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Essays in Industry Dynamics on Imperfectly Competitive Markets

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To my wife, Iuliana,
and my son, Rares.

Contents

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"Not everything that counts can be counted,
and not everything that can be counted counts."
Einstein

Short Introduction

This thesis consists of four empirical essays on imperfectly competitive markets. The essays are grouped by the methodology used.[1] Essay 1 studies the effect of large entrants on productivity dynamics in Swedish food retail. Essay 2 studies the productivity dynamics in high R&D spending manufacturing industries where competitive pressure plays a key role in the choice of R&D spending. Essay 3 analyses store format repositioning in Swedish food retail. Essay 4 studies the impact of the 2001 dot-com bust, a natural experiment, on productivity dynamics and cost structure in Swedish IT services. Essays 1 and 2 use a single agent dynamic framework, whereas Essays 3 and 4 use truly dynamic games.

Essay 1: *Productivity Dynamics and the Role of Big-Box Entrants in Retailing (with Matilda Orth)*

Products from the food sector fulfill our needs for basic survival and are purchased by almost everyone in society. Entry of large (big-box) stores along with a drastic fall in the total number of stores is a striking trend in retail markets in both US and many European countries. In retail, there is a lack of knowledge regarding the market structure effects caused by large entrants (Swedish Competition Authority, 2004:2). An interesting economic issue is whether entrants influence the productivity of incumbent stores. The question posed is of certain importance due to the existing entry regulation (common across European countries), giving the local governments the power to decide whether or not a store is allowed to enter the market. Essay 1 uses a dynamic structural model to estimate total factor productivity in retail. Then it assesses whether entry of large stores drives exit and growth in the productivity distribution of incumbents. Using detailed data on all retail food stores in Sweden, the paper finds that local market characteristics, selection, and nonlinearities in the productivity process are important when estimating retail productivity. We find that large entrants force low productivity stores to exit and surviving stores to increase their productivity growth. Growth increases most among incumbents in the bottom part of the productivity distribu-

[1] Ackerberg et al. (2008) and Pakes (2008) survey recent developments in the empirical analysis of imperfectly competitive markets.

tion, and then declines with the productivity level of incumbents. The essay uses political preferences in local markets to control for endogeneity of large entrants. The findings suggest that large entrants play a crucial role for driving productivity growth.

Essay 2: *Productivity Dynamics, R&D, and Competitive Pressure*

The link between investment in research and development (R&D) and firm performance is one of the most studied topics in industrial organization. Early literature on this relationship largely focused on estimating the average or expected returns (private or social) to R&D spending. However, R&D spending not only increases a firms productivity, it also affects the entire productivity distribution of the industry through exit of firms and reallocations as well as displacements of labor and capital. From a policy perspective, the analysis of the entire productivity distribution enhances our understanding of the dynamics of firms investment in R&D and physical capital.[2]

Essay 2 proposes a dynamic structural model to estimate productivity when productivity evolves as an endogenous process and firms decide how much to invest depending on the competitive pressure they face. Using data on all manufacturing firms in Sweden, this paper finds that open market policies and entrepreneurship policies complement R&D policies and are important drivers of the competitiveness of established firms. Conservative estimates suggest that the optimal investment is at least 0.7 to 2.5 times the actual investment in R&D for a median firm and 2 to 4 times for a firm located in the upper part of the productivity growth distribution.

Essay 3: *Industry Dynamics and Format Repositioning in Retail*

Powerful chains dominate the retail food markets in both Europe and US due to increasing importance of for example information technology, distribution systems, and demand. Each chain operates a number of well-defined store formats and continuously considers a trade-off between repositioning of store formats, entry of new stores, and exit of existing stores. Recent investment strategies aim to increase product differentiation in store formats. Each investment implies, however, a sunk cost. Since both entry and repositioning of formats are regulated, insights about the trade-off between entry and repositioning and its link to competition closely

[2] In the theoretical firm dynamics models proposed by Ericson and Pakes (1995), Hopenhayn (1992), and Jovanovic (1982), the stochastic evolution of firm productivity determines the success or failure of the firm in an industry.

connect to competition policy. A large variety of store formats can ensure that consumers gain access to low prices and wide and attractive product assortments (The Nordic Competition Authorities 2005:1). In Sweden, this is particularly important as municipalities have the obligation to evaluate the competitive impact of new stores (Swedish Competition Authority 2008:5).

Essay 3 proposes a fully dynamic oligopoly model to estimate the costs of repositioning store formats together with sunk costs of entry and sell-off values of exit in the retail industry. In differentiated product markets, when firms are affected by demand shocks, they may react by repositioning their products, which in turn affects market structure. The model gives important information about driving forces behind format changes and how such repositioning can be linked to entry and exit. Using data from Sweden, the results indicate that both repositioning and entry costs increase with market size, and their growth decreases when moving to larger markets. Small markets have higher sell-off values than repositioning costs, but large entry costs. The difference between higher entry and lower repositioning costs explains why the number of observed repositionings is higher than the number of entrants. Since entry is regulated in most OECD countries, repositioning costs and their link to competition have important implications for competition policy.

Essay 4: *From Boom to Bust: A Dynamic Analysis of IT Services*

The IT industry contributes significantly to increased productivity and improved service quality in virtually all sectors of the economy (Jorgenson et al., 2008). The lower adoption rate and small size of IT investments in Europe have been found to have been responsible for the lower productivity growth in Europe than in US in the 1990s (van Ark et al., 2008).

Essay 4 proposes a fully dynamic structural model to analyze the impact of the 2001 dot-com bust on the productivity dynamics and the cost structure for IT services. Aggregate demand shocks such as the burst of the 2001 dot-com bubble affect firms behavior and, therefore, the market structure. The empirical application builds on an eight year panel dataset that includes every IT service firm in Sweden and is representative for many other European countries. Incumbents are more productive than entrants and net exit contributed the most to productivity growth in the IT services after the dot-com bust. Essay 4 finds higher fixed investment and labor costs for software but lower for operational services after the dot-com bust. Finding the relative importance of fixed costs is a step closer to being able to link policies that affect adjustment costs in IT services.

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Paper I

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

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Abstract

Entry of large ("big-box") stores along with a drastic fall in the total number of stores is a striking trend in retail markets. We use a dynamic structural model to estimate total factor productivity in retail. Then we assess whether entry of large stores drives exit and growth in the productivity distribution of incumbents. Using detailed data on all retail food stores in Sweden, we find that local market characteristics, selection, and nonlinearities in the productivity process are important when estimating retail productivity. Large entrants force low productive stores to exit and surviving stores to increase their productivity growth. Growth increases most among incumbents in the bottom part of the productivity distribution, and then declines with the productivity level of incumbents. We use political preferences in local markets to control for endogeneity of large entrants. Our findings suggest that large entrants play a crucial role for driving productivity growth.

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

JEL Classification: O3, C24, L11.

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1 Introduction

Recent methods for structural estimation of production functions have almost only been applied to manufacturing industries.[1] There have been few attempts to estimate multi-factor productivity in retail markets, where entry and exit have been found to play a more crucial role for labor productivity growth than in manufacturing (Foster et al. 2006). The major structural change in retail markets during the last few decades is in fact the entry of large ("big-box") stores, along with a drastic fall in the number of stores. The most striking example is the expansion of Wal-Mart, which has been found to greatly lower retail prices, and increase exit of retail stores in the U.S., the "Wal-Mart effect".[2] For instance, the number of single-store retailers in the U.S. declined 55% from 1963 to 2002 (Basker 2007). Retail markets in Europe also follow the "big-box" trend, though on a smaller scale, with for example Carrefour, Metro, Schwartz, and Tesco. Although there is an emerging literature about retail markets, the impact of this structural change on productivity has not been given much attention.[3] Our goal is to combine recent extensions of the Olley and Pakes' (1996) framework to estimate total factor productivity (TFP) in retail markets, and to investigate the impact of increased competition from large entrants on exit and productivity growth of incumbents. That is, do large entrants drive reallocation of inputs and outputs, i.e., exit of low productive stores and growth of surviving stores with different positions in the productivity distribution? Detailed data on all retail food stores in Sweden give us unique opportunities to analyze the questions at hand.

Productivity analysis in retailing is more complex than in many other industries because of the problem of measuring output (Griffith and Harmgart 2005, Reynolds et al. 2005). We use a dynamic structural model to estimate productivity, which has the advantage of allowing stores to have heterogenous responses to industry shocks (Ackerberg et al. 2007). In detail, our model is based on the following key features of retail markets: First, the most common characteristics of retail

[1] Olley and Pakes (1996), Pavcnik (2002), Levinsohn and Petrin (2003), Ackerberg et al. (2006), Buettner (2004), De Loecker (2009), Doraszelski and Jaumandreu (2009).

[2] Basker (2005), Basker (2007), Basker and Noel (2009), Holmes (2008), and Jia (2008). Fishman (2006) and Hicks (2007) provide a general discussion on the Wal-Mart effect.

[3] Two European contributions are Bertrand and Kramarz (2002), who find that retail markets in France have lower labor growth and higher concentration as a consequence of regulation, and Sadun (2008), who finds that regulation in the UK reduces employment in independent stores.

data are lumpy investments and a weak measure of intermediate inputs.[4] Because labor and capital are key inputs in retail markets, we recover productivity from the optimal choice of labor (Doraszelski and Jaumandreu 2009). Second, because retail stores operate in local markets we control for local market characteristics, i.e. for large entrants and population density. We control for endogeneity of large entrants by using political preferences in local markets as instruments. Third, because large store types are more likely than smaller ones to survive larger shocks to productivity we control for selection, as do Olley and Pakes (1996). Fourth, recent literature emphasizes the importance of controlling for prices when estimating production functions in imperfect competitive markets (Foster et al. 2008, De Loecker 2009). Since store prices and quantities are rarely observed in retail data we control for unobserved prices by introducing a simple demand system as in Klette and Griliches (1996), and thus obtain mark-up estimates at the industry level.[5] Compared to two-step estimators (Olley and Pakes 1996, Ackerberg et al. 2006), our one-step estimator has the advantages of increased efficiency and reduced computational burden. Identification comes from that we recover unobserved productivity from the labor demand function of known parametric form using a good measure of store wages. The assumption that labor is a static input abstracts from training, hiring and firing costs. We argue that this assumption is less restrictive in retail food than in many other industries because part time working is common, the share of skilled labor is low, and stores frequently adjust labor due to variation in customer flows. We also test the validity of this assumption.

The role of large entrants has a direct link to competition policy because the majority of OECD countries have entry regulations, though much more restrictive in Europe than in the U.S. The main rationale is that new entrants generate both positive and negative externalities, which require careful evaluation by local authorities. Advantages, such as productivity gains, lower prices, and wider product assortments, stand in contrast to drawbacks, in terms of fewer stores, and environmental issues. Because we anticipate large entrants to have an extensive impact

[4]While Olley and Pakes (1996) assume strict monotonicity of the investment function to recover unobserved productivity, Levinsohn and Petrin (2003) use the intermediate input of materials.

[5]Other studies that introduce prices in the production function are Melitz (2000), Levinsohn and Melitz (2002), Katayama et al. (2003), and Doraszelski and Jaumandreu (2009). In contrast to Doraszelski and Jaumandreu, who observe prices, we account for unobserved store prices.

on market structure, they are carefully evaluated in the planning process. The consequences of regulation (e.g. supermarket dominance) are frequently debated among policy makers in Europe (European Parliament 2008). Our primary objective is not to quantify the magnitude of inter-firm reallocations over time, i.e., how (large) entrants, exits, and incumbents contribute to aggregate productivity growth.[6] Instead we provide evidence for how large entrants influence exit and the productivity growth of incumbents in local markets.

We focus on food retailing because it accounts for a large (15%) share of consumers' budgets (Statistics Sweden 2005) and thus constitutes a large share of retailing. Besides, many other service sectors follow similar trends as retail food. The Swedish market is appropriate to analyze because it follows two crucial trends common among nearly all OECD countries: There has been a structural change towards larger but fewer stores; in fact, the total number of stores in Sweden declined from 36,000 in the 1950s to below 6,000 in 2003 (Swedish National Board of Housing, Building, and Planning 2005). And there is an entry regulation that gives municipalities power to decide over the land use and, consequently, whether or not a store is allowed to enter the market.

Our study connects to the literature of dynamic models with heterogenous firms (Jovanovic 1982, Hopenhayn 1992, and Ericson and Pakes 1995). In particular, we build on the growing literature on productivity heterogeneity within industries that use dynamic structural models (Olley and Pakes 1996, Pavcnik 2002, Levinsohn and Petrin 2003, Ackerberg et al. 2006). Recent studies on productivity dynamics show two important facts: large and persistent productivity differences among firms, and substantial reallocation across firms in the same industry.[7] They found that the key mechanism to foster growth is reallocation from less to more productive firms, either through less productive firms exiting and more productive firms entering or through increased productivity among incumbents, or both. Thus, increased competition forces low productive firms to exit, increasing the market shares of more productive firms. The productivity distribution is thus truncated from below, increasing the mean, and decreasing dispersion (Melitz 2003, Asplund and Nocke 2006). Using a local market approach, Syverson (2004)

[6] We estimate the contribution of *all* entrants to aggregate productivity growth using various TFP decompositions (Griliches and Regev 1995, Foster et al. 2001, Melitz and Polanec 2009) but, due to data constraints, we cannot quantify the exact contribution of large entrants.

[7] Caves (1998) and Bartelsman and Doms (2000) provide surveys, mainly on manufacturing.

emphasizes that demand density result in similar improvements in productivity distribution. In retail, entry and exit have been found to contribute to almost all labor productivity growth in the U.S., where chains replace low productive firms with high productive entrants (Foster et al. 2006). In Sweden, large food stores have been found to offer lower prices than others (Asplund and Friberg 2002). However, how large entrants influence local market competition and changes in the productivity distribution of incumbents has not been analyzed in detail.[8]

The empirical results show that it is important to control for local market characteristics, prices, selection, and to allow for nonlinearities in the productivity process when estimating retail productivity. Large entrants force low productive stores to exit, and surviving stores to increase their productivity growth. Growth increases most among incumbents in the bottom part of the productivity distribution, and then declines with the productivity level of incumbents. Large entrants thus spur reallocation of resources towards more productive stores. Aggregate productivity growth was 8% from 1997 to 2001, of which most is due to incumbents that increase their productivity, and exit of stores with lower productivity than incumbents. From a policy perspective, we claim that a more liberal design and application of entry regulations would support productivity growth in the Swedish retail food market.

The next section describes the retail food market and the data. Section 3 presents the modeling approach for estimating productivity, and those results. Section 4 reports the link between large entrants and exit and productivity growth. Section 5 summarizes and draws conclusions.

2 The retail food market and data

Retail food markets in the OECD countries are fairly similar, consisting of firms operating uniformly designed store types. In Sweden, the food market is dominated by four firms that together had 92% of the market shares in 2002: ICA(44%), Coop(22%), Axfood(23%), and Bergendahls(3%). Various independent owners

[8]The paper also relates to the vast literature on how competition affects productivity, emphasizing both positive and negative effects theoretically, but often positive effects empirically. Recent theoretical contributions are Nickell (1996), Schmidt (1997), Boone (2000), Melitz (2003), and Raith (2003); whereas recent empirical contributions include Porter (1990), MacDonald (1994), Nickell (1996), Blundell et al. (1999), Sivadasan (2004), and Aghion et al. (2009).

make up the remaining 8% market share.[9] ICA consists mostly of independently owned stores with centralized decision making. Coop, on the other hand, consists of centralized cooperatives with decisions made at national or local level. Axfood and Bergendahls each have a mix of franchises and centrally owned stores, the latter mainly in the south and southwest of Sweden.[10]

A majority of OECD countries have entry regulations that give power to local authorities. The regulations differ substantially across countries, however (Hoj et al. 1995, Boylaud and Nicoletti 2001, Griffith and Harmgart 2005, Pilat 2005). While some countries strictly regulate large entrants, more flexible zoning laws exist, for instance, in the U.S. (Pilat 1997). The Swedish Plan and Building Act (PBA) gives power to the 290 municipalities to decide over applications for new entrants. In case of inter-municipality questions of entry, they are handled by the 21 county administrative boards. PBA is claimed to be one of the major barrier to entry, resulting in diverse outcomes, e.g., in price levels, across municipalities (Swedish Competition Authority 2001:4). Several reports stress the need to better analyze how regulation affects market outcomes (Pilat 1997, Swedish Competition Authority 2001:4, 2004:2). Large entrants are often newly built stores in external locations, making regulation highly important.[11] Appendix A describes PBA in greater detail.

■ **Data.** In order to cover various store productivity measures and define large entrants, we use two micro-data sets. The first data set, collected by Delfi Marknadsparter AB (DELFI), defines a unit of observation as a store based on its geographical location, i.e., its physical address (sources are described in Appendix A). This data, covering all retail food stores in the Swedish market during 1995-2002, include store type, chain, revenue class, and sales space (in square meters). The store type classification (12 different) depends on size, location, product assortment etc. An advantage with DELFI is that it contains all stores and their physical locations; shortcomings are a lack of input/output measures and the fact that revenue information is collected by surveys and reported in classes. There-

[9]International firms with hard discount formats entered the Swedish market after the study period: Netto in 2002, and Lidl in 2003.

[10]In 2000, Axel Johnson and the D-group (D&D) merged, initiating more centralized decision making and more uniformly designed store concepts.

[11]Possibly, firms can adopt similar strategies as their competitors and buy already established stores. As a result, more productive stores can enter without involvement of PBA and, consequently, the regulation will not work as an entry barrier that potentially affects productivity. Of course, we cannot fully rule out the opportunity that firms buy already established stores.

fore, we use DELFI only to define large entrants.

The most disaggregated level for which more accurate input and output measures exist is organization number (Statistics Sweden, SCB). SCB provides data at this level based on tax reporting. But due to anonymous codes, the two data sets cannot be linked. Financial Statistics (FS) provides input and output measures, and Regional Labor Statistics (RAMS) comprises data on wages for all organization numbers from 1996 to 2002 belonging to SNI code 52.1, "Retail sales in non-specialized stores", which covers the four dominant firms (ICA, Coop, Axfood, and Bergendahls).[12] This FS-RAMS data, at the organization number level, consist of "multi-store" units, which may be one store or more with the same organization number (e.g., due to having the same owner).[13] Over 80% of the stores in DELFI each have their own organization number, so that less than 20% of the observations in FS-RAMS consist of two or more stores (discussed in detail below). If a firm consists of two stores, we observe total, not average, inputs and outputs. Note that all stores are reported in both data sets. Appendix A gives more information about the FS-RAMS data. Finally, we connect demographic information (population, population density, average income, and political preferences) from SCB to FS-RAMS and DELFI.

■ **Local markets.** Food products fulfill daily needs, are often of relatively short durability, and stores are thus located close to consumers. The travel distance when buying food is relatively short (except if prices are sufficiently low), and nearness to home and work are thus key aspects for consumers choosing where to shop, though distance likely increases with store size.[14] The size of the local market for each store depends on its type. Large stores attract consumers from a wider area than do small stores, but the size of the local market also depends on the distance between stores. We assume that retail markets are isolated geographic units, with stores in one market competitively interacting only with other stores in the same local market. A complete definition of local markets requires information about the exact distance between stores. Without this information

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

[13]FS-RAMS does not rely on addresses like DELFI, so we could not do a more detailed investigation of TFP and geographical distance (location).

[14]The importance of these factors is confirmed by discussions with representatives from ICA, COOP, and Bergendahls. According to surveys made by the Swedish Institute for Transport and Communication Analysis, the average travel distance for trips with the *main* purpose of buying retail food products is 9.83 kilometers (1995-2002).

we must rely on already existing measures. The 21 counties in Sweden are clearly too large to be considered local markets for our purposes, while the 1,534 postal areas are probably too small, especially for large stores (on which we focus). Two intermediate choices are the 88 local labor markets or the 290 municipalities. Local labor markets take into account commuting patterns, which are important for the absolutely largest types such as hypermarkets and department stores, while municipalities seem more suitable for large supermarkets. As noted, municipalities are also the location of local government decisions regarding new entrants. We therefore use municipalities as local markets.

■ **Large entrants and endogeneity.** DELFI relies on geographical location (address) and classifies store types, making it appropriate for defining large entrants. Because of a limited number of large stores, we need to analyze several of the largest store types together. We define the five largest types (hypermarkets, department stores, large supermarkets, large grocery stores, and other[15]) as "large" and four other types (small supermarkets, small grocery stores, convenience stores, and mini markets) as "small".[16] Gas station stores, seasonal stores, and stores under construction are excluded due to these types not belonging in the SNI-code 52.1 in FS-RAMS. From the point of view of the Swedish market, we believe that these types are representative of being large.

A key problem when analyzing the link between large entrants and productivity growth is the endogeneity of large entry. We hence need to bring exogenous variation in large entry using instruments. No major policy reforms changing the conditions for large entrants have taken place in Sweden during the study period (see Appendix A for details about PBA).[17] Local authorities in Sweden decide however about entry of big-box stores. Following Bertrand and Kramarz (2002) and Sadun (2008) we use political preferences in municipalities as instruments for large entrants.[18] We use variation in political preferences across local markets

[15]Stores classified as other stores are large and externally located.

[16]Alternatively, we define observations in FS-RAMS with sales above the 5th percentile of large stores' sales in DELFI as large; otherwise as small. Even though the available data do not allow a perfect match, the number of large entrants in FS-RAMS (so defined) follows a trend over time similar to that of the large entrants in DELFI. The empirical results (available from the authors upon request) are consistent with those reported here.

[17]Studies based on UK data have used major policy reforms to handle endogeneity of entry (Sadun 2008, Aghion et al. 2009).

[18]Data on the number of formal applications for entry, and rejections, is unfortunately not available in Sweden.

throughout the election periods 1994-1998 and 1999-2002 to add exogenous variation in the number of large entrants. We expect non-socialist local governments to have a more liberal view of large entrants, though the number of applications and rejections to each municipality is unfortunately not available in Sweden. Our instruments are valid if political preferences capture decision-making about large entrants and are uncorrelated with unobserved shocks.

■ **Descriptive statistics.** Table 1 presents descriptive statistics of the Swedish retail food industry from the two data sets DELFI and FS-RAMS for 1996-2002. As noted, over 80% of the observation units in FS-RAMS are identical to the stores in DELFI. The rest (20% in the beginning and 14% in the end) are multi-store units in FS-RAMS. The number of stores in DELFI decreases over the period from 4,664 to 3,585, i.e., a reduction of over 23%, indicating that many stores closed. In FS-RAMS, the number of observations decreases by about 17% (from 3,714 to 3,067).[19] The share of large stores in DELFI increases from 19% to nearly 26%. While total sales space is virtually constant, mean sales space increases by 33%. Thus there has been a major structural change towards larger but fewer stores in the Swedish retail food market. Total wages (in FS-RAMS) increase over 22% (in real terms), while the number of employees increases only 9%.[20] Total sales increase about 26% (in FS-RAMS). Total sales in DELFI are lower and increase only 10% due to survey collection and interval reporting.

Table 2 shows median characteristics of local markets (municipalities) with and without large entrants during 1997-2002. The median number of stores varies between 22 and 54 in large entry markets, compared to 13-15 in non-entry markets. The number of markets with at least one large entrant varies between 6 and 23. Among these, up to 3 large entrants establish in the same market in the same year. As we expect, median entry and exit are higher in large entry than in non-entry markets, with median population, population density, and income also higher there. Large entry markets also have a lower concentration; the median four store concentration ratio is about 0.5 in these markets while it is over 0.7 in markets without large entrants.

[19]This indicates that entry and exit based on changes in organization numbers in FS-RAMS in some cases differ from entry and exit based on addresses in DELFI due to, e.g., re-organizations.

[20]The aggregate growth of real wages in Sweden was 24% during the period.

3 Productivity estimation

Our model of competition among retail stores is based on Ericson and Pakes' (1995) dynamic oligopoly framework. A store is described by a vector of state variables consisting of productivity $\omega \in \Omega$, capital stock $k \in \mathbb{R}_+$, and local market characteristics $z \in Z$. Incumbent stores maximize the discounted expected value of future net cash flows. Stores compete in the product market and collect their payoffs. At the beginning of each time period, incumbents decide whether to exit or continue to operate in the local market.[21] If the store exits, scrap value ϕ is received. If the store continues, it chooses optimal levels of labor l and investment $i \geq 0$. We assume capital is a dynamic input that accumulates according to $k_{t+1} = (1-\delta)k_t + i_t$, where δ is the depreciation rate. Labor, on the other hand, is a non-dynamic input chosen based on current productivity. Changes in investment do not guarantee a more favorable state tomorrow, but do guarantee more favorable distributions over future states. As in Olley and Pakes (1996)(hereafter OP), the transition probabilities of productivity follow a first order Markov process with $P(d\omega|\omega)$. We denote $V(\omega_{jt}, k_{jt}, z_{mt})$ to be the expected discounted value of all future net cash flows for store j in market m at period t. $V(\omega_{jt}, k_{jt}, z_{mt})$ is defined by the solution to the following Bellman equation with the discount factor $\beta < 1$

$$\begin{aligned} V(\omega_{jt}, k_{jt}, z_{mt}) = \quad & max \Big\{\phi, \sup_{i_{jt}}[\pi(\omega_{jt}, k_{jt}, z_{mt}) - c_i(i_{jt}, k_{jt}) - c_l(l_{jt}) + \\ & \qquad \beta E[V(\omega_{jt+1}, k_{jt+1}, z_{mt+1})|\omega_{jt}, i_{jt}]\} \end{aligned} \tag{1}$$

where $\pi(\omega_{jt}, k_{jt}, z_{mt})$ is the profit function, increasing in both ω_{jt} and k_{jt}; $c_i(i_{jt}, k_{jt})$ is investment cost in new capital, where $c_i(\cdot)$ is increasing in investment choice i_{jt} and decreasing in capital stock k_{jt}; and $c_l(l_{jt})$ is the cost of labor, where $c_l(\cdot)$ is increasing in labor l_{jt}. Incumbent stores are assumed to know their scrap value ϕ prior to making exit and investment decisions. The solution of the store's optimization problem (1) gives optimal policy functions for labor $l_{jt} = \tilde{l}_{jt}(\omega_{jt}, k_{jt}, z_{mt})$, investment $i_{jt} = \tilde{i}_{jt}(\omega_{jt}, k_{jt}, z_{mt})$, and exit decision $\chi_{jt+1} = \tilde{\chi}_{jt}(\omega_{jt}, k_{jt}, z_{mt})$. The exit rule χ_{jt+1} depends on the threshold productivity $\underline{\omega}_{mt}(k_{jt}, z_{mt})$, where z_{mt} is a vector of local market characteristics such as the number of large entrants e^L_{mt},

[21] The decision to exit or continue is made at the store level, though firms that operate several stores can influence the decision of each store through possible chain effects. However, the firm takes the decision based on store performance.

and population density p_{mt}^{dens}.

■ **Value added generating function.** We assume Cobb-Douglas technology where stores sell a homogeneous product, and that the factors underlying profitability differences among stores are neutral efficiency differences.[22] We follow the common notation of capital letters for levels and small letters for logs. The production function can be specified as

$$q_{jt} = \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + \omega_{jt} + u_{jt}^p \tag{2}$$

where q_{jt} is the log of quantity sold by store j at time t; l_{jt} is the log of labor input; and k_{jt} is the log of capital input. The unobserved ω_{jt} is productivity, and u_{jt}^p is either a measurement error (which can be serially correlated) or a shock to productivity that is not predictable during the period in which labor can be adjusted. Since physical output is complex to measure in retail markets and therefore not observed, we use deflated value added as a proxy for output.

■ **Imperfect competition.** Equation (2) assumes that prices are constant across stores.[23] Foster et al. (2008) analyze the relation between physical output, revenues, and firm-level prices in the context of market selection. They find that productivity based upon physical quantities is negatively correlated with establishment-level prices, but productivity based upon revenues is positively correlated with those prices. The retail food market is characterized by imperfect competition, and product differentiation is a key factor. When a store has some market power, its price influences its productivity. If a store cuts its price, then more inputs are needed to satisfy increasing demand. This negative correlation between inputs and prices leads to underestimation of the labor and capital parameters in the production function (Klette and Griliches 1996, Melitz 2000, De Loecker 2009).[24] Following this literature, we consider a standard horizontal product differentiation demand system

$$p_{jt} = p_{mt} + \frac{1}{\eta} q_{jt} - \frac{1}{\eta} q_{mt} - \frac{1}{\eta} \lambda_{jt} - \frac{1}{\eta} u_{jt}^d \tag{3}$$

[22] We can easily apply another specification; for example, translog with neutral efficiency across stores would do equally well.

[23] Under perfect competition, productivity of the price-taking stores is not influenced by store level prices.

[24] If the products are perfect substitutes, then deflated sales are a perfect proxy for unobserved quality adjusted output.

where p_{jt} is output price, p_{mt} and q_{mt} are output price and quantity in local market m, λ_{jt} is demand shifters (observed and unobserved), and u^d_{jt} is a simple i.i.d. shock to demand. The parameter η (< -1 and finite) captures the elasticity of substitution among stores.[25] Due to data constraints the demand system is quite restrictive, implying a single elasticity of substitution for all stores, so that there are no differences in cross price elasticities, i.e., we have a constant markup over marginal cost ($\frac{\eta}{1+\eta}$), and the Learner index is ($\frac{1}{|\eta|}$). We can however allow the elasticity of substitution to differ across local market groups such as counties (21 in total). The Learner index for county g is then $\frac{1}{|\eta_g|}$.

We decompose demand shifters λ_{jt} into observed local market characteristics z_{mt}, i.e., number of large entrants e^L_{mt}, population density p^{dens}_{mt}, and unobserved demand shocks υ_{jt} as

$$\lambda_{jt} = z^{'}_{mt}\beta_z + \upsilon_{jt}$$

where υ_{jt} are either correlated unexpected shocks to demand or i.i.d. The unobserved demand shocks υ_{jt} are unobserved by the econometrician but known to or predictable by the stores when they make their input, price or exit decisions.

Since we have unobserved store prices and quantities, we use the deflated value added y_{jt}, defined as $q_{jt}+p_{jt}-p_{mt}$, as output in the estimation of the sales (value added) generating function. However, if p_{mt} is unobserved, the consumer price index for food products p_{It} can be used as a proxy. Controlling for unobserved store price p_{jt} in the value added generating function in (2), we then have

$$\begin{aligned} y_{jt} \equiv \; & \left(1+\frac{1}{\eta}\right)[\beta_0 + \beta_l l_{jt} + \beta_k k_{jt}] - \frac{1}{\eta}q_{mt} - \frac{1}{\eta}z^{'}_{mt}\beta_z + \left(1+\frac{1}{\eta}\right)\omega_{jt} - \frac{1}{\eta}\upsilon_{jt} - \\ & \frac{1}{\eta}u^d_{jt} + \left(1+\frac{1}{\eta}\right)u^p_{jt} \end{aligned} \tag{4}$$

Assuming that store productivity follows an exogenous first order Markov process, actual productivity can be written as the sum of expected productivity given the store information set $\mathfrak{F}_{t-1}$, $E[\omega_{jt}|\mathfrak{F}_{t-1}]$, and the i.i.d. productivity shock ξ_{jt}

$$\omega_{jt} = E[\omega_{jt}|\mathfrak{F}_{t-1}] + \xi_{jt}. \tag{5}$$

The conditional expectation function $E[\omega_{jt}|\mathfrak{F}_{t-1}]$ is unobserved by the econometrician (though known to the store). The shock ξ_{jt} may be thought of as the

[25]The vertical dimension is to some extent also captured since deflated output measures both quantity and quality, which is correlated with store type (size).

realization of uncertainties that are naturally linked to productivity. Therefore, the value added generating function becomes

$$\begin{aligned} y_{jt} = & \left(1+\frac{1}{\eta}\right)[\beta_0+\beta_l l_{jt}+\beta_k k_{jt}] - \frac{1}{\eta}q_{mt} - \frac{1}{\eta}z'_{mt}\beta_z + \left(1+\frac{1}{\eta}\right)E[\omega_{jt-1}|\mathcal{F}_{t-1}]+ \\ & \left(1+\frac{1}{\eta}\right)\xi_{jt} - \frac{1}{\eta}\upsilon_{jt} - \frac{1}{\eta}u^d_{jt} + \left(1+\frac{1}{\eta}\right)u^p_{jt} \end{aligned} \tag{6}$$

We face a trade-off between a flexible approximation of the ω_{jt} process and separation of demand shocks from productivity.[26] The estimation strategy chosen depends on whether demand shocks υ_{jt} are thought to be correlated over time and on whether we use a linear or nonlinear approximation of the conditional expectation $E[\cdot]$ (Ackerberg et al. 2007). We first present Case (1) when υ_{jt} is correlated over time, which includes ω_{jt} and υ_{jt} following either a general Markov process or an AR(1). The Markov processes can be either dependent or independent. Under AR(1), ω_{jt} and υ_{jt} can follow either the same or different processes and no further assumptions are needed to estimate the parameters. Then we present Case (2) when υ_{jt} is i.i.d.

Case (1): *υ_{jt} are correlated over time*

First, if ω_{jt} and υ_{jt} follow dependent Markov processes then υ_{jt-1} will enter as a separate variable in the conditional expectation $E[\omega_{jt}|\omega_{jt-1}, \upsilon_{jt-1}]$. To solve the identification problem in (6) we need an estimate of υ_{jt-1}. The Berry et al. (1995) (BLP) literature produces estimates of a set of "unobserved product characteristics" that might be used as υ_{jt} (Ackerberg et al. 2007 discuss this in detail), which we might interpret as unobserved store quality. But in our case, it is impossible to back out υ_{jt} using this method because it requires more firm specific data such as prices and advertisement.

Second, if ω_{jt} and υ_{jt} follow independent Markov processes then expected productivity at time t conditional on information set $\mathcal{F}_{t-1}$ does not depend on υ_{jt-1}. But in this case υ_{jt} is an important determinant of optimal labor or investment, and thus affects actual productivity. Since we have two unobservables (ω_{jt} and υ_{jt}) and no other control variable for υ_{jt}, identification in (6) requires one of the following assumptions:

[26] The alternative of not controlling for prices at all requires even stronger assumptions.

(a) $\tilde{\omega}_{jt} \equiv (1+\frac{1}{\eta})(\omega_{jt} - \frac{1}{\eta}\upsilon_{jt})$, i.e., quality adjusted productivity, follows a first order nonlinear Markov process: $\tilde{\omega}_{jt} = E[\tilde{\omega}_{jt}|\mathcal{F}_{t-1}] + \xi_{jt} = \tilde{h}(\tilde{\omega}_{jt-1}) + \xi_{jt}$, where $\tilde{h}$ is an approximation of the conditional expectation (Melitz 2000, Levinsohn and Melitz 2002). In other words, a positive shock in either productivity or demand makes the store sell more but the exact source of the shock does not matter.

