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Abstract

This paper studies the determinants of economies of scope in retail using a dynamic framework and novel product and store data. We estimate store productivity and consumers' perceived shopping quality and analyze their relationship with intensive and extensive product margins, performance and welfare. We find that high productivity stores offer more products and sell more of each product. High quality stores offer fewer products and sell more of top products. Counterfactual experiments show that productivity innovations increase product variety, especially when demand uncertainty is low and in the long run. Higher shopping quality increases consumer surplus even if stores specialize.

Keywords: economies of scope; product variety; productivity; inventory; demand; competition

JEL Classification: L11, L13, L25, L81, M21

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1 Introduction

The core of retail businesses is buying multiple products from wholesalers and efficiently delivering them to consumers with quality. Buildings, equipment and supply chain facilities, for instance, yield economies of scope that make it cheaper to sell many products together than to sell them separately (Panzar and Willig, 1981). Whether broader product variety translates into higher profits is ambiguous and depends on consumer preferences. Economies of scale are often argued to drive the trend of increasing concentration in retail services but there is little research on the determinants of economies of scope (Ellickson, 2007; Basker et al., 2012; Hortacsu and Syverson, 2015; Hsieh and Rossi-Hansberg, 2019). Investments in new technologies induce productivity improvements that allow stores to deliver a wider variety of products and sell more existing products without increasing cost. This paper recovers key economic primitives of demand and supply to analyze economies of scope in retail.

We provide a dynamic structural model that allows for economies of scale and scope using a multi-product sales technology and a demand system. The model is estimated using novel and detailed data on products and stores in Swedish retail between 2003 and 2009. We recover two sources of store-level heterogeneity, i.e., total factor productivity and demand shocks related to consumers' perceived shopping quality, which are observed by stores but not by the researcher. Recovering these key primitives related to cost and demand plays a crucial role in understanding stores' decisions and their impact on local competition (Berry et al., 2019). Both sources of store heterogeneity are determinants of economies of scale and scope affecting stores' extensive margin (how many products to offer) and intensive margin (sales per product within the store). We also simulate a number of counterfactual experiments to explore trade-offs in optimal responses to hypothetical innovations in productivity and shopping quality.

Stylized facts based on Swedish data show that stores adjust product variety, inventory and inputs based on store-level characteristics and the local market environment. Median store-level capital stock, inventory, and wages increase over time. At the same time, there is a corresponding increase in median market share, Herfindahl index [HHI], and four-firm concentration ratio [C4] in local markets. The reduced-form results show that lower margins and an increase in local concentration are associated with fewer product categories, i.e., stores specialize. Average sales per product category are positively correlated with measures that affect productivity and shopping quality such as capital stock per employee. Stores with high local market shares have more products, low entropy of product sales, high labor productivity and inventory performance. This links to the recent literature on increasing differences between firms related to various factors such as market power (De Loecker et al., 2018; Van Reenen, 2018), the existence of superstar firms (Autor et al., 2018) and change in industry dynamism (Decker et al., 2018). As Berry et al. (2019) argue, only understanding changes in firms' key primitives provide a better understanding of what drives increasing differences between firms.

In our dynamic framework, economies of scope appear from both demand and supply in equilibrium. On the supply side, we model economies of scope through a transcendental multi-product sales technology (Mundlak, 1964; Maican and Orth, 2019a). Stores use their size and resources, such as systems (machinery and equipment), employees and centralized functions like finance and marketing, to sell a greater variety of products (Panzar and Willig, 1981). The gains from selling a larger variety arise from lower average costs or from increasing sales in new related product markets.[1] Innovations like bar codes and scanners have radically improved the frequency of delivery and inventory management. We allow investments in new technologies to improve productivity, which can sustain the observed increase in inventories over time and create incentives to increase product variety (Holmes, 2001; Basker et al., 2012).

On the demand side, we model the link between consumers' choice of a store and product variety (Berry, 1994; Draganska and Jain, 2005). Adjustments in product variety and inventory occur because retailers target a better match with consumers' preferences, and consumers obtain quality from the shopping experience that includes accessibility and variety on the shelves. Consumer surplus depends on the trade-off between product variety and shopping quality. Stores aim to offer more product categories to keep consumers loyal and prevent switching to competitors. How the number of product categories affects a store's market share and profits is an

[1]Product variety has been introduced by the entry literature (i.e., pay a fixed cost to increase variety), but we still need explanations for why firms hold multiple products in service industries. In general, economies of scope can appear from two sources: local complementarities and fixed costs (Gorman, 1985; Ellickson, 2007). Local complementarities imply that a higher level of output for one product reduces the marginal cost of other outputs. Fixed costs can ensure economies of scope in the absence of local complementarities.

empirical question since these measures also depend on consumers' perceived shopping quality.

We recover store productivity and shopping quality from a store's observed policies regarding labor and inventory demand accounting for investment in technology, product variety, and the local environment in which a store operates (Doraszelski and Jaumandreu, 2013; Kumar and Zhang, 2018; Maican and Orth, 2019a).[2] High inventory levels reduce the risk of stock-outs and provide shopping quality and a convenience yield to consumers but are costly to hold in stock.[3] Our measure of quality of the shopping experience also includes features such as product quality, location, checkout speed, the courteousness of store employees, parking, bagging services, and cleanliness. In our model, this implies that the relationship between store productivity and shopping quality affects product variety and inventory behavior and performance. Our model also allows stores to learn from demand, that is, the quality of the shopping experience provides information that is used by stores to improve their future productivity. This mechanism of learning about demand has not yet received much attention in the structural productivity literature that endogenizes the productivity process.[4]

This paper contributes to the recent literature on understanding the economies of scope and its link to increasing concentration in retail (Gorman, 1985; Ellickson, 2007; Basker et al., 2012; Bronnenberg and Ellickson, 2015; Hortacsu and Syverson, 2015; Berry et al., 2019; Elickson et al., 2019; Hsieh and Rossi-Hansberg, 2019). To better understand the aggregate trend of increasing concentration in retail, we argue that the relationship between scale and scope

[2]Kumar and Zhang (2018) use the cost of goods to recover the distribution of demand shocks in manufacturing but do not model product variety. The optimal inventory policy depends on a store's markups. There is a growing literature that uses the cost of goods sold as a variable input to recover markups (e.g., De Loecker and Eeckhout, 2017; De Loecker and Eeckhout, 2018). While we do not observe prices and recover markups, we recover important determinants of marginal costs and prices, such as store productivity and shopping quality, using a framework that accommodates inventory adjustments and the cost of goods sold. Aguirregabiria (1999) models the interaction between price and inventory and its impact on markup dynamics and sales promotion.

[3]Carrying cost of inventories represents about 25 percent of the value of inventories and includes: capital cost, storage space cost, inventory service cost, and inventory risk cost. To avoid stock-outs, retailers spend more money on financing inventories than on advertising.

[4]The recent literature emphasizes that external factors such as trade liberalization and entry regulations are important determinants of this heterogeneity (De Loecker, 2011; Maican and Orth, 2015; Maican and Orth, 2017). These explanations are added on top of factors inside the firm such as R&D investments (Doraszelski and Jaumandreu, 2013) or management (Syverson, 2011). Braguinsky et al. (2015) highlight the link between inventories, productivity and profitability.

must be modeled in a dynamic framework with both supply and demand. Analyzing the link between scale and scope, Basker et al. (2012) emphasize that the interaction of economies of scale on the cost side with demand for one-stop shopping yields an increase in the number of stores a firm operates, which induces an expansion in the range of products it sells. Hsieh and Rossi-Hansberg (2019) argue that the consolidation trend in services is tied to investments in ICT-technologies that enable stores to produce at scale, as well as to increasing specialization among the top firms. We explicitly model a store's choice of scope and the complementarities between economies of scale and scope, highlighting the supply and demand channels. More generally, we contribute to the literature that emphasizes the role of technology and demand in understanding firm performance and market structure (e.g., Olley and Pakes, 1996; Foster et al., 2008; Collard-Wexler, 2013; Asker et al., 2014; Collard-Wexler and De Loecker, 2015).

Second, by modeling the relationship between multi-product technology and productivity, this paper adds to the literature that explores heterogeneity in productivity in narrowly defined industries (e.g., Syverson, 2011; Decker et al., 2018) and to the scarce literature on productivity in services (e.g., Basker, 2007; Basker, 2015; Maican and Orth, 2015; Grieco and McDevitt, 2017; Maican and Orth, 2017). By modeling the multi-product technology on the supply-side together with the demand shocks, this paper complements the literature on product variety using demand data (e.g., Berry and Waldfogel, 2001; Draganska and Jain, 2005; Sweeting, 2010; Sweeting, 2013; Eizenberg, 2014; Berry et al., 2016).

Third, this paper contributes to the recent literature on structural estimation of production functions following Olley and Pakes (1996).[5] Most of the literature on productivity estimation uses single-output technology and ignores multi-product technology, which renders inference on multi-product questionable (Bailey and Friedlaend, 1982). We explicitly model how store productivity and shopping quality affect the sales of product categories. A store's market share contains information on how consumers choose stores in local markets that is used in the identification of shopping quality (Berry, 1994; Ackerberg et al., 2007). By applying our approach to rich data on products and stores, our work is linked to a recent strand of research on multi-product firms in manufacturing (e.g., De Loecker et al., 2016; Valmari, 2016; Dhyne et al., 2017;

[5]See Olley and Pakes (1996), Levinsohn and Petrin (2003), Doraszelski and Jaumandreu (2013), Ackerberg et al. (2015), Gandhi et al. (2018).

Orr, 2018) and a companion paper on entry regulations in retail (Maican and Orth, 2019a).[6]

Our empirical results highlight that stores trade off productivity and shopping quality when adjusting both their extensive and intensive margins related to product variety. Stores with high productivity and that invest in new technology offer a greater product variety and sell more of all products. Stores with high quality offer fewer product categories, sell more of their top performing products, and have higher inventory per product. Furthermore, stores learn from consumers' perceived quality of shopping experience to increase future productivity. We conclude that important trade-offs between productivity and quality determine the degree of economies of scope and a store's optimal product variety.

The estimated model is used to simulate counterfactual policy experiments for a deeper understanding of the trade-off between store productivity and shopping quality. First, innovations in productivity result in wider product variety, especially in the long run and when reducing uncertainty in demand. Second, innovations in shopping quality yield an increase in consumer surplus even if stores specialize and offer fewer product categories. Third, productivity improvements imply that stores hire more, invest more in technology and obtain higher inventory turnover. On the contrary, stimulating shopping quality and lowering uncertainty in productivity results in only a modest increase in inventory turnover.

The next section presents the model and discusses the identification and estimation. Section 3 presents the data. Section 4 presents the empirical results. Section 5 shows the findings of various policy experiments using the estimated model. Section 6 presents robustness checks, and Section 7 summarizes and draws conclusions.

[6]With the exception of Dhyne et al. (2017), this literature estimates input shares, which is difficult in retail. The nature of retail businesses suggest that it in most cases does not make sense to allocate employees to specific product categories. In addition, splitting capital is even more difficult in services. De Loecker et al. (2016) and Dhyne et al. (2017) estimate productivity in manufacturing accounting for multi-product and using physical quantity, i.e., they eliminate average price from the productivity measure. In a companion paper, Maican and Orth (2019a) present a general result on the identification of the transcendental multi-output service technology that is used to recover total factor productivity and discuss the restrictions on the parameters that need to be satisfied for profit maximization.

2 Empirical framework

This paper uses a model for multi-product stores that endogenizes a retailer's choices to study the relationship between store total factor productivity and shopping quality and the observed heterogeneity in product variety and inventory in retail. The proposed model underlines the factors behind the trend of increasing inventories in different retail industries, which is consistent with the development toward larger stores that offer more product categories, i.e., the utilization of economies of scale and scope.

We use a multi-product sales generating function together with a demand system to estimate a store's total factor productivity and demand shocks related to consumers' quality of shopping experience that affect store choices. Stores decide labor, investment in technology, the number of products, and inventory adjustments based on productivity and shopping quality to generate sales. To improve inventory management, stores invest in technology, which increases productivity and reduces the cost of inventories. There are endogeneity concerns caused by correlations between the decision variables and the store-level shocks in productivity and shopping quality. Product variety, shopping quality and income are factors that consumers consider when choosing a store.[7]

Multi-product service generating function. Stores use the same service technology to sell their products, and this technology does not depend on the product category. Stores compete in the product market and collect their payoffs. At the beginning of each time period, stores decide whether to exit or to continue operating in the local market. Stores are assumed to know their scrap value received upon exit prior to making exit and investment decisions. If a store continues, it chooses optimal levels of the number of products, products bought from the wholesaler and the adjustments in inventory before sales a, investment in capital/technology i, and labor l (the number of employees).[8]

[7]While prices also affect the choice of store, they might be difficult to access due to different, e.g., pack sizes or units of measure for retail census data-sets. However, the empirical literature on total factor productivity estimation shows how to treat unobserved prices and discusses the limitations (Klette and Griliches, 1996; Foster et al., 2008.)

[8]We treat each store as a decision maker. The majority of stores in our sample are single establishments in a local market. We use product categories as a proxy for product variety in a store. We focus on investments in machinery and equipment and refer to this as investments in capital and technology. In retail, technology is embedded in machinery equipment (hardware), which is used to generate sales.

The service-generating function for a multi-product store j can be described by a transcendental function that generalizes Cobb-Douglas (Mundlak, 1964; Maican and Orth, 2019a), i.e.,[9]

$$\sum_{i=1}^{d} \tilde{\alpha}_i q_{ijt} + \tilde{\alpha}_y Y_{jt} = \tilde{\beta}_l l_{jt} + \tilde{\beta}_k k_{jt} + \tilde{\beta}_a a_{jt} + \tilde{\omega}_{jt} + \tilde{u}^p_{jt}, \tag{1}$$

where q_{ijt} is the log of quantity of product i sold by store j in period t; Y_{jt} are total sales of store j in period t; l_{jt} is log of the number employees; k_{jt} is log of capital stock;[10] a_{jt} is log of the sum between the inventory level in the beginning of period t (n_{jt}) and the products bought during period t; $\tilde{\omega}_{jt}$ is quantity based total factor productivity (TFP, technical productivity); and $\tilde{u}^p_{jt}$ are i.i.d. remaining service output shocks.[11] Inventories enter as an input of the service generating function since the core activity of retail stores is to buy finished products from wholesalers and resell them to consumers (Bils and Kahn, 2000).[12] Moreover, decisions about inventories are strategic and dynamic, i.e., they affect long-run profits. A store's optimal inventory level balances two counteracting forces. Inventories reduce the risk of stock-outs and increase shopping quality but are costly to adjust and hold in stock. Inventories provide a convenience yield to consumers because they reflect the reduction in shopping cost, i.e., less frequent stock-outs, provision of variety, and other benefits associated with the underlying retail services (Working, 1949; Brennan, 1958; Pindyck, 1994; Cachon et al., 2018).

