demand is -2.04. Thus, the implicit assumption that $\eta=-\infty$, which is often used in empirical studies, does not hold. Our estimate is an average elasticity across stores with different products and that are located in different markets. The markup, defined as price over marginal cost, is 1.95. Our estimates are consistent with previous findings based on retail data.[35]

Large store entrants have an expected negative effect on residual demand and, hence, prices in the year of entry. An additional large store entrant decreases residual demand by, on average, 0.2 percent, but the effect is not statistically significant. That large stores have a modest impact on residual demand and hence prices is consistent with previous studies on the Swedish retail food market (Asplund and Friberg [2002]). Our model captures an average immediate impact of large entrants on prices, which can be larger if we allow for store type differentiation and traveling distance to the store. Incumbent stores might have difficulties reducing prices because of different factors such as long-term contracts, location, and distribution costs, but stores can respond by increasing in productivity to compensate for the decrease in demand after large entry. Stores in markets with growing population or income have a higher residual demand. However, stores in densely populated markets have a lower residual demand. This finding links to previous work indicating that markets with high population density are more competitive (Syver-

approximately 1.30 for fruits and vegetables based on Australian data. These estimates rely on Cobb-Douglas technology and value-added but do not control for simultaneity, selection or omitted price bias. As shown in the previous version of the paper, the scale is larger when including large cities in the estimation (Stockholm, Göteborg, and Malmö).

[35]The aggregate mark-up ($\eta/(1+\eta)$) depends on the estimated elasticity of demand η at the industry level; i.e., a larger $|\eta|$ implies a lower mark-up. Hall [1988] uses aggregate sector time series U.S. data and finds a markup of approximately 1.42 for retail trade and 1.53 for services. Using the same data, Roeger [1995] finds a mark-up of approximately 1.50 for food and kindred products. For Swedish retail food, Maican and Orth [2013] find an estimated average price elasticity of approximately -3 for large stores and -3.8 for small stores.

son [2004]).

First-stage results. The results of the first-step estimation of the service-generating function (8) are presented below. Readers not interested in these details can turn directly to Section V(ii).

To control for possible endogeneity of large store entrants (e_{mt}^{L}), aggregate market output (q_{mt}), and wages (w_{jt}) when recovering productivity, we estimate equation (8) using the 2SLS estimator. Political preferences, the previous number of large store entrants, the number of large store entrants in the neighborhood markets, and previous local market output and wages are used as instruments for e_{mt}^{L}, q_{mt}, and w_{jt}. Because of the polynomial expansion and large state space, equation (8) contains many parameters; for simplicity, we only discuss specification tests in the main text and do not show first-stage estimates from 2SLS.

The Sargan test of overidentifying restrictions fails to reject the null hypothesis that the instruments are uncorrelated with the residuals, and we conclude that the overidentifying restrictions are valid. We also report the partial F-test suggested by Staiger and Stock [1997] (Table IV). The statistically significant F-tests show that the instruments are not weakly correlated with the number of large store entrants, local market output, and wages. The partial F-tests when considering each potential endogenous variable are larger than 10 (Stainer and Stock's threshold), i.e., for large store entrants, F-value=65.66; for local market output, F-value=216.05; and for wages F-value=85.93.

To ensure the relevance of our instruments, we also run simple reduced-form regressions outside of our two-step framework. The findings are summarized here, and they are reported and discussed in detail in online appendix B.1. The findings show that the share of non-socialist seats in local markets and the number of large store entrants in other municipalities in the same county (neighboring markets) have a positive and statistically significant effect on the number of large store entrants after controlling for observed and unobserved market characteristics. Using simple reduced-form regressions with various controls, we also find that previous aggregate market output and previous wages have a positive and statistically significant effect on current aggregate market output and wages, respectively. In addition, we should recall that the only objective of the first step in our structural framework is to isolate demand shocks from the productivity measure (lower prices, new demand from product differentiation) associated with current large store entrants.

V(ii). Store productivity and large store entrants

In this section, we discuss the main findings on how large store entrants influence store productivity. Using the estimated parameters of the service-generating function and equation (9), we recover store productivity without i.i.d. shocks.[36]

Our structural framework provides information about stores' heterogeneous productivity responses with respect to large store entrants through the estimation of the nonlinear productivity process. The estimation of a simple linear $AR(1)$ productivity process shows that an additional large store entrant increases store productivity by 2.4 percent. While an exogenous $AR(1)$ process is not entirely consistent with our structural model, these results provide the first evidence of a positive effect of large store entrants on store productivity. These findings also show high persistence of productivity.[37] The conditional expectation of future productivity, $h(\omega_{jt-1}, e^L_{mt-1}, \mathscr{P}_{jt})$, is approximated using a third-order polynomial expansion in its arguments (Table V).[38] Large store entrants

[36]Productivity can also be recovered from the service-generating function: $\omega_{jt} = \frac{\eta}{1+\eta}[y_{jt} - (1+\frac{1}{\eta})[\beta_l l_{jt} + \beta_k k_{jt}] + \frac{1}{\eta}q_{mt} + \frac{1}{\eta}\beta_e e^L_{mt} + \frac{1}{\eta}\mathbf{x}'_{mt}\boldsymbol{\beta}_x]$. However, this productivity measure contains the i.i.d. ϵ_{jt} shocks. Our results on the impact of large store entrants on productivity are robust to using this alternative measure. The average productivities obtained from both measures (output and proxy) are close, but there are distributional differences and, as expected, a higher variance when using the service-generating function. For our preferred specification, the interquantile ranges are 1.192 and 1.438 for productivity recovered from labor demand and output, respectively.