(b) ω_{jt} and υ_{jt} follow different AR(1) processes.[27] We assume that $\omega_{jt} = \rho_1\omega_{jt-1} + \xi_{jt}$ and $\upsilon_{jt} = \rho_2\upsilon_{jt-1} + \mu_{jt}$. One way to eliminate the unobserved demand shock from the value added generating function (6) is to take the first difference $\tilde{y}_{jt} = y_{jt} - \rho_1 y_{jt-1}$. If $\rho_1 = \rho_2$, this is sufficient for identification. If $\rho_1 \neq \rho_2$, the unobserved demand shock υ_{jt} is completely removed if we apply the difference $\tilde{y}_{jt} - \rho_2\tilde{y}_{jt-1}$ in (6). Note that $\tilde{y}_{jt} - \rho_2\tilde{y}_{jt-1}$ is stationary if $\rho_1 > \rho_2$, i.e., if productivity is more persistent than the demand shock (the roots of $\tilde{y}_{jt} - \rho_2\tilde{y}_{jt-1}$ are $\rho_2 - \rho_1$ and $-\rho_2$).

The advantage of (a) is that it allows for nonlinearities in the productivity process and the possibility of controlling for selection (see Case (2)). The drawbacks of (a) are that we observe quality-adjusted productivity and that we need more assumptions to back out productivity. The advantage of (b) is that we can sort out persistent demand shocks from productivity and that no more assumptions are needed for identification. A drawback of allowing for two AR(1) processes in (b) is that it is more data demanding, because we need two lags and thus dropping two years of data, to make sure that we have removed the persistent unobserved demand shocks. Since a store needs to be present in the data for at least three years, this severely restricts the dynamics.

Case (2) υ_{jt} *are i.i.d.*

In this case, demand shocks are not correlated with inputs or with exit decisions. Therefore υ_{jt} collapses into the i.i.d. demand shocks from the price equation u^d_{jt}. Below we describe the estimation strategy when productivity follows a general Markov process.

■ **Inverse labor demand function.** A central feature of retail data is lumpy

[27] See the dynamic panel model of Blundell and Bond (2000).

investment and a weak measure of intermediate inputs. We recover productivity from the optimal choice of labor using a good measure of store specific wages (Doraszelski and Jaumandreu 2009).[28] The idea relies on Levinsohn and Petrin (2003) who recover unobserved productivity from the demand for static intermediate input of materials. We assume that labor is a static and variable input chosen based on current productivity. The functional form of the value added generating function provides a parametric form of the labor demand function, unlike Levinsohn and Petrin (2003) and Ackerberg et al. (2006) that are non-parametric in materials. The advantage is that we can include many stores with zero investment while not making any assumptions about the stores' dynamic programming problem. In abstract of store level wages it may however be hard to estimate the coefficients of static inputs in the Cobb-Douglas case (Bond and Söderbom 2005).

Our assumption that labor is a static and variable input abstracts from costs of training, hiring and firing employees, though for several reasons this is less restrictive in retail than in many other industries. Part time workers are common. As much as 40% of the employees in retail food work part time, compared to 20% for the Swedish economy as a whole (Statistics Sweden). The share of skilled labor is low. Only 15% of the retail employees had a university education in 2002, compared to 32% for the total Swedish labor force (Statistics Sweden). Stores have long opening hours and adjust their labor due to variations in customer flows over the day, week, month and year. Moreover, the training process might be shorter than in many other industries. We use the number of full-time adjusted employees as our measure of labor.

Our assumption that each store chooses labor based on its productivity implies that labor l_{jt} is correlated with the random productivity shock ξ_{jt}. In year t, stores chose current labor l_{jt} based on current productivity ω_{jt}, which gives labor demand as

$$l_{jt} = \frac{1}{1-\beta_l}[\beta_0 + ln(\beta_l) + \alpha + \beta_k k_j + \omega_{jt} - (s_{jt} - p_{jt})] \tag{7}$$

[28] The average wage contains both price of labor and its composition, e.g., ages, gender, and skill groups. Our measure of wage is a good reflection of exogenous changes in the price of labor because the 22% growth in total retail wages during the period (Table 1) is in line with the 24% growth in aggregate real wages in Sweden (Statistics Sweden).

where $\alpha = lnE[e^{\xi_{jt}}]$ and s_{jt} is the log of wage rate paid by store j in period t. Under the functional form assumption on the value added generating function, we have a known functional form for the labor demand and inverse labor demand functions. Solving for ω_{jt} in Equation (7) yields the inverse labor demand function from which we can recover unobserved productivity

$$\begin{aligned}\omega_{jt} = \; & \tfrac{\eta}{1+\eta}\Big[\delta_1 + [(1-\beta_l) - \tfrac{1}{\eta}\beta_l]l_{jt} + s_{jt} - p_{It} - \left(1+\tfrac{1}{\eta}\right)\beta_k k_{jt} \\ & +\tfrac{1}{\eta}q_{mt} + \tfrac{1}{\eta}z'_{mt}\beta_z\Big]\end{aligned} \tag{8}$$

where $\delta_1 = -ln(\beta_l) - ln(1+\frac{1}{\eta}) - \beta_0(1+\frac{1}{\eta}) - \ln E[e^{u^p_{jt}}] + \frac{1}{\eta}\ln E[e^{u^d_{jt}}] + \frac{1}{\eta}\ln E[e^{\upsilon_{jt}}]$. We then substitute the inverse demand function (8) in the value added generating function (6).[29]

It is important to stress again that we can estimate the value added generating function coefficients (6) because we have assumed that labor is a static variable. Comparing with non-parametric approaches, our estimator is more transparent in how real wages and unobserved demand shocks affect labor demand. Ackerberg et al. (2006) (ACF) is an alternative estimator for which we show results in the empirical part. We use OLS and ACF estimators as benchmarks, i.e., without controlling for unobserved prices and local market characteristics. In ACF, labor has dynamic implications and labor demand is assumed to be a non-parametric function. It possible to control for unobserved prices and local market conditions a similar way in ACF. Dorazelski and Jamandreu (2009) discuss the relative merits of the parametric and non-parametric approaches.

■ **Selection.** Selection can be essential in retail markets because large stores are more likely to survive larger shocks to productivity than are small stores. Stores' decisions to exit in period t depend directly on ω_{jt}, and therefore the decision is correlated with the productivity shock ξ_{jt}. The threshold productivity takes local market characteristics such as large entrants and population density into account (Appendix B gives a detailed description of selection). To estimate β_l and β_k while controlling for selection, we use predicted survival probabilities $\mathscr{P}_{t-1}$. Substituting

[29] The condition for identification is that the variables in the parametric part of the model are not perfectly predictable (in the least square sense) by the variables in the non-parametric part (Robinson 1988). Including additional variables that affect productivity guarantees identification, i.e., there cannot be a functional relationship between the variables in the parametric and non-parametric parts (Newey et al. 1999). For example, z_{mt} cannot be perfectly predicted from ω_{jt}.

the survival probabilities and the inverse labor demand function (8) into (6) yields the final value added generating function that we estimate:

$$\begin{aligned} y_{jt} = \; & \left(1+\tfrac{1}{\eta}\right)[\beta_0+\beta_l l_{jt}+\beta_k k_{jt}] - \tfrac{1}{\eta}q_{mt} - \tfrac{1}{\eta}z'_{mt}\beta_z + \left(1+\tfrac{1}{\eta}\right)h(\mathscr{P}_{t-1},\omega_{jt-1}) + \\ & \left(1+\tfrac{1}{\eta}\right)\xi_{jt} - \tfrac{1}{\eta}\upsilon_{jt} - \tfrac{1}{\eta}u^d_{jt} + \left(1+\tfrac{1}{\eta}\right)u^p_{jt}. \end{aligned} \tag{9}$$

■ **Estimation strategy.** The estimation of our extended Olley and Pakes model adjusted for retailers (EOP) consists of two parts. First, we use a probit model with a third order polynomial to estimate survival probabilities, which are then substituted into (9). Then, we estimate (9) using the sieve minimum distance procedure proposed by Ai and Chen (2003) and Newey and Powell (2003) for i.i.d. data (see Ackerberg et al. (2009) for a discussion of semiparametric inference to IO models). The goal is to obtain an estimable expression for the unknown parameters $\boldsymbol{\beta}$ and h_H, where H indicates all parameters in $h(\cdot)$. We approximate $h(\cdot)$ by a third order polynomial expansion in ω_{jt-1}, given by (8).[30] We use a tensor product polynomial series of labor (l_{jt-1}), capital (k_{jt-1}), total wages (s_{jt-1}), the consumer price index for food products (p_{It}), and local market conditions (z_{mt-1}) including large entrants (e^L_{mt-1}) and population density (p^{dens}_{mt-1}), plus local political preferences (pol_{mt}) as instruments. This set of instruments is also used to estimate the optimal weighting matrix. Using GMM, the parameters ($\boldsymbol{\beta}, h_H$) are then jointly estimated. Since there are non-linearities in the coefficients, we use the Nelder-Mead numerical optimization method to minimize the GMM objective function[31]

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

where A is the weighting matrix defined as $A = \left[\frac{1}{N}W'\psi\psi'W\right]^{-1}$, W is the matrix of instruments, and $\psi_{jt}(\cdot;\boldsymbol{\beta},h_H) = \left[\left(1+\frac{1}{\eta}\right)\xi_{jt} - \frac{1}{\eta}\upsilon_{jt} - \frac{1}{\eta}u^d_{jt} + \left(1+\frac{1}{\eta}\right)u^p_{jt}\right]$. Estimation is done at the industry level, controlling for local conditions. Estimation results at county level (21 municipality groups) are available from authors. An

[30] As a robustness check, we also expand $h(\cdot)$ using a fourth order polynomial, and the results are similar.

[31] This simplex method converges quickly and is more robust to the starting values than quasi-Newton methods such as BFGS. Our EOP estimation procedure is written in R (www.r-project.org). The procedure is more computationally demanding when controlling for selection. However, estimation at the county level reduces computing time substantially.

advantage of estimating at county level is that we obtain the mark-ups at the county level.[32] The major disadvantage is that we loose efficiency in estimation in the small counties. Another advantage of using counties is that they are responsible for inter-municipality implementation of entry regulation. However, we control for municipality characteristics in the estimation. Appendix B presents a detailed description of the estimation procedure.

■ **Results: store TFP.** We estimated coefficients of the value added generating function using OLS, the ACF two-stage estimator, and five specifications of our model. These five are: DP1 - productivity and persistent demand shocks follow the same AR(1) process, i.e., an updated version of the Blundell and Bond (2000) estimator; DP2 - productivity and persistent demand shocks follow different AR(1) processes; EOPs - productivity follows a nonlinear Markov process, and we control for selection, but not for prices or local market characteristics; EOPm - productivity follows a nonlinear Markov process, and we control for prices and local market characteristics but not for selection; and EOPms - productivity follows a nonlinear Markov process and we control for prices, selection and local market characteristics.[33] We include number of large entrants and population density, as local market covariates in the demand equation. We control for endogeneity of large entrants by using political preferences in local markets as instruments.[34]

[32] Another reason for estimating at county level is that our method requires more observations than is available at municipality level.

[33] To make our DP1 and DP2 estimators comparable with ACF and the dynamic panel estimator (Blundell and Bond 2000), we assume that productivity ω_{jt} is an AR(1) process, i.e., $\omega_{jt} = \rho_1 \omega_{jt-1} + \xi_{jt}$. We use k_{jt} and l_{jt-1} as instruments, i.e., they are assumed to be uncorrelated with the shocks ξ_{jt} and υ_{jt}. However, we need an additional moment in DP to identify ρ_1 and therefore assume that the shock ξ_{jt} is uncorrelated with $(\omega_{jt-1} + u^d_{jt-1})$. In ACF, we use k_{jt} and l_{jt-1} as second stage instruments, i.e., labor is chosen with full knowledge of ω_{t-1}. Ackerberg et al. (2006) provide a detailed comparison between OP-type estimators and dynamic panel estimators.

[34] As noted earlier, we base on the political preferences in each municipality because no major policy reforms took place in Sweden during the study period, and we do not have access to the number of applications and rejections in the planning process. The Social Democrats are the largest party nationally with 40.6% of seats on average, collaborating with the Left Party (8%) and the Green Party (4.2%). The non-socialist group consists of the Moderate Party (18%), most often together with the Center Party (13.2%), Christian Democrats (5.9%), and the Liberals (5.6%). 22% of the municipalities had a non-socialist majority during 1996-1998, increasing to 32% during 1999-2002. The non-socialists had 8.6%-85%, averaging 40.7% (1996-1998) and 44.1% (1999-2002). The correlation between the non-socialist share of seats and the number of large entrants is 0.005, or 0.086 if we exclude the Center Party, which is typically strong in the countryside where there is less likely to be large entrants. As we expect, we observe more large entrants in municipalities with non-socialist local government. We use a dummy for non-socialist majority in the estimations.

EOPs, EOPm, and EOPms require estimation of one non-parametric function, in contrast to ACF, which requires two. A major advantage of DP1, DP2, EOPm and EOPms is that they control for unobserved prices which otherwise might create a downward bias in the scale estimator (Klette and Griliches 1996). Another advantage is that the correction for omitted prices also yields an estimate of market output, which makes it possible to compute the elasticity of substitution η and an average industry mark-up.

Table 3 has two columns for each of the DP and EOP specifications. Column (1) shows the coefficients including elasticities, and Column (2) the larger true estimated coefficients, without elasticity. Since all specifications use deflated value added, we use Column (1) to compare OLS and ACF with DP and EOP.

The elasticity of scale estimate in the DP and EOP regressions is greater than in OLS (1.115) and ACF (0.931), it varies between 1.140 (EOPs) and 1.426 (DP2). The minimum point estimate of labor is 0.686 (DP2) and the maximum is 0.948 (OLS). The minimum point estimate of capital is 0.116 (EOPm) and the maximum is 0.426 (DP2). Controlling for local market characteristics is important: Including the number of large entrants and population density in the price equation change the demand elasticity and capital estimates substantially, making both smaller. When we allow productivity to follow an AR(1) process (DP1, DP2), estimates of capital are over 3 times larger than in EOP. The estimated productivity transition (ρ_1) is about 0.4 in both DP1 and DP2, i.e., a rather low persistency in over time. Furthermore, the estimated demand elasticity in DP1 (-5.674) seems unreasonably high in absolute value for retail food (Hall 1988). To test the assumption of linearity in productivity, we regress current productivity, recovered from DP1 and DP2, on a third order polynomial extension of previous productivity. The coefficients of ω_{jt-1}^2 and ω_{jt-1}^3 are statistically different from zero, indicating that productivity does not follow an AR(1) process. This might be one of the reasons for the large values of capital (over 0.4) in the DP specifications. We therefore recognize that it is important to allow for a nonlinear Markov process in productivity.

In ACF, EOPs, EOPm, and EOPms productivity follows a nonlinear Markov process. As noted, comparing with DP, the capital coefficients are smaller and the labor coefficients larger. As theory suggests the coefficients on both capital and labor decrease when controlling for prices in EOPm and EOPms, comparing with

OLS.[35]

EOPs and EOPms (as well as ACF) control for selection. Theory and empirical investigations then predict a lower labor and higher capital coefficients (Ackerberg et al. 2007).[36] The capital coefficient in EOPms (0.145) is in fact larger than in EOPm (0.116), but smaller than in ACF (0.163). Controlling for selection in EOPms yields a smaller labor coefficient 0.840 than in EOPs (0.945). Those results are in line with the OP literature.

The coefficients on large entrants and population density are negative and statistically significant in all specifications. The lowest demand elasticity (-2.96) is in EOPms, i.e., when we allow productivity to follow a nonlinear process and control for selection. Thus, the implicit assumption $\eta = -\infty$, often used in empirical studies, does not hold. In EOPms the the mark-up, defined as price over marginal cost, is 1.509. Our mark-up is consistent with previous findings based on retail data (see, e.g., Hall 1988).

We test the validity of our assumption that labor is static. If the inverse labor demand function is misspecified, the labor coefficient in the value added generating function differs from the one in the inverse labor demand function. We estimate the restricted and unrestricted models. Then we compute the GMM distance statistic, $D_N = N * [Q_N(\beta_{\text{restricted}}) - Q_N(\beta_{\text{unrestricted}})]$, to test the null of equal labor coefficients. Note that we could estimate only the unrestricted model and test the equality of the labor coefficients directly by Wald test. The two statistics are however asymptotically equivalent under the null hypothesis (Newey and West 1987). The results indicate that the null of equal coefficients is accepted for EOPms, i.e., our assumption of static labor is valid. For EOPm and EOPs, the unrestricted models are rejected by the Sargan test of overidentified restrictions. Although the labor coefficients are weakly identified, their values are very similar (we need additional moments for labor).

Summarizing, it seems important to allow for nonlinearities in the productivity process and to control for prices, local market characteristics and selection when

[35] If we do not control for unobserved demand shocks, we expect the coefficients of labor and capital to be upper biased. The reason is the positive correlation between inputs and demand shocks. In case that demand shocks are still present the coefficients would thus decrease even more. Nevertheless, our results when controlling for prices show that both coefficients decrease.

[36] Since stores with large capital stock can survive even if they have low productivity, we expect selection to induce a negative correlation between capital and the disturbance term in the selected sample.

estimating productivity in retail markets. It is thus central to deal with omitted price bias, unobserved demand characteristics and selection.

4 Large entrants and productivity

Next we proceed to investigate whether large entrants influence exit and productivity growth of surviving stores. Our goal is to evaluate whether large entrants have a greater impact on one part of the productivity distribution than another. To do this, we use TFP estimated by EOPms that allows for a general Markov process in productivity and selection, and DP2 that guarantees to clear out persistent demand shocks from productivity. Based on theories using dynamic models with heterogenous firms, our hypothesis for how increased competition from large entrants influences reallocation of resources is: Exit of low productive stores and higher productivity growth among surviving stores (Hopenhayn 1992, Melitz 2003, Syverson 2004, Asplund and Nocke 2006). We consider the role of large entrants for productivity levels, transitions in the productivity distribution in local markets, exit and productivity growth.[37] Finally, we decompose aggregate productivity growth of all entrants, exits and incumbents (due to data constraints we cannot measure the contribution of large entrants to aggregate productivity growth).

■ **Productivity levels.** Figure 1 shows kernel density estimates of TFP (estimated by EOPms) in markets the year of, and the year after, large entry. Though the differences are small, both the upper- and lower tails of the distribution are greater after large entry. However, productivity is to some extent lower in the middle of the distribution following large entry. Mean TFP of incumbents is higher the year after entry (-0.016) than the year of entry (-0.291) and the standard deviation is smaller (Table 4, panel A). Using t-test, the null of equal means is rejected at the 1% significance level. Using F-test, the null of equal standard deviations cannot be rejected.[38]

■ **Transitions in the productivity distribution.** To explore changes in pro-

[37]We primarily focus on changes after large entry because several permanent reasons might explain differences between markets with and without large entrants.

[38]Defining entry markets as municipalities with at least one large entrant, mean TFP is smaller in markets with entrants (-0.016) than in markets without (0.100) and the standard deviation is larger (Table 4, panel B). The null of equal means and equal standard deviations are both rejected and significant at the 1% level.

ductivity distributions in local markets we classify incumbents into six percentile bins (p10, p10-25, p25-50, p50-75, p75-90, p90) each year, based on their productivity. Then we follow movements between percentile bins or exit over time.

In markets with large entrants, more incumbents stay in the same percentile from one year to another, i.e., the diagonal shares are larger (Table 5). Large entrants thus make the percentile movements more persistent. The shares that stay in the same percentile are 33-49% in entry markets, but 32-42% in non-entry markets. The most pronounced difference occurs in the upper tail. That is, high productive incumbents stay high productive in entry markets. Almost 50% stay in p90, comparing with only 35% in markets without large entry. In the bottom part of the distribution, incumbents in entry markets either stay in their productivity percentile or exit. In contrast, bottom part incumbents in markets without large entry decrease their productivity without being forced to exit. The total share of stores that exit is higher in entry markets (17.3%) than non-entry markets (15.5%). Regardless of large entry, more stores increase their productivity in the bottom part of the distribution, while more stores decrease their productivity in the top, except p90. Finally, entry markets have less movements between extreme percentiles. For example, only about 4% move from p10 to an above median percentile in markets with large entry and over 6% in markets without. We discuss productivity growth in detail in Section 4.2, but first we analyze exit.

4.1 Exit

Over 50% of the exits come from the two lowest percentiles (p10, p10-25) in markets with large entrants, but less than 42% in markets without large entrants (Table 5, panel A). Large entrants thus result in more exit among low productive stores. In markets without large entrants, more stores have lower productivity and yet continue to operate. While exit mainly occurs from the bottom part of the distribution, entrants are found across the whole distribution (not reported) as in previous findings in retail markets (Foster et al. 2006).

According to our model, the survival probabilities imply that the decision to exit depends on productivity, capital stock and local market characteristics, i.e., large entrants and population density (see Section 3). Stores decide whether to exit or continue in the beginning of each period based on information regarding market conditions and we thus use large entrants in the previous year. Based on the stopping rule we show probit regressions of exit

$$\begin{aligned} Pr(exit_{jt} = 1|\omega_{jt}, e^L_{mt-1}, k_{jt}, p^{dens}_{mt-1}) = \quad & \phi(\gamma_0 + \gamma_e e^L_{mt-1} + D_{jt-1} * e^L_{mt-1}\Gamma + \\ & \gamma_k k_{jt} + \gamma_p p^{dens}_{mt-1} + \alpha_t) \end{aligned} \tag{11}$$

where $exit_{jt}$ is equal to one if a store exit and otherwise zero; k_{jt} is log of capital; e^L_{mt-1} is the number of large entrants; $D_{jt-1} * e^L_{mt-1}$ are interaction terms between productivity percentile dummies and the number of large entrants; p^{dens}_{mt-1} is log of population density; ϕ is the cumulative distribution function of the standard normal; and α_t is a vector of year dummies; p^{dens}_{mt-1} and e^L_{mt-1} constitute z_{mt-1} in our model in Section 3.

Table 6 shows regression results for the probability of exit. The first specification (columns 1 and 3) relies on the pure stopping rule and includes productivity, capital, large entrants and population density. In line with both theory and previous empirical studies (Olley and Pakes 1996, Pavcnik 2002), exit is less likely if productivity and capital stock are high for both the nonlinear (column 1) and linear (column 3) productivity process. That is, stores with lower productivity and capital stock are more likely to exit. Moreover, exit is more common from markets if population density is high whereas the coefficient on large entrants is positive but not significant at conventional significance levels.

The expanded specification (columns 2 and 4) includes interaction terms of large entrants with the six productivity dummies, using the middle group (p50-75) as reference. In the nonlinear estimation (column 2), the coefficient on large entrants is now negative and statistically significant at the 10 percent level. The coefficients on the interaction terms are all positive and jointly significant with the coefficient of large entry for p10 and p25-50. Exit is 0.29 percentage points more likely after large entry for stores is in the bottom part of the productivity distribution (p10 or p25-50) than for those in the middle. For the linear productivity process (column 4), the interaction terms are not significant, most likely because of lack of data (a store needs to be at least three years in the data).

To summarize, we find evidence that exit occurs from the bottom part of the productivity distribution after large entry which truncates the distribution from below in line with our hypothesis (Hopenhayn 1992, Olley and Pakes 1996, Melitz 2003, Syverson 2004, Asplund and Nocke 2006).

4.2 Productivity growth of incumbents

Productivity growth is given by the difference between log of productivity in time t and productivity in *t-1*: $\omega_{jt} - \omega_{jt-1}$. We only consider productivity growth of incumbents, and thus exclude stores that enter or exit. Figure 2 shows that incumbents' TFP growth (estimated by EOPms) is higher in markets with large entrants than in market without. While the largest difference occurs in the bottom part of the distribution, the top parts are similar. Mean productivity growth of incumbents is larger in markets with large entrants (15.9%) than in markets without (13.8%) and the standard deviation is smaller (Table 7, panel B). The t-test cannot reject the null of equal mean values but the F-test can reject the null of equal standard deviations at the 5% significance level.

In markets with large entrants, Figure 3 shows a striking improvement in incumbents' productivity growth between the year of, and the year after, entry: TFP growth is higher in all parts of the distribution after entry. Mean productivity growth of incumbents is -11% the year of large entry, whereas it is 15.9% the year after (Table 7, panel A). The t-test of equal mean values is rejected at the 1% significance level. The standard deviation is larger after entry, 0.56 compared to 0.53. Using F-test, the null of equal standard deviations is rejected at the 5% significance level.

Although Figure 2 and 3 indicate that large entrants might have an impact on the distribution of incumbents' productivity growth, we need to isolate the role of large entrants from store and market characteristics. Therefore, we regress the number of large entrants on incumbents' productivity growth the year after large entry,

$$\theta_{jt} = \alpha_0 + \alpha_e e^L_{mt-1} + D_{jt-1} * e^L_{mt-1} \boldsymbol{\alpha} + \alpha_p p^{dens}_{mt-1} + \alpha_m + \alpha_t + \varepsilon_{jt} \qquad (12)$$

where $\theta_{jt} = \omega_{jt} - \omega_{jt-1}$ is incumbents' productivity growth between periods *t-1* and t; e^L_{mt-1} is the number of large entrants; $D_{jt-1} * e^L_{mt-1}$ are six interaction terms between percentile productivity dummies and large entrants; p^{dens}_{mt-1} is population density; α_t and α_m are vectors of time and market dummies; and ε_{jt} is an i.i.d. error term.

To isolate the impact of large entrants, we control for unobserved local market heterogeneity by using fixed effects for local markets and years. To control for endogeneity because large entry depends on the productivity of incumbents, we use different specifications of the one-step GMM estimator. Table 8 shows the regression results. GMM specification (1) uses lagged political preferences, lagged population density, and lagged income as instruments for large entrants; GMM specification (2) uses lagged large entrants (e^L_{mt-2}) plus lagged population density and lagged income as instruments. It is important to note that adding income as demand shifter does not change our results. Since we get consistent results with all estimators, we primarily discuss the results of GMM (1) with TFP estimated by EOPms.

The coefficient on large entrants is positive and significant at the 1% level when we estimate with large entrants and productivity dummies but no interaction terms (Table 8). On average, large entrants thus increase productivity growth among incumbents. More importantly, large entrants have a greater impact on some parts on the incumbents' productivity distribution than others. The coefficient on large entry is then negative, whereas those on the interaction terms are all positive, and all significant at the 1% level. The coefficients of large entrants and the interaction terms are jointly significant. As a result of large entry, low productive incumbents increase their productivity growth, by 14% for those in p10 instead of in the middle group (p50-75), by 5% (for p10-25) and by 4% (for p25-50). On the other hand, large entry reduces productivity growth of incumbents in the upper distribution percentiles by -3% (for p75-90) and -7% (for p90), relative to the middle group. The growth increase is thus largest for surviving stores with low productivity, and then declines with survivors' productivity.

In a previous version of the paper we investigate how large entrants affect the distribution of local market productivity, without controlling for large entry and unobserved demand shocks when estimated productivity. We found that productivity dispersion increases as a result of large entrants; the most productive incumbents become more productive, and the least productive become less productive (results are available from the authors). One explanation why the least productive stores become less productive is that a demand shock hit them after large entry, but they still find demand to survive. Controlling for unobserved demand shocks when estimate productivity we find that the least productive become more productive. These results indicate importance of unobserved demand shocks when estimating productivity.

The results for the linear TFP process (DP2) are consistent with the ones we find for the nonlinear process (EOPms). The marginal effects of large entrants on productivity growth is larger for DP2 than for EOPms. One likely explanation is that DP2 only captures strong incumbents due to that stores need to be at least three years in the data. Our findings are in line with our hypothesis that competition increases productivity growth of incumbents.

The coefficient on population density is positive and significant at the 1% level for EOPms using GMM (1), but negative for DP2.

■ **Decomposition of aggregate productivity growth.** Because of data constraints we can not decompose the contribution of large entrants to aggregate TFP growth but only the contribution of all entrants, exits, and incumbents. We use three recent decompositions, the one by Foster et al. (2001) (FHK), Griliches and Regev (1995) (GR), and Melitz and Polanec (2009) (MP) which is a dynamic version of the static decomposition by Olley and Pakes (1996). All decompositions are discussed in detail in Appendix C.

Aggregate TFP growth was 8% from 1997 to 2001 (Tables 9 and 10). While overall industry growth is the same in all decompositions, the relative contribution of incumbents, entrants and exits differ. In both FHK and GR, incumbents that continue for the whole period contribute about 6%. Net entry stand for 1.85% in GR and 1.47% in FHK. Incumbents that increase both productivity and market shares stand for 0.75% of growth in FHK.

In MP, entrants and exits only have a positive contribution when their aggregate productivity is larger than that of continuing stores in the same period. As we expect, incumbents' contribution is larger in MP (9.53%) than in GR and FHK. Incumbents are more productive than both entrants (-3.67%) and exits (2.14%). Among incumbents, those that obtain productivity improvements are central (11.2%), whereas reallocation of market shares among them are not (-1.71%). The direct effect of exits is the largest component (11.7%) showing that exits with lower productivity than incumbents play a key role for growth. The indirect effects show that the covariance between market shares and productivity is greater for entrants and exits than for incumbents. The decomposition results confirm our findings based on large entrants, i.e., incumbents that increase their productivity, and low productive stores that exit foster productivity growth in retail.

5 Conclusions

The present study gives new insights into competition and productivity differences among retail stores. Net entry is found to foster almost all labor productivity growth in the U.S. retail sector (Foster et al. 2006). Multi-factor productivity in retail markets has however rarely been studied, contrary to manufacturing. We provide a first attempt to use recent advances in structural estimation of production functions to estimate total factor productivity in retail markets. Based on recent extensions of the Olley and Pakes' (1996) framework, we provide a model that takes key features of retail markets into account. In particular, we investigate one of the most crucial trends in retail markets: entry by large ("big-box") stores. On both sides of the Atlantic, the pros and cons of the big-box format have been widely debated (the Wal-Mart effect). We analyze whether large entrants force low productive stores out from the market and increase productivity growth among surviving stores with different positions in the productivity distribution. We use political preferences in local markets to control for endogeneity of large entrants. Our empirical application relies on detailed data on all retail food stores in Sweden, which is representative to many European markets in terms of market structure and regulation.

The results show that when estimating retail productivity, it is central to control for local market characteristics, and for selection, and to allow for non-linearities in the productivity process. We recognize that large entrants clearly drive reallocation of resources towards more productive stores. After large entry, low productive stores are more likely to exit. In addition, large entrants increase productivity growth of incumbent stores. The magnitude of the growth increase varies however with an incumbent's position in the productivity distribution. The increase in growth declines with productivity, implying that growth increases relatively more among low productive survivors than among high productive ones. The productivity distribution thus gets truncated from below and dispersion decreases. Decompositions of aggregate productivity growth, 8% from 1997 to 2001 in the Swedish retail food market, confirm importance of incumbents and low productive exits. We conclude that entry by big-box stores spurs reallocation of resources towards more productive stores, and thus works as a catalyst for retail productivity growth.

Our findings contribute with knowledge to competition policy because entry regulation issues greatly concern policy makers in Europe, where such regulations are generally much more restrictive than in the U.S. As an example, the European Parliament recently highlighted an investigation of supermarket dominance (European Parliament 2008). We argue that a more restrictive design and application of entry regulations can hinder reallocation towards more productive units and thus hinder aggregate productivity growth. Note however that we clarify the indirect link between regulation, large entrants, and productivity because the numbers of approvals and rejections are not available. Besides productivity, entry regulations compound a wide range of other aspects. How to balance potential productivity growth against increased traffic and broader environmental issues are interesting issues for future research. It would also be interesting to apply our extended Olley and Pakes (1996) framework to other service markets such as banking and health care services. Future work would also benefit from using fully dynamic models (Dunne et al. 2005, Beresteanu and Ellickson 2006, Aguirregabiria et al. 2007, Holmes 2008) that would more carefully consider the importance of sunk costs, chain effects, and market adjustments.

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Table 1: Characteristics of the Swedish Retail Food Market

A. DELFI						
Year	No. of stores	Large stores	Large entry	Mean sales space (m^2)	Total sales space (m^2)	Total sales
1996	4,664	905	21	538	2,510,028	129,326,000
1997	4,518	925	8	550	2,483,248	126,732,397
1998	4,351	926	9	587	2,552,794	130,109,604
1999	4,196	936	18	604	2,514,367	133,156,023
2000	3,994	948	23	654	2,587,952	138,314,044
2001	3,656	942	28	689	2,471,510	139,352,920
2002	3,585	932	5	718	2,525,084	142,532,944
B. FS-RAMS						
Year	No. of "multi-stores"	No. of employees	Total wages	Value added	Total sales	
1996	3,714	74,100	9,882,234	18,319,407	141,743,876	
1997	3,592	73,636	10,322,136	18,838,130	142,840,611	
1998	3,482	74,696	10,766,043	19,185,120	147,726,647	
1999	3,398	74,758	11,110,785	19,570,472	152,160,949	
2000	3,287	77,180	11,536,063	20,389,492	154,106,865	
2001	3,094	76,905	11,522,482	20,748,902	158,512,132	
2002	3,067	80,931	12,081,931	22,473,696	179,335,162	

NOTE: DELFI is provided by Delfi Marknadspartner AB and contains all retail food stores based on their geographical location (address). FS-RAMS is provided by Statistics Sweden and consists of all organization numbers in SNI-code 52.1, i.e., "multi-store" units that contain one store or several (e.g., due to the same owner). Sales (incl. 12% VAT), value-added, and wages are measured in thousands of 1996 SEK (1USD=6.71SEK, 1EUR=8.63 SEK). Sales in DELFI are collected by surveys and reported in classes, while sales are based on tax reporting in FS-RAMS. Therefore, total sales are lower in DELFI than in FS-RAMS. From 1996 to 2002, the total population in Sweden increased from 8,844,499 to 8,940,788.

Table 2: Medians of local market characteristics

Year	1997	1998	1999	2000	2001	2002
A. Markets with large entrants						
No. of stores	37.00	54.00	29.00	32.00	33.00	22.00
No. of all entrants	2.00	2.00	3.00	2.00	1.00	2.00
No. of all exits	3.00	2.00	2.00	3.00	1.00	-.-
Population	57,441.00	60,429.00	37,195.00	48,250.00	58,361.00	22,907.00
Population density	80.88	57,92.00	68.03	79.38	77.29	52.77
Per capita income	149.10	157.60	161.60	170.30	179.10	177.60
Store concentration (C_4)	0.53	0.49	0.62	0.60	0.53	0.70
Total no. of markets	10	9	20	20	23	6
B. Markets without large entrants						
No. of stores	15.00	15.00	15.00	14.00	13.00	14.00
No. of all entrants	0.00	0.00	1.00	0.00	0.00	0.00
No. of all exits	0.00	1.00	1.00	1.00	0.00	-.-
Population	14,827.00	15,133.00	14,322.00	14,154.00	14,068.00	15,207.00
Population density	25.80	25.78	25.22	25.60	24.75	26.20
Per capita income	143.30	149.10	155.90	162.50	168.40	175.90
Store concentration (C_4)	0.71	0.71	0.72	0.73	0.75	0.76
Total no. of markets	278	279	269	269	266	284

NOTE: 1996 is left out because entrants are not observed. Municipalities, considered as local markets, increase from 288 to 290 due to three municipality break-ups during the period. Stores, entrants and exits come from DELFI. Population density is defined as total population per square kilometer in the municipality. Concentrations (C_4) show the market share captured by the top four stores.