We follow the common notation of capital letters for levels and small letters for logs.

[9]In a companion paper, Maican and Orth (2019a) present a general result on the identification of multi-output service generating functions following Mundlak (1964) and discuss the restrictions of the parameters that must be satisfied for profit maximization. We assume that all stores use the same service technology to sell their product categories and that this technology does not depend on the product category. As discussed in Maican and Orth (2019a), this assumption helps to reduce the number of parameters to be estimated. However, it can be relaxed to allow a separate technology for each product when there are sufficient data for all products across markets over a long period.

[10]Capital stock is a dynamic input that accumulates according to $K_{jt+1} = (1-\delta)K_{jt} + I_{jt}$, where δ is the depreciation rate. The investment I_{jt} in machinery and equipment is chosen in period t and affects the store in period $t+1$.

[11]We can write a total sales generating function using Cobb-Douglas technology (in logs) at the store level instead of at the product level, i.e., no product information, $y_{jt} = \tilde{\beta}_l l_{jt} + \tilde{\beta}_k k_{jt} + \tilde{\beta}_a a_{jt} + \tilde{\omega}_{jt} + \tilde{\mu}_{jt} + u_{jt}$, where $\tilde{\mu}_{jt}$ are correlated demand shocks that include the quality of the shopping experience. Maican and Orth (2019a) use a simple demand and supply model to show the intuition behind the derivation of this aggregate service function equation.

[12]Recent literature on inventory explains the differences and the role of input and output inventories, e.g., Humphreys et al. (2001), Iacoviello et al. (2011), and Wen (2011).

Product demand. We assume that consumers are homogeneous and have CES preferences over differentiated products and services $i \in \{1, \cdots, d\}$ inside the store. We exploit the link between a CES demand system and a discrete choice demand system, which allow us to write the consumer choice probability equation from the CES preferences (Anderson et al., 1987; Anderson and De Palma, 2006; Hortacsu and Joonhwi, 2015). Using this relationship, the log of the price of product i (p_{ijt}) from the consumer choice probability equation is given by

$$p_{ijt} = -\frac{1}{\sigma}(q_{ijt} - q_{0t}) + \mathbf{x}'_{ijt}\frac{\boldsymbol{\beta}_x}{\sigma} + \frac{\sigma_a}{\sigma}a_{jt} + \frac{1}{\sigma}\tilde{\mu}_{ijt}, \tag{2}$$

where $\mathbf{x}_{ijt}$ are the observed determinants of the intensive and extensive margins of the utility function when consumers buy the product i; σ is the elasticity of substitution; $\tilde{\mu}_{ijt}$ are unobserved product characteristics for the econometrician, e.g., unobserved quality of shopping experience for product i in store j in period t; and q_{0t} is the outside option.[13] The presence of a_{jt} in equation (2) captures the fact that consumers prefer in-stock products to minimize the search cost. The vector $\mathbf{x}_{ijt}$ includes observed product and store characteristics and local market characteristics (for example, population, population density, and income). To simplify the notation, we omit the local market index m when the store index j is present and we refer to store j in market m.

We use the service production (1) and the price equation (2) to obtain the sales generating function at the store level, i.e., $y_{ijt} = q_{ijt} + p_{ijt}$ (Maican and Orth, 2019a):

$$y_{ijt} = -\alpha_y y_{-ijt} + (\beta_l l_{jt} + \beta_k k_{jt} + \beta_a a_{jt}) + \beta_q y_{mt} + \mathbf{x}'_{jt}\boldsymbol{\beta}_x + \omega_{jt} + \mu_{jt} + u^p_{ijt}, \tag{3}$$

where y_{ijt} is the log of the sales of product i in store j in market m in period t; y_{-ijt} is the log of the sales of products other than product i in store j; and y_{mt} measures sales of the outside option captured by the sales of products in a local market m that do not belong to the five-digit sub-sector of product i. By using sales of different products, we are able to reduce the number of parameters to be estimated, that is, we estimate only the coefficient of sales of

[13]Equation (2) is similar to the logit discrete choice demand system, but the price is in logs.

other products than product i at the store j, i.e. α_y, and not all coefficients α_i, $i = \overline{1,d}$.[14] The observed and unobserved product characteristics are aggregated at the store level using $\tilde{\alpha}_i$ as weights. For example, $\mu_{jt} \equiv (1/\sigma)\sum_{i=1}^{d} \tilde{\alpha}_i \mu_{ijt}$ sums all remaining unobserved product characteristics at the store level that affect consumer choices (i.e., demand shocks). We refer to demand shocks μ_{jt} as a measure of customer satisfaction and the quality of the shopping experience in store j in period t. Estimating only one coefficient for the other products (i.e., α_y) when controlling for unobserved prices has a cost, that is, we cannot obtain a clean measure of technical productivity $\tilde{\omega}_i$ because the coefficients of labor, capital and inventories include demand shocks even if we control for the elasticity of substitution. Therefore, the variable ω_{jt} ($\omega_{jt} \equiv (1 - 1/\sigma)\tilde{\omega}_{jt}$) measures the revenue total factor productivity (TFPR). The productivity measure ω_{jt} might include sales shocks due to approximations in (3), but all these sales shocks are different from the demand shocks μ_{jt} that affect consumers' preferences for a store. In other words, we are able to separate productivity shocks ω_{jt} from the demand shocks that are associated with a store's quality of shopping experience μ_{jt} (which is part of the demand system). Productivity ω_{jt} and demand shocks μ_{jt} are unobserved by the researcher, but they are known by the stores when making decisions. The vector $\mathbf{x}_{jt}$ sums all observed characteristics at the store and market levels. u^p_{ijt} are i.i.d. remaining shocks to sales that are mean independent of all the control variables and store inputs.

The coefficient α_y provides information on economies of scope and plays a key role for both the persistence and productivity level. The new parameters of the multi-product sales generating function (3), i.e., β_l, β_k, β_a are similar to the aggregate sales function at the store (firm) level, which allows us compare them with the previous estimates of single output technology.

Consumers' choice of store. Because the demand shocks μ_{jt} contain information about the quality of the shopping experience in a store, they affect consumers' store choice. Therefore, we can recover information about them from an aggregate discrete choice demand system at the store level, where the consumer's utility of choosing store j depends on the number of products (categories) np_{jt}, the log of average income in the local market inc_{mt}, and quality of the shopping experience μ_{jt}. Assuming i.i.d. Type-1 extreme value shocks on the preferences

[14] To obtain equation (3), we denote $\tilde{\alpha}_i y_{ijt} + \tilde{\alpha}_y Y_{ijt} \equiv \alpha_i y_{ijt}$ and $\tilde{\alpha}_i y_{-ijt} + \tilde{\alpha}_y Y_{-ijt} \equiv \alpha_y y_{-ijt}$ and normalize $\alpha_i = 1$. The coefficients are given by $\beta_c = \tilde{\beta}_c(1 - 1/\sigma)$ where $c \in \{l, k, x, a\}$.

for stores, we obtain the market share equation (see Berry, 1994)

$$ln(ms_{jt}) - ln(ms_{0t}) = \rho_{np} np_{jt} + \rho_{inc,1} inc_{mt} + \rho_{inc,2} inc_{mt}^2 + \mu_{jt} + \nu_{jt}, \tag{4}$$

where ms_{jt} is market share of store j in local market m in period t computed at the five-digit industry level; ms_{0t} is the outside option, i.e., the market share of other stores in market m; and ν_{jt} is mean independent of all the controls.

Sales are a commonly used output measure in services and depend on both demand and supply factors. In our model, sales depend on both the quality of the shopping experience μ_{jt} and productivity ω_{jt}, whereas a store's market share depends only on μ_{jt}. In other words, the market share equation (4) and the sales generating function (3) are linked through the quality of the shopping experience μ_{jt}. It is important to note that the shopping quality μ_{jt} measures factors other than product variety and demand shifters, for example, product quality, location, checkout speed, the courteousness of store employees, parking, bagging services, and cleanliness. Furthermore, because the sales generating function (3) controls for capital stock k_{jt} and inventory a_{jt}, they are not part of μ_{jt}, and we do not need to control for them in the market share equation.[15] The number of products (categories) np_{jt} is part of a_{jt}, but a_{jt} includes additional information, such as the volume of each product, and the products are aggregated based on monetary value.

Adjustment in inventory. We model inventory as a type of capital that evolves endogenously based on products bought from the wholesaler and adjustments in inventory, and it is characterized by adjustment and holding costs. The evolution and adjustments in inventory follow the previous literature (e.g., Coen-Pirani, 2004). The inventory level at the beginning of period $t+1$ evolves according to $N_{jt+1} = A_{jt} - Y_{jt}$, where A_{jt} is the adjusted inventory before sales, i.e., the inventory in the beginning of the period N_{jt} adjusted with the products bought in period t, and Y_{jt} is store-level sales. That is, N_{t+1} captures inventory in the beginning of period $t+1$ (or end of period t) after sales in period t are realized.

We build on previous work that emphasizes a link between inventory, demand, supply, pro-

[15] Even if we control for capital stock k_{jt} and inventory a_{jt} in the market share equation, we cannot separately identify their effects on demand and supply, i.e., we identify the net effect (Ackerberg et al., 2007).

ductivity, and sales over time (Kesavan et al., 2011; Kesavan and Mani, 2013; Alan et al., 2014; Cachon et al., 2018). Inventories affect store service output because high inventories are costly to keep in stock and low inventories reduce consumers' choices. There is a distinction between how μ_{jt} affects current inventories and products bought from the wholesaler, on the one hand, and the realization of inventories in the end of the year/start of next year on the other. A high quality of the shopping experience μ_{jt} creates incentives for stores to increase the products they buy from wholesalers. However, it might also lead to a drop in inventories at the beginning of the following year because of an unexpected increase in sales.

Stores trade off consumer quality and the risk of stock-outs against holding costs when deciding optimal inventory levels. Recent investments in new technologies in retail, such as bar codes and scanners, have drastically reduced information distortion, lead-time, uncertainty, and errors. For instance, stores can use real-time information about product flows to improve predictions of and adjustments to demand and to strengthen supply chain management, which implies that technological advancements increase the frequency of turnover and lower inventories. New technologies also create possibilities for stores to provide a wider variety of products and services at a lower cost. Lower holding costs for inventories increase the incentives to keep products in stock in order to guarantee consumer choices and high quality and to avoid stock-outs.

Evolution of productivity and shopping quality. Both store productivity ω_{jt} and the quality of the shopping experience μ_{jt} are correlated over time, and they are not observed by the researcher. Inventory holdings and investments in technology both have dynamic implications due to adjustment costs, and both ω_{jt} and μ_{jt} are important for such adjustments. We thus need to specify how productivity and demand shocks evolve over time. The quality of the shopping experience shocks μ_{jt} are correlated over time according to the following nonlinear AR(1) process

$$\mu_{jt} = \gamma_0^{\mu} + \gamma_1^{\mu}\mu_{jt-1} + \gamma_2^{\mu}(\mu_{jt-1})^2 + \gamma_3^{\mu}(\mu_{jt-1})^3 + \eta_{jt}. \tag{5}$$

Store productivity ω_{jt} follows an endogenous nonlinear AR(1) process where previous productivity ω_{jt-1} and the quality of the shopping experience μ_{jt-1} affect current productivity

$$\begin{aligned}\omega_{jt} = \;& \gamma_0^\omega + \gamma_1^\omega \omega_{jt-1} + \gamma_2^\omega (\omega_{jt-1})^2 + \gamma_3^\omega (\omega_{jt-1})^3 + \gamma_4^\omega \mu_{jt-1} \\ & + \gamma_5^\omega \omega_{jt-1} \times \mu_{jt-1} + \xi_{jt}.\end{aligned} \tag{6}$$

η_{jt} and ξ_{jt} are shocks to demand and productivity, respectively, which are mean-independent of all information known at $t-1$.

Our model allows store productivity to be influenced by the quality of the shopping experience that affects consumers' store choice and market share. The demand shocks associated with the quality of the shopping experience can influence store productivity in at least two ways. The first is through productivity gains within stores that arise, for instance, because stores obtain opportunities to analyze information from consumers and use it to improve the shopping process and inventory management. For example, store employees are responsible for many small improvements to shopping quality. The second channel is through a selection effect from the exit of low-productivity stores. Productivity changes as a result of changes in the quality of the shopping experience, although we also recognize that it is plausible that stores engage in other active efforts to increase their productivity. Our model quantifies the overall effect of the quality of the shopping experience on productivity rather than modeling all the possible sources of productivity improvement.

Store's optimal choices. Stores know their productivity ω_{jt} and the quality of the shopping experience μ_{jt} when they make their input and exit decisions. The model therefore yields stores' optimal choices, that is, the policy functions for inventory, investments, and labor, along with the number of products, as nonparametric functions of the store's state variables. That is, the optimal inventory is $a_{jt} = f_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, \mathbf{x}_{jt})$, investment is $i_{jt} = i_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, \mathbf{x}_{jt})$, labor is $l_{jt} = l_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, \mathbf{x}_{jt})$, and number of products is $np_{jt} = np_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, \mathbf{x}_{jt})$. The policy functions capture complex decisions by stores, where current choices affect the future development of the store. The estimation of policy functions is crucial for our empirical analysis and counterfactual simulations on how productivity and shopping quality influence inventory, investment, the number of employees, and the number of products (Ackerberg et al., 2007; Bajari et al., 2007).

Identification and estimation. The identification and estimation follow Olley and Pakes (1996) and the subsequent literature and include the estimation of the Markov processes for ω_{jt}

and μ_{jt} (Ackerberg et al., 2007; Maican and Orth, 2019a). We estimate θ=(β_l, β_k, β_a, β_x, α_y, β_q, ρ_{np}, $\rho_{inc,1}$, $\rho_{inc,2}$) using a two-step estimator and the store's labor demand function to recover productivity (Doraszelski and Jaumandreu, 2013; Maican and Orth, 2017).[16] In contrast to Olley and Pakes (1996), we have two unobservables to recover instead of one (see also Maican and Orth, 2019a). We use the store's demand for inventory a_{jt} to recover the quality of the shopping experience μ_{jt}. The online Appendix B provides additional details on the estimation and identification.