[37]

$$\omega_{jt} = \underset{(0.005)}{0.710\omega_{jt-1}} + \underset{(0.012)}{0.024e^L_{mt-1}} + \xi_{jt}, \quad \mathrm{R}^2 = 0.630$$

(standard errors are in parentheses). In the absence of large store entrants and other productivity shocks, 71 percent of actual productivity comes from previous productivity.

[38]The static entry process implies that there is no endogeneity problem of large store entrants in the productivity process because e^L_{mt-1} is uncorrelated with current innovation

can influence productivity differently depending on store productivity ω_{jt-1} and e^L_{mt-1}. Therefore, a gain is that we recover marginal effects of large store entrants on productivity for each store in the data set. We can then exploit heterogeneity in store productivity responses to large store entrants in multiple dimensions. We only consider incumbent stores and exclude stores that enter (see next section for exit). For brevity, we focus on marginal effects and specification tests in the main text.

Place TABLE V about here

Summary of store productivity responses. Table V shows the productivity changes from an additional large store entrant across all incumbent stores in Sweden (the three largest cities are excluded).[39] The median increase in incumbent productivity from a large store entrant is 3.1 percent. There is also substantial heterogeneity in the magnitudes across stores at the national level. The interquartile range of the distribution of the marginal effects is 2.7 percent. The 75th percentile marginal effect (4 percent) is approximately three times larger than that at the 25th percentile (1.3 percent). In the case of a nonlinear productivity process, the degree of persistence in productivity varies with ω_{jt-1} and e^L_{mt-1}. The average persistence in productivity is approximately 0.745, which is consistent with previous findings on retail and manufacturing (Aw *et al.* [2011], Doraszelski and Jaumandreu [2013], Maican and Orth [2015]). The findings also show that the remaining productivity shocks (ξ_{jt}) have a lower variance in the nonlinear specification than in $AR(1)$.

Productivity regression: specification tests. We perform F-tests of the null hypotheses of zero coefficients for all terms in the productivity process that include store productivity and the number of large store entrants. The null is rejected for both productivity (F-test=7.9, p-value=0.000) and large store entrants (F-test=3632.8, p-value=0.000). All coefficients of the polynomial expansion are reported in online appendix D.2.

in productivity ξ_{jt} (Section III). We model e^L_{mt-1} as a continuous variable in the Markov process because e^L_{mt-1} is larger than one in some local markets (see also online appendix B). The results remain robust when using a dummy variable for the entry of large stores.

[39] When including the three largest cities, Stockholm, Göteborg, and Malmö, the positive impact of large store entrants on productivity is approximately 1-2 percent greater.

Productivity distribution in local markets. To highlight descriptive patterns in the productivity distributions in local markets, incumbents are classified into six percentile bins (p10, p10-25, p25-50, p50-75, p75-90, p90) for each year based on productivity. We then follow transitions between percentile bins or exit over time.

Place TABLE VI about here

Table VI shows that low-productivity incumbents in markets without large store entry decrease their productivity or stay as low-productivity stores without being forced to exit. The share of incumbents that remain in p10 is 10 percentage points higher in markets without large store entry. Stores with low productivity are small, i.e., they have fewer employees, lower capital stock, and lower value-added.

Focusing on local markets, we evaluate whether large store entrants have a greater impact on one part of the productivity distribution than another. Table VII (Panel A) shows the marginal effects of large store entrants related to incumbents' position in the local market productivity distribution. To account for store productivity heterogeneity when measuring the impact of large store entrants across local markets, we evaluate the marginal effects of an additional large store entrant for different productivity percentiles at the local market level (10th, 25th, 50th, 75th, and 90th). First, we calculate the marginal effects of large store entrants for each productivity percentile measure in each local market. Second, we compute the median and standard deviation of the marginal effects for each productivity percentile measure across local markets. This approach provides us with robust productivity changes across local markets following entry by a large store for each productivity percentile.

Place TABLE VII about here

The median increase in store productivity from an additional large store entrant across local markets is 4 percent. There is, however, high dispersion in the impact across markets, as indicated by the standard deviation of 0.076. A key result is that the impact of large store entrants on productivity decreases toward the upper parts of the productivity distribution. Large store entrants force low-productivity incumbents to improve their productivity more than high-productivity incumbents. A large store entrant increases productivity by 2 percentage points more for a store in the 10th local market productivity percentile than for a store in the 90th percentile. The corresponding difference is 1 percentage point for a store in the 25th productivity percentile compared with a store in the 75th percentile.

Variation in the number of large store entrants across local markets creates differences in competitiveness and in store incentives to improve productivity. Increasing competition reduces productivity dispersion in local markets, and our findings are in line with the recent empirical literature on productivity (Syverson [2004], Asplund and Nocke [2006]). This result occurs because low-productivity stores have stronger incentives to reduce costs and slack to continue to operate than do high-productivity stores. Thus, the lower tail of the local productivity distribution moves faster than the upper tail as a result of increased competitiveness. Recognizing that stores are heterogeneous in their productivity response to large store entrants allows us to understand the productivity differences across local markets (Syverson [2011]).