Table 3: Value added generating function estimates

	OLS	ACF	DP1		DP2		EOPs		EOPm		EOPms	
			(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Log no. of labor	0.948	0.768	0.754	0.916	0.686	0.900	0.845	0.921	0.945	1.205	0.840	1.269
	(0.005)	(0.057)	(0.001)		(0.004)		(0.001)		(0.001)		(0.007)	
Log of capital	0.167	0.163	0.400	0.485	0.426	0.400	0.212	0.232	0.116	0.147	0.145	0.201
	(0.003)	(0.050)	(0.001)		(0.003)		(0.001)		(0.003)		(0.001)	
Market output $\left(-\frac{1}{\eta}\right)$			0.176		0.313		0.082		0.216		0.338	
			(0.002)		(0.001)		(0.001)		(0.001)		(0.001)	
Number of large entrants			-0.945	-5.371	-0.031	-0.098			-0.093	-0.430	0.034	0.100
			(0.002)		(0.001)				(0.001)		(0.004)	
Population density			-0.103	-0.421	-0.166	-0.529			-0.054	-0.252	-0.033	-0.186
			(0.002)		(0.001)				(0.001)		(0.001)	
Productivity transition (ρ_1)			0.417		0.449							
			(0.002)		(0.007)							
Demand shock transition (ρ_2)					0.353							
					(0.106)							
Scale ($\beta_l + \beta_k$)	1.115	0.931	1.402		1.426		1.140		1.362		1.420	
Demand elasticity (η)			-5.674		-3.198		-12.192		-4.659		-2.962	
Mark-up $\left(\frac{\eta}{1+\eta}\right)$			1.214		1.455		1.089		1.273		1.509	
Sargan (p-value)		0.081					0.296		0.990		0.935	
No. of obs.	23,521	16,186	15,640		15,640		15,640		15,640		15,640	

NOTE: The dependent variable is log of deflated value added. Labor is measured as number of full-time adjusted employees. All regressions include year dummies. OLS is ordinary least square regression. ACF is Ackerberg, Caves, and Fraser's (2006) two-stage estimation method; DP1 is linear estimation of equation (6) when ω_{jt} and υ_{jt} follow the same AR(1) process; DP2 is linear estimation of equation (6) when ω_{jt} and υ_{jt} follow two different AR(1) processes; EOPs is the semi-parametric estimation of equation (9) without local market characteristics but controlling for selection; EOPm is the semi-parametric estimation of equation (9) with control for prices and local market characteristics but not for selection; EOPms is the semi-parametric estimation of equation (9) specified in Section 3, i.e., we control for prices, local market characteristics, and selection. In the EOP specifications, columns (1) show estimated coefficients including elasticity (see Equation 6); columns (2) show estimated coefficients without elasticity. Reported standard errors (in parentheses) are robust to heteroscedasticity. In ACF, current capital stock and previous labor are used as instruments, and standard errors are computed using bootstrap. In EOP, two-step GMM is used for estimation. Market output is measured as the market share weighted output in the municipality. Demand refers to the elasticity of substitution. Mark-up is defined as price over marginal cost.

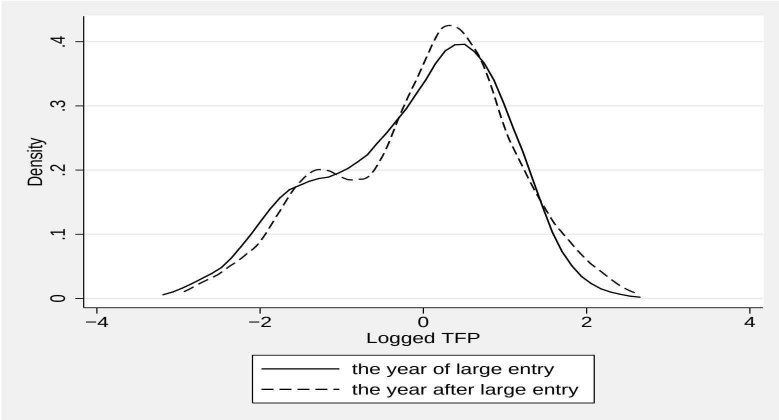

Figure 1: TFP kernel density estimates, incumbent stores in markets the year of, and the year after, large entry

Table 4: TFP and large entrants

A. Markets with large entrants	Mean	Std. Dev.
Year of entry	-0.291	1.064
Year after entry	-0.016	1.051
Test (p-value)	0.001	0.671
B. All markets		
With entry$_{t-1}$	-0.016	1.051
Without entry$_{t-1}$	0.100	0.909
Test (p-value)	0.001	0.001

NOTE: This table summarizes TFP levels of incumbents in markets before and after large entrants, and in markets with and without large entrants. T-test is used for mean, and F-test is used for standard deviation (p-values reported). TFP is estimated using the semi-parametric EOPms method described in Section 3. Large entrants are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores).

Table 5: Transition matrix from t-1 (column) to t (row) in percentage

Percentile	<p10	p10-p25	p25-p50	p50-p75	p75-p90	>p90	Exit
A. Markets with large entrants in t-1							
<p10	35.59	22.88	10.17	1.69	1.69	0.85	27.12
p10-p25	14.05	33.47	23.55	4.13	1.65	0.00	23.14
p25-p50	2.53	12.64	42.30	19.77	4.14	1.38	17.24
p50-p75	0.85	2.34	21.44	44.37	13.80	2.97	14.23
p75-p90	0.00	1.77	6.38	26.24	37.23	13.48	14.89
>p90	0.63	1.25	2.50	11.88	20.00	48.75	15.00
B. Markets without large entrants in t-1							
<p10	31.84	26.02	12.55	4.08	0.61	1.53	23.37
p10-p25	15.32	34.75	23.92	5.63	1.39	0.82	18.16
p25-p50	4.11	13.72	40.75	20.17	3.97	1.77	15.52
p50-p75	0.86	3.15	20.52	42.06	16.04	5.50	11.87
p75-p90	0.39	1.34	8.52	25.83	33.05	16.81	14.06
>p90	1.09	0.84	5.13	15.63	25.55	35.38	16.39

NOTE: TFP is estimated using the semi-parametric EOPms method described in Section 3. Municipalities are considered as local markets. Large entrants in period t-1 are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores).

Table 6: Regression results: Exit

	TFP nonlinear (EOPms)		TFP linear (DP2)	
	(1)	(2)	(3)	(4)
Log of productivity$_{t}$	-0.058		-0.013	
	(0.015)		(0.007)	
Large entrants$_{t\text{-}1}$	0.022	-0.152	0.014	0.061
	(0.037)	(0.088)	(0.057)	(0.109)
p10*Large entrants$_{t\text{-}1}$		0.293		0.121
		(0.118)		(0.155)
p10-p25*Large entrants$_{t\text{-}1}$		0.190		0.128
		(0.126)		(0.167)
p25-p50*Large entrants$_{t\text{-}1}$		0.293		-0.216
		(0.113)		(0.160)
p75-p90*Large entrants$_{t\text{-}1}$		0.071		-0.275
		(0.117)		(0.197)
p90*Large entrants$_{t\text{-}1}$		0.209		-0.036
		(0.129)		(0.192)
Log of capital$_{t}$	-0.083	-0.087	-0.077	-0.070
	(0.009)	(0.009)	(0.014)	(0.014)
Log of population density$_{t}$	0.018	0.020	-0.004	-0.004
	(0.008)	(0.008)	(0.011)	(0.011)
Year dummies	yes	yes	yes	yes
No. of obs.	11,132	11,132	7,376	7,376

NOTE: This table shows probit regressions on exit. TFP is estimated using the semi-parametric EOP method described in Section 3 (EOPms) and linear panel specification (DP2). Reported standard errors (in parentheses) are robust to heteroscedasticity. Large entrants in period t-1 are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). We use six percentile bins for productivity in each local market and year, with p50-75 used as reference group.

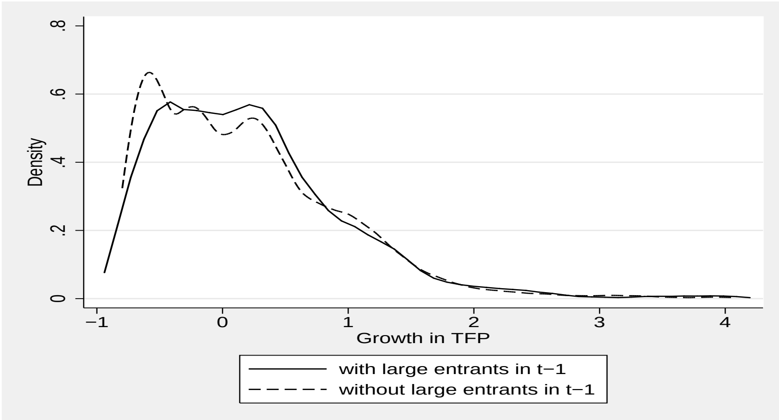

Figure 2: TFP growth kernel density estimates, incumbent stores in markets with and without large entrants

Table 7: TFP Growth and large entrants

A. Markets with large entrants	Mean	Std. Dev.
Year of entry	-0.110	0.535
Year after entry	0.159	0.568
Test (p-value)	0.001	0.049
B. All markets		
With entry$_{t-1}$	0.159	0.568
Without entry$_{t-1}$	0.138	0.598
Test (p-value)	0.227	0.021

NOTE: This table summarizes TFP growth of incumbents in markets before and after large entrants, and in markets with and without large entrants. T-test is used for mean, and F-test is used for standard deviation (p-values reported). TFP is estimated using the semi-parametric EOPms method described in Section 3. Large entrants are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores).

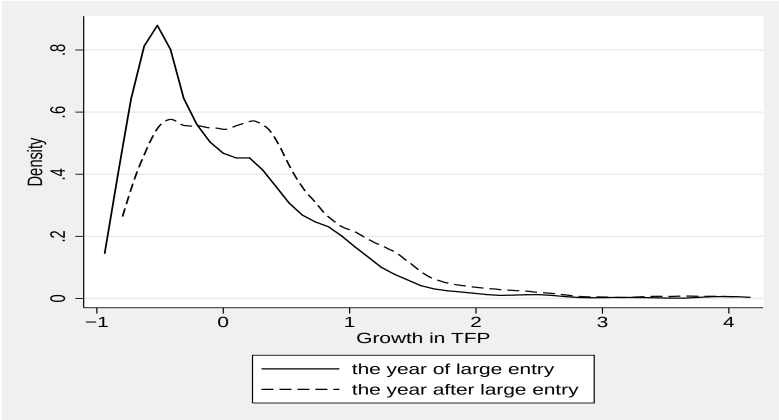

Figure 3: TFP growth kernel density estimates, incumbent stores in markets the year of, and the year after, large entrants

Table 8: Regression results: TFP growth

	TFP nonlinear (EOPms)					TFP linear (DP2)				
	OLS		Within	GMM		OLS		Within	GMM	
	(1)	(2)		(1)	(2)	(1)	(2)		(1)	(2)
Large entrants$_{t-1}$	0.040	-0.009	-0.021	-0.227	0.451	0.084	0.006	-0.073	-1.001	0.252
	(0.008)	(0.014)	(0.017)	(0.004)	(0.001)	(0.023)	(0.045)	(0.058)	(0.001)	(0.001)
p10* Large entrants$_{t-1}$		0.161	0.188	0.371	0.343		0.275	0.372	1.241	1.400
		(0.022)	(0.028)	(0.001)	(0.001)		(0.063)	(0.081)	(0.001)	(0.001)
p10-p25* Large entrants$_{t-1}$		0.079	0.107	0.281	0.593		0.154	0.273	1.087	1.840
		(0.020)	(0.025)	(0.001)	(0.001)		(0.060)	(0.081)	(0.001)	(0.001)
p25-p50* Large entrants$_{t-1}$		0.071	0.096	0.263	0.422		0.127	0.235	1.019	1.301
		(0.021)	(0.024)	(0.001)	(0.001)		(0.055)	(0.074)	(0.001)	(0.001)
p75-p90*Large entrants$_{t-1}$		0.004	0.017	0.196	-0.462		-0.084	0.005	0.798	-1.618
		(0.020)	(0.024)	(0.001)	(0.001)		(0.065)	(0.093)	(0.001)	(0.001)
p90*Large entrants$_{t-1}$		-0.031	-0.022	0.161	-0.314		-0.245	-0.090	0.625	-1.196
		(0.023)	(0.030)	(0.001)	(0.001)		(0.070)	(0.101)	(0.001)	(0.001)
Log of population density$_t$	0.180	0.110	-0.038	0.151	-1.166	-0.113	-0.264	-0.031	-0.244	-5.206
	(0.164)	(0.163)	(0.015)	(0.001)	(0.001)	(0.505)	(0.503)	(0.052)	(0.003)	(0.004)
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Market fixed effects	yes	yes	no	yes	yes	yes	yes	no	yes	yes
Adjusted R^2	0.745	0.746				0.253	0.258			
J-test (p-value)				0.994	0.998				0.997	0.998
No. of obs.	13,626	13,626	13,626	13,626	9,774	7,376	7,376	7,376	7,376	4,884

NOTE: TFP is estimated using the semi-parametric EOP method described in Section 3 (EOPms) and linear panel specification (DP2). Standard errors reported in parentheses, and one-step GMM estimator is used. GMM (1) uses lagged political preferences as instruments for large entry, GMM (2) also adds lagged large entrants (in t-2), lagged population density, and lagged income. J-test refers to the test for overidentified restrictions in GMM models. Large entrants in period t-1 are defined as the five largest store types in the DELFI data (hypermarkets, department stores, large supermarkets, large grocery stores, and other stores). We use six percentile bins for productivity in each market and year, with p50-75 used as reference group.

Table 9: Decomposition of retail food productivity growth, 1997 to 2001

	Percentage of growth from					
Overall industry growth	Within stores (1)	Between stores (2)	Cross stores (3)	Entry (4)	Exit (5)	Net entry (4) - (5)
A. Baily et al (1992) / Foster et al (2001)						
0.08	0.0572	0.0006	0.0075	0.0025	-0.0121	0.0147
B. Griliches and Regev (1995)						
0.08	0.0609	0.0005		0.0294	-0.0109	0.0185

NOTE: Decomposition using Equation (18) in Section 3; TFP is estimated using the semi-parametric estimation (EOPms) described in Section 3. Shares of local market sales are used as weights. Appendix C describes the decompositions in detail.

Table 10: Dynamic Olley and Pakes decomposition of TFP growth 1997-2001: Melitz and Polanec (2009)

	Percentage of growth from					
	Surviving		Entrants		Exits	
Overall Industry Growth	Unweigh.	Cov	Unweigh.	Weigh.	Unweigh.	Weigh.
0.08	0.1124	-0.0171	-0.0893	-0.0367	0.117	0.0214

NOTE: TFP is estimated using the semi-parametric estimation EOP described in Section 3 and 4. Shares of local market sales are used as weights. Appendix C describes the decomposition in detail.

Appendix A: PBA and data sources

■ **Entry regulation (PBA).** On July 1, 1987, a new regulation was imposed in Sweden, the Plan and Building Act (PBA). Compared to the previous legislation, the decision process was decentralized, giving local governments power over entry in their municipality and citizens a right to appeal the decisions. Since 1987, only minor changes have been implemented in PBA. From April 1, 1992 to December 31, 1996, the regulation was slightly different, making explicit that the use of buildings should not counteract efficient competition. Since 1997, PBA has been more or less the same as prior to 1992. Long time lags in the planning process make it impossible to directly evaluate the impact of decisions. In practice, differences because of the policy change seem small (Swedish Competition Authority 2001:4). Nevertheless, PBA is claimed to be one of the major entry barriers, resulting in different outcomes, e.g., price levels, across municipalities (Swedish Competition Authority 2001:4, Swedish Competition Authority 2004:2). Municipalities are then, through the regulation, able to put pressure on prices. Those that constrain entry have less sales per capita, while those where large and discount stores have a higher market share also have lower prices.

■ **The DELFI data.** DELFI Marknadspartner AB collects daily data on retail food stores from a variety of channels: (1) public registers, the trade press, and daily press; (2) the Swedish retailers association (SSLF); (3) Kuponginlösen AB (which deals with rebate coupons collected by local stores); (4) the chains' headquarters; (5) matching customer registers from suppliers; (6) telephone interviews; (7) yearly surveys; and (8) the Swedish Retail Institute (HUI). Location, store type, owner, and chain affiliation are double-checked in corporate annual reports.

Each store has an identification number linked to its geographical location (address). The twelve store types, based on size, location, product assortment, etc., are hypermarkets, department stores, large supermarkets, large grocery stores, other stores, small supermarkets, small grocery stores, convenience stores, gas-station stores, mini markets, seasonal stores, and stores under construction.

Sales and sales space are collected via yearly surveys. Revenues (including VAT) are recorded in 19 classes. Due to the survey collection, a number of missing values are substituted with the median of other stores of the same type in the same local market. In total, 702 stores have missing sales: 508 in 1996, and

194 in later years. For sales space, all 5,013 values are missing for 1996, and are therefore replaced with the mean of each stores' 1995 and 1997 values. In addition, 2,810 missing sales space values for later years are replaced similarly. In total, 698 observations are missing both sales and sales space.

■ **The FS-RAMS data.** FS-RAMS contains all registered organization numbers in the different Swedish industries from 1996 to 2002. *Value added* is defined as total shipments, adjusted for inventory changes, minus costs of materials. *Labor* is the total number of employees. We deflated sales, value added, wages, and investment by the consumer price index (CPI) from IMF-CDROM 2005.

Capital is constructed using a perpetual inventory method, $k_{t+1}(1-\delta)k_t + i_t$. Since the data distinguishes between buildings and equipment, all calculations of the capital stock are done separately for buildings and equipment. In the paper, we include equipment in the capital stock. Including both equipment and buildings in the capital stock does not change the results, however. As suggested by Hulten and Wykoff (1981), buildings are depreciated at a rate of 0.0361, and equipment at 0.1179. In order to construct capital series using the perpetual inventory method, an initial capital stock is needed. We set initial capital stock to its first occurrence in FS-RAMS, defining entry as the first year in FS (some of the stores have been in FS since 1973).

Appendix B: Selection and estimation strategy

■ **Selection.** A store's decision to exit in period t depends directly on productivity ω_{jt}, so that the decision will be correlated with the productivity shock ε_{jt}. To identify β_l and β_k, we use estimates of survival probabilities, given by

$$\begin{aligned} Pr(\chi_t = 1 | \underline{\omega}_t(k_{jt}, z_{mt-1}), \mathcal{F}_{t-1}) = \; & Pr(\omega_{jt} \geq \underline{\omega}_t(k_{jt}, z_{mt-1}) | \\ & \underline{\omega}_t(k_{jt}, z_{mt-1}), \omega_{jt-1}) \\ = \; & P_{t-1}(i_{jt-1}, l_{jt-1}, k_{jt-1}, s_{jt-1}, p_{mt-1}, q_{mt-1}, \\ & z_{mt-1}) \\ \equiv \; & \mathscr{P}_{t-1} \end{aligned} \tag{13}$$

where the second equality follows from (8). Controlling for selection, we can express the non-parametric function $h(\cdot)$ (the approximation of the conditional expectation $E[\omega_{jt}|\mathcal{F}_{t-1}]$) as a function of threshold market productivity $\underline{\omega}_t$ and the information set $\mathcal{F}_{t-1}$. As a result, threshold market productivity can be written as a function of $\mathscr{P}_{t-1}$ and $\mathcal{F}_{t-1}$. Substituting Equations (8) and (13) into (6) yields

$$\begin{aligned} y_{jt} = \; & \left(1+\tfrac{1}{\eta}\right)[\beta_0+\beta_l l_{jt}+\beta_k k_{jt}] - \tfrac{1}{\eta}q_{mt} - \tfrac{1}{\eta}z'_{mt-1}\beta_z + h\left(\mathscr{P}_{t-1}, \tfrac{\eta}{1+\eta}(\delta_1 + \right. \\ & [(1-\beta_l)-\tfrac{1}{\eta}\beta_l]l_{jt-1} - (1+\tfrac{1}{\eta})\beta_k k_{jt-1} + s_{jt-1} - p_{It-1} + \tfrac{1}{\eta}q_{mt-1} + \\ & \left.\tfrac{1}{\eta}z'_{mt-1}\beta_z)\right) + \left(1+\tfrac{1}{\eta}\right)\xi_{jt} - \tfrac{1}{\eta}\upsilon_{jt} - \tfrac{1}{\eta}u^d_{jt} + \left(1+\tfrac{1}{\eta}\right)u^p_{jt}. \end{aligned} \tag{14}$$

■ **Estimation strategy.** We first use a probit model with a third order polynomial to estimate the survival probabilities in (13). The predicted survival probabilities are then substituted into (9), which is estimated in the second step. We now turn to details about the estimation procedure of the latter step. The semiparametric regression (9) is estimated using the sieve minimum distance (SMD) procedure proposed in Newey and Powell (2003) and Ai and Chen (2003) for i.i.d. data.[39] The goal is to obtain an estimable expression for the unknown parameter of interest, $\boldsymbol{\alpha} = (\boldsymbol{\beta}, h)'$. We denote the true value of the parameters with the subscript "a", so that $\boldsymbol{\alpha}_a = (\boldsymbol{\beta}_a, h_a)'$. The moment conditions could then be written more compactly as

$$E[\psi_{jt}(\boldsymbol{X}_{jt}, \boldsymbol{\beta}_a, h_a)|\mathcal{F}^*_t] = 0 \quad j = 1, \cdots, N \quad t = 1, \cdots, T \tag{15}$$

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

$$\begin{aligned} \psi_{jt}(\boldsymbol{X}_{jt}, \boldsymbol{\beta}_a, h_a) \; & \equiv \left[\left(1+\tfrac{1}{\eta}\right)\xi_{jt} - \tfrac{1}{\eta}\upsilon_{jt} - \tfrac{1}{\eta}u^d_{jt} + \left(1+\tfrac{1}{\eta}\right)u^p_{jt}\right] \\ & = y_{jt} - \left(1+\tfrac{1}{\eta}\right)[\beta_0+\beta_l l_{jt}+\beta_k k_{jt}] + \tfrac{1}{\eta}q_{mt} + \tfrac{1}{\eta}z'_{mt}\beta_z - h(\omega_{jt-1}) \end{aligned}$$

Let $\mathcal{F}_t$ be an observable subset of $\mathcal{F}^*_t$. Then Equation (15) implies

$$E[\psi_{jt}(\boldsymbol{X}_{jt}, \boldsymbol{\beta}_a, h_a)|\mathcal{F}_t] = 0 \quad j = 1, \cdots, N \quad t = 1, \cdots, T \tag{16}$$

If the information set $\mathcal{F}_t$ is informative enough, such that $E[\psi_{jt}(\boldsymbol{X}_{jt}, \boldsymbol{\beta}, h)|\mathcal{F}_t] = 0$ for all j and for any $0 \leq \beta < 1$, then $(\boldsymbol{\beta}, h)' = (\boldsymbol{\beta}_a, h_a)'$. The true parameter

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

values must satisfy the minimum distance relation

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

where $m(\mathfrak{F}_t, \boldsymbol{\alpha}) = E[\psi(\boldsymbol{X}_t, \boldsymbol{\alpha})|\mathfrak{F}_t]$, $\psi(\boldsymbol{X}_t, \boldsymbol{\alpha}) = (\psi_1(\boldsymbol{X}_t, \boldsymbol{\alpha}), \cdots, \psi_N(\boldsymbol{X}_t, \boldsymbol{\alpha}))'$ for any candidate values $\boldsymbol{\alpha} = (\boldsymbol{\beta}, h)'$. The moment conditions are used to describe the SMD estimation of $\boldsymbol{\alpha}_a = (\boldsymbol{\beta}_a, h_a)'$. The SMD procedure has three parts. First, we can estimate the function $h(\cdot)$, which has an infinite dimension of unknown parameters, by a sequence of finite-dimensional unknown parameters (sieves) denoted h_H. Approximation error decreases as the dimension H increases with sample size N. Second, the unknown conditional mean $m(\mathfrak{F}_t, \boldsymbol{\alpha}) = E[\psi(\boldsymbol{X}_t, \boldsymbol{\alpha})|\mathfrak{F}_t]$ is replaced with a consistent nonparametric estimator $\hat{m}(\mathfrak{F}_t, \boldsymbol{\alpha})$ for any candidate parameter values $\boldsymbol{\alpha} = (\boldsymbol{\beta}, h)'$. Finally, the function h_H is estimated jointly with the finite dimensional parameters $\boldsymbol{\beta}$ by minimizing a quadratic norm of estimated expectation functions,

$$\hat{\boldsymbol{\alpha}} = arg\min_{\boldsymbol{\beta}, h_H} \frac{1}{T} \sum_{t=1}^{T} \hat{m}(\mathfrak{F}_t, \boldsymbol{\beta}, h_H)' \hat{m}(\mathfrak{F}_t, \boldsymbol{\beta}, h_H) \tag{17}$$

We approximate $h(\cdot)$ by a third order polynomial and substitute it in (16) as if it were the true model. Since the errors $\psi_t(\cdot)$ are orthogonal to the regressors $\mathfrak{F}_t = (1, l_{jt-1}, k_{jt}, q_{mt-1}, z_{mt-1})$, we use a third order power series of $\mathfrak{F}_t$, denoted $\boldsymbol{P}$, as instruments. We estimate $m(\mathfrak{F}, \boldsymbol{\alpha})$ as the predicted values from regressing the errors $\psi_t(\cdot)$ on the instruments. Using $\boldsymbol{P}$, we specify the weighting matrix as $\boldsymbol{A} = I_N \otimes (\boldsymbol{P}'\boldsymbol{P})^{-1}$, making the estimation a GMM case. The weighting matrix $\boldsymbol{A}$ gives greater weight to moments that are highly correlated with the instruments. Using the specified GMM implementation, the parameter values $(\boldsymbol{\beta}, h_H)$ are jointly estimated.

Appendix C: Productivity decompositions

Though we cannot determine the exact contribution of large entrants, our data allow us to decompose aggregate productivity growth due to entrants, exits, and incumbents. Industry level productivity (Ω_t) can then be expressed as the weighted average productivity: $\Omega_t \equiv \sum_{j\in N} ms_{jt}\omega_{mt}$, where N is the number of stores, and $ms_{jt} = sales_{jt}/sales_t$.

The change in retail food productivity from year t to year t' can be written as

$$\begin{aligned}\Delta\Omega_{t,t'} = \; & \textstyle\sum_{j\in C_{t,t'}} ms_{jt}\Delta\omega_{jt,t'} + \sum_{j\in C_{t,t'}} \Delta ms_{jt,t'}(\omega_{jt} - \Omega_t) \\ & + \textstyle\sum_{j\in C_{t,t'}} \Delta ms_{jt,t'}\Delta\omega_{jt,t'} + \sum_{j\in E_{t,t'}} ms_{jt'}(\omega_{jt'} - \Omega_t) \\ & - \textstyle\sum_{j\in X_{mt,t'}} ms_{jt}(\omega_{jt} - \Omega_t)\end{aligned} \tag{18}$$

where Δ is the difference operator ($\Delta\Omega_{t,t'} = \Omega_{t'} - \Omega_t$); $C_{t,t'}$ is the set of continuing stores, i.e., operating in both t and $t^{'}$; $E_{t,t'}$ is the set of entering stores, i.e., that operated in $t^{'}$ but not in t; and $X_{t,t'}$ is the set of exiting stores, i.e., that operated in t but not in $t^{'}$. This decomposition, derived by Foster et al. (2001)(FHK), is a modified version of the decomposition by Baily et al. (1992).

The decomposition (18) thus consists of five terms. The first term (Within) is the increase in productivity when the continuing stores increase their productivity at initial sales. The second term (Between) is the increase in productivity when continuing stores with above-average productivity expand their share of sales relative to stores with below-average productivity. The third term (Cross) captures the increase in productivity when continuing stores increase their market shares, while the fourth and fifth terms (Entry and Exit) are productivity increases due to entry and exit, respectively.

The second productivity decomposition used is given by Griliches and Regev (1995) (GR) and modified by FHK to allow for entry and exit

$$\begin{aligned}\Delta\Omega_{t,t'} = \; & \textstyle\sum_{j\in C_{t,t'}} \overline{ms}_j\Delta\omega_{jt,t'} + \sum_{j\in C_{t,t'}} \Delta ms_{jt,t'}(\overline{\omega}_j - \overline{\Omega}) \\ & + \textstyle\sum_{j\in E_{t,t'}} ms_{jt'}(\omega_{jt'} - \overline{\Omega}) \\ & - \textstyle\sum_{j\in X_{t,t'}} ms_{jt}(\omega_{jt} - \overline{\Omega})\end{aligned} \tag{19}$$

where bars over a variable indicate the average of the variable across t and t'. The within term in the GR decomposition consists of the growth rates of continuing stores' TFP weighted by the average of their shares across t and t'. Both decompositions compare aggregate productivity of entering and existing stores, either to the aggregate productivity of all stores (FHK) or to the unweighted average of aggregate productivity of all stores (GR).

Olley and Pakes (1996) (OP) proposes a static decomposition of aggregate productivity, in which the weighted productivity of continuing stores, Ω_t, has two components: (1) contribution of productivity improvements, $\overline{\Omega}_t$; and (2) market share reallocations for the continuing stores $cov(ms_{jt}, \omega_{jt}) \equiv \sum_j (ms_{jt} - \overline{ms}_t)(\omega_{jt} - \overline{\Omega}_t)$. The difference in productivity index, $\Delta\Omega_{t,t'}$, can be written as

$$\Delta\Omega_{t,t'} = \Delta\overline{\Omega}_{t,t'} + \Delta cov_{t,t'}. \tag{20}$$

The OP decomposition ignore the entry and exit. However, Melitz and Polanec (2009) (MP) suggest a dynamic OP decomposition where there is a positive contribution for entering and exiting stores only when the aggregate productivity of these stores is larger than that of continuing stores in corresponding periods. The aggregate productivity in periods t and $t^{'}$ can be decomposed as

$$\begin{aligned} \Omega_t &= ms_{C_t}\Omega_{C_t} + ms_{X_t}\Omega_{X_t} \\ \Omega_{t'} &= ms_{C_{t'}}\Omega_{C_{t'}} + ms_{E_{t'}}\Omega_{E_{t'}} \end{aligned} \tag{21}$$

where ms_{C_t}, $ms_{C_{t'}}$, $ms_{E_{t'}}$, and ms_{X_t} are the aggregate market shares of incumbents (in period t and $t^{'}$), entrants and exits, respectively. The change in aggregate productivity can be written as

$$\Delta\Omega_{t,t'} = \Delta\overline{\Omega}_{C_{t,t'}} + \Delta cov_{C_{t,t'}} + ms_{E_{t'}}(\Omega_{E_{t'}} - \Omega_{C_{t'}}) + ms_{X_t}(\Omega_{C_t} - \Omega_{X_t}). \tag{22}$$

where the contribution of continuing firms is divided into within-firm productivity improvements ($\Delta\overline{\Omega}_{C_{t,t'}}$) and market share reallocations ($\Delta cov_{C_{t,t'}}$) as in OP. The contribution of entrants and exits contains two parts, unweighted average productivity (direct effect) and the covariance term (indirect effect). For entrants: $ms_{E_{t'}}(\overline{\Omega}_{E_{t'}} - \overline{\Omega}_{C_{t'}})$, and $ms_{E_{t'}}(cov(\Omega_{E_{t'}}) - cov(\Omega_{C_{t'}}))$. For exits: $ms_{X_t}(\overline{\Omega}_{C_t} - \overline{\Omega}_{X_t})$, and $ms_{X_t}(cov(\Omega_{C_t}) - cov(\Omega_{X_t}))$.

Paper II

Productivity Dynamics, R&D, and Competitive Pressure*

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Abstract

This paper proposes a dynamic structural model to estimate productivity when productivity evolves as an endogenous process and firms decide how much to invest depending on the competitive pressure they face. Using data from Sweden, this paper finds that open market policies and entrepreneurship policies complement R&D policies and are important drivers of the competitiveness of established firms. Conservative estimates suggest that optimal investment is at least 0.7 to 2.5 times the actual investment in R&D for a median firm and 2 to 4 times for a firm located in the upper part of the productivity growth distribution.

Keywords: R&D; productivity; production function; selection; competitive pressure; market dynamics.

JEL Classification: O3, C51, L11, L13, D24.

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1 Introduction

The link between investment in research and development (R&D) and firm performance is one of the most studied topics in industrial organization. Early literature on this relationship largely focused on estimating the average or expected returns (private or social) to R&D spending.[1] However, even if R&D spending increases a firm's productivity, it also affects the entire productivity distribution of the industry through the exit of firms and reallocations as well as displacements of labor and capital. From a policy perspective, the analysis of the entire productivity distribution enhances our understanding of the dynamics of firms' investment in R&D and physical capital.[2] The paper's objective is to investigate the impact of R&D spending and competitive pressure on the industry-wide distribution of productivity.

The analysis is based on a dynamic model that allows for the effect of competitive pressure on R&D spending and productivity. The model is an extension of Olley and Pakes (1996)' (OP) semiparametric framework for estimating production function parameters, which accounts for the selection induced by liquidation as well as for the simultaneity induced by the endogeneity of input demands. Recent production function estimation studies extend the OP framework by endogenizing productivity. For example, Buettner (2004) extends the OP method by allowing the distribution of future productivity to evolve endogenously over time - a firm's R&D spending affects the distribution of future productivity conditional on the current productivity. Ackerberg et al. (2007) (ABBP) suggest introducing a technological indicator, i.e., they introduce two Markov processes: one controlled and one exogenous. Muendler (2005) suggests that firm-level capital investment interacted with sector-level competition variables is a superior model to capture a firm's individual market expectations and to correct for transmission bias. Aw et al. (2009) and Doraszelski and Jaumandreu (2009) also endogenize productivity, allowing it to depend on the amount of R&D investment.

In many industries firms engage in R&D with the aim of improving future productivity, and they decide how much to spend depending on the competitive pressure they face. If one believes that the true underlying model of firm dynamics should include R&D spending and competitive pressure, then without an explicit

[1] Griliches (1998) provides a survey of the effect of R&D on productivity.

[2] In the theoretical firm dynamics models proposed by Ericson and Pakes (1995), Hopenhayn (1992), and Jovanovic (1982), the stochastic evolution of firm productivity determines the success or failure of the firm in an industry.

model it is unclear whether a framework with exogenous productivity process approach can be applied. A further improvement to previous work is that the present paper explicitly incorporate the effect of competitive pressure on productivity and its link to R&D and discuss the identification when a dynamic framework is used.

