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Florin Maican and Matilda Orth

Research Institute of Industrial Economics
P.O. Box 55665
SE-102 15 Stockholm, Sweden
info@ifn.se
www.ifn.se

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Florin Maican[†] and Matilda Orth[‡]

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Abstract

Quantifying possible inefficiencies stemming from regulations is important to both policymakers and researchers. We use a dynamic structural model to evaluate the role of local market entry regulations for productivity in retail trade. Our model endogenizes productivity, is flexible with respect to how local market regulations influence store productivity, and controls for demand in local markets. We combine the structural approach with detailed data on all stores in the Swedish retail trade. The results show that a more liberal entry regulation increases store's future productivity and contributes significantly to weighted aggregated productivity in local markets.

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

JEL Classification: L11, L81, L88, O30.

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[†]University of Gothenburg and Research Institute of Industrial Economics (IFN), Box 640, SE-405 30, Göteborg, Sweden, Phone +46-31-786 4866, Fax +46-31-786 1326, E-mail: florin.maican@economics.gu.se

[‡]Research Institute of Industrial Economics (IFN), Box 55665, SE-102 15, Stockholm, Sweden, Phone +46-8-665 4531, Fax +46-8-665 4599, E-mail: matilda.orth@ifn.se

1 Introduction

The impact of regulations on market outcomes is frequently debated in many countries because the policy interventions that aim to prevent market failure may also lead to inefficiencies. Firms' reactions to changes in the market environment depend on their productivity levels, which have been found to be determined by both internal factors, in control of the firm, and external environments. Yet little work has been done to quantify the effect of regulations on productivity (Syverson, 2011). If regulations come at the cost of restricting productivity development, it is crucial for both policymakers and researchers to quantify the magnitude of these costs to ultimately evaluate welfare and decide the optimal regulation levels. In this paper, we propose a dynamic structural model to assess the implications of local market entry regulations for productivity dynamics in retail trade.

To isolate and empirically quantify the effect of regulations on productivity requires both careful modeling and comprehensive data. First, regulation affects productivity, which must be taken into account when estimating the service production function. Second, stores have different incentives to change productivity based on the regulation depending on their current productivity levels and local market conditions, which in turn affect their future productivity relative to competitors. Any welfare analysis of regulations needs to consider the full distribution of store responses in local markets. Third, the impact of regulation on productivity must be disentangled from demand shocks such that an increase in market size or structural changes in shopping behavior is not interpreted as an increase in productivity, for example. Fourth, there are standard problems of simultaneity of input choices and selection in estimating the service production function and potential endogeneity concerns regarding the stringency of the regulation.

To account for these modeling challenges and to accurately measure the effect of regulatory stringency on productivity, we propose a dynamic structural model that builds on the growing literature on heterogeneity in productivity within industries (Ericson and Pakes, 1995; Olley and Pakes, 1996).[1] The model endogenizes the productivity process with respect to local market regulation, allows stores to react differently to changes in the regulation, and controls for demand in local markets. Importantly, with the simple analysis of regressing labor productivity (value-added per full-time adjusted employee) or multi-factor productivity on a regulation measure, it is difficult to assess these modeling challenges. We combine the structural model with rich panel data on all retail stores in Sweden from the period 1996-2002 and perform the analysis separately for eleven different subsectors.

Our approach is particularly attractive because we recover the full distribution of productivity responses by all stores and calculate the change in aggregated weighted productivity in local markets stemming from a more liberal regulation. This quantification exercise attempts to shed light on a question of direct policy interest. The framework provides a point of departure for a more complete welfare analysis of local market entry regulations, and it can be applied to other imperfectly competitive industries that are subject to regulation. Stores cannot influence or form expectations regarding the future stringency of the regulation, and thus to alleviate possible endogeneity concerns regarding the regulation, we use a two-step estimation procedure. Our model captures the net effect of regulation on productivity and provides a clear identification strategy for understanding stores' heterogeneous responses to regulatory changes, which does

[1] Recent contributions on manufacturing and/or trade include Levinsohn and Petrin (2003); Ackerberg et al. (2006); Ackerberg et al. (2007); De Loecker (2011); De Loecker and Warzynski (2012); De Loecker et al. (2012); Asker et al. (2013); De Loecker and Collard-Wexler (2013); Doraszelski and Jaumandreu (2013) and Gandhi et al. (2013).

not require the same additional assumptions that are necessary when using a dynamic game framework.[2]

Retail is an industry with a number of features that make it appropriate for studying the consequences of regulations on productivity. First, retail markets are subject to substantial regulations, that are much more restrictive in Europe than in the U.S. In Europe, one of the most powerful policy tools in the retail sector is entry regulations that empower local authorities to make decisions regarding the entry of new stores. Second, the retail trade is often claimed to substantially contribute to the frequently debated productivity gap between Europe and the U.S. (Gordon, 2004; Schivardi and Viviano, 2011). Third, retail has become increasingly important for overall economic activity in modern economies and currently accounts for up to 6 percent of GDP and 10 percent of employment. Retail markets in both Europe and the U.S. have trended toward larger but fewer stores and have changed dramatically owing to the adoption of information technology such as scanners, barcodes and credit card processing machines in recent years. In the U.S. retail trade, entry and exit have been found to explain nearly all labor productivity growth. This stands in contrast to the manufacturing sector, in which entry and exit are found to account for only approximately 30 percent of total growth (Bartelsman and Doms, 2000; Schmitz, 2005; Foster et al., 2006).

All stores are subject to the regulation in Sweden, providing the 290 municipalities with the power to make land use decisions. Each new potential entrant is required to make a formal application to the local government. The decision to change a geographic zoning restriction, and thus allow a new store to enter the

[2]This raises concerns about, for instance, functional forms of cost functions, multiple equilibria and aggregation to reduce the computational complexity (Bajari et al., 2007; Pakes et al., 2007; Ryan, 2012; Abbring et al., 2013; Collard-Wexler, 2013; Dunne et al., 2013; Fowlie et al., 2013; Maican and Orth, 2013; and Sweeting, 2013).

market should more broadly consider the consequences for, e.g., market structure, prices, traffic, and the environment. The regulation is binding, and it is extremely rare that all applications are approved by the local authorities. To measure the stringency of regulation, we draw on previous work on land use and entry regulations and employ rich data that vary across local markets and time and that allow us to control for market size and the potential endogeneity of the regulation. We use political preferences in local governments and the share and number of approved applications by local authorities (Bertrand and Kramarz, 2002; Schivardi and Viviano, 2011; Sadun, 2014). In addition to using each measure separately, we combine them by constructing index variables for regulation that are independent of market size (Suzuki, 2013; Turner et al., 2014).

The estimation of the service production function shows increasing returns to scale in most subsectors of the Swedish retail trade. The results suggest that a more liberal regulation increases store productivity, although there is great heterogeneity in the marginal effects across stores and local markets. Aggregate productivity in local markets increases annually in the range of 2 to 5 percent for most subsectors when the regulation index increases toward being more liberal by one standard deviation. The findings are robust to various semiparametric estimators and different measures of regulation and to controlling for the potential endogeneity of the regulation. We find that it is important to endogenize productivity, be flexible in how stores react to the regulation and control for local market demand, simultaneity and omitted price variable bias. Our findings emphasize the non-trivial importance of regulations for productivity in local retail markets.

The paper makes several contributions to the literature. Surprisingly few attempts have been made to examine the importance of regulations for productivity, which is currently claimed to be a key issue in the productivity literature (Syverson, 2011). To the best of our knowledge, this is one of the first papers to

use a dynamic structural model to quantify the effects of regulations on productivity in retail. The paper adds a structural framework to previous work on how regulations affect productivity (Djankov et al., 2002; Syverson, 2011; Greenstone et al., 2012; Buccirossi et al., 2013), and relates to a growing literature on land use regulations (Maican and Orth, 2013; Suzuki, 2013; Turner et al., 2014). The proposed framework complements the existing retail literature (Bertrand and Kramarz, 2002; Haskel and Sadun, 2011; Schivardi and Viviano, 2011; Sadun, 2014),[3] and contributes to recent work on productivity dynamics in retail (Foster et al., 2006; Basker, 2007; Basker, 2012). The study's strengths are that we combine a structural framework with rich data on all stores, which allows for the careful investigation of the dynamics and heterogeneity in store-level responses to changes in the regulation. Isolating demand effects from productivity recently received attention in a local market setting for services in a companion paper on retail food (Maican and Orth, 2009) and in estimating the supply function for housing (Epple et al., 2010), whereas it previously has been examined at the industry level in manufacturing (Klette and Griliches, 1996; Levinsohn and Melitz, 2006; Katayama et al., 2009; De Loecker, 2011; Pozzi and Schivardi, 2012; Doraszelski and Jaumandreu, 2013).[4] The difficulties of measuring physical output

[3]Schivardi and Viviano (2011) find that more strict entry regulations hinder productivity in Italian retail trade. Sadun (2014) finds that an increase in approved applications results in higher employment growth, and Haskel and Sadun (2011) find that total factor productivity in retail decreased following the 1996 planning regulation in U.K. Another study using U.K. data is Reynolds et al. (2005). In France, regulation is found to slow labor growth (Bertrand and Kramarz, 2002).

[4]Recent research use linked establishment-level data and product-level data on prices and quantities for samples of narrowly defined manufacturing firms (e.g., De Loecker et al., 2012; Petrin and Warzynski, 2012; Roberts et al., 2012). Relying on only a small sample of stores in retail, however, severely limits the possibilities to evaluate regulations in local markets. We are, to the best of our knowledge, not aware of any study of productivity in retail that combines

and defining retail prices suggest that both technical and quality-adjusted productivity measures, i.e., true productivity without demand shocks and the sum of technical productivity and remaining demand shocks, should be considered.

Section 2 presents the entry regulation and data. Section 3 describes the modeling approach. Section 4 discusses productivity and the results of the impact of the regulation on productivity, followed by conclusions in Section 5. In several places, we refer to an online appendix containing various analysis that we do not discuss in detail in the paper.

2 Entry regulation and data

The majority of OECD countries have entry regulations that empower local authorities to make decisions regarding the entry of new stores. The purpose of these regulations is to prevent possible negative externalities regarding, for instance, competition, lack of access for consumers and environmental aspects. The restrictions, however, differ substantially across countries. Whereas some countries strictly regulate large entrants, more flexible zoning laws exist, for instance, in the U.S. (Hoj et al., 1995; Pilat, 1997; Boylaud and Nicoletti, 2001; Nicoletti and Scarpetta, 2003; Griffith and Harmgart, 2005; Pilat, 2005).

In Sweden, the Plan and Building Act ("Plan och Bygglagen", PBL) empowers the 290 municipalities to make decisions on applications for new entrants. There is geographical zoning such that municipalities have power over land use, i.e., all stores are subject to the regulation.[5] The PBL is binding, and it is extremely rare that all applications are approved by a local authority. Inter-

detailed store-level information with store-level prices for the total population of stores. Griffith and Harmgart (2005); Reynolds et al. (2005), and Maican and Orth (2009) provide more details regarding retail markets.

[5]Hours of operation are also regulated in some countries, but not in Sweden.

municipality questions regarding entry are addressed by the 21 county administrative boards. The PBL is held to be a major barrier to entry, resulting in diverse outcomes, e.g., price levels across local markets (Swedish Competition Authority, 2001:4). Several reports stress the need to better analyze how regulations affect market outcomes (Pilat, 1997; Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2). Appendix A describes the PBL in greater detail.

Measures of regulation. To measure the regulatory stringency in local markets, we draw on previous work on regulations and collect rich data from a variety of sources (Bertrand and Kramarz, 2002; Gyourko et al., 2008; Schivardi and Viviano, 2011; Suzuki, 2013; Sadun, 2014; Turner et al., 2014). The literature on land use and that on entry regulations share a common obstacle in that there is no one ideal measure of regulation. In line with previous work, we use a number of different measures that vary across markets and years and allow us to control for market size and the potential endogeneity of the regulation. We analyze each measure separately and combine them together by constructing index variables with different weighting schemes.

The first data include information on the share of seats to each political party in local municipal governments.[6] How local governments implement the

[6]The Social Democratic Party is the largest party nationally, with 40.6 percent of seats on average, and it collaborates with the Left Party (8 percent) and the Green Party (4.2 percent). The non-socialist group consists of the Moderate Party (18 percent), and it is most often aligned with the Center Party (13.2 percent), the Christian Democratic Party (5.9 percent), and the Liberal Party (5.6 percent). The Center Party is traditionally strong in rural areas. For our purposes, therefore, we only consider the Moderate Party, the Liberal Party and Christian Democrats in the non-socialist group. Twenty-two per cent of municipalities had a non-socialist majority during 1996-1998, increasing to 32 percent during 1999-2002. The non-socialists had 8.6-85 percent support, with an average of 40.7 percent in 1996-1998 and 44.1 percent in 1999-2002.

PBL depends on the preferences of the politicians (Bertrand and Kramarz, 2002; Schivardi and Viviano, 2011). In Sweden, the expectation is that non-socialist local governments will apply the PBL more liberally.[7] The exogeneity of political preferences for measuring regulatory stringency relies on local economic issues' not determining future election outcomes. In Sweden, we believe it is reasonable to rely on the idea that land use issues do not turn local elections around. Swedish municipalities have many responsibilities. Child care, schooling and elderly care are main spending areas that are likely to influence voter's decisions more heavily.

The second data set contains information on the actual implementation of the entry regulation. First, we access the number of approved PBL applications that allow the entry of retail stores. The data were collected from surveys from 163 out of the 290 municipalities and exist for three time periods: 1987-1992, 1992-1996, and 1997-2000 (Swedish Competition Authority, 2001:4). Second, we access the total number of PBL approvals in each municipality and year (Swedish Mapping, Cadastral and Land Registration Authority (Lantmäteriet)). The total number of PBL approvals differs from the PBL approvals that allow the entry of retail stores in that it contains all types of commercial activities (not only retail) and residential purposes. Our data differ from that used by Suzuki (2013) in that we access applications for both commercial and residential purposes, bringing us closer to measuring actual regulation enforcement.[8] The two different definitions of the number of PBL approvals are all flow variables, i.e., they capture the number of new applications that are approved. The correlation between the

[7]This is contrary to, for instance, France and Italy. It is well established that the Swedish non-socialist government is more positive to liberalization. The non-socialist government has deregulated the pharmacy and telecom markets, for example.

[8]Suzuki (2013) uses data on applications for residential purposes to evaluate cost changes in the lodging industry.

two measures is 0.83. In order to be able to use all local markets and years, and because of the high correlation, we focus only on all approvals (instead of only approvals of the entry of retail stores).

Third, we observe the total number of so-called zoning plans in each municipality and year (Swedish Mapping, Cadastral and Land Registration Authority (Lantmäteriet)). Each local market is divided into a number of well-defined geographic areas, called zoning plans, that are subject to the entry regulation. The existing number of zoning plans is a stock variable, i.e., it captures the number of geographic areas for each market-year observation. When a PBL application is approved, it can change the number of zoning plans the next year. We incorporate information on the number of zoning plans to control for market size and the fact that larger municipalities might have a higher number of approvals only because of their size. Specifically, we use the share of PBL approvals (PBL approvals divided by number of zoning plans) and the number of PBL approvals per number of stores for each municipality and year, which do not depend on the size of the market.

To obtain a solid measure of the regulatory stringency and employ the richness of the different data sets that we collected, we construct index variables of the regulation similar to Suzuki (2013). In particular, we combine the share of non-socialist seats in the local government, the share of PBL approvals and the number of approvals per number of stores. In the main specification, we apply half of the weight to the share of non-socialist seats and one-quarter each to the two measures of shares of PBL approvals. A higher regulation index value indicates a more liberal regulatory environment. To simplify the evaluation of the marginal effects of how a more liberal regulation changes store's productivity, we standardize the regulation index to a mean of zero and a standard deviation of

one. This index variable is our preferred measure of regulation.[9] For robustness, we also use equal weights for the three measures in the index, consider each measure separately and control for possible endogeneity of the regulation variable (see estimation and robustness sections for details).

Municipalities with a non-socialist majority approved more applications. The correlation between the share of non-socialist seats and the number of approved applications is 0.45. The corresponding correlation for the share (rather than the number) of approved applications is 0.25. There is also a high correlation between the share of non-socialist seats and the regulation index variables (0.74-0.87) and between the index variables defined using different weighting (about 0.9).

If the local authorities approve all PBL applications, then the number of approvals measures competition, not regulation. Although we do not access the number of rejections, it is extremely rare that all applications are approved (small local markets). That the regulation is binding confirms that we measure regulatory stringency. In Sweden, we do not expect the politicians' implementation of the PBL or the number of approvals to be correlated with other local policies such that our regulation index would measure a set of correlated regulations. That is, we believe that our findings relate solely on the link between productivity and entry regulations.