Heterogeneity by ownership. To further exploit store heterogeneity, we examine whether the store productivity changes resulting from large store entrants vary by ownership structure in local markets. Interestingly, the productivity gains from large store entrants are higher if more retail groups operate in the local market. The median increase in store productivity is 2.3 percent in markets with two groups and 2.8 percent in markets with three groups. The corresponding figures are 3 and 3.2 percent for markets with four and five groups, respectively. Furthermore, the interquantile range in the impact of large store entrants is smaller in markets with many groups, e.g., 0.037 and 0.026 in markets with two and five groups, respectively.

Further, the increases in store productivity due to a large store entrant are positively correlated with the joint market shares of stores affiliated with ICA (i.e., the market share of the ICA group) in the municipality but are negatively correlated with the market share of Coop. The Coop group started to reorganize their store formats after 2002. These results reflect differences in store productivity changes from large store entry across groups and ownership structures in local markets.[40]

V(iii). Aggregate productivity in local markets

Policymakers making decisions about the entry of new stores need to consider the responses of all of the incumbents in local markets. For an overall cost-benefit analysis of allowing large new stores to enter a local market, it is important to evaluate the changes in aggregate productivity due to the large store entrants.

Aggregate productivity in market m is $\omega_{mt} = \sum_{j=1}^{n_m} s_{jt}\omega_{jt}$, where s_{jt} is the market share of store j in period t and n_m is the number of stores. We compute the change in aggregate local market productivity due to a large store entrant as a weighted sum of individual stores' marginal effects using store market shares as weights, i.e., $\sum_{j=1}^{n_m} s_{jt}\frac{\partial h(\cdot)}{\partial e^L_{mt-1}}$.[41] As before, we only focus on changes in the productivity of incumbent stores.

Table VII (Panel B) shows the distribution of the weighted aggregate local market productivity growth of incumbents following a large store entrant, i.e., $\sum_{j=1}^{n_m} s_{jt}\frac{\partial h(\cdot)}{\partial e^L_{mt-1}}$. The median contribution of a large store entrant to the local market productivity growth of incumbents is 1.5 percent, with a maximum of 3.4 percent. These figures are 2.5 percentage points lower than the median increase in productivity computed using distribution measures of local market productivity reported as averages across markets (4 percent – Panel A in Table VII). There are at least two possible explanations for these results. It is likely that stores with relatively low productivity increases from a large store entrant have larger market shares and therefore receive larger weights. It could also be

[40] It is important to highlight that these results are only descriptive statistics of the impact of large store entrants on store productivity conditional on group affiliation and the market shares of groups in local markets. However, we do not explicitly model the affiliation of stores with groups in our single agent dynamic framework. The number of groups and the market shares of stores affiliated with different groups are constructed using DELFI. Anonymous identification codes hinder us from obtaining group affiliates of stores in the SCB data, which provide inputs and outputs for our productivity estimation.

[41] We do not model the changes in market shares due to large store entrants. To model the impact of large store entrants on market share in various types of markets, we need a dynamic oligopoly model, which is beyond the scope of this paper.

that more stores have low productivity increases rather than high productivity increases from a large store entrant (marginal effect).

Heterogeneity by market size. We also consider the relationship between productivity and market size. The average aggregated weighted local market productivity is the same in small and large markets (1.4 percent). However, the dispersion (measured by the interquantile range) is lower in large markets, i.e., 0.020 in small markets and 0.014 in large markets.[42] The lower dispersion in large markets may reflect the fact that higher demand substitutability implies more intense competition (Syverson [2004]).

V(iv). Exit

A negative relationship between productivity and exit is one of the most robust findings in the productivity literature (Olley and Pakes [1996]; Bartelsman and Doms [2000]; Syverson [2011]). Table VI shows the transitions between the productivity percentile bins and exit in local markets. A higher share of exit occurs from the lower half of the productivity distribution in large store entry markets than in non-entry markets. More than 25 percent of stores in the p10 bin exit in large store entry markets, but only 20 percent of such stores exit in non-entry markets.[43]

A store's dynamic optimization problem provides the policy function for exit, which states that a store's optimal decision to exit is a function of the state variables (Olley and Pakes [1996]). The probability of exit is thus a function of the store's state variables. We

[42]The null hypothesis of equal means of aggregated weighted local market productivity in small and large markets cannot be rejected by the t-test. The F-test and Bartlett test reject the null of equal variances. These tests are sensitive, however, because they assume that the data are normally distributed.

