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IFN Working Paper No. 939, 2012

# **A Dynamic Analysis of Regulation and Productivity in Retail Trade**

Florin Maican and Matilda Orth

# A Dynamic Analysis of Regulation and Productivity in Retail Trade\*

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

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## Abstract

Liberalization is widely recognized to drive productivity growth. Retail trade is often thought to substantially contribute to the frequently debated productivity gap between Europe and the U.S. In Europe, entry regulations empower local authorities to decide on the entry of new stores. We use a dynamic structural model and data on all retail stores in Sweden during the period 1996-2002 to quantify the effect of entry regulations on productivity in retail. The results show that the approval of an additional application by local authorities increases median productivity by approximately 2 percent in most subsectors. A stricter regulation in terms of one fewer approved application in each local market corresponds to an annual economic cost for the retail trade sector of nearly 10 percent of total annual capital investments. Our findings suggest that a restrictive entry regulation limits the role of entry and exit in local market dynamics and productivity growth.

*Keywords:* Retail trade, regulation, imperfect competition, dynamic structural model, productivity decomposition.

*JEL Classification:* L11, L81, L88, O30.

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# 1 Introduction

Liberalization is widely recognized to drive productivity growth. Despite being a question of great importance to both researchers and policy makers, the literature is still in the initial stages of learning how to quantify the effects of regulations on productivity in different industries.<sup>1</sup> Retail trade is an industry with several features that make it appropriate for studying the consequences that regulations have on productivity. First, retail markets are subject to substantial regulations, which are much more restrictive in Europe than in the U.S. In Europe, one of the most powerful policy tools in the retail sector are entry regulations that empower local authorities to make decisions regarding the entry of new stores. Second, retail trade is often claimed to substantially contribute to the frequently debated productivity gap between Europe and the U.S. (Gordon, 2004; Schivardi and Viviano, 2011). Third, retail has become increasingly important for overall economic activity in modern economies and currently accounts for up to 6 percent of GDP and 10 percent of employment. Retail markets in both Europe and the U.S. have trended toward larger but fewer stores and changed dramatically due to the adoption of information technology such as scanners, barcodes and credit card processing machines in recent years. In U.S. retail trade, entry and exit have been found to explain almost all labor productivity growth. This stands in contrast to the manufacturing sector, where entry and exit are found to account for only approximately 30 percent of total growth (Bartelsman and Doms, 2000; Foster et al., 2006). In this paper, we use a dynamic structural model to quantify the impact of entry regulations on productivity in retail trade.

Our structural framework extends Olley and Pakes (1996) to model the effect of regulation on productivity while considering local markets and controlling for prices. We first estimate a value-added generating function and then evaluate how productivity changes with the degree of local market regulation and decompose aggregate productivity. The model is general and can be applied to other imperfectly competitive industries that are subject to regulation. We combine our structural model with rich data on all retail stores in Sweden from the period 1996-2002 and several measures of the degree of local market regulation that vary both across local markets and time. The analysis is performed separately for 12

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<sup>1</sup>Examples of recent contributions are, e.g., Olley and Pakes (1996); Djankov et al. (2002); Pavcnik (2002); Aghion et al. (2005b); Acemoglu et al. (2006); Aghion et al. (2008); Djankov (2009) (survey); De Loecker (2011); Syverson (2011) (survey); Buccirossi et al. (2012); Greenstone et al. (2012); and Yakovlev and Zhuravskaya (2012).

different subsectors. In Sweden, all stores are subject to the regulation, providing the 290 municipalities with the power to make land use decisions.<sup>2</sup> Each new potential entrant is required to make a formal application to the local government. The decision to change a geographic zoning restriction, and thus allow a new store to enter the market, is supposed to consider the consequences for, e.g., market structure, prices, traffic, and the environment more broadly. Based on previous retail studies, we define local markets as having a liberal (non-liberal) regulatory environment if they have above (below) the median number of approved applications or a non-socialist (socialist) majority in local governments (Bertrand and Kramarz, 2002; Sadun, 2011; Schivardi and Viviano, 2011).

This paper makes several contributions to the literature. First, we are among the first to use a dynamic structural model to analyze regulation and productivity in retail markets. We thus provide a general approach for assessing the consequences regulations have on productivity in retail trade, which complements the existing literature (Bertrand and Kramarz, 2002; Haskel and Sadun, 2011; Sadun, 2011; Schivardi and Viviano, 2011).<sup>3</sup> Because our goal is to understand how regulations affect productivity, we explicitly model the relationship between regulations and productivity in our structural framework. The basic intuition is that a more liberal regulatory framework implies higher potential competition, which forces incumbents to improve their productivity to stay in the market. The mechanism involves the X-inefficiency hypothesis that is often emphasized in the theoretical literature on competition and productivity.<sup>4</sup> Recent work on the effects of liberalization emphasizes heterogeneous responses by firms within sectors and across local markets with different institutions (Aghion et al., 2005b; Ace-

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<sup>2</sup>Although the basic concepts behind entry regulations are the same, the design and degree of regulation differ somewhat across Europe. While some countries explicitly regulate the entry of large stores (e.g., U.K.), other countries have zoning restrictions on entire geographical areas.

<sup>3</sup>Schivardi and Viviano (2011) find that more strict entry regulations hinder productivity in Italian retail trade. Sadun (2011) finds that an increase in approved applications results in higher employment growth, and Haskel and Sadun (2011) find that retail TFP decreased following the 1996 planning regulation in U.K. Other studies using U.K. data are Griffith and Harmgart (2008); Haskel and Khawaja (2003) and Reynolds et al. (2005). In France, regulation is found to slow labor growth (Bertrand and Kramarz, 2002). There is also related work on (local) productivity growth, agglomeration and spillovers using Italian data (Cingano and Schivardi, 2004; Guiso and Schivardi, 2007; Guiso and Schivardi, 2011; Michelacci and Schivardi, 2012; Pozzi and Schivardi, 2012).

<sup>4</sup>This also relates to the longstanding literature on competition and productivity (Aghion and Griffith, 2005). See, e.g., Schmidt (1997); Boone (2000); Raith (2003); Vives (2004), and Aghion et al. (2005a) for theoretical contributions, and Porter (1990); MacDonald (1994); Nickell (1996); Blundell and Van Reenen (1999); Sivadasan (2004); and Aghion et al. (2009) for empirical contributions.

moglu et al., 2006; Aghion et al., 2008; Yakovlev and Zhuravskaya, 2012). The current paper complements this literature by focusing on heterogeneous effects of local market regulations in a country with strong institutions. Our model is flexible with respect to how regulations influence productivity, i.e., stores can react differently to regulatory changes depending on their location in the local market productivity distribution. A main advantage of the structural approach is that it ensures consistency between the theoretical and empirical modeling. Although we allow for a flexible productivity process, our structural productivity estimation relies on assumptions that we argue are reasonable for the Swedish retail industry and empirically validated by our data. In contrast, estimating a value-added generating function using the OLS estimator and then regressing regulation (or other productivity shifters) on productivity often impose “few assumptions” on the production function but many on the productivity process.

The second contribution to the literature involves the structural estimation of production functions. Our model for retail markets builds on the growing literature on heterogeneity in productivity within industries that use dynamic structural models (Olley and Pakes, 1996; Pavcnik, 2002; Levinsohn and Petrin, 2003; Ackerman et al., 2006). Apart from allowing local market entry regulation to influence productivity, our model considers a number of key aspects of retail trade. Following the recent extensions of the framework by Olley and Pakes (1996) that emphasize the importance of controlling for price and demand shocks when estimating productivity, we implement a simple demand system to control for unobserved prices (Katayama et al., 2003; Levinsohn and Melitz, 2006; Foster et al., 2008; Maican and Orth, 2009; De Loecker, 2011; Doraszelski and Jaumandreu, 2011; De Loecker and Warzynski, 2012). This approach has the additional advantage of yielding markup estimates at the subsector level. The complexity of defining a price and measuring output in retail suggests considering both technical and quality-adjusted productivity measures, i.e., true productivity without demand shocks and the sum of technical productivity and remaining demand shocks.<sup>5</sup> A key aspect of retail markets is that stores make lumpy investments, and we rarely

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<sup>5</sup>Recent studies on manufacturing industries estimate production functions and demand separately (Dhyne et al., 2011; De Loecker et al., 2012; Petrin and Warzynski, 2012). This requires linked establishment level data and product-level data on prices and quantities. To the best of our knowledge such data are not available for services. Complications of retail trade are its multi-product and multi-market nature and that we require data on all stores in local markets. Griffith and Harmgart (2005); Reynolds et al. (2005); and Maican and Orth (2009), provide more details regarding retail markets.

observe data on intermediate inputs such as materials. By considering this, we back out unobserved productivity from the labor demand function (Doraszelski and Jaumandreu, 2011). The assumption that labor is a static input ignores training, hiring, and firing costs. We argue that this assumption is reasonable in retail. Part-time work is common in retail, the share of skilled labor is low, and stores frequently adjust labor due to variation in customer flows (Maican and Orth, 2009).

The results show that the elasticity of scale in most subsectors of Swedish retail trade is 1.04 (Footwear) - 1.46 (Computers), and it is important to control for simultaneity and imperfect competition in local markets. Subsector markups, defined as price over marginal cost, are between 1.15 (Electronics) and 3.12 (Furniture). The results are robust to various semiparametric estimators, and the estimated markups are in line with previous results based on U.S. data (Hall, 1988). The approval of an additional application by local authorities increases the productivity of the median store by 1.5-2.6 percent for most subsectors. A stricter regulation in terms of one fewer approved application in each local market translates to annual subsector economic costs of 2.8 million euros (Toys) - 194 million euros (Furniture).<sup>6</sup> The numbers are non-trivial and correspond to nearly 10 percent of the annual capital investments in Swedish retail trade. For the period 1996-2002, the subsector cost aggregates to as much as 20 million euros (Toys) - 1,361 million euros (Furniture).

The third contribution is to the recent literature on productivity decomposition. To understand the productivity differences across local markets with different degrees of regulation, we use an extension of the Olley and Pakes (1996) decomposition to allow for the contribution of entry and exit to aggregate productivity levels in local markets. The results demonstrate that a more liberal regulatory environment increases the contribution of entry and exit to aggregate productivity. Using the decomposition approaches developed by Griliches and Regev (1995) and Foster et al. (2001), we find that entry, together with incumbent stores, plays a crucial role in growth.<sup>7</sup> We conclude that a more liberal entry regulation drives productivity dynamics in local markets and increases productivity growth.

Section 2 presents the entry regulation and data. Section 3 describes the mod-

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<sup>6</sup>Numbers are in 2012 values, where 1EUR=9.01SEK and 1EUR=1.30USD. In these calculations, we multiply the average annual cost per store by the average number of stores in the subsector over the 1996-2002.

<sup>7</sup>Foster et al. (2006) analyze labor productivity growth in U.S. retail trade. In addition, we use recent decomposition methods, previously applied to the manufacturing industries, to decompose productivity growth in retail (Melitz and Polanec, 2012; Petrin and Levinsohn, 2012).

eling approach employed to estimate productivity. Section 4 reports the impact of the regulation and decompositions of aggregate productivity, followed by conclusions in Section 5.

## 2 Entry regulation and data

The majority of OECD countries have entry regulations that empower local authorities. The restrictions, however, differ substantially across countries. While some countries strictly regulate large entrants, more flexible zoning laws exist for instance in the U.S. (Hoj et al., 1995; Pilat, 1997; Boylaud and Nicoletti, 2001; Nicoletti and Scarpetta, 2003; Griffith and Harmgart, 2005; Pilat, 2005). In Sweden, the Plan and Building Act (“Plan och Bygglagen”, PBL) empowers the 290 municipalities to make decisions on applications for new entrants. There is geographical zoning such that municipalities have power over land use, i.e., all stores are subject to the regulation. Each municipality is divided into smaller geographical areas for which there exist zoning plans. A zoning plan can change for different reasons, and for our purposes municipalities can change a zoning plan to (i) allow for retail trade; (ii) change the land use for any reason, i.e., this can include purposes other than retail trade.<sup>8</sup> Inter-municipality questions regarding entry are addressed by the 21 county administrative boards. The PBL is held to be a major barrier to entry, resulting in diverse outcomes, e.g., in price levels across local markets (Swedish Competition Authority, 2001:4). Several reports stress the need to better analyze how regulations affect market outcomes (Pilat, 1997; Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2).<sup>9</sup>

To measure the degree of regulation in local markets, we employ different measures. First, we observe the total number of approvals in the PBL for each municipality and year. This captures the implementation intensity of the PBL and/or a high total number of applications. The data are collected by the Swedish Mapping, Cadastral and Land registration Authority (Lantmäteriet). Second, we have

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<sup>8</sup>Opening hours are also regulated in some countries, but not in Sweden.

<sup>9</sup>Firms could adopt strategies similar to those of their competitors and buy already established stores. As a result, more productive stores can enter without involvement of the PBL and, consequently, the regulation will not operate as a barrier to entry that potentially affects productivity. Large entrants, however, are often newly built stores in external locations, making the regulation highly important. Of course, we cannot fully rule out the possibility of firms purchasing established stores.



data on the number of approved PBL applications that allow the entry of retail stores. A high number of approved applications that allow retail stores to enter the market indicates a more liberal application of the PBL. The data are collected by surveys of 163 out of the 290 municipalities and exist for three time periods: 1987-1992, 1992-1996, and 1997-2000 (Swedish Competition Authority, 2001:4). The average total number of approvals in each municipality and year is 5.43 with a standard deviation of 7.50, whereas the corresponding values for approvals of entry of new stores are 5.39 and 8.06. The correlation between the two measures is 0.83. To be able to use all local markets and years and because of the high correlation, we use the total number of approvals in the empirical implementation.<sup>10</sup> In addition, we use information on political preferences measured as the share of non-socialist seats in local municipal governments (Bertrand and Kramarz, 2002; Sadun, 2011; Schivardi and Viviano, 2011). The expectation is that non-socialist local governments apply the PBL more liberally.<sup>11</sup> Appendix A describes the PBL in greater detail.

**Local markets.** Our modeling approach takes local competition into account, and market size is determined by subsector, store size, and distance to competitors. We expect the local market to be narrower the shorter the durability of goods. The 21 counties are most likely too large, whereas the more than 1,600 localities are most likely too small. The 290 municipalities that make entry decisions are, however, a reasonable local market size for the majority of Swedish retail trade products. We therefore use the 290 municipalities as our definition of local markets.

**Data.** We use detailed data from Statistics Sweden (SCB) that include all retail stores from 1996 to 2002. The unit of observation is a store based on the firm's tax reporting number. The data contain two parts: (i) Financial Statistics (FS) at the store level, which contain input and output measures such as sales, value-added, investments, etc.; (ii) Regional Labor Market Statistics (RAMS) at the store level, which include the number of employees and wages. Each store consists of one unit or several due to, e.g., joint ownership.<sup>12</sup> Anonymity hinders us from

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<sup>10</sup>Note that we observe the number of approved applications (in total and for entry of retail stores), but not the number of rejections. However, we also observe the total number of zoning plans ("detaljplaner") that explicitly restrict retail food stores.

<sup>11</sup>We use political preferences for robustness because one could argue that the number of applications (and rejections) is not completely exogenous if the number of applications is easily influenced by current local government policies.

<sup>12</sup>For example, over 80 percent of the observations are single unit stores in Food.

identifying owners and connecting individual units with stores (see Appendix B for a detailed description of the data). We use all stores that belong to SNI-code 52, “Retail trade, except of motor vehicles and motorcycles; repair of personal household goods.” As we have access to detailed information, it is possible to use the five-digit industry codes (for retail 74 in total). To simplify the presentation and jointly analyze similar product groups, we use the following 12 subsectors (discussed in detail in Appendix C) in the empirical application: Food, Textiles, Clothing, Footwear, Furniture, Electronics, Hardware, Books, Sports, Watches, Toys and Computers.

Sales, value-added, investments and capital are deflated by sub-groups of the Consumer Price Index (CPI). It is important to control for subsector prices because subsectors are heterogeneous. Retail food prices are used for Food. Separate and individual sub-groups are also used for Textiles, Clothing, Footwear, Furniture, Hardware, Books and Computers. For the remaining groups we use the CPI.