Local markets. Our modeling approach takes local competition into account, and market size is determined by subsector, store size, and distance to competi-

[9]Our study shares the common obstacle of not observing one ideal measure of regulation with previous work on land use and entry regulations. A valid alternative to the index variable is to use only the share (and number) of approved applications and/or political preferences (Bertrand and Kramarz, 2002; Schivardi and Viviano, 2011; Sadun, 2014). One could argue that the number of applications (and rejections) is not completely exogenous if the number of applications is easily influenced by current local government policies.

tors. We expect the local market to be narrower the more limited the durability of goods. The 21 counties are most likely too large, whereas the more than 1,600 localities are most likely too small. The 290 municipalities that make entry decisions are, however, a reasonable local market size for the majority of Swedish retail trade products. We therefore use the 290 municipalities as our definition of local markets.

Store data. We use detailed data from Statistics Sweden (SCB) that include all retail stores from 1996 to 2002. The unit of observation is a store, based on its tax reporting number. The data contain two parts: (i) Financial Statistics (FS) contain input and output measures such as sales, value-added, investments, etc., and (ii) Regional Labor Market Statistics (RAMS) include the number of employees and wages. Almost all stores consist of one unit, but some stores can consist of several units because of, e.g., joint ownership.[10] If the data consists of more than one store, we observe total, not average, inputs and outputs. We use all stores that belong to SNI-code 52, "Retail trade, except of motor vehicles and motorcycles; repair of personal household goods." Because we have access to detailed information, it is possible to use the five-digit industry codes (74 in total for retail). To simplify the presentation and jointly analyze similar product groups, we use the following eleven subsectors (discussed in detail in Appendix C) in the empirical application: textiles, clothing, footwear, furniture, electronics, hardware, books, sports, watches, toys and computers.

SCB provides direct value-added measures. Sales, value-added, investments and capital are deflated by sub-groups of the Consumer Price Index (CPI). It is important to control for subsector prices because subsectors are heterogeneous. Separate and individual sub-groups are also used for textiles, clothing, footwear, furniture, hardware, books and computers. For the remaining groups, we use the

[10] Anonymity hinders us from identifying owners and connecting individual units with stores (see Appendix B for a detailed description of the data).

CPI.

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

Table 2 presents median and dispersion measures for the key variables from 1996 to 2002. Dispersion is defined as the difference between the 75th and 25th percentiles of stores divided by the median. This measure, which indicates the spread of the distribution, is selected to avoid measurement problems and outliers. The median store increases sales by 26 percent over the period. The corresponding increase in value-added is 31 percent, while investments increase 19 percent. The median store has three employees (full-time adjusted) over the entire period, most likely because stores that change size are located in the tails of the distribution. For all variables, dispersion increases over time. A comparison across variables shows that investment has the highest values, i.e., investment is the variable that differs the most across stores. The level of dispersion is approximately three times larger than those for investment than for sales, value-added,

and the number of employees.

Table 3 presents entry and exit rates organized by subsector and size. Exit rates are high, and large entrants are common in toys, for example. The entry of small stores is most common in clothing, furniture, hardware, and sports. Hardware and sports are the only subsectors with net entry; all others have net exit with the highest outflow of stores in textiles, books, and footwear.

Table 4 reports descriptive statistics of annual store-level growth in terms of value-added, number of employees, wages, and capital over the study period. The share of small stores in each subsector is highest in textiles but lowest in hardware. The mean value-added increases the most in sports and toys but the least in textiles, footwear, and books. Employment growth is highest in toys and small sport stores but lowest in electronics and watches. Capital growth is high in electronics, and sports but low in textiles and watches. The mean values are also high for furniture, whereas low corresponding values are found for books and toys.

Regulation and labor productivity. To empirically document the relationship between the degree of regulatory stringency and productivity, we regress labor productivity on different regulation indexes. We pool all stores from all subsectors, use each store's value-added per full-time adjusted employee to measure labor productivity and use three different proxies for local market regulation. Table 5 shows that the coefficient on the regulation is positive for all specifications, and statistically significant for a majority of the specifications. This shows initial evidence that there is a link between regulation and productivity.

3 Modeling approach

The framework begins with a definition of store productivity. Stores maximize their expected discounted profits and choose their inputs and investments based

on current productivity ω_{jt}, capital stock k_{jt}, wages w_{jt}, and other exogenous observed local market characteristics.[11] Capital stock is a dynamic input and accumulates according to $K_{t+1} = (1-\delta)K_t + I_t$, where δ is the deprecation rate and I_t measures the difference between real gross expenditures on capital and gross retirement of capital. To analyze how the regulation influences productivity and how productivity evolves for individual stores over time, we endogenize productivity. Productivity follows a controlled first-order Markov process, $P(d\omega_{jt}|\omega_{jt-1}, r_{mt-1})$, where r_{mt-1} measures regulation in local market m in period $t-1$. Two stores with the same current productivity but located in markets with different regulation will have different future productivity realizations because they have different incentives to improve productivity given the stringency of the regulation. A more liberal regulation might result in better distributions of tomorrow's productivity, conditional on current productivity, i.e., $P(\cdot)$ is stochastically increasing in r_{mt-1} for a given ω_{jt-1}.

The service production function for store j is

$$q_{jt} = \tilde{\beta}_l l_{jt} + \tilde{\beta}_k k_{jt} + \tilde{\omega}_{jt} + \tilde{e}_{jt}, \tag{1}$$

where q_{jt} is the log of quantity sold by store j at time t; l_{jt} is the log of labor (number of full-time adjusted employees); k_{jt} is the log of capital stock; and $\tilde{\beta}_l$ and $\tilde{\beta}_k$ are the true technology parameters.[12] The unobserved $\tilde{\omega}_{jt}$ is technical productivity, and $\tilde{e}_{jt}$ are the shocks to service production (quantity sold) that are not predictable during the period in which inputs can be adjusted and stores make exit decisions.

In services industries such as retail, it is difficult to measure output. The best proxy for output is sales or value-added, which implies that we will underesti-

[11] Lowercase letters are used for variables in logs.

[12] The model is easy to apply to a general specification; for example, translog with neutral efficiency across stores would perform equally well.

mate the labor and capital parameters without controlling for prices (Klette and Griliches, 1996; Melitz, 2000; Foster et al., 2008; De Loecker, 2011).[13] Based on our application to Sweden and the available data, we assume a demand function with a negative slope and that stores operate in a market with horizontal product differentiation, where η_s (< -1 and finite) captures the elasticity of substitution among products in subsector s:

$$p_{jt} = p_{smt} + \frac{1}{\eta_s} q_{jt} - \frac{1}{\eta_s} q_{smt} - \frac{1}{\eta_s} \xi_{jt}, \tag{2}$$

where p_{jt} is the log of output price, p_{smt} and q_{smt} are the logs of output price and quantity sold in subsector s in the local market m, and ξ_{jt} are demand shocks to store j. Using (2) to control for prices in (1), we obtain

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} - \beta_q q_{smt} - \frac{1}{\eta_s} \xi_{jt} + \omega_{jt} + e_{jt}, \tag{3}$$

where $y_{jt} = q_{jt} + p_{jt} - p_{smt}$ is deflated value-added (or sales); p_{smt} is the subsector consumer price index in the local market m; $\beta_{l,k} = \left(1 + \frac{1}{\eta_s}\right) \tilde{\beta}_{l,k}$ are the coefficients for labor and capital, respectively; $\beta_q = \frac{1}{\eta_s}$ is the coefficient of market output; and $\omega_{jt} = \left(1 + \frac{1}{\eta_s}\right) \tilde{\omega}_{jt}$ and $e_{jt} = \left(1 + \frac{1}{\eta_s}\right) \tilde{e}_{jt}$ are technical productivity and shocks to production adjusted for the elasticity of demand. If store level prices are observed, we directly substitute (1) into (2). In estimating (3), we need to control for unobserved demand shocks ξ_{jt} and unobserved productivity shocks ω_{jt}.

The demand system allows for one elasticity of substitution for all stores

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

within each subsector, i.e., no differences in cross-price elasticities. In other words, there are completely symmetric price responses and differentiation across stores in each subsector; therefore, we have a constant markup over marginal cost across subsector s, $(\frac{\eta_s}{1+\eta_s})$, and the Lerner index is $\frac{1}{|\eta_s|}$.[14]

A common and well-known obstacle in retail studies is how to measure prices, because of the complexity of products and the mix of product assortments. In our setting, this is even more difficult because we recover productivity for all stores, which requires a separate price measure for each store. To the best of our knowledge, we are not aware of any study of retail productivity and market structure that combines detailed store-level information on all stores with store-level prices.

The nature of the available data requires that we use a simple demand system, and we argue that our empirical application has features that support a CES demand system. First, the Swedish retail trade has characteristics similar to those of monopolistic competition, i.e., each local market consists of a large number of stores such that a price change in one store likely has a minor impact on market price or on influencing the regulation process. Most local markets consist of 5-12 stores per subsector, and there are no local monopolies. We analyze each store as a separate unit. This implies that we focus on the fairly substantial share of stores operating as independent or franchise units and abstract from the fact that some stores may belong to international or national chains such as H&M or IKEA, which would severely complicate the analysis.[15] Second, from

[14] We can allow the elasticity of substitution to differ across the segment groups g in subsector s. The Lerner index for segment g in subsector s is then $\frac{1}{|\eta_{sg}|}$, but this would require data on price indices p_{sgmt}. Ideally, we would like to access different indices across local markets. Needless to say, the lack of data forces us to use a common price index by subsector. This may partially collapse based on the extent to which we are able to control for prices.

[15] A careful and complete demand analysis requires store-level data on prices and product characteristics for all stores, which is unfortunately not available

a theoretical standpoint, the Swedish retail market fulfills all key restrictions under which the CES demand system with one elasticity is consistent with an underlying model in the characteristics space (Anderson et al., 1989). That is, all people buy retail products, stores are located in different geographic areas, and the limited number of retail store formats is smaller than the number of store characteristics, e.g., age, square-meters, owner.

Apart from variation in inputs and aggregate local demand q_{smt} in subsector s, other factors may also capture unobserved prices in (3). To control for unobserved demand shocks, we decompose ξ_{jt} into two parts

$$\xi_{jt} = \mathbf{z}'_{mt}\boldsymbol{\beta}_z + u^d_{jt}, \tag{4}$$

where $\mathbf{z}'_{mt}$ is the observed local demand characteristics and u^d_{jt} are the remaining store-specific unobserved demand shocks. In the empirical implementation, we control for a large number of observed local market demand shifters in $\mathbf{z}'_{mt}$, i.e., population, population density, and income. Because retail products are bought

in many datasets. This would allow us to consider heterogeneous products and consumers in a Berry et al. (1995) (BLP) framework. Because we use all stores in local markets for a long period, and because of the difficulty in obtaining store-level prices, it is beyond the scope of our analysis to allow stores to have different product assortments and consider heterogeneous consumers. Katayama et al. (2009) propose a model that incorporates oligopolistic competition using a nested logit approach (Berry, 1994). They make assumptions in addition to the ones that are common in the discrete choice demand literature (Bertrand-Nash equilibrium, outside option, choice of nests). There are assumptions on the evolution of and shocks in the product quality and marginal cost equations and on the posterior distribution of the demand parameters. In addition, a VAR system is used to identify the demand parameters. Adding local market competition and regulation in this framework requires even more assumptions. A CES demand function extended to incorporate regulation and local market competition, in which the identification is transparent, is preferred in our application to Swedish retail.

by most people in society and we consider store-level demand, we expect these demand shifters to capture the most important demand shocks to the stores. In addition, we remove the immediate effect of regulation on prices by including the current regulation index r_{mt} in $\mathbf{z}'_{mt}$. Combining equations (3) and (4), we obtain

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} - \beta_q q_{smt} - \frac{1}{\eta_s}\mathbf{z}'_{mt}\boldsymbol{\beta}_z - \frac{1}{\eta_s}u^d_{jt} + \omega_{jt} + e_{jt}. \tag{5}$$

To identify technical productivity separately from demand, we rely on the assumption that u^d_{jt} are i.i.d. shocks and they collapse into e_{jt}. If there are correlated demand shocks, u^d_{jt} enters in ω_{jt} and we identify quality-adjusted productivity, i.e., the sum of technical productivity and remaining demand shocks (Appendix D). An important difference between technical and quality-adjusted productivity is the interpretation of the results, i.e., what remaining demand shocks are in ω_{jt}. In what follows, we will refer to ω_{jt} as productivity.

The paper uses value-added as a proxy for output, which controls for the stock of products bought from wholesalers.[16] Gandhi et al. (2013) provide an extensive discussion on measuring productivity using sales and value-added when using materials to recover productivity. Statistics Sweden provides a value-added measure for each store in the data, but it does not provide an accurate and separate measure of materials or energy in retail. Therefore, we will use labor rather than materials to recover productivity (discussed in detail below). Furthermore, because of the difficulty of measuring physical output in retail, we use aggregated sales in subsector s in local market m as proxy for q_{smt} (Klette and Griliches, 1996).

Regulation and productivity process. To analyze the role of regulation on productivity, we endogenize productivity and explicitly model local market reg-

[16]Elasticity of demand using value-added might not be equal to that defined on sales, but they are not substantially different.

ulation in the productivity process. The proposed model deviates from previous work in that it endogenizes the productivity process with respect to local market regulation in different retail industries. This links to Olley and Pakes (1996) and, more specifically, to De Loecker (2011), who evaluates the role of trade liberalization for productivity in the Belgian textile market. From an empirical point of view, we motivate the incorporation of regulation in the productivity process by descriptive evidence that regulation influences labor productivity (Table 5).

Regulation influences the productivity of incumbent stores with a one-year lag to capture the time stores require to cut slack and change features such as their management to increase productivity.[17] Productivity ω_{jt} follows a first-order controlled Markov process:

$$\omega_{jt} = E[\omega_{jt}|\omega_{jt-1}, r_{mt-1}] + \upsilon_{jt} = g(\omega_{jt-1}, r_{mt-1}) + \upsilon_{jt}, \tag{6}$$

where r_{mt-1} measures the entry regulation in local market m in period $t-1$ and υ_{jt} are i.i.d. shocks to productivity that are not related to regulation or inputs. The shocks υ_{jt} may be understood as the realization of uncertainties that are naturally linked to productivity. The conditional expectation function $E[\omega_{jt}|\omega_{jt-1}, r_{mt-1}]$ is unobserved by the econometrician (but known to the store) and is approximated by the nonparametric function $g(\omega_{jt-1}, r_{mt-1})$. A key advantage of our model over previous work on regulation and productivity is that the regulation affects each store's productivity in a flexible manner, i.e., $g(\omega_{jt-1}, r_{mt-1})$ captures that the impact of a more liberal regulation on a store's productivity will differ depending on the store's productivity and the stringency of local market regulation. Stores' immediate actions after observing the regulation level relate to prices to secure their market-share and customers, captured

[17]Similar approaches are, for example, adopted when analyzing productivity and R&D (Aw et al., 2011; and Doraszelski and Jaumandreu, 2013) or productivity and trade liberalization (De Loecker, 2011).

by r_{mt} in $\mathbf{z}'_{mt}$, and the lagged effect is on productivity. In case of quality-adjusted productivity, the previous degree of local market regulation r_{mt-1} affects both prices and productivity, and these effects cannot be separated.

There are two important remarks to make here: First, the main aim of the paper is to measure the net effect of the regulation on productivity rather than to model all channels through which this occurs. The advantage of the single agent framework is that it allows for a better understanding of store heterogeneity, whereas endogenizing competition by considering strategic interactions in a dynamic game framework severely complicates the analysis and imposes additional assumptions (Bajari et al., 2007; Pakes et al., 2007; Ryan, 2012; Abbring et al., 2013; Collard-Wexler, 2013; Maican and Orth, 2013; Sweeting, 2013). For example, dynamic games raise concerns about the functional forms of cost functions, multiple equilibria, equilibrium selection mechanisms and aggregation to reduce computational complexity. Concerns of aggregation and computational complexity, for instance, are especially pertinent when analyzing retail trade in which each local market consists of many stores. For an illustration, let the degree of local market competition be a function of regulation $c_{mt} = c(r_{mt})$, and the marginal effect of regulation on productivity is $\partial\omega_{jt}/\partial r_{mt-1} = (\partial\omega_{jt}/\partial c_{mt-1})(\partial c_{mt-1}/\partial r_{mt-1})$ when the regulation proxy is replaced with a competition measure in the productivity process.[18] Modeling the effect of regulation on competition requires a complex model including institutional details of each subsector in a dynamic game setting, which imposes addi-

[18]Because entry regulations work as barriers to entry, we expect more liberal regulatory stringency to increase competition. In fact, there is evidence that a more liberal regulation results in more entrants and exits and a net increase in number of retail food stores in local markets (Maican and Orth, 2013). If there is increasing competition through more entrants, the relatively low productive incumbents try to improve their productivity to compensate for the decreasing market shares from stronger competition.

tional assumptions. Instead, our focus is on measuring store-level multi-factor productivity to carefully evaluate the consequences of the regulation, which is of direct interest to both policymakers and researchers.