[43]In both market groups, approximately 3-4 percent of stores exit in p90. This result might be due to the re-structuring and re-organization of incumbent stores. Most importantly, there are no systematic differences in the exit of high-productivity stores in markets with or without large store entry. Although large store entrants represent "physical entry", the data only allow us to link estimated productivity and exit based on organization number. The proposed estimation approach accounts for these possible selection problems by controlling for survival probabilities when estimating store productivity (Olley and Pakes [1996]).

work under the assumption that shocks to demand u_{jt}^d are i.i.d. and are not predictable by stores when exit decisions are made.[44]

Place TABLE VIII about here

Table VIII shows regression results from simple probit specifications for the probability to exit, with our estimates of productivity, the number of large store entrants, capital, and demand shifters as explanatory variables. The coefficient of large store entry has the expected positive sign and is significant at conventional significance levels in all of the specifications. The probability of exit is approximately 0.18 higher for stores after a large store enters a local market. In line with both theory and previous empirical studies (e.g., Olley and Pakes [1996]), exit is less likely if productivity and the capital stock are high.

The interaction term between large store entrants and a dummy variable for stores with productivity below the 25th percentile is positive and jointly statistically significant with large store entry. These results are robust to additional controls. Hence, the entry of large stores forces low-productivity stores to exit. Exit is also less likely in high income growth markets and markets with low population density.

V(v). Robustness and specification tests

This section discusses the main robustness and specification tests. The online appendix presents additional robustness results.

Alternative specifications. Table IX shows robustness checks using alternative empirical specifications. First, we present robustness checks on our main specification (column (2) of Table IV), with the only difference that we do not control for endogeneity of large store entrants, aggregate quantity, or wages. The results are reported in column (3) of Table IX. The goal is to see how the results change when we treat these variables as exogenous. The positive marginal effects of large store entrants on store productivity remain robust

[44]If stores can observe or predict the demand shocks u_{jt}^d after controlling for observable demand shifters, it is not possible to estimate the exit regression as below without including the demand shocks in the productivity process. Exit decisions include physical exit and the re-structuring/re-organization of stores, which cause changes in stores' organization numbers.

when we do not control for endogeneity. The median increase in store productivity due to a large store entrant is 5 percent. However, the standard deviation of the marginal effect is slightly larger when we do not control for endogeneity. The service-generating function estimates show a slightly smaller capital coefficient ($\beta_k = 0.308$) and a slightly larger labor coefficient ($\beta_l = 0.966$).[45] The demand elasticity ($|\eta|$) increases from 2.04 to 2.62, and the scale increases from 1.16 to 1.27. The modest impact of a large store entrant on residual demand and hence prices remains when not controlling for endogeneity. The coefficient of large store entrants (β_e) is small and negative (-0.003) but not statistically significant.[46]

Place TABLE IX about here

Second, not controlling for the effect of current large store entrants on prices in our main specification results in a 2 percentage-point lower median impact of large store entrants on store productivity (results not reported); this result is in line with the theoretical predictions presented in Section III. Hence, part of the productivity increase caused by large store entrants is in fact an effect on prices, which is important to control for (De Loecker [2011]).

Third, the fact that the impact of large store entrants on productivity is biased when not controlling for the impact on demand is confirmed by a robustness check presented in column (1) of Table IX. Considering a simple parametric specification that explains productivity by the number of large store entrants, $\omega_{jt} = \beta_e e^L_{mt} + u^e_{jt}$, where u^e_{jt} are i.i.d., we can interpret β_e as the effect on productivity when estimating the service-generating function, $y_{jt} = \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + \beta_e e^L_{mt} + u^e_{jt} + \upsilon_{jt}$, by OLS. The results show that the coefficient for large store entrants is positive but small (0.009) and not statistically significant. In addition to the standard problems of production function estimation and

[45]When not controlling for the fact that large store entrants affect prices, we expect the coefficients for labor and capital to be biased because of the positive correlation between inputs and demand shocks, which are part of the productivity measure in this case. After controlling for local market competition, the capital coefficient increases, which is in the direction of controlling for selection bias (Olley and Pakes [1996]).

[46]This small effect might be due to the fact that, because of data constraints, our simple demand system only allows us to estimate average effects and does not consider distributional effects. Large store entrants may, e.g., reduce prices in nearby stores.

the use of strong assumptions to identify β_e (i.e., $E[u^e_{jt} + \upsilon_{jt}|e^L_{mt}] = 0$), this specification does not address the effect of large store entrants on prices.

Fourth, the robustness specification in column 2 of Table IX considers the role of omitting imperfect competition. This specification corresponds to the implementation of the OP method with labor demand as a proxy. A new large store decreases median productivity by approximately 2 percent. The negative impact of a large store entrant suggests that we must control for demand in local markets.

Parametric labor demand. An attractive alternative is to use a parametric labor demand function to recover productivity (Doraszelski and Jaumandreu [2013]). The functional form of the parametric labor demand function is shown in Section III. Our identification strategy and empirical findings are robust to the choice of the labor demand function. The estimates are presented in column (4) of Table IX; they are very close to the estimates obtained using the nonparametric estimator and have lower standard errors. The two-step estimator provides, however, a larger scale and lower demand elasticity, which is in line with the previous findings on food retailing. Online appendix E shows additional results and discusses the empirical strategy using parametric labor demand.

In the parametric labor demand specification, we test the validity of our assumption that labor is static. If the inverse labor demand function is misspecified, the labor coefficient in the service-generating function differs from that in the inverse labor demand function. We estimate the restricted and unrestricted models and compute the GMM distance statistic, $D_N = N * [Q_N(\beta_{\text{restricted}}) - Q_N(\beta_{\text{unrestricted}})]$, to test the null of equal labor coefficients.[47] The null is not rejected, i.e., our assumption of static labor is valid.