Because productivity ω_{jt} and μ_{jt} are functions of coefficients of the service generating function and market shares, we can identify θ coefficients using moment conditions based on $(\xi_{jt} + u_{ijt})$ and $(\eta_{jt} + \nu_{jt})$ and the generalized method of moments (GMM) estimator. To identify θ the following moment conditions are used, i.e., $E[\xi_{jt} + u_{ijt}|\ y_{-ijt-1},\ l_{jt-1},\ k_{jt-1},\ a_{jt-1},\ \mathbf{x}_{mt-1}] = 0$ and $E[\eta_{jt} + \nu_{jt}|np_{jt-1}, inc_{mt-1}, inc^2_{jt-1}] = 0$.[17] That is, we use that the remaining shocks are not correlated with the previous variables to form the moments.[18] It is important to note that having the parameters of the multi-product sales generating function and the market share equation, we estimate the parameters of the Markov processes. The parameters $\boldsymbol{\theta}$ are estimated by minimizing the GMM objective function

$$\min_{\boldsymbol{\theta}} Q_N = \left[\frac{1}{N} W' v(\boldsymbol{\theta})\right]' A \left[\frac{1}{N} W' v(\boldsymbol{\theta})\right], \tag{7}$$

where $v_{jt} = (\xi_{jt} + u_{ijt}, \eta_{jt} + \nu_{jt})'$, W is the matrix of instruments, and A is the weighting matrix defined as $A = \left[\frac{1}{N} W' v(\boldsymbol{\theta}) v'(\boldsymbol{\theta}) W\right]^{-1}$.[19]

The relationship with input share estimators. Our model is closely related to De Loecker et al. (2016) even if their method estimates input shares and our method uses output shares. As in De Loecker et al. (2016), we have separability in inputs and outputs in the production

[16]Levinsohn and Petrin (2003) use intermediate inputs to recover productivity.

[17]Using Monte-Carlo simulations, Maican and Orth (2019a) and Maican and Orth (2019b) show identification of the multi-product sales technology using labor demand to proxy for productivity. They also show that the product sales system of equations at the store level (non-linear) has a unique solution, which implies that we can compute product sales if we have information on inputs, productivity and demand shocks.

[18]Ackerberg et al. (2007) and Wooldridge (2009) provide an extensive discussion on using previous variables as instruments in a two-step control function approach when estimating production functions.

[19]Standard errors are computed according to Ackerberg et al. (2012).

technology and model firm/store productivity and not product-firm productivity (Dhyne et al., 2016; Valmari, 2016; Orr, 2018). In the retail context, it is difficult to define a meaningful measure of product-store productivity. Using the aggregation over inputs and outputs, Maican and Orth (2019b) show that there is a direct relationship between the input shares from a Cobb-Douglas technology at the product level and output shares of transcendental technology. The relationship exists because both technologies use firm/store productivity, i.e., do not need to aggregate product productivity.

Separating input allocations per product can be difficult in service industries. For example, different machinery and equipment are used to carry or to store different product categories in the same time to increase efficiency. Separation of all inputs is not fully consistent with economies of scale and scope. Since our focus is on economies of scope and not recovering product markups, transcendental technology that uses observed output shares is preferable because it does not require additional assumptions as are required to recover input shares (not observed in the data).

3 Data description

The empirical application focuses on *Retail sale of new goods in specialized stores* (Swedish National Industry (SNI) three-digit code 524). This retail sector includes the following sub-sectors at the five-digit SNI: clothing, footwear and leather goods, furniture and lighting equipment, electrical household appliances and radio and television goods, hardware, paints and glass, books, newspapers and stationery, and specialized stores.

We use two data-sets provided by Statistics Sweden. The first data-set covers detailed annual information about all retail firms in Sweden (census) from 2000 to 2009. The data contain financial statistics of input and output measures, i.e., sales, value-added, the number of employees, capital stock, inventories, cost of products, and investment. Inventories capture the value of products held in stock by the end of each year and are taken from book values (accounting data). Sales are measured in output prices, whereas the cost of products and inventories are measured in input prices (what stores pay to the wholesaler). Because of difficulties in measuring quantity units in retailing (and services) arising from the nature and complexity of the product assortments, quantity measures of output and inventories are not available in many data-sets such as census data. In retail, we often refer to firms as stores. In our data, a unit of observation is an organization number.[20] We observe the municipality in which each organization number is physically located. Following previous work on Swedish retail, we use municipalities as local markets (Maican and Orth, 2015; Maican and Orth, 2018). Therefore, an advantage of our data is that we can exploit local variation and study the impact of competition.

Our second data-set covers store-level information on the number of products (product categories) and their values sold each year. To the best of our knowledge, such detailed data on the number of products across stores and local markets in services industries have not previously been used in the literature. The data cover all product categories that a store sells on a yearly basis. Unique identification codes allow us to match products perfectly to stores.[21] To reduce the dimensionality of the product space in the empirical application, we use well-defined product categories to define store products, e.g., shoes for women, shoes for men, and shoes for children. The number of product categories captures the extensive margin of product variety inside a store. Data on sales per product category capture the intensive margin of product lines (range) inside a category. Most importantly, the combination of the two data sets allows us to compute product market shares inside a store and a store's market share in a geographic market, which provides rich information related to competition. The mix of product-level and store-level data is novel and, to the best of our knowledge, has not been used in service industries before. We apply commonly used measures of inventory productivity. First, we define inventory turnover as the cost of goods sold over average inventory. Second, we define inventory turnover as sales over inventory.[22] We also use the inverse of inventory turnover based on sales, that is, the inventory-to-sales ratio that is commonly used in the macroeconomics literature.

Descriptive statistics and stylized facts. Table 1 shows the median in the interquartile

[20] In a few cases in our data, an organization number can consist of more than one physical store (a multi-store) in the same municipality, for which we observe total, not average, inputs and outputs. Multi-store reporting is less than 5 percent in our sample (Maican and Orth, 2015).

[21] The product data set follows a similar classification system to the one used for the sample data collected on prices and quantities in manufacturing (PRODCOM).

[22] The average inventory between period t and $t+1$ is often used. Based on annual data, we can also construct the number of days inventory is at hand, for example, $365/(sales_{jt}/inventory_{jt})$.

range for the key variables in our data. The median store in our data has approximately 11 million SEK in sales, seven employees, and approximately four product categories. The number of product categories varies between one and 17 in our sample. The five-digit sector median market share is approximately 34-38 percent in a local market, and it is increasing over time. There is an increase in the local concentration over time in our sample, for example, median C4 computed at the five-digit sector increases from 91 to 94 percent.

Figure 1 shows a strong positive trend in inventories, investments in new technology and inventory turnover (the sales-to-inventory ratio) using aggregate data at the retail industry level. The positive co-movement between inventory and inventory turnover is consistent with the view of inventory as a convenience yield that helps to avoid stock-outs. In addition, the positive co-movement between inventory and investment in technology suggests that there are common factors that affect these variables. In particular, we exploit the fact that stores make endogenous input choices of both investments and inventories, and the implications for productivity (Holmes, 2001).

For a better understanding of the relationship between store performance and product variety (extensive and extensive margins), we investigate the evolution of correlations over time in Table 2. The number of product categories (extensive margin) is negatively correlated with sales per cost of goods, which suggests that stores with fewer product categories sell more per unit cost. In addition, the number of product categories is positively correlated with capital stock per employee and the local market share (benefits of economies of scope). These findings suggest that the trade-off between productivity and quality might play a key role for product selection. Capital per employee is positively correlated with cost of goods per product category implying that stores with high technology sell a larger range of products into a product category or sell high-quality products.

On the intensive margins related to product variety, we focus on the average sales per product category and the entropy of product sales. Entropy measures store diversification in sales and is computed for each store j based on market share of each product category i inside store, i.e., $E_{jt} = \sum_i ms_{ijt} ln(ms_{ijt})$ (Bernard et al., 2011). A large measure of entropy suggests that the store focuses on top sales categories. The average sales per product category is positively correlated with measures that affect productivity and shopping quality, such as capital stock per employee and average wage at the store. Stores with sales driven by top products (i.e., large entropy) have high inventory per product category and thus high quality. Stores with high local market shares have low entropy, a large end of year inventory, and high labor productivity and capital stock per employee.

The correlations show that labor (the number of employees) and investments are important for understanding inventory behavior, which provides information on demand shocks such as the quality of shopping experience. We find a strong positive correlation between labor productivity and inventory measures, such as the end of year inventory, inventory turnover (cost of goods sold over inventory), and inventory per product category. The correlation between labor productivity and inventory turnover increases over time. Inventory turnover was negatively correlated with labor and investments before the 2008 crisis and positively correlated after the crisis, which highlights the importance of demand shocks and technology for inventory performance. The negative correlation between sales and inventory-to-sales ratio is consistent with the findings of the literature in macroeconomics (e.g., Ramey and West, 1999; Kryvtsov and Midrigan, 2012).

Using reduced-form regressions, we investigate the role of local competition and of a store's measures related to market power in driving changes in product variety and inventory. Table 3 shows evidence of the relationships between the degree of local competition, a store's market share and margins and the number of product categories at the store level using the fixed-effect estimator that controls for store heterogeneity.[23] The findings show that an increase in local concentration decreases the number of product categories, i.e., stores specialize. Second, stores with large margins have a smaller number of product categories.

Table 4 shows the evidence of the relationships between the degree of local competition and store market power and inventory measures such as the end of year inventory and inventory-to-sales ratio using the fixed-effect estimator. Store productivity and quality of shopping quality are main determinants of market power, and they drive the heterogeneity across stores. The results show that an increase in local market concentration (C4 and HHI) has a positive effect on the end of year inventories. Second, the end of year inventories also increases with a rise in store's market power measured by market share and margins. Third, our reduced-form regres-

[23] A store's margins are proxied using the (net sales - cost of goods)/net sales ratio.

sions also show that the inventory-to-sales ratio decreases with an increase in local concentration and a store's market power.

Because of the increasing concentration in retail over time, we investigate whether stores with market power have high productivity. Table 5 presents reduced-form evidence of the relationship between sales per employee (labor productivity) and stores' market share using an AR(1) specification. We find that an increase in market share is associated with higher labor productivity. Thus, stores use their market power benefits to improve their productivity. In other words, stores use their information on demand to improve productivity. The persistence in labor productivity is about 86 percent. While all the reduced-form results might be biased because of the endogeneity of local competition and market power, they help to understand the variation in the data and show evidence of the existence of superstar firms discussed in Autor et al. (2018).

4 Results

This section presents the empirical results. First, we discuss the results of the estimated multi-product sales generating function, which include estimates of store productivity and consumers' perceived quality of the shopping experience and how they evolve over time.[24] Second, we examine the determinants of stores' optimal choices of the number of product categories and inventory per product, which are functions of the state variables. We also estimate labor and investment demand functions that are used in the simulations to evaluate counterfactual policy experiments. Our aim is to explore the heterogeneity in productivity and shopping quality and their role in explaining economies of scope and performance across retail stores.

Service generating function estimates. Table 6 shows the estimates of the multi-product sales generating function (equation (3)) by the ordinary least squares (OLS) estimator and the nonparametric two-step estimator presented in Section 2. The two-step estimator controls for the endogeneity of store input choices (i.e., simultaneity) and allows us to identify store produc-

[24]To allow for comparisons across specifications, we show the results using the two-step estimator where coefficients are adjusted for the elasticity of substitution σ and the coefficient of other product categories inside the store $\tilde{\alpha}_y$.

tivity separately from shocks to market share. By using the two-step estimator, the coefficients of labor and inventories decrease from 0.786 (OLS) to 0.558 and from 1.036 (OLS) to 0.493, respectively. The coefficient of capital increases from 0.059 (OLS) to 0.283 (the two-step estimator). These changes in the estimates are in line with the production function literature following Olley and Pakes (1996), which suggests an upper bias for the coefficients of labor and inventories when omitting control for the correlation between inputs and productivity.

The estimated elasticity of demand for product substitution ($1/\sigma$) is 4.63. There is clear evidence of competition for limited shelf space among products in a store. Sales of a product category decrease when sales in other product categories increase. With the same resources, a 1 percent increase in sales of a product category decreases sales of other product categories by 0.856 percent. This finding is consistent with the profit maximization behavior of multi-product firms (see Mundlak, 1964; Maican and Orth, 2019a). The coefficient of a store's other product categories influences the input coefficients, which affect the productivity measure. Our estimates also show that stores in markets with high population and population density sell more in each product category (i.e., demand effect).

The results from the market share equation (4) clearly show that a store's market share increases in product variety (0.213). In other words, a wider span of products increases the market share. For example, a store with a 30 percent local market share increases its market share to 35 percent by adding one more product category. Income has a positive effect on the consumers' utility function and, therefore, on a store's market share.

Productivity and consumers' perceived quality. The heterogeneity of productivity and shopping quality is informative because it drives the heterogeneity in sales across stores. Using the estimated parameters from the sales generating function, we recover productivity ω_{jt} and shopping quality μ_{jt} for each store and year. Store shopping quality μ_{jt} has a larger variance than productivity ω_{jt}. For productivity, a store in the 75th percentile has 27 percent greater productivity than a store in the 25th percentile. However, the shopping quality is approximately 50 percent higher for a store in the 75th percentile than for a store in the 25th percentile.

Table 7 shows the estimates of the processes for store productivity ω_{jt} and shopping quality μ_{jt}, i.e., equations (6) and (5). The persistence of the productivity process (0.85) is lower than the persistence of the shopping quality (0.92). The magnitude of the persistence in productivity is similar to the findings in other studies in the productivity literature (e.g., Doraszelski and Jaumandreu, 2013 – manufacturing; Maican and Orth, 2017 – retail).

In our model, shopping quality can affect store productivity, and the size of the impact depends on the level of store productivity. The results in Table 7 show that we reject the null hypothesis that the coefficients of shopping quality μ_{jt} in the productivity process are equal to zero (*p-value*=0.000). The shopping quality has a positive impact on productivity, i.e., a one percent increase in μ_{jt} raises productivity by 0.013 percent on average. This finding suggests that stores use information from consumers' choice to improve productivity, that is, learning from managing demand. For example, consumers assign high shopping quality to stores with skilled and service-minded employees who help them during the shopping process. These high-ability employees use information from consumers to create appealing innovations that shift store productivity.

4.1 Product variety, inventory, and market power

The solution of the dynamic programming at the store level given by Bellman equation states that store's choices such as the number of products, inventory, investment and labor are functions of the state variables. In our case, the state variables that are used to decide optimal choices are productivity (ω_{jt}), shopping quality (μ_{jt}), previous capital (k_{jt-1}), inventories at the beginning of the period (n_{jt}), and local market characteristics ($\mathbf{x}_{jt}$).

Product variety. To analyze the determinants of economies of scope, Table 8 shows the estimates of store's product variety and diversification as functions of the state variables using a linear specification that controls for store fixed-effects. The changes in the number of products capture stores' adjustments in the extensive margin. To evaluate the adjustments in intensive margins, we use two measures of store diversification. The first measure is the Herfindahl index (HHI) calculated based on sales of product categories inside the store. The second measure of diversification is the entropy of product sales that measures the extent to which a store's product sales are skewed toward the largest (main) products rather than the smallest.