Second, regulation enters as exogenous in the productivity process such that individual stores do not affect the outcome of the regulation or form expectations over the future stringency of the regulation. Although we use a two-step estimation procedure (discussed below), which alleviates possible endogeneity concerns regarding regulation, we check the robustness of our findings using an instrumental variable approach in the Markov regression. We provide more details on the endogeneity of the regulation in the estimation and robustness sections.[19]

Proxy for productivity. To estimate the service production function (5) while controlling for unobserved demand shocks, we need to proxy for unobserved productivity. To do this, we use the labor demand function from stores' profit maximization problem (static or dynamic) together with a good measure of store-specific wages (Doraszelski and Jaumandreu, 2013). Retail stores make lumpy investments, i.e., invest one year followed by several years without investment, which constrains the sample substantially when using the policy function for investment (Olley and Pakes, 1996). Levinsohn and Petrin (2003) use the demand for static inputs, i.e., materials, and Doraszelski and Jaumandreu (2013) consider a parametric approach of labor demand based on Cobb-Douglas technology, whereas Ackerberg et al. (2006) use the unknown policy function for

[19]To endogeneize regulation, we need detailed information about how regulation works in each local market, e.g., institutional details. However, the lack of institutional details about regulation can be substituted with additional modeling assumptions, which we expect to influence the final results. In our setting, a structural framework that uses few assumptions and all stores is preferred to one with many assumptions. The proposed model facilitates adjustments for our data and many other datasets that use the entire population of stores/firms. For this reason, we treat regulation as exogenous in the main specification.

investment in capital, labor or materials to control for unobserved productivity. In retail, a common limitation is the lack of information about materials (wholesale quantities) in many data sets.

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

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

$$l_{jt} = \tilde{l}_t(\omega_{jt}, k_{jt}, w_{jt}, q_{smt}, \mathbf{z}_{mt}), \tag{7}$$

where $\tilde{l}_t(\cdot)$ is an unknown function strictly increasing in ω_{jt}, and w_{jt} is the log of the wage rate at the store level. We also consider a static and parametric labor demand function based on the short-run optimization problem and rely on Cobb-Douglas technology in Appendix E (Doraszelski and Jaumandreu, 2013). In both of these cases, we assume that wages follow an exogenous process. In the general case in which labor demand solves store's dynamic problem,[20] labor demand is a function of wages because store wages are part of the state space (Sargent, 1978).[21]

[20]Stores choose current labor to maximize future expected profits.

[21]Because of the linearization property, the Euler equation (first-order condition with respect to number of employees) is a function of current wages. This is similar to the static case in Doraszelski and Jaumandreu (2013) in which the first-order condition with respect to the number of employees is also a function

The scalar unobservable assumption, i.e., that productivity ω_{jt} is the only unobservable in equation (7), is required for identification. The strict monotonicity condition also holds under the simple constant elasticity of substitution (CES) demand system. At the aggregate level, the number of employees increased during the study period. By looking at the evolution of the median number of employees per store, we cannot infer if the monotonicity condition holds because Swedish retail is a dynamic industry in which entry and exit are common, and this brings variation into the data, which helps to non-parametrically estimate the labor demand function. In the empirical implementation, we check that the monotonicity condition holds by visualizing the surface pictures constructed using $l_{jt} = l(\omega_{jt}, k_{jt})$. In the parametric case, the monotonicity condition holds because of the linearity property (Appendix E). Because stores set wages and part-time work and temporary job contracts are common in retail, identification relies on variation in store-specific wages.

Estimation. The estimation of the service production function is performed in two steps. By inverting the labor demand function to recover productivity and substituting into the service production function, we obtain

$$y_{jt} = \phi_t(l_{jt}, k_{jt}, w_{jt}, q_{smt}, \mathbf{z}_{mt}) + \epsilon_{jt},$$

where ϵ_{jt} is the sum of demand and production (quantity sold) shocks and $\phi_t(\cdot) = \beta_l l_{jt} + \beta_k k_{jt} - \beta_q q_{smt} - \frac{1}{\eta_s}\mathbf{z}'_{mt}\beta_z + \omega_{jt}$. We approximate the unknown function $\phi_t(\cdot)$ using a third-order polynomial expansion in its arguments. The aim of the first step is to separate productivity ω_{jt} from i.i.d. shocks to production ϵ_{jt}. The first step only provides an estimate of $\phi_t(\cdot)$, $\hat{\phi}_t(\cdot)$, which helps in recovering

of current wages (Appendix E).

productivity as follows:

$$\omega_{jt}(\boldsymbol{\beta}) = \hat{\phi}_t(\cdot) - \beta_l l_{jt} - \beta_k k_{jt} + \beta_q q_{smt} + \tfrac{1}{\eta_s}\mathbf{z}'_{mt}\boldsymbol{\beta}_z, \tag{8}$$

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

$$E\left\{ \upsilon_{jt}(\boldsymbol{\beta}) | \begin{pmatrix} l_{jt-1} \\ k_{jt} \\ q_{smt-1} \\ \mathbf{z}_{mt-1} \end{pmatrix} \right\} = 0. \tag{9}$$

The moment $E[\upsilon_{jt}(\boldsymbol{\beta})|l_{jt-1}] = 0$ then identifies β_l. The assumption that stores decide on investment in capital at $t-1$ implies that the coefficient of capital β_k is identified from $E[\upsilon_{jt}(\boldsymbol{\beta})|k_{jt}] = 0$. To identify parameters η_s and $\boldsymbol{\beta}_z$, we use $E[\upsilon_{jt}(\boldsymbol{\beta})|q_{smt-1}] = 0$ and $E[\upsilon_{jt}(\boldsymbol{\beta})|\mathbf{z}_{mt-1}] = 0$. When local regulation r_{mt} is a component of $\mathbf{z}_{mt}$, a moment based on r_{mt} or the current share of approved applications can be used to identify the coefficient of r_{mt}. Again, this does not imply that we can truly separate the effect of regulation on prices, i.e., regulation may have lagged effects on prices. If one is concerned that current regulation is correlated with shocks to the service production function and demand in the first step of the estimation, one can use moments based on r_{mt-1} or the average stringency of regulation in other local markets.

The identification of the impact of regulation on productivity relies on the current productivity shocks' being unrelated to the previous period's regulation measure. The nature of the structural semiparametric model helps to address the possible endogeneity of the regulation on productivity. Removing the effect of the current regulation status and other local market characteristics from the

sum of demand and production shocks ϵ_{jt} in the first step reduces the endogeneity concerns in the second step (i.e., when estimating the productivity process) and clarifies our identification. In other words, we remove all shocks related to local market characteristics from our productivity measure, which decreases the likelihood that the remaining productivity shocks υ_{jt} are correlated over time, i.e., that the i.i.d. assumption on productivity shocks does not hold. However, if the remaining productivity shocks are still correlated with previous regulation (e.g., they include demand shocks correlated with the regulation measure), we may overestimate the impact of a more liberal regulation on productivity. In this case, we can identify the coefficient on regulation in the second step using moment conditions based on Hausman-type instruments (Hausman, 1997), e.g., average regulatory stringency in other local markets (Section 4.3).[22]

The $\boldsymbol{\beta}$ parameters are estimated by minimizing the sample analogue of the moment conditions (9). Because there are nonlinearities in the coefficients, we use the Nelder-Mead numerical optimization method to minimize the GMM objective function

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

where A is the weighting matrix defined as $A = \left[\frac{1}{N} W' \upsilon(\boldsymbol{\beta}) \upsilon'(\boldsymbol{\beta}) W\right]^{-1}$ and W is the matrix of instruments.[23]

[22]This study shares a feature with the existing literature on land use regulations, namely, that there is not an ideal measure of entry regulations. Our preferred index variable follows previous work by Suzuki (2013), who emphasizes the difficulty of finding valid instruments and does not control for the possible endogeneity of the regulation index. Alternatively, one can use only the share and number of PBL approvals as a measure of regulation and add political seats as an additional instrument (Bertrand and Kramarz, 2002; Schivardi and Viviano, 2011; Sadun, 2014).

[23]An additional estimator that can be used is the GMM one-step estimator suggested by Wooldridge (2005) and Ackerberg et al. (2006) (equation (27) in

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

$$\begin{aligned} Pr(\chi_t = 1|\underline{\omega}_t(k_{jt}, \mathbf{z}_{mt-1}), \boldsymbol{F}_{t-1}) = & \; Pr(\omega_t \geq \underline{\omega}_t(k_{jt}, \mathbf{z}_{mt-1})|\underline{\omega}_t(k_{jt}, \\ & \mathbf{z}_{mt-1}), \omega_{jt-1}) \\ = & \; P_{t-1}(l_{jt-1}, k_{jt-1}, w_{jt-1}, p_{st-1}, \\ & q_{smt-1}, \mathbf{z}_{mt-1}) \equiv \mathscr{P}_{jt-1}, \end{aligned} \tag{11}$$

where the threshold market productivity $\underline{\omega}_t$ and the information set $\boldsymbol{F}_{t-1}$ will enter the function $g(\cdot)$, and regulation r_{mt-1} is included in $\mathbf{z}_{mt-1}$. As a result, threshold market productivity can be expressed as a function of $\mathscr{P}_{t-1}$ and $\boldsymbol{F}_{t-1}$. Therefore, the controlled Markov process (6) becomes $g(\omega_{jt-1}, r_{mt-1}, \mathscr{P}_{jt-1})$.

Recovering productivity. We can recover productivity based on our estimates using either the labor demand function (8) or the service production function. To allow for comparisons between different estimators, we use the service production function:[24]

$$\begin{aligned} \omega_{jt} = & \; y_{jt} - \beta_l l_{jt} - \beta_k k_{jt} \\ & + \beta_q q_{smt} + \tfrac{1}{\eta_s} \mathbf{z}'_{mt} \boldsymbol{\beta}_z. \end{aligned} \tag{12}$$

their paper). On the one hand, the one-step estimator is more efficient than the two-step approaches. On the other hand, a limitation of the one-step estimator for the current application is that there are many parameters to be estimated. This is because the local market characteristics are a component of the nonparametric function.

[24] Although we expect the mean productivity to be similar, the variance is expected to be higher under the service production function. This is because the productivity recovered from the service production function contains the i.i.d. shocks to production and demand.

4 Results

The first part of this section discusses the service production function estimates and compares them with standard approaches such as simple OLS and alternative semiparametric specifications that do not control for prices and local markets. We then use the productivity estimates to analyze how a more liberal regulation changes store-level productivity (Section 4.1) and weighted productivity in local markets for each subsector (Section 4.2), and we conduct a number of robustness checks (Section 4.3).

Service production function estimates. Table 6 presents the results from the service production function estimates using the following estimators: the OLS estimator; NP_l – a two-step estimation approach with labor as a proxy for productivity (Levinsohn and Petrin, 2003; Ackerberg et al., 2006; Doraszelski and Jaumandreu, 2013); and NP_{lm} – our main specification described in Section 3 that extends the NP_l estimator by controlling for prices and local market conditions. We present the estimated parameters for each subsector.

The NP estimators use an endogenous Markov process for productivity, i.e., future productivity is a nonparametric function of current productivity and a regulation index that measures the degree of regulation. The results rely on the standardized version of the regulation index constructed as a weighted sum of three variables that are independent of market size, i.e., share of non-socialist seats, share of PBL approvals (PBL approvals divided by number of zoning plans) and number of PBL approvals per number of stores for each municipality and year (Section 2). For robustness, we use a number of alternative measures of the regulation (Section 4.3). Moreover, Appendix E presents estimation results under the parametric approach based on Doraszelski and Jaumandreu (2013).

The OLS and NP results suggest the importance of controlling for simultaneity, selection, and price biases when estimating the service production function.

First, the coefficient of labor decreases when using NP estimators (simultaneity bias). Books, computers and electronics are the subsectors with the highest labor elasticity, and books and furniture have the highest capital elasticity. Second, the coefficient of capital increases in most subsectors when controlling for local market characteristics (NP_{lm} estimator). This has the same effect as controlling for the selection bias, i.e., adding the estimated survival probability as a control in the productivity process (Olley and Pakes, 1996). Third, not controlling for unobserved prices creates a downward bias in the scale estimator (Klette and Griliches, 1996). The returns to scale is higher after controlling for prices in NP_{lm} than in OLS and NP_l. For several subsectors, at least one of the coefficients of labor and capital are larger after controlling for prices (column (2) in Table 6).

In the main specification NP_{lm}, the results indicate increasing returns to scale ($\beta_l + \beta_k$) for a majority of the subsectors. This is consistent with the literature suggesting increasing returns to scale in retail. Without controlling for local market demand (NP_l), we find decreasing returns to scale in ten of eleven subsectors. We expect increasing returns to scale in the service industries, but there is scarce literature that uses production function approaches to analyze returns to scale in retail trade.[25] One exception is Ofer (1973), who finds increasing returns to scale for food, furniture and clothing.[26] In summary, controlling for

[25]The increasing returns to scale in services is due to geographic dispersion and multi-market contact. Furthermore, there is an increasing returns to scale "illusion" attributable to self-services, i.e., the volume of self-services is larger than the amount of services performed by the stores (Ofer, 1973).

[26]Ofer (1973) uses data from Israel, value-added as an output, and a Cobb-Douglas specification but does not control for simultaneity or omitted price bias. Using Australian data and a Cobb-Douglas specification, Bairam (1994) finds increasing returns to scale in fruit and vegetables. Maican and Orth (2009) find an elasticity of scale of approximately 1.50 for Swedish retail food when controlling for the impact of the entry of large stores.

different biases has key implications not only for the estimated elasticity of scale but also for the productivity distribution, i.e., stores' heterogeneity in response to the regulation.

Demand elasticity and markups. A key feature of the NP_{lm} estimator is that we obtain an estimate of the demand elasticity for each subsector. The average estimated demand elasticity across subsectors is -4.30, varying between -8.43 (clothing) and -1.31 (books). There is an inverse relationship between estimated demand elasticity and the implied markup, i.e., the subsectors with large demand elasticity have low markups. The average markup (price over marginal cost) across subsectors is 1.76, and it ranges from 1.13 (clothing) to 3.12 (furniture). A high degree of product differentiation might explain the observed large values for the markups in some subsectors. Clothing, electronics and sports have relatively low markups and high exit rates (Table 3). Our findings on markups are in line with previous results based on U.S. data (Hall, 1988). In subsectors with high demand elasticity, there are small differences between the labor and capital coefficients from the quantity and value-added service production functions, e.g., electronics and sports. For subsectors with low demand elasticity, we have high estimates of the returns to scale.

4.1 Quantifying the effect of local market regulation on store productivity

The goal is now to quantify how productivity changes at the store and local market levels with a more liberal regulation for each subsector. First, we provide descriptive evidence of the role of regulation for stores' productivity. Second, we show the results of the dynamic model, which allows for flexibility in how the stringency of regulation influences stores' future productivity depending on their current productivity (equation 6).

Descriptive analysis. To provide benchmark results of the relationship between the stringency of local market regulation and productivity, we run simple regressions for both labor and multi-factor productivity. First, the pooled results across all subsectors from regressing value-added per full-time adjusted employee on different regulation measures in Table 5 show that more liberal regulatory stringency increases stores' labor productivity (Section 2).

Second, we use a simple parametric specification to obtain baseline results for multi-factor productivity in each subsector (Table 7). We let productivity be a linear function of regulation, which we in turn substitute into the service production function. The log of the deflated value-added is a linear function of the log of labor, log of capital and the standardized regulation index discussed in Section 2. That is, we estimate the specification $y_{jt} = \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + \beta_r r_{mt} + u_{jt}$, where u_{jt} are i.i.d., using the OLS estimator for each subsector. We can interpret the coefficient of regulation as the effect of regulation on productivity. This is the same as obtaining productivity from regressing output on labor and capital and then regressing productivity on regulation. This identification strategy relies on strong assumptions such as that the current regulation is not correlated with the remaining shocks, which might include demand shocks and correlated shocks across markets that most likely are correlated with local regulation. In addition, the facts that store productivity is correlated over time and regulation has a feedback on productivity are not part of this identification strategy.

The coefficient of the regulation variable is positive and statistically significant for most subsectors. The effect of a more liberal regulation on both productivity and demand is fairly small, however. A one standard deviation change in the regulation index toward being more liberal increases productivity by, on average, 1.5 percent for most subsectors.

Overall, the benchmark results for both labor and multi-factor productivity suggest a positive correlation between a more liberal regulation and store pro-

ductivity. To model endogenous productivity, be flexible in how the regulation influences productivity and disentangle the effect of the regulation on productivity from that on demand, we need a dynamic structural model.

Endogenous productivity process. To more accurately quantify the effect of a more liberal regulation on stores' future productivity, we use regression results from the controlled Markov process that controls for demand in local markets.[27] We approximate $g(\omega_{jt-1}, r_{mt-1})$ by a third-order polynomial expansion in its arguments, where r_{mt-1} is the standardized regulation index (Section 2). An advantage of our dynamic framework is that we obtain marginal effects for each store in the data. That is, we use stores' observed values of previous productivity ω_{jt-1} and regulation r_{mt-1} to recover the full distribution of how productivity changes in each local market.