Does competition affect productivity? In the Schumpeterian view causality between R&D and market structure goes in both directions.[3] Although there exists a theoretical basis for the conjecture that competition enhances productivity, the empirical evidence is somewhat ambiguous. Aghion et al. (2005) develop a theoretical growth model where competition may increase the incremental profit from innovation and reduce the innovation incentive for firms with low productivity. Using U.K. firm data, they find an inverted U-shape between innovation and competition, i.e., increasing competition has a positive impact on innovation at low levels of competition but a negative impact when competition is already high.[4] However, their findings of a positive net impact of competition on innovation are in line with the previous literature. Geroski (1990) and Nickell (1996) find empirical evidence that increases in competition are good for innovation. Comparing firms' productivity, R&D investment, and survival in the same industry in Korea and Taiwan, Aw et al. (2003) emphasize selection effects based on productivity induced by the high competitive pressure in Taiwan, e.g., a less concentrated market structure and low dispersion in productivity among survivors, and explain the low productivity of Korean firms by lack of entry and exit. The impact of competition on productivity is also emphasized by Syverson (2004a,b), who analyzes how product substitutability (demand-side aspects) affects performance and market structure in the U.S. ready-mixed concrete industry. He finds that an increase in product substitutability, i.e., an increase in competitive pressure, increases median productivity and decreases productivity dispersion in the market.

Competitive pressure faced by firms affects their choice of R&D and then both R&D and competitive pressure influence the stochastic evolution of a firm's productivity. In my setting the decision to invest and how much to invest in R&D and

[3]Vives (2004) analyzes the effects of competition on R&D effort for a variety of market structures. His findings are: an increasing number of firms tend to reduce R&D spending-provided that the total market for varieties does not shrink; an increasing total market size increases both the R&D effort and the number of varieties.

[4]Analyzing the effects of competitive pressure on a firm's incentive to invest in product and process innovations, Boone (2000) derives the conditions under which a rise in competitive pressure increases each firm's investments in process innovations to improve efficiency. He finds that the effects of a rise in competitive pressure on firm's incentive to innovate depend on the firm's type, which is determined by its efficiency level relative to that of its opponents.

physical capital depends on the competitive pressure faced by firms. In the OP setting two firms with the same current productivity and different capital stock will have different distributions of future productivity, while in the Buettner (2004) setting, current capital influences R&D spending, which affects future productivity. The present paper endogenizes the productivity process highlighting two channels through which competitive pressure affects productivity. It shows that under few restrictions on the model primitives, the policy function for capital investments generated by the structural model is still invertible (Pakes, 1994). The unobserved productivity state can be expressed as a function of capital, investment, and competitive pressure. The endogenous productivity choice model justifies the retention of observations with non-positive investment when competitive pressure is included. I use four measures, computed using five-digit information, as proxies for competitive pressure: the number of small (fewer than 100 employees) firms, median R&D spending at the industry level, change in concentration (C4), and foreign demand, i.e., total sales to foreign firms.

Accounting for competitive pressure when estimate productivity, the paper also links to the recent trade literature. There is a well documented positive correlation between productivity and export market participation. Costantini and Melitz (2007) provide a theoretical dynamic model of firm-level adjustment to trade liberalization modeling the joint entry, exit, export, and innovation decisions of heterogeneous firms. Their model captures the following channels for productivity improvements: (i) the selection effect of more productive firms into export markets and (ii) the effect of trade on productivity resulting in improvements in firms' productivity.[5] Recent empirical studies point out that R&D investment and access to new technology increase productivity as well as the pay-off to exporting (Aw et al., 2008). Investment decisions depend on the expected future profitability and fixed and sunk costs. Aw et al. (2009) provide a dynamic structural model of firms' decision to invest in R&D and to export.[6] My model framework does not explicitly model the choice of R&D, it does it in an indirect way. Jones and

[5]They find that anticipation of liberalization and a gradual path of liberalization induce firms to innovate ahead of export market entry. Using a general equilibrium model of the decision to innovate and export, Atkeson and Burstein (2007) find analytically that a decline in marginal trade costs raises process innovation (higher productivity) in exporting firms relative to non-exporting firms (comparative advantages).

[6]Using Taiwanese plant-level data, they find that (i) self-selection of high productive plants is the dominant channel driving participation in the export market and R&D investment, and that (ii) both R&D investment and exporting have a positive direct effect on a plant's future productivity.

Williams (1998) link the gap between the recent growth literature and the empirical productivity literature by constructing a relationship between social rate of return to R&D and the coefficient estimates of the productivity literature. They show that the latter represent a lower bound.

My model is applied to three Swedish manufacturing industries. In an international perspective, Swedish firms are big spenders on R&D.[7] Little work, however, has been done on the impact of R&D spending on the distribution of firm performance in Sweden.[8] The data used covers 1996-2002, a period of significant adjustment, and include all Swedish firms in three important manufacturing industries: machinery and equipment (MME), electrical and optical equipment (EOE), and transport equipment (MTE). The comprehensive nature of the data allows analysis of the dynamics of small plants that are often unobserved due to data limitations. I find that both selection bias and simultaneity bias induced by firm dynamics affect the magnitude of the capital coefficient in the value-added generating function. Structural dynamic models with R&D and capital investments based on the value added-generating function approach neglect competitive pressure which may lead to inconsistent coefficient estimates. A failure to adequately account for the dynamics of non-technical labor or/and technical labor can lead to severe under-estimations of capital stock when endogenizing productivity process (Ackerberg et al., 2006). Since the measure of productivity depends on these estimates, their consistency is crucial for the analysis.

My analysis yields several important findings. First, I find support for productivity improvements related to R&D and competitive pressure. Second, not endogenizing productivity when accounting for competitive pressure might result in high rates of return to R&D, which implies underinvestment. I find that a positive change in concentration has a negative effect on firms' productivity growth, and this effect is larger in the upper part of the productivity growth distribution. On the other hand, my results indicate that an increase in the number of small firms (fewer than 100 employees) has a positive impact on all parts of productivity distribution in the MME and EOE industries. Therefore, my findings suggest that entrepreneurship policies can complement policies that promote R&D spending.

[7] There are sixteen Swedish manufacturing firms in the *2009 EU Scoreboard rank*, which is a list of the EU-1000 group of firms ranked by their R&D spending in the 2008 financial year (EU, 2009). R&D investments were around 4 percent of GDP in 2001. Even if Sweden is ranked in the top in terms of national R&D intensity, the R&D content of Swedish production was found to be low in previous studies (Blomström and Kokko, 1994).

[8] Svensson (2008) provides a survey of the research on R&D in Sweden.

Foreign market penetration has a positive impact on productivity growth only for MME and MTE firms that are located in the upper tail of the productivity growth distribution. An increase in the median R&D spending at the subsector level has a positive impact only for median growth firms, i.e., firms that have very low or high productivity growth are not affected by more R&D spending at the subsector level. Third, the paper finds that the aggregate productivity gains from 1996 to 2002 are around 8 percent in the MME industry and around 22 percent in the EOE and MTE industries. The continuing firms that have increased both their productivity and market share are responsible for most of the productivity growth in the MME industry. These firms also contributed to the productivity growth in the EOE industry, where the entrants have a contribution of about 8 percent. In the MTE industry, the productivity growth is driven by the continuing firms that have increased their productivity. Fourth, the study finds that the private rate of return to R&D depends on the firm's location in the productivity growth distribution. Looking at the median firms, there is a rate of return to R&D around 20 percent in the MME industry, around 10 percent in the EOE industry, and around 21 percent in the MTE industry. The firms in the upper part of the distribution have a higher private rate of return, which implies underinvestment. Fifth, the paper tries to find whether the chosen manufacturing industries engage too much or too little in R&D. Using Jones and Williams (1998) relation between social rate of return to R&D and productivity estimates, I find that optimal R&D investment for a median firm is at least around 1.3 to 2.5 times the actual spending in the MME and MTE industries, and at least around 0.7 to 1.3 in the EOE industry. The ratio between optimal and actual R&D spending is higher for firms located in the upper part of the productivity growth distribution: at least 2 to 4 times the actual spending in the MME and the MTE industries, and 1 to 2 times in the EOE industry.[9] My results also suggest that an estimate of average rate of return to R&D might give an under-evaluation of the actual investment.

In the reminder of this paper, Section 2 describes the data and presents an overview of three Swedish industries, and documents some changes in their structures. The dynamic modeling framework used to compute productivity is outlined in Section 3, while Section 4 discusses econometric implementation. Section 5 presents results of productivity estimation and rates of return to R&D. It also dis-

[9] Analyzing the Swedish multinational plants, Fors (1997) finds that around four-fifths of the value added is attributed to home R&D and R&D in foreign plants seems to not be used as input in home plants.

cusses the optimal R&D investment and identifies the factors behind productivity growth at the industry level. Section 6 summarizes and concludes the paper.

2 Overview of the Industries

This section provides an overview of the selected industries and helps motivate the empirical strategy. The empirical strategy was chosen based on the information provided by entries, exits, and R&D-to-sales ratios.

Data. The paper draws on a census of all Swedish manufacturing firms provided by Statistics Sweden, Financial Statistics(FS) and Regional Labor Statistics(RAMS). While FS contains annual information about firm input and output, RAMS contains annual information on employee education and wages. The panel data set covers the period from 1996-2002 belonging to Swedish Standard Industrial Classification (SNI) code 29 ("Manufacture of machinery and equipment"), codes 30-33 ("Manufacture of electrical and optical equipment"), and codes 34-35 ("Manufacture of transport equipment").[10] The unit of observation is a firm; over 99 percent of the firms are single-plant establishments. Appendix A gives more information about the data as well as variable definitions.

Table 1 presents characteristics of the chosen manufacturing industries. The MME industry is the largest, and MTE is the smallest. In all industries, the largest amount of R&D spending occurred after 2000. In 2000 and 2001 the Swedish economy had entered a cyclical downturn. The slowdown was partially explained by weaker international demand. Another impact on the Swedish economy during this period was the bursting of the IT bubble on the stock exchanges.

International companies like Atlas Copco (mining and construction equipment) and Tetra Laval (liquid food packaging and dairy equipment) dominate the MME industry. In 2002, the industry produced a value added of SEK 47.6 billion, employed 87,741 people in Sweden, and spent SEK 4.6 billion on R&D. The EOE industry is dominated by international companies like ABB (power and automation equipment) and Electrolux (appliances). In 2002, this industry produced a value added of SEK 30.3 billion, employed 86,156 people in Sweden and spent SEK 34.7 billion on R&D. The MTE industry is one of the most important manufacturing industries in Sweden. It includes cars, trucks and buses, aircraft, trains, and

[10]The SNI standard builds on the Statistical Classification of Economic Activities in the European Community (NACE). The SNI standard is maintained by Statistics Sweden (http://www.scb.se).

marine and aircraft engines. Volvo, Saab, and Scania dominate final vehicle assembly. The existence of a large number of subcontractors underscores the importance of the industry. In the past few years, the industry has undergone rapid restructuring. The Volvo trademark is used by two separate companies: Volvo Group, a manufacturer of construction and farm machinery as well as heavy trucks and Volvo Cars, a manufacturer of automobiles owned by Ford Motor Company since 1998. In 1989, General Motors (GM) acquired 50 percent of Saab Automobile AB, the second manufacturer of automobiles (Investor AB controlled 50 percent). GM acquired the remaining Saab shares in 2000, turning the company into a wholly-owned subsidiary. Subcontractors suffer from extensive restructuring as well since final vehicle makers tend to cut down on the number of suppliers when introducing new models. In 2002, the industry produced a value added of SEK 46.9 billion, employed 91,474 people in Sweden and spent SEK 24.2 billion on R&D. This industry was seriously affected by the global downturn in 2008. While a job in this industry was not long ago considered to be a secure position this changed in 2009.

Entry. Table 2 presents an analysis of the entrants in all three industries. Around 8 percent of the firms active in 2001 in the MME industry entered in 1973 or before, and accounted for 31 percent of the technical employment and 63 percent of the industry's R&D spending in 2001. Of the firms active in 2001, the proportion that entered after 1996 is constant around 3 percent. Their share of R&D spending is smaller than 1 percent after 1997. In the EOE industry, around 2 percent of the firms active in 2001 entered in the 1980s, and they account for 33 percent of the sales and 60 percent of R&D spending. The highest share of the industry's employment in 2001, 20 percent, is linked to firms that entered in 1997. These firms have 7 percent of the technical employment and around 1.5 percent of the industry's R&D spending in 2001. Around 15 percent of the MTE industry's R&D spending in 2001 cames from firms that entered in 1983 or earlier. The firms that entered after 1997 and that were still active in 2001 seem to not be R&D incubators since they have almost no R&D spending in 2001. They might be subsidiaries of the larger firms in this industry. In all three industries, the high share of 1996 entry firms that were active in 2001 is due to the sample selection prior to 1996. Most of the post-1996 entrants in the database are small firms, accounting for no more than 8 percent of all employment in 2001. The MTE industry is the only industry where the large share of R&D spending does not imply a large share of technical employment.

Exit. Table 3 provides information about the exit process. Exit seems to play an important role in the adjustment process after 1996. Around 29 percent of the firms in all industries that were active in 1997 did not survive until 2001. These firms spent about 20 percent of the 1997 R&D and produced about 30 percent of the 1997 output in the MME and the EOE industries. The lowest amount of R&D spent in 2000 by firms that did not survive until 2001 was in the MTE industry (1 percent of the 2000 R&D spending). Most likely, those firms are subcontractors of large firms.

R&D spending. Table 4 shows the evolution of R&D-to-sales ratios for firms with sales below and above the median, respectively. The scale effect (R&D-to-sales ratios) analysis gives us information about the advantages of the industry newcomers. In all three industries, firms that are larger than the median (based on sales) tend to spend a higher share of sales on R&D than those that are smaller than the median, except for in 2001, when the opposite occurred. The EOE and the MTE industries differ largely in spending. In the MTE industry, the larger-than-median firms spent more than double the proportion of sales on R&D than the smaller-than-median ones. In the EOE industry, firms spent more than double the proportion of sales on R&D than in the MME industry.

What does high R&D spending yield in the three Swedish industries? Spending more does not necessarily help, while spending too little will hurt. My data emphasize that R&D budget levels vary substantially, even within sub-industries. There is not one specific approach to spending money on innovation development, but there are some successful stories in the discussed industries. The aim of the paper is to investigate whether there exists a statistical relation between R&D spending and future productivity at the industry level.

3 Modeling Framework

This section presents the structure of the behavioral model of firms. I begin by introducing the assumptions and structural properties of the stochastic dynamic model, and then derive theoretical results that justify the empirical work in the rest of the paper. I assume a stochastic dynamic single-agent model for the industry. A firm maximizes the expected discounted value of future net cash flows. Firm's state variables are productivity, ω, capital stock, k, and competitive pressure, θ.

The dynamic model is formulated by the following Bellman equation with the discount factor β ($\beta < 1$):[11]

(1)

$$V(\omega, k, \theta) = max\left\{\phi, \sup_{\psi', i}\left[\pi(\omega, k, \theta) - c(i, k) - z(\psi', \omega) + \beta\int V(\omega', k', \theta')P(d\omega'|\psi', \theta)\right]\right\},$$

where (ω', k', θ') denotes the random next-period state, where the probabilities associated with the next-period state are conditioned on the starting state (ω, k, θ) and choosing action (ψ', i); $z(\psi', \omega)$ is the R&D spending function; $c(i, k)$ is the cost of physical capital; and i is the investment choice of the firm.

The firm makes a discrete decision whether to exit or stay in business after observing its state variables at the beginning of each period. If it exits, the firm receives a termination value, ϕ. If the firm stays in business, it earns the net profit $r(\tilde{\psi}, \tilde{i}, \omega, k, \theta) = \pi(\omega, k, \theta) - c(i, k) - z(\psi', \omega)$ in state (ω, k, θ) when action $(\tilde{\psi}, \tilde{i})$ is selected. The action represents the choice of the next period's productivity through R&D spending, ψ', and the decision to invest in capital, i.

I assume that the profit function, $\pi(\omega, k, \theta)$, is bounded from above; non-decreasing in ω and k; strict supermodular in (ω, k) and (ω, θ); and continuously differentiable. A rise in competitive pressure truncates the distribution of profits, i.e., low profitable firms exit and surviving firms increase their marginal profits. The firm adapts to increased competitive pressure by raising its productivity. The cost of physical capital $c(i, k)$ is bounded from below; non-decreasing in i and decreasing in k; submodular; and continuously differentiable. The R&D spending function $z(\psi', \omega)$ is non-negative, non-decreasing in ψ' and decreasing in ω; submodular; and strictly submodular on the set $\{(\psi', \omega, \theta)|z(\psi', \omega) > 0\}$.

Investment in capital has a deterministic effect on future capital stock. Spending on R&D influences future productivity stochastically. Both investments depend on competitive pressure, θ. In each period, the firm chooses how much to invest in capital stock (and indirectly in the next period's capital stock), the quantity of intermediate inputs, labor, and distribution of the next period's productivity through its R&D spending. The accumulation equation for capital is given by

$$k' = (1 - \delta)k + i,$$

[11] See Ericson and Pakes (1995).

where k' denotes the next period's capital stock; δ is the rate of capital depreciation; and i is the investment choice of the firm at the beginning of the current period that enters in capital stock at the end of the current period.

The firm invests in R&D to improve its productivity in the future years, yet the outcomes of the research process are uncertain. The distribution of future productivity ω' conditional on information at time t depends on actual productivity, ω; R&D spending, z; physical investment in capital, i; and competitive pressure, θ. R&D spending and current productivity affect the distribution of future productivity only through a single index, $\psi' = (\omega, z)$ (Buettner, 2004). For simplicity we introduce a single index, $\psi' = (\omega, z)$, which implies that both productivity and R&D spending affect the distribution for ω' only through ψ'. The productivity process $\{\omega\}$ is a controlled first order Markov process and its primitives are given by the family of conditional distributions,

$$\mathbb{P} = \{P(\cdot|\psi', \theta, i), (\psi', \theta, i) \in \Psi \times \Theta \times \mathbb{R}_+ \subset \mathbb{R}^3\}$$

The family $\mathbb{P}$ is assumed be stochastically increasing in i for each value (ψ', θ) (increases in investment lead to better, in a stochastic dominance sense, distribution for future efficiency), stochastically increasing in ψ' for each given (θ, i) (conditional on i, the higher the choice ψ', the better the distribution of tomorrow's ω). It is also assumed to be stochastically increasing in θ for each given (ψ', i) (conditional on i and ψ', the higher pressure θ the better the distribution of tomorrow's ω), and continuous in the sense that when integrated against a continuous bounded function of ω', it produces a continuous bounded function of i, θ, and ψ'.

The return to R&D is uncertain, and the probability distribution over future productivity is parametrized by competitive pressure, θ. Competitive pressure, θ, indexes the *sensitivity* of the probability distribution to future distribution choice ψ': higher values of θ correspond to probability distributions where future distribution choice is more effective at shifting probability weights towards high realizations of productivity.

The optimal policies of exit, investment, and choice distribution of future productivity are $\{\tilde{\chi}(\omega, k, \theta),\ \tilde{i}(\omega, k, \theta),\ \tilde{\psi}(\omega, k, \theta)\}$. Solving the dynamic model, we obtain the following optimal policy functions:

$$(2) \quad \text{Exit rule:} \quad \chi' = \tilde{\chi}(\omega, k, \theta) = \begin{cases} 1 & \text{(continue) if} \quad \omega \geq \underline{\omega}(k, \theta) \\ 0 & \text{(exit) otherwise} \end{cases}$$

$$(3) \quad \text{Physical investment choice:} \quad i = \tilde{i}(\omega, k, \theta)$$

$$(4) \quad \text{Distribution choice:} \quad \psi' = \tilde{\psi}(\omega, k, \theta)$$

The function $\underline{\omega}(k, \theta)$ denotes the threshold productivity. For each capital stock, k, and competition pressure, θ, there exists an exit threshold productivity: if the value of productivity is below $\underline{\omega}(k, \theta)$, then the firm exits; otherwise it stays in business.

Competitive pressure affects the investment demand function and R&D spending. Pakes (1994) and Buettner (2004) prove the monotonicity for physical investment function in a model that does not allow for the effect of competitive pressure. This present paper takes the next step and demonstrates that the optimal physical investment choice is non-decreasing in choice of distribution, capital stock, and competitive pressure.

***Lemma* 1** *The value function $V(\omega, k, \theta)$ is bounded above, non-decreasing in productivity ω and capital k, supermodular in (ω, k) and (ω, θ), and unique.*

Proof: see appendix B.

Lemma* 2** *The optimal* ***physical investment choice *conditional on ψ', k, and θ*

$$\tilde{i}(\psi', k, \theta) = arg \sup_{i} \left[-c(i, k) + \beta \int V(\omega', k', \theta') P(d\omega' | \psi', \theta) \right]$$

is non-decreasing in ψ', k, and θ.

Proof: see appendix B.

Lemma* 3** *The policy function for the* ***choice of distribution

$$\tilde{\psi}(\omega, k, \theta) = arg \sup_{\psi'} \left[\pi(\omega, k, \theta) - c(\tilde{i}(\psi', k, \theta), k) - z(\psi', \omega) + \beta \int V(\omega', k', \theta') P(d\omega' | \psi', \theta) \right]$$

is non-decreasing in ω and strictly non-decreasing in ω on the sets

$$\left\{ (\omega, k, \theta) | z(\tilde{\psi}'(\omega, k, \theta), \omega) > 0 \right\} \cup \{ (\omega, k, \theta) | \pi(\omega, k, \theta) \quad \textit{is supermodular in} \quad (\omega, \theta) \} .$$

Proof: see appendix B.

Theorem* 1** *The policy function for the* ***investment choice $\tilde{i}(\omega, k, \theta) = \tilde{i}(\tilde{\psi}(\omega, k, \theta), k, \theta)$ *is non-decreasing in* ω *and strictly non-decreasing in* ω *on the sets*

$$\left\{(\omega, k, \theta)|\tilde{i}(\omega, k, \theta) > 0 \wedge z(\tilde{\psi}(\omega, k, \theta), \omega) > 0\right\} \cup$$
$$\{(\omega, k, \theta)|\pi(\omega, k, \theta) \quad \textit{is supermodular in} \quad (\omega, \theta)\}.$$

Proof: see appendix B.

The results from Theorem 1 suggest that the data with zero physical investment can be used when controlling for competitive pressure. Muendler (2005) finds the same result, but he uses a particular dynamic framework with a quadratic adjustment cost including fixed adjustment cost, but without R&D data. My theoretical results indicate that the productivity function is strictly non-decreasing when competitive pressure increases and the firm invests in R&D. Syverson (2004a) argues that demand-side features also play a role in creating the observed productivity variation. Investigating the effect of spatial substitutability on productivity distribution in the US cement industry, he finds that increases in substitutability truncate the productivity distribution from below. This implies a higher minimum, average productivity levels, and less productivity dispersion. Increasing product substitutability can be seen as in an increase in competitive pressure.

Endogenous productivity and competition. This study extends the OP framework by endogenizing the productivity process (ABBP; and Doraszelski and Jaumandreu, 2009). I propose an extension of previous estimators, including the effect of competitive pressure on R&D spending and on physical investment. While ABBP and Doraszelski and Jaumandreu (2009) discuss endogeneity of the productivity process, their proposed estimators omit the link between productivity and competitive pressure. The present paper relates to the vast literature on how competition affects productivity, emphasizing both positive and negative effects theoretically, but often positive effects empirically. Recent theoretical contributions are Nickell (1996), Schmidt (1997), Boone (2000), Melitz (2003), and Raith (2003); whereas recent empirical contributions include Porter (1990), MacDonald (1994), Nickell (1996), Blundell et al. (1999), Sivadasan (2004), Syverson (2004a), and Aghion et al. (2009).

4 Productivity estimation

This section discusses the estimation of a value-added generating function including competitive pressure when the strict monotonicity of the optimal investment or intermediate inputs choice is used to recover the parameters of this function (Olley and Pakes, 1996).

Value-added generating function. I assume a Cobb Douglas production technology:

$$Q_j = A_j K_j^{\beta_k} L_j^{\beta_l}, \tag{5}$$

where Q_j is physical output, K_j is capital stock, and L_j is labor. The variable A_j represents the Hicksian neutral efficiency level of firm j, and it is not observed by the econometrician. The physical output Q_{jt} is not observed and is usually replaced by deflated value-added or sales using an industry price deflator. Taking the natural logs in expression (5) and indexing my variables by time t yield

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \varepsilon_{jt}, \tag{6}$$

where lowercase symbols represent natural logs of variables and $\ln A_{jt} = \beta_0 + \varepsilon_{jt}$, and y_{jt} represents the deflated value-added. The coefficient β_0 is the mean efficiency level across firms, and ε_{jt} is the deviation from that mean for firm j in period t. The unobserved ε_{jt} is divided into two components: ω_{jt} and η_{jt}. The unobservables that are neither observed nor predictable by the firm before its input and exit decisions at time t are represented by η_{jt}. The component ω_{jt} is observed by the firm when it chooses inputs or makes exit decisions. It represents *unobserved productivity*, and the endogeneity problems are consolidated into it and not into η_{jt}. The component η_{jt} represents either a serially uncorrelated additional productivity shock or a measurement error that can be serially correlated. Output, input factors, productivity, and error terms are time and firm specific. Value-added generating function coefficients are constant across time and firms.

Ackerberg et al. (2007) discuss various approaches that can be used to solve the bias problem in estimation of value-added generating function: fixed effects, or the Blundell and Bond (2000) instrumental variable approach, and the control function approach used in the OP framework. The OP estimation framework solves the problem of firm-specific time-varying unobserved productivity in the estimation of the production function.

Marschak and Andrew (1944) point out that the endogeneity of input choices might cause problems in estimation of the value-added generating function (6). On the one hand, highly productive firms invest more in physical capital, and the future capital stock is positively correlated with ω_{jt}. On the other hand, highly productive firms have higher employment conditional on capital because they have a higher marginal product of labor in (6). Selection of firms through exit is another source of bias. A firm optimally decides to exit when its productivity is less than its exit threshold, which is a function of capital stock and competitive pressure. The exit threshold is decreasing in capital because firm's profit is strictly increasing in capital. Firms with large capital stock might operate even if they are not productive. It follows that the lower bound of the range of productivity realizations for surviving firms in the data is decreasing in capital. Therefore, average productivity among survivors is decreasing in the capital stock leading to a downward bias in the capital coefficient. Another source of bias is *omitted price variable bias* (Klette and Griliches, 1996). If the firm has some pricing power, then the estimates of (β_k, β_l) will be biased since the amount of inputs used might be correlated with the price a firm charges. First, firm-level price deviation from the industry-wide price is captured in the error term. If this price variation is correlated with the inputs, the estimated coefficients will be biased. Intermediate inputs and labor are negatively correlated with the unobserved price, yielding a downward bias in intermediate inputs and labor coefficients. Omitted price bias works in a direction opposite that of a simultaneity bias, making any prior on the direction of the bias difficult. This paper compares estimators based on different identification methods. I do not control explicitly for omitted price bias. To control for unobserved prices is straightforward by including as simple demand system (Klette and Griliches, 1996; De Loecker, 2009; Melitz, 2000; Maican and Orth, 2009; and Foster et al., 2008). In the empirical section, the paper controls for this bias in an indirect way by accounting for competitive pressure.

Timing assumptions. ABBP provide a detailed discussion about the assumptions needed to estimate a production function using the OP framework (control function approach). Three types of assumptions are important in this approach. First, there is an assumption that refers to the points in time when inputs are chosen by the firm relative to when they are used to generate value-added. Second, there is a scalar assumption that limits the dimensionality of the econometric unobservables that impact firm behavior. The third assumption is a strict monotonicity on the investment demand or on one of the intermediate inputs choice demand-investment (intermediate inputs choice) is strictly monotonic in the scalar unobservable for a firm whose investment (intermediate inputs choice) is strictly positive.[12]

At the beginning of each period t, the firm observes its state variables: productivity state, ω_{jt}; the capital stock, k_{jt}; and competitive pressure, θ_{jt}. Then it decides whether it to stay in business or exit. If it stays in business, it then decides the levels of investment in capital, intermediate inputs, how much of the variable factor labor to employ, and R&D spending given competitive pressure, θ_{jt}. The shock η_{jt} is realized after those choices are made. Thus, labor l_{jt} responds to the productivity ω_{jt}, but is uncorrelated with the error term η_{jt}. The physical investment decision in period t is made in period $t-1$ based on the information available, i.e., the productivity ω_{jt-1} and the values of the competitive pressure θ_{jt-1}.[13] In other words, actual capital, k_{jt}, is not affected by current productivity shocks, ξ_{jt}. In addition, η_{jt} is uncorrelated with k_{jt} and with previous η's.

Identification. Exploiting the monotonicity property of the investment function, unobserved productivity is a function of the current investment, i_{jt}, actual capital stock, k_{jt}, and competitive pressure, θ_{jt}:

$$\omega_{jt} = \tilde{\omega}_t(i_{jt}, k_{jt}, \theta_{jt}), \tag{7}$$

where the functional form $\tilde{\omega}_t(\cdot)$ is unknown, i.e., it depends in a complex way on all the primitives of the structural model. If the investment demand function is not invertible in productivity, then another way to back out productivity is from the competitive pressure function. Competitive pressure faced by a firm in the market is a function of its productivity, investment, and capital stock, i.e., $\theta_{jt} = \tilde{\theta}_{jt}(\omega_{jt}, k_{jt}, i_{jt})$. Thus, productivity is given by $\omega_{jt} = \tilde{\theta}_t^{-1}(i_{jt}, k_{jt}, \theta_{jt})$. To avoid the collinearity problems discussed in Ackerberg et al. (2006) (ACF), I assume that labor has dynamic implications (part of state space).[14] Thus, labor l_{jt} is also an unknown function of the state variables and the proxy variable (investment and/or

[12]While OP assumes strict monotonicity of the investment demand function, Levinsohn and Petrin (2003) assume strict monotonicity of intermediate inputs choice demand.

[13]Levinsohn and Petrin (2003) present a detailed discussion on the timing of data collection and of the actual investment decisions. Those details are not known in my case, but the investment decision affects the proxy's implementation. Current investment is ordered before the productivity shock in period t is known.

[14]This assumption can be tested, however.

competition in this case):

$$l_{jt} = \tilde{l}_t(\omega_{jt}, k_{jt}, \theta_{jt}) = h_t(i_{jt}, k_{jt}, \theta_{jt}). \tag{8}$$

Rewriting the value-added generating function (6) yields:

$$y_{jt} = \phi_t(i_{jt}, k_{jt}, \theta_{jt}) + \eta_{jt}, \tag{9}$$

where $\phi_t(i_{jt}, k_{jt}, \theta_{jt}) \equiv \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + \tilde{\omega}_t(i_{jt}, k_{jt}, \theta_{jt})$. The function $\phi_t(\cdot)$ combines all the dynamic variables (labor and capital), investment, and competitive pressure. An estimate of the unknown function $\phi_t(\cdot)$, denoted $\tilde{\phi}_t(\cdot)$, can be obtained from equation (9). Since labor and capital have dynamic implications, they cannot be estimated in the first stage (Robinson, 1988). The coefficients β_l and β_k are estimated in the second stage. The present paper assumes that productivity ω_{jt} follows a first-order endogenous Markov process, and that capital does not immediately respond to the innovation (shocks) in productivity, ξ_{jt}. The innovation in productivity over last period's expectation is given by $\xi_{jt} = \omega_{jt} - E[\omega_{jt}|\psi_{jt}, \theta_{jt-1}]$, where the index $\psi_{jt} = (\omega_{jt-1}, r_{jt-1})$ implies that the R&D investment and current productivity affect the distribution of future productivity ω_{jt} only through ψ_{jt}. For any value of β_k and β_l, the conditional expectation $E[\omega_{jt}|\psi_{jt}, \theta_{jt-1}]$ can be computed.

Identification of β_l and β_k depends on whether self-selection of firms through exit is a concern and whether there exists R&D investment data. Since productivity follows a Markov process, the value-added generating function can be written as

$$y_{jt} = \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + E[\omega_{jt}|\psi_{jt}, \chi_{jt} = 1, \theta_{jt-1}] + \xi_{jt} + \eta_{jt}. \tag{10}$$

By assumption, the choice distribution ψ_{jt} in $t-1$ is sufficient to characterize the distribution of ω_{jt} given the competitive pressure θ_{jt-1}.

The expected productivity conditional on survival and firms' information set at $t-1$ is an unknown function. However, it can be estimated by a non-parametric approach. The present paper presents the models where self-selection of firms through exit is an issue. In this case, the expectation of productivity conditional on past information and survival becomes

$$\begin{aligned} E[\omega_{jt}|\psi_{jt},\chi_{jt}=1,\theta_{jt-1}] &= \frac{\int_{\omega_j\geq\underline{\omega}_{jt}}\omega_j P(d\omega_j|\psi_{jt},\theta_{jt-1})}{\int_{\omega_j\geq\underline{\omega}_{jt}}P(d\omega_j|\psi_{jt},\theta_{jt-1})} \\ &= \left[Pr(\chi_{jt}=1|\underline{\omega}_{jt},\psi_{jt},\theta_{jt-1})\right]^{-1}\cdot\int_{\omega_j\geq\underline{\omega}_{jt}}\omega_j P(d\omega_j|\psi_{jt},\theta_{jt-1}) \\ &= g(\psi_{jt},\underline{\omega}_{jt},\theta_{jt-1})-\beta_0. \end{aligned}$$

The bias term $g(\psi_{jt},\underline{\omega}_{jt},\theta_{jt-1})$ is a function of state variables because $\psi_{jt} = \tilde{\psi}(\omega_{jt-1},k_{jt-1},\theta_{jt-1})$ and $\underline{\omega}_{jt}(k_{jt}(k_{jt-1}),\theta_{jt})$. To control for the impact of the unobservable on selection, we need a measure of productivity ω_{jt} that makes the firm indifferent between continuing and selling off. In a model without R&D data, an estimate of the survival probability, which is a proxy for the threshold $\underline{\omega}_t$, can be obtained as follows:

$$\begin{aligned} Pr(\chi_{jt}=1|\underline{\omega}_{jt},\mathcal{F}_{jt-1}) = &\ Pr(\chi_{jt}(\omega_{jt},k_{jt},\theta_{jt})=1|\underline{\omega}_t(k_{jt},\theta_{jt}) \\ &\ ,\tilde{\psi}_t(\omega_{jt-1},k_{jt-1},\theta_{jt-1}),\theta_{jt}) \\ = &\ \tilde{pr}_{jt-1}(k_{jt},k_{jt-1},\theta_{jt},\theta_{jt-1})\equiv Pr_{jt}. \end{aligned}$$

I obtain estimates for the survival probabilities, Pr_{jt}, by regressing survival in t on polynomial extension in k_{jt}, k_{jt-1}, l_{jt-1}, θ_{jt}, and θ_{jt-1}.[15] The probability of survival is strictly decreasing in the exit threshold, $\underline{\omega}_{jt}$. This implies that the threshold $\underline{\omega}_{jt}$ can be obtained inverting the survival probability Pr_{jt}: $\underline{\omega}_{jt}=f(\psi_{jt},Pr_{jt},\theta_{jt-1})$.