Timing assumption of large store entrants. In our setting, large store entrants immediately affect stores' residual demand and thus local market equilibrium prices but affect store productivity with a one-year lag. Reduced-form evidence shows that this assumption is not rejected by our data; e.g., when regressing store sales or value-added on both e^L_{mt} and e^L_{mt-1}, the coefficient on lagged large store entrants is not significant using OLS

[47] We acknowledge that this test might be biased when labor is quasi-fixed because the wage is no longer the "right" wage and the shadow wage should be used (see Doraszelski and Jaumandreu [2013]).

or 2SLS estimators. Most importantly, the coefficient for e^L_{mt-1} is positive in all of the regressions, i.e., our hypothesis is not rejected (online appendix B.1). Therefore, the findings suggest that we cannot reject the timing assumption regarding the number of large store entrants. However, this reduced-form empirical evidence on the timing assumption should be interpreted with care, as the regressions do not control for other simultaneity and selection bias issues (specific to production functions).

Relaxing the timing assumption on labor. If there are hiring and firing costs of employees, labor is a static and fixed input. We can then use current labor l_{jt} as an instrument in our main specification. The results are directly comparable with those when labor is static and variable, i.e., Tables IV and VII. Under perfect competition, the coefficient for labor (adjusted with elasticity) increases from 0.406 to 0.647, and the coefficient for capital increases from 0.188 to 0.240. Controlling for imperfect competition, the labor coefficient increases to 0.491, the capital coefficient increases to 0.412, and demand elasticity is -2.88 (slightly larger than in Table IV). Using the moment condition based on current labor provides similar support of the marginal effect of large entrants (Table VII).

Alternative production technology. For our main specification, we relax the Cobb-Douglas technology in equation (1) and consider a translog production function $q_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l^2_{jt} + \beta_{kk} k^2_{jt} + \beta_{lk} l_{jt} k_{jt} + \omega^p_{jt} + u^p_{jt}$, which requires the estimation of three additional parameters: labor squared (β_{ll}), capital squared (β_{kk}), and the interaction between labor and capital (β_{lk}). The results, which are not reported but are available from the authors upon request, are consistent with our previous findings. Large store entrants have a greater impact on low-productivity incumbents than on high-productivity incumbents. An additional large store entrant increases productivity by approximately 4 percent for a 10th percentile productivity store, by approximately 2 percent for a median store, and by approximately 0.1 percent for a 90th percentile store.

Alternative moments. As suggested in Section III, an alternative set of moments that can be used in the estimation of the service-generating function $\boldsymbol{\beta}$ is $E[\xi_{jt} | l_{jt-1}, k_{jt-1}, pol_{mt-1}, \sum_{o \neq m} e^L_{ot-1}, q_{mt-1}, \mathbf{x}_{mt-1}] = 0$ (i.e., an overidentified specification). This set of moments can be used when the moment $E[\xi_{jt} | e^L_{mt}] = 0$ does not hold. Using this overidentified specification, there is no significant change in the estimation of $\boldsymbol{\beta}$. The Sargan test cannot reject the null hypothesis of overidentified restrictions (p-value=0.963), which suggests that the overidentifying restrictions are valid. In addition, the median marginal effect of large entrants on productivity (3.6 percent) is close to the findings presented in Section V (4 percent).

Decomposition. We also estimate the contribution of all store entrants to aggregate productivity growth during the period from 1997 to 2002 using various productivity decompositions (Foster *et al.* [2001]). Incumbent stores that increase their productivity at the initial sales level contribute approximately 8 percent (within), and net entry contributes 2-4 percent (online appendix F). These findings suggest the importance of understanding the factors that drive productivity growth.

VI. Conclusions

The present study provides 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, total factor productivity in retail markets has rarely been studied, in contrast with manufacturing. We present a first attempt to use recent advances in the semiparametric estimation of production functions to estimate productivity in retail markets and to investigate how the 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 "Walmart effect").

We provide a dynamic structural model to obtain accurate measures of total factor productivity in retail food. The framework addresses a set of measurement issues in services, i.e., substitution of capital and labor, difficulties in measuring output, and the importance of modeling the external environment in local markets. We analyze whether large store entrants force low-productivity stores out of the market and increase productivity among the surviving stores with different positions in the productivity distribution.

Our empirical application relies on detailed data on all retail food stores in Sweden, a sector that is representative of many OECD markets in terms of market structure and regulation.

The results show substantial heterogeneity in the positive effects of large store entrants on future productivity. A large store entrant increases productivity in the median store by 3.1 percent. A key finding is that productivity increases decline toward the upper part of the productivity distribution. Productivity increases by 1-2 percentage points more for a store in the 25th local market productivity percentile than for a store in the 75th percentile. Stores with low productivity are smaller, and large store entrants force them either to exit or to increase their productivity to survive. These stores increase their productivity relatively more than do stores with high productivity.

These results can be rationalized by the fact that increased competition from large store entry forces existing stores to improve their productivity and low-productivity stores to exit. Productivity improvements are larger in the bottom part of the local market productivity distribution, which decreases productivity dispersion. Our findings support previously discussed mechanisms of how competition affects productivity (Asplund and Nocke [2006], Syverson [2011]). Furthermore, not controlling for the contemporaneous effect of large store entrants on prices leads to underestimation of their impact on store productivity. We conclude that the entry of big-box stores catalyzes retail productivity.