**Descriptive statistics.** Table 1 presents summary statistics for the Swedish retail sector during the period 1996-2002. The general trend is that total sales, value-added, and the number of employees increases over time, while the number of stores decreases. There is a decrease in the rate of sales and in investments in 2001, which then recovers in 2002. Total sales increase by 34 percent to 326 billion SEK in 2002. Value-added is 59 billion SEK in 2002, implying an increase of 27 percent since 1996, which is somewhat lower than for sales. Investments increase rapidly until 2000 and then decline. Over the full period, investments increase by 47 percent to a total of 5 billion SEK. The number of employees (full-time adjusted yearly average) increases from 144,000 to 159,000, i.e., by 10 percent. The opposite trend is found for the number of stores. Except for the year 2000, Table 1 reveals a monotonic decline in the number of stores. There is an overall decline of 10 percent during the period. These industry level statistics exhibit a pronounced trend of restructuring towards larger but fewer stores. Food is the largest subsector, accounting for nearly half of total sales and 20 percent of all stores in 2002, followed by Clothing and Furniture.

Table 2 presents median and dispersion measures for the key variables from 1996 to 2002. Dispersion is defined as the difference between the 75th percentile and 25th percentile of stores divided by the median. This measure, which indicates the spread of the distribution, is selected to avoid measurement problems and outliers. The median store increases sales by 26 percent over the period. The

corresponding increase in value-added is 31 percent, while investments increase 19 percent. The median store has three employees (full-time adjusted) over the entire period, most likely because stores that change size are located in the tails of the distribution. For all variables, dispersion increases over time. A comparison across variables shows that investment has the highest values, i.e., investment is the variable that differs the most across stores. The level of dispersion is approximately three times larger for investment than for sales, value-added, and the number of employees.

Table 3 presents entry and exit rates organized by subsector and size. Exit rates are high, and large entrants are common in Food and Toys. The entry of small stores is most common in Clothing, Furniture, Hardware, and Sports. Hardware and Sports are the only subsectors with net entry; all others have net exit with the highest outflow of stores in Textiles, Books, and Footwear.

Table 4 reports descriptive statistics of annual store level growth in terms of value-added, number of employees, wages, and capital over the study period. The share of small stores is highest in Textiles but lowest in Food. The mean value-added increases the most in Sports and Toys but the least in Textiles, Footwear, Books, and small Food stores. Employment growth is highest in Toys and small Sport stores but lowest in Food, Electronics and Watches. Capital growth is high in Electronics, and Sports but low in Textiles and Watches. The mean values are also high for Furniture whereas low corresponding values are found in Books and Toys.

### 3 Modeling approach

Our model follows the approach developed by Olley and Pakes' (1996) (hereafter OP), but adapted to address the key characteristics of the retail sector. Incumbent stores maximize the expected discounted value of future net cash flows. After they collect their payoffs in the product market, incumbents decide whether to exit or to continue to operate at the beginning of each time period. The state variables are productivity  $\omega \in \Omega$ , capital stock  $k \in \mathbb{R}_+$ , and local market characteristics  $\mathbf{z} \in \mathbb{R}_+^m$  including local market characteristics such as population, population density, income, and the degree of regulation. Importantly, local market regulation  $r \subset \mathbf{z}$  is a state variable that influences stores' decisions regarding inputs and exit.

The decision variables are investment  $i \geq 0$  and/or labor  $l$ . If the store exits, it receives scrap value  $\kappa$ . If the store continues, it chooses optimal levels of investment and labor. Labor is chosen based on current productivity, while capital accumulates according to  $K_{t+1} = (1 - \delta)K_t + exp(i_t)$ , where  $\delta$  is the depreciation rate. Observing the realization of productivity  $\omega_{jt-1}$  and local market regulation  $r_{mt-1}$  in period  $t - 1$ , stores form expectations of future productivity using the distribution  $P(\omega_{jt}|\omega_{jt-1}, r_{mt-1})$ . We assume that the productivity process is a time-homogeneous controlled Markov process, i.e.,  $P(\cdot)$  is not indexed by  $t$ . As our goal is to estimate the impact of regulation on productivity, it is crucial to explicitly model local market regulation in the productivity process. The degree of regulation measures the intensity of potential competition in the local market and is exogenous to stores. Through the X-inefficiency hypothesis, more liberal regulation of new stores induces stronger competitive pressure in the local market. In turn, we expect incumbent stores to reduce slack and improve their productivity, which induces reallocation and exit. Regulation influences the productivity of incumbent stores with a one-year lag to capture the time stores require to cut slack and change features such as their management to increase productivity.<sup>13</sup>

We assume the following production function with Cobb-Douglas technology:

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

where  $q_{jt}$  is the log of quantity sold by store  $j$  at time  $t$ ;  $l_{jt}$  is the log of labor input; and  $k_{jt}$  is the log of capital input.<sup>14</sup> The unobserved  $\omega_{jt}^p$  is technical productivity, and  $\xi_{jt}$  are shocks to production (quantity sold) that are not predictable during the period in which inputs can be adjusted and stores make exit decisions. Standard estimators of (1) such as OLS, fixed effects, and instrumental variables are inconsistent due to simultaneity and selection biases (Olley and Pakes, 1996; Akerberg et al., 2006).

To estimate productivity in retail, we consider the following key features of retail markets in our model: (i) imperfect competition that makes it crucial to control for prices, (ii) local market competition, (iii) labor and capital are key inputs while we often have weak measures of intermediate inputs such as prod-

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<sup>13</sup>Similar approaches are, for example, adopted when analyzing productivity and R&D (Aw et al., 2011; Doraszelski and Jaumandreu, 2011; Petrin and Warzynski, 2012), or productivity and trade liberalization (De Loecker, 2011).

<sup>14</sup>The model is easy to apply to a general specification; for example, translog with neutral efficiency across stores would perform equally well.

ucts purchased. A similar approach is adopted by Maican and Orth (2009), who analyze the entry of big-box stores and productivity in retail food.

**Imperfect competition.** The best proxy for output is sales or value-added, which implies that prices set by stores that operate in imperfectly competitive markets will enter into productivity when we estimate the production function in (1). Thus, a negative correlation emerges between inputs and prices, as more inputs are necessary to capture the increase in demand when stores reduce prices. As a result, we will underestimate the labor and capital parameters in (1) without controlling for prices (Klette and Griliches, 1996; Melitz, 2000; Foster et al., 2008; De Loecker, 2011).<sup>15</sup> We assume a demand function with a negative slope and that stores operate in a market with horizontal product differentiation, where  $\eta$  ( $< -1$  and finite) captures the elasticity of substitution among products:

$$p_{jt} = p_{smt} + \frac{1}{\eta}q_{jt} - \frac{1}{\eta}q_{smt} - \frac{1}{\eta}\mathbf{z}'_{mt}\boldsymbol{\beta}_z - \frac{1}{\eta}u_{jt}^d, \quad (2)$$

where  $p_{jt}$  is output price,  $p_{smt}$  and  $q_{smt}$  are output price and quantity in subsector  $s$  in local market  $m$ , and  $u_{jt}^d$  are the remaining demand shocks.

Because of the multi-product and multi-market nature of retail trade, it is difficult to measure store prices. Therefore, the demand system is an approximation and only allows for one elasticity of substitution for all stores within each subsector, i.e., no differences in cross-price elasticities. In other words, it assumes completely symmetric price responses and differentiation across stores in each subsector. Although quite restrictive, implementing a demand system for each subsector makes it possible to control for variation in demand conditions across subsectors. We observe deflated value-added (sales)  $y_{jt} = q_{jt} - p_{jt}$ , thus if store level prices are observed we directly substitute (1) into (2).<sup>16</sup> Store level prices are difficult to measure in retail markets, and due to this data constraint we deflate value-added with the subsector consumer price index, which is constant across local markets,

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<sup>15</sup>If the products are perfect substitutes, deflated sales are a perfect proxy for unobserved quality adjusted output. Foster et al. (2008) analyze the relationship between physical output, revenues, and firm-level prices in the context of market selection, finding that productivity based on physical quantities is negatively correlated with store-level prices, while productivity based on revenues is positively correlated with those prices.

<sup>16</sup>We use deflated value-added and not deflated sales. The advantage of using value-added is that we control for the impact of materials, i.e., the stock of products bought from the wholesaler. This is important because we have (as is common in retail) a weak measure of intermediate inputs. A drawback of using value-added is that the elasticity of demand is theoretically defined for sales and not for value-added.

i.e.,  $p_{smt} = p_{st}$ . However, it is important to emphasize that we use one consumer price index for each subsector. Using (2) to control for prices in (1), we obtain

$$y_{jt} = \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta} q_{smt} - \frac{1}{\eta} \mathbf{z}'_{mt} \boldsymbol{\beta}_z + \left(1 + \frac{1}{\eta}\right) \omega_{jt}^p - \frac{1}{\eta} u_{jt}^d + \left(1 + \frac{1}{\eta}\right) \xi_{jt}. \quad (3)$$

The value-added generating function allows us to estimate the elasticity of demand  $\eta$  and hence to compute markups for each subsector. The identification and interpretation of the results depend on the assumption regarding the remaining demand shocks  $u_{jt}^d$ . To limit the presence of correlated demand shocks, we control for a large number of observed local market demand shifters  $\mathbf{z}'_{mt}$  (population, population density, and income). We remove the immediate effect of regulation on prices by including the number of approved PBL applications in local markets  $r_{mt}$  in  $\mathbf{z}'_{mt}$ .

If  $u_{jt}^d$  are i.i.d. shocks, not predicted or anticipated by stores when they make input and exit decisions, we can identify technical productivity  $\omega_{jt}^p$  separately from demand. Due to data limitations, we cannot guarantee that we remove all remaining shocks to demand. That is, unobserved prices imply that we need to consider persistent demand shocks that may enter our productivity measure.

If  $u_{jt}^d$  are correlated demand shocks, we need additional assumptions for identification because the scalar unobservable assumption in OP is violated. This situation is more likely in retail trade, where regulation might have a lagged effect on both prices and productivity, for example. In this case, it is difficult to separately identify technical productivity  $\omega_{jt}^p$  and demand shocks  $u_{jt}^d$ .

The shocks  $\omega_{jt}^p$  and  $u_{jt}^d$  can follow either dependent or independent Markov processes. If  $\omega_{jt}^p$  and  $u_{jt}^d$  follow dependent Markov processes, the demand shock will enter the information set that forms expected productivity  $E[\omega_{jt}^p | \omega_{jt-1}^p, r_{mt-1}, u_{jt-1}^d]$ . We can use an estimate of  $u_{jt}^d$  in line with Berry et al. (1995), but this is not feasible due to data limitations (we would need additional store specific information). If  $\omega_{jt}^p$  and  $u_{jt}^d$  follow independent Markov processes, the demand shock will determine the optimal choices of labor and/or investment through which it affects productivity. We can then identify quality-adjusted productivity, i.e., the sum of technical productivity and remaining demand shocks  $(\omega_{jt}^p - \frac{1}{1+\eta} u_{jt}^d)$ .<sup>17</sup>

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<sup>17</sup>Alternatively, we can assume that  $\omega_{jt}^p$  and  $u_{jt}^d$  follow AR(1) processes, which allow us to distinguish persistent demand shocks from productivity. If  $\omega_{jt}^p$  and  $u_{jt}^d$  follow the same AR(1) process, the exact source of the shock is irrelevant (Melitz, 2000; Levinsohn and Melitz, 2006). If

To simplify notation in what follows, we denote productivity  $\omega_{jt}$  and refer to it as technical productivity ( $\omega_{jt} = \omega_{jt}^p$ ) when  $u_{jt}^d$  are i.i.d., and quality-adjusted productivity ( $\omega_{jt} = \omega_{jt}^p - \frac{1}{1+\eta}u_{jt}^d$ ) when  $u_{jt}^d$  are correlated across time. An important difference between technical productivity and quality-adjusted productivity is the interpretation of the results.

**Regulation and productivity process.** Productivity  $\omega_{jt}$  follows a controlled Markov process:

$$\omega_{jt} = E[\omega_{jt}|\omega_{jt-1}, r_{mt-1}] + v_{jt} = g(\omega_{jt-1}, r_{mt-1}) + v_{jt}, \quad (4)$$

where  $r_{mt-1}$  is the entry regulation in local market  $m$  and  $v_{jt}$  are random shocks to productivity. The shocks  $v_{jt}$  may be understood as the realization of uncertainties that are naturally linked to productivity. The conditional expectation function  $E[\omega_{jt}|\omega_{jt-1}, r_{mt-1}]$  is unobserved by the econometrician (but known to the store) and is approximated by the nonparametric function  $g(\omega_{jt-1}, r_{mt-1})$ . In case of quality-adjusted productivity, the previous degree of local market regulation  $r_{mt-1}$  affects both prices and productivity, but these effects cannot be separated.

We explicitly model the channel through which regulation influences productivity. This approach has several advantages over previous work on regulation and productivity in retail trade. First, our model provides a clear link between theory and empirics. Second,  $g(\omega_{jt-1}, r_{mt-1})$  allows regulation to affect productivity in a flexible manner, i.e., the impact of regulation varies with stores' productivity. In addition, we employ rich data on the number of approved PBL applications, varying both across local markets and years, to measure the degree of regulation.

### 3.1 Identification and estimation

To estimate the value-added generating function (3), we need to recover information about unobserved productivity, i.e., either  $\omega_{jt} = \omega_{jt}^p$  or  $\omega_{jt} = \omega_{jt}^p - \frac{1}{1+\eta}u_{jt}^d$  depending on the assumption regarding the demand shocks. Our choice of control function relies on the following facts about retail: First, a common limitation is the

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$\omega_{jt}^p$  and  $u_{jt}^d$  follow two different AR(1) processes, we are less restrictive with respect to the source of the shock. Note however that this is very data demanding because we can only use stores that are present in the data for at least three consecutive years. This consequently abstracts from a substantial part of the dynamics that might be central for productivity growth. Under the assumption of AR(1) processes (the same or different), identification follows immediately and no additional assumptions are required for estimation.

lack of information about materials (wholesale quantities). Second, stores make lumpy investments, i.e., invest one year followed by several years without investment, which constraints the sample substantially when using the policy function for investment. We follow the static input approach developed by Levinsohn and Petrin (2003) using labor demand as a nonparametric control function. Our framework is similar to that of Akerberg et al. (2006) (ACF) who use the unknown policy function for investment in capital and labor/materials. In addition, we consider a parametric approach based on Cobb-Douglas technology (Doraszelski and Jaumandreu, 2011). Appendix D presents details regarding the identification, estimation and results using a parametric function.

Assuming that labor is a static and variable input based on current productivity is not as restrictive as would be the case in many other industries. Part-time work is common, the share of skilled labor is relatively low, and stores frequently adjust their labor due to variations in customer flows over time. The static labor assumption also has the advantage of allowing us to abstract from assumptions about the stores' dynamic programming problem. In addition, we can allow labor to have dynamic implications and thus consider training, hiring, and firing costs.

We consider a general labor demand function based on the stores' short-run optimization problem. A general labor demand function can then be specified as

$$l_{jt} = \tilde{l}_t(\omega_{jt}, k_{jt}, w_{jt}, q_{smt}, \mathbf{z}_{mt}), \quad (5)$$

where  $\tilde{l}_t(\cdot)$  is an unknown function strictly increasing in  $\omega_{jt}$ , and  $w_{jt}$  is the log of the wage rate at the store level. The scalar unobservable assumption, i.e., that productivity  $\omega_{jt}$  is the only unobservable in equation (5), is required for identification. The strict monotonicity condition also holds under the simple constant elasticity of substitution (CES) demand system. Because stores set wages, and that part-time work and temporary job contracts are common in retail, identification relies on variation in store specific wages.