Buettner (2004) demonstrates the invertibility of the investment policy function in an extended OP framework where productivity evolves as an endogenous Markov process assuming that R&D investment of a function of k_{jt} and ω_{jt}, i.e., $z_{jt}=z_t(\omega_{jt},k_{jt})$. If the R&D spending is increasing in the capital stock k_{jt}, then k_{jt} can be obtained from the inversion of $z_t(\cdot)$ function. Thus, future capital stock k_{jt+1} can be inferred from k_{jt} and investment function, $i(\cdot)$, creating an identification problem. There might be empirical evidence that the invertibility of the investment function fails (Greenstreet, 2005). However, if this is the case, then it is more likely that the invertibility of the R&D spending function in k_{jt} does not hold. This paper shows that model can be identified when account for the competitive pressure faced by firms when making their investments. Doraszelski and Jaumandreu (2009) propose a model that endogenize the productivity by considering the effect of the R&D spending on productivity. Their one-step estimation model relies on the assumption that labor is a static variable, i.e., it has

[15] The future capital stock appears in the last expression because $\omega_{jt-1}=\tilde{\omega}(i_{jt-1},k_{jt-1},\theta_{jt-1})$.

no dynamic implications. This approach is problematic if there are training costs, strong union support, or more general large costs associated with hiring and/or laying off as in Sweden.

Since R&D investment takes place on a longer period of time, it is expected that labor has dynamic implications in intensive R&D industries. Based on one step estimation, the Doraszelski and Jaumandreu (2009) framework is more efficient than the two-step framework.[16] Doraszelski and Jaumandreu (2009) discuss the relative merits of the parametric and non-parametric approaches (used here).

Competitive advantage has important implications for innovation. Competition makes firms invest in reducing their costs, and hence improve their productivity. This aspect is ignored in both the Buettner and Dorazelski-Jaumandreu frameworks. The present paper fills this gap. It also puts forth additional evidence on the link between productivity and competition.

(i) Use data on R&D investment

The distribution choice ψ_{jt} is obtained by inverting the R&D investment function $z_{t-1}(\psi_{jt}, \omega_{jt-1}, \theta_{jt-1})$, i.e, $\psi_{jt} = \tilde{z}_{t-1}^{-1}(z_{jt-1}, \omega_{jt-1}, \theta_{jt-1})$. In this case, the second-stage estimation becomes

(11)

$$\begin{aligned} y_{jt} = \; & \beta_k k_{jt} + \beta_l l_{jt} \\ & + g(\tilde{z}_{t-1}^{-1}(z_{jt-1}, \omega_{jt-1}, \theta_{jt-1}), f(\tilde{z}_{t-1}^{-1}(z_{jt-1}, \omega_{jt-1}, \theta_{jt-1}), Pr_{jt}, \theta_{jt-1}), \theta_{jt-1}) \\ & + \xi_{jt} + \eta_{jt} \\ = \; & \beta_k k_{jt} + \beta_l l_{jt} + \tilde{g}(\hat{\phi}_{jt-1} - \beta_k k_{jt-1} - \beta_l l_{jt-1}, z_{jt-1}, Pr_{jt}, \theta_{jt-1}) + \xi_{jt} + \eta_{jt}, \end{aligned}$$

where $\tilde{g}(\cdot)$ is an unknown non-parametric function in $\hat{\phi}_{jt-1} - \beta_k k_{jt-1} - \beta_l l_{jt-1}$, P_{jt}, z_{jt-1}, and θ_{jt-1}. I assume that R&D investment is uncorrelated with the error term in (11). R&D investment and the error term are correlated if R&D investment is used in the construction of the value-added measure y_t.

(ii) No R&D investment data

Buettner (2004) suggests the following way to proxy for ψ_{jt} without having to use k_{jt-1}. None of the terms is a function of k_{jt-1} and ψ_{jt} in the Bellman equation (1). I use the threshold function combined with the fact that $\psi_t =$

[16] Wooldridge (2005) also suggests a one-step formulation of the OP methodology.

$\tilde{\psi}(\omega_{jt-1}, k_{jt-1}, \theta_{jt-1})$. This yields the following equation for the second stage:

$$
(12) \quad \begin{aligned} y_{jt} = & \ \beta_k k_{jt} + \beta_l l_{jt} + g(\tilde{\psi}_t(\omega_{jt-1}, k_{jt}, \theta_{jt-1}), \underline{\omega}_{jt}(k_{jt}, \theta_{jt}), \theta_{jt-1}) + \xi_{jt} + \eta_{jt} \\ = & \ \beta_k k_{jt} + \beta_l l_{jt} + \tilde{g}(\hat{\phi}_{jt-1} - \beta_k k_{jt-1} - \beta_l l_{jt-1}, k_{jt}, \theta_{jt}, \theta_{jt-1}) + \xi_{jt} + \eta_{jt}, \end{aligned}
$$

which is the same equation as for the non-selection case. This is my preferred model to estimate productivity in the empirical part of the paper. However, I also control if firms invest in R&D. The advantage is that there is no need to do the inversion in the R&D spending function. It is less probable that competitive pressure θ_{jt} impacts a firm's choice of l_{jt} but does not impact choice of investment at t. To estimate labor in the first stage, competitive pressure θ_{jt} must bring additional variance that is independent of ω_{jt} and k_{jt}. If competitive pressure θ_{jt} is serially correlated and unobserved, it is part of the state space, and we are not able to do the inversion. If θ_{jt} is serially correlated and observed, we are able to do the inversion, but labor cannot be estimated in the first stage because of perfect collinearity.

Estimation. The residuals $\xi_{jt}\hat{+}\eta_{jt}$ from equation (11) or (12) are functions of parameters $\boldsymbol{\beta}^* \equiv (\beta_l^*, \beta_k^*)$. To identify β_l and β_k, the following moment conditions can be used: $E[(\xi_{jt} + \eta_{jt})k_{jt}] = E[\xi_{jt}k_{jt}] = 0$, $E[(\xi_{jt} + \eta_{jt})k_{jt-1}] = E[\xi_{jt}k_{jt-1}] = 0$, and $E[(\xi_{jt} + \eta_{jt})l_{jt-1}] = E[\xi_{jt}l_{jt-1}] = 0$. The first two moment conditions help identify β_k. They imply that capital does not respond to the innovation in productivity ξ_{jt}. The third moment condition implies that previous labor must be uncorrelated with actual innovation in productivity. This is true because l_{jt-1} is apart of a firm's information set at $t-1$ and should be uncorrelated with ξ_{jt}. Thus, we get estimates of $\boldsymbol{\beta}^* = (\hat{\beta}_k, \hat{\beta}_l)$ minimizing the GMM criterion function:

$$
(13) \quad Q(\boldsymbol{\beta}^*) = \min_{\boldsymbol{\beta}^*} \sum_{h=1}^{\#\mathbf{w}} \left(\sum_j \sum_{t=T_{j_0}}^{T_{j_1}} \left(\xi_{jt}\hat{+}\eta_{jt}\right) (\boldsymbol{\beta}^*) \mathbf{w}_{jht} \right)^2,
$$

where j indexes firms; h indexes the instruments; T_{j_0} and T_{j_1} index the first and ante last period that firm j is observed; and $\mathbf{w}_{jt} = \{k_{jt}, k_{jt-1}, l_{jt-1}\}$.

5 Empirical Results

This section presents empirical results from estimation of value-added generating function, summary statistics for both level and growth, the estimated rate of return to R&D investment, optimal R&D spending, and productivity decomposition at the industry level.

Value-added generating function estimation. Table 5 reports the coefficient estimates of value-added generating function based on OLS and semiparametric estimators. The semiparametric estimators that treat productivity as an exogenous process are OP, LP, and ACF (ACF-i and ACF-m). The estimators that treat productivity as an endogenous process are B-1, B-2, and B-3, as proposed by Buettner (2004). In addition to these, the paper proposes EP-i and EP-all, estimators that eliminate the potential identification problems in Buettner's estimators. In total, there are ten estimators used for each industry. While the main aim of the paper is not to compare of the different semiparametric two-step estimators in detail, I discuss the main findings and their implications for productivity level and growth in three R&D intensive Swedish manufacturing industries.[17] Conditional on the estimator used, the study uses the following factors that generate value added: non-technical labor, technical labor, and capital. In the OP estimator, non-technical and technical labor are static, i.e., they are estimated in the first-stage, and productivity is recovered from an inverse investment demand function. In the LP estimator both labor variables are static but productivity is recovered from inverse demand function for materials. In the ACF estimators, non-technical and technical labor have dynamic implications and productivity is recovered from investment (ACF-i) or materials (ACF-m). I control for selection in the semiparametric estimators. The OLS and EP-all use the full sample. The three versions of the Buettner estimator (B-1, B-2, and B-3) that endogenize productivity are the following: B-1, - which uses capital stock as a proxy for R&D; B-2, which - uses previous R&D spending in the non-linear function that determines future productivity; and B-3, which controls for selection in addition to B-2. Value-added generating function estimation with R&D data might suffer from persistent unobserved shocks that vary within firms but resist treatment and cause bias (unobserved demand factors correlated over time) (Muendler, 2005).

The proposed estimators (EP-i and EP-all), which endogenize the productivity

[17] While I discuss only the robustness of semiparametric methods, Biesebroeck (2007) discusses the robustness of different methods used to measure productivity: index numbers, data envelopment analysis, stochastic frontiers, instrumental variables, and semiparametric estimation (OP).

process, capture the effects of R&D spending and competitive pressure on future productivity. In the EP-i estimator, labor has dynamic implications and productivity is recovered from the investment demand function, i.e., only the data with positive investment are used. The EP-all estimator is the EP-i estimator that uses all the data, i.e., including zero investment. In the theoretical part of the paper (Section 3), I show that identification is still possible when competitive pressure is included. The estimators ACF-i, B-1, and EP-i have in common that labor is estimated in the second stage. In contrast to ACF-i, the B-1 and EP-i estimators endogenize productivity allowing for R&D (in B-1 only through capital stock).

The degree of competitive pressure in a market is difficult to determine with precision, and cannot be captured by one variable (Geroski, 1990). The present paper uses four measures as a proxy for competitive pressure: (i) the number of small (fewer than 100 employees) firms, (ii) median R&D spending at the industry level, (iii) change in concentration (C4), and (iv) foreign demand, i.e., total sales to foreign firms. Foreign demand captures international demand and competition conditions as well as aggregate demand. All variables are computed using five-digit information. The estimation takes place at the two-digit industry level for the following industries: machinery and equipment (MME), electrical and optical equipment (EOE), and transport equipment (MTE). This implies that firms producing various two-digit goods use the same factor proportions, but goods are imperfect substitutes in consumption, which can lead to different investment behavior in physical capital and in R&D within an industry. Firm differences in exposure to domestic and international competition might lead to differences in investment behavior and in productivity response to international shocks. According to theory and previous empirical findings, the coefficients on variable inputs, such as labor, should be biased upwards in the OLS estimation. But the direction of the bias on the capital coefficient is ambiguous. The estimates of the coefficients on labor and capital using semiparametric estimates move in a direction that points to successful elimination of simultaneity and selection bias (Section 4). In what follows, I discuss the estimates separately for each industry.

Panel A presents the estimates for the MME industry. When one of the two-step semiparametric estimators is used, the both labor coefficients (non-technical and technical) are lower than the OLS ones. The lowest value for non-technical labor (0.410) is obtained when productivity is endogenous and we account for competitive pressure (the EP-i estimator). Among the estimators that recover productivity from investment, EP-i also gives the lowest value for the technical labor coefficient (0.206). The low values for the coefficient of capital in OLS and the Buettner estimators (less than 0.100) indicates a possible selection (OLS) or identification problem in the Buettner estimator (Ackerberg et al., 2007; Doraszelski and Jaumandreu, 2009). The omission of controlling for aggregate demand shocks and competition in the market in the estimation is a possible explanation. The negative demand shocks and lack of competition imply a decrease in elasticity of capital, i.e., large firms stay in the market even if they are not productive; they do not face competition from new entrants due to the low demand. Accounting for selection and keeping productivity exogenous increases the capital coefficient value (e.g., 0.191 in OP). The largest capital coefficient (0.214) is obtained from the EP-i estimator, i.e., controlling for R&D spending and competitive pressure in the productivity process. There is a difference between a large low-productive firm that does not invest in R&D and one that does. Endogenizing productivity implies that productivity is not a simple first order Markov process, i.e., R&D spending might affect future productivity. R&D spending might have higher future productivity. Furthermore, comparing two incumbent firms with equal capital, the firm facing higher competitive pressure has higher productivity. Dropping observations depending on the used proxy implies sample selection; this can be observed from magnitude differences among coefficients (EP-all versus others).

Panel B in Table 5 presents the estimates for the EOE industry. The lowest value for the non-technical labor coefficient (0.442) is given by LP estimator; for technical labor (0.240) by the LP estimator; and for capital (0.110) by the B-2 and B-3 estimators. The largest value for the non-technical labor coefficient (0.545) is given by the OP estimator; for technical labor (0.307) by the OLS; and for capital (0.241) by the ACF-i estimator. There is an interesting story in the Buettner estimates, where labor has dynamic implication and productivity is recovered from investment. Controlling for R&D in the productivity process (B-2 and B-3) increases the coefficient of technical labor and decrease the coefficients of capital, i.e., an increase in R&D spending will increase the coefficient of technical labor and decreases the coefficient of capital and non-technical labor. Allowing labor to have dynamic implications, the labor coefficients decreases from 0.545 (OP) to 0.493 (ACF-i) and 0.469 (EP-all). The labor estimates in EP-all are close to the ACF-i estimates and the capital coefficient (0.204) is close to the OP estimate (0.209).

The value-added-generating function estimates for the MTE industry are presented in Panel C. The lowest value for the non-technical labor coefficient (0.389) is given by the EP-i estimator; for technical labor (0.165) by the LP estimator; and for capital (0.110) by the B-2 and B-3 estimators. The largest value for the non-technical labor coefficient (0.714) is given by the OLS estimator; for technical labor (0.259) by the B-2 and B-3; and for capital (0.170) by the ACF-i estimator.[18] If we compare ACF-i and EP-i estimates, by endogenizing productivity in the EP-i estimator, the labor coefficients decrease and the capital coefficient increases (0.133 in ACF-i and 0.170 in EP-i).

Summarizing, I find that selection plays an important role. Allowing labor to have dynamic implications is important when endogenizing the productivity process. Over 75 percent of the observations are dropped when only data with positive R&D spending is used (the B-2 and B-3 estimators). Using the B-1 estimator, where capital is used as a proxy for the choice distribution of productivity, does not improve the estimates for capital. In addition to R&D spending, other factors, which are not captured by the model, affect the distribution of productivity. The estimated capital coefficient drops drastically to unreasonable levels when lagged positive R&D spending is introduced to control for expected productivity in the Buettner (2004) specification. On the one hand, this might be due to an endogeneity problem with respect to R&D, i.e., if R&D data is used in the construction of the value-added measure.

The present paper estimates various specifications with the competitive pressure variables mentioned earlier; however, it presents only partial results. Accounting for competitive pressure gives better estimates for capital, i.e., the capital coefficient increases and the labor coefficients move in the direction suggested by theory and previous empirical findings. Presence in foreign markets exposes firms to international competition. Facing international competition makes them invest in the latest technologies. Hence , the observed increase in the capital coefficient is expected.

Summary statistics: firms' productivity level and growth. Giving the estimated coefficients of the value-added generating function, the paper analyzes the summary statistics for both productivity level and growth in order to point out the importance of each estimator. Table 6 shows summary statistics for estimated productivity levels and growth distributions at the firm level when investment is used as a proxy for productivity. The EP-i and EP-all estimators provide the largest productivity levels, i.e, accounting for R&D spending and competitive pressure

[18]The very large value of capital (0.694) from the B-1 estimator indicates an identification problem.

shifts productivity distribution to the right. The ACF-i estimator provides the smallest interquantile range (0.068) among all estimators in the MME industry, EP-i in the EOE industry, and OP and EP-all in the MTE industry (0.064).[19] All estimators indicate a productivity growth of the 75th percentile of firm around 13 percent in the MME industry; 15 percent in the EOE; and around 13 percent in the MTE industry. There is a negative productivity growth for the 25th percentile firms. The paper finds mixed results for median productivity growth: only ACF-i and EP-all indicate a positive growth in the MME industry, and only EP-i and EP-all in the EOE industry. All estimators show a positive median firm productivity growth in the MTE industry. On the one hand, those results should be interpreted with care since all statistics are calculated for the whole period from 1996 to 2002 and are influenced by the 2001 downturn. On the other hand, the findings emphasize that allowing for endogeneity in the productivity process has important implications for the firms located between the 25th and 75th percentiles, i.e., it corrects possible underevaluation of productivity growth for an exogenous productivity process.

Though early literature on R&D and productivity studied the average effect of R&D on productivity, my approach treats R&D subject to stochastic accumulation. This allows estimation of the entire conditional distribution of productivity realizations, and gives a more complete picture of the effect of R&D investment on productivity and links productivity with competition.

Effect of R&D spending on productivity growth. Using the estimated productivity, the study investigates the impact of R&D spending per value-added on the empirical distribution of productivity growth. Table 7 presents OLS and percentile regressions of productivity growth, defined as $\omega_{jt}-\omega_{jt-1}$, on R&D intensity (R&D spending/Value added) and competitive pressure (number of firms with fewer than 100 employees, change in industry concentration [C4], median/mean R&D spending at the five-digits industry level, and foreign demand):

$$(14) \quad \Delta\hat{\omega}_{jt} = \mu + r^P(R\&D/ValueAdded)_{jt-1} + CompetitivePressure_{t-1}\boldsymbol{\beta} + \epsilon_{jt},$$

where r^P is the private rate of return to R&D and the shocks ϵ_{jt} are i.i.d. The OLS regression estimates the mean effect of R&D intensity on productivity growth, while the quantile regression estimates the effect of the conditional distribution on

[19]Interquantile range is defined as the difference between the 75th percentile and the 25th percentile over the median.

different quantiles. The quantile regressions' reported standard errors are bootstrapped. I have to distinguish between the private return and the social return to R&D. In my case, I estimate the private return to R&D using firms' own shares as explanatory variables. The social return to R&D captures inter-firms technology spillovers by focusing on the industry level and alleviates measurement problems. The regressions are run on all firms since the productivity is constructed from the EP-all estimator, i.e, there is no need to control for censoring of the distribution through exit or through negative investments.

My findings, in Table 7, indicate a median rate of return to R&D of around 20 percent in the MME industry; of around 10 percent in the EOE industry; and about 21 percent in the MTE industry. I find 5 (the EOE industry) and 10 percentage point (the MME and MTE industries) higher return rates - for firms with productivity growth such that 75 percent of all productivity growth in the 75th percentile. The number of small firms has a positive impact on productivity growth in the MME and EOE industries. The magnitude of the effect on percentiles is the same for the MME industry and somewhat larger in the tails for the EOE industry. A positive change concentration has a negative impact on firms' productivity growth in the MME and MTE industries and the effect is larger in the higher percentiles.[20] The paper finds a positive effect of median/mean R&D spending on firms' productivity growth only at the median in the MME industry and at the mean in the EOE industry.[21] In addition, an increase in foreign demand has a positive impact on productivity growth only for firms in the higher percentiles (the MME and MTE industries). My results are in line with previous private rate of return findings based on U.S. data (Hall, 1995) and they are robust to the method used to estimate productivity (EP-i versus EP-all).[22]

Optimal R&D investment. Do manufacturing industries engage too much or too little in R&D? - The paper provides an estimate of how much private investment in research differs from optimal investment. High rates of return to R&D would suggest substantial underinvestment. Table 7 suggests that not accounting for competitive pressure might lead to an overestimated private rate of return to R&D (underinvestment), e.g., by about 4 percentage points in the MTE industry (median regression). This is important since the private rates of return

[20]The results remain valid when concentration level is used.

[21]Due to the numerical problems in estimation, mean of R&D spending is used in the estimation of productivity for the EOE and MTE industries.

[22]A detailed appendix that includes the estimates using different productivity methods is available from the author upon request.

are already overestimated due to the unobserved variable correlated over time (or other unobserved demand factors at the industry level). Jones and Williams (1998) emphasize that r^P represents an underestimate of the true rate of return to R&D with a maximum down-bias equal to the rate of output growth. Their argument is based on the following assumption: we allocate one unit of output from consumption to R&D today and then consume the proceeds tomorrow, i.e., we reduce the R&D tomorrow to have the subsequent stock of ideas unchanged. They define the true rate of return to R&D as the gain in consumption associated with this variation, and the optimal amount of research as the condition where the rate of return is equal to the real interest rate, r. Using a growth model, Jones and Williams (1998) show that actual rate of investment in R&D by the industry, s^{actual}, satisfies the equation $r^P = \lambda g_\omega / s^{actual}$, where g_ω is the productivity growth and λ is a parameter in the production function for new ideas and the presence of $0 < \lambda \leq 1$ may reflect duplication of effort in research process - the social marginal product of R&D may be less than the private marginal product (Jones and Williams, 1998 provide a fruitful discussion). The optimal rate of investment in R&D along a balanced growth path is $s^{optimal} = \lambda g_\omega (r - (1-\lambda) g_{output})$, where g_{output} is the output growth. Therefore, the ratio of optimal investment to actual investment in R&D is

$$(15) \quad \frac{s^{optimal}}{s^{actual}} = \hat{r}^P / (r - (1-\lambda) g_{output}).$$

Having the estimate of $\hat{r}^P$, we can compute a *lower bound* on this ratio. The denominator is no greater than the real rate of return for the economy. The yearly average real return on the stock market in Sweden was around 7.6 percent in 2000. Table 8 shows conservative estimates of the ratio $s^{optimal}/s^{actual}$ using the estimated private rates of return from the OLS and percentile regressions (Table 7). With an average rate of return of 7.6 percent, the figures indicate a ratio of about 2.5 for the MME industry, of 1.3 for the EOE industry, and of 4 for the MTE industry (using median estimates). If we double the private rates of return to 15 percent, the ratios are about 1.3 for the MME, 0.7 for the EOE industry (i.e., over-investment), and 1.4 for the MTE industry. Hence, the optimal share of resources to invest in R&D is estimated to be 2-4 times larger than the actual amount invested in the MME and MTE industries. The EOE industry is close to the optimal rate of investment. It is important to stress that those ratios are computed with the actual rates of return estimated for median firms, i.e., they have a productivity growth that is higher than 50 percent of all firms in the industry. Using the actual rate of return to R&D estimated for firms in higher productivity growth percentiles, the conservative estimates suggest that the optimal R&D spending is at least 2-4 times the actual spending in the MME and MTE industries, and 1-2 times in the EOE industry.

Productivity decomposition. To check the importance of productivity gains stemming from the reshuffling of resources from the less to the more efficient firms, I compute aggregate industry productivity measures for each year. The aggregate industry productivity, Ω_t, is a weighted average of firms' individual productivities, ω_{jt}, with an individual firm's market share, s_{jt}. Following Foster et al. (2001), the change in industry productivity from year t_0 to year t_1 can be written as

$$\begin{aligned}\Delta\Omega_{t_0,t_1} = \; & \textstyle\sum_{j\in C_{t_0,t_1}} s_{jt_0}\Delta\omega_{jt_0,t_1} + \sum_{j\in C_{t_0,t_1}} \Delta s_{jt_0,t_1}(\omega_{jt_0} - \Omega_{t_0}) \\ & + \textstyle\sum_{j\in C_{t_0,t_1}} \Delta s_{jt_0,t_1}\Delta\omega_{jt_0,t_1} + \sum_{j\in E_{t_0,t_1}} s_{jt_1}(\omega_{jt_1} - \Omega_{t_0}) \\ & - \textstyle\sum_{j\in X_{mt_0,t_1}} s_{jt_0}(\omega_{jt_0} - \Omega_{t_0})\end{aligned} \tag{16}$$

where Δ is the difference operator ($\Delta\Omega_{t_0,t_1} = \Omega_{t_1} - \Omega_{t_0}$); C_{t_0,t_1} is the set of continuing firms, i.e., operating both in t_0 and t_1; E_{t_0,t_1} is the set of entering firms, i.e., that operated in t_1 but not in t_0; and X_{t_0,t_1} is the set of exiting firms, i.e., that operated in t_0 but not in t_1. The decomposition (16) consists of five terms. The first term (*Within*) is the increase in productivity when the continuing firms increase their productivity at initial market share. The second term (*Between*) is the increase in productivity when continuing firms with above-average productivity expand their market shares relative to firms with below-average productivity. The third term (*Cross*) captures the increase in productivity when continuing firms increase their market shares, while the fourth and fifth terms (*Entry* and *Exit*) are productivity increases due to entry and exit, respectively.[23] [24]

Table 9 shows the results of the productivity decomposition for the three in-

[23]Decomposition of productivity is based on entry and exit defined by organization number (FS-RAMS database).

[24]Another decomposition is proposed by Olley and Pakes (1996), where the weighted aggregate measure Ω_t is decomposed into two parts: the unweighted aggregate productivity measure and the total covariance between a firm's share of the industry output and its productivity:

$$\Omega_t = \sum_j s_{jt}\omega_{jt} = \overline{\omega}_{jt} + \sum_j (s_{jt} - \overline{s}_t)(\omega_{jt} - \overline{\omega}_t),$$

where the bar over a variable denotes a mean of all firms in a given year. Melitz and Polanec (2009) propose a dynamic version of OP decomposition and discuss possible bias contribution of surviving, entering, and exiting firms in widely-used decomposition methods.

dustries 1996-2000 and 1996-2002 using Foster et al. (2001). I consider the decomposition over these two periods to control for the possible effect of the bursting of the dot-com bubble on productivity growth. From 1996 to 2002, the aggregate productivity gains range from around 8 percent in the MME industry to around 22 percent in the EOE and MTE industries. The aggregate productivity growth from 1996 to 2000 is around 4 percent in the MME industry, around 59 percent in the EOE industry, and around 47 percent in the MTE industry. These results might emphasize a possible negative impact of the bursting of the dot-com bubble on productivity in the EOE industry and the MTE industries in 2001-2002. During this period, productivity growth was reduced to half in the EOE and MTE industries. Almost all productivity growth in the MME industry comes from firms that increased both productivity and market share. Net entry had a contribution of around 4 percent, mostly driven by exit (EP-all). The positive contribution of net entry compensates the negative *Within* and *Between* terms. The productivity growth in EOE was driven by continuing firms that had increased both productivity and market shares (*Cross*) and by continuing firms that had increased their productivity at their initial market shares (*Within*). The latter ones have a positive contribution only in 1996-2000. While the entrants contributed around 8 percent to the productivity growth, their contribution was substantial after 2000. In the MTE industry, the productivity growth from 1996 to 2002 was by the continuing firms that increased their productivity (*Within* and *Cross*). However, both contribution channels to productivity growth shrunk proportionally due to the decrease in productivity growth after 2000.

6 Discussion and conclusions

This paper proposes a dynamic structural model to estimate productivity in intensive R&D industries where competitive pressure is a key factor for investment. The model, an extension of the two-step structural technique suggested by Olley and Pakes (1996), endogenizes productivity. In an industry where competitive pressure affects both firms' R&D spending and productivity, the true underlying model of firm dynamics should explicitly account for these factors. If this is not the case, then it is unclear whether the Olley and Pakes (1996) or the Buettner (2004) approach can be applied.

This paper explores how R&D spending and competitive pressure influence the stochastic evolution of productivity in the Swedish R&D intensive manufacturing industries: machinery and equipment, electrical and optical equipment, and transport equipment. The paper also uses different semiparametric estimators derived from the OP framework to measure productivity in the three Swedish manufacturing industries. Not accounting for competitive pressure when productivity evolves as an endogenous process results in an underestimation of productivity. This paper shows in a theoretical framework how competitive pressure and R&D spending affect firm dynamics productivity. Productivity is expressed as a function of capital, investment, and competitive pressure. The endogenous productivity choice model justifies the retention of observations with non-positive investment when competitive pressure is included.

The paper also provides an analysis of rates of return to R&D on different parts of the productivity growth distribution. The results show that by analyzing the average rates of return to R&D, the researcher might obtain upper bias estimates, which implies an underestimation of the actual investment for median firms. Furthermore, those rates are also overestimated if the researcher fails to control for competitive pressure in productivity growth regression. Using Swedish data from 1996-2002, I find evidence that R&D spending enhances performance in Swedish manufacturing industries - but the overall effect on R&D depends of actual firm productivity and market conditions (domestic and foreign). My results indicate that the optimal investment in R&D should be 2 to 4 times the actual investment (the machinery and equipment industry, and the transport and equipment industry). The actual R&D investment in the electrical and optical equipment industry is closer to the optimum for median firms, but not for firms in the upper part of the productivity growth distribution (75th percentile).

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Table 1: Characteristics of the data

Year	Firms	Sales	Value Added	Employment	Technical Employment	R&D Spending
A. Machinery and equipment industry						
1996	1053	136,343,571	44,739,164	93,847	14,089	5,047,750
1997	1083	133,722,006	45,996,676	92,422	13,844	4,517,149
1998	1093	138,645,778	45,965,565	92,880	14,203	4,309,608
1999	1118	141,833,765	45,870,843	92,752	13,918	4,907,777
2000	1101	147,492,842	46,241,629	90,805	14,763	5,238,998
2001	1080	149,811,427	46,423,050	88,544	15,271	7,793,836
2002	1052	153,673,625	47,627,956	87,741	15,967	4,589,227
B. Electrical and optical equipment industry						
1996	741	157,691,151	40,351,568	80,231	21,447	18,252,000
1997	798	176,798,204	52,169,050	86,082	22,038	22,658,616
1998	825	200,601,253	54,560,220	88,670	22,866	28,076,795
1999	827	232,935,044	56,349,046	91,548	22,213	33,557,319
2000	843	290,674,021	52,103,204	100,608	28,383	42,609,466
2001	843	233,316,414	24,521,650	112,650	28,925	41,988,748
2002	785	194,929,847	30,347,840	86,156	28,292	34,700,542
C. Transport equipment industry						
1996	328	179,072,921	36,994,328	85,445	13,025	5,362,125
1997	346	200,714,936	41,600,851	86,075	13,133	11,979,013
1998	345	221,813,950	50,986,649	89,018	14,216	4,511,031
1999	359	243,678,772	60,958,372	90,780	14,745	12,148,561
2000	368	265,993,715	62,874,146	93,229	15,643	12,975,308
2001	373	216,054,572	53,704,239	93,515	16,109	16,930,037
2002	369	215,549,473	46,973,965	91,474	17,205	24,164,467

NOTE: Firms have at least one technical employee (at least three years of undergraduate school) or made at least one R&D investment during 1996-2002. Sales, value-added, and R&D spending are measured in thousand 1996 SEK.

Table 2: Entrants active in 2001

Year of Entry	Number	Share of Number Active in 2001(%)	Share of 2001 Sales(%)	Share of 2001 Employment(%)	Share of 2001 Technical Employment(%)	Share of 2001 R&D(%)
A. Machinery and equipment industry: entrants active in 2001.						
1973	82	7.59	31.50	30.51	30.86	63.44
1983	19	1.76	6.69	5.01	5.55	7.82
1993	51	4.72	4.59	4.66	4.75	2.56
1996	396	36.67	6.30	8.18	6.68	0.87
1997	34	3.15	1.42	2.21	1.26	1.32
1998	32	2.96	1.07	1.38	1.00	0.37
1999	27	2.50	1.67	1.64	1.36	0.67
B. Electrical and optical equipment industry: entrants active in 2001.						
1973	33	3.91	7.25	10.12	8.20	1.84
1983	13	1.54	32.72	12.94	22.44	60.12
1993	41	4.86	0.73	1.27	0.74	0.00
1996	328	38.91	5.38	7.90	6.67	0.78
1997	45	5.34	9.63	20.69	7.08	1.35
1998	23	2.73	2.41	2.23	1.18	0.15
1999	30	3.56	0.94	1.64	0.81	0.02
C. Transport equipment industry: entrants active in 2001.						
1973	41	10.99	13.70	19.73	20.57	5.42
1983	7	1.88	10.75	7.94	7.04	14.95
1993	14	3.75	0.68	1.11	0.55	0.01
1996	98	26.27	4.44	6.71	3.46	0.74
1997	12	3.22	0.95	1.22	2.17	0.09
1998	11	2.95	0.25	0.58	0.27	0.00
1999	17	4.56	1.14	1.38	0.58	0.02

NOTE: The sample contains firms that had at least one technical employee or made at least one R&D investment during 1996-2002.

Table 3: Incumbents exiting by 2001

Activ in	Number	Share of Number Active in Base Year(%)	Share of Sales in Base Year(%)	Share of Employment in Base Year(%)	Share of Technical Employment in Base Year(%)	Share of R&D in Base Year(%)
A. Machinery and equipment industry: incumbents exiting by 2001.						
1997	311	28.72	28.74	17.33	19.62	19.50
1998	273	24.98	24.99	15.90	17.53	18.43
1999	213	19.05	19.06	11.87	12.39	12.35
2000	131	11.90	11.91	7.52	7.20	7.20
B. Electrical and optical equipment industry: incumbents exiting by 2001.						
1997	248	31.08	31.09	17.64	23.10	19.48
1998	229	27.76	27.76	16.56	21.44	18.74
1999	165	19.95	19.95	13.41	17.15	12.82
2000	100	11.86	11.86	8.33	10.14	10.48
C. Transport equipment industry: incumbents exiting by 2001.						
1997	97	28.03	28.06	11.33	18.85	12.92
1998	81	23.48	23.50	10.01	16.32	14.81
1999	62	17.27	17.28	9.53	15.32	14.43
2000	32	8.70	8.71	0.82	2.14	1.06

NOTE: The sample contains firms that had at least one technical employee or made at least one R&D investment during 1996-2002.

Table 4: Scale effects: R&D-to-sales ratio during 1996-2002

Year	Average R&D-to-sales Ratio by year(%)	Median R&D-to-sales Ratio for firms with sales below median sales(%)	Median R&D-to-sales Ratio for firms with sales above median sales(%)
A. Machinery and equipment industry			
1996	3.07	1.26	2.74
1997	3.49	2.01	2.51
1998	3.41	2.15	2.68
1999	3.66	2.17	2.72
2000	3.60	2.16	2.81
2001	4.19	2.57	2.54
2002	4.89	2.41	3.36
B. Electrical and optical equipment industry			
1996	6.83	3.46	6.24
1997	7.69	4.36	5.82
1998	7.19	3.05	7.17
1999	8.73	4.01	7.92
2000	18.35	3.73	6.40
2001	58.29	5.77	6.82
2002	14.57	5.44	8.01
C. Transport equipment industry			
1996	2.74	0.72	1.74
1997	3.37	1.00	3.93
1998	3.45	1.32	2.95
1999	3.73	1.32	3.31
2000	4.81	2.74	2.90
2001	5.37	1.83	5.02
2002	57.26	1.88	5.42

NOTE: The sample contains firms with a positive R&D investment.