Table 8 documents the link between heterogeneity in store productivity changes stemming from a more liberal regulation. We present marginal effects for individual stores when the regulation index increases by one standard deviation. To keep the presentation tractable, we focus on the median marginal effect in each local market and present the mean and standard deviation across local markets and years. A more liberal regulation increases store productivity for virtually all subsectors. The median store increases productivity on average by 2-4 percent for most subsectors. In addition, there is variation in the impact of regulations across local markets, as indicated by the standard deviations of the marginal effects. Clothing, footwear and books have the largest marginal effects. This result may be associated with the fact that these subsectors have relatively high rates of net exit, forcing incumbents to increase their productivity, and that footwear

[27]This does not imply that a liberal regulatory environment serves as a productivity growth machine in the local markets. The reason is that the increased competition also induces exit, which implies a decrease in product differentiation that negatively affects consumers. Thus, our model only measures the net effect.

and books are subsectors with relatively low mean value-added growth (Tables 3-4).

We also present the support of the impact of a more liberal regulation on productivity. For each subsector, the support is determined based on 1,000 simulated values from all parts of the productivity distribution. The support provides additional information on the heterogeneity of how productivity changes with a more liberal regulation and complements the mean marginal effects. Large and positive upper bounds in clothing, footwear and books indicate that some stores obtain substantial productivity gains from a more liberal regulation in these subsectors. These bounds also confirm the relatively large mean marginal effects in these subsectors. The negative lower bounds in toys and computers are in line with the fact that these subsectors also have relatively small mean marginal effects.

An advantage of our two-step modeling framework is the identification strategy of the effect of regulation on productivity. We control for demand, remove the demand shocks in the first-stage of estimation, and allow productivity to be correlated over time and regulation to have a feedback on productivity. These actions also allow for a nonlinear productivity process, which is important when there is heterogeneity in stores' responses to changes in the regulation.

In comparing the average marginal effect of regulation on productivity in Table 8 with the results from the descriptive analysis of multi-factor productivity in Table 7, we find larger marginal effects in seven out of eleven retail subsectors using the structural approach. These findings are in line with the theory predictions because the effect from a simple parametric regression measures the impact on both productivity and prices. A more liberal regulation may induce an increase in competition and then a decrease in prices, which gives a net effect smaller when using a simple parametric approach. The structural approach implicitly controls for simultaneity and selection biases, which affect the

productivity measure and the marginal effects owing to the nonlinearity of the productivity process.

To investigate the sensitivity of the marginal effects of regulation on productivity in the structural approach, we use simulation methods. Estimation results of the endogenous productivity process based on productivity recovered from a service production function with different coefficients on labor and capital than those in our main specification (NP_{lm} in Table 6) show changes in the marginal effects of regulation on productivity.[28] In sum, the results from the simulations and the comparison between the nonparametric two-step approach with a nonlinear and endogenous productivity process and the simple parametric specification emphasize the importance of using sophisticated methods to accurately estimate productivity and evaluate how it changes with the regulation.

4.2 Aggregated local market productivity

A key issue for policymakers is to assess the change in aggregated local market productivity when the regulation becomes more liberal. To quantify the cost of regulations in terms of changes in local market productivity is a first step toward a more complete welfare analysis of entry regulations. The magnitude of these effects can thus be put in contrast to other demand and supply side aspects that local authorities should evaluate when evaluating the consequences of a new entrant. In Sweden, municipalities have to consider the availability of stores and store product assortment, prices, market shares and traffic, for example.

We evaluate the change in aggregated local market productivity when increasing the regulation index by one standard deviation. To do so, we sum over the marginal effect of all stores in each local market and year, which is based

[28] The simulations are available from the authors upon request.

on stores' actual values of previous productivity and regulation, using output market shares as weights. This is interpreted as what would happen to weighted aggregated local market productivity if the regulation become more liberal. Table 9 shows the distribution of annual changes in local market productivity with a more liberal regulation. There are substantial differences between subsectors. Median local market productivity increases approximately 2-5 percent in most subsectors, but it increases to at most 13 percent (clothing). Across all subsectors, the corresponding increase in aggregated median local market productivity is on average 3.5 percent. A majority of subsectors have a small difference between the mean and median, with a 75th percentile increase in local market productivity that is roughly double that of the 25th percentile. Toys, computers, hardware and electronics are examples of subsectors with relatively high dispersion of changes in local market productivity owing to a more liberal regulation. For toys and computers, this may relate to the high share of large entrants and the relatively high mean growth in value-added and number of employees (Tables 3-4). In addition, it ties back to the negative support of the store-level marginal effects for these subsectors.

The next step is to understand the contribution of *observed* changes in the local market regulation to the weighted aggregated productivity growth in market m in period t. To do this, we construct a productivity decomposition based on total differentiation of the productivity process, i.e.,

$$d\omega_{jt} = \frac{\partial g(\cdot)}{\partial \omega_{jt-1}} d\omega_{jt-1} + \frac{\partial g(\cdot)}{\partial r_{mt-1}} dr_{mt-1}. \tag{13}$$

Using the discrete version of (13), we can write the weighted productivity growth in local market m as

$$\begin{aligned}\Delta\omega_{mt} &\equiv \textstyle\sum_{j\in m} s_{jt}\omega_{jt} - \sum_{j\in m} s_{jt-1}\omega_{jt-1} \\ &\simeq \textstyle\sum_{j\in m} s_{jt}\frac{\partial g(\cdot)}{\partial \omega_{jt-1}}\Delta\omega_{jt-1} + \sum_{j\in m} s_{jt}\frac{\partial g(\cdot)}{\partial r_{mt-1}}\Delta r_{mt-1} \\ &+ \textstyle\sum_{j\in m} \Delta s_{jt}\omega_{jt-1},\end{aligned} \tag{14}$$

where s_{jt} is the market share of store j that operates in local market m in period t. The first term of the decomposition shows the contribution to the local productivity growth attributable to factors other than regulation. The second term shows the contribution to local productivity growth attributable to changes in the local regulation. The third term is the contribution to productivity growth of stores that increased their market shares at the initial productivity level. The change Δr_{mt-1} includes the *actual* changes in the regulation that we observe directly in the data.[29]

Table 10 presents the median of each term in the decomposition based on the observed market-year values. This simplifies the exposition and implies that the sum of the computed medians of the three terms in the decompositions is not equal to the weighted aggregated productivity growth in local markets. The results show substantial heterogeneity in yearly productivity growth across local markets. The median aggregated productivity growth increases on average by 3.3 percentage points across all subsectors. The contribution from observed changes in the regulation is on average 0.12 percentage points across all subsectors (second term). This relies on all actual changes in the regulation in our data. Hence, there is a net positive contribution from the de facto observed changes in the regulation. The largest contribution comes, as expected, from productivity growth within firms independent of current changes in the regulation (first term).

[29] Appendix G shows a number of standard decompositions of productivity levels and productivity growth that have been used in the literature.

This confirms previous findings of persistent productivity differences across firms. There is a positive, though relatively small, contribution from stores that increase their market shares for a given productivity (third term). These findings suggest that a more liberal regulation can make a non-trivial contribution to aggregated productivity growth, especially in subsectors where the within productivity is small.

4.3 Robustness

This section verifies the sensitivity of our empirical results. We conduct a variety of robustness checks of the results from the endogenous productivity process, the service production function and alternative decomposition methods. Overall, the main results are robust to a large number of specification tests.

Controlling for selection using equation (11) in our main specification NP_{lm} gives similar parameter estimates of the service production function and similar magnitudes of the marginal effects for how a more liberal regulation influences productivity. As noted in the results of the service production function estimates, we find evidence that it is crucial to control for local market demand and simultaneity bias. That is, not controlling for local market demand gives decreasing returns to scale (NP_l). The parameters of the service production function parameters move in the directions predicted by theory when controlling for simultaneity and prices.

Our proposed framework allows us to control for the possible endogeneity of the regulation measure. In the Markov process regression, we control for the endogeneity of our preferred index variable using the average value of the regulation index in other local markets as an instrument for regulation. The marginal effects remain positive and somewhat larger in a small number of subsectors.

The use of this type of instrument is valid if the regulation index does not contain common productivity shocks across local markets.[30] Suzuki (2013) argues that it is challenging to find valid instruments for the regulation index and does not control for endogeneity. In our setting, it is important to highlight that our two-step estimation approach alleviates possible endogeneity concerns of the regulation measure. If one is still concerned about correlated shocks, however, our approach allows for forming moments that control for the possible endogeneity of regulation in both stages of estimating the service production function. Furthermore, the approach also allows for controlling for the endogeneity of wages in the first step of the estimation and lets us account for the fact that labor has dynamic implications rather than being a static and variable input.

To demonstrate the robustness of our regulation variable, we consider a number of alternative measures. We use alternative weighting schemes of the regulation index. The marginal effects remain similar if we use equal weights for each of the three measures in the regulation index, i.e., (0.33,0.33,033) weights instead of (0.5,0.25,0.25) weights as in the main specification. In addition, we only use the number of PBL approvals to measure the degree of regulation. Appendix F presents a detailed analysis of the results using the number of approved PBL applications, whereas results using the number of PBL approvals of retail stores for the sample of 163 (out of 290) local markets are available from the authors. The approval of one fewer application by local authorities decreases the productivity of the median store by 1.5-2.6 percent for most subsectors. Aggregating across all local markets, this translates to annual subsector economic costs of 2.8

[30] As noted, we share the common obstacle of not observing one ideal measure of regulation in previous work on land use and entry regulations. A valid alternative to the index variable is to use only the share (and number) of approved applications, similar to Sadun (2014) (discussed below). In terms of possible endogeneity, the share of non-socialist seats can then be added as an additional instrument (Bertrand and Kramarz, 2002; Schivardi and Viviano, 2011).

million euros (Toys) to 194 million euros (Furniture).[31] The numbers are non-trivial and correspond to nearly 10 percent of the annual capital investments in the Swedish retail trade. For the period 1996-2002, the subsector cost aggregates from as much as 20 million euro (toys) to 1,361 million euro (furniture). Lastly, the results remain robust when using only political preferences to measure the stringency of regulation (the results are available from the authors).

An attractive candidate for our nonparametric two-step approach of estimating the service production function is a parametric labor demand function used as a proxy for productivity (Doraszelski and Jaumandreu, 2013). A key difference from our main specification is that the parametric approach forms moments based on shocks to both service production and demand, and estimation proceeds in one step. The parametric approach is explained in detail in Appendix E. The main result that a more liberal regulation increases productivity holds when using a parametric approach (available from the authors upon request).

The final part of our robustness checks include a number of alternative decomposition methods. To understand the productivity differences across local markets with different degrees of regulation, we use an extension of the Olley and Pakes (1996) decomposition to allow for the contribution of entry and exit to aggregate productivity levels in local markets. The results in Appendix G show that a more liberal regulatory environment increases the contribution of both entry and exit to aggregate productivity. Using the decomposition approaches developed by Griliches and Regev (1995) and Foster, Haltiwanger, and Krizan (2001), we find that entry, together with incumbent stores, plays a crucial role in growth.

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

5 Conclusions

This paper investigates the impact of regulations on productivity. Although the question is of great importance to both researchers and policymakers, the literature is still in the initial stages of learning how to quantify the effects of regulations on productivity in different industries. We use a dynamic structural model to estimate multi-factor productivity and evaluate how it varies with the degree of local market entry regulation in the retail trade. Specifically, we analyze how a more liberal regulation changes stores' future productivity and weighted aggregated productivity in local markets. The model controls for local market demand and allows for different technologies across subsectors. Our approach has the advantages of endogenizing productivity with respect to regulation and being flexible on how stores react to regulatory changes by considering the responses of each individual store. We recover the full distribution of productivity responses by all stores, which is an important starting point for ultimately evaluating welfare.

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

The empirical application relies on detailed data on all retail stores in Sweden in the period 1996-2002, which is representative of many retail markets in the

OECD in terms of market structure and regulation. The results show that there are increasing returns to scale in a majority of subsectors of the Swedish retail trade. There is large heterogeneity across stores and local markets in the effect of regulation on productivity. In most local markets and subsectors, a one standard deviation change in the regulation index induces aggregated local market productivity increases by 2-5 percent. Our results are robust to using different measures of regulatory stringency and controlling for the possible endogeneity of the regulation measure.

The results relate to competition policy through entry regulations in the OECD. We find that a more liberal use or design of entry regulations stimulates productivity growth in local markets. However, these gains must be balanced against drawbacks in terms of the environment, traffic, and access for target consumers such as pensioners. Our findings contribute to an improved understanding of the frequently debated productivity gap between Europe and the U.S.

References

Abbring, J., J. Campbell, J. Tilly, and N. Yang (2013): "Very Simple Markov-Perfect Industry Dynamics," Mimeo, Federal Reserve Bank of Chicago.

Ackerberg, D., L. Benkard, S. Berry, and A. Pakes (2007): "Econometric Tools for Analyzing Market Outcomes," *Handbook of Econometrics*, 6, 4171–4276.

Ackerberg, D., K. Caves, and G. Fraser (2006): "Structural Identification of Production Functions," Mimeo, UCLA.

Ackerberg, D., X. Chen, and J. Hahn (2011): "A Practical Asymptotic Variance Estimator for Two-Step Semiparametric Estimators," Discussion Paper 1803, Cowles Foundation Discussion Paper.

Anderson, S. P., A. De Palma, and J.-F. Thisse (1989): "Demand for Differentiated Products, Discrete Choice Models, and the Characteristics Approach," *The Review of Economic Studies*, 56(1), 21–35.

Asker, J., A. Collard-Wexler, and J. De Loecker (2013): "Dynamic Inputs and Resource (Mis)Allocation," *Journal of Political Economy (*forthcoming*)*.

Aw, B. Y., M. J. Roberts, and D. Xu (2011): "R&D Investment, Exporting, and Productivity Dynamics," *American Economic Review*, 101(4), 1312–1344.

Bairam, E. (1994): *Homogeneous and Nonhomeogeneous Production Functions*. Avebury, Ashate Publishing Ltd.

Bajari, P., L. Benkard, and J. Levin (2007): "Estimating Dynamic Models of Imperfect Competion," *Econometrica*, 75(5), 1331–1370.

Bartelsman, E., and M. Doms (2000): "Understanding Productivity: Lessons from Longitudinal Microdata," *Journal of Economic Literature*, 38(3), 569–594.

Basker, E. (2007): "The Causes and Consequences of Wal-Mart's Growth," *Journal of Economic Perspectives*, 21(3), 177–198.

——— (2012): "Raising the Barcode Scanner: Technology and Productivity in the Retail Sector," *American Economic Journal: Applied Economics*, 4(3), 1–27.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4), 841–890.

Bertrand, M., and F. Kramarz (2002): "Does Entry Regulation Hinder Job Creation? Evidence from the French retail industry," *Quarterly Journal of Economics*, 117(4), 1369–1413.

Boylaud, O., and G. Nicoletti (2001): "Regulatory Reform in Retail Distribution," OECD Working Paper 32.

Buccirossi, P., L. Ciari, T. Duso, G. Spagnolo, and C. Vitale (2013): "Competition Policy and Productivity Growth: An Empirical Assessment," *Review of Economics and Statistics*, 95(4), 1324–1336.

Collard-Wexler, A. (2013): "Demand Fluctuations in the Ready-Mix Concrete Industry," *Econometrica*, 81(3), 1003–1037.

De Loecker, J. (2011): "Product Differentiation, Multi-Product Firms and Estimating the Impact of Trade Liberalization on Productivity," *Econometrica*, 79(5), 1407–1451.

De Loecker, J., and A. Collard-Wexler (2013): "Reallocation and Technology: Evidence from the U.S. Steel Industry," Mimeo, Princeton University.

De Loecker, J., P. Goldberg, A. Khandelwal, and N. Pavcnik (2012): "Prices, Markups and Trade Reform," Mimeo, Princeton University.

De Loecker, J., and F. Warzynski (2012): "Markups and Firm-Level Export Status," *American Economic Review*, 102(6).

Djankov, S., R. La Porta, F. Lopez-de Silanes, and A. Shleifer (2002): "The Regulation of Entry," *Quarterly Journal of Economics*, CXVII(1), 1–37.

Doraszelski, U., and J. Jaumandreu (2013): "R&D and Productivity: Estimating Endogenous Productivity," *Review of Economic Studies*, 80(4), 1338–1383.

Dunne, T., S. Klimek, M. Roberts, and Y. Xu (2013): "Entry, Exit and the Determinants of Market Structure," *The RAND Journal of Economics (*forthcoming*)*.

Epple, D., B. Gordon, and H. Sieg (2010): "A New Approach to Estimating the Production Function for Housing," *American Economic Review*, 100, 905–924.

Ericson, R., and A. Pakes (1995): "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62(1), 53–83.

Foster, L., J. Haltiwanger, and C. Krizan (2006): "Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s," *Review of Economics and Statistics*, 88(4), 748–758.

Foster, L., J. Haltiwanger, and C. Syverson (2008): "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?," *American Economic Review*, 98(1), 394–425.

Fowlie, M., M. Reguant, and S. Ryan (2013): "Market-Based Emissions Regulation and Industry Dynamics," Mimeo, MIT.

Gandhi, A., S. Navarro, and D. Rivers (2013): "On the Identification of Production Functions: How Heterogenous is Productivity?," Mimeo, University of Wisconsin-Madison.

Gordon, R. (2004): "Why was Europe Left at the Station when America's Productivity Locomotive Departed?," (Working Paper 10661, NBER).

Greenstone, M., J. List, and C. Syverson (2012): "The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing," (Working Paper 18392, NBER).