**Estimation.** The estimation of the value-added generating function is performed in two steps. The aim of the first step is to separate productivity  $\omega_{jt}$  from i.i.d. shocks to production  $\xi_{jt}$  (and demand  $u_{jt}^d$  if these shocks are i.i.d.). The first step only provides an estimate of  $\phi_t(\cdot)$ ,  $\hat{\phi}_t(\cdot)$ , which helps in recovering productivity as follows:

$$\omega_{jt}(\boldsymbol{\beta}) = \frac{\eta}{(1+\eta)} \left[ \hat{\phi}_t(\cdot) - \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] + \frac{1}{\eta} q_{smt} + \frac{1}{\eta} \mathbf{z}'_{mt} \boldsymbol{\beta}_z \right], \quad (6)$$



where  $\boldsymbol{\beta} = (\beta_l, \beta_k, \eta, \boldsymbol{\beta}_z)$ . In the second step, we non-parametrically regress  $\omega_{jt}(\boldsymbol{\beta})$  on a polynomial expansion of order three in  $\omega_{jt-1}(\boldsymbol{\beta})$  and  $r_{mt-1}$ . Identification of the parameters  $\boldsymbol{\beta} = (\beta_l, \beta_k, \eta, \boldsymbol{\beta}_z)$  comes from the following moments

$$E \left\{ v_{jt}(\boldsymbol{\beta}) \mid \begin{pmatrix} l_{jt-1} \\ k_{jt} \\ q_{smt-1} \\ \mathbf{z}_{mt-1} \end{pmatrix} \right\} = 0. \quad (7)$$

The moment  $E[v_{jt}(\boldsymbol{\beta})|l_{jt-1}] = 0$  then identifies  $\beta_l$ . The assumption that stores decide investment in capital at  $t - 1$  implies that the coefficient of capital  $\beta_k$  is identified from  $E[v_{jt}(\boldsymbol{\beta})|k_{jt}] = 0$ . To identify parameters  $\eta$  and  $\boldsymbol{\beta}_z$ , we use  $E[v_{jt}(\boldsymbol{\beta})|q_{smt-1}] = 0$  and  $E[v_{jt}(\boldsymbol{\beta})|\mathbf{z}_{mt-1}] = 0$ . When local regulation  $r_{mt}$  is a component of  $\mathbf{z}_{mt}$ , a moment based on  $r_{mt}$  or the current share of approved applications can be used to identify the coefficient of  $r_{mt}$ . Again, this does not imply that we can separate the effect of regulation on prices, i.e., regulation may have lagged effects on prices. The  $\boldsymbol{\beta}$  parameters are estimated by minimizing the sample analogue of the moment conditions (7). As there are nonlinearities in the coefficients, we use the Nelder-Mead numerical optimization method to minimize the GMM objective function

$$\min_{\boldsymbol{\beta}} Q_N = \left[ \frac{1}{N} W' v(\boldsymbol{\beta}) \right]' A \left[ \frac{1}{N} W' v(\boldsymbol{\beta}) \right], \quad (8)$$

where  $A$  is the weighting matrix defined as  $A = \left[ \frac{1}{N} W' v(\boldsymbol{\beta}) v'(\boldsymbol{\beta}) W \right]^{-1}$  and  $W$  is the matrix of instruments.

An additional estimator that can be used is the GMM one-step estimator suggested by Wooldridge (2005) and ACF (equation (27) in their paper). On the one hand, the one-step estimator is more efficient than the two-step approaches. On the other hand, a limitation of the one-step estimator for the current application is that there are many parameters to be estimated. This is because the local market characteristics are a component of the nonparametric function.

**Selection.** To account for large retail stores being more likely to survive larger shocks to productivity than small stores, we can control for selection. The decision to exit is correlated with  $v_{jt}$  because it relies on current productivity. We can

control for selection by estimating survival probabilities as

$$\begin{aligned}
Pr(\chi_t = 1 | \underline{\omega}_t(k_{jt}, \mathbf{z}_{mt-1}), \mathbf{F}_{t-1}) &= Pr(\omega_t \geq \underline{\omega}_{jt}(k_{jt}, \mathbf{z}_{mt-1}) | \underline{\omega}_t(k_{jt}, \\
&\quad \mathbf{z}_{mt-1}), \omega_{jt-1}) \\
&= P_{t-1}(i_{jt-1}, l_{jt-1}, k_{jt-1}, w_{jt-1}, p_{st-1}, \\
&\quad q_{smt-1}, \mathbf{z}_{mt-1}) \equiv \mathcal{P}_{t-1},
\end{aligned} \tag{9}$$

where the threshold market productivity  $\underline{\omega}_t$  and the information set  $\mathbf{F}_{t-1}$  will enter the function  $g(\cdot)$ , and regulation  $r_{mt-1}$  is included in  $\mathbf{z}_{mt-1}$ . As a result, threshold market productivity can be expressed as a function of  $\mathcal{P}_t$  and  $\mathbf{F}_t$ .

### 3.2 Results value-added generating function estimates

Table 5 presents results from the value-added generating function estimates using OLS, the two-step estimation approach developed by Akerberg et al. (2006) with labor as proxy for productivity ( $ACF_l$ ), and our main specification that also controls for prices and local market conditions ( $ACF_{lm}$ ). We present results for each subsector. All ACF specifications include the number of approved PBL applications in the productivity process. Appendix D presents results estimated under the parametric approach based on Doraszelski and Jaumandreu (2011).

In the main specification  $ACF_{lm}$ , the elasticity of scale ( $\beta_l + \beta_k$ ) is between 1.04 (Footwear) and 1.46 (Computers) for most subsectors.<sup>18</sup> While we expect increasing returns to scale in the service industries, there is scarce literature using production function approaches to estimate and understand returns to scale in retail trade.<sup>19</sup> One exception is Ofer (1973), who finds returns to scale of 1.42 for Food and 1.10 for Furniture and Clothing.<sup>20</sup> Our scale estimates are 1.12 for Food,

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<sup>18</sup>Two subsectors (Furniture and Toys) have an elasticity of scale above 1.50. Both subsectors have a high share of (large) entrants (Table 3). Furthermore, Furniture has high capital growth whereas Toys has high growth in value-added and labor (Table 4). Three subsectors (Hardware, Sports, and Textiles) have a scale elasticity below 1. Hardware and Sports have the highest shares of small entrants, and Textiles has the highest share of small stores and net exit (Table 3).

<sup>19</sup>The increasing returns to scale in services is due to geographic dispersion and multi-market contact. Furthermore, there is an increasing returns to scale “illusion” due to self-services, i.e., the volume of self-services is larger than the amount of services performed by the stores (Ofer, 1973).

<sup>20</sup>Ofer (1973) uses data from Israel, value-added as an output, and a Cobb-Douglas specification but does not control for simultaneity or omitted price bias. Using Australian data and a Cobb-Douglas specification, Bairam (1994) finds that the return to scale in fruit and vegetables is approximately 1.30. Maican and Orth (2009) find an elasticity of scale of approximately 1.50

greater than 1.50 for Furniture, and 1.06 for Clothing. Books and Toys are the subsectors with the highest labor elasticity, while Furniture, Toys, and Computers have the highest capital elasticity.

Our results confirm some well-known patterns in the existing productivity literature. First, after controlling for simultaneity, the labor coefficient decreases and the capital coefficient increases in most subsectors (OLS versus  $ACF_l$ ). All of these changes have implications not only for the estimated elasticity of scale but also for the productivity distribution. Second, controlling for imperfect competition ( $ACF_{lm}$ ) emphasizes the importance of the omitted price bias for the true returns to scale in retail. Not controlling for unobserved prices might create a downward bias in the scale estimator (Klette and Griliches, 1996). As expected from theory, the scale is higher when controlling for prices in  $ACF_{lm}$  than in OLS and  $ACF_l$ . For several subsectors, the coefficients of labor and capital, respectively, are larger when controlling for prices. This is consistent with the literature suggesting increasing returns to scale in retail. That the capital coefficient increases when controlling for prices is also consistent with the anticipated change when controlling for selection.

**Demand elasticity and markups.** The estimated demand elasticity varies in absolute terms between 1.46 (Furniture) and 4.88 (Clothing).<sup>21</sup> In subsectors with high demand elasticity, there are small differences between the labor and capital coefficients from the quantity and value-added generating functions, e.g., Electronics and Sports. The corresponding markups (price over marginal cost) range from 1.15 (Electronics) to 3.12 (Furniture). While Electronics (1.15), Textiles (1.21), and Footwear (1.25) have relatively low markups, these subsectors also have high exit rates (Table 3). Our findings on markups are in line with previous results based on U.S. data (Hall, 1988).

## 4 Entry regulation and productivity

The goal is now to evaluate how productivity changes with the degree of local market entry regulation and analyze aggregate productivity by subsector. First, we illustrate the productivity process graphically. Second, we quantify the effect

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for Swedish retail food when controlling for the impact of the entry of large stores.

<sup>21</sup>The elasticity of demand is, in absolute terms, above 5 for Textiles and Footwear, Electronics and Sports.

of local market regulation on stores' future productivity using regression results from the controlled Markov process. We also calculate the economic cost of the regulation faced by stores. Third, we present the evolution of aggregate subsector productivity over time in markets with a liberal (non-liberal) regulatory environment and decompose the contributions of incumbents, entrants, and exits to aggregate subsector productivity growth.

We can recover productivity based on our estimates using either the labor demand function or the value-added generating function. To allow for comparisons between different estimators, we use the value-added generating function<sup>22</sup>

$$\omega_{jt} = \frac{\eta}{(1+\eta)}[y_{jt} - (1 + \frac{1}{\eta})[\beta_l l_{jt} + \beta_k k_{jt}] + \frac{1}{\eta}q_{mt} + \frac{1}{\eta}\mathbf{z}'_{mt}\boldsymbol{\beta}_z]. \quad (10)$$

## 4.1 Graphic illustration

Figure 1 presents kernel density estimates of productivity in markets with liberal (non-liberal) regulatory environments defined as those with above (below) the median number of approved PBL applications at the municipal level. This graph presents preliminary evidence that there are productivity differences across markets depending on the degree of regulation. For example, in the bottom part of the distribution, productivity levels are higher in liberal markets than non-liberal markets (Food, Textiles, Footwear, Hardware, Toys). Stores with the highest productivity levels are more likely to be in liberal markets (Food, Textiles, Toys). The patterns remain consistent when liberal (non-liberal) markets are defined as those with a non-socialist (socialist) majority in the local government. Thus, the results are robust to alternative measures of regulation.

Figures 2 (3D-plot) and 3 (contour-plot) show the aggregate relationship across local markets and time between current productivity, previous productivity, and previous number of approved PBL applications in the municipality. The figures aim to provide preliminary information about the productivity process.<sup>23</sup> Current productivity increases under a more liberal regulatory environment for Food, Clothing, Footwear, Electronics, Books, and Sports. The corresponding relationship tends to be an inverted-U shaped one for Hardware, Watches, and Comput-

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<sup>22</sup>Although we expect the mean productivity to be similar, the variance is expected to be higher under the value-added generating function.

<sup>23</sup>The surface is obtained using polynomial approximations of order two on different intervals. In the regression analysis, we approximate the productivity process using a polynomial expansion of order three.

ers. There are small differences in current productivity depending on the degree of regulation for Furniture and Toys, given previous productivity. These subsectors exhibit a strong positive relationship between current and previous productivity. This high persistency in productivity over time also holds for Electronics and Watches. Figures 2 and 3 indicate that it is crucial to analyze the effect of regulation on different parts of the productivity distribution for each subsector.<sup>24</sup>

## 4.2 Quantifying the effect of local market regulation on productivity

According to the structural model, productivity evolves according to a controlled Markov process, where the entry regulation explicitly influences stores' future productivity (equation 4). A more liberal regulatory environment affects productivity through the X-inefficiency explanation.<sup>25</sup> We approximate  $g(\omega_{jt-1}, r_{mt-1})$  by a third-order polynomial expansion in its arguments.

Table 6 presents the marginal effects of the impact of a more liberal entry regulation (one additional PBL approval) on stores' future productivity. The empirical results highlight the heterogeneity in the (net) marginal effect of the regulation on productivity. The table presents averages and standard deviations for different distribution measures across local markets. For each subsector, the impact of the approval of one additional PBL application on productivity is computed for different parts of the productivity distribution in local markets. This result is due to productivity differences across local markets, and the impact of a more liberal regulatory environment might differ for stores with high and low productivity. The marginal effects are computed as follows for the median, for example. First, we compute median productivity in each local market. Second, we use the estimated

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<sup>24</sup>Figures representing how productivity varies with population density and the number of approved PBL applications are not reported but are available from the authors upon request. In markets with a large number of PBL approvals, stores in dense markets have higher productivity (Food, Footwear, Hardware, Sports, Computers). This finding is in line with Syverson (2004). Furthermore, for Textiles, Clothing, Books, and Furniture, stores located in markets characterized by high population density and PBL approvals have low productivity. In these subsectors, high productivity stores are located in low density markets with a large number of PBL approvals.

<sup>25</sup>This does not imply that a liberal regulatory environment represents a productivity growth machine in the local markets. The reason is the increased competition also induces exit, which implies a decrease in product differentiation that negatively affects consumers. Our model allows us to measure the net effect of a more liberal regulatory environment on productivity, but the data do not allow us to distinguish between different channels.

productivity process to compute the impact of an additional PBL approval on the median store in each local market. Finally, we compute averages and standard deviations for the marginal effects across local markets. Thus, the mean value for the  $x$ th percentile, reported in Table 6, is the average impact across local markets of a more liberal regulatory environment on the future productivity of a store with current productivity equal to the  $x$ -th percentile value in its local market.

Before turning to the full model, we estimate the value-added generating function by simple OLS and then regress the degree of regulation on productivity while controlling for other local market characteristics. The coefficient of regulation has an unexpectedly negative sign for all subsectors except two (Clothing and Furniture). The coefficients are, in absolute values, fairly small and not statistically significant for three of the subsectors. The OLS specification suffers from simultaneity and omitted price variable bias, and the findings strongly suggest the use a structural approach to model the channels through which regulation affects productivity.<sup>26</sup>

The results from our full model reveal the following patterns. First, the impact of an additional PBL approval is now positive. Productivity increases by 1.5-2.6 percent in Food, Footwear, Hardware, Clothing, and Sports for stores with productivity values between 10th and 90th percentiles. For the median stores, an additional PBL approval increases productivity by approximately 2 percent in most subsectors. Second, the impact of regulation on productivity is larger among low productivity stores (10th percentile) than high productivity stores (90th percentile), e.g., Food (2.6 and 1.6 percent), Clothing (2.5 and 2.0 percent), Footwear (2.6 and 1.7 percent), Hardware (2.2 and 1.5 percent), and Sports (2 and 1.8 percent). Third, the marginal effects are close to zero for Watches and negative for Books (approximately -2 percent). The Books subsector was affected by the increasing competition from on-line stores, e.g., Amazon, Adlibris and Bokus, and had a net exit rate of 4 percent during the study period. Fourth, the highest impact of a more liberal regulatory environment is in Computers and Furniture

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<sup>26</sup>For example, if we recover productivity from a Cobb-Douglas production function with the coefficients obtained using an OLS estimator and regress previous productivity and a regulation variable on productivity, the estimated marginal effect of regulation on productivity in food retailing is approximately 4 times higher than using a simple polynomial expansion of order three. The data cannot reject a nonlinear specification for this industry. Using simulation methods, we find that the average marginal effect of regulation on productivity is sensitive to the production function coefficients in specifications which control for omitted price bias (simulations are available from authors upon request). These results emphasize the importance of using sophisticated methods to estimate productivity.

(8.2 and 13.1 percent for the 10th percentile, 8.6 and 13.5 percent for the 90th percentile).

We also present the support of the impact of the regulation on productivity. The support is determined based on 1,000 simulated values from all parts of the productivity distribution. The support provides additional information regarding the heterogeneity of the impact of regulation on productivity. Footwear and Furniture have the highest upper bound, i.e., approximately 13 percent. The highest lower bound (approximately 12 percent) is in Furniture.<sup>27</sup>

**Counterfactual exercise.** The impact of regulation on productivity is directly linked to the efficiency of the retail sector. Given the use of inputs (labor and capital), we quantify how the degree of regulation affects how effectively stores use their inputs to generate sales (or value-added). Using our structural estimates, our goal is now to calculate the economic cost borne by stores due to less liberal entry regulation.<sup>28</sup>

Table 6 shows that one fewer approved PBL application decreases median store productivity by between 1 (Electronics) and 13 percent (Furniture).<sup>29</sup> Holding labor and capital constant, this is equivalent to a decline in output of 1-13 percent. Store sales for the period 1996-2002 are on average 0.576 million euros (Footwear) - 2.887 million euros (Food).<sup>30</sup> For a store, this implies that the annual economic cost of one fewer approved PBL application is 0.004 million euros (Electronics) - 0.143 million euros (Computers) on average.<sup>31</sup> At the subsector level, the annual economic cost of a less liberal regulatory environment ranges from 2.8 million euros (Toys) to 194 million euros (Furniture). This corresponds to a total subsector cost as high as 20 million euros (Toys) - 1,361 million euros (Hardware) for the

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<sup>27</sup>In Textiles and Books, the lower bound of the marginal effect is negative but close to zero (-0.9 and -0.2 percent).

<sup>28</sup>Greenstone et al. (2012) adopt a similar approach when evaluating the economic cost of environmental regulation in the U.S. manufacturing industry.

<sup>29</sup>We do not include three subsectors where the marginal effects of the regulation are close to zero (Textiles, Books, and Hardware).

<sup>30</sup>Numbers are in 2012 values, where 1EUR=9.01SEK and 1EUR=1.30USD.