Productivity improvements allow stores to offer a wider product variety. The results show that a 10 percent increase in productivity yields a 3 percent increase in the number of product categories. Stores that invest in technology have more product categories, for example; to add an additional product category an average store needs approximately a 3 percent increase in the stock of technology. We find that stores that offer a higher quality have a lower number of product category. On average, a 10 percent increase in quality reduces the number of product categories by 0.4 percent. Therefore, we find evidence of specialization for stores that offer high shopping quality to consumers, that is, it is costly for stores to keep the same quality and offer a large product variety (dis-economies of scope). Stores with large inventory at the end of year reduce their product variety. Our results highlight the trade-off between productivity and quality for a store's optimal product variety.

Table 8 shows key results for store diversification, i.e., how stores react in the intensive margin to changes in store and market primitives. A one percent increase in productivity yields a drop of 7 percent in HHI inside the store, that is, a lower concentration inside the store. Investments in technology also reduce concentration inside the store. An increase in the stock of technology by one percent decreases concentration by 2 percent. On the other hand, an increase in shopping quality increases concentration, which is consistent with the results from the extensive margin.

The findings on entropy show the importance of the trade-off between productivity and quality for the diversification inside a store. Highly productive stores have lower entropy in product sales, which implies higher sales across all product categories. That is, the entropy decreases by about 15 percent when productivity increases by one percent. On the contrary, an increase in shopping quality by one percent raises entropy by 2 percent, which suggests that stores with high quality focus on their top sales. The results also show that stores with large end of year inventory have large entropy. In other words, stores characterized by top selling products have high inventory, which help them to avoid stock-outs.

Determinants of inventory per product. Table 9 shows the determinants of average inventory per product before sales are realized ($log(A_{jt}/np_{jt})$) and average inventory per product after sales are realized ($log(N_{jt+1}/np_{jt})$). Higher productivity and quality yields higher inventory per product before sales, that is, higher demand for inventory. A one percent increase in store productivity (quality) shifts average demand for inventory per product by about 0.05

percent (0.06 percent). More productive stores have lower inventory per product after sales are realized. That is, stores that sell more of a product due to their high productivity remain with less inventory per product after sales are realized. A 10 percent increase in productivity is associated with 1.2 percent lower end-of-period inventory per product. Stores with higher quality provided to consumers have higher inventory per product after sales are realized, which again suggests the importance of inventory for strategic competition (i.e., eliminate stock-outs).

Market share. Table 9 also provides reduced-form information on the determinants of a store's local market share. Improvements in productivity and quality yield a higher market share to stores in local markets. Productivity increases a store's market share substantially more than quality, i.e., 0.16 versus 0.01 percent. The positive effect of productivity and quality on market share comes from two channels. First, stores that increase their productivity offer more products and sell more of each product. Second, stores that increase their quality focus on increasing sales of top products. Taken together, stores with higher productivity and higher quality achieve a higher market share.

The determinants of the demand for investment in technology and inputs. Table 10 shows the estimates of the policy functions for investment demand in technology, labor demand, and total inventory demand before sales as functions of the state variables. Understanding these estimates plays a key role in studying store's dynamics. Panel A shows the linear specifications of the determinants of the policy functions controlling for store fixed effects. Panel B shows that prediction of the observed data using b-splines approximation and OLS estimator. This specification is consistent with the nonlinear propriety of policy functions from solving the Bellman equation. For all policy functions, b-splines approximations provide a good prediction of the observed data.

The findings in Panel A show that stores with high productivity and shopping quality invest more in technology. This result is consistent with the store's dynamic programming property used for identification in the Olley and Pakes' framework, i.e., the optimal investment demand increases with productivity.[25] A 10 percent increase in productivity increases the demand for

[25] In this paper, investments in machinery and equipment are associated with investments in technology. For example, a new refrigerator includes innovations in both design and technology, which saves space and costs and allows more products to be exposed efficiently.

investment by 2.4 percent on average. Shopping quality also increases a store's optimal investments. A 10 percent increase in shopping quality increases investments by 1 percent. These findings are consistent with the positively correlated trends of inventories and investments in new technology in Figure 1.

In our model, labor demand plays a key role as a proxy variable in recovering productivity and shopping quality. Most important, the industry facts emphasize that consumers' shopping experience depends on the employees inside the store. We find that the number of employees is increasing in productivity and shopping quality. As we expect, the impact of productivity on labor demand is larger than of quality. Furthermore, stores in markets with a large population and high income have more employees.

Stores with high productivity and shopping quality have high inventories a_{jt}. Inventory increases substantially more from productivity than from shopping quality. A 3.3 percent increase in inventory before sales (a_{jt}) is the optimal response to a 10 percent increase in store productivity. The corresponding increase in inventory from a 10 percent increase in shopping quality is 0.1 percent. Store productivity thus plays a more important role for inventory than demand shocks related to quality of shopping experience.[26] As expected, stores that have large capital stock, and that are located in markets with high population density have higher inventories.

Summary of main results. Our estimates of optimal decisions suggest that productivity improvements bring an increase in the flow of products to consumers and allow stores to manage a wider product variety. Productivity as a main driver of product variety links closely to the work by Holmes (2001). At the same time, stores hold more inventories to avoid declining sales due to stock-outs (e.g., consumers might switch to other stores). We show that there are complex trade-offs between productivity and shopping quality that are important for stores to account for when deciding the optimal product mix in the store.

[26]Because higher productivity and shopping quality increase a store's market power, these findings are consistent with Amihud and Mendelson (1989), who show that firms with greater market power hold more inventories and have higher volatility in inventories.

5 Counterfactual experiments

We use the estimated model to perform several counterfactual policy experiments. Knowledge about the underlying primitives related to multi-product sales technology and demand is crucial for simulating changes in a store's outcomes following hypothetical changes. The counterfactual experiments highlight recent trends in retail businesses and relate directly to the hands-on decisions of retailers, offering implications for understanding the development of economies of scope in retail.

Retailers face trade-offs between investing to reduce costs and stimulating demand in their budget allocation. Investments are subject to uncertainty and affect both extensive and intensive product margins. By using the estimated model and numerical tools, this paper measures the impact of uncertainty and provides an understanding of these trade-offs faced by retailers. We compare stores' optimal decisions and store outcomes before and after a hypothetical cost reduction (through improvements in productivity) and/or an enhanced customer base (shopping quality). Examples of productivity enhancing activities in retail are new innovations made by employees on the floor when handling multi-product and innovations that arise from investments in new technologies such as self-scanning and new payment systems, technology upgrades, and new software to improve supply chain management. Activities that stimulate the quality of the shopping experience for consumers relate to improved customer service through, for instance, the repositioning of products inside the store, better product information from digitalization, and more specialized employees.

The sign and size of the changes in a stores' optimal decisions from a counterfactual experiment and how they affect extensive and intense margins are theoretically ambiguous and depend on the trade-off between store's primitives productivity and shopping quality. For instance, stores face incentives to expand product variety as a result of productivity improvements, whereas product variety may either expand or contract as a result of demand shocks. In particular, we estimate net changes in short- and long-run product variety, consumer surplus, investments, input levels and performance such as inventory performance from hypothetical changes in productivity and demand, which is not possible without tools that model stores' optimal decisions. Using the market share equation (4) in Section 2, we compute consumer surplus in local markets under the assumption of a logit demand model and no changes in the characteristics of local markets (i.e., population, population density, and income).[27] For each store, we compute averages of over 100 simulations over five years, starting with the last year in the data.[28] The proposed counterfactual policy experiments assume that the new equilibrium is consistent with the observed equilibrium in the data, which allows us to use the estimated policy functions in the simulations (Bajari et al., 2007).

This paper implements four policy experiments. The first (CF_1) analyzes the impact of positive innovation shocks to productivity by shifting the mean of ξ_{jt}. The estimated mean of these shocks is close to zero, and the mean is set to 0.05 in CF_1. Second, counterfactual CF_2 adds a decrease in uncertainty in shopping quality innovations to the positive shocks to productivity (CF_1). To be comparable to CF_1, we reduce the standard deviation of innovations in shopping quality η_{jt} by 30 percent and increase the mean of productivity shocks ξ_{jt} to 0.05. The third counterfactual (CF_3) studies the effect of positive innovations on the quality of the shopping experience by shifting the mean of innovations in shopping quality η_{jt} to 0.05. The fourth counterfactual (CF_4) decreases uncertainty in productivity innovations in addition to increasing shopping quality in CF_3. To compare CF_3 and CF_4, we decrease the standard deviation of innovations in productivity ξ_{jt} by 30 percent, and the mean of innovations in shopping quality η_{jt} is set to 0.05.

Table 11 shows the mean and interquartile range of the changes in the number of product categories, consumer surplus, the number of employees, investments, inventory (end of the year and turnover).[29] Changes in the labor and inventory affect store's intensive margins. The dynamic nature of our theoretical model allows the counterfactual simulations to explore both

[27]Stores that are not in the sample for which we observe product-level information are included in the outside option. We access input and output measures for all stores, whereas the product-level data are available for a sample. See the data section for details (Section 3).

[28]The base simulations use estimated means and standard deviations of the innovations in productivity and shopping quality (i.e., ξ_{jt} and η_{jt}). Using the logit demand system to compute market shares for the years in the data, we predict the observed store market shares well (e.g., the last year in the data), which suggests that the logit demand is not a restrictive assumption in our case, although cross-price elasticities are not the primary focus of this paper (Berry, 1994).

[29]Following Small and Rosen (1981), the consumer surplus in market m in period t is computed from equation (4) $W_{mt} = M \times ln(\sum_j exp(\rho_{np} np_{jt}(\mathbf{s}_{jt}) + \rho_{inc,1} inc_{mt} + \rho_{inc,2} inc^2_{mt} + \mu_{jt}))/\sigma$, where M is market size (population) and $np_{jt}(\mathbf{s}_{jt})$ is the predicted number of product categories using the store's state variables $\mathbf{s}_{jt}$.

short- and long-run implications following hypothetical changes in productivity and/or shopping quality. We discuss the changes in store decisions and outcomes after one, three, and five years in detail.

5.1 Counterfactual I: Innovations in productivity

The direct effect of improving productivity (CF_1) is an increase in the volume of transactions, which affects sales, input choices, the number of products and inventory (Holmes, 2001). The number of products and consumer surplus increase slightly. On average, the number of products increases by 1.2 percent after one year and by 2 percent after five years. The findings show that higher productivity connects to more labor, investments in technology and inventories to support store growth. The productivity increase yields a 1.5 percent increase in the number of employees in the coming year and a 9.4 percent increase after five years. The demand for investments increases by 3 percent in the coming year, reaching up to 20 percent after five years. Inventories at the end of the year also increase. Inventory turnover increases by 1.7 percent in the first year and increases up to 2.6 percent after five years. The finding that both inventory at the end of year and the number of product categories increase suggests that stores use cost savings from productivity improvements to ensure that consumers access a larger product variety. In summary, our simulations in CF_1 confirm that productivity improvement is a crucial determinant of positive changes in the number of products, investments and inputs.

5.2 Counterfactual II: Innovations in productivity and reduced uncertainty in shopping quality innovations

The second policy experiment CF_2 adds a reduction in the dispersion of shopping quality innovations to CF_1 (i.e., it reduces the extreme values in the shopping quality received by stores). Reducing uncertainty in shopping quality innovations makes stores specialize in the short run and increase the number of product categories in the long run (about 12 percent after five years). In the short run, stores specialize because even if they might receive positive innovations in shopping quality, they are not large enough to shift the potential demand. As a result, stores face stronger competition, which creates incentives for them to reposition. In the long run, there is room for market expansion because stores can predict demand and productivity changes more accurately as a result of reduced uncertainty. Consumer surplus follows the same pattern and increases about 2 percent after five years.

Stores hire and invest in technology more when uncertainty in demand is reduced, which implies that local communities benefit because stores hire more.[30] There is clear evidence that inventory performance increases more in CF_2 than in CF_1, which is especially true in the long run, where inventory turnover increases by about 7 percent after five years. By reducing uncertainty in shopping quality, stores avoid drops in shopping quality that accumulate over time and affect future productivity. For example, avoiding a decrease in shopping quality due to consumers' misunderstanding about product information reduces the amount of time that employees spend on nonproductive tasks, such as searching for the right information or product. We conclude that both higher productivity and lower dispersion in shopping quality are crucial for a substantial increase in the number of products, consumer surplus and demand for investments in technology in the long run.

5.3 Counterfactual III: Innovations in shopping quality

The third policy experiment (CF_3) increases the mean of innovations in shopping quality, i.e., the mean of η_{jt}. Because the average shopping quality increases by the same magnitude in CF_3 as innovations in productivity increase in CF_1 and CF_2, these counterfactuals are directly comparable. The direct effect is that consumers are more willing to buy from a store that increases sales. The number of product categories decreases, i.e., there is an increase in store-level specialization on average. The increase in consumer surplus is approximately twice as high as it was in the experiments that raise productivity (CF_1 and CF_2). Thus, consumer surplus increases even if stores specialize and offer fewer product categories. Store shopping quality drives this increase in consumer surplus and outweighs the decrease in the number of products. Given that the shopping quality comprises various factors that increase consumer satisfaction to buy but that are unobservable to the researcher (e.g., shopping experience, product quality,

[30]Note that this benefit is not part of our consumer surplus measure.

etc.), our findings suggest that benefits from economies of scope are modest, and that store size expansion and performance improvements can be slow if retailers target only consumer satisfaction without considering productivity improvements.

The simulations also show that investment demand, labor, inventory, and inventory turnover increase, but the changes are substantially lower than in the policy experiments that increase the mean of innovation shocks in productivity (CF_1 and CF_2). For instance, the increase in the number of employees in CF_3 is only about one-third of that in CF_1 (i.e., labor increases 0.4 percent in the coming year, 1.5 percent after three years, and about 3 percent after five years). Inventory turnover experiences an increase below 1 percent on average in the short-run, which is indeed distinctively lower than the outcomes when productivity shocks increase.