Table 5: Estimates of value-added generating function parameters

A. Machinery and equipment industry										
Estimation						Buettner (2004) procedure			Endogenous productivity	
procedure	OLS	OP	LP-m	ACF-i	ACF-m	B-1	B-2	B-3	EP-i	EP-all
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Non-technical labor	0.693	0.678	0.592	0.675	0.680	0.649	0.626	0.626	0.410	0.498
Std. error	(0.008)	(0.013)	(0.035)	(0.024)	(0.016)	(0.012)	(0.032)	(0.056)	(0.010)	(0.005)
Technical labor	0.265	0.265	0.194	0.247	0.225	0.239	0.233	0.231	0.206	0.241
Std. error	(0.007)	(0.007)	(0.011)	(0.015)	(0.022)	(0.012)	(0.029)	(0.018)	(0.009)	(0.007)
Capital	0.099	0.191	0.179	0.145	0.139	0.072	0.051	0.025	0.214	0.179
Std. error	(0.005)	(0.010)	(0.036)	(0.045)	(0.032)	(0.032)	(0.029)	(0.008)	(0.022)	(0.029)
R&D spending	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Competitive pressure	No	No	No	No	No	No	No	No	Yes	Yes
# Obs. stage I	7,393	6,739	7,018	6,739	7,018	5,915	1,075	1,075	6,739	7,393
# Obs. stage II	-	4,795	5,350	4,795	5,350	4,361	774	774	4,795	5,915
B. Electrical and optical equipment industry										
Non-technical labor	0.535	0.545	0.442	0.493	0.445	0.544	0.531	0.531	0.528	0.469
Std. error	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.012)	(0.011)	(0.010)	(0.010)	(0.006)
Technical labor	0.307	0.296	0.240	0.283	0.251	0.263	0.287	0.287	0.288	0.280
Std. error	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.010)	(0.009)	(0.008)	(0.008)	(0.006)
Capital	0.184	0.209	0.183	0.241	0.166	0.134	0.125	0.110	0.199	0.204
Std. error	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.009)	(0.007)	(0.005)
R&D spending	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Competitive pressure	No	No	No	No	No	No	No	No	Yes	Yes
# Obs. stage I	5,344	4,880	5,040	4,880	5,040	4,880	720	720	4,880	5,344
# Obs. stage II	-	3,437	3,780	3,437	3,780	3,437	502	502	3,437	4,053
C. Transport equipment industry										
Non-technical labor	0.714	0.713	0.684	0.447	0.720	0.676	0.639	0.639	0.389	0.679
Std. error	(0.014)	(0.015)	(0.014)	(0.016)	(0.014)	(0.070)	(0.066)	(0.049)	(0.015)	(0.011)
Technical labor	0.193	0.192	0.165	0.192	0.180	0.173	0.258	0.259	0.190	0.205
Std. error	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.009)	(0.012)
Capital	0.136	0.156	0.142	0.133	0.115	0.694	0.098	0.098	0.170	0.137
Std. error	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.046)	(0.064)	(0.057)	(0.013)	(0.010)
R&D spending	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Competitive pressure	No	No	No	No	No	No	No	No	Yes	Yes
# Obs. stage I	2,409	2,189	2,214	2,189	2,214	2,189	389	389	2,189	2,409
# Obs. stage II	-	1,543	1,656	1,543	1,656	1,543	275	275	1,543	1,826

NOTE: The dependent variable is the log of value added. The models are as follows: OLS - ordinary least square, OP - the Olley and Pakes (1996) method; LP-m - the Levinsohn and Petrin (2003) method using intermediate inputs as proxy for productivity; ACF-i - the Ackerberg et al. (2006) method using investment as proxy for productivity; ACF-m - the Ackerberg et al. (2006) method using intermediate inputs as proxy for productivity; B-1 - the Buettner (2004) method that captures the effect of R&D via capital and control for selection; B-2 - the Buettner (2004) method that captures the effect of R&D, but that does not control for selection; B-3 - the Buettner (2004) method that captures the effect of R&D and controls for selection; EP-i - uses positive investment as proxy for productivity, captures the effects of R&D and competitive pressure on productivity process; EP-all - uses all data, captures the effects of R&D and competitive pressure on productivity process. The following measures are included to account for competitive pressure: number of firms with fewer than 100 employees, median R&D spending at the sub-industry level (five digits), change in concentration measure (c4), foreign demand - total sales to other foreign firms. All standard errors for semiparametric methods are bootsrapped using 50 replications.

Table 6: Summary statistics: productivity level and growth

A: Machinery and equipment industry									
	Productivity level					Productivity growth			
	Q25	Q50	Mean	Q75	IQM	Q25	Q50	Mean	Q75
OP	5.104	5.300	5.315	5.517	0.078	-0.137	-0.005	-0.012	0.124
ACF-i	5.542	5.730	5.738	5.936	0.068	-0.129	0.001	-0.004	0.128
EP-i	5.831	6.099	6.098	6.377	0.089	-0.132	-0.001	-0.008	0.128
EP-all	5.809	6.047	6.039	6.288	0.079	-0.135	0.002	-0.002	0.139
B: Electrical and optical equipment industry									
OP	5.356	5.571	5.568	5.802	0.080	-0.157	-0.001	-0.006	0.147
ACF-i	5.285	5.506	5.497	5.740	0.082	-0.160	-0.003	-0.008	0.146
EP-i	5.501	5.716	5.711	5.944	0.077	-0.155	0.001	-0.003	0.150
EP-all	5.640	5.867	5.864	6.121	0.081	-0.156	0.004	-0.004	0.157
C: Transport equipment industry									
OP	5.350	5.520	5.525	5.706	0.064	-0.118	0.006	0.011	0.130
ACF-i	6.271	6.592	6.584	6.909	0.096	-0.106	0.020	0.027	0.140
EP-i	6.276	6.628	6.622	6.968	0.104	-0.111	0.021	0.026	0.140
EP-all	5.608	5.792	5.784	5.984	0.064	-0.122	0.009	0.012	0.131

NOTE: Productivity levels are in logs. Productivity growth is defined as $log(\omega_{jt}) - log(\omega_{jt-1})$. IQM is standardized interquantile range, i.e., the difference between the quantile 75 and the quantile 25 over the median.

Table 7: Quantile regressions on the conditional distribution of productivity growth

A. Machinery and equipment industry								
Estimation		Quantile				Quantile		
procedure	OLS	0.25	0.50	0.75	OLS	0.25	0.50	0.75
Intercept	-0.009	-0.138	-0.002	-0.135	-0.930	-0.804	-0.748	-0.672
Std. error	(0.004)	(0.004)	(0.003)	(0.004)	(0.255)	(0.236)	(0.177)	(0.208)
R&D intensity$_{t-1}$	0.312	0.173	0.217	0.372	0.314	0.140	0.196	0.369
Std. error	(0.031)	(0.105)	(0.101)	(0.138)	(0.031)	(0.122)	(0.107)	(0.134)
No. of small firms $(< 100)_{t-1}$					0.0009	0.0007	0.0008	0.0008
Std. error					(0.0002)	(0.0002)	(0.0001)	(0.0002)
Change in $C4_{t-1}$					-0.114	-0.077	-0.076	-0.129
Std. error					(0.040)	(0.034)	(0.027)	(0.028)
Median R&D spending$_{t-1}$					0.00001	0.000	0.0001	0.0001
Std. error					(0.00001)	(0.0001)	(1e-6)	(0.001)
Foreign demand$_{t-1}$					3.335e-9	0.000	0.000	1e-8
Std. error					(1.945e-9)	(0.000)	(0.0001)	(1e-9)
#Obs.	5,692	5,692	5,692	5,692	5,692	5,692	5,692	5,692
B. Electrical and optical equipment industry								
Intercept	-0.008	-0.156	0.001	0.154	-0.116	-0.183	-0.231	-0.167
Std. error	(0.007)	(0.006)	(0.004)	(0.005)	(0.185)	(0.142)	(0.107)	(0.133)
R&D intensity$_{t-1}$	0.086	-0.025	0.102	0.159	0.087	0.140	0.102	0.159
Std. error	(0.015)	(0.155)	(0.031)	(0.050)	(0.015)	(0.161)	(0.020)	(0.081)
No. of small firms $(< 100)_{t-1}$					0.0002	5e-5	0.0003	0.0005
Std. error					(0.0002)	(0.0002)	(0.0001)	(0.0002)
Change in $C4_{t-1}$					-0.005	0.816	0.018	-0.017
Std. error					(0.060)	(0.053)	(0.037)	(0.047)
Mean R&D spending$_{t-1}$					5.254e-7	0.000	0.000	0.000
Std. error					(2.281e-7)	(0.0001)	(0.001)	(0.0001)
Foreign demand$_{t-1}$					-7.942e-9	0.000	0.000	0.000
Std. error					(2.927e-9)	(0.0001)	(0.0001)	(0.0001)
#Obs.	4,053	4,053	4,053	4,053	4,053	4,053	4,053	4.053
C. Transport equipment industry								
Intercept	0.004	-0.124	0.003	0.125	0.156	-0.079	0.223	0.501
Std. error	(0.008)	(0.007)	(0.005)	(0.007)	(0.284)	(0.258)	(0.200)	(0.226)
R&D intensity$_{t-1}$	0.259	0.150	0.241	0.333	0.261	0.148	0.208	0.313
Std. error	(0.041)	(0.011)	(0.135)	(0.074)	(0.042)	(0.023)	(0.140)	(0.040)
No. of small firms $(< 100)_{t-1}$					-0.0005	-0.0001	-0.0008	-0.001
Std. error					(0.001)	(0.0009)	(0.0007)	(0.0008)
Change in $C4_{t-1}$					-0.211	-0.160	-0.118	-0.172
Std. error					(0.081)	(0.074)	(0.052)	(0.059)
Mean R&D spending$_{t-1}$					-8.619e-8	0.000	0.000	0.000
Std. error					(1.485e-7)	(0.0001)	(0.001)	(0.0001)
Foreign demand$_{t-1}$					3.214e-10	0.000	0.000	1.e-9
Std. error					(1.068e-9)	(0.0001)	(0.0001)	(1e-10)
#Obs.	1,826	1,826	1,826	1,826	1,826	1,826	1,826	1.826

NOTE: The dependent variable is productivity growth. All standard errors are bootsrapped using 50 replications in quantile regressions.

Table 8: The ratio of optimal investment to actual investment in R&D

		Quantile		
	OLS	0.25	0.50	0.75
Machinery and equipment	2.09,4.13	0.93,1.84	1.30,2.58	2.46,4.85
Electrical and optical equipment	0.58,1.14	0.93,1.84	0.68,1.34	1.06,2.09
Transport equipment	1.74,3.43	0.98,1.94	1.38,2.73	2.08,4.11

NOTE: The figures -,- give the minimum and the maximum for the ratio of optimal investment to actual investment in R&D. The ratio, $s^{optimal}/s^{actual}$ is approximated by the ratio between the rate of return to R&D and the average real return on the stock market (7.6% is considered here). The minimum ratio is obtained when the average real return on the stock market doubles (15%).

Table 9: Decomposition of productivity growth, 1996 to 2000 and 1996 to 2002 (percent)

Period	Productivity measure	Overall industry growth	Within firms (1)	Between firms (2)	Cross firms (3)	Entry (4)	Exit (5)	Net Entry (4) - (5)
			Percentage of growth from					
A. Machinery and equipment industry								
1996-2000	Labor	11.27	2.80	-0.50	6.28	-0.18	-2.33	2.15
1996-2000	TFP-OP	7.10	-3.30	1.42	5.77	3.19	-0.01	3.20
1996-2000	TFP-ACF-i	6.60	-2.15	0.17	6.27	1.48	-0.83	2.31
1996-2000	TFP-EP-i	4.19	-2.84	-1.42	7.27	-1.18	-2.07	0.88
1996-2000	TFP-EP-all	4.19	-2.84	-1.42	7.27	-1.19	-2.07	0.88
1996-2002	Labor	14.51	3.86	-0.92	6.38	2.23	-2.96	5.18
1996-2002	TFP-OP	8.87	-2.38	0.55	5.25	6.89	1.47	5.42
1996-2002	TFP-ACF-i	8.58	-1.19	-0.39	5.84	4.89	0.57	4.32
1996-2002	TFP-EP-i	7.00	-2.47	-2.26	7.23	1.16	-3.33	4.49
1996-2002	TFP-EP-all	7.00	-2.47	-2.26	7.23	1.16	-3.33	4.49
B. Electrical and optical equipment industry								
1996-2000	Labor	60.91	30.41	8.10	23.29	-0.48	0.39	-0.88
1996-2000	TFP-OP	57.61	23.40	-0.69	27.44	3.28	-4.17	7.46
1996-2000	TFP-ACF-i	57.41	22.51	0.69	27.43	2.82	-3.95	6.78
1996-2000	TFP-EP-i	59.18	23.61	1.09	27.78	2.65	-3.98	6.63
1996-2000	TFP-EP-all	59.61	26.39	7.33	24.11	1.58	-0.20	1.78
1996-2002	Labor	19.86	2.24	-7.94	12.61	8.42	-4.53	12.96
1996-2002	TFP-OP	21.41	-1.12	0.52	9.91	9.20	-2.92	12.12
1996-2002	TFP-ACF-i	17.68	-1.42	-0.99	10.17	8.38	-1.54	9.92
1996-2002	TFP-EP-i	16.79	-0.92	-1.59	10.60	7.56	-1.14	8.71
1996-2002	TFP-EP-all	21.55	10.75	-6.71	5.19	8.25	-4.06	12.31
C. Transport equipment industry								
1996-2000	Labor	49.29	36.91	-1.57	13.91	1.22	1.19	0.03
1996-2000	TFP-OP	47.26	27.38	-6.40	23.00	7.12	-3.84	3.28
1996-2000	TFP-ACF-i	51.68	28.29	2.90	24.44	-0.03	4.32	-4.35
1996-2000	TFP-EP-i	52.27	28.06	4.06	24.91	-0.47	4.29	-4.76
1996-2000	TFP-EP-all	47.48	35.50	-3.91	13.43	4.73	2.28	2.45
1996-2002	Labor	25.00	14.35	-1.97	6.31	6.89	0.59	6.31
1996-2002	TFP-OP	25.42	13.02	-0.87	5.73	11.28	3.78	7.54
1996-2002	TFP-ACF-i	22.54	13.05	-1.73	7.43	0.16	-3.63	3.79
1996-2002	TFP-EP-i	21.81	12.78	-1.72	7.54	-1.35	-4.57	3.22
1996-2002	TFP-EP-all	22.66	11.87	-1.27	5.65	8.93	2.52	6.41

NOTE: The Foster,Haltiwanger, and Krizan's (2001) decomposition is used (Section 5). Labor productivity is defined as log of value added per employee. The shares of value added at the industry level are used as weights in the decomposition.

Appendix A: Data sources. I here describe the variables used. Value added is total shipments, adjusted for changes in inventories, minus the cost of materials. Real value added is constructed by deflating value added by a five-digit industry output deflater. The deflectors are taken from Statistics Sweden. The technical labor variable is the total number of employees with at least 3 years of technical school education. The non-technical labor defines the remaining employees. Data on the research and development variable stems from FS and covers all firms with at least one employee who works at least half-time in R&D activities. The FS is updated annually and it is compulsory for firms to reply. Firms must give an exact figure for R&D spending or answer in an interval scale. I deflated the R&D spending, sales, and investment by the consumer price index(CPI) from IMF-CDROM 2005. The capital measure is constructed using a perpetual inventory method, $k_{t+1}(1-\delta)k_t + i_t$. Since the capital data distinguishes between buildings and equipment, all calculations of the capital stock are done separately for buildings and equipment. As suggested by Hulten and Wykoff (1981) buildings are depreciated at a rate of 0.361 and equipment at 0.1179.

In order to construct capital series using the perpetual inventory method, I need an initial capital stock. Some of the firms are in FS since 1973. I set the initial capital stock to the first occurrence in FS. I define entry when the year of entry in FS is the same as the year of first data collection. FS contains all firms in different industries after 1996.

Appendix B. Properties of the value function. The Bellman equation can be rewritten in terms of the expected value of profits in the following period and the continuation thereafter

$$\begin{aligned}
&V(\omega,k,\theta) = max\{\phi, \pi(\omega,k,\theta) - c(\tilde{i}(\omega,k,\theta),k) - z(\tilde{\psi}(\omega,k,\theta),\omega)\\
&+\beta \textstyle\int \chi(\omega',k',\theta')\left[\pi(\omega',k',\theta') - c(\tilde{i}(\omega',k',\theta'),(1-\delta)k + \tilde{i}(\omega,k,\theta))\right.\\
&\left.-z(\tilde{\psi}(\omega',(1-\delta)k+\tilde{i}(\omega,k,\theta),\theta'),\omega',\theta')\right] P(d\omega'|\tilde{\psi}(\omega,k,\theta),\tilde{i}(\omega,k,\theta),\theta)\\
&+\beta\phi \textstyle\int [1-\chi(\omega',k',\theta')] + \beta^2 \int \chi(\omega",k",\theta")V(\omega",k",\theta")\\
&P(d\omega"|\tilde{\psi}(\omega',k',\theta'),\tilde{i}(\omega',k',\theta'),\theta')P(d\omega'|\tilde{\psi}(\omega,k,\theta),\tilde{i}(\omega,k,\theta),\theta).
\end{aligned} \tag{17}$$

We want to find a set of alternative programs that leave the last term in this expression unchanged. The distribution of $\omega"$ conditional on ω and each alternative policy is the same as the distribution of $\omega"$ conditional on ω and optimal policy. We select the optimal policy such that

$$
\begin{aligned}
&\textstyle\int_{\omega'} P(\omega" > \tilde{\omega}|\psi", i(\omega', k', \theta'), \theta') P(d\omega'|\psi', i(\omega, k, \theta), \theta) = \\
(18)\quad &\textstyle\int_{\omega'} P(\omega" > \tilde{\omega}|\psi" + \Delta(\psi", \omega', \theta', \epsilon), i(\omega', k', \theta') + \Delta(\psi", \omega', \theta', \epsilon), \theta') \cdot \\
&P(d\omega'|\psi' - \epsilon, i(\omega, k, \theta) - \epsilon, \theta),
\end{aligned}
$$

where ϵ and $\Delta(\cdot)$ are chosen such that $\Delta(\cdot, \epsilon) = 0$ at $\epsilon = 0$. The optimal policy produces a distribution of ω" conditional on ψ' as a convolution of $P(\cdot|\psi', i(\omega, k, \theta), \theta)$ and $P(\cdot|\psi", i(\omega', k', \theta'), \theta')$. This gives the same convoluted distribution by perturbing i and ψ' by ϵ and i' and ψ" by $\Delta(\psi", \omega', \theta', \epsilon)$.

Lemma 1 *The value function $V(\omega, k, \theta)$ is bounded, non-decreasing in ω and k, supermodular in (ω, θ) and (ω, k), and unique.*

Proof: The proof is a consequence of the Proposition 5 in Smith and McCardle (2002). I reformulate Smith and McCardle (2002)'s proposition in Proposition 1. All the properties in Lemma 1 are closed convex cone properties.

Definition **1** *P is a* ***closed convex cone property*** *(CCC) if the set of functions satisfying P forms a closed convex cone in the topology of pointwise convergence.*

Proposition **1 (Smith and McCardle, 2002)** *Let U be a set of functions on $\Omega \times K \times \Theta$ satisfying a CCC property P, and let P^* be a joint extension of P on $\Psi \times \mathbb{R}_+ \times \Theta$. If, for all t, (a) the net profit functions $r_t(\psi', i, \omega, k, \theta)$ satisfy P^* and (b) the transitions $\tilde{\psi}$ and $\tilde{i}$ satisfy P^* ($\succsim_U$), then each V_t satisfies P and $\lim_{t\to\infty} V_t$, if it exists, also satisfies P.*

The properties P and P^* are the following: P - $V(\omega, k, \theta)$ is bounded, increasing in ω and k, and supermodular in (ω, k) and (ω, θ); and P^* - for each $\tilde{\psi}(\omega, k, \theta)$ and $\tilde{i}(\omega, k, \theta)$, $r(\psi', i, \omega, k, \theta)$ is bounded, nondecreasing in ω and k, and supermodular in (ω, k) and (ω, θ).

The net profit function is bounded above because the profit function is bounded above. In addition, cost and R&D functions are nonnegative. The expected net present value of the future one period return is bounded above due to the fact that $\beta < 1$. In addition, ϕ puts a lower bound on the value function so that $V_t(\cdot)$ is bounded.

The net profit is a non-decreasing function in (ω, k), and is supermodular (Athey, 2000); this combination of properties is the P that we want to show that the value function $V(\cdot)$ satisfies. Each of these properties is a *single-point property*, and so is P. The joint extension P^* of P requires that P holds for each action $(\tilde{\psi}, \tilde{i})$. The net profit function satisfies P^* for each choice of action and therefore satisfies P^*. From Lemma 2 and Lemma 3, we have that the transitions $\tilde{\psi}$ and $\tilde{i}$ satisfy P^* ($\succsim_U$). Thus, each $V_t(\cdot)$ satisfies P and so does $\lim_{t\to\infty} V_t(\cdot)$.■

Lemma 2 *The optimal* ***physical investment choice*** *conditional on* (ψ', k, θ)

$$\tilde{i}(\psi', k, \theta) = arg \sup_i \left[-c(i,k) + \beta \int V(\omega', k', \theta') P(d\omega' | \psi', \theta) \right]$$

is non-decreasing in ψ', k, *and* θ.

Proof: The value function $V(\omega', k', \theta')$ is supermodular in (ω', k') and (ω', θ'). The integral $\int V(\omega', k', \theta')\ P(d\omega'|\psi', \theta)$ is supermodular in (ψ', θ) because $P(d\omega'|\psi', \theta)$ is stochastically non-decreasing in ψ' and θ (Athey, 2000). This implies that the optimal investment choice $\tilde{i}(\psi', k, \theta)$ is non-decreasing in capital k, non-decreasing in ψ' and θ. The function $-c(i, k)$ is supermodular implying that the objective function is supermodular.■

Lemma 3 *The policy function for the* ***choice of distribution***

$$\begin{aligned} \tilde{\psi}(\omega, k, \theta) = arg \sup\nolimits_{\psi'} \quad & \big[\pi(\omega, k, \theta) - c(\tilde{i}(\psi', k, \theta), k) - z(\psi', \omega) + \\ & \beta \textstyle\int V(\omega', k', \theta') P(d\omega'|\psi', \theta)\big] \end{aligned}$$

is non-decreasing in ω *and strictly non-decreasing in* ω *on the sets*

$$\left\{(\omega, k, \theta) | z(\tilde{\psi}'(\omega, k, \theta), \omega) > 0\right\} \cup \{(\omega, k, \theta) | \pi(\omega, k, \theta) \quad \text{is supermodular in} \quad (\omega, \theta)\}.$$

Proof: The objective function, $r(\cdot)$ is supermodular in (ψ', ω) and (ω, θ). It is a sum of supermodular functions (by assumption, the R&D spending $-z(\psi', \omega)$ is supermodular, and so is the profit function). This implies that the objective function is non-decreasing in ω.

To prove strict monotonicity, I use an Euler equation $F(\omega, k, \psi', \theta) = 0$ for a perturbation of the optimal $\tilde{\psi}(\cdot)$ between periods t and $t+1$ (Pakes, 1994). We want to see what the implications of an increasing in productivity are on the Euler equation. The Euler equation has to remain satisfied for an increasing in productivity. The choice of distribution $\tilde{\psi}(\cdot)$ given competitive pressure θ affects the stochastic evolution of the future productivity ω'. The future productivity ω' affects the future pressure θ'. We construct an alternative program that leaves the joint distribution of the state variables from period $t+2$ and onwards unchanged (conditional on the state in t). If ψ' denotes the choice distribution under the optimal program, let us consider the perturbation $\psi^* = \psi' - \epsilon$. The next period productivity has the distribution $P(d\omega'|\psi' - \epsilon, \theta)$ under this perturbation. Let us define

$$\omega^* = P^{-1}\left(P(d\omega'|\psi', \theta)|\psi' - \epsilon, \theta\right) = g(\omega', \psi', \theta, \epsilon),$$

$$\Delta(\omega', \psi', \theta, \epsilon) = \omega' - \omega^* = \omega' - g(\omega', \psi', \theta, \epsilon),$$

$$\Gamma(\omega', \psi', \theta, \epsilon) = \theta' - \theta^*,$$

where $\Delta(\cdot, \epsilon) = 0$ and $\Gamma(\cdot, \epsilon) = 0$ at $\epsilon = 0$; $\Delta(\cdot)$ and $\Gamma(\cdot)$ are differentiable as P and P^{-1} are differentiable. The difference in period t between the value function of the original and alternative program is

$$\begin{aligned}
&V(\omega, k, \theta) - V(\omega, k, \theta, \epsilon) = -z(\psi', \omega, \theta) + z(\psi' - \epsilon, \omega, \theta) \\
&+\beta \int \chi(\omega', k', \theta')\left[\pi(\omega', k', \theta') - \pi[\omega' - \Delta(\omega', \psi', \theta, \epsilon), k', \theta' - \Gamma(\omega', \psi', \theta, \epsilon)]\right. \\
&\left.-z(\psi", \omega') + z(\psi", \omega' - \Delta(\omega', \psi', \theta, \epsilon))\right] P(d\omega'|\psi', \theta).
\end{aligned}$$

This expression must be non-negative in a neighborhood of the $\epsilon = 0$ since the original program is optimal. Its differentiable in ϵ, in a neighborhood of the $\epsilon = 0$, must be zero, which implies the Euler equation

$$\begin{aligned}
F(\omega, k, \theta, \psi') = \quad & -\tfrac{\partial z(\psi', \omega, \theta)}{\partial \psi'} + \beta \int \chi(\omega', k', \theta')\left[\tfrac{\partial \pi(\omega', k', \theta')}{\partial \omega'} - \tfrac{\partial z(\psi", \omega')}{\partial \omega'}\right] \tfrac{\partial \Delta(\omega', \psi', \theta, \epsilon))}{\partial \epsilon} \\
& P(d\omega'|\psi', \theta) + \beta \int \chi(\omega', k', \theta')\left[\tfrac{\partial \pi(\omega', k', \theta')}{\partial \theta'} - \tfrac{\partial z(\psi", \omega')}{\partial \theta'}\right] \tfrac{\partial \Gamma(\omega', \psi', \theta, \epsilon))}{\partial \epsilon} \\
& P(d\omega'|\psi', \theta) = 0,
\end{aligned}$$

for each (k, θ, ψ'). $F(\omega, k, \theta, \psi')$ is a continuous, strictly increasing function of ω for every (k, θ, ψ'). For a fixed k, an increase in ω has to trigger change in ψ' and θ for $F(\omega, k, \theta, \psi') = 0$ to remain satisfied. My setting accounts for the effect of competitive pressure on the firm's profit when we have an increase in productivity. Thus, the choice distribution $\tilde{\psi}(\omega, k, \theta)$ is non-decreasing in ω on the set $\{(\omega, k, \theta)|z(\tilde{\psi}(\omega, k, \theta), \omega) > 0\}$ and where the profit function in supermodular in (ω, θ).■

Theorem 1 *The policy function for the* ***investment choice*** $\tilde{i}(\omega, k, \theta) = \tilde{i}(\tilde{\psi}(\omega, k, \theta), k, \theta)$ *is non-decreasing in ω and strictly non-decreasing in ω on the sets*

$$\begin{aligned}
&\left\{(\omega, k, \theta)|\tilde{i}(\omega, k, \theta) > 0 \wedge z(\tilde{\psi}(\omega, k, \theta), \omega) > 0\right\} \cup \\
&\{(\omega, k, \theta)|\pi(\omega, k, \theta) \quad \text{is supermodular in} \quad (\omega, \theta)\}
\end{aligned}$$

Proof: Lemma 2 and 3 give us that the investment choice $\tilde{i}(\psi', k, \theta)$ is non-decreasing in ψ', which is non-decreasing in ω and θ. This implies that the optimal investment choice $\tilde{i}(\omega, k, \theta)$ is non-decreasing in ω and θ. Let us consider the following alternative programme: $i^*(\omega, k, \theta) = \tilde{i}(\omega, k, \theta) - \epsilon$, $\theta'^* = \theta' - \Gamma(\epsilon)$ (actual investment affects future productivity that affects competitive pressure), $i^*(\omega', k', \theta') = \tilde{i}(\omega', k', \theta' - \Delta(\epsilon))$, $\psi^* = \tilde{\psi}(\omega, k + \epsilon, \theta)$, and $\chi^*(\omega, k, \theta) = \chi^*(\omega, k + \epsilon, \theta)$. The difference in period t between the value function of the original and alternative programme is

$$\begin{gathered} V(\omega, k, \theta) - V(\omega, k, \theta, \epsilon) = -c(i, k) + c(i - \epsilon, k) \\ +\beta \int \chi(\omega', k', \theta') \left[\pi(\omega', k', \theta') - \pi(\omega', k' - \epsilon, \theta' - \Delta(\epsilon))\right. \\ \left. -c(\tilde{i}(\omega', k', \theta'), k') + c(\tilde{i}(\omega', k', \theta' - \Delta(\epsilon)), k' - \epsilon)\right] P(d\omega'|\psi', \theta) \end{gathered}$$

This expression must be non-negative in a neighborhood of the $\epsilon = 0$ because the original programme is optimal. Its differentiable in ϵ, in a neighborhood of $\epsilon = 0$, must be zero at $\epsilon = 0$, which implies the Euler equation

$$\begin{aligned} F(\omega, k, \theta, i) = \; & -\tfrac{\partial c(i,k)}{\partial i} + \beta \int \chi(\omega', k', \theta') \left[\left(\tfrac{\partial \pi(\omega', k', \theta')}{\partial i} - \tfrac{\partial c(\tilde{i}(\omega', k', \theta'), k')}{\partial i}\right) \tfrac{\partial \Delta(\epsilon)}{\partial \epsilon}\right. \\ & \left.\left(\tfrac{\partial \pi(\omega', k', \theta')}{\partial \theta'} - \tfrac{\partial c(\tilde{i}(\omega', k', \theta'), k')}{\partial \theta'}\right) \tfrac{\partial \Gamma(\epsilon)}{\partial \epsilon}\right) \cdot P(d\omega'|\psi', \theta) = 0 \end{aligned}$$

for each (θ, k, i). $F(\omega, k, \theta, i)$ is a continuous, strictly increasing function of ω for every (k, θ, i). For a fixed k, an increase in ω has to trigger change in i and θ for $F(\omega, k, \theta, i) = 0$ to remain satisfied.■

Paper III

Industry Dynamics and Format Repositioning in Retail*

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Abstract

In differentiated product markets, when firms are affected by demand shocks, they may react by repositioning their products, which in turn affects market structure. This paper proposes a dynamic oligopoly model to estimate the costs of repositioning store formats together with sunk costs of entry and sell-off values of exit in the retail industry. The model gives important information about driving forces behind format changes and how such repositioning can be linked to entry and exit. Using data from Sweden, the results indicate that both repositioning and entry costs increase with market size, and their growth decreases when moving to larger markets. Small markets have higher sell-off values than repositioning costs, but large entry costs. The difference between higher entry and lower repositioning costs explains why the number of observed repositionings is higher than the number of entrants. Since entry is regulated in most of OECD countries, repositioning costs and their link to competition have important implications for competition policy.

Keywords: imperfect competition; dynamic oligopoly; dynamic estimation; industry dynamics; repositioning; retail.
JEL Classification: L1, L13, L81

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1 Introduction

There have been major structural changes in retail markets during the last decades, e.g., decreasing number of stores and the rise of the "big-box" format. Due to the increasing importance of information technology and distribution systems, large retail firms dominate, each operating a number of well-defined store formats, and continuously reconsidering store formats as well as possible entry of new stores, or exit. Recent investments in retail aim to increase product differentiation in store formats. However, each investment implies sunk costs. There are only a few studies that emphasize firms' strategies on format repositioning in local markets in response to strategies of rival firms (Sweeting, 2007; Gandhi et al., 2008). But, the retail industry has large scale-and-scope economies where format repositioning has key implications for competition.[1]

The aim here is to provide a model that estimates and links respositioning costs with sunk costs of entry and sell-off (exit) values. If rival firms enter with new stores, the reaction of the firm may be to change the formats of affected stores or to shut down some stores. Shifts in costs of entry and repositioning can then lead to markets with few stores, with little product differentiation and low competition. A retail market increasingly dominated by a small number of stores is bad for both consumers and suppliers. In Europe, there are countries where the top five firms made up 70 percent or more of the grocery market in 2005: Germany (70 percent), France (70 percent), Austria (79 percent), Estonia (79 percent), Ireland (81 percent), Slovenia (82 percent), Sweden (82 percent), and Finland (90 percent). Since entry is regulated in most of OECD countries, sunk costs of entry, and repositioning-format costs, have important implications for policy analysis.[2]

This paper uses a fully dynamic oligopoly model to estimate the costs of format repositioning, sunk costs of entry, and sell-off values of exit in the Swedish

[1]Focusing on food prices in the EU, the European Commission published a report in December 2008, recommending among other things that, "regulations that restrict entry of new companies into the market need to be scrutinized and removed when appropriate, while keeping in mind their environmental and social goals" (European Commision 2008:321).

[2]Pilat (1997) surveys entry regulations in OECD countries.

retail food industry.[3] [4]During the period 2001-2006 the number of stores that changed format was substantially larger than the number of stores that entered. For example, over 80 percent more stores changed format than entered in 2006. Four important firms dominate the Swedish retail food market. The focus here is on the individual store, but the paper also accounts for firm's strategies.[5] This is important, since firms try to change the formats of their stores in response to local competition. The format of the store is chosen to maximize the store's expected future profits.[6] But these choices may affect the future format choices of other stores in the market.

In each period, a discrete choice demand model, that accounts foe spatial differentiation, is estimated to recover unobserved store quality. Store quality is defined as the mean of unobserved store characteristics across consumers. It is unobserved by the researcher but known to the store. Section 3.1 provides a detailed discussion about what I measure by quality. By changing format, stores try to increase the their store quality (quality effect), but this changing cannot be done without any cost. First, though stores try to keep their old consumers while hoping to also gain new ones, there may be a fall in sales in the short-run until the customers adjust to the new format. But second, there may also be sunk costs of investment associated with format repositioning. Important factors for format repositioning that are observable and differ across markets, e.g., local demographic characteristics allow to estimate mean repositioning costs the for observed changes.

Returns from format repositioning are realized over future periods and, therefore, a dynamic model is best for estimating repositioning costs and benefits. The dynamic approach used here is based on the two-step procedure proposed by Bajari et al. (2007) (BBL). In the first step, I estimate price adjusted quality of each

[3]Maican (2008) uses a similar approach to estimate the sunk costs of store-type repositioning, i.e., switching from a grocery store to a convenience store. But due to the small number of observed changes in store type, an accurate estimation of sunk costs is hard to obtain. The present paper extends Maican (2008) by introducing spatial competition and uses store concept instead of store type to define store-format. This is important, since store type is more related to size, while store concept is related to the firm's business model. A firm can change store concept to adjust to market competition. A more detailed discussion about the store-format definition is given in Section 2.

[4]There are studies that estimate costs paid by individuals/households when moving between different cities offering different market opportunities (Kennan and Walker, 2006; Bayer and Falko, 2006; and Gemici, 2007).

[5]While the dynamic setting at firm level could be problematic, since techniques for estimating dynamic games with incomplete information assume stationarity, the growth of the retail industry may be a non-stationary process, since some firms never exit.