<sup>31</sup>The counterfactual output for store  $j$ , if the regulation allows for one fewer PBL approval, is calculated as follows:  $y_j^{CF} = \frac{1}{(1-x)}y_j$ , where  $x$  is the estimated marginal effect of the impact of regulation on productivity and  $y_j$  is the observed output of store  $j$ . For simplicity, we consider average output and use values in 2012 euros. For Clothing, for example, average store level sales equal 0.605 million euros (1996-2002) and the median marginal effect is 2.2 percent (Table 6). The annual cost of the regulation is calculated as the difference from the counterfactual level of output, i.e.,  $(\frac{1}{1-0.022})0.605-0.605$ . Under the assumption that firms are price takers, Greenstone et al. (2012) also interpret their findings in terms of profits.

complete time period 1996-2002.<sup>32</sup>

Our estimated economic cost of less liberal entry regulation is intended to be interpreted as a lower bound. The reason is that we compute the values conditional on survival, which implies that the true effect may be larger.<sup>33</sup> While we control for the effect of regulation on demand, there might still be persistent demand shocks to productivity that are affected by the regulation. Note that we evaluate the cost of one fewer approved PBL application per local market and year in each subsector. Overall, the counterfactual calculations suggest that less liberal entry regulation induces non-trivial economic costs for stores in Swedish retail trade.

### 4.3 Aggregate productivity and decompositions

The next step is to understand how aggregate subsector productivity evolves over time in markets with a liberal (non-liberal) regulatory environment and to decompose the contributions from entering, exiting, and incumbent stores to aggregate subsector productivity growth. We use productivity decompositions in both levels and growth. First, we use an extension of the Olley and Pakes (1996) decomposition to allow for the contributions of entry and exit to aggregate productivity levels in liberal (non-liberal) local markets. The proposed decomposition complements previous work by focusing on the key aspects of retail markets. Retail stores compete in local markets, and we therefore consider weighted local market shares and then aggregate to the subsector level. Furthermore, we consider the contributions of the local entry regulation to productivity dynamics at the subsector level. To do this, we need to evaluate the contribution of incumbents, entrants, and exits to subsector productivity in local markets with different degrees of regulation. Second, to decompose aggregate productivity growth by subsector, we consider various methods but primarily focus on the approaches developed by Griliches and Regev (1995) (GR) and Foster et al. (2001) (FHK). FHK has previously been

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<sup>32</sup>The annual subsector cost is computed as the average economic cost per store times the average number of stores in each subsector during the period 1996-2002. The subsector cost for the full period is calculated as the average economic cost per store times the number of stores in the subsector in each of the years from 1996 to 2002.

<sup>33</sup>By controlling for local market characteristics when estimating productivity, we reduce the impact of selection on our productivity estimates. We empirically confirm this in our data, i.e., we find no major changes in the value-added generating function estimates when controlling for selection (results are not reported but are available from the authors on request).



applied to labor productivity growth in U.S. retail trade (Foster et al., 2006).<sup>34</sup>

**Productivity level decomposition.** In the OP decomposition, the weighted subsector productivity  $\Omega_t$  is the sum of two components: (a) unweighted average productivity  $\bar{\omega}_t$  and (b) sample covariance between productivity and output, i.e.,  $cov(s_{jt}, \omega_{jt}) \equiv \sum_j (s_{jt} - \bar{s}_t)(\omega_{jt} - \bar{\omega}_t)$ , where  $\bar{s}_t$  and  $\bar{\omega}_t$  are unweighted subsector averages of market shares and productivity. The covariance term states that aggregate productivity increases when a larger share of output goes to more productive stores.

In our local market setting, weighted subsector productivity in market  $m$  is given by

$$\Omega_{mt} = \bar{\omega}_{mt} + \sum_{j_m} (s_{jmt} - \bar{s}_{mt})(\omega_{jmt} - \bar{\omega}_{mt}), \quad (11)$$

where  $\bar{s}_{mt}$  and  $\bar{\omega}_{mt}$  are unweighted averages of local market shares and productivity in market  $m$ . Weighted subsector productivity is obtained by averaging the local market productivities  $\Omega_{mt}$  using the market shares of the local markets as weights

$$\begin{aligned} \Omega_t &= \sum_m v_{mt} \Omega_{mt} = \sum_m v_{mt} \bar{\omega}_{mt} + \sum_m v_{mt} \sum_j (s_{jmt} - \bar{s}_{mt})(\omega_{jmt} - \bar{\omega}_{mt}) \\ &= \sum_m v_{mt} \bar{\omega}_{mt} + \sum_m v_{mt} \left[ \sum_j s_{jmt} \omega_{jmt} - \bar{\omega}_{mt} \right] \\ &= \sum_m v_{mt} \bar{\omega}_{mt} + \sum_m \sum_j v_{mt} s_{jmt} \omega_{jmt}, \end{aligned} \quad (12)$$

where  $v_{mt} = \frac{\sum_{jm} y_{jmt}}{\sum_j y_{jt}}$  and  $s_{jmt} = \frac{y_{jmt}}{\sum_{jm} y_{jmt}}$ . This implies that  $v_{mt} s_{jmt} = \frac{y_{jmt}}{\sum_j y_{jt}}$ .

We extend the OP decomposition to allow for the contributions of entry and exit to aggregate productivity levels in the local markets. In our setting, the aggregate productivity in period  $t$  in market  $m$  is the sum of the weighted productivity levels of incumbents ( $C_{mt}$ ), entrants ( $E_{mt}$ ), and exits ( $X_{mt}$ )

$$\begin{aligned} \Omega_{mt} &= \sum_{j \in C_{mt}} s_{jmt} \omega_{jmt} + \sum_{j \in E_{mt}} s_{jmt} \omega_{jmt} + \sum_{j \in X_{mt}} s_{jmt} \omega_{jmt} \\ &= \sum_{j \in C_{mt}} (\bar{s}_{mt} + \Delta s_{jmt})(\bar{\omega}_{mt} + \Delta \omega_{jmt}) \\ &\quad + \sum_{j \in E_{mt}} (\bar{s}_{mt} + \Delta s_{jmt})(\bar{\omega}_{mt} + \Delta \omega_{jmt}) \\ &\quad + \sum_{j \in X_{mt}} (\bar{s}_{mt} + \Delta s_{jmt})(\bar{\omega}_{mt} + \Delta \omega_{jmt}) \\ &= \frac{N_m^C}{N_m} \bar{\omega}_{mt} + \frac{N_m^E}{N_m} \bar{\omega}_{mt} + \frac{N_m^X}{N_m} \bar{\omega}_{mt} + \sum_{j \in C_{mt}, E_{mt}, X_{mt}} \Delta s_{jmt} \Delta \omega_{jmt}, \end{aligned} \quad (13)$$

where  $\Delta s_{jmt} = s_{jmt} - \bar{s}_{mt}$ ,  $\Delta \omega_{jmt} = \omega_{jmt} - \bar{\omega}_{mt}$ ,  $N_m^C$  is the number of continuing stores in period  $t$ ,  $N_m^E$  is the number of entrants in period  $t$ ,  $N_m^X$  is the number of

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<sup>34</sup>FHK and GR both modify the method developed by Baily et al. (1992). Appendix E presents the GR framework and recent decompositions by Melitz and Polanec (2012) (MP) and Petrin and Levinsohn (2012) (PL).

stores that exit the market in period  $t$ , and  $N = N_m^C + N_m^E + N_m^X$ . A few remarks need to be made regarding this decomposition. First, it provides the direct contributions of incumbents, entrants, and exits to the aggregate productivity in each period. Second, entrants in period  $t$  are incumbents in period  $t + 1$ . The contribution of the entrants is given in the period in which they enter, which we believe is noteworthy because the theoretical literature often emphasizes that entrants have higher productivity than incumbents. While there might be less support for this hypothesis in the empirical literature, comparing the productivity of entrants and stores that exit is important for the dynamics of the market structure. Third, this decomposition shows the evolution of the contributions of incumbents, entrants, and exits to aggregate productivity over time. In other words, we can compare the contributions of the entrants in  $t$  and  $t'$ . Fourth, the decomposition emphasizes the contributions to the unweighted productivity and covariance (stores with high market share and productivity) for each category (incumbent, entrant, and exit).

Figure 4 presents aggregate subsector productivity in markets with and without a liberal regulatory environment during the period 1996-2002. These results rely on estimated productivity using  $ACF_{lm}$  and liberal markets being defined as those with above the median number of PBL approvals.<sup>35</sup> Figure 5 presents the relative contributions from incumbents, entrants, exits, and covariance to aggregate subsector productivity. The covariance term captures reallocation for all types of stores, i.e., incumbents, entrants and exits, according to equation (13).

Aggregate productivity increases for nearly all subsectors over time, especially after 1999 (Figure 4). Incumbents contribute 75-90 percent of aggregate subsector productivity, exits up to 15 percent, entrants up to 10 percent, and covariance up to 5 percent (Figure 5). There are two striking findings. First, incumbents contribute less, and entry, exit and covariance more, in liberal than in non-liberal local markets. This finding holds for all subsectors, and the magnitudes of the differences are often considerable (above 5 percentage points).<sup>36</sup> Second, the patterns over time demonstrate that the contribution from incumbents is inversely

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<sup>35</sup>The corresponding figures when non-socialist (socialist) local governments are used to define liberal (non-liberal) markets yield similar patterns. Results are not reported but are available from the authors on request.

<sup>36</sup>The differences across markets are fairly small for Computers. Entry and exit are crucial for Toys, which is consistent with the high entry and exit rates in Table 3. Reallocation in liberal markets is important for Books and Textiles, and entrants in liberal markets have a relatively low contribution for Textiles. This is in line with Books and Textiles being the only subsectors with negative lower supports for a more liberal local market regulation's effect on productivity in Table 6.

related to that of entry and exit. We conclude that a more liberal regulatory environment implies a higher contribution from entrants, exits and covariance to aggregate productivity. This supports our previous finding in Table 6, i.e., that more liberal entry regulation increases productivity across local markets.

**Productivity growth decomposition.** To decompose aggregate productivity growth, we apply the approaches developed by Foster et al. (2001)(FHK) and Griliches and Regev (1995)(GR) to Sweden as a whole. Using FHK, the change in national subsector productivity from year  $t$  to year  $t'$  can be written as

$$\begin{aligned} \Delta\Omega_{t,t'} = & \sum_{j \in C_{t,t'}} s_{jt} \Delta\omega_{jt,t'} + \sum_{j \in C_{t,t'}} \Delta s_{jt,t'} (\omega_{jt} - \Omega_t) \\ & + \sum_{j \in C_{t,t'}} \Delta s_{jt,t'} \Delta\omega_{jt,t'} + \sum_{j \in E_{t,t'}} s_{jt'} (\omega_{jt'} - \Omega_t) \\ & - \sum_{j \in X_{t,t'}} s_{jt} (\omega_{jt} - \Omega_t), \end{aligned} \quad (14)$$

where  $\Omega_t$  is the weighted average subsector productivity;  $\Delta$  is the difference operator ( $\Delta\Omega_{t,t'} = \Omega_{t'} - \Omega_t$ );  $s_{jt}$  is the market share of store  $j$  in the subsector;  $C_{t,t'}$  is the set of continuing stores, i.e., operating both in  $t$  and  $t'$ ;  $E_{t,t'}$  is the set of entering stores, i.e., that operated in  $t'$  but not in  $t$ ; and  $X_{t,t'}$  is the set of exiting stores, i.e., that operated in  $t$  but not in  $t'$ . The decomposition (14) thus consists of five terms. The first term (Within) is the increase in productivity when the continuing stores increase their productivity at initial sales. The second term (Between) is the increase in productivity when continuing stores with above-average productivity expand their share of sales relative to stores with below-average productivity. The third term (Cross) captures the increase in productivity when continuing stores increase their market shares, while the fourth and fifth terms (Entry and Exit) are productivity increases due to entry and exit, respectively. Appendix E provides details on the GR decomposition.<sup>37</sup>

Table 7 presents the results for the FHK and GR decompositions of subsector productivity growth between the base year  $t = 1997$  and  $t' = \{1998, \dots, 2002\}$ , using productivity from  $ACF_{lm}$ .<sup>38</sup> National productivity growth is positive for all

<sup>37</sup>Both FHK and GR compare the aggregate productivity of entering and existing stores to either aggregate productivity of all stores (FHK) or the unweighted average of the aggregate productivity of all stores (GR). Both methods also use fixed weights (market shares) for continuing stores when distinguishing between within-store improvements and the reallocation of market shares. Initial period weights are used in FHK while time averages are used in GR.

<sup>38</sup>For Food, Clothing, and Furniture, we trim 10 percent of the observations in each tail of the productivity distribution, and extreme values in the lower tail of the productivity growth distribution, which otherwise influence the averages substantially. Results for the MP-decomposition are presented in Table E.3 in Appendix E. The decomposition results for estimated productivity using the parametric approach are presented in Tables E.4 (FHK and GR) and E.5 (MP) in

subsectors. Subsector growth ranges from 2 to 32 percent, with approximately half of the subsectors experiencing growth greater than 15 percent. Entry has a significant contribution to productivity growth in Food, Textiles, Clothing, Footwear, Hardware, Sports, and Computers. Incumbents that continue throughout the entire period also contribute substantially to growth (Within). Incumbent stores that increase both their productivity and market shares are also important for growth in several of the subsectors (Cross). Conversely, expanding incumbents with above-average productivity (Between) and exit have a negative effect on growth. The importance of entry is in line with previous studies on labor productivity in U.S. retail trade (Foster et al., 2006).

## 5 Conclusions

This paper quantifies how local market entry regulations influence retail productivity. The issue is particularly interesting because retail markets have undergone a dramatic shift connected to the increased use of technology in terms of scanners, barcodes and online credit card processing machines. In addition, there has been a structural change towards larger but fewer stores. The combination of improved information technology and economies of scale, density, and scope has dramatically changed the retail sector, which today plays an important role in overall economic activity. Despite these striking trends, few studies have investigated regulations and multi-factor productivity using a structural framework.

We provide a dynamic structural model to estimate multi-factor productivity and evaluate how it varies with the degree of local market regulation. We analyze the dynamics of aggregate subsector productivity in markets with and without a liberal regulatory environment and decompose the relative importance of entrants, exits, and incumbents for aggregate productivity growth. As our goal is to understand how regulation affects productivity in retail trade, we model the relationship between regulation and productivity in our structural framework. Our approach has the advantages of ensuring consistency between the theoretical and empirical modeling, being flexible in how stores react to regulatory changes, and providing markups at the subsector level. In detail, we control for unobserved prices through the use of a simple demand system, back out productivity from the labor demand

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Appendix E.

function, and control for subsector and local market characteristics.

The empirical application relies on detailed data on all retail stores in Sweden in the period 1996-2002, which is representative of many retail markets in the OECD in terms of market structure and regulation. The results demonstrate that the elasticity of scale in most Swedish retail subsectors ranges from 1.04 (Footwear) to 1.46 (Computers). We find that it is important to control for simultaneity and imperfect competition in local markets. Estimated markups, defined as price over marginal cost, vary between 1.15 (Electronics) and 3.12 (Furniture). The approval of an additional application by local authorities increases the median store's productivity by approximately 2 percent in most subsectors. A stricter regulation in terms of one fewer approved application in each local market corresponds to an annual economic cost for the retail trade sector of nearly 10 percent of total annual capital investments. For the period 1996-2002, the aggregate subsector costs are approximately 20 million euros (Toys) - 1,361 million euros (Furniture) in 2012 values. Our decomposition of aggregate productivity growth confirms the role of entry emphasized in previous work on labor productivity in U.S. retail trade (Foster et al., 2006). Lastly, we find that a more liberal regulatory environment increases the contribution of entry and exit to aggregate productivity.

The results relate to competition policy through governmental subsidies and the presence of entry regulations in Europe. We find that a restrictive use or design of entry regulations limits the role of entry and exit in local market dynamics and hinder productivity growth. However, these gains need to be balanced against drawbacks in terms of the environment, traffic, and accessibility for target consumers such as pensioners. Our findings contribute to an improved understanding of the frequently debated productivity gap between Europe and the U.S.