Griffith, R., and H. Harmgart (2005): "Retail Productivity," *International Review of Retail, Distribution and Consumer Services*, 15(3), 281–290.

Gyourko, J., A. Saiz, and A. Summers (2008): "A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index," *Urban Studies*, 45, 693–729.

Hall, R. (1988): "The Relation between Price and Marginal Cost in U.S. Industry," *Journal of Political Economy*, 96(5), 921–947.

Haskel, J., and R. Sadun (2011): "Regulation and UK Retailing Productivity: Evidence from Microdata," *Economica*, 79, 425–448.

Hausman, J. (1997): *The Economics of New Goods*chap. Valuation of New Goods Under Perfect and Imperfect Competition, pp. 207–248. University of Chicago Press.

Hoj, J., T. Kato, and D. Pilat (1995): "Deregulation and Privatisation in the Service Sector," OECD Working Paper 25.

Katayama, H., S. Lu, and J. Tybout (2009): "Firm-level Productivity Studies: Illusions and a Solution," *International Journal of Industrial Organization*, 27(3), 403–413.

Klette, T., and Z. Griliches (1996): "The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous," *Journal of Applied Econometrics*, 11(4), 343–361.

Levinsohn, J., and M. Melitz (2006): "Productivity in a Differentiated Products Market Equilibrium," Mimeo, Harvard University.

Levinsohn, J., and A. Petrin (2003): "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 70(2), 317–341.

Maican, F., and M. Orth (2009): "Productivity Dynamics and the role of "Big-Box" Entrants in retailing," Working Paper no. 328, Department of Economics, University of Gothenburg.

——— (2013): "Entry Regulations, Product Differentiation and Determinants of Market Structure," Mimeo, Reserach Institute of Industrial Economics (IFN) and University of Gothenburg.

Melitz, M. (2000): "Estimating Firm Level Productivity in Differentiated Product Industries," Mimeo, Harvard University.

Nicoletti, G., and S. Scarpetta (2003): "Regulation, Productivity and Growth: OECD Evidence," *Economic Policy*, 18(36), 9–72.

Ofer, G. (1973): "Returns to Scale in Retail Trade," *Review of Income and Wealth*, 19(4), 363–384.

Olley, S., and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263–1297.

Pakes, A., S. Berry, and M. Ostrovsky (2007): "Simple Estimators for the Parameters of Dyscrete Dynamic Games, with Entry/Exit Examples," *RAND Journal of Economics*, 38(2), 373–399.

Petrin, A., and F. Warzynski (2012): "The Impact of Research and Development on Quality, Productivity and Welfare," Mimeo, University of Minnesota.

Pilat, D. (1997): "Regulation and Performance in the Distribution Sector," OECD Working Papers 180.

——— (2005): "Assessing the Productivity of the UK Retail Sector: Some Further Reflections," *The International Review of Retail, Distribution and Consumer Research*, 15(3), 291–296.

Pozzi, A., and F. Schivardi (2012): "Demand or Productivity: What determines firm growth?," Mimeo, EIEF Rome.

Reynolds, J., E. Howard, D. Dragun, B. Rosewell, and P. Ormerod (2005): "Assessing the Productivity of the UK Retail Sector," *International Review of Retail, Distribution and Consumer Research*, 15(3), 237–280.

Roberts, M., D. Xu, X. Fan, and Z. Shengxing (2012): "A Structural Model of Demand, Cost, and Export Market Selection for Chinese Footwear Producers," (Working Paper 17725, NBER).

Ryan, S. (2012): "The Costs of Environmental Regulation in a Concentrated Industry," *Econometrica*, 8(3), 1019–1061.

Sadun, R. (2014): "Does Planning Regulation Protect Independent Retailers?," *Review of Economics and Statistics (*forthcoming*)*.

Sargent, T. (1978): "Estimation of Dynamic Labor Demand Schedules under Rational Expectations," *Journal of Political Economy*, 86(6), 1009–44.

Schivardi, F., and E. Viviano (2011): "Entry Barriers in Retail Trade," *Economic Journal*, 121(155), 145–170.

Schmitz, J. (2005): "What Determines Productivity? Lessons From the Dramatic Recovery of the U.S. and Canadian Iron Ore Industries Following Their Early 1980s Crisis," *Journal of Political Economy*, 113(3), 582–625.

Suzuki, J. (2013): "Land Use Regulation as a Barrier to Entry: Evidence from the Texas Lodging Industry," *International Economic Review*, 54(2), 495–523.

Swedish Competition Authority (2001:4): "Kan Kommunerna Pressa Matpriserna? (Can the Municipalities Put Pressure on Prices?)," Technical Report 4, Stockholm.

——— (2004:2): "Konsumenterna, Matpriserna och Konkurrensen (Consumers, Retail Food Prices, and Competition)," Technical Report 2, Stockholm.

Sweeting, A. (2013): "Dynamic Product Positioning in Differentiated Product Markets: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry," *Econometrica*, 81(5), 1763–1803.

Syverson, C. (2011): "What Determines Productivity?," *Journal of Economic Literature*, 49(2), 326–365.

Turner, M., A. Haughwout, and W. van der Klaauw (2014): "Land Use Regulation and Welfare," *Econometrica (*forthcoming*)*.

Wooldridge, J. (2005): "On Estimating Firm-Level Production Functions using Proxy Variables to Control for Unobservables," Mimeo, Michigan State University.

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

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

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

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

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

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

Table 3: Entry and exit by subsector 1996-2002

	Entry rate			Exit rate					
Subsector	Small	Large	Total	Small	Large	Total	Net entry	No. of stores	No. of obs.
Textiles	0.071	0.007	0.078	0.129	0.007	0.136	-0.055	355	2,486
	(0.021)	(0.003)	(0.021)	(0.027)	(0.003)	(0.026)	(0.047)	(41)	
Clothing	0.082	0.011	0.094	0.097	0.013	0.110	-0.015	2,467	17,273
	(0.014)	(0.001)	(0.016)	(0.014)	(0.003)	(0.015)	(0.021)	(72)	
Footwear	0.063	0.008	0.071	0.093	0.011	0.104	-0.033	591	4,142
	(0.008)	(0.003)	(0.008)	(0.011)	(0.004)	(0.011)	(0.018)	(41)	
Furniture	0.094	0.012	0.106	0.097	0.014	0.111	-0.003	1,603	11,227
	(0.016)	(0.003)	(0.015)	(0.018)	(0.005)	(0.020)	(0.019)	(23)	
Electronics	0.066	0.007	0.073	0.087	0.009	0.096	-0.023	1,291	9,037
	(0.020)	(0.002)	(0.020)	(0.015)	(0.002)	(0.017)	(0.024)	(62)	
Hardware	0.080	0.018	0.099	0.073	0.019	0.092	0.008	1,313	9,193
	(0.013)	(0.003)	(0.013)	(0.013)	(0.006)	(0.016)	(0.020)	(22)	
Books	0.062	0.009	0.071	0.100	0.016	0.116	-0.044	561	3,929
	(0.014)	(0.002)	(0.012)	(0.012)	(0.008)	(0.012)	(0.019)	(50)	
Sports	0.096	0.011	0.107	0.095	0.013	0.108	0.001	1,101	7,707
	(0.026)	(0.002)	(0.025)	(0.009)	(0.004)	(0.010)	(0.014)	(10)	
Watches	0.054	0.004	0.058	0.075	0.006	0.081	-0.021	594	4,160
	(0.019)	(0.004)	(0.019)	(0.016)	(0.004)	(0.015)	(0.019)	(26)	
Toys	0.078	0.025	0.103	0.112	0.025	0.137	-0.027	228	1,599
	(0.018)	(0.011)	(0.024)	(0.028)	(0.009)	(0.023)	(0.047)	(13)	
Computers	0.112	0.025	0.137	0.108	0.031	0.139	-0.001	1,176	8,237
	(0.024)	(0.008)	(0.031)	(0.006)	(0.008)	(0.008)	(0.027)	(26)	

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

Table 4: Store level growth by subsector 1996-2002

	Value Added		Employees		Capital		Wages		Share	No. of
	Small	All	Small	All	Small	All	Small	All	small	stores
Textiles	0.046	0.056	0.037	0.044	0.109	0.120	0.051	0.059	0.893	355
	(0.275)	(0.274)	(0.329)	(0.316)	(0.423)	(0.421)	(0.284)	(0.270)	(0.012)	(41)
Clothing	0.087	0.089	0.045	0.060	0.163	0.176	0.059	0.073	0.772	2,467
	(0.340)	(0.318)	(0.336)	(0.318)	(0.507)	(0.495)	(0.279)	(0.254)	(0.022)	(72)
Footwear	0.050	0.054	0.029	0.040	0.127	0.150	0.037	0.049	0.777	591
	(0.246)	(0.228)	(0.314)	(0.294)	(0.436)	(0.459)	(0.235)	(0.210)	(0.008)	(41)
Furniture	0.102	0.098	0.045	0.063	0.198	0.222	0.069	0.080	0.748	1,603
	(0.337)	(0.300)	(0.330)	(0.309)	(0.544)	(0.549)	(0.278)	(0.239)	(0.019)	(23)
Electronics	0.064	0.069	0.036	0.032	0.193	0.201	0.048	0.061	0.793	1,291
	(0.274)	(0.260)	(0.291)	(0.190)	(0.477)	(0.458)	(0.223)	(0.206)	(0.019)	(62)
Hardware	0.076	0.073	0.032	0.034	0.185	0.185	0.051	0.061	0.686	1,313
	(0.284)	(0.243)	(0.302)	(0.188)	(0.441)	(0.402)	(0.245)	(0.200)	(0.010)	(22)
Books	0.052	0.051	0.024	0.044	0.129	0.136	0.039	0.051	0.716	561
	(0.255)	(0.218)	(0.323)	(0.297)	(0.412)	(0.397)	(0.256)	(0.214)	(0.027)	(50)
Sports	0.100	0.106	0.060	0.075	0.186	0.197	0.079	0.091	0.798	1,101
	(0.333)	(0.312)	(0.347)	(0.331)	(0.450)	(0.451)	(0.293)	(0.268)	(0.021)	(10)
Watches	0.031	0.036	0.031	0.024	0.107	0.132	0.033	0.043	0.829	594
	(0.208)	(0.202)	(0.299)	(0.198)	(0.393)	(0.418)	(0.211)	(0.196)	(0.013)	(26)
Toys	0.097	0.104	0.061	0.082	0.153	0.155	0.064	0.084	0.698	228
	(0.351)	(0.320)	(0.359)	(0.336)	(0.433)	(0.427)	(0.302)	(0.271)	(0.036)	(13)
Computers	0.196	0.212	0.042	0.080	0.211	0.221	0.162	0.186	0.754	1,176
	(0.377)	(0.356)	(0.307)	(0.273)	(0.490)	(0.474)	(0.303)	(0.279)	(0.018)	(26)

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

Table 5: Reduced-form regressions: The impact of regulation on store's labor productivity in Swedish retail 1996-2002

Model specification	(1)	(2)	(3)	(4)	(5)	(6)
Regulation index	0.0273	0.0377	0.0018	0.0042	0.0004	0.0040
	(0.0120)	(0.0121)	(0.0027)	(0.0028)	(0.0025)	(0.0025)
Log of population	0.0163	0.0098	0.0205	0.0159	0.0203	0.0161
	(0.0030)	(0.0031)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Log of population density	0.0013	0.0133	-0.0035	0.0059	-0.0031	0.0060
	(0.0028)	(0.0029)	(0.0021)	(0.0022)	(0.0021)	(0.0022)
Log of income	0.3298	0.1319	0.3292	0.1275	0.3344	0.1291
	(0.0170)	(0.0233)	(0.0194)	(0.0255)	(0.0185)	(0.0249)
R^2	0.0117	0.0147	0.0117	0.0146	0.0117	0.0146
Year fixed effect	No	Yes	No	Yes	No	Yes
No. of obs.	69,526	69,526	69,526	69,526	69,526	69,526

NOTE: Standard errors are in parentheses. To measure local market regulation, (1)-(2) use number of approved PBL in the municipality over population density; (3)-(4) use the index: 0.5*(share of non-socialist seats) + 0.25*(stock of PBL approvals/no. of stores) +0.25*(share of approved PBL); and (5)-(6) use the index: 0.33*(share of non-socialist seats) + 0.33(stock of PBL approvals/no. of stores)+0.33*(share of approved PBL).

Table 6: Value-added generating function estimates: nonparametric approach

	OLS		NP_l		NP_{lm}						
	Labor	Capital	Labor	Capital	Labor		Capital		Demand	Markup	
					(1)	(2)	(1)	(2)			No. of obs.
Textiles	0.821	0.123	0.856	0.321	0.640	0.785	0.101	0.124	-5.39	1.23	1,623
	(0.020)	(0.010)	(0.025)	(0.013)	(0.002)		(0.001)				
Clothing	0.757	0.120	0.417	0.311	0.752	0.853	0.073	0.083	-8.43	1.13	12,625
	(0.007)	(0.004)	(0.015)	(0.008)	(0.001)		(0.001)				
Footwear	0.735	0.121	0.802	0.112	0.433	0.730	0.329	0.555	-2.45	1.68	3,188
	(0.011)	(0.006)	(0.002)	(0.001)	(0.002)		(0.001)				
Furniture	0.814	0.135	0.332	0.029	0.265	0.830	0.327	1.023	-1.47	3.12	8,203
	(0.008)	(0.005)	(0.011)	(0.005)	(0.082)		(0.010)				
Electronics	0.821	0.144	0.739	0.391	0.916	1.078	0.381	0.448	-6.65	1.17	6,897
	(0.008)	(0.004)	(0.011)	(0.005)	(0.485)		(0.131)				
Hardware	0.782	0.189	0.551	0.196	0.684	0.829	0.171	0.207	-5.73	1.21	7,067
	(0.007)	(0.004)	(0.014)	(0.008)	(0.005)		(0.004)				
Books	0.737	0.149	0.824	0.143	0.474	1.973	0.180	0.751	-1.31	4.16	2,922
	(0.012)	(0.007)	(0.005)	(0.002)	(0.015)		(0.006)				
Sports	0.744	0.141	0.431	0.485	0.645	0.753	0.162	0.189	-6.96	1.17	5,796
	(0.009)	(0.005)	(0.023)	(0.013)	(0.002)		(0.001)				
Watches	0.804	0.101	0.679	0.367	0.254	0.378	0.354	0.527	-3.04	1.48	3,156
	(0.012)	(0.006)	(0.012)	(0.006)	(0.019)		(0.008)				
Toys	0.682	0.216	0.662	0.476	0.461	0.699	0.188	0.285	-2.93	1.51	1,208
	(0.021)	(0.013)	(0.012)	(0.006)	(0.003)		(0.004)				
Computers	0.795	0.212	0.108	0.317	0.728	1.095	0.160	0.240	-2.98	1.50	6,350
	(0.009)	(0.006)	(0.026)	(0.007)	(0.007)		(0.001)				

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

Table 7: The impact of regulation on productivity without local market and price controls

	Regulation (1)	Adjusted R^2 (2)	No. Obs. (3)
Textile	0.0207	0.63	1,079
	(0.012)		
Clothing	0.0171	0.65	9,677
	(0.004)		
Footwear	0.0455	0.73	2,386
	(0.008)		
Furniture	0.0201	0.69	6,336
	(0.005)		
Electronics	0.0191	0.68	5,290
	(0.006)		
Hardware	0.0166	0.77	5,597
	(0.004)		
Books	0.0296	0.72	2,261
	(0.007)		
Sports	0.0053	0.69	2,261
	(0.005)		
Watches	0.0369	0.63	2,468
	(0.008)		
Toys	0.0143	0.71	899
	(0.013)		
Computers	0.0675	0.80	4,804
	(0.006)		

NOTE: Column (1) shows the estimated coefficient of regulation (β_r) from the following regression equation: $y_{jt} = \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + \beta_r r_{mt} + u_{jt}$, where u_{jt} are i.i.d. The OLS estimator is used.

Table 8: The impact of regulation on stores' productivity using nonparametric estimation

Subsector	Mean	Std.dev.	Adj. R^2	No. of obs.	Support	
Textile	0.031	0.015	0.376	1,079	[0.027,	0.073]
Clothing	0.142	0.061	0.635	9,677	[0.155,	0.484]
Footwear	0.133	0.068	0.796	2,386	[0.099,	0.640]
Furniture	-0.111	0.032	0.645	6,336	[-0.147,	-0.066]
Electronics	0.018	0.019	0.440	5,290	[0.016,	0.062]
Hardware	0.021	0.019	0.378	5,597	[0.025,	0.048]
Books	0.094	0.061	0.628	2,261	[0.054,	0.279]
Sports	0.043	0.008	0.305	4,358	[0.045,	0.074]
Watches	0.035	0.027	0.656	2,468	[0.016,	0.135]
Toys	0.020	0.038	0.404	899	[-0.059,	0.072]
Computers	-0.002	0.034	0.371	4,804	[-0.010,	0.052]

NOTE: This table shows means and standard deviations, across local markets and years, of the median marginal effect on stores' productivity when the regulation index changes by one standard deviation. Marginal effects are computed for individual stores using the estimated endogenous Markov process and their observed values of previous productivity and the regulation index. The regulation index is defined in Section 2. The support is computed using 1,000 simulation draws from the estimated distribution of productivity.