Our findings contribute knowledge that is relevant to competition policy, as entry regulation issues are a significant concern for policymakers in Europe, where such regulations are generally much more restrictive than in the U.S. As an example, the European Commission recently highlighted an investigation of the food sector (European Commission [2012]). We argue that a more restrictive design and application of entry regulations can hinder aggregate productivity growth in local markets. In addition to productivity, entry regulations compound a wide range of other aspects. How to balance potential productivity growth against increased traffic and broader environmental effects and the consideration of dynamic game frameworks are interesting topics for future research.

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Table I

Characteristics of the Swedish Retail Food Market

A. SCB						
Year	No. of stores	No. of employees	Wage bill	Value added	Total sales	Value added per employee
1996	3,714	74,100	9,882,234	18,319,407	141,743,876	247.22
1997	3,592	73,636	10,322,136	18,838,130	142,840,611	255.83
1998	3,482	74,696	10,766,043	19,185,120	147,726,647	256.84
1999	3,398	74,758	11,110,785	19,570,472	152,160,949	261.78
2000	3,287	77,180	11,536,063	20,389,492	154,106,865	264.18
2001	3,094	76,905	11,522,482	20,748,902	158,512,132	269.79
2002	3,067	80,931	12,081,931	22,473,696	179,335,162	277.69

B. DELFI						
Year	Large stores	Large entry	Mean sales space m^2 (ft^2)	Total space space m^2 (ft^2)	Total sales	Value added per sales space m^2 (ft^2)
1996	905	21	538 (5,792)	2,510,028 (27,017,711)	129,326,000	7.29 (0.67)
1997	925	8	550 (5,916)	2,483,248 (26,729,464)	126,732,397	7.58 (0.70)
1998	926	9	587 (6,315)	2,552,794 (27,478,041)	130,109,604	7.52 (0.69)
1999	936	18	604 (6,500)	2,534,082 (27,276,632)	133,156,023	7.72 (0.71)
2000	948	23	654 (7,040)	2,612,566 (28,121,432)	138,314,044	7.80 (0.72)
2001	942	28	689 (7,419)	2,520,110 (27,126,244)	139,352,920	8.23 (0.76)
2002	932	5	718 (7,733)	2,575,784 (27,725,503)	142,532,944	8.72 (0.81)

NOTE: SCB 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, wages, value-added per employee and sales space are measured in thousands of 1996 SEK (1USD=6.71SEK, 1EUR=8.63 SEK). DELFI is provided by Delfi Marknadspartner AB. Sales in DELFI are collected by surveys and reported in classes, while sales are based on tax reporting in SCB. Therefore, total sales are lower in DELFI than in SCB. Value-added per employee is defined using the number of full-time adjusted employees in SCB. Value-added per square meter of sales space (m^2) and value-added per square feet of sales space (ft^2) are defined using value-added from SCB and sales space from DELFI. From 1996 to 2002, the total population in Sweden increased from 8,844,499 to 8,940,788.

Table II

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 III
Local market characteristics

Year	1997	1998	1999	2000	2001	2002
A. Productivity measures for all markets: mean (std. dev.)						
Value-added per employee	249.33	252.11	271.66	256.93	258.93	266.28
	(70.04)	(49.95)	(149.64)	(54.98)	(64.79)	(57.62)
Value-added per square meter (m^2)	4.85	5.01	5.11	4.95	5.16	5.55
	(4.77)	(5.16)	(5.29)	(5.72)	(5.71)	(5.97)
Value-added per square feet (ft^2)	0.43	0.45	0.46	0.44	0.46	0.49
	(0.38)	(0.43)	(0.45)	(0.46)	(0.46)	(0.49)
Total no. of markets	285	285	286	286	286	287
B. Markets with large entrants: median						
No. of stores	35	45	28	30	33	20
No. of all entrants	2	2	2	2	1	1
No. of all exits	2	2	2	3	1	-
Population	43,646	54,933	37,054	40,363	58,266	13,150
Population density	69.30	48.70	66.92	78.65	69.30	31.80
Per capita income	149.20	157.70	161.40	170.70	179.10	177.80
Total no. of markets	8	8	19	19	21	5
C. Markets without large entrants: median						
No. of stores	15	15	15	14	13	14
No. of all entrants	0	0	1	0	0	0
No. of all exits	0	1	1	1	0	-
Population	14,825	14,709	14,244	14,090	14,047	15,049
Population density	25.80	25.76	25.10	24.99	24.66	25.90
Per capita income	143.20	149.10	155.90	162.50	168.40	175.90
Total no. of markets	277	277	267	267	265	282

NOTE: 1996 is left out because entrants are not observed. Municipalities are considered as local markets. The three largest municipalities are excluded (Stockholm, Göteborg, Malmö). Municipalities increase from 285 to 287 due to three municipality break-ups during the period. Value-added per employee is defined using the number of full-time adjusted employees in SCB. Value-added per employee and sales space are in thousands of 1996 SEK (1USD=6.71SEK, 1EUR=8.63 SEK). Sales space, stores, entrants and exits come from DELFI. Population density is defined as total population per square kilometer in the municipality.