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**Table 1:** Descriptive statistics, Swedish retail trade 1996-2002

	1996	1997	1998	1999	2000	2001	2002	$\Delta(\%)$
Sales	244.0	250.0	264.0	278.0	295.0	302.0	326.0	34.0
Value added	43.1	44.7	47.8	50.0	54.8	54.9	59.2	27.0
Investment	3.4	3.4	3.6	4.5	5.3	4.8	5.0	47.0
Capital stock	10.0	11.0	12.0	15.0	17.0	19.0	20.0	100.0
No. of employees	144.0	144.0	151.0	149.0	155.0	158.0	159.0	10.0
No. of stores	21,464.0	20,787.0	20,318.0	20,085.0	20,169.0	19,618.0	19,233.0	-10.0

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

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

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

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

**Table 3:** Entry and exit by subsector 1996-2002

Subsector	Entry rate			Exit rate			Net entry	No. of stores	No. of obs.
	Small	Large	Total	Small	Large	Total			
Food	0.063 (0.012)	0.046 (0.010)	0.109 (0.015)	0.091 (0.008)	0.051 (0.018)	0.142 (0.024)	-0.031 (0.016)	3,376.28 (243.43)	23,634
Textiles	0.071 (0.021)	0.007 (0.003)	0.078 (0.021)	0.129 (0.027)	0.007 (0.003)	0.136 (0.026)	-0.055 (0.047)	355.14 (41.36)	2,486
Clothing	0.082 (0.014)	0.011 (0.001)	0.094 (0.016)	0.097 (0.014)	0.013 (0.003)	0.110 (0.015)	-0.015 (0.021)	2,467.57 (72.83)	17,273
Footwear	0.063 (0.008)	0.008 (0.003)	0.071 (0.008)	0.093 (0.011)	0.011 (0.004)	0.104 (0.011)	-0.033 (0.018)	591.71 (41.49)	4,142
Furniture	0.094 (0.016)	0.012 (0.003)	0.106 (0.015)	0.097 (0.018)	0.014 (0.005)	0.111 (0.020)	-0.003 (0.019)	1,603.86 (23.12)	11,227
Electronics	0.066 (0.020)	0.007 (0.002)	0.073 (0.020)	0.087 (0.015)	0.009 (0.002)	0.096 (0.017)	-0.023 (0.024)	1,291.00 (62.15)	9,037
Hardware	0.080 (0.013)	0.018 (0.003)	0.099 (0.013)	0.073 (0.013)	0.019 (0.006)	0.092 (0.016)	0.008 (0.020)	1,313.29 (22.66)	9,193
Books	0.062 (0.014)	0.009 (0.002)	0.071 (0.012)	0.100 (0.012)	0.016 (0.008)	0.116 (0.012)	-0.044 (0.019)	561.29 (50.06)	3,929
Sports	0.096 (0.026)	0.011 (0.002)	0.107 (0.025)	0.095 (0.009)	0.013 (0.004)	0.108 (0.010)	0.001 (0.014)	1,101.00 (10.94)	7,707
Watches	0.054 (0.019)	0.004 (0.004)	0.058 (0.019)	0.075 (0.016)	0.006 (0.004)	0.081 (0.015)	-0.021 (0.019)	594.29 (26.72)	4,160
Toys	0.078 (0.018)	0.025 (0.011)	0.103 (0.024)	0.112 (0.028)	0.025 (0.009)	0.137 (0.023)	-0.027 (0.047)	228.43 (13.23)	1,599
Computers	0.112 (0.024)	0.025 (0.008)	0.137 (0.031)	0.108 (0.006)	0.031 (0.008)	0.139 (0.008)	-0.001 (0.027)	1176.71 (26.93)	8,237

NOTE: The figures represent mean (standard deviation) by subsector and year for the period 1996-2002. Small represents stores with less than five employees; Large otherwise.

**Table 4:** Store level growth by subsector 1996-2002

	Value Added		Employees		Capital		Wages		Share	No. of stores
	Small	All	Small	All	Small	All	Small	All	Small	
Food	0.036 (0.298)	0.059 (0.238)	0.013 (0.334)	0.032 (0.201)	0.141 (0.418)	0.182 (0.428)	0.017 (0.310)	0.047 (0.194)	0.448 (0.027)	3,376.285 (243.428)
Textiles	0.046 (0.275)	0.056 (0.274)	0.037 (0.329)	0.044 (0.316)	0.109 (0.423)	0.120 (0.421)	0.051 (0.284)	0.059 (0.270)	0.893 (0.012)	355.142 (41.357)
Clothing	0.087 (0.340)	0.089 (0.318)	0.045 (0.336)	0.060 (0.318)	0.163 (0.507)	0.176 (0.495)	0.059 (0.279)	0.073 (0.254)	0.772 (0.022)	2,467.571 (72.828)
Footwear	0.050 (0.246)	0.054 (0.228)	0.029 (0.314)	0.040 (0.294)	0.127 (0.436)	0.150 (0.459)	0.037 (0.235)	0.049 (0.210)	0.777 (0.008)	591.714 (41.495)
Furniture	0.102 (0.337)	0.098 (0.300)	0.045 (0.330)	0.063 (0.309)	0.198 (0.544)	0.222 (0.549)	0.069 (0.278)	0.080 (0.239)	0.748 (0.019)	1,603.857 (23.118)
Electronics	0.064 (0.274)	0.069 (0.260)	0.036 (0.291)	0.032 (0.190)	0.193 (0.477)	0.201 (0.458)	0.048 (0.223)	0.061 (0.206)	0.793 (0.019)	1,291.000 (62.150)
Hardware	0.076 (0.284)	0.073 (0.243)	0.032 (0.302)	0.034 (0.188)	0.185 (0.441)	0.185 (0.402)	0.051 (0.245)	0.061 (0.200)	0.686 (0.010)	1,313.285 (22.654)
Books	0.052 (0.255)	0.051 (0.218)	0.024 (0.323)	0.044 (0.297)	0.129 (0.412)	0.136 (0.397)	0.039 (0.256)	0.051 (0.214)	0.716 (0.027)	561.285 (50.062)
Sports	0.100 (0.333)	0.106 (0.312)	0.060 (0.347)	0.075 (0.331)	0.186 (0.450)	0.197 (0.451)	0.079 (0.293)	0.091 (0.268)	0.798 (0.021)	1,101.000 (10.939)
Watches	0.031 (0.208)	0.036 (0.202)	0.031 (0.299)	0.024 (0.198)	0.107 (0.393)	0.132 (0.418)	0.033 (0.211)	0.043 (0.196)	0.829 (0.013)	594.285 (26.719)
Toys	0.097 (0.351)	0.104 (0.320)	0.061 (0.359)	0.082 (0.336)	0.153 (0.433)	0.155 (0.427)	0.064 (0.302)	0.084 (0.271)	0.698 (0.036)	228.428 (13.227)
Computers	0.196 (0.377)	0.212 (0.356)	0.042 (0.307)	0.080 (0.273)	0.211 (0.490)	0.221 (0.474)	0.162 (0.303)	0.186 (0.279)	0.754 (0.018)	1,176.714 (26.930)

NOTE: The figures presents mean (standard deviation) of store level growth by subsector and year during the period 1996-2002. Small represents stores with less than five employees. Value added, capital and wages are measured in thousands of 1996 SEK (1USD=6.71SEK, 1EUR=8.63 SEK).

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

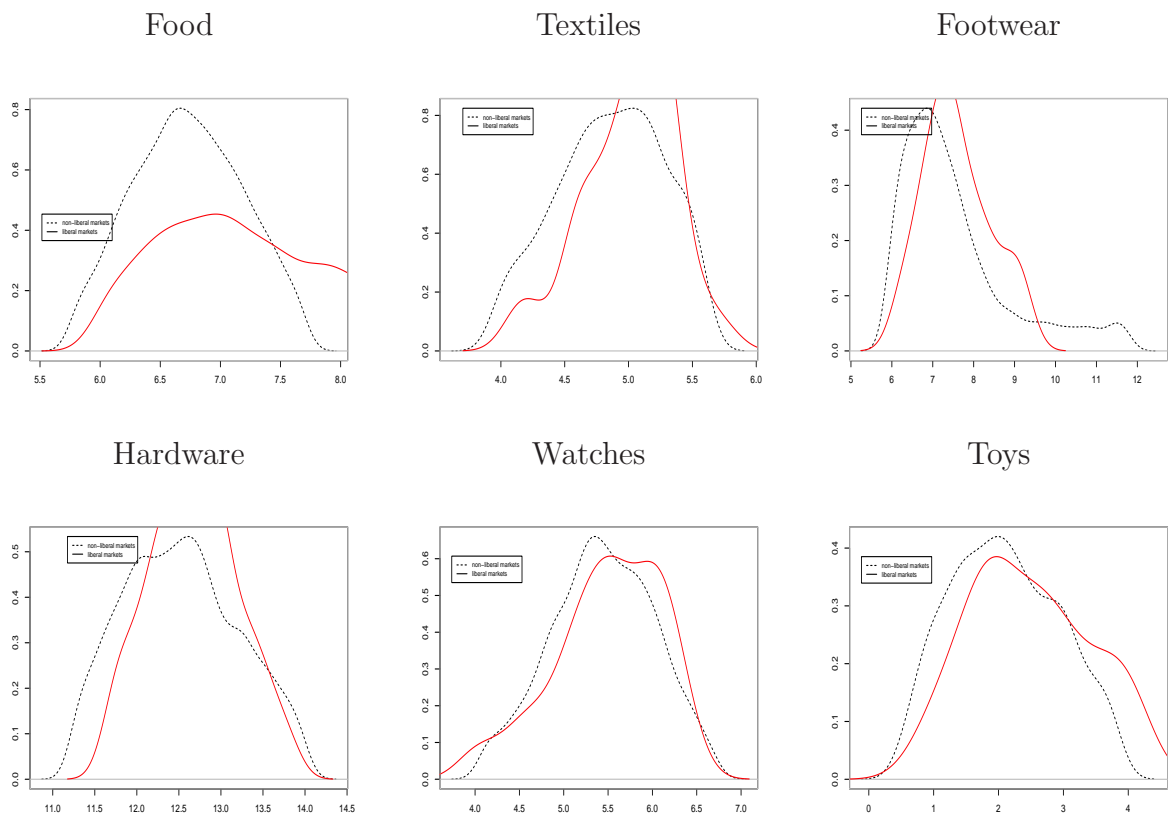
	<i>OLS</i>		<i>ACF<sub>l</sub></i>		<i>ACF<sub>lm</sub></i>				Scale	Demand	Markup	No. of obs.
	Labor	Capital	Labor	Capital	Labor		Capital					
					(1)	(2)	(1)	(2)				
Food	0.697 (0.005)	0.181 (0.004)	0.559 (0.005)	0.140 (0.002)	0.616 (0.011)	0.824 (0.011)	0.226 (0.007)	0.302 (0.007)	1.12	-3.96	1.34	14,827
Textiles	0.821 (0.020)	0.123 (0.010)	0.856 (0.025)	0.321 (0.013)	0.669 (0.004)	0.809 (0.004)	0.077 (0.001)	0.093 (0.001)	0.90	-5.78	1.21	1,623
Clothing	0.757 (0.007)	0.120 (0.004)	0.417 (0.015)	0.311 (0.008)	0.668 (0.002)	0.840 (0.002)	0.172 (0.001)	0.216 (0.001)	1.06	-4.88	1.26	12,625
Footwear	0.735 (0.011)	0.121 (0.006)	0.802 (0.002)	0.112 (0.001)	0.461 (0.002)	0.575 (0.002)	0.370 (0.002)	0.462 (0.002)	1.04	-5.04	1.25	3,188
Furniture	0.814 (0.008)	0.135 (0.005)	0.332 (0.011)	0.029 (0.005)	0.278 (0.021)	0.868 (0.021)	0.318 (0.012)	0.993 (0.012)	1.86	-1.47	3.12	8,203
Electronics	0.821 (0.008)	0.144 (0.004)	0.739 (0.011)	0.391 (0.005)	0.622 (0.021)	0.716 (0.021)	0.434 (0.008)	0.499 (0.008)	1.21	-7.68	1.15	6,897
Hardware	0.782 (0.007)	0.189 (0.004)	0.551 (0.014)	0.196 (0.008)	0.493 (0.045)	0.649 (0.045)	0.165 (0.007)	0.217 (0.007)	0.87	-4.16	1.32	7,067
Books	0.737 (0.012)	0.149 (0.007)	0.824 (0.005)	0.143 (0.002)	0.495 (0.013)	1.115 (0.013)	0.139 (0.006)	0.312 (0.006)	1.43	-1.80	2.25	2,922
Sports	0.744 (0.009)	0.141 (0.005)	0.431 (0.023)	0.485 (0.013)	0.595 (0.008)	0.695 (0.008)	0.171 (0.005)	0.199 (0.005)	0.91	-6.96	1.17	5,796
Watches	0.804 (0.012)	0.101 (0.006)	0.679 (0.012)	0.367 (0.006)	0.461 (0.012)	0.684 (0.012)	0.374 (0.006)	0.556 (0.006)	1.24	-3.06	1.48	3,156
Toys	0.682 (0.021)	0.216 (0.013)	0.662 (0.012)	0.476 (0.006)	0.662 (0.066)	1.099 (0.066)	0.446 (0.084)	0.739 (0.084)	1.83	-2.52	1.66	1,208
Computers	0.795 (0.009)	0.212 (0.006)	0.108 (0.026)	0.317 (0.007)	0.568 (0.030)	0.827 (0.030)	0.439 (0.026)	0.641 (0.026)	1.46	-3.19	1.46	6,350

NOTE: The dependent variable is log of deflated value-added. Standard errors are reported in parentheses. Labor is measured as number of full-time adjusted employees. All regressions include year dummies. *OLS* is ordinary least square regression. All *ACF* specifications include previous year's number of approved PBL applications in the municipality in the productivity process. *ACF<sub>l</sub>* is Akerberg, Caves, and Fraser's (2006) two-step estimation method using labor as proxy for productivity; *ACF<sub>lm</sub>* is two-step estimation using a nonparametric labor demand function as proxy for productivity and controlling for imperfect competition. Columns (1) shows estimated coefficients including elasticity, i.e.,  $(1 + \frac{1}{\eta})\beta_l$  for labor and  $(1 + \frac{1}{\eta})\beta_k$  for capital; columns (2) show the estimated coefficients without elasticity (equation 3). The returns to scale is reported as  $\beta_l + \beta_k$ . In *ACF*, current capital stock and previous labor are used as instruments and standard errors are computed using Akerberg et al. (2011). Market output is measured as the market share weighted output in the municipality. Demand refers to the elasticity of substitution. Markup is defined as price over marginal cost.