[6]Since the store format is based on the business model given by the firm, the model presented at the store level surprises also the firm effect.

store from a random-coefficients demand model (Berry et al., 1995; Nevo, 2001; Davis, 2006). Using assumptions on the timing of innovations in store-quality relative to store-format choices, this estimation allows for endogenous format choices. These timing assumptions are used in the production-function estimation literature (Olley and Pakes, 1996; Blundell and Bond, 2000; Levinsohn and Petrin, 2003; and Ackerberg et al., 2006). The estimated quality is then used to estimate the sales-generating function. In addition, the paper also estimates entry, exit, and format-attractiveness policies. In the second step, using an inequality estimator (Pakes et al., 2007b), the paper recovers the sunk costs of entry, sell-off (exit) value, and format-repositioning costs. An advantage of using inequality estimator is that it is robust to simulation errors in the value function. This estimation approach is also used by Ho (2007) and Ishii (2005) when estimating models in a static setting, and by Holmes (2008) in a dynamic study of Wal-Mart's store locations.

Recent literature on estimation of dynamic games with Markov perfect equilibria has developed alternative extensions to the Hotz and Miller (1993) and Hotz et al. (1994) approaches (Aguirregabiria and Mira, 2007; Bajari et al., 2007; Pakes et al., 2007a; and Pesendorfer and Schmidt-Dengler, 2003). Several recent papers have estimated dynamic oligopoly games using industry data. First, there are studies of entry and exit in homogenous product markets: Ryan (2009) analyzes the cement industry and Collard-Wexler (2006) studies the ready-mix concrete industry. Second, there are papers that allow for vertical product differentiation by using logit-demand models: Beresteanu and Ellickson (2006) and Macieira (2006) analyze the supermarket and supercomputer industries, respectively. Third, there are few studies of both horizontal and vertical product differentiation: Analyzing the U.S. radio industry, Sweeting (2007) uses a random coefficients demand model to measure the costs of product repositioning.

This paper is closely related to Sweeting (2007) and Ryan (2009). Both those papers use the BBL dynamic framework to estimate sunk costs. Sweeting (2007) does not model entry and exit. This paper explicitly model entry and exit since there is a close connection between entry, exit, and format repositioning in retail markets. To my knowledge, this is the first paper that models entry, exit as well as repositioning at the same time. The sunk costs of entry are backed out as in Ryan (2009). However, an important difference is that I also account for spatial competition. Location is a key factor for a store, and consumers have preferences over both geographic and store characteristics. Finally, this paper is first, to my knowledge, to estimate repositioning costs in the retail industry.

Another alternative is to model at the firm level (Aguirregabiria and Vicentini, 2006; Jia, 2008). Using a static setting, Jia (2008) provides an empirical model for measuring the impact of chain stores on other discount retailers and quantifying the scale-economies within a chain. Her model allows for flexible competition patterns among all players. However, it has some limitations, such as that it cannot be applied to oligopoly games with three or more chains. In this case the strategy of the firm is modeled choosing the number, format, and location of its stores. The researcher then explicitly models firm behaviour, but might miss important information at store level. The researcher assumes that stores in the same format are identical, the only difference between two stores in the same format being their location. By aggregating stores, the researcher loses important information, such that why a firm changed the format of one store but kept others in the same format, if all were in similar locations. In addition, the researcher can then only estimate the distribution of store quality. In my case, recovering the quality of individual store is important, since store quality influences demand, and therefore is an important decision-factor for the firm.

This paper uses detailed data on all retail food stores in Sweden during 2001 to 2006. This is the first model of the store format repositioning. Given the complexity of this industry (multiple ownership, spatial differentiation, and regulation), the estimated parameters are preliminary, i.e. they cannot be used as a direct guide for policies. This paper provides initial estimates of these costs while future research should consider robustness tests and consider the implications of the results. I assume that the estimated repositioning costs are the same for each store within each group market. The results indicate that the costs of format repositioning increase with market size. For three groups by market-size, the ratio between median sales and average repositioning costs is over 20. Format repositioning seems most profitable, however, in medium-sized markets, with a population between 20,000 and 60,000. I find higher entry costs per median sales in medium than in large markets. Sell-off values on exit are about twice as high in the large markets as in the small ones.

The findings show that stores are less likely to exit if they have high quality, if they are located in large markets, or if the firm operates many stores in the same format. Entry is more likely in large markets and if rivals have high quality, i.e., if there is room for product differentiation. Stores with high quality are more likely to be in large formats, and old stores are less likely to reposition themselves.

Furthermore, distance is found to be a key factor when consumers choose a store. Store's quality is more persistent for non-repositioning stores.

The next section gives a brief overview of the Swedish retail food industry and relevant recent events, and also discusses the data sources and introduce the variables. Section 3 then presents the theoretical model, while Section 4 discusses the results whereas Section 5 summarises and draw conclusions.

2 Overview of the Swedish Retail Food Industry

Annual retail sales in Sweden in 2004 were around SEK 400 billion, one-third of private consumption, of which 52 percent was grocery sales and 48 percent is non-food. Four large firms dominate Swedish food retail: ICA, Coop, Axfood, and Bergendahls together had more than 90 percent of all food retail sales in 2004. ICA, the largest firm (with 44 percent), consists of independently owned stores but with a fairly high degree of centralized decision-making. Axfood is a mix of franchisees and fully-owned stores.[7] Coop, on the other hand, consists of centralized cooperatives where decisions are made at the cooperative level (national or local). Axfood and Coop together have market shares slightly over 20 percent each. Bergendahls (4 percent), operates mainly in the south/south-western parts of the country. In addition, international firms with well-defined discount formats (Netto and Lidl) entered the Swedish market in 2002 and 2003, respectively. So far, they have fairly modest market shares. Finally, independent stores have about 8 percent market share.

Data. The data-set comes from Delfi Marknadsparter AB (DELFI); details of its sources are given in Appendix A. The unit of observation is stores defined by physical location. The data contains yearly information on all retail food stores in the Swedish market during 2001 to 2006, including format, age, owner/firm, sales, sales space, and location. Store format depends on firm/owner, sales space (size), parking, product assortment, etc. Since retail food demand is a function of the market's population but varies across income levels, I connected demographic information from Statistics Sweden(SCB), such as population by age-groups and average income, to the store data from DELFI.

Store format. The retail food industry consists of firms that operate stores in

[7] Axel Johnson and the D-group merged at the end of the 1990s, to create Axfood, again with fairly centralized decision-making and uniformly-designed stores.

different sizes, where each store has a well defined business concept. The name of a store is usually affiliated with the owner/firm and its self-defined store-concept (such as "very large" or "near you"). The main purpose of the paper is to measure average repositioning costs from one concept to another. However, since the number of store concepts is large (over 30), to reduce the space-dimensionality I group them into 18 *formats* (Table 1), each format containing one or more close store concepts of the same firm. The most important store concepts of one firm are kept in one format, however.

I distinguish cases where, the firm decided to replace one format with another for all its stores in that format. These aggregate format changes, decided at the firm level, are not considered as format repositioning for purposes of this study. On the other hand, a store can change format within or across firms, limited to some extend by sales space available. For example, a hypermarket is not likely to switch to a convenience store (more below). Because of the restricted entry (regulations), the reserve is also unlikely.[8]

To define the possible repositioning alternatives, I re-group the stores in four size groups based on sales space: very large (i.e., hypermarkets), large (i.e., supermarkets), medium (i.e., convenience stores), and small. The four main firms have store concepts in all these four size-groups. I only allow stores to change to other formats within the current size-group or in the next larger or smaller size-group.

Table 1 presents summary statistics for all formats grouped by firm. The largest is *ICA Maxi* (3,3378 m^2) followed by *Coop Large*, *ICA Kvantum*, and *Axfood Willys*, while the smallest is *Others*, i.e., gas station stores, small corner stores and the hard discounters Netto and Lidl. *ICA Maxi* has the highest average sales per square meter (SEK 88,000/m^2), followed by *Begendahls Vi* (SEK 81,000/m^2), while *Axfood Handlarń* has the lowest (SEK 36,000/m^2). *Axfood Vivo* and *ICA Rimi* disappeared from 2001 to 2006, while *Begendahls Vi* and *Coop Nära* appeared.

Figure 1 shows how the numbers of stores by format evolve during the study period. ICA increased the number of *ICA Maxi* hypermarkets, but reduced the number of *ICA Nära* small stores. Axfood increased the number of *Willys* supermarket, and of *Tempo* and *Handlarń* small stores, but reduced the number of *Hemköp* supermarket. During the study period, Coop tries to redefine its store

[8]The Swedish Plan and Building Act (PBA) authorizes the 290 municipalities to decide over applications for new entrants, while inter-municipality cases are handled by the 21 county administrative boards. Several reports have stressed the need to better analyze how regulation affects market outcomes (Pilat 1997; Swedish Competition Authority 2001:4, 2004:2, 2008:5).

formats towards well defined formats such as *Nära* and *Forum* (in different sizes). Finally, besides starting *Vi*, Bergendahls expanded the number of its *Other* stores.

Market definition. Food products fulfill basic needs and consumers typically travel relatively short distances when buying food (except if prices are sufficiently low). Consequently, nearness to work and home are key aspects for consumers when choosing a store, though the distance likely increases with store-size.[9]

Local markets must be isolated geographic units, such that stores competitively interact only with other stores in the same one. *Postal areas* (in total 1534) are not large enough for large stores, which leaves the 88 *local labor markets* defined by the 290 *municipalities*. The *local labor markets* take commuting patterns into account, which are important for largest stores. *Municipalities* are more appropriate for, while matching the local-government decisions. Therefore, I use municipalities as local markets.

Descriptives. Table 2 presents store characteristics during the study period. The total number of stores decreases from 6,524 in 2001 to 5,953 in 2006 (about 9%), which confirms the trend towards fewer retail stores discussed above. In all years, the number of exits exceed the number of entrants. The number of format repositionings vary between 589 (in 2005) and 243 (in 2006). Average annual sales increases around 25 percent during the period, but only 14 percent for industry as a whole, implies more larger stores at the end of the period. Median population at the local-market (municipality) level increased almost 6 percent, while the median number of families increases by almost 5 percent. The median sales of repositioning stores are lower than the average sales for the full sample, indicating that repositioning is most common among small stores.

The next step is to analyze the difference between repositioning markets (where at least one repositioning occurred during the study period) and non-repositioning markets. There are 52 markets where I observe repositioning every year (2001-2006); 41 with at least one during 4 years; 71 during 3 years; 63 during 2 years; 51 during only 1 year; and 12 markets where there are no format repositionings during the whole period.

Table 3 presents median characteristics for markets with and without repositioning. Repositioning markets have about twice the median population and twice the median number of stores throughout period. Repositioning markets are less

[9]According to surveys made by the Swedish Institute for Transport and Communication Analysis, the average travel distance for trips with the main purpose of buying retail food products was 9.83 kilometers (1995-2002).

concentrated, with C_4 only 0.19 in 2006 compared to 0.39 in non-repositioning markets. They also have more entrants and exits. There is persistent high correlation between the numbers of repositionings and of entries, increasing over time (0.63 in 2002 compared to 0.88 in 2006), as does the correlation between the numbers of repositionings and exits (0.50 in 2002 compared to 0.66 in 2005). These high correlations are why it is important to analyze entry, exit, and repositioning at the same time as done here.

Another important question is what characterizes markets where each format is present. Table 4 shows median characteristics of repositioning and non-repositioning markets by format. The formats present in most municipalities are *ICA Supermarket* (230 markets), *ICA Nära* (247 markets), and *Coop Medium* (219 markets). For all formats, markets with repositioning have larger median populations than markets without. Median market-share in repositioning markets is lower than in non-repositioning markets for all formats except *Coop OBS* and *Vi*. All formats expect *Rimi*, *OBS et al.*, *Axfood Others*, *Bergendahls Others*, and *Others* have median sales per square meter.

The total numbers of format repositionings from 2001 to 2006 for each firm are presented in Tables 5-8. For example, there are 8 repositionings from *ICA Kvantum* to *ICA Maxi*, and 2 repositionings from *ICA Maxi* to *ICA Kvantum* during the period (Table 5). The highest number of repositionings are from *ICA Nära* to *Others* (220). As mentioned earlier, the format *Rimi* disappeared with most of the stores switching to *ICA Supermarket* (100) and *ICA Nära* (30). There are also many repositionings from *ICA Nära* to Axfood's formats *Handlarń* and *Tempo*.

Table 6 presents repositionings from Axfood, including many from *Vivo* to *Hemköp et al.* and to *Vi*, as well as many from *Hemköp et al.* to *Willys et al.* and to *Tempo*, and from *Axfood Others* to *Handlarń* and to *Others*. The number of repositionings from Bergendahls' formats is small and mostly to other firms (Table 7). Finally, most Coop repositionings were from *Coop Medium* to *Coop Nära* or *Coop Large*, and to other firms' formats such as *Handlarń* and *Bergendahs Others* (Table 8).

3 The Modeling Approach

Local markets in the retail industry are characterized by simultaneous entry, exit, and format repositioning. My model, built on the work of Ericson and Pakes (1995), provides a theoretical framework of industry dynamics to account for these features.

All economically important characteristics of stores are included in a vector of commonly-observed state variables. Stores receive state-dependent revenues from selling products and services in each period. Store format, local demand, and competition influence the evolution of the state-vector. Equilibrium is attained when stores follow strategies that maximize the discounted present value of their expected stream of revenues given the expected strategies of their competitors. An important assumption is that stores are maximizing their individual payoffs even if they have the same owner/firm. However, since firms try to avoid cannibalization, and also benefit from economies of scope, common ownership may affect store formats. This effect of common ownership is not modeled explicitly. However I control, for the effect of common ownership on store revenues and policies (as discussed in the Introduction).

Timing. There is an infinite sequence of periods, years in this case. The timing of the simultaneous game is as follows:

1. Incumbent stores observe their current store-quality, formats, and local market demographics.

2. Each potential entrant receives a draw from the distribution of entry costs, and then makes decisions.

3. Consumers choose to buy from a store based on its quality. Consumers and local market demographics generate the store's revenues. There is also a fixed cost for incumbent stores.

4. Each store receives a private shock υ to its payoffs from choosing a specific format for the following year. The private shocks are assumed i.i.d over stores, formats, and years. After observing its private shock, the store decides its format for the year after that.

5. Stores choose their formats. State space variables quality and local market demographics evolve according to stochastic processes described below (section 3.3).

6. Incumbent stores that exit the market receive their sell-off values. Stores that enter pay an entry fee.

Stores that exit of course sell products and services in the year before leaving the market. Furthermore, stores change formats (or not) without knowing the decisions of their competitors. At the beginning of each year, they observe quality and the entry, exit, and repositioning decisions of their rivals in the previous period. Since private shocks are i.i.d., stores do not update their expectations of their rivals future behavior after observing their actions.

Equilibrium. The actions that a store takes in a given period (exit or repositioning) affect current profits and the state variables, and, therefore, future strategic interactions. In this way, the model captures dynamic competition via entry, exit, and repositioning decisions. There are N_m stores in market m, denoted $j = 1, \cdots, N_m$, that make decisions at times $t = 1, 2, \cdots, \infty$. Store characteristics at t are summarized by the vector of state variables, *quality* $\boldsymbol{\omega}_t \in \mathbb{R}^{N_m}$. Given states $\boldsymbol{\omega}_t$, the stores choose entry, exit, and repositioning simultaneously. Each store j receives a private shock υ_{jt}, drawn independently across stores and over time from a distribution $Q_j(\cdot|\boldsymbol{\omega}_t)$. Differences in each store's productivity might be one explanation for the existence of private shocks. I denote $a_{jt} \in A_j$ the action of store j and $\boldsymbol{a}_t = (a_{1t}, \cdots, a_{Nt}) \in \boldsymbol{A}$ the vector of actions at time t. The vector of private shocks is $\boldsymbol{\upsilon}_t = (\upsilon_{1t}, \cdots, \upsilon_{Nt})$.

The profits of store j at time t, $\pi_j(\boldsymbol{a}_t, \boldsymbol{\omega}_t, \upsilon_{jt})$, depend on its quality (state) ω_{jt}, the actions of all the stores in the market $\mathbf{a}_t$, and the store's private shock υ_{jt}. Profits are net of fixed and sunk costs at time t, such as entry costs, and repositioning costs, as well as sell-off value. In addition, all stores are assumed to have a common discount factor $0 < \beta < 1$. Conditional on current quality $\boldsymbol{\omega}_t$, the expected future profit of store j, evaluated prior to realization of the private shock, is

$$\mathbb{E}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \pi_j(\boldsymbol{a}_\tau, \boldsymbol{\omega}_\tau, \upsilon_{j\tau}) | \boldsymbol{\omega}_t\right]$$

Finally, to define the transition between states, I assume that quality evolves as an AR(1) process, where the speed of quality-adjustment is estimated from a static-demand model. To be more precise, quality at $t+1$, $\boldsymbol{\omega}_{t+1}$, is drawn from a probability distribution $P(\boldsymbol{\omega}_{t+1}|\boldsymbol{a}_t, \boldsymbol{\omega}_t)$. This implies that entry, exit, or changing format might affect future competition.

I focus on pure strategy Markov perfect equilibria (MPE). As in Bajari et al. (2007), I assume that there is at least one MPE (Doraszelski and Satterthwaite, 2010) for details on existence and uniqueness). The existence of which implies that each store's behaviour depends on its current quality and its current private shock. If Ω is the quality space, a profile of vector strategies is $\sigma = (\sigma_1, \cdots, \sigma_N)$, where $\sigma : \Omega \times \Upsilon_1 \times \cdots \times \Upsilon_N \to A$, Υ_j is the space for the private shock υ_j and A is the space of actions. Assuming Markov behaviour implies that store j's expected profit, given state $\boldsymbol{\omega}$, can be written

$$V_j(\boldsymbol{\omega}|\sigma) = \mathbb{E}_\upsilon \left[\pi_j(\sigma(\boldsymbol{\omega}, \boldsymbol{\upsilon}), \boldsymbol{\omega}, \upsilon_j) + \beta \int V_j(\boldsymbol{\omega}|\sigma) dP(\boldsymbol{\omega}' | \sigma(\boldsymbol{\omega}, \boldsymbol{\upsilon}), \boldsymbol{\omega}) | \boldsymbol{\omega} \right].$$

A strategy profile $\boldsymbol{\sigma}^*$ is a Markov perfect equilibrium given opponent profile σ_{-j} if each store j prefers strategy σ_j to all Markov strategies σ_j', so that

$$(1) \quad V_j(\boldsymbol{\omega}|\sigma_j^*, \sigma_{-j}^*) \geq V_j(\boldsymbol{\omega}|\sigma_j', \sigma_{-j}^*)$$

for all j, $\boldsymbol{\omega}$, and σ_j'.

4 Estimation

Store demand. The utility of consumer i from buying from store j in market m in period t is a function of observed and unobserved vector of store characteristics ($\mathbf{x}_{jmt}$,ω_{jmt}), a vector of observed consumer characteristics $\mathbf{z}_{imt}$, and a vector of unobserved consumer characteristics $\boldsymbol{\nu}_{imt}$. Unobserved store quality is difficult to quantify but is a determinant of demand. Stores may have the same format but differ in consumers' perceptions of their display, variety offered, advertising, and service, all elements of quality.

Each store's market-share also depends on its format, as well as other store characteristics such as owner, age, sales space, local demand, and competition. Since quality is not directly observed in the data, it is backed out through estimation of the demand model.

The utility of consumer i from buying from store j is then given by the scalar $u_{ijmt} = u(\mathbf{z}_{imt}, \mathbf{x}_{jmt}, \omega_{jmt}; \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of parameters to be estimated. Consumers with different characteristics ($\mathbf{z}_{imt}$, $\boldsymbol{\nu}_{imt}$) make different store choices. By integrating out the choice function over the distribution of $\mathbf{z}_{imt}$ and $\boldsymbol{\nu}_{imt}$, the aggregate demand of the store can be obtained. It is assumed that $\boldsymbol{\nu}_{imt}$ follows a normal distribution, so that its parameters can be estimated. The mean and standard deviation of $\boldsymbol{\nu}_{imt}$ then appear in the utility function as part of the vector $\boldsymbol{\theta}$. Consumer i chooses store j if and only if

$$(2) \quad u(\mathbf{z}_{imt}, \boldsymbol{\nu}_{imt}, \mathbf{x}_{jmt}, \omega_{jmt}; \boldsymbol{\theta}) \geq u(\mathbf{z}_{imt}, \boldsymbol{\nu}_{imt}, \mathbf{x}_{rmt}, \omega_{rmt}; \boldsymbol{\theta}) \quad \text{for} \quad j \neq r$$

where the alternatives $r = 1, \cdots, N_m$ represent the competing stores in the market m.

An outside alternative is the option of buying from stores with different formats. I set stores that never changed format during the study period as outside alternative for each local market. In my case the outside alternative is *Others* (Table 1). The presence of this outside alternative allows us to model changes in total sales as a function of store characteristics.
Consider

$$B_{jmt} = \{\boldsymbol{\nu} | u(\mathbf{z}_{imt}, \boldsymbol{\nu}_{imt}, \mathbf{x}_{jmt}, \omega_{jmt}; \boldsymbol{\theta}) \geq u(\mathbf{z}_{imt}, \boldsymbol{\nu}_{imt}, \mathbf{x}_{rmt}, \omega_{rmt}; \boldsymbol{\theta}), \quad j = 0, 1, \cdots, N_m\},$$

where B_{jmt} is the set of values for $\boldsymbol{\nu}_{imt}$ that induces the choice of store j rather than store r. Assuming that the $F_0(\boldsymbol{\nu})$ provides the density of $\boldsymbol{\nu}$ in the population of interest, the market-share of store j as a function of the characteristics of all stores in the market is

$$(3) \quad \mathbf{s}_{jmt}(\mathbf{x}_{jmt}, \omega_{jmt}; \boldsymbol{\theta}) = \int_{\boldsymbol{\nu} \in B_{jmt}} F_0(d\boldsymbol{\nu}).$$

Let $\mathbf{s}(\cdot)$ be the N_m-element vector of functions whose j^{th} component is given by (3)

$$\mathbf{s}(\mathbf{x}, \boldsymbol{\omega}; \boldsymbol{\theta}) = [s_1(\mathbf{x}_1, \omega_1; \boldsymbol{\theta}), \cdots, s_{N_m}(\mathbf{x}_{N_m}, \omega_{N_m}; \boldsymbol{\theta})]'.$$

Then, if *pop* is the number of consumers in market m, the vector of demand for the N_m stores is *pop* $\times\, \mathbf{s}(\mathbf{x}, \boldsymbol{\omega}; \boldsymbol{\theta})$. In the empirical application I set *pop* equal to the population in each market.

In the demand model, I allow for interaction between individual and store characteristics. Following Berry et al. (1995), I also allow each individual to have different preferences for some observed store characteristics. The random-coefficients model generated is then

$$u_{ijmt} = \mathbf{D}_{jmt}\overline{\boldsymbol{\theta}}_1 + \mathbf{x}_{jmt}\boldsymbol{\theta}_1 + \mu_{ijmt} + \omega_{jmt} + \epsilon_{ijt} \tag{4}$$

where u_{ijmt} is the utility of consumer i from buying from store j in market m in period t; $\mathbf{D}_{jmt}$ is a row vector that contains 0 and 1, where 1 indicates the format of the store; the term μ_{ijmt} captures the interaction between the store's format and consumer characteristics; and $\mathbf{x}_{jmt}$ are store characteristics j i.e. age and distance to center of zip code; ω_{jmt} is quality of store j; and ϵ_{ijt} represents unobserved sources of variation that are independent across consumers, given the store, and across stores, given the consumer. The term μ_{ijmt} contains two components: (i) interaction between observed consumer characteristics ($\mathbf{z}_{imt}$) and store format ($\mathbf{D}_{jmt}$), and (ii) interaction between unobserved consumer characteristics (the $\boldsymbol{\nu}_{imt}$) and store format, or

$$\mu_{ijmt} = \mathbf{z}_{imt}\mathbf{D}_{jmt}\boldsymbol{\theta}_2 + \boldsymbol{\nu}_{imt}\mathbf{D}_{jmt}\boldsymbol{\Psi}, \qquad \boldsymbol{\nu}_{imt} \sim N(0, \boldsymbol{\psi}^2),$$

where $\boldsymbol{\nu}_{imt}$ is assumed to have multivariate normal distribution.

In the demand specification, I also control for spatial differentiation between stores. Store location is one of the most important factors that generate sales. Consumers tend to shop closer to their home and work, though of course the choice of store also depends on store format, prices, and product assortment, etc. Location is defined by three digit postal-codes, with the assumption that consumers are located in the center of each one. One of the reasons for using postal-codes is that competition is more intense in smaller areas. With the geographical coordinates of each store and its postal-code, I compute the distance between the store and the center of the postal-code area using the Haversine formula.[10]

An alternative measure would be the distance to that store of the same size or format that is closest to the center of the postal-code area. First, the minimum distance for each size-groups (4 different) in the postal-code area is computed. Then, relative distance is computed as the difference between each store's distance and the minimum distance. To be more precise, I give an example. Assume

[10] The Haversine formula is based on latitude and longitude measures with R the radius of the earth, the distance between two points A and B is given by

$$d_{A,B} = 2R\arcsin\left[min\left\{\left((sin(0.5(lat_B - lat_A)))^2 + cos(lat_A)cos(lat_B)(sin(0.5(lon_B - lon_A)))^2\right)^{0.5}, 1\right\}\right].$$

a postal area where three stores operate with the following distances to the center: *ICA Nära* (300m), *Coop Nära* (600m), and *Tempo* (500m). The relative distances are then: *ICA Nära* (0m), *Coop Nära* (300m), and *Tempo* (200m). Consequently, *ICA Nära* has an advantage over *Coop Nära* (300m) of being closer to consumers. Choosing size-groups instead of formats to define relative distance allows consumers to shop from other firms that have a store of the same size. The advantage of relative distance is that it models consumer preference for size-groups, but it restricts consumer choices. In the empirical part I use distance to the center of the postal area to account for spatial differentiation.

Demand estimation. The main objective of the demand estimation is to obtain a measure of the store's quality, ω_{jmt}. To back out the quality, I use the same method used in the production function literature to back out the unobserved productivity. I assume that a store's quality evolves as an AR(1) process, and that all customers value it in the same way. The evolution of store quality is estimated using a standard approach for random-coefficient demand (Berry et al., 1995, Nevo, 2000, and Ackerberg et al., 2008). A drawback of this approach is that it assumes that observed product characteristics is exogenous. In my case, ω_{jmt} measures price adjusted quality because the store prices are unobserved. It is a difficult task to construct an informative and consistent price index at the store level, e.g., different stores offer different product varieties. One strategy is to specify a price equilibrium equation and introduce it in the demand specification. However, this might be problematic due to the existence of multiple equilibria.

Innovations in the quality of format repositioning and non-repositioning stores, ξ^{re}_{jmt} and ξ^{nre}_{jmt}, are unknown when stores make decisions for the following year, so that

$$\text{(5)} \quad \text{Repositioning:} \qquad \omega_{jmt} = \rho_1^{re}\omega_{jmt-1} + \rho_0^{re} + \xi^{re}_{jmt}$$

$$\text{(6)} \quad \text{Non-repositioning:} \qquad \omega_{jmt} = \rho_1^{nre}\omega_{jmt-1} + \rho_0^{nre} + \xi^{nre}_{jmt},$$

where $\xi^{re}_{jmt} \in N(0, \eta^{re})$ and $\xi^{nre}_{jmt} \in N(0, \eta^{nre})$. Moreover, innovations ξ^{re}_{imt} and ξ^{nre}_{imt} are assumed to evolve independently across markets.

I use these innovations to form a set of moment conditions used in the estimation (Berry et al., 1995; Sweeting, 2007). The mean utility provided by store j in market m at time t is then

$$\text{(7)} \quad \delta_{jmt} = \mathbf{D}_{jmt}\overline{\boldsymbol{\theta}}_1 + \mathbf{x}_j\boldsymbol{\theta}_1 + \omega_{jmt} = \mathbf{y}_{jmt}\tilde{\boldsymbol{\theta}}_1 + \omega_{jmt},$$

where $\tilde{\boldsymbol{\theta}}_1 = (\overline{\boldsymbol{\theta}}_1, \boldsymbol{\theta}_1)$. In the first step of the estimation, I obtain an estimate of quality $\omega_{jmt}(\cdot)$ as a function of $\boldsymbol{\theta}$. In the second step, an identification assumption that $\boldsymbol{\theta} = \boldsymbol{\theta}_0$ is needed, where $\boldsymbol{\theta}_0$ is the true value of $\boldsymbol{\theta}$. In the third step, I use method of moments to find $\boldsymbol{\theta}$.

An approximation of the market-shares conditional on $(\boldsymbol{\delta},\boldsymbol{\theta})$ is given by

$$(8) \quad s_{jmt}(\boldsymbol{\theta}, \boldsymbol{\delta}) = \int \frac{\exp[\delta_{jmt} + \mu_{ijmt}]}{1 + \sum_r \exp[\delta_{rmt} + \mu_{irmt}]} f(\boldsymbol{\nu}) d(\boldsymbol{\nu}).$$

Pakes's (1986) simulation method is used to find this approximation, $s_{jmt}(\boldsymbol{\theta}, \boldsymbol{\delta}, P^{ns})$, where P^{ns} is the empirical distribution of the simulation draws.[11] For a given $\boldsymbol{\theta}$ and the set of simulation draws for $\boldsymbol{\nu}$, the unique values of $\boldsymbol{\delta}$ that predict the observed market-shares are found using contraction mapping (Berry et al., 1995). Equation (7) implies that

$$(9) \quad \omega_{jmt}(\boldsymbol{\theta}, P^{ns}) = \delta_{jmt} - \mathbf{D}_{jmt}\overline{\boldsymbol{\theta}}_1 - \mathbf{x}_j\boldsymbol{\theta}_1 = \delta_{jmt} - \mathbf{y}_{jmt}\tilde{\boldsymbol{\theta}}_1$$

i.e., that quality $\omega_j(\cdot)$ is a function of parameters, the data, and simulation draws.

Identification. An endogeneity problem arises because unobserved quality ω_{jmt} might be correlated with store-format. For each store, innovation in quality ξ_{jmt} is given by

$$(10) \quad \xi_{jmt} = \omega_{jmt} - \rho_1\omega_{jmt-1} - \rho_0(\delta_{jmt} - \rho_1\delta_{jmt-1}) - (y_{jmt} - y_{jmt-1})\tilde{\boldsymbol{\theta}}_1 - \rho_0$$

These innovations are uncorrelated with store-format at t and $t-1$, which allows us to form the following moment-conditions:

$$(11) \quad E[w_{jmt}\hat{\xi}_{jmt}(\boldsymbol{\theta})] = 0,$$

where $\boldsymbol{\theta}$ are all parameters of the demand-system and quality-transitions, and w_{jmt} is a set of instruments. y_{jmt}, y_{jmt-1}, and δ_{jmt-1} together with log of population plus competition variables interacted with store format, are used as instruments to estimate $\boldsymbol{\theta}$ by minimizing $\| G_{N,ns}(\boldsymbol{\theta}) \|$, where

$$(12) \quad G_{N,ns}(\boldsymbol{\theta}) = \sum_j \xi_{jmt}(\boldsymbol{\theta}, P^{ns}) \times w_j.$$

[11] When using simulation to compute the integral, a simulation error is introduced, the variance of which error decreases with the number of simulations used. Pakes (1996) and Berry et al. (1995) discuss this in detail.

In addition, in order to identify ρ_1, I also include the log of market-share at $t-1$ interacted with an indicator of whether if the store changes format or not.

Payoffs, entry, and exit. A store's full period payoff function depends on whether it is an entrant, a continuing incumbent, a repositioning incumbent, or exits. Store payoff depends on store format, repositioning costs, and fixed costs.

The payoff for an incumbent store j in market m in period t is

(13)
$$\pi_{jmt}(\omega_{jmt}, \boldsymbol{\omega}_{-jmt}; \boldsymbol{\alpha}, \boldsymbol{\gamma}) = r(\boldsymbol{\omega}; \boldsymbol{\alpha}) - \gamma_1 I(f_{jmt+1} \neq f_{jmt}) - \gamma_2 I(f_{jmt} \neq 0) + \gamma_3 \upsilon_{jmt},$$

where $r(\cdot)$ is the revenue function, γ_1 are the sunk costs of repositioning format, and γ_2 are fixed costs paid every period the store operates. The coefficient γ_3 is scale of the i.i.d payoff shocks υ_{jmt}, which are assumed to be drawn from a Type I extreme-value distribution. The revenues of store j in market m in period t are:

$$(14) \quad r_{jmt}(\omega_{jmt}, \boldsymbol{\omega}_{-jmt}) = \boldsymbol{\alpha}_{mt}(1 + K_{jmt}\boldsymbol{\alpha}^K)(1 + H\boldsymbol{\alpha}^H) + \epsilon^r_{jmt},$$

where $\boldsymbol{\alpha}_{mt}$ are the set of year-market fixed-effects dummies. While additional store characteristics are collected in K, H contains variables that measure the competition from other formats in the local market, including estimated store-quality of competitors.

Incumbent stores that choose to exit have the payoff

$$(15) \quad \pi_{jmt}(\omega_{jmt}, \boldsymbol{\omega}_{-jmt}) = \tilde{r}_{jmt} + \gamma_4,$$

where γ_4 is the sell-off value associated with closing down the store and exiting the market. Finally, the payoff for an entrant is a simple function of the fixed cost of entry $(entry_f)$:

$$\pi_{jmt}(\boldsymbol{\omega}_{-jmt}) = -sunk_{jmt},$$

where $sunk_{jmt}$ is the sunk cost of entry.

Evolution of state space. The probability of moving to another state is given by the combinations of all paths that lead to that state. To obtain a new state, an incumbent has two options: (i) it stays in the market and moves to a new state; or (ii) it exits and is replaced by a new entrant in the new state. For any change in the state vector, I have to account for the entry, exit, and repositioning decisions of incumbents and potential entrants. I model entry is a restricted way because in my data entry is based on the address. Therefore, in the forward simulations, potential entrants can enter only in locations where stores exit. The probability of entry and exit can be written in terms of optimal entry and exit strategies:

$$(16) \quad Pr(entry|\omega_j) = \int \Theta(\omega_j, sunk_j) dG(sunk_j)$$

$$(17) \quad Pr(exit|\omega_j) = \Phi(\omega_j).$$

There are a few further assumptions required. First, because in many cases, entry and exit strategies take the form of simple cutoff rules in dynamic oligopoly models (Beresteanu and Ellickson, 2006), I assume that both conditional probabilities (16) and (17) can be approximated using probit models. Second, from the demand-estimation assumption we have that quality evolves stochastically according to the AR(1) processes described by (5) and (6). Third, since each market m is defined by its characteristics, e.g., the total number of formats and population groups, I assume that the growth rates for population groups evolve according to the following AR(1) processes

$$(18) \quad pop^g_{mt} = \delta^{pop}_{1,g} pop^g_{mt-1} + \delta^{pop}_{0,g} + \upsilon^{pop}_{mt},$$

where g is one of population groups and $\upsilon^{pop}_{mt} \sim N(0, \eta^{pop})$.