Table IV

Service generating function estimates

	OLS	Two-step estimation	
	(1)	(2)	(3)
Log no. of labor	0.735	0.406	0.797
	(0.004)	(0.008)	(0.012)
Log of capital	0.194	0.188	0.368
	(0.003)	(0.007)	(0.019)
Number of large store entrants		-0.001	-0.002
		(0.001)	(0.002)
Population growth		0.534	1.090
		(0.956)	(0.992)
Log of population density		-0.016	-0.033
		(0.007)	(0.013)
Income growth		0.567	1.158
		(0.128)	(0.195)
Market output $\left(-\frac{1}{\eta}\right)$		0.499	
		(0.010)	
Scale $(\beta_l + \beta_k)$	0.929	1.165	
Demand elasticity (η)		-2.042	
Markup $\left(\frac{\eta}{1+\eta}\right)$		1.95	
Sargan test (p-value)		0.985	
Test for ortogonality and weak intruments in the first-step of OP framework			
Sargan test (p-value)		0.094	
Partial-F test: Large entrants		65.665	
(p-value)		(0.000)	
Partial-F test: Agggregate quantity		236.053	
(p-value)		(0.000)	
Partial-F test: Wages		85.930	
(p-value)		(0.000)	
No. of obs.	15,318	11,079	

NOTE: The dependent variable is the log of deflated value-added. Labor is measured as the number of full-time adjusted employees. All regressions include year dummies. *OLS* refers to ordinary least squares regression. OP refers to the Olley and Pakes (1996) estimation method. The specification in column (2) is a two-step estimation method that uses a nonparametric labor demand function and controls for imperfect competition and the endogeneity of large store entrants, aggregated local market quantity and wages in the first step of the OP framework (see Section V). In specification (2), the reported parameters include elasticity, specifically, $(1+\frac{1}{\eta})\beta_l$ 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 store entry (equation (3)). Column (3) shows the estimated coefficients for specification (2) without elasticity (structural parameters). Market output is measured as the market share weighted output in the municipality. Markup is defined as price over marginal cost. Reported standard errors (in parentheses) are computed using Ackerberg *et al.* [2012]. The largest cities Stockholm, Gothenburg, and Malmo are excluded.

Table V

Estimation of productivity process

Panel A: Estimation of Markov productivity process using 3rd order polynomial expansion in ω_{jt-1} and e^{L}_{mt-1}		
	F-test	p-value
H_0 : Coefficients of ω_{jt-1} terms are zero	7.973	0.000
H_0 : Coefficients of e^{L}_{mt-1} terms are zero	3632.800	0.000
Adjusted R^2	0.986	
No. of obs.	11,079	
Panel B: Distribution of the marginal effect at store level across entry markets		
25th percentile	0.013	
50th percentile	0.031	
75th percentile	0.040	
Mean	0.022	

NOTE: Productivity is recovered from the labor demand function using the semiparametric two-step approach controls for simultaneity, selection, and imperfect competition (see Sections III and V). We control for endogeneity of large entrants, market output and wages in the first stage. 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). *Panel B* shows the distribution of the marginal effect across stores and years. For each store and year, the marginal effects are computed using store estimated productivity. The largest cities Stockholm, Gothenburg, and Malmo are excluded.

Table VI

Transition matrix from t-1 (row) to t (column)

Percentile	<p10	p10-p25	p25-p50	p50-p75	p75-p90	>p90	Exit
Markets with large store entrants in $t-1$							
<p10	0.2424	0.3333	0.1364	0.0152	0.0152	0.0000	0.2576
p10-p25	0.2105	0.3158	0.2316	0.0632	0.000	0.0000	0.1789
p25-p50	0.1143	0.1486	0.3829	0.1943	0.0343	0.0171	0.1086
p50-p75	0.0278	0.0833	0.1944	0.3556	0.2333	0.0389	0.0667
p75-p90	0.0244	0.0122	0.1220	0.2927	0.3293	0.1707	0.0488
>p90	0.0149	0.0448	0.1194	0.1045	0.2985	0.3881	0.0299
Markets without large store entrants in $t-1$							
<p10	0.3468	0.2347	0.1468	0.0474	0.0116	0.0069	0.2058
p10-p25	0.2241	0.2848	0.2586	0.0817	0.016	0.0126	0.1222
p25-p50	0.0681	0.1923	0.3716	0.2017	0.0432	0.0199	0.1033
p50-p75	0.0245	0.0558	0.2576	0.3822	0.1465	0.0506	0.0829
p75-p90	0.0113	0.0199	0.0832	0.2946	0.3224	0.1958	0.0728
>p90	0.0141	0.0129	0.0516	0.1455	0.3239	0.4096	0.0423

NOTE: Productivity is estimated using our preferred specification of the model described in Section III. Productivity is backed out from the labor demand function. Municipalities are considered as local markets. Large store 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). The largest cities Stockholm, Gothenburg, and Malmo are excluded.