5.4 Counterfactual IV: Innovations in shopping quality and reduced uncertainty in productivity innovations

The policy experiment CF_4 adds to CF_3 a 30 percent reduction in the standard deviation of the innovation shock in productivity (i.e., ξ_{jt}). That is, stores experience an average increase in shopping quality μ_{jt} and fewer extreme innovation shocks in productivity. By raising shopping quality consumers benefit and extract more surplus, and stores increase specialization (similar to CF_3). Because the opportunity to gain large improvements in productivity decreases and productivity depreciates yearly (property of an AR(1) process), stores reduce their labor force (about 1.5 percent after three years, and 8.5 percent after five years). Investments decline in the short run but rise in the long run. Therefore, stores substitute labor for capital in the long run. This substitution pattern highlights the importance of productivity improvements for store development. There is a small increase in inventory turnover in CF_4 compared to CF_3, which is driven mainly by avoiding large drops in productivity. Moreover, because of reduced uncertainty in productivity, the growth in inventories at the end of the year is smaller than in CF_3. We conclude that stores specialize, and thus modestly exploit economies of scope, and reduce employment after decreasing uncertainty in productivity and increasing the level of shopping quality. In the long run, stores experience a labor-capital substitution. Most importantly, stores do not hire or invest as much as in policy experiments that raise productivity, which also dampens inventory performance.

All four counterfactual experiments together point to productivity being key to driving of product variety (extensive margin), and thus opportunities to take advantage of economies of scope, and inventory performance (which is affected by both intensive and extensive margins). Shopping quality, on the other hand, induces specialization and only minor improvements in inventory turnover if it is not sustained together with productivity improvements. Our results confirm the theoretical findings in Holmes (2001).

6 Robustness

This section discusses the robustness of the results using alternative modeling specifications.

Estimation of the service generating function. In this paper, the labor and the cost of products bought are used as proxy variables to recover productivity and shopping quality. However, instead of labor demand, the investment demand function can be used to recover productivity. The estimation results remain robust when using investment as a proxy, e.g., the estimated persistence in productivity and shopping quality is similar to our main results. Most importantly, productivity is still the main driver of a store's choices. We prefer the specification using labor demand because it uses all observations in the data and does not require positive investments.

The identification of the model uses the variables in $t-1$ as instruments (Ackerberg et al., 2007; Ackerberg et al., 2015). The estimates do not change when using local market variables in the current period t as instruments. The persistence of productivity increases if the sales of other product categories in period t (y_{-ijt}) are used as an instrument. As we expect, this finding indicates that the moment condition based on y_{-ijt} does not hold and affects the identification of all parameters of the sales generating function. For this reason, using previous sales of other products y_{-ijt-1} as an instrument is a better choice.

Inventory, market size, and competition. Appendix B presents in the first part a simple model that highlights the dynamic relationship between productivity and inventory performance measured by inventory turnover. In the second part of online Appendix B, we discuss in great detail the determinants of inventory turnover. We show that productivity has a greater effect than shopping quality on inventory turnover in all parts of the distribution. Furthermore, the marginal effects of both productivity and shopping quality are larger for stores with already high inventory turnover. A productivity increase yields an increase in inventory turnover that is 1.5-2 times higher in the 75th percentile than in the 25th percentile. The difference becomes even more evident for an increase in shopping quality, where inventory turnover increases 2-3 times more in the 75th percentile than in the 25th.

In both small and large markets, a store's own productivity is the main driver of improvements in inventory turnover. Stores in small markets with intense competition from rivals (i.e., rivals' productivity and shopping quality) have higher inventory turnover. This finding suggests that surviving stores learn from increasing competitive pressure to improve inventory efficiency. Importantly, the impact of rivals' productivity on inventory is approximately double that of rivals' demand. Again, the impact of rivals' competition on inventory turnover is small (and not statistically significant for productivity) in large markets. In those markets, with stronger competitive pressure from rivals' productivity, stores specialize, i.e., they decrease the number of product categories. Furthermore, if the rivals offer a high-quality shopping experience, then a store offers more product categories to counterbalance the drop in market share.

Alternative counterfactual experiments. The fifth counterfactual experiment (CF_5) evaluates positive shocks to productivity to compensate for negative shopping quality. CF_5 assumes that stores experience larger positive shocks to productivity than in CF_1, i.e., the shocks in productivity are four times larger than the negative shocks to demand. That is, we increase the mean of ξ_{jt} to 0.2 and decrease the mean of ν_{jt} to -0.05. Due to productivity improvements, stores grow in size (labor) and expand their product categories. Consumers experience more product variety to compensate for the negative effect caused by the decrease in shopping quality μ. The detailed results from this alternative counterfactual are presented in online Appendix D, which also discusses heterogeneity across markets in the counterfactual experiments.

7 Conclusions

There is evidence that the long-lasting increase in concentration in retail industries is driven by economies of scale. Still, we need more knowledge about the importance of economies of scope. This paper studies the determinants of economies of scope in retail by recovering key economic primitives of demand and supply. We provide a dynamic structural model that allows for economies of scale and scope using a multi-product sales technology and a demand system to estimate total factor productivity and demand shocks related to shopping quality. We use the recovered primitives to evaluate their role in extensive and intensive margins related to product variety (i.e., the number of products, entropy of product sales) and inventory. In our model, stores optimally adjust product variety, labor, inventory holdings, and decide on investments in technology based on their productivity, consumers' perceived shopping quality and the local market environment.

We estimate the model using novel data on a store's product variety, inputs, outputs, inventories, and products bought from the wholesaler in the retail sale of new goods in specialized stores in Sweden from 2003 to 2009. Important contributions to the existing literature are that we recover two unobserved store-level primitives to researchers, account for multi-product sales technology, and allow stores to learn about demand to improve future productivity. The model is used to investigate the underlying theoretical primitives behind economies of scope and to perform counterfactual experiments that evaluate retailers' responses to changes in levels and the uncertainty of productivity and shopping quality.

Our empirical findings highlight the trade-off between productivity and shopping quality for retail development. We find that stores learn from consumers' perceived quality of shopping experience to increase future productivity. Stores with high productivity and investment in new technology have a wider variety of products and sell more of all products. On the contrary, stores with high quality have a narrower variety of products and sell more of their top products. Stores with high shopping quality also have higher inventory per product. We conclude that there are two counteracting forces of productivity and quality determining stores' ability to utilize economies of scope and thus the optimal product variety offered to consumers.

The counterfactual experiments show that positive shocks to productivity result in wider product variety, especially in the long run and when reducing uncertainty in demand. Innovations in shopping quality yield an increase in consumer surplus even if stores specialize and offer fewer product categories. Productivity improvements imply that stores hire more, invest more in technology and have higher inventory turnover. These improvements are larger when demand uncertainty is reduced. On the contrary, stimulating shopping quality and lowering uncertainty in productivity only results in a modest increase in inventory turnover.

Although our suggested modeling framework is applied to detailed data on Swedish retailers, our analysis has broad implications for the many industries world-wide in which firms offer multiple products. In future research, the multi-product framework can be extended to fully model the dynamics of the number of products, inventory behavior, and importance of stores' cost structure for retail development.

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Table 1: Descriptive statistics

Year	Sales		No. of employees		Capital stock		Cost of goods		Inventory end year		Wages	
	Q_{50}	IQR	Q_{50}	IQR	Q_{50}	IQR	Q_{50}	IQR	Q_{50}	IQR	Q_{50}	IQR
2004	11.620	27.767	7	10	0.394	0.970	7.282	18.892	1.823	5.154	1.432	2.674
2005	11.207	20.463	7	7	0.392	0.979	6.865	13.378	2.060	4.050	1.363	2.197
2006	14.214	25.135	7	9	0.475	1.101	8.783	17.943	2.378	4.987	1.680	2.614
2007	11.193	23.452	7	9	0.435	1.129	6.572	15.191	1.990	5.040	1.444	2.604
2008	11.328	24.713	7	10	0.468	1.217	6.805	16.382	2.042	5.816	1.528	3.088
2009	11.417	24.818	7	10	0.522	1.283	6.785	15.840	2.162	5.572	1.553	2.981
Year	**No. of products**		**HHI product**		**Inventory turnover**		**Market share**		**HHI market**		**C4 market**	
	Q_{50}	IQR	Q_{50}	IQR	Q_{50}	IQR	Q_{50}	IQR	Q_{50}	IQR	Q_{50}	IQR
2004	3	2	0.738	0.380	3.818	4.773	0.349	0.694	0.363	0.493	0.919	0.306
2005	4	2	0.495	0.333	3.215	3.322	0.339	0.635	0.364	0.437	0.918	0.286
2006	4	2	0.549	0.332	3.446	3.498	0.375	0.658	0.381	0.467	0.929	0.291
2007	4	3	0.601	0.364	3.261	3.615	0.372	0.626	0.361	0.427	0.925	0.272
2008	3	3	0.707	0.468	3.152	3.498	0.341	0.657	0.361	0.466	0.930	0.267
2009	3	3	0.655	0.448	3.153	3.508	0.378	0.665	0.393	0.448	0.941	0.238

NOTE: Sales (excl. VAT), capital stock, inventories, cost of goods, and wages are measured in millions of 2000 SEK (1 USD= 7.3 SEK, 1 EUR= 9.3 SEK). Q_{50} and IQR are interquartile range. Capital stock includes only machinery and equipment and is computed using perpetual inventory method. Inventory turnover is computed as the cost of goods sold over inventory at end of the year. HHI product is the Herfindahl-Hirschman index for the product categories at the store level computed using sales. HHI and C4 market are the Herfindahl-Hirschman index and the four-store concentration ratio in a local market for a five-digit industry and are computed using sales.

Table 2: The correlations in the data and their evolution

Correlation (x,y)	Year						
	2003	2004	2005	2006	2007	2008	2009
Extensive margin							
(Number of products, Capital stock per employee)	0.047	0.040	0.003	-0.019	0.074	0.067	0.121
(Number of products, Sales per cost of goods)	-0.030	-0.027	-0.003	-0.011	-0.017	-0.012	-0.015
(Number of products, Market share)	0.137	0.075	0.071	0.060	0.071	0.071	0.048
(Cost of goods per product, Capital per employee)	-0.205	0.251	0.124	0.029	0.074	0.140	0.125
Intensive margins							
(Sales per product, Capital per employee)	0.204	0.250	0.111	0.029	0.090	0.136	0.119
(Sales per product, Wages per employee)	0.320	0.236	0.207	0.225	0.192	0.228	0.252
(Entropy of product sales, Inventory per product)	0.022	0.098	0.089	0.068	0.053	0.022	0.021
(Entropy of product sales, Sales per employee)	0.046	0.075	0.063	0.070	0.057	0.012	-0.061
Local market power							
(Market share, Entropy of product sales)	-0.071	-0.042	-0.076	-0.090	-0.065	-0.067	-0.038
(Market share, Inventory end of year)	0.255	0.182	0.142	0.145	0.086	0.187	0.185
(Market share, Sales per employee)	0.194	0.059	0.071	0.123	0.084	0.093	0.111
(Market share, Capital stock per employee)	0.052	0.102	0.011	-0.025	-0.010	0.025	0.019
Store performance measures							
(Sales, Inventory-to-sales)	-0.068	-0.008	-0.005	-0.043	-0.007	-0.009	-0.008
(Sales per employee, Inventory end of year)	0.204	0.054	0.089	0.099	0.626	0.114	0.135
(Sales per employee, Inventory turnover)	0.030	0.046	0.140	0.224	0.084	0.103	0.117
(Sales per employee, Inventory per product)	0.166	0.066	0.068	0.078	0.532	0.138	0.113
(Inventory turnover, Number of employees)	-0.048	-0.055	-0.027	-0.024	0.058	0.028	0.025
(Inventory turnover, Investment)	-0.046	-0.053	-0.029	-0.027	0.024	0.010	0.041
(Inventory per product, Capital stock per employee)	0.200	0.228	0.098	0.026	0.120	0.149	0.126
(Inventory per product, Wages per employee)	0.285	0.217	0.198	0.198	0.192	0.240	0.252

NOTE: Entropy measures store diversification in sales and is computed for each store j based on market share of each product category i inside store, i.e., $E_{jt} = \sum_i ms_{ijt} ln(ms_{ijt})$ (Bernard et al., 2011). A large measure of entropy suggests that the store focuses on top sales categories.

Table 3: Reduced-form: The effect of local competition, store's market share and margins on the number of product categories

	Number of product categories				HHI product category			
	Est.	Std.	Est.	Std.	Est.	Std.	Est.	Std.
Panel A: The effect of local competition								
HHI	-0.1400	0.4589			-0.0047	0.0253		
C4			-0.6704	0.7670			0.0941	0.0494
Log of capital stock	-0.0102	0.0689	-0.0102	0.0680	0.0125	0.0053	0.0125	0.0051
Store fixed-effect	Yes		Yes		Yes		Yes	
Year fixed-effect	Yes		Yes		Yes		Yes	
R^2-adjusted	0.0052		0.0057		0.0096		0.0104	
Panel B: The effect of store's market share and margins								
Log of store's market share	0.1087	0.1021			0.0141	0.0093		
Log of store's margin			-0.2755	0.1055			0.0451	0.0181
Log of capital stock	-0.0164	0.0645	-0.0223	0.0709	0.0118	0.0053	0.0136	0.0089
Store fixed-effect	Yes		Yes		Yes		Yes	
Year fixed-effect	Yes		Yes		Yes		Yes	
R^2-adjusted	0.0056		0.0065		0.0102		0.0114	

NOTE: HHI and C4 are the Herfindahl-Hirschman index and the four-store concentration ratio in a local market for a five-digit industry and are computed using sales. A store's margins are proxied using the ratio (net sales - cost of goods)/net sales. The first difference estimator is used. Standard errors are clustered at the five-digit industry.

Table 4: Reduced-form: The effect of local competition and store's market share and margins on inventory

	Inventory end of year				Inventory-to-sales ratio			
	Est.	Std.	Est.	Std.	Est.	Std.	Est.	Std.
Panel A: The effect of local competition								
HHI	0.1873	0.0770			-0.2046	0.0880		
C4			0.3366	0.1320			-0.1822	0.0811
Log of capital stock	0.0491	0.0148	0.0495	0.0188	-0.0289	0.0186	-0.0295	0.0187
Store fixed-effect	Yes		Yes		Yes		Yes	
Year fixed-effect	Yes		Yes		Yes		Yes	
R^2-adjusted	0.0358		0.0361		0.0061		0.004	
Panel B: The effect of store's market share and margins								
Log of store's market share	0.0983	0.0410			-0.2452	0.0293		
Log of store's margin			0.0651	0.0682			0.1626	0.0603
Log of capital stock	0.0446	0.0203	0.0483	0.0211	-0.0167	0.0162	-0.0248	0.0209
Store fixed-effect	Yes		Yes		Yes		Yes	
Year fixed-effect	Yes		Yes		Yes		Yes	
R^2-adjusted	0.0426		0.0396		0.0552		0.0228	

NOTE: HHI and C4 are the Herfindahl-Hirschman index and the four-store concentration ratio in a local market for a five-digit industry and are computed using sales. A store's margins are proxied using the ratio (net sales - cost of goods)/net sales. The first difference estimator is used. Standard errors are clustered at the five-digit industry.