Table 9: Change in aggregate local market productivity following a more liberal regulation

Subsector	25th perc.	Median	75th perc.	Mean	Std. dev.
Textile	0.019	0.029	0.037	0.029	0.015
Clothing	0.089	0.134	0.173	0.130	0.057
Footwear	0.088	0.117	0.166	0.129	0.066
Furniture	-0.126	-0.108	-0.080	-0.098	0.036
Electronics	0.006	0.020	0.031	0.017	0.017
Hardware	0.012	0.026	0.035	0.021	0.018
Books	0.053	0.071	0.107	0.087	0.056
Sports	0.035	0.043	0.047	0.041	0.010
Watches	0.019	0.033	0.055	0.038	0.029
Toys	-0.008	0.015	0.046	0.021	0.038
Computers	-0.016	0.006	0.024	0.002	0.031

NOTE: This table shows summary statistics of the changes in aggregate local market productivity when the regulation index increases by one standard deviation. Municipalities (290 in total) are used as local markets. Marginal effects for individual stores are used (Table 8) with output market shares as weights.

Table 10: Decomposition: The impact of regulation on weighed aggregate productivity growth in local markets

		Median		
	Productivity growth (1)	Change due to regulation (2)	Change due to internal factors (3)	Change in market share (4)
Textile	0.0737	0.0011	0.0360	0.0002
Clothing	0.1559	0.0051	0.0553	0.0001
Footwear	0.0984	0.0035	0.0326	0.0004
Furniture	0.0306	-0.0001	-0.0242	0.0005
Electronics	0.0106	0.0009	-0.0194	0.0001
Hardware	0.0112	0.0006	0.0048	-0.0001
Books	0.0668	0.0008	0.0691	0.0001
Sports	0.0399	0.0003	0.0067	0.0001
Watches	0.0112	0.0012	-0.0160	-0.0000
Toys	0.0521	-0.0001	0.0123	0.0003
Computers	0.0708	0.0005	0.0298	0.0003

NOTE: Figures represent median values across markets and years. Column (1) shows the median change in weighted productivity growth across markets between year $t-1$ and t. Column (2) shows median contribution to local market productivity growth of stores associated with changes in local market regulation. Column (3) shows median contribution to local market productivity growth that is not associated with regulation. Column (4) shows median contribution to local market productivity growth from stores that increased their market share without changing their productivity. Because we show the median of each decomposition term, the sum (2)+(3)+(4) is different from (1).

ONLINE APPENDIX

A Dynamic Analysis of Regulation and Productivity in Retail Trade

Florin Maican* and Matilda Orth†
April 21, 2014

The online appendix contains seven parts. Appendix A provides additional information about entry regulation in Sweden. Appendix B presents additional information about data sources. Appendix C provides details about data selection and retail trade subsectors. Appendix D discusses the identification and productivity measure using nonparametric approach. Appendix E discusses the identification and estimation of the model using a parametric approach. Appendix F discusses the estimation results using alternative measures of regulation and the nonparametric approach. Appendix G presents various productivity decompositions at the local market and industry level.

Appendix A: Entry regulation

On July 1, 1987, a new regulation was imposed in Sweden, the Plan and Building Act ("Plan och Bygglagen", PBL).[1] Compared to the previous legislation, the decision process was decentralized, giving local governments authority over entry in their municipalities, and citizens could now appeal these decisions. Since 1987, only minor changes have

*Research Institute of Industrial Economics (IFN) and University of Gothenburg, Box 640, SE-405 30, Göteborg, Sweden, Phone +46-31-786 4866, Fax +46-31-786 4154, E-mail: florin.maican@economics.gu.se

†Research Institute of Industrial Economics (IFN), Box 55665, SE-102 15, Stockholm, Sweden, Phone +46-8-665 4531, Fax +46-8-665 4599, E-mail: matilda.orth@ifn.se

[1]The Swedish Competition Authority (2001:4) provides a detailed description.

been implemented in the PBL. From April 1, 1992 to January 1, 1997, the regulation was slightly different, making it explicit that the use of buildings should not hamper efficient competition. Since 1997, the PBL has been essentially the same as it was prior to 1992. Long time lags in the planning process make it impossible to directly evaluate the impact of decisions. In practice, differences due to the policy change seem small (Swedish Competition Authority, 2001:4). The PBL is argued to be one of a major barrier to entry, resulting in different outcomes, e.g., price levels across municipalities. Municipalities are then, through the regulation, able to affect prices. In detail, the Swedish Competition Authority finds that the number of square meters of sales space per capita is lower in municipalities that constrain entry, while municipalities with a higher market shares occupied by large and discount stores have lower prices (Swedish Competition Authority, 2001:4; Swedish Competition Authority, 2004:2).

Appendix B: The FS-RAMS data

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

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

Appendix C: Retail subsectors (SNI codes)

We take all stores that belong to SNI code 52 (Retail trade, except motor vehicles and motorcycles; repair of personal household goods), and exclude monopolies and food, SNI 52111-52129 - Retail sales in non-specialized stores where food, beverages, or tobacco are predominant;

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

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

Appendix D: Identification and productivity measure

The identification and interpretation of the results depend on the assumption regarding the remaining demand shocks u^d_{jt}. If u^d_{jt} are i.i.d. shocks, not predicted or anticipated by stores when they make input and exit decisions, we can identify technical productivity ω_{jt} separately from demand. If u^d_{jt} are correlated demand shocks, we need additional assumptions for identification because the scalar unobservable assumption in OP is violated. In retail trade, regulation might have a lagged effect on both prices and productivity, for example. If ω_{jt} and u^d_{jt} follow independent Markov processes, the demand shock will determine the optimal choices of labor and/or investment through which it affects productivity. We can then identify quality-adjusted productivity, i.e., the sum of technical productivity and remaining demand shocks $(\omega_{jt} - \frac{1}{1+\eta_s}u^d_{jt})$.[2] An important difference between technical productivity and quality-adjusted productivity is the interpretation of the results.

Appendix E: Parametric approach

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

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

Solving for ω_{jt} yields the inverse labor demand function

$$\begin{aligned}\omega_{jt} = \; & \tfrac{\eta_s}{1+\eta_s}\Big[\lambda_0 + [(1-\beta_l) - \tfrac{1}{\eta_s}\beta_l]l_{jt} + w_{jt} - p_{st} - \left(1 + \tfrac{1}{\eta_s}\right)\beta_k k_{jt} \\ & + \tfrac{1}{\eta_s}q_{smt} + \tfrac{1}{\eta_s}\mathbf{z}'_{mt}\boldsymbol{\beta}_z\Big],\end{aligned} \tag{E-2}$$

[2] If ω_{jt} and u^d_{jt} follow dependent Markov processes, the demand shock will enter the information set that forms expected productivity $E[\omega_{jt}|\omega_{jt-1}, r_{mt-1}, u^d_{jt-1}]$. We can use an estimate of u^d_{jt} in line with Berry, Levinsohn, and Pakes (1995), but this is not feasible due to data limitations (we would need additional store specific information).

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

$$\begin{aligned} y_{jt} = & \left(1 + \tfrac{1}{\eta_s}\right)[\beta_l l_{jt} + \beta_k k_{jt}] - \tfrac{1}{\eta_s} q_{smt} - \tfrac{1}{\eta_s} \mathbf{z}'_{mt} \boldsymbol{\beta}_z + \left(1 + \tfrac{1}{\eta_s}\right) g(\omega_{jt-1}, r_{mt-1}) \\ & + \left(1 + \tfrac{1}{\eta_s}\right) \upsilon_{jt} - \tfrac{1}{\eta_s} u^d_{jt} + \left(1 + \tfrac{1}{\eta_s}\right) \xi_{jt}, \end{aligned} \tag{E-3}$$

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

Estimation. The estimation of our semi-parametric model adjusted for retailers (EOP) proceeds as follows. We first use a probit model with a third-order polynomial to estimate survival probabilities and then substitute the predicted survival probabilities into productivity process equation. We use the sieve minimum distance (SMD) procedure proposed by Newey and Powell (2003) and Ai and Chen (2003) for independent and identically distributed (i.i.d.) data. The goal is to obtain an estimable expression for the unknown parameters $\boldsymbol{\beta}$ and g_{K_T}, where K_T indicates all parameters in $g(\cdot)$. We approximate $g(\cdot)$ by a third-order polynomial expansion in $\mathscr{P}_{t-1}$, ω_{jt-1} (given by (E-2)) and r_{mt-1}.[4] We use a tensor product polynomial series of labor (l_{jt-1}), capital (k_{jt-1}), wages (w_{jt-1}), the consumer price index in the subsector (p_{st}) and local market conditions ($\mathbf{z}_{mt-1}$) as instruments, where the local market conditions include population, population density, and income. The same set of instruments is used to estimate the optimal weighting matrix. As there are nonlinearities in the coefficients, we use the Nelder-Mead numerical optimization method to minimize the GMM objective function

$$\min_{\boldsymbol{\beta}, g_{K_T}} Q_N = \left[\frac{1}{N} W' \rho(\boldsymbol{\beta})\right]' A \left[\frac{1}{N} W' \rho(\boldsymbol{\beta})\right], \tag{E-4}$$

[3]The condition for identification is that the variables in the parametric section of the model are not perfectly predictable (in the least squares sense) on the basis of the variables in the non-parametric section (Robinson, 1988). Therefore there cannot be a functional relationship between the variables in the parametric and non-parametric sections (Newey, Powell, and Vella, 1999).

[4]For robustness, we also expand $g(\cdot)$ using a fourth-order polynomial, but the results are similar.

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

Details regarding the estimation strategy. We first use a probit model with a third-order polynomial expansion to estimate the survival probabilities. The predicted survival probabilities are then substituted into the final value-added generating function, which is estimated in the second step. We now turn to details regarding the estimation procedure in the latter step. The semi-parametric regression is estimated using the sieve minimum distance (SMD) procedure proposed in Newey and Powell (2003) and Ai and Chen (2003) for independent and identically distributed (i.i.d.) data.[5] The goal is to obtain an estimable expression for the unknown parameter of interest, $\boldsymbol{\alpha} = (\boldsymbol{\beta}, g)'$. We denote the true value of the parameters with the subscript "a": $\boldsymbol{\alpha}_a = (\boldsymbol{\beta}_a, g_a)'$. The moment conditions could then be written more compactly as

$$E[\rho_j(\boldsymbol{x}_t, \boldsymbol{\beta}_a, g_a)|\boldsymbol{F}^*_t] = 0, \quad j = 1, \cdots, N \tag{E-5}$$

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

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

Let $\boldsymbol{F}_t$ be an observable subset of $\boldsymbol{F}^*_t$, then equation (E-5) implies

$$E[\rho_j(\boldsymbol{x}_t, \boldsymbol{\beta}_a, g_a)|\boldsymbol{F}_t] = 0 \quad j = 1, \cdots, N. \tag{E-6}$$

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

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

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

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

$$\hat{\boldsymbol{\alpha}} = arg \min_{\boldsymbol{\beta}, g_{K_T}} \frac{1}{T} \sum_{t=1}^{T} \hat{m}(\boldsymbol{F}_t, \boldsymbol{\beta}, g_{K_T})' \hat{m}(\boldsymbol{F}_t, \boldsymbol{\beta}, g_{K_T}). \tag{E-7}$$

We approximate $g(\cdot)$ by a third-order polynomial and substitute it into (E-6) as if it were the true model. As the errors $\rho_j(\cdot)$ are orthogonal to the regressors $\boldsymbol{F}_t = (1, l_{t-1}, k_t, r_{t-1}, \mathbf{z}_{t-1})$, we use a third-order power series of $\boldsymbol{F}_t$, denoted $\boldsymbol{P}$, as instruments. We estimate $m(\boldsymbol{F}, \boldsymbol{\alpha})$ as the predicted values from regressing the errors $\rho_j(\cdot)$ on the instruments. Using $\boldsymbol{P}$, we specify the weighting matrix as $\boldsymbol{W} = I_N \otimes (\boldsymbol{P}'\boldsymbol{P})^{-1}$, making the estimation a GMM case. The weighting matrix $\boldsymbol{W}$ places greater weight on moments that are highly correlated with the instruments. Using the specified GMM implementation, the parameter values $(\boldsymbol{\beta}, g_{K_T})$ are jointly estimated. The results from parametric approach are available from authors.

Appendix F: Alternative measures of regulation using the nonparametric approach

This appendix discusses the findings using the number of approved PBL applications as proxy for regulation measure. Figure 1 (3D-plot) shows the aggregate relationship across local markets and time between current productivity, previous productivity, and previous number of approved PBL applications in the municipality. The figure aims to provide preliminary information about the productivity process.[6] Current productivity increases under a more liberal regulatory environment for Clothing, Footwear, Electronics, Books, and Sports. The corresponding relationship tends to be an inverted-U shaped one for Hardware, Watches, and Computers. There are small differences in current productivity depending on the degree of regulation for Furniture and Toys, given previous productivity. These subsectors exhibit a strong positive relationship between current and previous productivity. This high persistency in productivity over time also holds for Electronics and Watches. Figure 2 indicates that it is crucial to analyze the effect of regulation on different parts of the productivity distribution for each subsector.[7]

Marginal effects for percentiles of local market productivity distributions. Table F.1 presents the marginal effects of the impact of a more liberal entry regulation (one additional PBL approval) on stores' future productivity. The empirical results highlight the heterogeneity in the (net) marginal effect of the regulation on productivity. The table

[6]The surface is obtained using polynomial approximations of order two on different intervals. In the regression analysis, we approximate the productivity process using a polynomial expansion of order three.

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

shows averages and standard deviations for different distribution measures across local markets. For each subsector, the impact of the approval of one additional PBL application on productivity is computed for different parts of the productivity distribution in local markets. This result is due to productivity differences across local markets, and the impact of a more liberal regulatory environment might differ for stores with high and low productivity. The marginal effects are computed as follows for the median, for example. First, we compute median productivity in each local market. Second, we use the estimated productivity process to compute the impact of an additional PBL approval on the median store in each local market. Finally, we compute averages and standard deviations for the marginal effects across local markets. Thus, the mean value for the xth percentile, reported in Table F.1, is the average impact across local markets of a more liberal regulatory environment on the future productivity of a store with current productivity equal to the x-th percentile value in its local market.

The results from our full model reveal the following patterns. First, the impact of an additional PBL approval is now positive. Productivity increases by 1.5-2.6 percent in Footwear, Hardware, Clothing, and Sports for stores with productivity values between 10th and 90th percentiles. For the median stores, an additional PBL approval increases productivity by approximately 2 percent in most subsectors. Second, the impact of regulation on productivity is larger among low productivity stores (10th percentile) than high productivity stores (90th percentile), e.g., clothing (2.5 and 2.0 percent), footwear (2.6 and 1.7 percent), hardware (2.2 and 1.5 percent), and sports (2 and 1.8 percent). Third, the marginal effects are close to zero for watches and negative for books (approximately -2 percent). The books subsector was affected by the increasing competition from on-line stores, e.g., Amazon, Adlibris and Bokus, and had a net exit rate of 4 percent during the study period. Fourth, the highest impact of a more liberal regulatory environment is in computers and furniture (8.2 and 13.1 percent for the 10th percentile, 8.6 and 13.5 percent for the 90th percentile).

Counterfactual exercise. We also calculate the economic cost of the regulation faced by stores. The impact of regulation on productivity is directly linked to the efficiency of

the retail sector. Given the use of inputs (labor and capital), we quantify how the degree of regulation affects the effectiveness with which stores use their inputs to generate sales (or value-added). Using information about the marginal effects (Table F.1), our goal is now to calculate the economic cost of a less liberal entry regulation for each subsector and the whole retail sector.[8] The counterfactuals are not reported in a table but discussed in the text.

An alternative interpretation of the marginal effects is that one fewer approved PBL application decreases median store productivity by between 1 (electronics) and 13 percent (furniture).[9] Holding labor and capital constant, this is equivalent to a decline in output of 1-13 percent. Store sales for the period 1996-2002 are on average 0.576 million euros (footwear) - 2.887 million euros (clothing).[10] For a store, this implies that the annual economic cost of one fewer approved PBL application is 0.004 million euros (electronics) - 0.143 million euros (computers) on average.[11] At the subsector level, the annual economic cost of a less liberal regulatory environment ranges from 2.8 million euros (toys) to 194 million euros (furniture). This corresponds to a total subsector cost as high as 20 million euros (toys) - 1,361 million euros (furniture) for the complete time period 1996-2002.[12]

[8]Greenstone, List, and Syverson (2012) adopt a similar approach when evaluating the economic cost of environmental regulation in the U.S. manufacturing industry. Note that the marginal effects in Table F.1 are at the local market level whereas the counterfactuals are at the aggregate level (sum across all local markets).

[9]We exclude three subsectors where the marginal effects of the regulation are close to zero (textiles, books, and hardware).

[10]Numbers are in 2012 values, where 1EUR=9.01SEK and 1EUR=1.30USD.