**Table 6:** Productivity and entry regulations in local markets: nonparametric approach

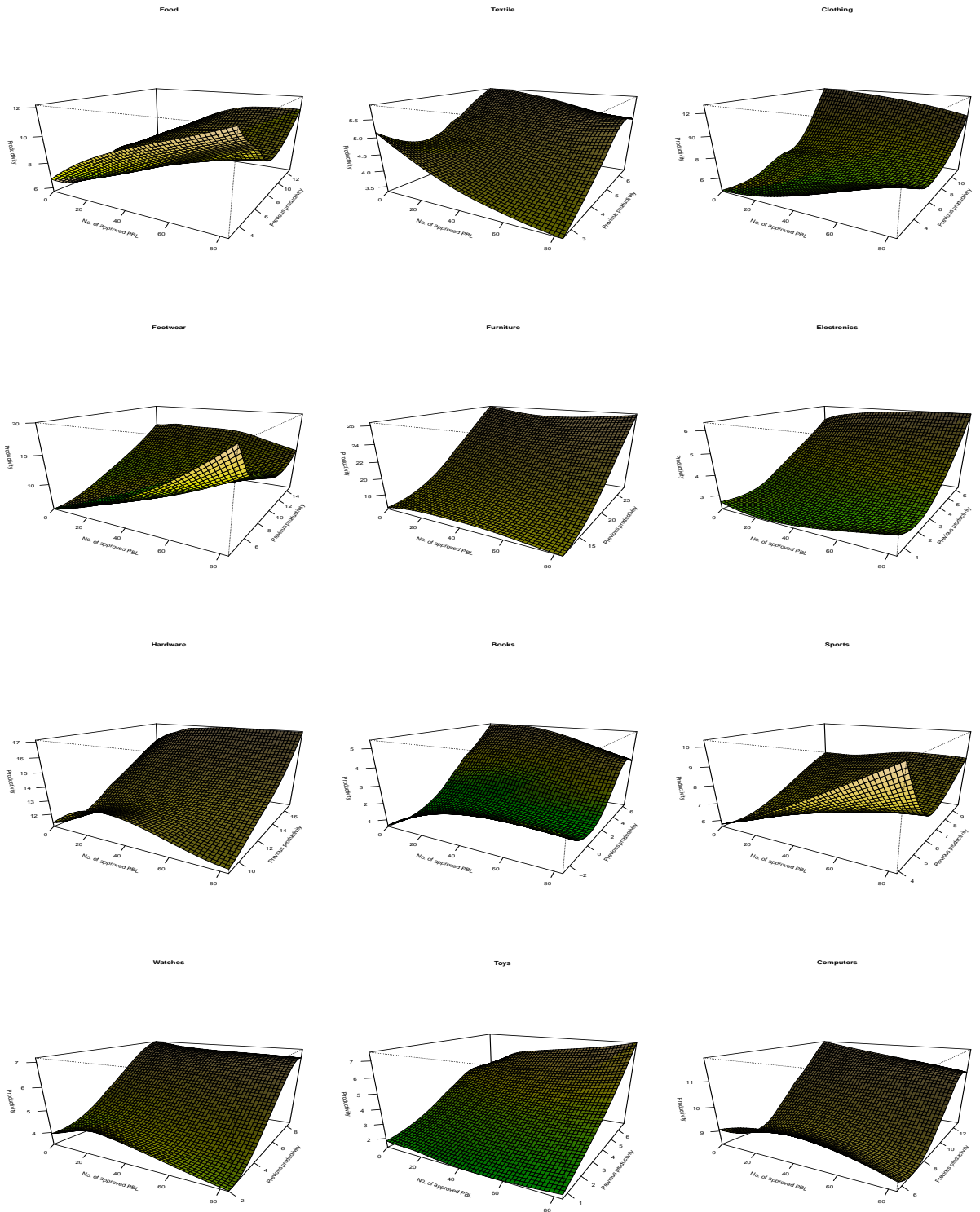
	Percentile of Productivity <sub>t-1</sub>					Support	Adj. $R^2$	No. of obs.
	10th	25th	50th	75th	90th			
Food	0.026 (0.012)	0.022 (0.009)	0.019 (0.007)	0.017 (0.006)	0.016 (0.005)	[ 0.013 , 0.042 ]	0.724	14,827
Textiles	0.0007 (0.003)	0.0008 (0.002)	0.0009 (0.002)	0.0012 (0.002)	0.0014 (0.001)	[-0.009 , 0.002 ]	0.397	1,623
Clothing	0.025 (0.004)	0.024 (0.003)	0.022 (0.003)	0.021 (0.002)	0.020 (0.002)	[ 0.015 , 0.032 ]	0.597	12,625
Footwear	0.026 (0.026)	0.024 (0.025)	0.021 (0.025)	0.018 (0.026)	0.017 (0.028)	[ 0.001 , 0.128 ]	0.848	3,188
Furniture	0.131 (0.004)	0.132 (0.003)	0.133 (0.003)	0.134 (0.002)	0.135 (0.002)	[ 0.123 , 0.138 ]	0.579	8,203
Electronics	0.006 (0.001)	0.006 (0.001)	0.005 (0.001)	0.004 (0.001)	0.004 (0.001)	[ 0.004 , 0.008 ]	0.422	6,897
Hardware	0.022 (0.009)	0.021 (0.008)	0.018 (0.008)	0.016 (0.007)	0.015 (0.007)	[ 0.005 , 0.038 ]	0.738	7,067
Books	-0.017 (0.003)	-0.018 (0.002)	-0.021 (0.002)	-0.023 (0.001)	-0.024 (0.001)	[-0.002 , 0.008 ]	0.546	2,922
Sports	0.020 (0.003)	0.020 (0.002)	0.020 (0.002)	0.019 (0.002)	0.018 (0.002)	[ 0.017 , 0.028 ]	0.491	5,796
Watches	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	[ 0.000 , 0.000 ]	0.588	3,156
Toys	0.016 (0.000)	0.016 (0.000)	0.016 (0.000)	0.016 (0.000)	0.016 (0.000)	[ 0.016 , 0.016 ]	0.549	1,208
Computers	0.082 (0.003)	0.083 (0.003)	0.084 (0.002)	0.085 (0.002)	0.086 (0.002)	[ 0.077 , 0.089 ]	0.399	6,350

NOTE: The number of approved PBL applications in the municipality measures the degree of regulation. Marginal effects are computed using percentile measures of previous productivity in each local market and year (Section 4.2 provides details).  $ACF_i$  is Akerberg, Caves, and Fraser's (2006) two-step estimation method using labor as proxy for productivity;  $ACF_{lm}$  is two-step estimation using a nonparametric labor demand function as proxy for productivity and controlling for imperfect competition. Productivity is recovered from the value-added generating function:  $\omega_{jt} = (\eta/(1 + \eta)) [y_{jt} - (1 + 1/\eta)[\beta_l l_{jt} + \beta_k k_{jt}] + (1/\eta)q_{mt} + (1/\eta)\mathbf{z}'_{mt}\beta_z]$ .

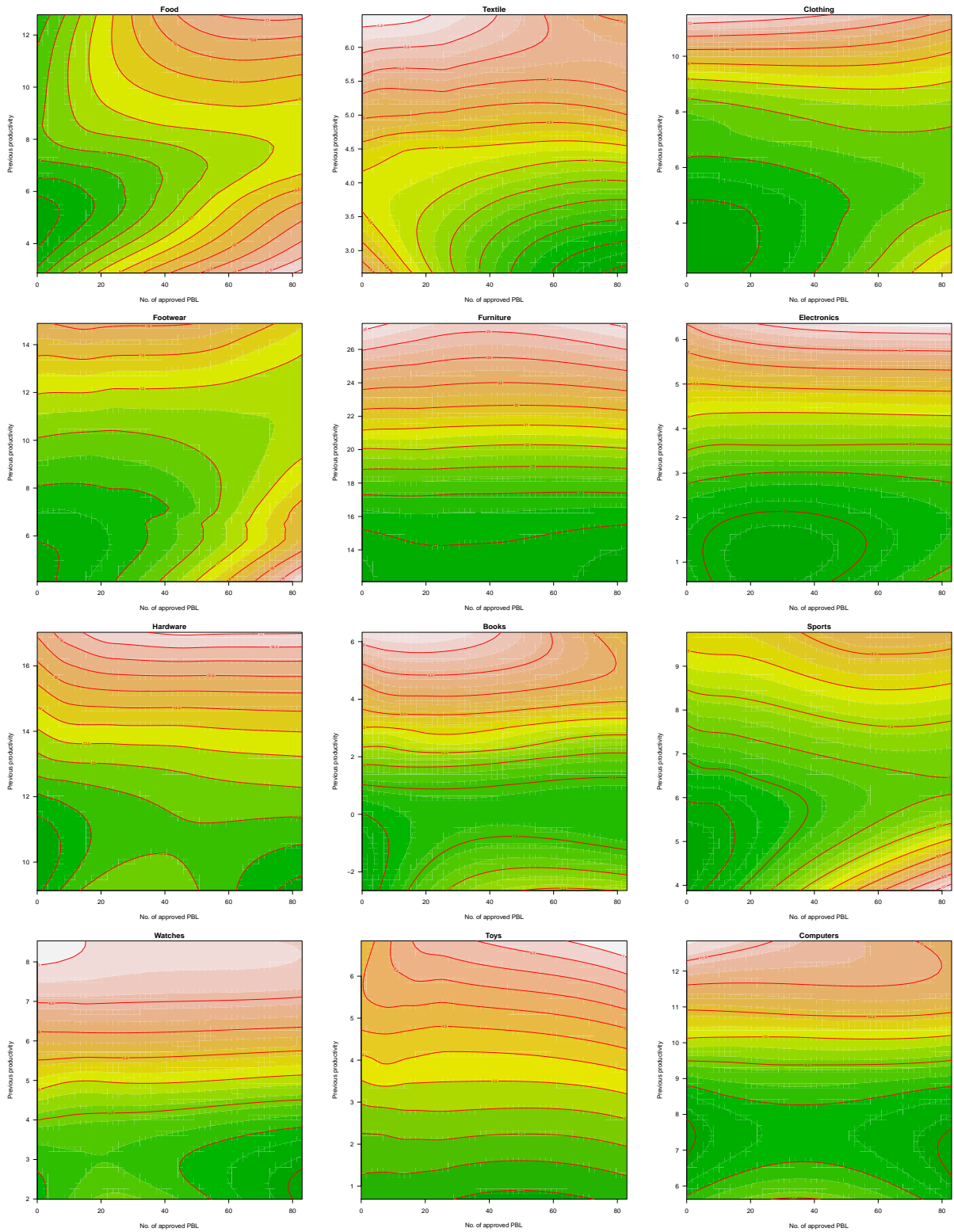


**Figure 1:** Productivity kernel density estimates in markets with above median (liberal) and below median (non-liberal) number of approved PBL applications

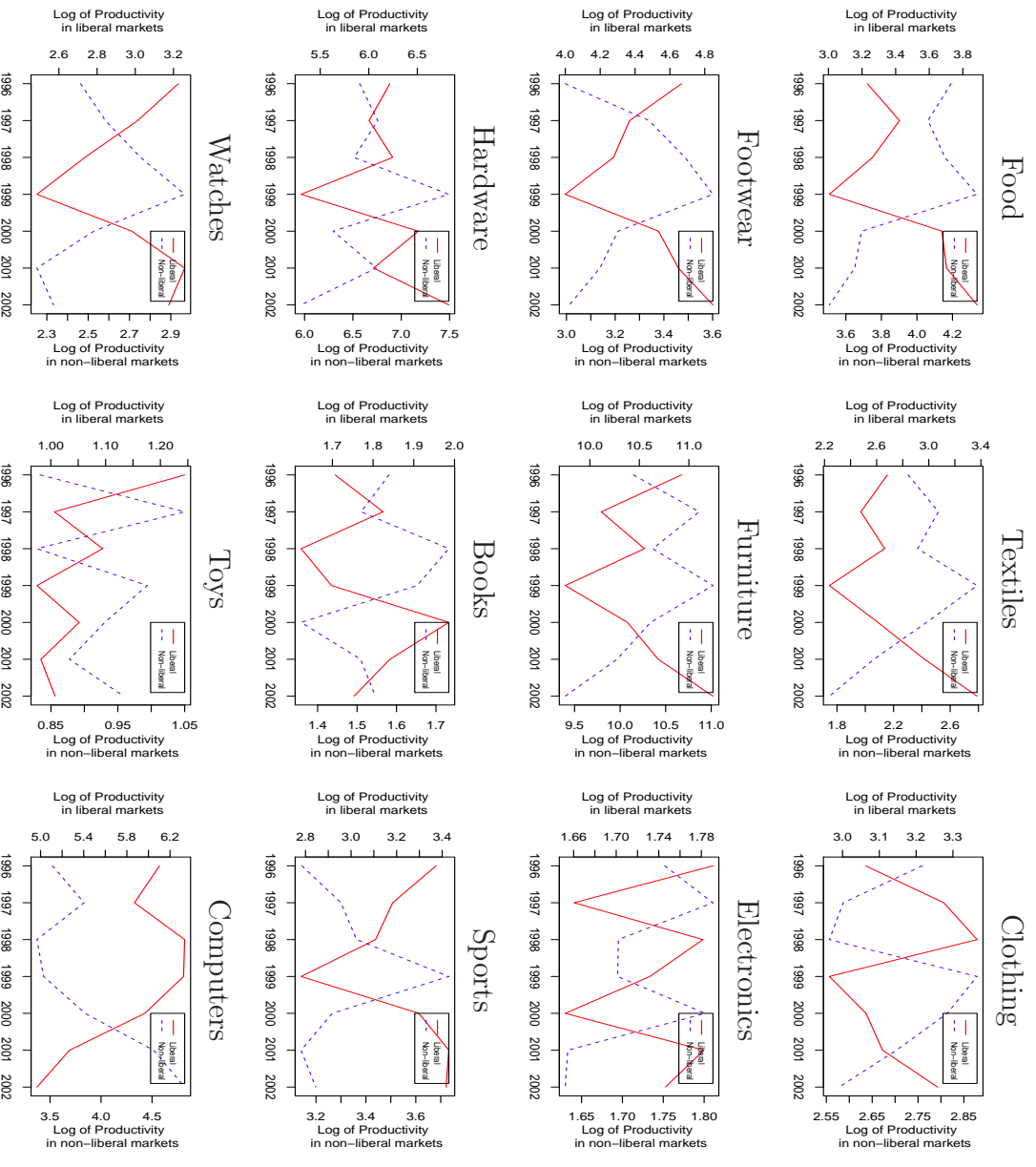




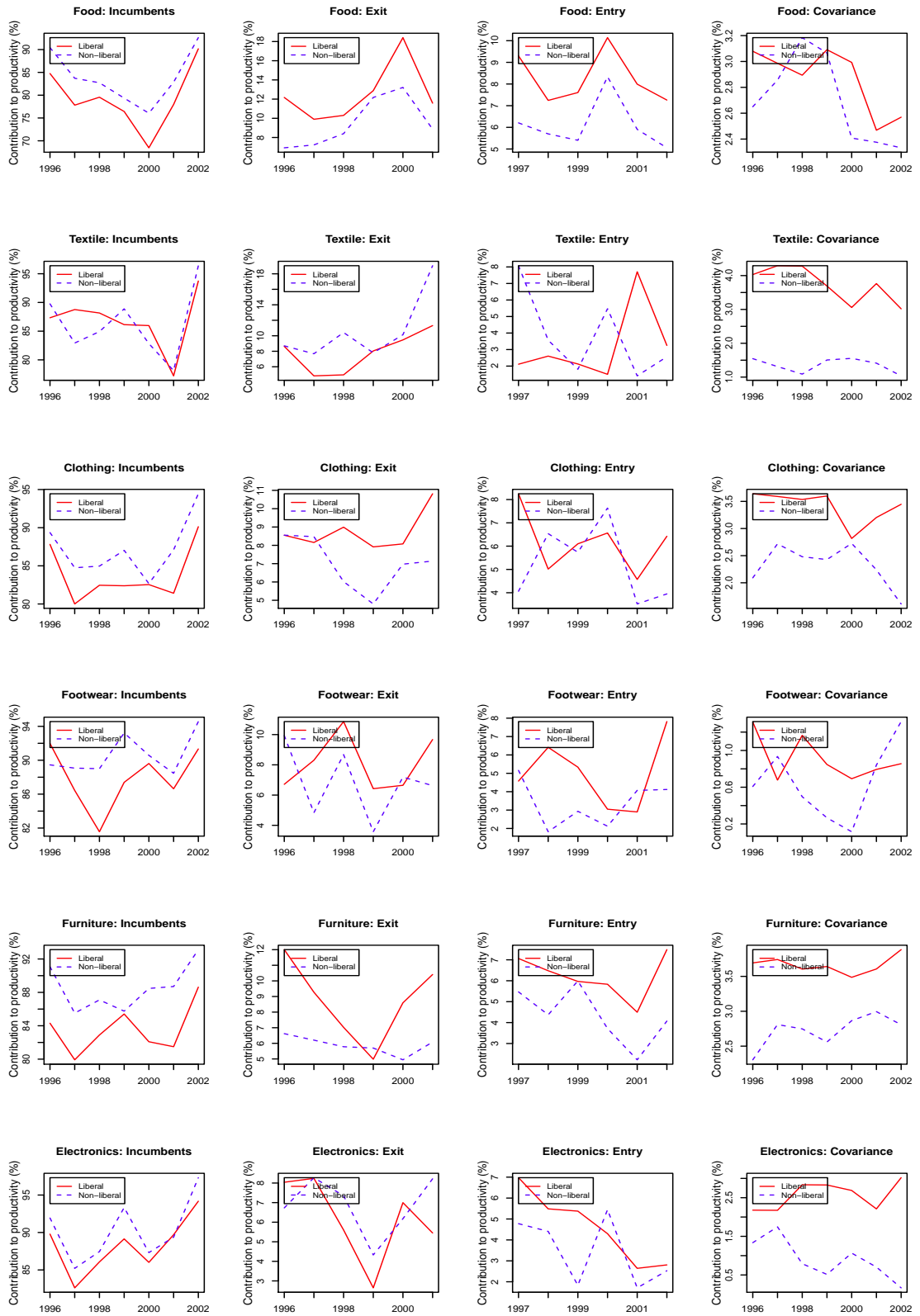
**Figure 2:** The industry relation between productivity, previous productivity, and number of approved PBL applications, 1996 to 2002