Table 5: The relationship between productivity and market share at store level

	Log of labor productivity in period t			
	Static		Dynamic	
	Est.	Std.	Est.	Std.
Market share period t	0.4048	0.1009		
Log of labor productivity in period $t-1$			0.8577	0.0289
Market share in period $t-1$			0.0453	0.0259
Store fixed-effects	Yes		No	
Year fixed-effects	Yes		Yes	
R^2-adjusted	0.0254		0.8167	

NOTE: Standard errors are clustered at the five-digit industry.

Table 6: Estimation of the multi-product sales generating function

	OLS		Two-step estimation	
	Estimate	Std.	Estimate	Std.
Log no. of employees	0.7866	0.0290	0.5582	0.0423
Log of capital	0.0599	0.0129	0.2833	0.0276
Log of inventory	1.0367	0.0212	0.4937	0.0237
Log of sales of other products	-0.8959	0.0098	-0.8562	0.0115
Log of sales outside option	-0.0055	0.0065	0.2240	0.014
Log of population	0.0233	0.0218	0.1396	0.036
Log of population density	0.0076	0.0151	0.1903	0.049
Log of income	34.7509	13.2213	0.9340	0.057
Log of income squared	-3.2989	1.2435	-0.0915	0.017
Coef. of no. of products (ρ_{np})			0.2137	0.0364
Elasticity of substitution ($1/\sigma$)			4.630	
Year fixed-effect	Yes		Yes	
No. of obs.	16,759		16,759	

NOTE: The dependent variable is the log of sales of a product category at the store level. Labor is measured as the number of full-time adjusted employees. Sales of other product categories are measured at the store level. Sales of the outside option measures total sales of the other products of all other five-digit SNI codes at the local market. All regressions include year dummies and five-digit SNI dummies. *OLS* refers to an ordinary least squares regression. Two-step estimation refers to the extended Olley and Pakes (1996) estimation method presented in Section 2 (Maican and Orth, 2019a). Reported standard errors (in parentheses) are computed using Ackerberg et al. (2012).

Table 7: Estimation of structural parameters: Productivity and demand shock processes

Productivity (ω_t) process	Estimate	Std.	Shopping quality (μ_t) process	Estimate	Std.
Productivity (ω_{t-1})	0.8540	0.0649	Shopping quality (μ_{t-1})	0.8596	0.0224
Productivity squared (ω_{t-1}^2)	-0.0375	0.0181	Shopping quality squared (μ_{t-1}^2)	-0.0195	0.0022
Productivity cubic (ω_{t-1}^3)	-0.0043	0.0015	Shopping quality cubic (μ_{t-1}^3)	-0.0005	0.0002
Prod.*Ext. shock ($\omega_{t-1} \times \mu_{t-1}$)	0.0946	0.0123			
External shock (μ_{t-1})	0.0172	0.0025			
Year fixed-effects	Yes		Year fixed-effects	Yes	
Sub-sector fixed-effects	Yes		Sub-sector fixed-effects	Yes	
Adjusted R-squared	0.981		Adjusted R-squared	0.792	
Coefficients of ω_{t-1} terms are zero	F-test	p-value			
	424.139	0.000			
Coefficients of μ_{t-1} terms are zero	F-test	p-value			
	27.713	0.000			
Persistence ($d\omega_t/d\omega_{t-1}$)	0.856		Persistence ($d\mu_t/d\mu_{t-1}$)	0.929	
Effect of shopping quality ($d\omega_t/d\mu_{t-1}$)	0.013				

NOTE: Productivity is estimated using the two-step estimation method in Section 2. Mean values are presented for the marginal effects.

Table 8: The impact of store's and market's characteristics on product category

Dependent variable	No. product categories (np_{jt})		HHI product categories in a store		Entropy of sales of product categories	
	Est.	Std.	Est.	Std.	Est.	Std.
Productivity (ω_t)	1.2058	0.1876	-0.0738	0.0094	-0.1568	0.0234
Shopping quality (μ_t)	-0.1647	0.0377	0.0116	0.0018	0.0228	0.0044
Log of capital (k_t)	0.3469	0.0978	-0.0162	0.0070	-0.0348	0.0130
Log of inventories (n_t)	-0.1218	0.0306	0.0060	0.0173	0.0231	0.0268
Log of population (pop_t)	-1.2601	0.2976	0.0309	0.0390	0.0746	0.0627
Log of population density ($popdens_t$)	0.4861	0.3686	-0.0101	0.0690	-0.0235	0.1090
Log of income (inc_t)	-2.6027	3.2836	-0.4403	0.1413	-0.7676	0.3607
Store fixed-effects	Yes		Yes		Yes	
Year fixed-effects	Yes		Yes		Yes	
Adjusted R-squared	0.119		0.053		0.061	

NOTE: Productivity and shopping quality are estimated using the two-step estimation method in Section 2. Entropy is computed for each store j based on market share of each product category i inside store, i.e., $E_{jt} = \sum_i ms_{ijt} ln(ms_{ijt})$. Store regressions control for the average wage. The intercept is included in all specifications.

Table 9: Determinants of inventory performance and store's market share

Dependent variable	Inventory per product before sales ($ln(A_{jt}/np_{jt})$)		Inventory per product after sales $ln(N_{jt+1}/np_{jt})$		Store's market share	
	Est.	Std.	Est.	Std.	Est.	Std.
Productivity (ω_t)	0.0483	0.0239	-0.1208	0.0255	0.1654	0.0120
Shopping quality (μ_t)	0.0599	0.0049	0.0550	0.0053	0.0132	0.0025
Log of capital (k_t)	0.0823	0.0177	-0.0119	0.0189	0.0945	0.0089
Log of inventories (n_t)	0.0212	0.0177	0.0229	0.0189	0.0517	0.0089
Log of population (pop_t)	0.6717	0.0876	0.5717	0.0934	-0.6770	0.0442
Log of population density ($popdens_t$)	-0.4953	0.0963	-0.3958	0.1026	-0.0884	0.0486
Log of income (inc_t)	0.0878	0.9702	1.1587	1.0338	1.9653	0.4901
Store fixed-effects	Yes		Yes		Yes	
Year fixed-effects	Yes		Yes		Yes	
Adjusted R-squared	0.079		0.051		0.257	

NOTE: Productivity and shopping quality are estimated using the two-step estimation method in Section 2. Store regressions control for the average wage.

Table 10: Estimation of the investment, labor, and inventory demand functions

	Log of labor (i_t)		Log of investment (l_t)		Log of products and inventories (a_t)	
Panel A: Linear specifications						
Productivity (ω_t)	0.2456	0.0945	0.1029	0.0058	0.3368	0.0402
Shopping quality (μ_t)	0.0342	0.0191	0.0084	0.0029	0.0129	0.0026
Log of capital (k_t)	-0.4541	0.0657	0.0614	0.0125	0.1694	0.0141
Log of inventories (n_t)	-0.1761	0.0786	0.0281	0.0071	-0.0195	0.0120
Log of population (pop_t)	0.6855	0.3112	0.2991	0.1654	0.3168	0.1209
Log of pop. density ($popdens_t$)	-0.5583	0.3289	-0.2161	0.1393	-0.3635	0.1214
Log of income (inc_t)	-0.7944	3.5450	0.6819	0.8813	-1.3234	1.8809
Store fixed-effects	Yes		Yes		Yes	
Year fixed-effects	Yes		Yes		Yes	
Adjusted R-squared	0.093		0.171		0.343	
Panel B: Non-linear specification using b-splines of degree 5						
	Data	Prediction	Data	Prediction	Data	Prediction
25th Percentile	-2.9239	-2.6560	1.6094	1.7183	1.780	1.7754
50th Percentile	-1.6507	-1.8764	2.1972	2.2175	2.738	2.7188
Mean	-1.2917	-1.2917	2.5887	2.5887	2.945	2.9446
75th Percentile	-0.0092	-0.5624	2.9444	2.8759	3.771	3.7464
Year fixed-effects	Yes		Yes		Yes	
Sub-sector fixed-effects	Yes		Yes		Yes	
Adjusted R-squared	0.667		0.929		0.717	

NOTE: The dependent variables are the log of investment in capital (i_t), the log of the sum between the inventories at the beginning of the year (n_t) and the cost of products bought during the year (a_t), and the log of inventories at the end of the year (n_{t+1}). All regressions include an intercept and control for the average wage. Productivity and shopping quality are estimated using the two-step estimation method in Section 2.

Table 11: Counterfactual experiments: Changes in number of products, consumer surplus, inputs and investment

	After 1 year		After 3 years		After 5 years	
	Mean	IQR	Mean	IQR	Mean	IQR
CF_1: The impact of positive shocks to productivity						
Number of products	1.230	0.987	1.745	1.074	1.981	1.344
Consumer surplus	0.979	2.322	1.403	2.370	1.903	3.192
Number of employees	1.484	0.201	4.663	1.305	9.465	3.569
Investment in technology	3.051	1.023	10.088	3.720	19.106	9.165
Inventory turnover	1.779	0.571	2.397	0.676	2.621	0.750
Inventory end of year	0.747	0.222	3.495	1.154	7.903	3.275
CF_2: The impact of positive shocks to productivity and reducing uncertainty of shopping quality						
Number of products	-0.083	2.348	-6.131	5.892	12.346	7.889
Consumer surplus	0.089	7.422	-3.157	13.870	1.621	19.322
Number of employees	2.118	1.229	11.420	5.266	29.522	12.777
Investment in technology	3.374	1.042	13.654	4.500	30.300	11.443
Inventory turnover	2.332	1.338	5.551	2.330	7.294	3.451
Inventory end of year	1.413	1.276	11.843	6.925	35.285	18.093
CF_3: The impact of positive shocks to demand						
Number of products	-0.841	0.661	-1.720	1.025	-2.188	1.038
Consumer surplus	2.736	6.231	5.298	9.013	6.788	12.726
Number of employees	0.446	0.257	1.502	1.147	2.964	2.237
Investment in technology	0.086	0.127	0.251	0.606	0.876	1.430
Inventory turnover	0.337	0.240	0.240	0.358	-0.048	0.344
Inventory end of year	0.458	0.269	2.122	1.518	4.547	3.234
CF_4: The impact of reducing uncertainty in productivity shocks and positive shopping quality						
Number of products	-0.782	1.140	-2.261	1.709	-3.774	2.066
Consumer surplus	2.797	6.242	4.884	8.461	4.995	11.240
Number of employees	0.201	1.163	-1.522	4.084	-8.511	11.203
Investment in technology	-1.142	2.331	-8.884	9.083	27.356	25.530
Inventory turnover	0.619	1.395	0.596	2.005	0.035	2.324
Inventory end of year	0.191	0.655	-0.547	3.384	-5.350	10.231

NOTE: The computations are based on 100 simulations. The mean and interquartile range ($IQR = Q90 - Q10$) of changes are computed based on the simulated data using the last year in the data as the starting value, and the estimated policy functions and Markov processes. All numbers are in percentages. Market groups are defined as above and below the median of the population.

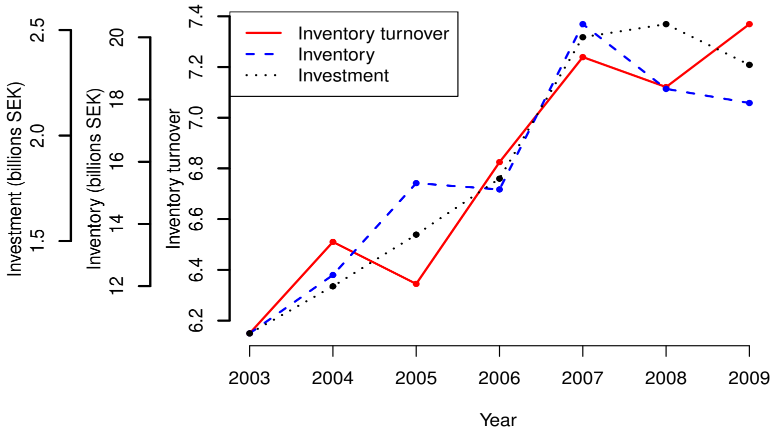

Figure 1: The evolution of inventory and investment in Swedish retail

Online Appendix: Determinants of Economies of Scope in Retail

Florin Maican[1] and Matilda Orth[2]

Appendix A: Recovering productivity and shopping quality

The general labor demand and inventory functions that arise from stores' optimization problem are $\mathrm{l}_{jt} = \tilde{l}_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, w_{jt}, \mathbf{x}_{mt})$ and $\mathrm{a}_{jt} = \tilde{a}_t(\omega_{jt}, \mu_{jt}, k_{jt}, n_{jt}, w_{jt}, \mathbf{x}_{mt})$. To back out ω_{jt} and μ_{jt}, functions $\tilde{l}_t(\cdot)$ and $\tilde{a}_t(\cdot)$ must be strictly monotonic in ω_{jt} and μ_{jt}, which holds under mild regularity conditions of the dynamic programming problem (Pakes, 1994). Maican and Orth (2019a) discuss in detail all these conditions required for invertibility. By inverting these policy functions to solve for ω and μ, we obtain $\omega_{jt} = f_t^1(l_{jt}, k_{jt}, n_{jt}, w_{jt}, a_{jt}, \mathbf{x}_{mt})$ and $\mu_{jt} = f_t^2(l_{jt}, k_{jt}, n_{jt}, w_{jt}, a_{jt}, \mathbf{x}_{mt})$, i.e., the productivity and exogenous shocks are non-parametric functions of the observed variables in the state space and the controls.

In our setting, the estimation of the service-generating function (3) is in two-steps. In the first step, we isolate stores' shopping quality perceived by customers μ_{jt} using information about stores' market shares ms_{jt}, i.e., $ln(ms_{jt}) - ln(ms_{ot}) = \rho_{np} np_{jt} + \rho_{inc,1} inc_{mt} + \rho_{inc,2} inc^2_{mt} + \mu_{jt} + \nu_{jt}$, according to equation (4). The use of another output measure apart from sales of product category, and the distinction between stores' market shares and sales of a category, are important for identification. Our model contains two unobserved shocks and two Markov processes. We show how this additional output equation helps to recover shopping quality separate from productivity and ensures the identification of the model.

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By substituting the nonparametric inversion $f_t^2(l_{jt}, k_{jt}, n_{jt}, w_{jt}, a_{jt}, \mathbf{x}_{mt})$ for μ_{jt} in (4), we obtain an estimate of $b_t(\cdot)$ (i.e., predicted market shares, $\hat{b}_t$, where $b_t(\cdot) = f_t^2(\cdot)$). This allows us to write the shocks μ_{jt} as a parametric function, i.e., $\mu_{jt} = \hat{b}_{jt} - \rho_{np} np_{jt} - \rho_{inc,1} inc_{jt} - \rho_{inc,2} inc_{jt}^2$, which will be treated as an input in the multi-output service-generating function.