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

[12]The annual subsector cost is computed as the average economic cost per store times the average number of stores in each subsector during the period 1996-2002. The subsec-

Our estimated economic cost of less liberal entry regulation is intended to be interpreted as a lower bound. The reason is that we compute the values conditional on survival, which implies that the true effect may be larger.[13] While we control for the effect of regulation on demand, there might still be persistent demand shocks to productivity that are affected by the regulation. Note that we evaluate the cost of one fewer approved PBL application per local market and year in each subsector. Overall, the counterfactual calculations suggest that less liberal entry regulation induces non-trivial economic costs for stores in Swedish retail trade.

tor cost for the full period is calculated as the average economic cost per store times the number of stores in the subsector in each of the years from 1996 to 2002.

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

Table F.1: Productivity and entry regulations in local markets: nonparametric approach

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

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

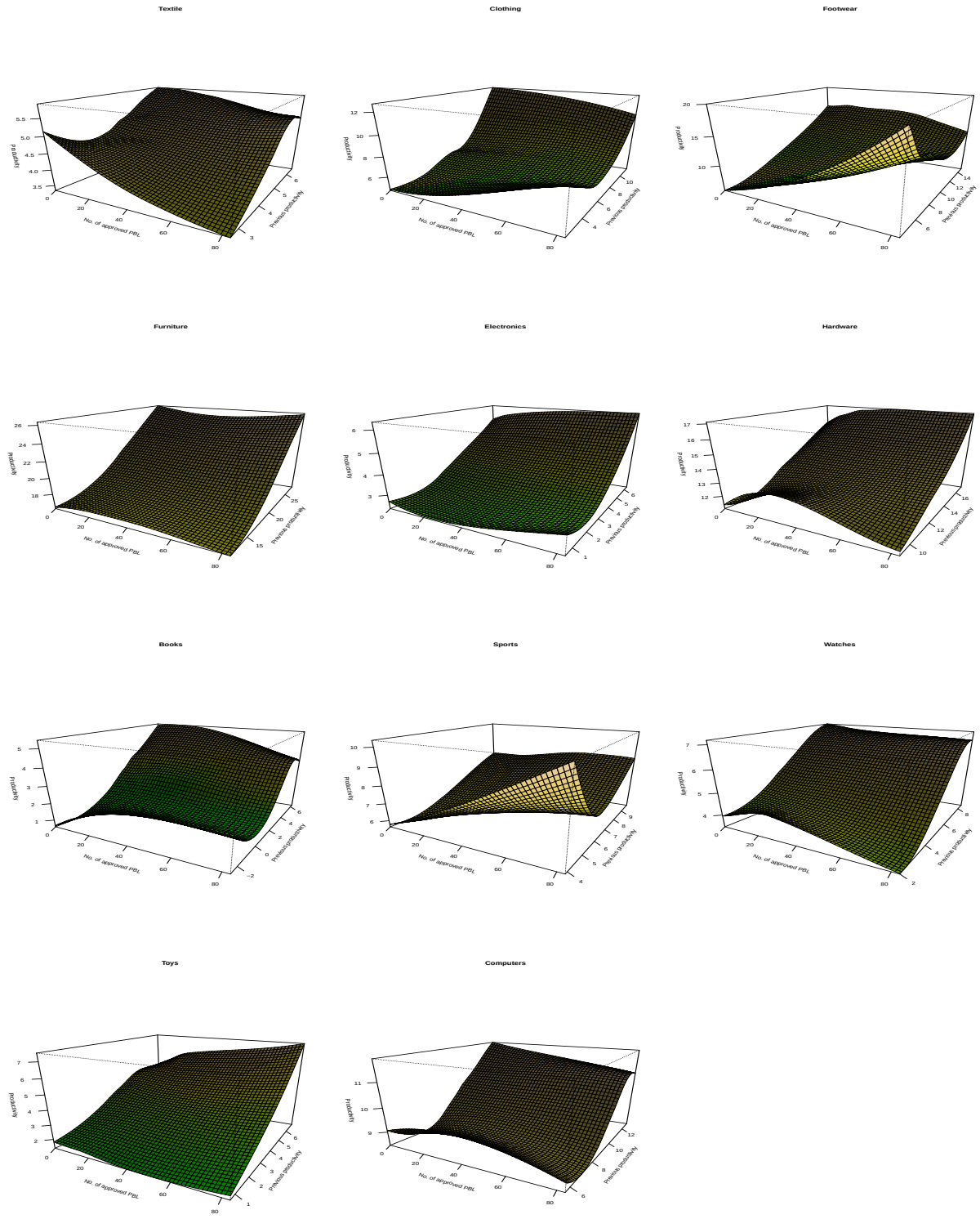


Figure 1: The industry relation between productivity, previous productivity, and number of approved PBL applications, 1996 to 2002

Appendix G: Productivity decompositions

We also analyze how aggregate subsector productivity evolves over time decompose the contributions from entering, exiting, and incumbent stores to aggregate subsector productivity growth. We use productivity decompositions in both levels and growth. First, we use an extension of the Olley and Pakes (1996) decomposition to allow for the contributions of entry and exit to aggregate productivity levels in liberal (non-liberal) local markets. The proposed decomposition complements previous work by focusing on the key aspects of retail markets. Retail stores compete in local markets, and we therefore consider weighted local market shares and then aggregate to the subsector level. Furthermore, we consider the contributions of the local entry regulation to productivity dynamics at the subsector level. To do this, we need to evaluate the contribution of incumbents, entrants, and exits to subsector productivity in local markets with different degrees of regulation. Second, to decompose aggregate productivity growth by subsector, we consider various methods but primarily focus on the approaches developed by Griliches and Regev (1995) (GR) and Foster, Haltiwanger, and Krizan (2001) (FHK) as well as recent decompositions by Melitz and Polanec (2012) (MP) and Petrin and Levinsohn (2012) (PL).

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

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

$$\Omega_{mt} = \overline{\omega}_{mt} + \sum_{j_m} (s_{jmt} - \overline{s}_{mt})(\omega_{jmt} - \overline{\omega}_{mt}), \tag{G-8}$$

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

$$\begin{aligned}\Omega_t = \textstyle\sum_m v_{mt}\Omega_{mt} = & \textstyle\sum_m v_{mt}\overline{\omega}_{mt} + \sum_m v_{mt}\sum_j (s_{jmt} - \overline{s}_{mt})(\omega_{jt} - \overline{\omega}_{mt}) \\ = & \textstyle\sum_m v_{mt}\overline{\omega}_{mt} + \sum_m v_{mt}\left[\sum_j s_{jmt}\omega_{jmt} - \overline{\omega}_{mt}\right] \\ = & \textstyle\sum_m v_{mt}\overline{\omega}_{mt} + \sum_m \sum_j v_{mt}s_{jmt}\omega_{jmt},\end{aligned} \tag{G-9}$$

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

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

$$\begin{aligned}\Omega_{mt} = & \textstyle\sum_{j\in C_{mt}} s_{jmt}\omega_{jmt} + \sum_{j\in E_{mt}} s_{jmt}\omega_{jmt} + \sum_{j\in X_{mt}} s_{jmt}\omega_{jmt} \\ = & \textstyle\sum_{j\in C_{mt}} (\overline{s}_{mt} + \Delta s_{jmt})(\overline{\omega}_{mt} + \Delta\omega_{jmt}) \\ & + \textstyle\sum_{j\in E_{mt}} (\overline{s}_{mt} + \Delta s_{jmt})(\overline{\omega}_{mt} + \Delta\omega_{jmt}) \\ & + \textstyle\sum_{j\in X_{mt}} (\overline{s}_{mt} + \Delta s_{jmt})(\overline{\omega}_{mt} + \Delta\omega_{jmt}) \\ = & \frac{N_m^C}{N_m}\overline{\omega}_{mt} + \frac{N_m^E}{N_m}\overline{\omega}_{mt} + \frac{N_m^X}{N_m}\overline{\omega}_{mt} + \textstyle\sum_{j\in C_{mt},E_{mt},X_{mt}} \Delta s_{jmt}\Delta\omega_{jmt},\end{aligned} \tag{G-10}$$

where $\Delta s_{jmt} = s_{jmt} - \overline{s}_{mt}$, $\Delta\omega_{jmt} = \omega_{jmt} - \overline{\omega}_{mt}$, N_m^C is the number of continuing stores in period t, N_m^E is the number of entrants in period t, N_m^X is the number of stores that exit the market in period t, and $N = N_m^C + N_m^E + N_m^X$. A few remarks need to be made regarding this decomposition. First, it provides the direct contributions of incumbents, entrants, and exits to the aggregate productivity in each period. Second, entrants in period t are incumbents in period $t+1$. The contribution of the entrants is given in the period in which they enter, which we believe is noteworthy because the theoretical literature often emphasizes that entrants have higher productivity that incumbents. While there might be less support for this hypothesis in the empirical literature, comparing the productivity of entrants and stores that exit is important for the dynamics of the

market structure. Third, this decomposition shows the evolution of the contributions of incumbents, entrants, and exits to aggregate productivity over time. In other words, we can compare the contributions of the entrants in t and t'. Fourth, the decomposition emphasizes the contributions to the unweighted productivity and covariance (stores with high market share and productivity) for each category (incumbent, entrant, and exit).

Figure 3 presents aggregate subsector productivity in markets with and without a liberal regulatory environment during the period 1996-2002. These results rely on estimated productivity using NP_{lm} and liberal markets being defined as those with above the median number of PBL approvals.[14] Figure 4 presents the relative contributions from incumbents, entrants, exits, and covariance to aggregate subsector productivity. The covariance term captures reallocation for all types of stores, i.e., incumbents, entrants and exits, according to equation (G-10).

Aggregate productivity increases for nearly all subsectors over time, especially after 1999 (Figure 3). Incumbents contribute 75-90 percent of aggregate subsector productivity, exits up to 15 percent, entrants up to 10 percent, and covariance up to 5 percent (Figure 4). There are two striking findings. First, incumbents contribute less, and entry, exit and covariance more, in liberal than in non-liberal local markets. This finding holds for all subsectors, and the magnitudes of the differences are often considerable (above 5 percentage points).[15] Second, the patterns over time demonstrate that the contribution from incumbents is inversely related to that of entry and exit. We conclude that a more liberal regulatory environment implies a higher contribution from entrants, exits and covariance to aggregate productivity. This supports our previous finding in Table F.1, i.e.,

[14]The corresponding figures when non-socialist (socialist) local governments are used to define liberal (non-liberal) markets yield similar patterns. Results are not reported but are available from the authors on request.

[15]The differences across markets are fairly small for computers. Entry and exit are crucial for toys, which is consistent with the high entry and exit rates in Table **??**. Reallocation in liberal markets is important for books and textiles, and entrants in liberal markets have a relatively low contribution for textiles. This is in line with books and textiles being the only subsectors with negative lower supports for a more liberal local market regulation's effect on productivity in Table F.1.

that more liberal entry regulation increases productivity across local markets.

Productivity growth decomposition. Here we present the GR and FHK frameworks and recent decompositions by Melitz and Polanec (2012) (MP) and Petrin and Levinsohn (2012) (PL). FHK has previously been applied to labor productivity growth in U.S. retail trade (Foster, Haltiwanger, and Krizan, 2006). FHK and GR both modify the method developed by Baily, Hulten, and Campbell (1992).

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

$$\begin{aligned}\Delta\Omega_{t,t'} = \; & \textstyle\sum_{j\in C_{t,t'}} \overline{s}_j \Delta\omega_{jt,t'} + \sum_{j\in C_{t,t'}} \Delta s_{jt,t'}(\overline{\omega}_j - \overline{\Omega}) \\ & + \textstyle\sum_{j\in E_{t,t'}} s_{jt'}(\omega_{jt'} - \overline{\Omega}) - \sum_{j\in X_{t,t'}} s_{jt}(\omega_{jt} - \overline{\Omega}),\end{aligned} \tag{G-11}$$

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

Foster, Haltiwanger and Krizan (2001). Using FHK, the change in national subsector productivity from year t to year t' can be written as

$$\begin{aligned}\Delta\Omega_{t,t'} = \; & \textstyle\sum_{j\in C_{t,t'}} s_{jt} \Delta\omega_{jt,t'} + \sum_{j\in C_{t,t'}} \Delta s_{jt,t'}(\omega_{jt} - \Omega_t) \\ & + \textstyle\sum_{j\in C_{t,t'}} \Delta s_{jt,t'} \Delta\omega_{jt,t'} + \sum_{j\in E_{t,t'}} s_{jt'}(\omega_{jt'} - \Omega_t) \\ & - \textstyle\sum_{j\in X_{t,t'}} s_{jt}(\omega_{jt} - \Omega_t),\end{aligned} \tag{G-12}$$

where Ω_t is the weighted average subsector productivity; Δ is the difference operator ($\Delta\Omega_{t,t'} = \Omega_{t'} - \Omega_t$); s_{jt} is the market share of store j in the subsector; $C_{t,t'}$ is the set of continuing stores, i.e., operating both in t and $t^{'}$; $E_{t,t'}$ is the set of entering stores, i.e., that operated in $t^{'}$ but not in t; and $X_{t,t'}$ is the set of exiting stores, i.e., that operated

in t but not in $t^{'}$. The decomposition (G-12) thus consists of five terms. The first term (Within) is the increase in productivity when the continuing stores increase their productivity at initial sales. The second term (Between) is the increase in productivity when continuing stores with above-average productivity expand their share of sales relative to stores with below-average productivity. The third term (Cross) captures the increase in productivity when continuing stores increase their market shares, while the fourth and fifth terms (Entry and Exit) are productivity increases due to entry and exit, respectively.[16]

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

$$\begin{aligned}\Delta\Omega_{t,t'} = \; & \Delta\overline{\Omega}_{C_{t,t'}} + \Delta cov_{C_{t,t'}} + \Delta\overline{\Omega}_{E_{t,t'}} + \Delta cov_{E_{t,t'}} \\ & + \Delta\overline{\Omega}_{X_{t,t'}} + \Delta cov_{X_{t,t'}}\end{aligned} \tag{G-13}$$

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

$$\begin{aligned}\Omega_t &= ms_{C_t}\Omega_{C_t} + ms_{X_t}\Omega_{X_t} \\ \Omega_{t'} &= ms_{C_{t'}}\Omega_{C_{t'}} + ms_{E_{t'}}\Omega_{E_{t'}},\end{aligned} \tag{G-14}$$

where ms_{C_t}, $ms_{C_{t'}}$, $ms_{E_{t'}}$, and ms_{X_t} are the aggregate market shares of incumbents (in periods t and $t^{'}$), entrants, and exits, respectively. In OP, the difference in productivity

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

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

$$\Delta\Omega_{t,t'} = \Delta\overline{\Omega}_{t,t'} + \Delta cov_{t,t'}. \tag{G-15}$$

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

$$\Delta\Omega_{t,t'} = \Delta\overline{\Omega}_{C_{t,t'}} + \Delta cov_{C_{t,t'}} + ms_{E_{t'}}(\Omega_{E_{t'}} - \Omega_{C_{t'}}) + ms_{X_t}(\Omega_{C_t} - \Omega_{X_t}), \tag{G-16}$$

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

Petrin and Levinsohn (2012). The decomposition methods described above all rely on changes in technical efficiency. Based on growth accounting, Petrin and Levinsohn (2012) (PL) propose an alternative decomposition and define aggregate productivity growth (APG) as the change in aggregate final demand minus the change in aggregate expenditures on labor and capital. To connect changes in production to those in aggregate final demand, they exploit the fact that aggregate value-added equals aggregate final demand. This stems from the National Income Identity stating that the use of intermediate inputs is canceled out at the aggregate level (Hulten, 1978; Basu and Fernald, 2002). Consequently, PL link micro-level plant data to a macro perspective (the Solow residual). In particular, they extend Basu and Fernald (2002) to allow for jumps in productivity growth, differences in input costs, and non-differentiable cost functions (by using production function estimates).

PL decompose APG into three terms: (i) technical efficiency, i.e., the effect of plants generating more output without increasing inputs; (ii) reallocation, i.e., the effect of

changes in input reallocation across plants; and (iii) fixed and sunk costs. The relationship between APG and these three terms holds when taking the sum over all or different subsets of plants in the economy. An advantage of the PL decomposition is thus that it can be divided into different types of plants, e.g., incumbents, entrants and exits.

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

Results. Table G.1 presents the results for the FHK and GR decompositions of subsector productivity growth between the base year $t = 1997$ and $t' = \{1998, \cdots, 2002\}$, using productivity from NP_{lm}.[17] National productivity growth is positive for all subsectors. Subsector growth ranges from 2 to 32 percent, with approximately half of the subsectors experiencing growth greater than 15 percent. Entry has a significant contribution to productivity growth in textiles, clothing, footwear, hardware, sports, and computers. Incumbents that continue throughout the entire period also contribute substantially to growth (Within). Incumbent stores that increase both their productivity and market shares are also important for growth in several of the subsectors (Cross). Conversely, expanding incumbents with above-average productivity (Between) and exit have a negative effect on growth. The importance of entry is in line with previous studies on labor productivity in U.S. retail trade (Foster, Haltiwanger, and Krizan, 2006).