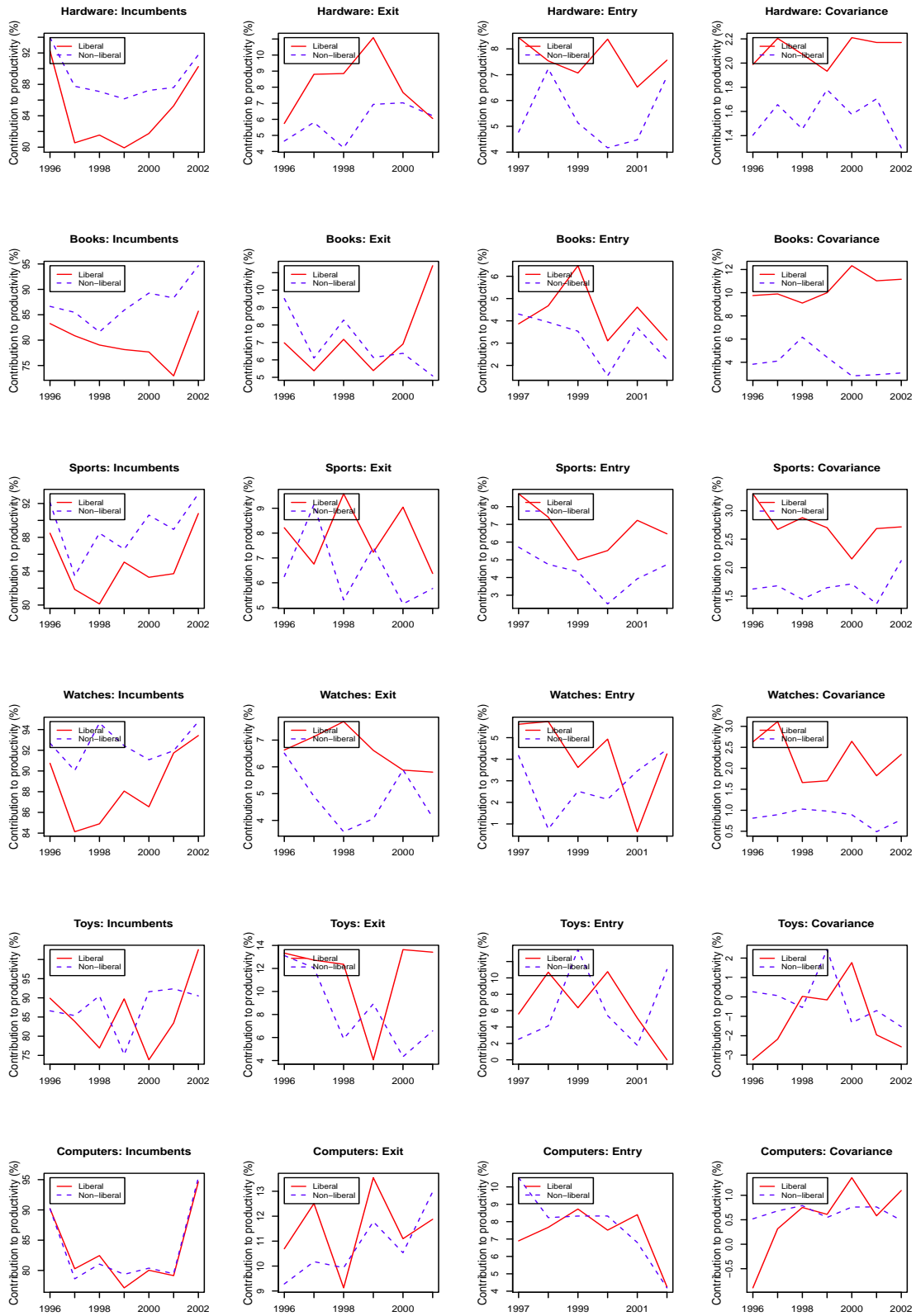


**Figure 3:** The industry relation between productivity, previous productivity, and number of approved PBL applications, 1996 to 2002



**Figure 4:** Aggregate productivity dynamics in markets with above median (liberal) and below median (non-liberal) number of approved PBL applications, 1996 to 2002





**Figure 5:** The dynamics of the contribution of average productivity and covariance for incumbents, entrants, and exit to aggregate productivity in in markets with above median (liberal) and below median (non-liberal) number of approved PBL applications, 1996 to 2002

**Table 7:** Decomposition of retail productivity growth 1997-2002 using Foster et al. (2001) and Griliches and Regev (1995): nonparametric approach

Subsector	Decomp.	Overall industry growth	Percentage of growth from					Net Entry (4) - (5)
			Within firms (1)	Between firms (2)	Cross firms (3)	Entry (4)	Exit (5)	
Food	FHK	0.0434	-0.009	-0.009	0.017	0.092	-0.047	0.045
	GR		-0.001	-0.002		0.079	-0.033	0.046
Textiles	FHK	0.1724	0.135	-0.069	0.085	0.109	-0.088	0.021
	GR		0.178	-0.038		0.064	-0.031	0.033
Clothing	FHK	0.0260	0.011	-0.017	0.035	0.037	-0.040	-0.003
	GR		0.029	0.001		0.031	-0.034	-0.003
Footwear	FHK	0.1550	0.141	-0.030	0.042	0.097	-0.094	0.003
	GR		0.161	-0.017		0.071	-0.060	0.011
Furniture	FHK	0.0157	0.021	-0.036	0.071	-0.008	-0.031	-0.040
	GR		0.056	-0.001		-0.013	-0.028	-0.040
Electronics	FHK	0.0360	0.019	-0.004	0.035	0.026	-0.041	-0.015
	GR		0.037	0.013		0.019	-0.033	-0.014
Hardware	FHK	0.0794	0.081	-0.006	0.035	0.072	-0.101	-0.030
	GR		0.098	0.011		0.055	-0.084	-0.029
Books	FHK	0.1819	0.115	-0.025	0.081	-0.023	0.034	0.011
	GR		0.155	0.010		-0.059	0.076	0.017
Sports	FHK	0.1999	0.153	-0.024	0.061	0.123	-0.113	0.010
	GR		0.183	0.003		0.078	-0.065	0.014
Watches	FHK	0.0843	0.063	-0.006	0.021	0.013	-0.011	0.003
	GR		0.075	0.006		-0.002	0.006	0.003
Toys	FHK	0.0493	0.114	-0.013	0.058	-0.049	-0.060	-0.109
	GR		0.143	0.014		-0.062	-0.045	-0.108
Computers	FHK	0.3116	-0.073	-0.008	0.144	0.243	0.006	0.249
	GR		-0.002	0.067		0.176	0.071	0.246

NOTE: The decomposition is done using Foster et al. (2001)(FHK) and Griliches and Regev (1995)(GR). The approach by FHK is explained in Section 4.3, and the one by GR in Appendix E. Productivity is estimated using the two-step estimation  $ACF_{lm}$  described in Section 3. Shares of local market sales are used as weights.

## Appendix A: Entry regulation

On July 1, 1987, a new regulation was imposed in Sweden, the Plan and Building Act (“Plan och Bygglagen”, PBL).<sup>39</sup> Compared to the previous legislation, the decision process was decentralized, giving local governments authority over entry in their municipalities, and citizens could now appeal these decisions. Since 1987, only minor changes have been implemented in the PBL. From April 1, 1992 to January 1, 1997, the regulation was slightly different, making it explicit that the use of buildings should not hamper efficient competition. Since 1997, the PBL has been essentially the same as it was prior to 1992. Long time lags in the planning process make it impossible to directly evaluate the impact of decisions. In practice, differences due to the policy change seem small (Swedish Competition Authority, 2001:4). The PBL is argued to be one of a major barrier to entry, resulting in different outcomes, e.g., price levels across municipalities. Municipalities are then, through the regulation, able to affect prices. In detail, the Swedish Competition Authority finds that the number of square meters of sales space per capita is lower in municipalities that constrain entry, while municipalities with a higher market shares occupied by large and discount stores have lower prices (Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2).

## Appendix B: The FS-RAMS data

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

*Capital* is constructed using a perpetual inventory method,  $K_{t+1} = (1 - \delta)K_t + I_t$ . Because the data distinguish between buildings and equipment, all calculations of the capital stock are performed separately for buildings and equipment. In the paper, we include equipment in the capital stock. However, including both equipment and buildings in the capital stock does not change our results. As suggested by Hulten and Wykoff (1981), buildings are depreciated at a rate of 0.0361 and

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<sup>39</sup>The Swedish Competition Authority (2001:4) provides a detailed description.

equipment by 0.1179. To construct capital series using the perpetual inventory method, an initial capital stock is needed. We set initial capital stock to the first available observation in FS-RAMS, defining entry as the first year a store has data in FS (some of the stores have been in FS since 1973).

## **Appendix C: Retail subsectors (SNI codes)**

We take all stores that belong to SNI code 52 (Retail trade, except motor vehicles and motorcycles; repair of personal household goods), and exclude monopolies, SNI 52250 - Retail sales of alcoholic and other beverages; SNI 52210-52242, 52271-52279, 52330 - Retail sales of food and beverages in specialized stores; SNI 52260 - Retail sales of tobacco in specialized stores; SNI 52310 and 52320 - Dispensing chemists and Retail sales of medical and orthopedic goods; SNI 52488, 52491-52499, 52501-52509, 52710-52740 - Retail sales in specialized stores, including spectacles and other optical goods, photographic equipment and related services, flowers and other plants, pet animals, second-hand goods, art, art gallery activities, coins and stamps, computers, office machinery and computer software, telecommunication equipment, wallpaper, carpets, rugs and floor coverings, boats and boating accessories, office furniture, specialized stores n.e.c.; SNI 5261 - Retail sales via mail.order houses; SNI 5262 and 5263 - Retail sales via stalls, markets and other non-store retail sales, and other stores.

SNI “Food” represents Retail sales in non-specialized stores where food, beverages, or tobacco are predominant (52111-52129); “Textiles” Retail sales of textiles (52410); “Clothing” Retail sales of clothing (52421-52425); “Footwear” Retail sales of footwear and leather goods” (52431-52432); “Furniture” Retail sales of furniture, lighting equipment, and household articles n.e.c. (52441-52444); “Electronics” Retail sales of electrical household appliances and radio and television goods (52451-52454); “Hardware” Retail sales of hardware, paints and glass (52461-52462); “Books” Retail sales of books, newspapers and stationery (52471-52472); “Watches” Retail sales of watches and clocks, jewelery, gold wares, and silverware (52483-52484); “Sports” Retail sales of sports and leisure goods (52485); “Toys” Retail sales of games and toys (52486); “Computers” Retail sales of computers, software and telecommunications equipment (52493-52494).



## Appendix D: Parametric approach

Under the assumptions of Cobb-Douglas technology and that labor is a static and variable input, the labor function from the stores' short-run optimization problem takes the form

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

Solving for  $\omega_{jt}$  yields the inverse labor demand function

$$\omega_{jt} = \frac{\eta}{1+\eta} \left[ \lambda_0 + [(1 - \beta_l) - \frac{1}{\eta}\beta_l]l_{jt} + w_{jt} - p_{st} - \left(1 + \frac{1}{\eta}\right) \beta_k k_{jt} + \frac{1}{\eta}q_{smt} + \frac{1}{\eta}\mathbf{z}'_{mt}\boldsymbol{\beta}_z \right], \quad (16)$$

where  $p_{st}$  is used as a proxy for  $p_{smt}$  and  $\lambda_0 = -\ln(\beta_l) - \ln(1 + 1/\eta) - \ln E[\exp(\xi_{jt})] + \frac{1}{\eta} \ln E[\exp(\varepsilon_{jt})]$ .<sup>40</sup> The labor demand function (15), with  $\omega_{jt} = g(\omega_{jt-1}, r_{mt-1}) + v_{jt}$ , and the final value-added generating function (3) above, i.e.,

$$y_{jt} = \left(1 + \frac{1}{\eta}\right) [\beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta}q_{smt} - \frac{1}{\eta}\mathbf{z}'_{mt}\boldsymbol{\beta}_z + \left(1 + \frac{1}{\eta}\right) g(\omega_{jt-1}, r_{mt-1}) + \left(1 + \frac{1}{\eta}\right) v_{jt} - \frac{1}{\eta}u_{jt}^d + \left(1 + \frac{1}{\eta}\right) \xi_{jt}, \quad (17)$$

form a system of equations with  $y_{jt}$  and  $l_{jt}$  as endogenous variables.

**Estimation.** The estimation of our semi-parametric model adjusted for retailers (EOP) proceeds as follows. We first use a probit model with a third-order polynomial to estimate survival probabilities and then substitute the predicted survival probabilities into (3). We use the sieve minimum distance (SMD) procedure proposed by Newey and Powell (2003) and Ai and Chen (2003) for independent and identically distributed (i.i.d.) data. The goal is to obtain an estimable expression for the unknown parameters  $\boldsymbol{\beta}$  and  $g_{K_T}$ , where  $K_T$  indicates all parameters in  $g(\cdot)$ . We approximate  $g(\cdot)$  by a third-order polynomial expansion in  $\mathcal{P}_{t-1}$ ,  $\omega_{jt-1}$  (given by (16)) and  $r_{mt-1}$ .<sup>41</sup> We use a tensor product polynomial series of labor ( $l_{jt-1}$ ), capital ( $k_{jt-1}$ ), wages ( $w_{jt-1}$ ), the consumer price index in the subsector ( $p_{st}$ ) and local market conditions ( $\mathbf{z}_{mt-1}$ ) as instruments, where the local market conditions

<sup>40</sup>The condition for identification is that the variables in the parametric section of the model are not perfectly predictable (in the least squares sense) on the basis of the variables in the non-parametric section (Robinson, 1988). Therefore there cannot be a functional relationship between the variables in the parametric and non-parametric sections (Newey et al., 1999).

<sup>41</sup>For robustness, we also expand  $g(\cdot)$  using a fourth-order polynomial, but the results are similar.

include population, population density, and income. The same set of instruments is used to estimate the optimal weighting matrix. As there are nonlinearities in the coefficients, we use the Nelder-Mead numerical optimization method to minimize the GMM objective function

$$\min_{\boldsymbol{\beta}, g_{K_T}} Q_N = \left[ \frac{1}{N} W' \rho(\boldsymbol{\beta}) \right]' A \left[ \frac{1}{N} W' \rho(\boldsymbol{\beta}) \right], \quad (18)$$

where  $\rho(\boldsymbol{\beta}) = \left( \left(1 + \frac{1}{\eta}\right) v_{jt} - \frac{1}{\eta} u_{jt}^d + \left(1 + \frac{1}{\eta}\right) \xi_{jt} \right) (\boldsymbol{\beta})$ ,  $A$  is the weighting matrix defined as  $A = \left[ \frac{1}{N} W' \rho(\boldsymbol{\beta}) \rho'(\boldsymbol{\beta}) W \right]^{-1}$  and  $W$  is the matrix of instruments. Using the specified GMM implementation, the parameter values  $(\boldsymbol{\beta}, g_{K_T})$  are jointly estimated. We control for local market characteristics in all estimations.

**Details regarding the estimation strategy.** We first use a probit model with a third-order polynomial to estimate the survival probabilities in (9). The predicted survival probabilities are then substituted into the final value-added generating function, which is estimated in the second step. We now turn to details regarding the estimation procedure in the latter step. The semi-parametric regression is estimated using the sieve minimum distance (SMD) procedure proposed in Newey and Powell (2003) and Ai and Chen (2003) for independent and identically distributed (i.i.d.) data.<sup>42</sup> The goal is to obtain an estimable expression for the unknown parameter of interest,  $\boldsymbol{\alpha} = (\boldsymbol{\beta}, g)'$ . We denote the true value of the parameters with the subscript "a":  $\boldsymbol{\alpha}_a = (\boldsymbol{\beta}_a, g_a)'$ . The moment conditions could then be written more compactly as

$$E[\rho_j(\mathbf{x}_t, \boldsymbol{\beta}_a, g_a) | \mathbf{F}_t^*] = 0, \quad j = 1, \dots, N \quad (19)$$

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

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

Let  $\mathbf{F}_t$  be an observable subset of  $\mathbf{F}_t^*$ , then equation (19) implies

$$E[\rho_j(\mathbf{x}_t, \boldsymbol{\beta}_a, g_a) | \mathbf{F}_t] = 0 \quad j = 1, \dots, N. \quad (20)$$

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<sup>42</sup>Chen and Ludvigson (2007) show that the SMD procedure and its large sample properties can be extended to stationary ergodic time series data.