Inventories can increase from a higher μ_{jt} and more products in the store, i.e., a higher love-for-variety. New technologies such as bar codes, scanners and business systems affect inventory levels, and positive adjustments avoid stock-outs and increase quality. Technological advances can benefit the existing number of products that the store has in its assortment, e.g., through faster product lines and a higher frequency of turnover. Importantly, however, higher store productivity creates incentives for stores to increase their product variety and increase their size.[3]

By substituting μ_{jt} (predicted) and ω_{jt} into (1), the service generating function becomes

$$y_{ijt} = -\alpha_y y_{-ijt} + \phi_t(l_{jt}, k_{jt}, n_{jt}, w_{jt}, a_{jt}, \mathbf{x}_{mt}) + u_{ijt}, \tag{8}$$

where $\phi_t(\cdot) = \beta_l l_{jt} + \beta_k k_{jt} + \beta_a a_{jt} + \beta_x \mathbf{x}_{mt} + \omega_{jt} + \mu_{jt}$. The estimation of (8) using OLS and the polynomial expansion of order 2 yields an estimate of service output without service output shocks u_{ijt}, which gives us $\hat{\phi}_t$, which is used to obtain store productivity ω_{jt} as a function of the parameters, $\omega_{jt} = \hat{\phi}_{jt} - \beta_l l_{jt} - \beta_k k_{jt} - \beta_a a_{jt} - \beta_q y_{0t} - \beta_x \mathbf{x}_{mt} - (\hat{b}_{jt} - \rho_{np} np_{jt} - \rho_{inc,1} inc_{jt} - \rho_{inc,2} inc_{jt}^2)$. Then, we use the information from the Markov processes to obtain the shocks $(\xi_{jt} + u_{ijt})$ and $(\eta_{jt} + \nu_{jt})$ as functions of parameters, which are used to form the moment conditions as described in the main text.

[3]Viewing the number of products as a measure of store size is in line with Holmes (2001) and is unarguably reasonable when using yearly data such that stores have time to adjust storage places, shelf space, etc., to an increasing number of products. Note that we consider the intensive margin in terms of increasing store size.

Appendix B: The relationship between store productivity and inventory performance

This appendix section presents a stylized model that shows the relationship between store productivity and inventory performance and highlights key factors that affect the changes in inventory performance (i.e., dynamics).

The total sales-generating function y_{jt} (in logs) for store j is given by

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_a a_{jt} + \omega_{jt} + u_{jt}, \tag{9}$$

where l_{jt} is log of the number of employees; k_{jt} is log of capital stock; a_{jt} is log of the sum of inventory at the beginning of the period (n_{jt}) and the products bought during period t; ω_{jt} is total factor productivity based on sales data (TFPR), i.e., revenue productivity; and u_{jt} are i.i.d. shocks to sales. It is well documented that there is high persistence in productivity over time in a given store (Ackerberg et al., 2007; Syverson, 2011). For illustrative purposes, we assume that productivity ω_{jt} follows a simple $AR(1)$ process, i.e., $\omega_{jt} = \rho\omega_{jt-1} + \xi_{jt}$, where ρ is a coefficient capturing the persistence in store productivity, and ξ_{jt} are i.i.d. innovation shocks to productivity. The shocks ξ_{jt} provide information about uncertainty in productivity changes due to external or internal factors that are not under the control of the manager, for example, shocks related to the information technology system inside the store and logistics, shocks related to changes in regulation.

The goal of the stylized model is to provide a link between the common measures of inventory performance, such as inventory turnover and a store's total factor productivity. We define the log of inventory turnover in period t after the realization of sales as $it_{jt} = y_{jt} - n_{jt+1}$, where n_{jt+1} is the inventory at the beginning of period $t+1$ (end of period t) after sales are realized.[4] Using the sales generating function (9), the productivity process, and the inventory turnover

[4]In many empirical applications, average inventory is used to compute inventory turnover.

equations, we derive a simple dynamic equation for inventory turnover

$$\begin{aligned} it_{jt} = \quad & \rho it_{jt-1} + \beta_l(l_{jt} - \rho l_{jt-1}) + \beta_k(k_{jt} - \rho k_{jt-1}) + \beta_a(a_{jt} - \rho a_{jt-1}) \\ & -(n_{jt+1} - \rho n_{jt}) + \xi_{jt} + u_{jt} - \rho u_{jt-1}. \end{aligned} \tag{10}$$

The simple stylized model highlights that inventory turnover and productivity have several important implications for managers. First, equation (10) shows that the productivity persistence coefficient ρ drives inventory turnover, i.e., the dynamics of productivity over time is a key determinant of inventory turnover. Therefore, the persistence in store productivity provides information about the persistence in inventory turnover. Recent studies on retail find an average persistence in store productivity of approximately 70-80 percent (Maican and Orth, 2017). Second, innovation shocks to productivity ξ_{jt} and to sales u_{jt} affect inventory turnover, which is important since innovation shocks ξ_{jt} provide information on uncertainty in store productivity and affect optimal inventory and input choices (labor and capital), and their effect cumulates over time. Therefore, managers can learn how uncertainty in store total factor productivity affects inventory performance by understanding the distribution of ξ_{jt}. If the innovation shocks ξ_{jt} have large variance, managers must prevent negative consequences of large variance in inventory performance by implementing policies to increase the persistence in store productivity (for example, investments in technology, optimal labor-capital substitution, and the optimal choice of product variety). Third, adjustments in inventory and input choices (labor and capital) over time directly influence inventory turnover because the optimal changes in labor and capital affect store productivity and, therefore, inventory performance.

Our illustrative stylized model has several limitations and does not consider key features of retail business. Therefore, we provide a structural framework that accounts for (i) the role of multi-product stores for store performance, that is, capturing product variety inside a store; (ii) the role of demand for inventory performance and a store's choices, i.e., how stores can use the information from consumer preferences for products to make optimal decisions. We estimate demand shocks that capture quality of the shopping experience. We allow stores to learn from demand to improve future productivity; (iii) endogenous total factor productivity, inventory, investments, and input choices; and (iv) heterogeneity in stores' responses to productivity changes, that is, we allow for a nonlinear productivity process.[5] The two sources of unobserved store-level heterogeneity (i.e., productivity and demand shocks) affect a store's input choices and, ultimately, its performance.

B.1: Endogenous inventory performance

We study the determinants of inventory turnover and begin by presenting the results following the existing approaches to our data (Gaur et al., 2005). Then, we extend the analysis by including store productivity and shopping quality and allowing the empirical specification of inventory turnover to be consistent with the store's short- and long-run profit maximization.

In our model in main text, differences in inventories and inventory performance across stores can arise because of differences in (i) productivity; (ii) quality of the shopping experience; (iii) internal factors such as stock of capital/technology inside the store; and (iv) external factors, i.e., local market characteristics.[6] To improve inventory management, stores invest in technology, which increases productivity and reduces the cost of inventories. The proposed model focuses mainly on understanding the relationship between store-level inventory and performance, productivity, quality of the shopping experience and omits explicitly modeling stock-outs, depreciation, and fixed costs.

A key advantage of our model is that it endogenizes inventory performance measured as inventory turnover, where the determinants of inventory turnover are theoretically consistent with the store's dynamic optimization problem. It is important to emphasize that the relationship between inventory performance and store TFP can be more complex than the relationship between labor productivity and TFP because of the dynamic effects related to adjustment costs in inventory. Second, we add estimated productivity and shopping quality as measures of store heterogeneity. Third, we extend the analysis by using an empirical specification that is entirely consistent with endogenous inventory turnover and long-run profit maximization. Our specifi-

[5]Nonlinearities in productivity complicate the dynamics of inventory turnover compared to the illustrative example in equation (10) that is valid only if productivity follows an AR(1) process (e.g., Ackerberg et al., 2007).

[6]Lower markups decrease inventories, whereas a large choice set for consumers increases inventories (Cachon and Olivares, 2010).

cation is derived using retailers' optimal choices while controlling for demand and economies of scale, and it provides a direct link between store productivity and inventory performance.

Simple reduced-form regression results confirm the empirical findings in the operations management literature using inventory turnover, which show a positive correlation between inventory turnover and capital intensity and a negative correlation between inventory turnover and gross margins. [7] Capital intensity and gross margins are correlated with store primitives such as productivity and demand shocks, i.e., they are endogenous variables. Our findings undoubtedly suggest that store productivity and shopping quality are two additional key factors that increase inventory turnover in addition to the factors emphasized in the operations management literature.

Table B.1 shows the specification that is consistent with the structural dynamic model in Section 2, that is, inventory turnover (cost of goods sold over inventory) is a function of the state variables. To explore the large variation in inventory turnover across and within stores over time, we use OLS and quantile estimators. In particular, we explore the following determinants of a store's inventory turnover: productivity shocks ω_{jt}, shopping quality μ_{jt}, investment, labor, the number of product categories, and local market characteristics.

Both productivity and shopping quality increase inventory turnover, and the magnitude of the marginal effects decline with the level of productivity and shopping quality. Importantly, productivity has a greater effect than shopping quality on inventory turnover in all parts of the distribution. Furthermore, the marginal effects of both productivity and shopping quality are larger for stores with already high inventory turnover. A productivity increase yields an increase in inventory turnover that is 1.5-2 times higher in the 75th percentile than in the 25th percentile. The difference becomes even more evident for an increase in shopping quality, where inventory turnover increases 2-3 times more in the 75th percentile than in the 25th.

Inventory turnover increases when a store invests in technology. The marginal effect of investment is approximately twice as large in the 75th percentile than at the median or in the 25th percentile of inventory turnover. Market size and population density have a positive and statistically significant impact on inventory turnover. Moreover, stores with low inventory turnover

[7] The effects are not causal. All specifications control for fixed effects for year and sub-sector. The results are reported and discussed in details in online Appendix C.

benefit relatively more from market size expansions (i.e., increase in population). These results are consistent with previous work on productivity, market size, and population density (Syverson, 2004; Syverson, 2011).

In summary, the findings emphasize that store productivity plays a crucial role in increasing inventory turnover. Consumers' perceived shopping quality also improves inventory turnover, but the marginal effect is lower than the effect of productivity. For improvements in both productivity and shopping quality, stores with already high inventory turnover benefit the most.

Table B.1: Determinants of inventory turnover in retail

			Quantile regression					
	OLS		Q25		Q50		Q75	
	Est.	Std.	Est.	Std.	Est.	Std.	Est.	Std.
Productivity (ω_t)	0.2222	0.0333	0.1717	0.0295	0.2171	0.0474	0.2917	0.0595
Productivity squared ($(\omega_t)^2$)	-0.0269	0.0050	-0.0300	0.0058	-0.0246	0.0076	-0.0126	0.0087
Shopping quality (μ_t)	0.0173	0.0075	0.0148	0.0085	0.0218	0.0077	0.0397	0.0109
Shopping quality squared ($(\mu_t)^2$)	-0.0009	0.0006	-0.0019	0.0007	-0.0023	0.0009	-0.0023	0.0011
Log of investment (i_{t-1})	0.0186	0.0068	0.0103	0.0075	0.0159	0.0075	0.0314	0.0073
Log of capital (k_{t-1})	0.1780	0.0105	0.1702	0.0170	0.1919	0.0141	0.1814	0.0163
Log of inventories (n_t)	-0.4358	0.0139	-0.4009	0.0239	-0.4580	0.0234	-0.4972	0.0206
Log of population (pop_t)	0.0175	0.0206	0.0487	0.0214	0.0477	0.0212	0.0253	0.0244
Log of pop. density ($popdens_t$)	0.0501	0.0123	0.0248	0.0113	0.0379	0.0129	0.0687	0.0124
Log of income (inc_t)	0.0379	0.1748	-0.0102	0.1631	0.3313	0.1656	0.1313	0.1821
Year fixed-effect	Yes		Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes		Yes	

NOTE: Inventory turnover is defined as the cost of goods sold over average inventory. The intercept and average wage are included in all regressions. Productivity and shopping quality are estimated using the two-step estimation method in Section 2.

Alternative specifications. Our empirical results confirm the empirical findings in the operations management literature using inventory turnover, which is defined as the cost of goods sold over inventory, as the dependent variable (Gaur et al., 2005). The figures in Table B.2 show a positive correlation between inventory turnover and capital intensity and a negative correlation between inventory turnover and gross margins. We use previous sales and its squared term to control for store size, and we use sales growth to control for economies of scale and scope. The joint test of the coefficients of previous sales equal zero rejects the null hypothesis, indicating a positive association between store size and inventory turnover. The existence of economies of scale and scope explains the positive correlation between inventory turnover and store size (Shockley and Turner, 2015). The coefficient of store size squared is negative, which implies that there are diminishing returns to scale as store size increases. The coefficient on sales growth is positive but insignificant at conventional levels.[8] All specifications control for fixed effects for year and sub-sector.

By adding store productivity and shopping quality (i.e., measures of store heterogeneity) as controls, we investigate the extent to which these variables explain the variation in inventory turnover. The second specification in Table B.2 shows positive and statistically significant coefficients of both productivity and shopping quality. A 10 percent increase in productivity for the median store increases inventory turnover by 3 percent. Consumers' perceived shopping quality has a small positive effect on inventory turnover. We expect this result because the gross margin (included as a control variable) and shopping quality are correlated, and both affect demand. After controlling for store heterogeneity, the negative correlation between gross margins and inventory turnover decreases, and the positive correlation between inventory turnover and capital intensity increases. That the recovered ω_{jt} and μ_{jt} comprise information about previous store performance makes the coefficient of store size (lagged sales) statistically insignificant.[9]

Productivity and shopping quality still have explanatory power when using adjusted inventory turnover as an output measure, as suggested by Gaur et al. (2005). We conclude that our recovered measures of store-level heterogeneity are essential even when using the more restrictive measure of inventory turnover, i.e., adjusted inventory turnover controls for gross margin, capital intensity and sales surprises. In summary, the findings undoubtedly suggest that store productivity and shopping quality are two additional key factors that increase inventory turnover in addition to the factors emphasized in the operations management literature.

[8] The effects are not causal. Several of the explanatory variables are endogenous because they are correlated with supply and demand shocks that are part of the residual. Previous sales are commonly used as a measure of store size in the inventory management literature. Gaur et al. (2005) use an expected measure of sales surprises as an explanatory variable instead of sales growth.

[9] This result is because ω_{jt} and μ_{jt} follow AR(1) processes and include information about previous store sales.