Using the MP decomposition and productivity estimated using NP_{lm}, incumbents

[17]Following Doraszelski and Jaumandreu (2013), we trim 10 percent of the observations in each tail of the productivity distribution, and extreme values in the lower tail of the productivity growth distribution for clothing and furniture, which otherwise influence the averages substantially.

contribute more to aggregate productivity growth than under FHK or GR (Table G.2). This is exactly what we expect. In fact, surviving stores that improve their productivity constitute the most important source of productivity growth for all subsectors except Watches. Tables G.3 and G.4 present decomposition results for FHK, GR and MP for productivity estimated using the parametric approach based on Doraszelski and Jaumandreu (2013).

Table G.1: Decomposition of retail productivity growth 1997-2002 using Foster, Haltiwanger, and Krizan (2001) and Griliches and Regev (1995): nonparametric approach

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

NOTE: The decomposition is done using Foster, Haltiwanger, and Krizan (2001)(FHK) and Griliches and Regev (1995)(GR). Productivity is estimated using the two-step estimator described in Section 3. Shares of local market sales are used as weights.

Table G.2: Dynamic Olley and Pakes decomposition of retail productivity growth 1996-2002 using Melitz and Polanec (2012): nonparametric approach

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

Decomposition of retail productivity growth. Productivity is estimated using the two-step estimator described in Section 3. Shares of local market sales are used as weights.

Table G.3: Decomposition of retail productivity growth 1996-2002 using Foster, Haltiwanger, and Krizan (2001) and Griliches and Regev (1995): parametric approach

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

NOTE: The decomposition is done using Foster et al. (2001)(FHK) and Griliches and Regev (1995)(GR). Productivity is estimated using the parametric estimator. Stores' shares of local market sales are used as weights.

Table G.4: Dynamic Olley and Pakes decomposition of retail productivity growth 1996-2002 using Melitz and Polanec (2012): parametric approach

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

Decomposition of retail productivity growth. Productivity is estimated using the parametric estimator. Stores' shares of local market sales are used as weights.

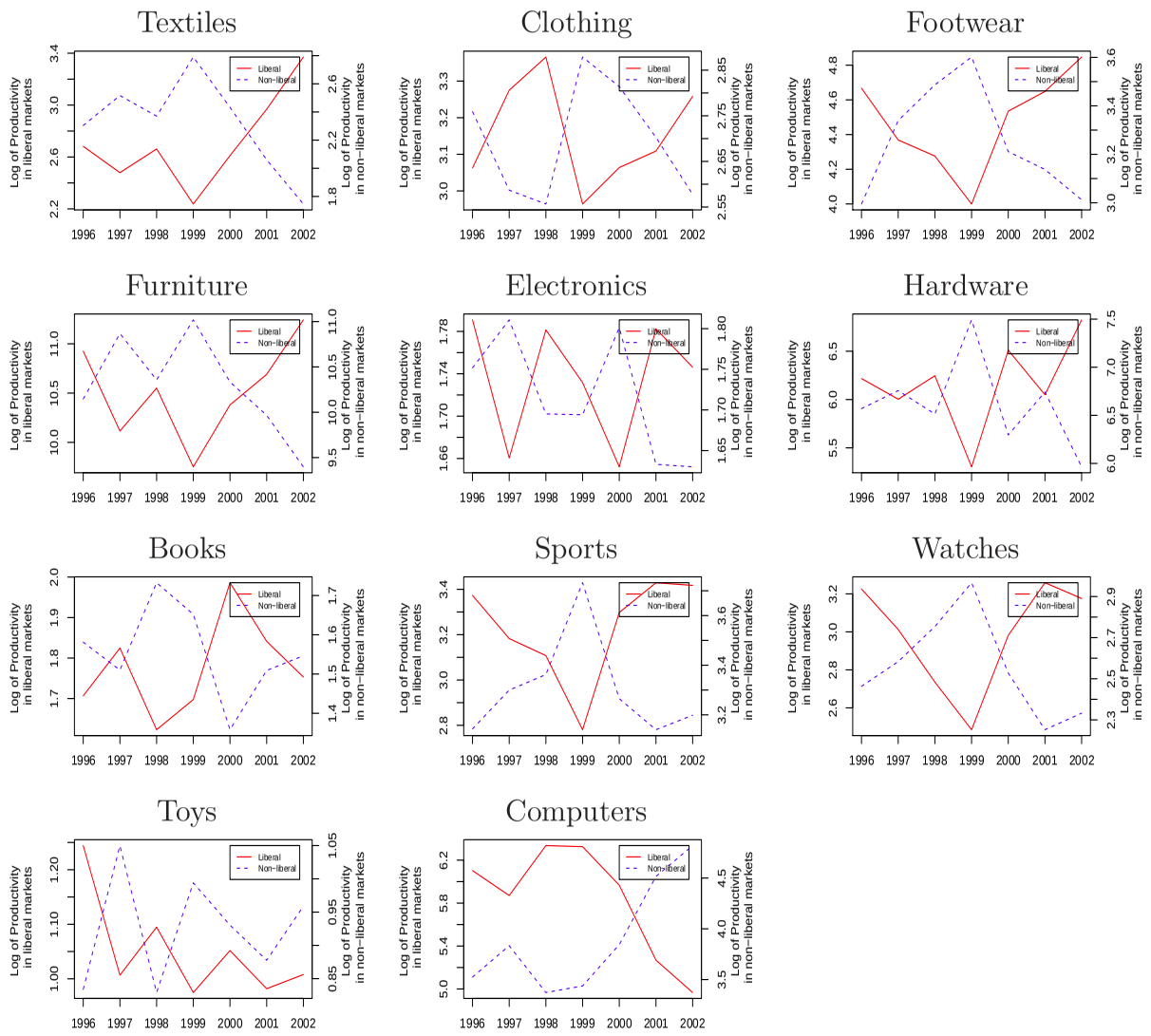
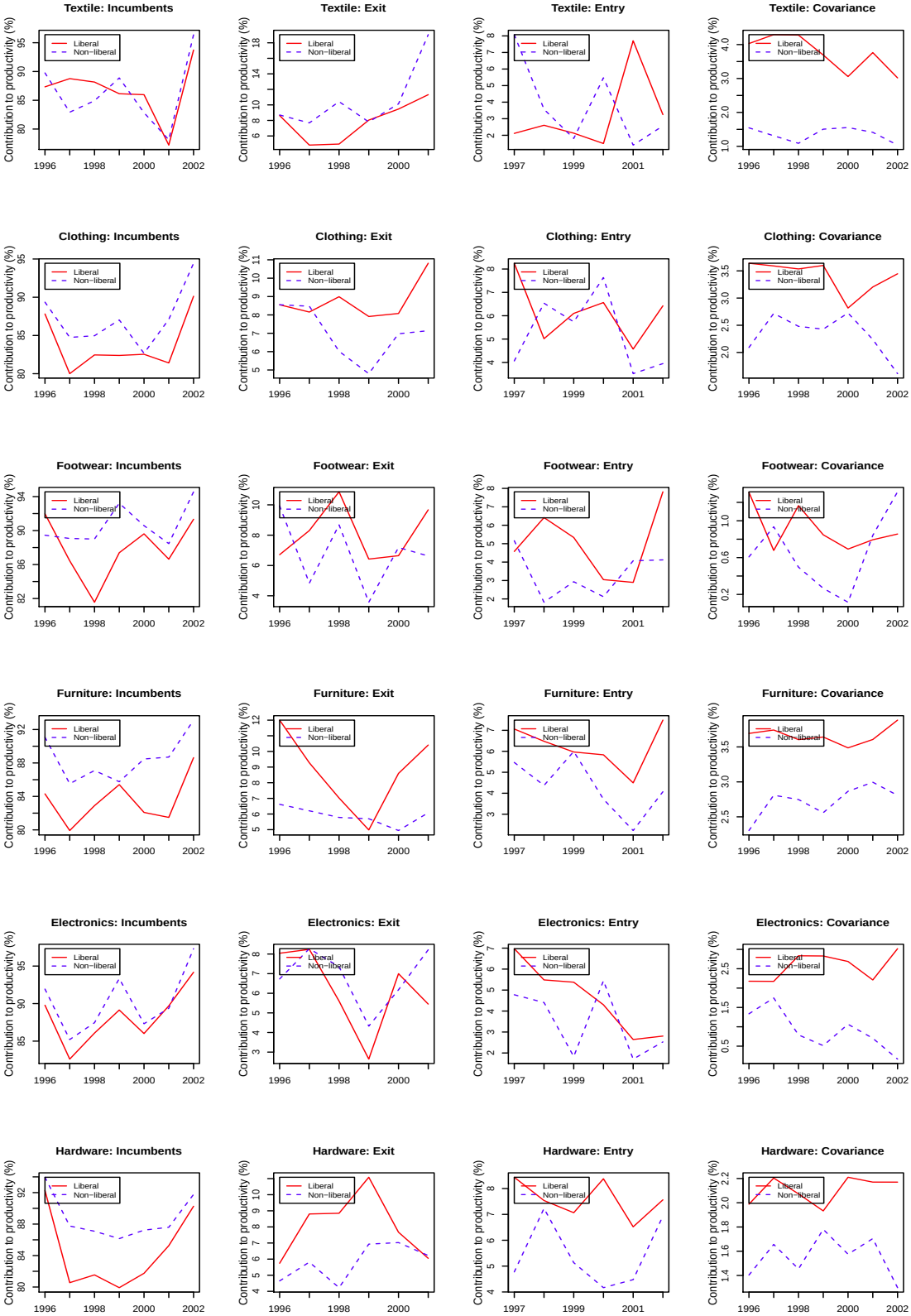


Figure 2: Aggregate productivity dynamics in markets with above median (liberal) and below median (non-liberal) number of approved PBL applications, 1996 to 2002


Textile: Incumbents
Textile: Exit
Textile: Entry
Textile: Covariance
Clothing: Incumbents
Clothing: Exit
Clothing: Entry
Clothing: Covariance
Footwear: Incumbents
Footwear: Exit
Footwear: Entry
Footwear: Covariance
Furniture: Incumbents
Furniture: Exit
Furniture: Entry
Furniture: Covariance
Electronics: Incumbents
Electronics: Exit
Electronics: Entry
Electronics: Covariance
Hardware: Incumbents
Hardware: Exit
Hardware: Entry
Hardware: Covariance
Liberal
Non−liberal
Contribution to productivity (%)

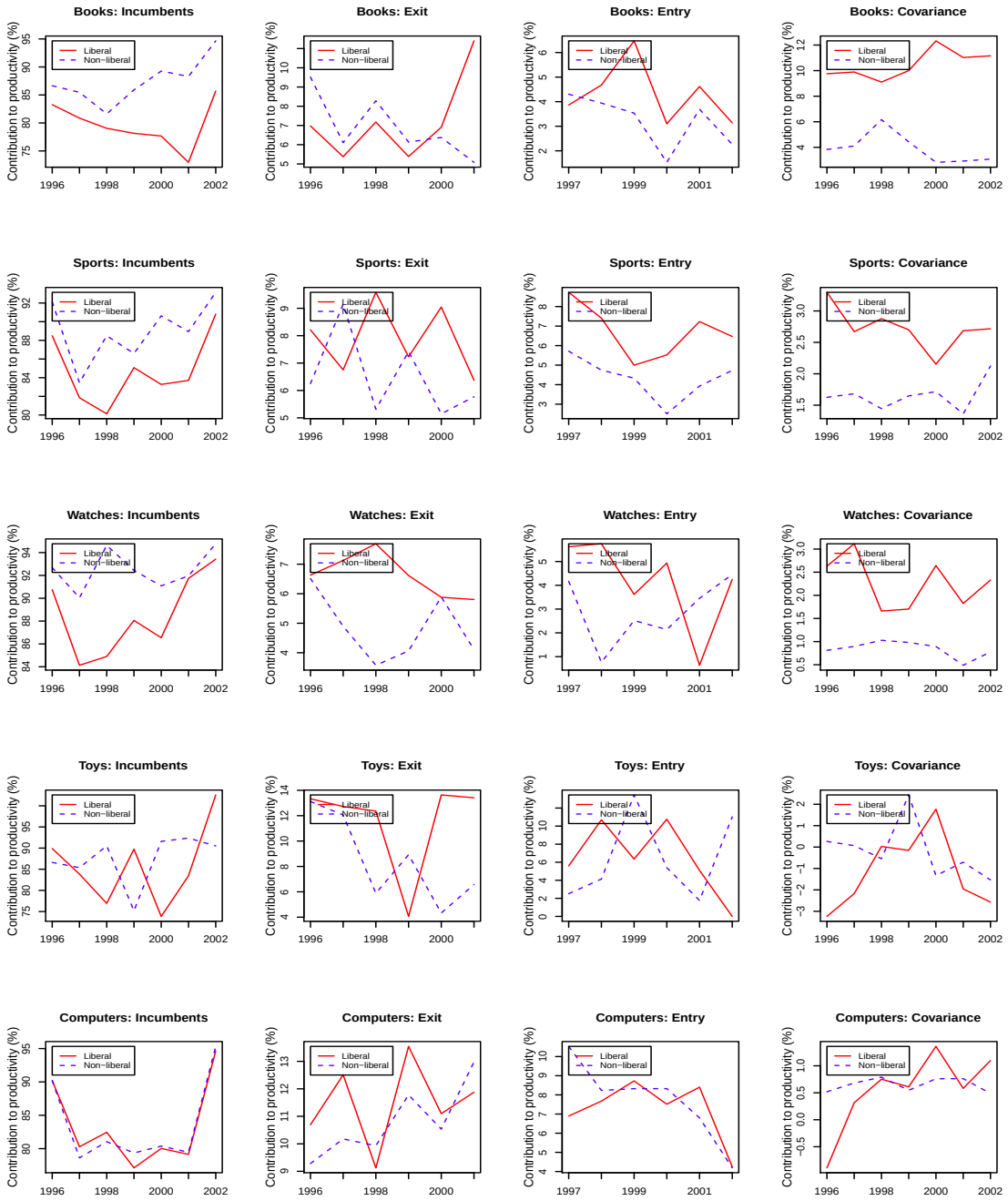


Figure 3: The dynamics of the contribution of average productivity and covariance for incumbents, entrants, and exit to aggregate productivity in in markets with above median (liberal) and below median (non-liberal) number of approved PBL applications, 1996 to 2002

References

Ai, C., and X. Chen (2003): "Efficient Estimation of Models with Conditional Moment Restrictions Containing Unknown Functions," *Econometrica*, 71(6), 1795–1843.

Baily, M., C. Hulten, and D. Campbell (1992): "Productivity Dynamics in Manufacturing Establishments," *Brookings Papers on Economic Activity*, pp. 187–249.

Basu, S., and J. Fernald (2002): "Aggregate Productivity and Aggregate Technology," *European Economic Review*, 46(6), 963–991.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4), 841–890.

Chen, X., and S. Ludvigson (2007): "Land of Addicts? An Empirical Investigation of Habit-Based Asset Pricing Models," Mimeo, New York University.

Doraszelski, U., and J. Jaumandreu (2013): "R&D and Productivity: Estimating Endogenous Productivity," *Review of Economic Studies*, 80(4), 1338–1383.

Foster, L., J. Haltiwanger, and C. Krizan (2001): "The Link Between Aggregate and Micro Productivity Growth: Evidence from Retail Trade," NBER Working Paper 13783.

——— (2006): "Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s," *Review of Economics and Statistics*, 88(4), 748–758.

Greenstone, M., J. List, and C. Syverson (2012): "The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing," (Working Paper 18392, NBER).

Griliches, Z., and H. Regev (1995): "Productivity and Firm Turnover in Israeli Industry: 1979-1988," *Journal of Econometrics*, 65, 175–203.

Hulten, C. (1978): "Growth Accounting with Intermediate Inputs," *Review of Economic Studies*, 45(3), 511–518.

Hulten, C., and F. Wykoff (1981): chap. The Measurement of Economic Depreciation, in C. Hulten (ed.), *Depreciation, Inflation, and Taxation of Income from Capital*, Urban Institute Press, Washington, D.C.

Melitz, M., and S. Polanec (2012): "Dynamic Olley-Pakes Productivity Decomposition with Entry and Exit," Mimeo, Princeton University.

Newey, W., and J. Powell (2003): "Instrumental Variables Estimation of Nonparametric Models," *Econometrica*, 71(3), 1557–1569.

Newey, W., J. Powell, and F. Vella (1999): "Nonparametric Estimation of Triangular Simultaneous Equations Models," *Econometrica*, 67(3), 565–603.

Olley, S., and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263–1297.

Petrin, A., and J. Levinsohn (2012): "Measuring Aggregate Productivity Growth Using Plant-level Data," *RAND Journal of Economics*, 43(4), 705–725.

Robinson, P. (1988): "Root-N-Consistent Semiparametric Regression," *Econometrica*, 56(4), 931–954.

Swedish Competition Authority (2001:4): "Kan Kommunerna Pressa Matpriserna? (Can the Municipalities Put Pressure on Prices?)," Technical Report 4, Stockholm.

——— (2004:2): "Konsumenterna, Matpriserna och Konkurrensen (Consumers, Retail Food Prices, and Competition)," Technical Report 2, Stockholm.

Syverson, C. (2004): "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy*, 112(2), 1181–1222.