Table VII

The impact of large store entrants on incumbents' productivity in local markets

Panel A: Marginal effects by productivity percentiles in local markets		
	Median	Std.Dev.
10th percentile productivity	0.041	0.061
25th percentile productivity	0.041	0.067
50th percentile productivity	0.040	0.076
75th percentile productivity	0.030	0.085
90th percentile productivity	0.022	0.094

Panel B: Change in aggregate local market productivity	
Minimum	-0.010
25th percentile	0.003
50th percentile	0.015
75th percentile	0.023
Maximum	0.034
Mean	0.013

NOTE: The figures are computed using the estimated controlled Markov process of productivity. *Panel A* shows the medians and standard deviations of the marginal effects across local entry markets and years. For each market and year, we computed the effects for various local productivity percentiles. *Panel B* shows the distribution of changes in aggregate local market productivity after large store entry. The figures are computed as weighted averages of the productivity of individual stores, using market shares as weights, i.e., $\sum_{j=1}^{n_m} s_{jt}(\partial h(\cdot)/\partial e^L_{mt-1}))$. Productivity is recovered from the labor demand function using semiparametric two-step approach controls for simultaneity, selection, and imperfect competition (see Sections III and V). We control for endogeneity of large store entrants, market output and wages in the first stage. We drop extreme values by removing 3 percent of the observations from each tail of the marginal effect distribution. 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). The largest cities Stockholm, Gothenburg, and Malmo are excluded.

Table VIII

Regression results: Exit

	(1)	(2)	(3)	(4)	(5)
Log of productivity	-0.217			-0.179	
	(0.033)			(0.037)	
Productivity in p25		0.102			
		(0.038)			
No. of large entrants (eL)	0.107		0.006	0.081	0.004
	(0.047)		(0.067)	(0.048)	(0.068)
No. of large entrants × Productivity in p25 ($inter$)			0.181		0.169
			(0.090)		(0.091)
Log of capital				-0.044	-0.076
				(0.017)	(0.015)
Income growth				-8.237	-8.499
				(2.382)	(2.379)
Population growth				-3.266	-2.269
				(2.600)	(2.723)
Population density				0.050	0.050
				(0.017)	(0.017)
H_0 : Sum of the coef. of eL and $inter$=0			(0.003)		(0.006)
Year fixed-effect	Yes	Yes	Yes	Yes	Yes
No. of obs.	7,486	7,486	7,486	7,486	7,486

NOTE: This table shows probit regressions on exit. Productivity is estimated using the model described in Section III. Reported standard errors are in parentheses. Large entrants are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). The p-values are reported for the null hypothesis of the zero sum of the coefficients of the number of large store entrants and the interaction variable. The largest cities Stockholm, Gothenburg, and Malmo are excluded.

Table IX

Robustness on service-generating function estimates

	OLS	Two-step framework		Parametric
	(1)	(2)	(3)	(4)
Log no. of labor	0.732	0.843	0.597	0.403
	(0.004)	(0.006)	(0.015)	(0.004)
Log of capital	0.199	0.162	0.190	0.200
	(0.003)	(0.004)	(0.009)	(0.0003)
Number of large entrants	0.009		-0.001	-0.0009
	(0.009)		(0.003)	(0.0001)
Population growth			0.484	0.498
			(0.814)	(0.014)
Log of population density			-0.026	0.011
			(0.006)	(0.002)
Income growth			0.485	0.488
			(0.091)	(0.004)
Market output $\left(-\frac{1}{\eta}\right)$			0.381	0.457
			(0.007)	(0.004)
Scale $(\beta_l + \beta_k)$	0.930	1.005	1.274	1.021
Demand elasticity (η)			-2.624	-2.186
Markup $\left(\frac{\eta}{1+\eta}\right)$			1.615	1.842
No. of obs.	15,318	11,079	11,079	11,079

NOTE: The dependent variable is the log of deflated value added. *OLS* refers to ordinary least squares regression. Standard errors are in parentheses. The reported parameters in specifications (3) and (4) 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 store entry (equation (5)). Labor is measured as the number of full-time adjusted employees. All regressions include year dummies. Specifications (2) and (3), which are based on the two-step estimation framework, include previous large store entrants and use the nonparametric labor demand function as a proxy for productivity; Specification (3) controls for imperfect competition but assumes that large entrants, aggregate local market quantity and wages are exogenous; Specification (4) is a one-step estimation using a parametric labor demand function and controlling for imperfect competition and endogeneity of large store entrants, aggregate local market quantity and wages (Doraszelski and Jaumandreu [2013]). Market output is measured as the market share weighted output in the municipality. Markup is defined as price over marginal cost. The largest cities Stockholm, Gothenburg, and Malmo are excluded.

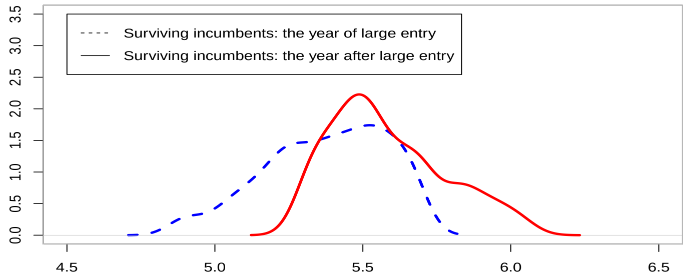

Figure 1
Log of labor productivity kernel density estimates in markets in the year of and the year after large entry