Table B.2: Determinants of inventory turnover in retail

	Model 1		Model 2	
	Est.	Std.	Est.	Std.
Productivity (ω_t)			0.2301	0.0496
Productivity squared ($(\omega_t)^2$)			-0.0171	0.0062
Shopping quality (μ_t)			-0.0167	0.0097
Shopping quality squared ($(\mu_t)^2$)			0.0020	0.0008
Log of gross margin (gm_t)	-0.6382	0.0417	-0.5409	0.0401
Log of capital intensity (ci_t)	0.2935	0.0170	0.4170	0.0181
Store size (y_{t-1})	0.0475	0.0320	-0.0327	0.0365
Store size squared (y_{t-1}^2)	-0.0062	0.0036	-0.0139	0.0040
Sales growth ($y_t - y_{t-1}$)	0.0800	0.0520	-0.1007	0.0523
Year fixed-effects	Yes		Yes	
Sub-sector fixed-effects	Yes		Yes	
Local market fixed-effects	Yes		Yes	
Adjusted R-squared	0.504		0.558	

NOTE: The dependent variable is the log of inventory turnover (cost of goods sold over average inventory). Productivity and shopping quality are estimated using the two-step estimation method in Section 2.

Table B.3 presents the impact of productivity and demand shocks on adjusted inventory turnover, defined as the residual in the inventory turnover regression when controlling for differences in gross margin, capital intensity, store size, and store size squares (Gaur et al., 2005). The figures show that the results in the main text remain robust (Table B.1).

Table B.3: Determinants of adjusted inventory turnover in retail

			Quantile regression					
	OLS		Q25		Q50		Q75	
	Est.	Std.	Est.	Std.	Est.	Std.	Est.	Std.
Productivity (ω_t)	0.7170	0.0843	0.1397	0.0366	0.1893	0.0399	0.3406	0.0469
Productivity squared ($(\omega_t)^2$)	0.0158	0.0129	-0.0470	0.0066	-0.0316	0.0062	-0.0118	0.0065
Shopping quality (μ_t)	0.0762	0.0200	0.0170	0.0085	0.0340	0.0081	0.0375	0.0072
Shopping quality squared ($(\mu_t)^2$)	-0.0070	0.0018	-0.0017	0.0009	-0.0033	0.0008	-0.0028	0.0010
Log of investment (i_{t-1})	0.0328	0.0172	0.0082	0.0065	0.0115	0.0066	0.0226	0.0058
Log of capital (k_{t-1})	-0.0453	0.0275	0.0106	0.0128	-0.0019	0.0118	-0.0056	0.0090
Log of inventories (n_t)	-0.5843	0.0381	-0.3014	0.0233	-0.3169	0.0148	-0.3358	0.0140
Log of population (pop_t)	0.1764	0.0561	0.0045	0.0230	0.0484	0.0203	0.0446	0.0174
Log of pop. density ($popdens_t$)	0.0400	0.0327	0.0580	0.0139	0.0542	0.0119	0.0536	0.0115
Log of income (inc_t)	0.4970	0.4970	-0.0542	0.1440	0.1921	0.1493	0.2849	0.1612
Year fixed-effect	Yes		Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes		Yes	

NOTE: Adjusted inventory turnover is defined as the residual in the inventory turnover regression when controlling for differences in the gross margin, capital intensity, store size, and store size squares (Gaur et al., 2005). The intercept and average wage are included in all regressions. Productivity and the demand shock are estimated using the two-step estimation method in Section 2.

Appendix C: Heterogeneity across markets

Table C.4 shows the estimated the impact of the rivals' productivity and shopping quality on inventory turnover, the number of product categories, and market share, given that the impact remains constant, i.e., there is no heterogeneity in impact by adding a quadratic term. The estimated results of this specification are consistent with the results in the main text in the paper.

Table C.4: Market size and the impact of rivals on inventory turnover, the number of product categories and market share

	Inventory turnover		No. of product categories		Market share	
	Est.	Std.	Est.	Std.	Est.	Std.
Panel A: Small local markets						
Productivity (ω_t)	0.1999	0.0580	1.3295	0.1978	0.0069	0.0210
Productivity squared ($(\omega_t)^2$)	-0.0325	0.0085	0.0379	0.0291	0.0057	0.0031
Rivals productivity ($\sum_{k\neq i}\omega_{kt}$)	0.0439	0.0091	-0.1687	0.0305	0.0170	0.0032
Shopping quality (μ_t)	-0.0298	0.0132	-0.4409	0.0446	0.0656	0.0047
Shopping quality squared ($(\mu_t)^2$)	0.0021	0.0012	0.0396	0.0042	-0.0042	0.0004
Rivals shopping quality ($\sum_{k\neq i}\mu_{kt}$)	0.0138	0.0062	0.0130	0.0252	-0.0141	0.0026
Log of investment (i_{t-1})	0.0016	0.0128	0.0833	0.0422	-0.0008	0.0045
Log of capital (k_{t-1})	0.2476	0.0204	0.2239	0.0692	0.0048	0.0073
Log of inventories (n_t)	-0.4718	0.0293	-0.0691	0.1021	0.0376	0.0108
Year fixed-effect	Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes	
Adjusted R-squared	0.514		0.480		0.513	
Panel B: Large Local markets						
Productivity (ω_t)	0.2129	0.0420	0.4079	0.1767	0.0600	0.0172
Productivity squared ($(\omega_t)^2$)	-0.0249	0.0057	-0.0622	0.0238	0.0056	0.0023
Rivals productivity ($\sum_{k\neq i}\omega_{kt}$)	0.0000	0.0043	0.0058	0.0184	0.0131	0.0018
Shopping quality (μ_t)	0.0335	0.0070	-0.3520	0.0299	0.0839	0.0029
Shopping quality squared ($(\mu_t)^2$)	-0.0005	0.0006	0.0300	0.0028	-0.0046	0.0002
Rivals shopping quality ($\sum_{k\neq i}\mu_{kt}$)	-0.0058	0.0028	0.0080	0.0122	-0.0069	0.0011
Log of investment (i_{t-1})	0.0397	0.0071	0.0501	0.0308	0.0013	0.0030
Log of capital (k_{t-1})	0.1603	0.0105	0.2672	0.0471	-0.0026	0.0046
Log of inventories (n_t)	-0.4381	0.0138	-0.0337	0.0657	0.0038	0.0064
Year fixed-effect	Yes		Yes		Yes	
Sector fixed-effect	Yes		Yes		Yes	
Adjusted R-squared	0.664		0.346		0.709	

NOTE: Inventory turnover is defined as the cost of goods sold over average inventory. All regressions include an intercept and control for average wage and income. Productivity and the demand shock are estimated using the two-step estimation method described in Section 4.

Appendix D: Alternative counterfactual experiments

An additional policy experiment CF_5 is presented in Table D.5. The fifth counterfactual experiment (CF_5) evaluates positive shocks to productivity to compensate for negative shopping quality. That is, we increase the mean of ξ_{jt} to 0.2 and decrease the mean of ν_{jt} to -0.05.

An increase in productivity and a decrease in shopping quality. CF_5 assumes that stores experience larger positive shocks to productivity than in CF_1, i.e., the shocks to productivity are four times larger than the negative shocks to demand. Similar to CF_1 and CF_2, stores expand the number of employees because of gains in productivity (Table D.5). Both investments and inventories increase (especially in the long run, e.g., over 30 percent after five years). Compared to CF_1, inventory turnover grows more quickly on average than the increase in productivity shocks (e.g., 6.8 percent in the coming year, 9.4 percent after three years, and 10.5 percent after five years). The positive productivity shocks drive the increase in the number of product categories (5.7 percent in the coming year and 10.5 percent after five years). The average consumer surplus changes are similar to the ones in CF_1, but the interquartile range is larger in CF_5 (especially in the next year).

In summary, due to productivity improvements stores grow in size (labor) and expand their product categories. Consumers experience more product variety to compensate for the negative effect caused by the decrease in shopping quality μ (e.g., shopping quality, product quality).

Table D.5: Counterfactual experiment: Changes in inventory, number of products, inputs and consumer surplus

CF_5: The impact of positive shocks productivity to compensate negative shocks to shopping quality						
Number of products	5.756	4.543	8.844	4.757	10.506	5.628
Consumer surplus	1.178	3.147	0.417	1.032	1.151	2.400
Number of employees	5.542	0.676	17.80	5.189	37.527	15.142
Investment in technology	12.390	4.012	42.186	14.977	82.344	39.295
Inventory end of year	2.586	0.747	12.439	4.708	29.330	14.390
Inventory turnover	6.842	2.220	9.446	2.940	10.553	3.395

NOTE: The computations are based on 100 simulations. The mean and interquartile range ($IQR = Q90 - Q10$) of changes are computed based on the simulated data using the last year in the data as the starting value, and the estimated policy functions and Markov processes. All numbers are in percentages. Market groups are defined as above and below the median of the population.

D.1: Heterogeneity across markets

Table D.6 summarizes counterfactual changes for small and large markets. By increasing the impact of positive shocks to productivity (CF_1), on average, there are small differences between small and large markets. However, small markets have a larger interquartile range in labor and investment changes than large markets. The consumer surplus gains are higher in small markets in short run but not in the long run (after three years). In addition, large markets have a higher interquartile range of the consumer surplus measure than small markets (i.e., a high heterogeneity in consumer surplus across large markets).

Reducing uncertainty in shopping quality and increasing productivity shocks (CF_2) affect small and large markets differently in terms of market share and consumer surplus. Small markets have a lower dispersion in changes in the short run, but this dispersion is higher in small markets than in large markets in the long run due to stronger competition. Consumers benefit from the consumer surplus improvements in small markets in the short run, whereas the surplus drops in both small and large markets in the long-run. As mentioned previously, the drop in consumer surplus is caused by increased store specialization when uncertainty in demand decreases.

Raising shopping quality (CF_3) creates a difference between small and large markets even if the mean increase of these shocks is the same. The positive changes in inventory turnover, labor, and investment are higher in large markets than in small markets. In addition, stores tend to specialize more in large markets. On average, consumer surplus gains are higher in small markets than in large markets, but this rank changes in the long run. Again, large markets have a higher dispersion in the consumer surplus changes.

Reducing uncertainty in productivity and increasing shopping quality (CF_4) affect small and large markets differently in the short and long run. For example, on average, there is no difference in inventory turnover in small and large markets in the short run, but stores in small markets have a higher inventory turnover in the long run. As in CF_3, stores specialize more in large markets (a larger drop in the number of product categories). There is more hiring in the short-run in both types of markets, but stores decrease their labor force in the long run, with a larger magnitude for small stores. Overall, consumer surplus increases in both types of markets, and large markets have a larger interquartile range in surplus changes than small markets.

Raising productivity to compensate for a drop in demand in the CF_5 does not create large differences between small and large markets. The most important finding is that inventory turnover changes are higher in small markets than in large markets. The number of product categories grows more quickly in large markets than in small markets. In contrast, on average, stores in small markets hire relatively more than stores in large markets, i.e., local community expansion.

In summary, the policy experiments show that the trade-off between productivity and demand plays a key role in driving differences across markets. The results highlight that understanding heterogeneity in shopping quality is important for the observed difference across markets, even if productivity drives the changes. The effect of shopping quality is more complex since it affects the dynamics of productivity shocks.

Table D.6: Counterfactual experiments: Market size and changes in inventory, the number of products, inputs and consumer surplus

	After 1 year				After 3 years			
	Small markets		Large markets		Small markets		Large markets	
	Mean	IQR	Mean	IQR	Mean	IQR	Mean	IQR
CF_1: The impact of positive shocks to productivity								
Number of products	1.270	0.967	1.200	0.974	1.690	0.957	1.785	1.137
Consumer surplus	1.228	1.815	0.801	5.250	1.099	1.937	1.622	3.206
Number of employees	1.486	0.350	1.482	0.153	4.763	2.075	4.590	1.026
Investment in technology	3.063	1.784	3.042	0.778	10.329	6.223	9.916	3.056
Inventory end of year	0.749	0.387	0.745	0.169	3.565	1.974	3.445	0.966
Inventory turnover	1.788	0.588	1.772	0.558	2.474	0.645	2.341	0.656
CF_2: The impact of positive shocks to productivity and reducing uncertainty of shopping quality								
Number of products	-0.169	1.948	-0.021	2.562	-5.580	5.803	-6.526	5.742
Consumer surplus	1.263	6.410	-0.752	8.151	-0.560	12.165	-5.017	17.308
Number of employees	2.156	1.106	2.091	1.272	11.324	5.060	11.489	5.460
Investment in technology	3.394	1.787	3.359	0.872	13.710	6.291	13.615	3.806
Inventory end of year	1.452	1.149	1.385	1.317	11.715	6.709	11.935	7.228
Inventory turnover	2.374	1.313	2.302	1.295	5.467	2.385	5.611	2.377
CF_3: The impact of positive shocks to demand								
Number of products	-0.682	0.625	-0.955	0.546	-1.417	0.869	-1.937	0.846
Consumer surplus	3.455	4.782	2.220	13.952	4.081	7.683	6.171	12.782
Number of employees	0.389	0.257	0.486	0.234	1.280	0.995	1.661	1.049
Investment in technology	0.057	0.127	0.106	0.116	0.141	0.474	0.330	0.588
Inventory end of year	0.398	0.269	0.501	0.246	1.824	1.331	2.336	1.384
Inventory turnover	0.294	0.252	0.367	0.238	0.184	0.319	0.280	0.364
CF_4: The impact of reducing uncertainty in productivity shocks and positive shocks to shopping quality								
Number of products	-0.593	1.100	-0.918	1.142	-1.917	1.539	-2.508	1.634
Consumer surplus	3.455	4.792	2.325	14.920	3.810	7.421	5.653	12.169
Number of employees	0.171	1.132	0.222	1.165	-1.778	4.017	-1.338	4.087
Investment in technology	-1.119	2.268	-1.159	2.361	-9.248	8.887	-8.623	9.100
Inventory end of year	0.144	0.658	0.224	0.636	-0.893	3.443	-0.300	3.383
Inventory turnover	0.613	1.343	0.624	1.414	0.623	2.103	0.577	1.942
CF_5: The impact of positive shocks to productivity to compensate negative shocks to shopping quality								
Number of products	5.761	4.350	5.753	4.413	8.312	4.268	9.225	4.930
Consumer surplus	1.452	2.356	0.981	6.792	0.392	0.650	0.435	1.123
Number of employees	5.609	1.448	5.490	0.560	18.454	8.846	17.338	4.301
Investment in technology	12.469	7.242	12.334	2.990	43.350	25.598	41.350	12.611
Inventory end of year	2.657	1.594	2.536	0.621	13.041	8.351	12.008	3.824
Inventory turnover	6.924	2.379	6.782	2.123	9.818	3.028	9.180	2.862

NOTE: The computations are based on 100 simulations. The mean and interquartile range ($IQR = Q90-Q10$) of changes are computed based on the simulated data using the last year in the data as the starting value, and the estimated policy functions and Markov processes. All numbers are in percentages. Market groups are defined as below and above the median of the population.