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

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

where  $m(\mathbf{F}_t, \boldsymbol{\alpha}) = E[\rho(\mathbf{x}_t, \boldsymbol{\alpha}) | \mathbf{F}_t]$ ,  $\rho(\mathbf{x}_t, \boldsymbol{\alpha}) = (\rho_1(\mathbf{x}_t, \boldsymbol{\alpha}), \dots, \rho_N(\mathbf{x}_t, \boldsymbol{\alpha}))'$  for any candidate values  $\boldsymbol{\alpha} = (\boldsymbol{\beta}, g)'$ . The moment conditions are used to describe the SMD estimation of  $\boldsymbol{\alpha}_a = (\boldsymbol{\beta}_a, g_a)'$ . The SMD procedure has three parts. First, we can estimate the function  $g(\cdot)$ , which has an infinite dimension of unknown parameters, by a sequence of finite-dimensional unknown parameters (sieves) denoted  $g_{K_T}$ . The approximation error decreases as the dimension  $K_T$  increases with sample size  $N$ . Second, the unknown conditional mean  $m(\mathbf{F}_t, \boldsymbol{\alpha}) = E[\rho(\mathbf{x}_t, \boldsymbol{\alpha}) | \mathbf{F}_t]$  is replaced with a consistent nonparametric estimator  $\hat{m}(\mathbf{F}_t, \boldsymbol{\alpha})$  for any candidate parameter values  $\boldsymbol{\alpha} = (\boldsymbol{\beta}, g)'$ . Finally, the function  $g_{K_T}$  is estimated jointly with the finite dimensional parameters  $\boldsymbol{\beta}$  by minimizing a quadratic norm of estimated expectation functions:

$$\hat{\boldsymbol{\alpha}} = \arg \min_{\boldsymbol{\beta}, g_{K_T}} \frac{1}{T} \sum_{t=1}^T \hat{m}(\mathbf{F}_t, \boldsymbol{\beta}, g_{K_T})' \hat{m}(\mathbf{F}_t, \boldsymbol{\beta}, g_{K_T}). \quad (21)$$

We approximate  $g(\cdot)$  by a third-order polynomial and substitute it into (20) as if it were the true model. As the errors  $\rho_j(\cdot)$  are orthogonal to the regressors  $\mathbf{F}_t = (1, l_{t-1}, k_t, r_{t-1}, \mathbf{z}_{t-1})$ , we use a third-order power series of  $\mathbf{F}_t$ , denoted  $\mathbf{P}$ , as instruments. We estimate  $m(\mathbf{F}, \boldsymbol{\alpha})$  as the predicted values from regressing the errors  $\rho_j(\cdot)$  on the instruments. Using  $\mathbf{P}$ , we specify the weighting matrix as  $\mathbf{W} = I_N \otimes (\mathbf{P}'\mathbf{P})^{-1}$ , making the estimation a GMM case. The weighting matrix  $\mathbf{W}$  places greater weight on moments that are highly correlated with the instruments. Using the specified GMM implementation, the parameter values  $(\boldsymbol{\beta}, g_{K_T})$  are jointly estimated.

**Results: parametric approach.** The value-added production function coefficients from our extended Olley and Pakes estimation using a parametric labor demand (EOP) are presented in Table D.1. EOP yields a lower elasticity of scale than OLS. These results do not control for entry regulation in the productivity process. The results in EOP show that the elasticity of scale is approximately one for all subsectors, though some interesting differences occur across subsectors.

The labor coefficient varies between 0.316 (Toys) and 0.896 (Food) whereas the capital coefficient varies between 0.086 (Computers) and 0.253 (Electronics).

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

An advantage of EOP is that the correction for omitted prices also yields an estimate of market output, which makes it possible to compute the elasticity of demand and the markup defined as price over marginal cost. We find an elasticity of demand between -2.15 (Furniture) and -3.62 (Toys). The markup (price over marginal cost) ranges from 1.38 (Toys) to 1.87 (Furniture).<sup>43</sup>

**Summary statistics: productivity.** Table D.2 shows descriptive statistics for multi-factor productivity (estimated by EOP) and labor productivity. We define labor productivity as value-added per employee. Median productivity increases until the year 2000 and then decreases, which tracks closely with the investment pattern over time. Over the full period, median productivity increases by 5, percent while the dispersion in productivity decreases by 6 percent. For labor productivity, the corresponding figures are 3 percent and 1 percent, respectively. Thus, the magnitude of the changes over time is larger for productivity than for labor productivity.

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<sup>43</sup>Two subsectors (Books and Sports) have an elasticity of demand above 5 in absolute terms and markups below 1.25.

**Table D.1:** Value-added generating function estimates: parametric approach

	OLS		EOP						No. of obs.
	Labor	Capital	Labor	Capital	Scale	Demand	Markup	Selection	
Food	0.871 (0.005)	0.161 (0.003)	0.896 (0.0001)	0.158 (0.0001)	1.51	-2.20	1.83	no	15,329
Textiles	0.900 (0.021)	0.140 (0.01)	0.607 (0.001)	0.118 (0.0006)	1.06	-2.97	1.51	yes	1,273
Clothing	0.945 (0.008)	0.118 (0.004)	0.843 (0.0002)	0.103 (0.0006)	1.29	-2.94	1.52	no	11,488
Footwear	0.918 (0.01)	0.110 (0.007)	0.519 (0.0003)	0.003 (0.0002)	0.82	-3.36	1.42	no	2,879
Furniture	0.962 (0.009)	0.114 (0.005)	0.417 (0.0001)	0.140 (0.00003)	1.02	-2.15	1.87	no	7,508
Electronics	0.951 (0.010)	0.136 (0.005)	0.426 (0.0002)	0.253 (0.0001)	1.05	-2.68	1.60	no	6,302
Hardware	0.924 (0.008)	0.153 (0.005)	0.495 (0.00001)	0.188 (0.00001)	0.97	-3.55	1.39	no	6,591
Books	0.889 (0.01)	0.137 (0.008)	0.663 (0.006)	0.157 (0.003)	0.89	-15.5	1.07	yes	2,773
Sports	0.896 (0.01)	0.119 (0.006)	0.687 (0.0006)	0.092 (0.0006)	0.96	-5.58	1.22	yes	5,302
Watches	0.937 (0.01)	0.106 (0.007)	0.682 (0.002)	0.093 (0.003)	1.48	-3.08	1.48	yes	2,943
Toys	0.802 (0.03)	0.211 (0.02)	0.316 (0.003)	0.251 (0.001)	0.84	-3.62	1.38	no	1,093
Computers	0.955 (0.009)	0.133 (0.006)	0.779 (0.002)	0.086 (0.003)	1.16	-3.41	1.41	yes	6,998

NOTE: Productivity (in logs) is estimated using the semi-parametric estimation EOP based on Doraszelski and Jaumandreu (2011).

**Table D.2:** Summary statistics productivity: parametric approach

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

NOTE: Multi-factor productivity and labor productivity in logs. Multi-factor productivity is estimated using the semi-parametric estimation EOP. Labor productivity is defined as log of value added per employee. Dispersion=interquartile range/median.

## Appendix E: Decompositions

**Griliches and Regev (1995).** The productivity decomposition by Griliches and Regev (1995) (GR) is

$$\begin{aligned} \Delta\Omega_{t,t'} = & \sum_{j \in C_{t,t'}} \bar{s}_j \Delta\omega_{jt,t'} + \sum_{j \in C_{t,t'}} \Delta s_{jt,t'} (\bar{\omega}_j - \bar{\Omega}) \\ & + \sum_{j \in E_{t,t'}} s_{jt'} (\omega_{jt'} - \bar{\Omega}) - \sum_{j \in X_{t,t'}} s_{jt} (\omega_{jt} - \bar{\Omega}), \end{aligned} \quad (22)$$

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

**Petrin and Levinsohn (2012).** The decomposition methods described above all rely on changes in technical efficiency. Based on growth accounting, Petrin and Levinsohn (2012) (PL) propose an alternative decomposition and define aggregate productivity growth (APG) as the change in aggregate final demand minus the change in aggregate expenditures on labor and capital. To connect changes in production to those in aggregate final demand, they exploit the fact that aggregate value-added equals aggregate final demand. This stems from the National Income Identity stating that the use of intermediate inputs is canceled out at the aggregate level (Hulten, 1978; Basu and Fernald, 2002). Consequently, PL link

micro-level plant data to a macro perspective (the Solow residual). In particular, they extend Basu and Fernald (2002) to allow for jumps in productivity growth, differences in input costs, and non-differentiable cost functions (by using production function estimates).

PL decompose APG into three terms: (i) technical efficiency, i.e., the effect of plants generating more output without increasing inputs; (ii) reallocation, i.e., the effect of changes in input reallocation across plants; and (iii) fixed and sunk costs. The relationship between APG and these three terms holds when taking the sum over all or different subsets of plants in the economy. An advantage of the PL decomposition is thus that it can be divided into different types of plants, e.g., incumbents, entrants and exits.

**Melitz and Polanec (2012).** Melitz and Polanec (2012) suggest a dynamic OP decomposition of productivity growth with entry and exit. Following MP, we separate productivity growth into incumbents, entrants and exits.

$$\begin{aligned} \Delta\Omega_{t,t'} = & \Delta\bar{\Omega}_{C_{t,t'}} + \Delta cov_{C_{t,t'}} + \Delta\bar{\Omega}_{E_{t,t'}} + \Delta cov_{E_{t,t'}} \\ & + \Delta\bar{\Omega}_{X_{t,t'}} + \Delta cov_{X_{t,t'}} \end{aligned} \quad (23)$$

where we evaluate the extent to which incumbents ( $C$ ), entrants ( $E$ ) and exits ( $X$ ) contribute to productivity growth through productivity improvements and reallocation, respectively. There is a only positive contribution for entering and exiting stores when the aggregate productivity of these stores is larger than that of continuing stores in corresponding periods. The aggregate productivity in period  $t$  and  $t'$ , respectively, can be decomposed as

$$\begin{aligned} \Omega_t &= ms_{C_t}\Omega_{C_t} + ms_{X_t}\Omega_{X_t} \\ \Omega_{t'} &= ms_{C_{t'}}\Omega_{C_{t'}} + ms_{E_{t'}}\Omega_{E_{t'}}, \end{aligned} \quad (24)$$

where  $ms_{C_t}$ ,  $ms_{C_{t'}}$ ,  $ms_{E_{t'}}$ , and  $ms_{X_t}$  are the aggregate market shares of incumbents (in periods  $t$  and  $t'$ ), entrants, and exits, respectively. In OP, the difference in productivity index,  $\Delta\Omega_{t,t'}$ , can be written as

$$\Delta\Omega_{t,t'} = \Delta\bar{\Omega}_{t,t'} + \Delta cov_{t,t'}. \quad (25)$$

In MP, the change in aggregate productivity can be written as

$$\Delta\Omega_{t,t'} = \Delta\bar{\Omega}_{C_{t,t'}} + \Delta cov_{C_{t,t'}} + ms_{E_{t'}}(\Omega_{E_{t'}} - \Omega_{C_{t'}}) + ms_{X_t}(\Omega_{C_t} - \Omega_{X_t}), \quad (26)$$

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

There are some key differences between the different decomposition methods. In MP, entrants and exits will only have a positive contribution if their aggregate productivity is larger than that of continuing stores. The other two methods compare the aggregate productivity of entrants and exists to the aggregate productivity of all stores in the initial period (FHK) and the unweighted time average productivity of all stores (GR), respectively. Moreover, FHK and GR use fixed weights for continuing stores, whereas MP (and OP) define reallocation as a change in the unweighted covariance between market shares and productivity.

**Results.** Using the MP decomposition and productivity estimated using  $ACF_{lm}$ , incumbents contribute more to aggregate productivity growth than under FHK or GR (Table E.3). This is exactly what we expect. In fact, surviving stores that improve their productivity constitute the most important source of productivity growth for all subsectors except Watches. Tables E.4 and E.5 present decomposition results for FHK, GR and MP for productivity estimated using the parametric approach based on Doraszelski and Jaumandreu (2011).

**Table E.3:** Dynamic Olley and Pakes decomposition of retail productivity growth 1996-2002 using Melitz and Polanec (2012): nonparametric approach

Subsector	Total Growth	Surviving		Entrants		Exits	
		Unweigh.	Cov	Unweigh.	Weigh.	Unweigh.	Weigh.
Food	0.0434	0.018	-0.006	0.112	0.156	-0.079	-0.125
Textiles	0.1724	0.451	-0.056	0.008	0.038	-0.195	-0.261
Clothing	0.0260	0.083	-0.028	0.005	0.047	-0.049	-0.076
Footwear	0.1550	0.282	-0.028	0.048	0.067	-0.183	-0.166
Furniture	0.0157	0.201	-0.091	-0.173	-0.034	0.019	-0.059
Electronics	0.0360	0.088	0.002	-0.050	0.019	-0.039	-0.074
Hardware	0.0794	0.217	-0.026	-0.016	0.067	-0.102	-0.178
Books	0.1819	0.356	-0.079	-0.179	-0.158	0.024	0.063
Sports	0.1999	0.333	0.026	-0.031	0.061	-0.076	-0.220
Watches	0.0843	-0.007	0.137	-0.097	-0.029	0.038	-0.017
Toys	0.0493	0.021	0.323	-0.151	-0.153	-0.138	-0.142
Computers	0.3116	0.056	0.055	0.044	0.191	0.022	0.010

Decomposition of retail productivity growth. The decomposition is done using Melitz and Polanec (2012), explained in detail in Appendix E. Productivity is estimated using the two-step estimation  $ACF_{lm}$  described in Section 3. Shares of local market sales are used as weights.



**Table E.4:** Decomposition of retail productivity growth 1996-2002 using Foster et al. (2001) and Griliches and Regev (1995): parametric approach

Subsector	Decomp.	Overall industry growth	Percentage of growth from					Net Entry (4) - (5)
			Within firms (1)	Between firms (2)	Cross firms (3)	Entry (4)	Exit (5)	
Food	FHK	0.4160	0.186	0.005	0.038	0.181	0.007	0.187
	GR		0.205	0.007		0.098	0.106	0.203
Textiles	FHK	-0.3008	-0.209	-0.025	0.035	-0.090	-0.013	-0.103
	GR		0.125	0.007		-0.002	0.048	0.046
Clothing	FHK	0.3119	0.147	-0.012	-0.008	0.113	0.072	0.185
	GR		0.143	-0.008		0.056	0.121	0.177
Footwear	FHK	0.0344	0.084	-0.081	0.133	-0.122	0.021	-0.101
	GR		0.150	-0.019		-0.125	0.028	-0.097
Furniture	FHK	0.0905	0.017	0.057	0.081	-0.085	0.020	-0.065
	GR		0.058	0.097		-0.099	0.034	-0.065
Electronics	FHK	0.194	0.030	-0.028	0.128	0.031	0.034	0.065
	GR		0.093	0.023		0.001	0.077	0.078
Hardware	FHK	-0.0018	-0.039	-0.009	0.050	0.020	-0.024	-0.004
	GR		-0.014	0.016		0.021	-0.025	-0.004
Books	FHK	0.3650	0.202	0.005	0.106	0.083	-0.031	0.052
	GR		0.255	0.023		0.028	0.059	0.087
Sports	FHK	-0.0233	-0.032	-0.020	0.049	0.007	-0.027	-0.020
	GR		-0.008	0.005		0.011	-0.031	-0.020
Watches	FHK	-0.6573	-0.612	-0.020	0.075	-0.094	-0.007	-0.101
	GR		-0.574	-0.0007		-0.014	-0.068	-0.083
Toys	FHK	1.3699	-0.026	-0.053	0.102	1.434	-0.087	1.346
	GR		0.025	-0.022		1.086	0.281	1.367
Computers	FHK	0.2190	0.128	-0.036	0.003	0.120	0.004	0.124
	GR		0.130	-0.032		0.072	0.049	0.121

NOTE: The decomposition is done using Foster et al. (2001)(FHK) and Griliches and Regev (1995)(GR). The approach by FHK is explained in Section 4.3, and the one by GR in Appendix E. Productivity is estimated using the semi-parametric estimation EOP. Stores' shares of local market sales are used as weights.

**Table E.5:** Dynamic Olley and Pakes decomposition of retail productivity growth 1996-2002 using Melitz and Polanec (2012): parametric approach

Subsector	Total Growth	Surviving		Entrants		Exits	
		Unweigh.	Cov	Unweigh.	Weigh.	Unweigh.	Weigh.
Food	0.4160	0.381	-0.001	0.024	-0.055	0.013	0.147
Textiles	-0.3008	-0.395	0.127	-0.011	0.011	-0.022	0.034
Clothing	0.3119	0.363	-0.155	-0.002	-0.089	0.105	0.125
Footwear	0.0344	0.134	0.021	-0.156	-0.102	0.035	0.266
Furniture	0.0905	0.085	0.140	-0.162	-0.164	0.029	0.171
Electronics	0.1942	0.071	0.103	-0.040	-0.106	0.061	0.240
Hardware	-0.0018	-0.019	0.022	0.036	-0.132	-0.041	0.104
Books	0.3650	0.406	0.057	-0.038	-0.064	-0.060	0.131
Sports	-0.0233	-0.034	0.029	0.021	-0.069	-0.040	0.089
Watches	-0.0978	-0.077	-0.020	-0.007	-0.022	0.007	0.013
Toys	1.3699	0.037	0.022	1.499	-0.104	-0.189	0.268
Computers	0.2190	0.123	0.048	0.042	-0.052	0.007	0.107

Decomposition of retail productivity growth. The decomposition is done using Melitz and Polanec (2012), explained in detail in Appendix E. Productivity is estimated using the semi-parametric estimation EOP. Stores' shares of local market sales are used as weights.