Value functions. Given the policy functions and the evolution of the state space, the value functions for incumbents and entrants can be computed, giving the expected discounted present value of the store of a given quality. The value function has two components: the per period payoff function (profit of incumbents, or sunk costs of entry for entrants), and the expected value of next period. Stores use the value function to choose their optimal format, entry, or exit. When a store considers changing format, it compares the marginal benefit of having a new quality against the cost of achieving it. Similarly sell-off value at exit is compared with its continuation value.

A potential entrant compares its draw from the distribution of sunk entry-costs against its expected value if it enters. Since private shocks on profits are assumed to be i.i.d, I integrate out all private information in the store's per-period payoff function when computing these value functions. In other words, stores choose their optimal strategy on given the ex-ante value function of next period's potential store qualities.

I assume that the potential entrant only lives one year, so that there is no reason to solve for an optimal stopping rule. If it has a higher sunk-costs draw in the current period, it may postpone entering until it receives a more favorable draw. Given current quality and its sunk-costs of entry draw, $sunk_j$, the value function of the potential entrant that decides to enter is

$$(19) \quad V_j^e(\boldsymbol{\omega}, sunk_j) = max_{f_j^e} \left\{ -sunk_j + \beta \int V_j(\boldsymbol{\omega}') dP(\boldsymbol{\omega}' | \boldsymbol{\omega}, \boldsymbol{\upsilon}) \right\}.$$

This value function includes the optimal choice of store-format. Since the potential entrant is forward-looking and rational, its expected value of entering accounts for the chosen formats of other stores and their entry and exit decisions. The choice of store-format does not depend on $sunk_j$, i.e., stores choose format f_j^e conditional on entering. In other words, for a given quality there is a draw from the distribution of sunk-costs of entry such that a store would be indifferent between entering or not,

$$(20) \quad \overline{sunk}_j = \beta \int V_j(\boldsymbol{\omega}') dP(\boldsymbol{\omega}' | \boldsymbol{\omega}, \boldsymbol{\upsilon}).$$

The entry function is denoted $\Theta(\omega_j, sunk_j)$. In equilibrium, a store enters the market if it receives a sunk-costs of entry draw less than this value.

If a store decides to leave the market, it obtains profit $\pi_j(\boldsymbol{\omega})$ and sell-off value $scrap_j$. On the other hand, if it stays in the market it receives the following payoff, which depends on the cost of repositioning if it changes format

(21)
$$V_j^{stay}(\boldsymbol{\omega}) = max_{f_j} \left\{ -\gamma_1 I(f_{jt+1} \neq f_{jt}) - \gamma_2 I(f_j \neq 0) + \beta \int V_j(\boldsymbol{\omega}') dP(\boldsymbol{\omega}' | \boldsymbol{\omega}, \boldsymbol{\upsilon}) \right\}.$$

Summarizing, then the value function of an incumbent is a combination of its expected payoffs if it stays in the market and if it exits,

$$(22) \quad V_j(\boldsymbol{\omega}) = \int V_j(\boldsymbol{\omega}') dP(\boldsymbol{\omega}' | \boldsymbol{\omega}, \boldsymbol{\upsilon}) + (1 - \Phi(\omega_j)) V_j^{stay}(\boldsymbol{\omega}) + \Phi(\omega_j)\gamma_4.$$

Distribution of sunk entry-costs. The estimated policy functions describe how a store will behave at each point. In addition, given the primitives of the model, which quantify the benefits and costs of those actions, it is possible to find the distribution of sunk entry-costs (Bajari et al., 2007; Ryan, 2009). Knowledge about store behaviour whether it enters, exits, or repositions, and the revenues associated with those behaviours, allows computation of the expected value of entry. If that value is positive yet the store did not enter, the store must have received a large entry-costs drawn that made it unprofitable to enter. The distribution of sunk entry-costs can be recovered by matching its cumulative distribution to the predicted probability of entry. A store enters when the value of doing so, $EV^e(\boldsymbol{\omega})$, is larger than $sunk_j$. By simulating many forward paths of possible outcomes given that the firm entered, and averaging over those paths, I obtain the expected value of entry, which I then match against observed rates of entry at different quality states. Therefore, the probability that a store enters is given by

$$(23)\quad Pr(sunk_j \leq EV^e(\boldsymbol{\omega})) = F^e(EV^e(\boldsymbol{\omega}); \mu_F, \sigma_F^2),$$

where $F^e(\cdot)$ is the cumulative distribution of sunk entry-costs. The entry probability estimated, by probit, gives us $Pr(entry|\boldsymbol{\omega})$. If ns is the number of quality states from which I simulate EV^e, I recover the parameters of the distribution by market-size from the following optimization problem:

$$(24)\quad min_{\mu_F,\sigma_F} \frac{1}{ns}\sum_{k}^{ns}[Pr(entry|\boldsymbol{\omega}) - F^e(EV^e(\boldsymbol{\omega})]^2; \mu_F, \sigma_F^2).$$

Estimation of sunk repositioning costs. The next step is estimation of average sunk repositioning costs (γ_1), fixed costs of operation (γ_2), the scaling parameter for heterogeneity of sunk costs (γ_3), and the scrap value (γ_4). The estimation is done using Pakes et al. (2007b)'s (PPHI) moment-inequality estimator. The inequalities are formed from the condition that the payoffs obtained using stores' actual strategies must have been higher than those from any alternative strategy (equation 1): $V_j(\boldsymbol{\omega}|\sigma_j^*, \sigma_{-j}^*) - V_j(\boldsymbol{\omega}|\sigma_j^{'}, \sigma_{-j}^*) \geq 0$. By construction, the value function

$$(25)\quad \begin{aligned} V_j(\boldsymbol{\omega}|\sigma_j^*, \sigma_{-j}^*) \; &= \mathbb{E}_{\sigma_j^*,\sigma_{-j}^*}\textstyle\sum_{t=0}^{\infty}\beta^t r(\cdot;\hat{\boldsymbol{\alpha}}) - \gamma_1\mathbb{E}_{\sigma_j^*,\sigma_{-j}^*}\textstyle\sum_{t=0}^{\infty}\beta^t I(f_{jt} \neq f_{jt+1}) \\ &-\gamma_2\mathbb{E}_{\sigma_j^*,\sigma_{-j}^*}\textstyle\sum_{t=0}^{\infty}\beta^t I(f_{jt} \neq 0) + \gamma_3\mathbb{E}_{\sigma_j^*,\sigma_{-j}^*}\textstyle\sum_{t=0}^{\infty}\beta^t \upsilon_{jt}(f_{jt+1}), \\ &+\gamma_4\mathbb{E}_{\sigma_j^*,\sigma_{-j}^*}\textstyle\sum_{t=0}^{\infty}\beta^t I(\chi_{jt+1=1}), \end{aligned}$$

where $\mathbb{E}_{\sigma_j^*,\sigma_{-j}^*}$ is the expectation operator over future states conditional on strategies, is linear in $\boldsymbol{\gamma}$. Having an estimator for the value function, I use the PPHI estimator, which allows for simulation error in the estimated value function.[12] While the simulation error can also be reduced by increasing the number of forward simulations, this would be expensive here and, therefore, it is more efficient to use the PPHI estimator.[13]

Since we are not able to measure profits $\pi(\cdot)$ exactly, we can calculate an approximation, denoted $\tilde{\pi}(\cdot;\boldsymbol{\gamma})$, which is known up to the parameter-vector $\boldsymbol{\gamma}$. This approximation has the arguments: strategies σ_j and σ_{-j} ; the observed vector of determinants of profits, $\boldsymbol{y}$; and the parameter vector $\boldsymbol{\gamma}$. An approximation to the difference in profits that the store would have earned if it had chosen $\sigma_j^{'}$ instead of σ_j is denoted $\Delta\tilde{\pi}(\sigma_j, \sigma_j^{'}, \cdot)$. The change in true profits can be written as

$$(26)\quad \Delta\pi(\sigma_j, \sigma_j^{'}, \boldsymbol{\sigma}^*_{-j}, \boldsymbol{y}, \boldsymbol{\gamma}) = \Delta\tilde{\pi}(\sigma_j, \sigma_j^{'}, \boldsymbol{\sigma}^*_{-j}, \boldsymbol{y}; \boldsymbol{\gamma}) + \nu_{1,j,\sigma_j,\sigma_j^{'}} + \nu_{2,j,\sigma_j,\sigma_j^{'}},$$

where ν_1 and ν_2 are unobserved determinants of true profits, differing in what the store knows about them. The store knows ν_2 before it chooses its strategy for the next period, so ν_2 is part of its information set $\mathcal{I}_j$. I assume that the store-decision does not depend on ν_1, so $\mathbb{E}[\nu_{1,j,\sigma_j,\sigma_j^{'}}|\mathcal{I}_j] = 0$ by construction and profits are observable up to the parameter-vector $\boldsymbol{\gamma}$ plus an error which is mean-conditional on the store's information set (ν_1), i.e., I assume that $\nu_{2,j,\sigma_j,\sigma_j^{'}}$ is identically zero for all σ_j and $\sigma_j^{'}$.

The PPHI estimator requires that expected profits using the actual strategy σ_j^* be higher than under alternative $\sigma_j^{'}$

$$(27)\quad \mathbb{E}[\Delta\pi(\sigma_j^*, \sigma_j^{'}, \boldsymbol{\sigma}^*_{-j}, \boldsymbol{y})|\mathcal{I}_j] \geq 0.$$

But assumption $\mathbb{E}[\nu_{1,j,\sigma_j,\sigma_j^{'}}|\mathcal{I}_j] = 0$, yields the inequality in approximated profits

$$(28)\quad \mathbb{E}[\Delta\tilde{\pi}(\sigma_j^*, \sigma_j^{'}, \boldsymbol{\sigma}^*_{-j}, \boldsymbol{y}, \boldsymbol{\gamma})|\mathbf{w}_j] \geq 0,$$

where $\mathbf{w}_j \in \mathcal{I}_j$. Taking sample averages across observations yields the following moment-inequalities

$$(29)\quad \frac{1}{N}\sum_{j=1}^{N}\Big[\Delta\pi(\sigma_j^*, \sigma_j^{'}, \boldsymbol{\sigma}^*_{-j}, \boldsymbol{y}, \boldsymbol{\gamma}) \otimes h(\mathbf{w}_j)\Big] \geq 0,$$

[12]Sweeting (2007) and Holmes (2008) also use the PPHI estimator in their dynamic framework.

[13]Simulation error appears since store-quality and format-decisions, as well as market demographics, can evolve in so many ways.

where $h(\mathbf{w}_j)$ is a set of instrument functions. The number of moment-inequalities can be increased by increasing the number of alternative strategies or by expanding the number of instruments. The moment-inequalities here are

$$\begin{aligned}
\frac{1}{N}\sum_{j=1}^{N}\Big[\quad & (T_{1,\sigma_j^*,\sigma_{-j}^*} - T_{1,\sigma_j',\sigma_{-j}^*}) - \gamma_1(T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}) \\
& -\gamma_2(T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}) + \gamma_3(T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}) \\
& +\gamma_4(T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*})\Big] \geq 0,
\end{aligned} \tag{30}$$

for five alternatives of σ_j', where T_k is the sample average of the term k in equation (25). Using inequality (30), the lower bound for the sunk cost of repositioning from the following inequality:

$$\begin{aligned}
\gamma_1 \geq \quad & \tfrac{T_{1,\sigma_j^*,\sigma_{-j}^*} - T_{1,\sigma_j',\sigma_{-j}^*}}{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}} - \gamma_2\tfrac{T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}}{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}} + \gamma_3\tfrac{T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}}{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}} \\
& +\gamma_4\tfrac{T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*}}{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}}
\end{aligned} \tag{31}$$

(if $T_{2,\sigma_j^*,\sigma_{-j}^*} < T_{2,\sigma_j',\sigma_{-j}^*}$). By increasing the number of format repositioning both the revenues and cost of repositioning increase. Thus, this policy that is not preferred by stores gives us the lower bound for the repositioning cost. The upper bound is obtained using a strategy that decreases the number of repositionings, which implies a decrease in revenues:

$$\begin{aligned}
\gamma_1 \leq \quad & \tfrac{T_{1,\sigma_j^*,\sigma_{-j}^*} - T_{1,\sigma_j',\sigma_{-j}^*}}{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}} - \gamma_2\tfrac{T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}}{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}} + \gamma_3\tfrac{T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}}{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}} \\
& +\gamma_4\tfrac{T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*}}{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}}
\end{aligned} \tag{32}$$

(if $T_{2,\sigma_j^*,\sigma_{-j}^*} > T_{2,\sigma_j',\sigma_{-j}^*}$).

The lower bound for the fixed cost is zero. The upper bound of the fixed cost is obtained implementing a strategy that reduces the number of format repositioning:

$$\begin{aligned}
\gamma_2 \leq \quad & \tfrac{T_{1,\sigma_j^*,\sigma_{-j}^*} - T_{1,\sigma_j',\sigma_{-j}^*}}{T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}} - \gamma_1\tfrac{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}}{T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}} + \gamma_3\tfrac{T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}}{T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}} \\
& +\gamma_4\tfrac{T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*}}{T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}}
\end{aligned} \tag{33}$$

(if $T_{3,\sigma_j^*,\sigma_{-j}^*} > T_{3,\sigma_j',\sigma_{-j}^*}$). In the empirical section, this strategy is implemented by reducing by 0.05 the probability to repositioning in every state. Another alternative strategy is not allowing repositioning.

A store that changes the format receives a large draw of ν. Large repositioning costs can explain why some stores never change their format even if they receive favorable draws of ν. The upper bound of the scale parameter γ_3 is obtained using an alternative strategy that increases ν, reduce the revenues, and makes repositioning a constant strategy, i.e., format choices are made equal. I implement this strategy by equalizing the choice probabilities for other formats and leaving unchanged the choice of the current format (Sweeting, 2007).

$$\begin{aligned}\gamma_3 \leq \; & \frac{T_{1,\sigma_j^*,\sigma_{-j}^*} - T_{1,\sigma_j',\sigma_{-j}^*}}{T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}} + \gamma_1 \frac{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}}{T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}} + \gamma_2 \frac{T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}}{T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}} \\ & + \gamma_4 \frac{T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*}}{T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}}\end{aligned} \tag{34}$$

(if $T_{4,\sigma_j^*,\sigma_{-j}^*} < T_{4,\sigma_j',\sigma_{-j}^*}$). The drawback of this strategy is that the store can also choose to exit.

The next step is to propose an alternative strategy to estimate the upper bound of the sell-off value (scrap value), γ_4. This bound is obtained by increasing the likelihood to exit. In the empirical implementation, I increase exit probability by 0.05.

$$\begin{aligned}\gamma_4 \leq \; & -\frac{T_{1,\sigma_j^*,\sigma_{-j}^*} - T_{1,\sigma_j',\sigma_{-j}^*}}{T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*}} + \gamma_1 \frac{T_{2,\sigma_j^*,\sigma_{-j}^*} - T_{2,\sigma_j',\sigma_{-j}^*}}{T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*}} + \gamma_2 \frac{T_{3,\sigma_j^*,\sigma_{-j}^*} - T_{3,\sigma_j',\sigma_{-j}^*}}{T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*}} \\ & - \gamma_3 \frac{T_{4,\sigma_j^*,\sigma_{-j}^*} - T_{4,\sigma_j',\sigma_{-j}^*}}{T_{5,\sigma_j^*,\sigma_{-j}^*} - T_{5,\sigma_j',\sigma_{-j}^*}}\end{aligned} \tag{35}$$

(if $T_{5,\sigma_j^*,\sigma_{-j}^*} < T_{5,\sigma_j',\sigma_{-j}^*}$). Due to heterogeneity across Swedish local markets, I estimate the cost-parameters for a groups of markets.[14]

5 Results

This section presents the results from: demand estimation; revenue generating function estimation; entry, exit, and repositioning policies; and repositioning and entry costs.

Demand. Table 9 shows the estimates from the demand model presented in Section 3.1. The demographic format-taste parameters show to some extent expected

[14]Appendix C presents an alternative estimator for repositioning costs.

patterns. Stores in markets with a large proportion of children (population 0-14) tend to have large and very large formats (Table 9). *ICA Supermarket* is the most preferred format in these markets. The very large formats *ICA Maxi* (1.03) and *Coop Large* (0.88) are are preferred in these markets. *ICA Kvantum*, also a large format, is found to be less preferred in markets with a high proportion of children, however. Perhaps the effect of demographics is captured by other demographics. Axfood's large format *Willys et al.*, which is promoted as "Sweden's cheapest bag of groceries", is the one preferred in markets with the most kids (1.25), however. Young adults (15-34) prefer small formats such as *ICA Nära* (0.69), *Tempo* (0.80), and *Coop Nära* (1.99). *ICA Maxi* (0.68) is the most preferred very large format in markets with large share of young adults. The medium format *ICA Supermarket* (0.82), and small formats such as *Tempo* (1.98) are preferred in markets with large share of older people (over 65). As with young adults, *ICA Maxi* is the most preferred very large format in markets with large share of older people.

As discussed earlier, distance to the center of postal-code (three digit postal-code area) is used to control for spatial differentiation in the demand estimation, allowing us to explore the benefits of a store being closer to consumers. The estimated coefficients of distance represents the travel costs. *ICA Supermarket*, *Vi*, and *Coop Nära* are the formats that are close to the consumers. However, they are found to have relatively large travel cost. Consumers are less likely to choose these formats based on distance, i.e., there are other factors that affect consumers choices.

The age of the store is positive (0.65) and significant at traditional levels. Perhaps indicating that older stores might have better location. Sales space is also positive and significant, because large stores usually provide a wider range of products and lower prices.

The standard deviations of the random components format-tests are small and mostly are insignificantly different from zero. Demographics, therefore, seems to capture most of the systematic differences in tastes for formats within markets. Given the small standard deviation of the random coefficient on *Others*, there is an acceptable degree of substitution with the outside good.

As explained earlier, unobserved is backed out quality from the demand estimation. The AR(1) parameters for repositioning and non-repositioning are both less than one. This implies that the processes that describe quality are stationary, through quality is more persistent for the non-repositioning stores ($\rho_{nre} = 0.62$), as one might expect.

Repositioning stores have higher quality than non-repositioning stores in the upper tail of the distribution, but lower in the lower tail. The median quality of a repositioning store is larger that of a non-repositioning store, however.

Sales generating function estimation. Table 10 shows estimates of four sales-generating function specifications, each including market demographics and store characteristics such as age and quality. Including quality and quality squared allows control for its effect on sales.

Model 2 adds repositioning, while Model 3 also controls for format competition. Model 4 also controls for the effect of current on future sales (non-linear sales-effects) by including a dummy that specifies whether the store's market-share is less than the market-average. Increasing in sales due to an increase in store quality decreased with quality in all four models.

Increasing the proportion of kids has a positive impact on sales, while the effect of young adults is negative, perhaps because a higher proportion of this group might imply a lower income-level relative to the control group (35-65). While the store's age has a positive effect on sales (Model 4), the distance has a negative impact. As might be expected, both the number of stores in the same format and the number of stores owned by other firms have negative effects on sales. The direct effect of repositioning is positive, but not significant, which is not surprising since it might take time for consumers to adjust to the new format. Low previous market-share has a negative impact on sales.

To estimate sunk costs of entry and repositioning, I use Model 4 since it provides the highest correlation between observed and predicted sales for both repositioning and non-repositioning stores.

Policy functions. Table 11 reports the multinomial logit estimates of incumbent stores' format strategies. The first part of the table reports the market-demographic variables that affect the prevalence of each format, i.e., the proportion of the population in by age group and changes in those groups. In markets with a large proportion of children, stores are more likely to choose large formats such as *ICA Maxi* (345), *ICA Kvantum* (334), *Coop Large* (336), and *Bergendahls Others* (341). In markets with a large proportion of young adults or with increasing proportion of young adults, large formats such as *ICA Maxi* (72), *Coop Large* (49), and *Willys et al.* (16) are more likely. In markets with a large proportion of adults, *Coop Nära* is the most preferred format.

Stores with high quality are more likely to be in large formats (*ICA Maxi*, *Coop Large*). Axfood's small formats, *Tempo* and *Handlarń*, are also associated to have high quality (Axfood increased the number of stores in these formats during the period).

In markets where rivals have high quality, ICA focuses most on *ICA Kvantum* (0.098), *ICA Supermarket* (0.018), and *ICA Nära* (0.020); Axfood on *Handlarń* (0.039) and Coop on *COOP Medium* (0.026). Thus, three of ICA's formats are more likely in markets where rivals have high quality (product differentiation). All formats are less likely the more other stores there were the same format. The positive parameters on other formats show that stores try to differentiate in format.

The right part of Table 11 reports the coefficients on age, distance from other stores in rival format, and market-share. I allow the coefficients to differ depending on whether a store remains in the same format or changes format. Old stores in large formats are less likely to change format. Old stores that change are less likely to be in one of ICA's formats. On the other hand, old stores that change are more likely to become *Coop Nära*, *Axfood Others*, or *Hemköp et al.*. Stores far from others that changed format are more likely to become *Bergendahls Others*, *Handlarń*, or *OBS et al.*.

Table 12 reports estimates of entry and exit policies, aggregated for all formats, but accounting for market and format fixed-effects. Stores with high quality are less likely to exit. Exit is also less likely in large markets, and if the firm has many stores of the same format in the same market, which might indicate economies of density (Holmes 2008). On the other hand, stores are more likely to exit if they are old or if rivals have high quality.

Entry is more likely if rivals have high quality, and in markets with large population. Entry is less likely if the firm already operates many stores in that format in the same market, or if there are many other-firm rivals.

Repositioning costs and sell-off values. Using estimated quality, sales estimates, and policy functions, I can recover the cost parameters. Table 13 presents repositioning-cost estimates (identified sets) for markets with population below 20,000, population 20,000-60,000, and over 60,000, as well as median sales of repositioning stores, and the median number of repositioning stores per year during the period.

The confidence intervals for the estimated parameters are simulated (see Pakes et al., 2007b). To apply bootstrap is very time consuming because of the forward simulations. In addition to PPHI, there are different approaches for inferences with moment inequalities (Imbens and Manski, 2004; Chernozhukov et al., 2007; and Andrews and Soares, 2010). In this case, the confidence intervals are the extreme points of identified set. PPHI suggests a simulation method to construct the "inner" and "outer" confidence intervals. These intervals are asymptotically the true confidence intervals for the estimated bounds. I only report the "outer" threshold, i.e., the conservative values. The "outer" confidence intervals are obtained using 100 simulations.[15] The small number of simulations is due to computation burden, i.e., 100 programming problems have to be solved.[16]

Average repositioning costs depend on the size of the market, being about 63 percent higher in markets with population 20,000-60,000 than in smaller markets, and another 16 percent higher in the largest.[17] Median sales are more than 20 times higher than average repositioning costs, especially high for markets of 20,000-60,000. By far most repositioning are in large markets, though repositioning seems to be most profitable in middle size-group ones. Sell-off values on exit are twice as high in the large markets as in the small ones. Due to store heterogeneity, there is a large spread in sell-off values in large markets.

For robustness, Table 15 (Appendix C) shows the point estimates of the repositioning and sell-off values using the minimum distance estimator. The values of estimated parameters belong to the identified sets estimated using PPHI.

Entry costs. Table 14 shows estimated sunk costs of entry, again for markets grouped by size. It is far more expensive to enter a market than to reposition. This might explain why the number of repositioning is larger than the number of entrants. Mean entry costs increases substantially with market size. Entry costs are more than twice median sales in small markets, over four times median sales in medium markets, and a bit less in large markets. Thus, there is higher entry costs per median sales in medium than in large markets. The large estimation of entry costs in large markets may be due to big entrants that shift the mean.

[15]In Pakes et al. (2007b), Section 3.1.2 presents the estimation details of the confidence intervals.

[16]IPOPT optimizer is used (https://projects.coin-or.org/Ipopt). Ipopt is an optimizer for large scale nonlinear problems. In case that absolute norm is used, it is computationally efficient to used linear programming solvers. For example, the GLPK (http://www.gnu.org/software/glpk/), which is a package for solving large-scale linear programming.

[17]To get a conservative estimate, I used the upper bound to measure the changes in costs.

6 Conclusions

While there have been important contributions in modelling both static and dynamic consumer demand for differentiated products, there have been few attempts at modelling their supply. The fact the products are differentiated means that shocks might cause firms to change their product assortment.

A dynamic oligopoly model is estimated in Swedish retail food industry to measure the costs associated with repositioning by changing store formats, which also often includes major changes in product assortment. The estimation gives important information about driving forces behind repositioning, associated costs, and how it can be linked to entry and exit.

There are high correlations between entry, exit, and repositioning. More generally, the paper provides a framework for studying repositioning in any industry where entry and exit are important. Understanding the potential role of repositioning in the trade-off between repositioning, entry, and exit is one of the aims of this paper. Since entry is regulated in most OECD countries, knowledge about repositioning and entry costs has important implications for policy.

In the Swedish retail food industry, repositioning costs increase with the size of the market, though at a decreasing rate. Stores are less likely to exit if they have high quality, are in large markets, or if there are many same-format stores in the same market. Entry is more likely in large markets or if rivals have high quality, so that there is room for product differentiation. Stores with high quality are more likely to be in large formats. Old stores are less likely to reposition. Distance is an important factor for consumers choosing a store. Finally, store's quality is more persistent for non-repositioning stores.

In future work, cost estimates of the four different size groups (see Section 2) of stores will provide valuable information about repositioning. Having the estimated structural parameters, different policy experiments can be implemented. My interest is to evaluate how the cost of repositioning could be affected by lowering the cost of entry, and how sunk cost of entry could be affected by lowering the cost of repositioning. I modelled multi-product ownership, i.e., the fact that each firm operates many stores, in a limited way. Since I only control for owners in stores' policies, I did not explicitly model the dynamics of their product selection. Selection of products in multi-product firms is an important topic for future research. Understanding it will give us more information about market power, business cannibalization, and economies of scope.

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Table 1: Store formats by firm

Format	Firm	Store concepts into the defined format	Sales space m^2	Average sales per m^2(SEK)	Number of stores 2001	2002	2003	2004	2005	2006
1	ICA	ICA Maxi	3,378	88	31	32	34	35	41	49
2	ICA	ICA Kvantum	2,205	75	119	121	124	126	127	122
3	ICA	ICA Supermarket	875	66	450	437	534	524	496	484
4	ICA	ICA Nära	263	52	1,226	1,134	1,152	1,044	937	930
5	Axfood	Willys et al.	1,559	69	56	76	111	135	146	150
6	Axfood	Vivo	745	70	253	121	91	88	0	0
7	Axfood	Hemköp et al.	1,214	56	180	269	251	224	174	161
8	Axfood	Handlarn	167	36	117	172	187	208	217	221
9	Axfood	Tempo	286	43	89	103	103	111	147	151
10	ICA	Rimi	801	63	134	135	0	0	0	0
11	Axfood	Axfood Others	281	61	281	172	162	129	158	157
12	COOP	Coop Nära	302	68	0	0	0	0	97	114
13	COOP	Coop Large	2,349	59	63	60	61	88	99	112
14	COOP	Coop Medium	535	54	801	815	786	725	576	508
15	COOP	OBS et al.	1,382	65	122	61	60	56	40	25
16	Bergendahls	Vi	867	81	0	0	0	0	86	98
17	Bergendahls	Bergendahls Others	1,290	47	62	73	80	83	92	108
18	Others	Others	134	45	2,540	2,447	2,440 2	638	2,679	2,563

NOTES: Data from DELFI. Average sales per square meter are in 2001 thousand SEK (1 EUR=9 SEK, 1 USD= 8 SEK). Each format contains one or more store concepts. *ICA Nära* includes also ICA Express stores; *Willys et al.* includes Willys and Willys Hemma; *Hemköp et al.* includes Exet, Spar, Matex, Axfood Storlivs, and Billhälls; *Axfood Others* (format number 11) includes Jour Livs, Matnära, Axfood Närlivs Rätt Pris, Axfood Lågpris, and Östenssons; *Coop Large* (format number 13) includes COOP Forum level 2 and 3, B & W, Gröna Konsum, COOP Extra, and Konsum Extra; *Coop Medium* includes stores Coop Konsum level 1 and 4; *OBS et al.* includes OBS, Robin Hood, Domus, Prix, and Fakta; *Bergendahls Others* (format number 17) includes Favör, Matöppet, Prisxtra, City Gross, and Ekohallen, Eko, and AG-Favör; *Others* includes Statoil, OKQ8, Nära Dej, Matbutiken, Fri Mat, 7-Eleven, Pressbyrån Närlivs, Shell, Preem, Bilisten, Lidl, Netto, Norsk Hydro, Din-X, Uno-X, Pump, Samuelsons Servicehandeln, Pressbyrån Franchise, Q Star, and yet others.

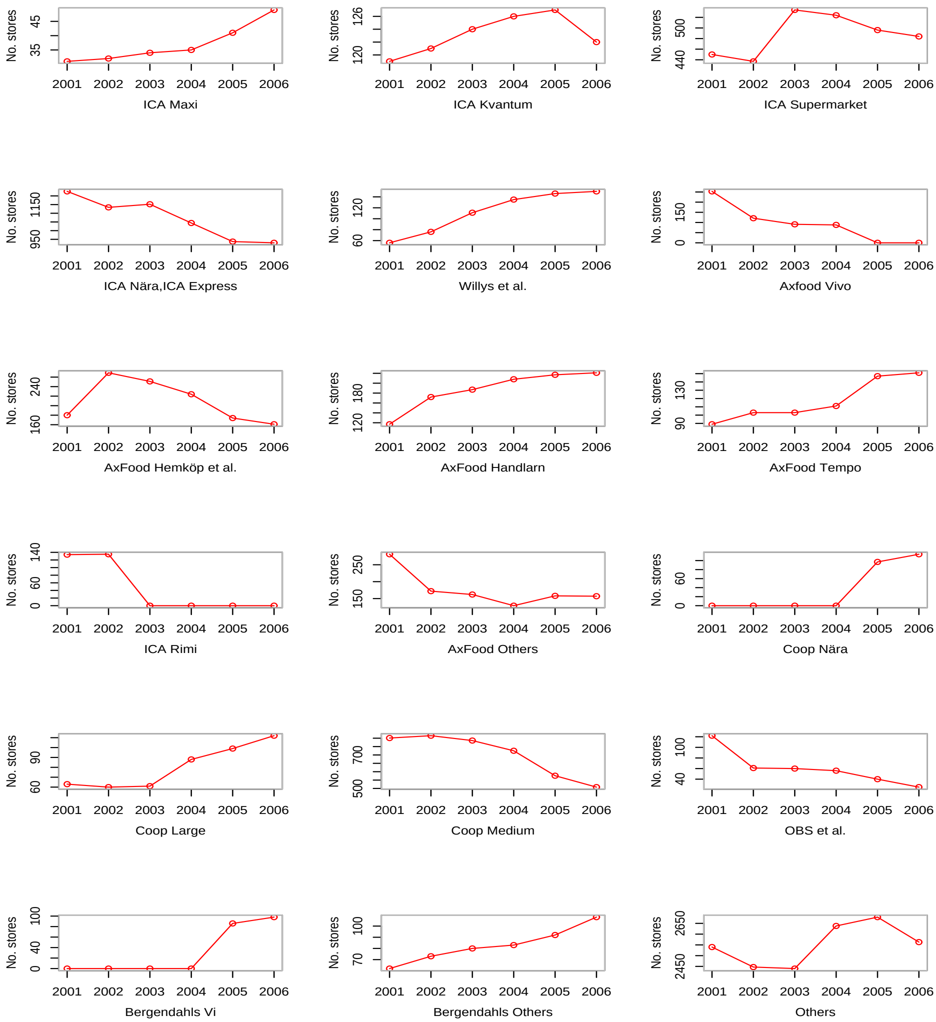

Figure 1: Evolution of the number of stores by format (see Table 1) during 2001-2006.

Table 2: Store characteristics, 2001-2006

Year	# of Stores	# of Repos. Format	# of Entries	# of Exits	Average Sales	Total Sales	Format repositioning sales 25%	Format repositioning sales 50%	Format repositioning sales 75%	Median pop.	Median families
2001	6,524	-	-	339	23,594	153,927,750	-	-	-	38,706	19,852
2002	6,228	481	94	167	25,368	157,993,250	5,500	17,500	45,000	38,706	19,852
2003	6,176	321	134	239	27,080	167,247,500	12,500	35,000	55,000	38,706	19,852
2004	6,214	300	311	261	27,386	170,178,020	3,500	9,000	35,000	39,145	20,410
2005	6,112	589	171	293	28,242	172,613,250	4,500	12,500	27,500	39,477	20,554
2006	5,953	243	134	-	29,463	175,395,290	4,500	9,000	31,250	40,873	20,770

NOTES: Sales are reported in thousands of 2001 SEK. Population and numbers of families are at municipality level (290).

Table 3: Median characteristics of repositioning and non-repositioning markets

Year	Population		# of Stores		# of Entries (E)		# of Exits (X)		C_4		$Cor(R,E)$	$Cor(R,X)$
	Repos.	Non-Repos.	Repos.	Non-Repos.	Repos.	Non-Repos.	Repos.	Non-Repos.	Repos.	Non-Repos		
2002	21,450	10,549	33.5	15.5	2.5	1.0	3.5	1.0	0.236	0.365	0.63	0.50
2003	26,355	11,014	32.5	17.0	3.0	1.0	3.5	1.0	0.168	0.370	0.72	0.53
2004	22,319	12,615	32.0	18.5	5.0	2.0	4.5	2.0	0.165	0.358	0.78	0.80
2005	23,104	11,270	31.0	13.0	3.5	1.0	4.0	1.0	0.221	0.450	0.76	0.66
2006	27,120	11,804	31.0	17.0	2.5	2.5	-	-	0.186	0.394	0.88	-

NOTE: *Repositioning* markets are those where at least one repositioning occurred during the year. *Non-Repositioning* markets are all others. $Cor(R,E)$ and $Cor(R,X)$ are correlations between the numbers of repositionings (R) and entries (E), and (R) or exit (X) across markets where repositioning occurred.

Table 4: Median characteristics of markets where formats are present, 2001-2006

Format (see Table 1)	Number of Markets						Population		Market Share		Sales per m^2	
	2001	2002	2003	2004	2005	2006	Repos.	Non-Repos.	Repos.	Non-Repos.	Repos.	Non-Repos.
ICA Maxi	31	32	33	34	39	45	69,741	45,266	0.233	0.284	89.10	83.05
ICA Kvantum	93	95	101	102	104	99	37,057	26,270	0.193	0.290	72.29	68.77
ICA Supermarket	211	209	234	233	233	230	23,922	13,324	0.056	0.145	61.87	61.51
ICA Nära	261	257	259	258	248	247	24,935	13,725	0.014	0.024	46.79	43.75
Willys et al.	31	47	73	89	93	99	49,863	30,532	0.086	0.136	59.21	56.94
Vivo	122	49	26	20	0	0	54,357	32,269	0.023	0.036	76.24	53.25
Hemköp et al.	111	138	135	125	108	100	33,234	20,116	0.051	0.131	53.57	52.76
Handlarń	80	104	111	124	128	126	27,120	15,453	0.006	0.012	30.77	30.22
Tempo	56	61	63	68	81	90	36,690	21,715	0.011	0.021	40.12	39.56
Rimi	88	90	0	0	0	0	37,448	30,229	0.047	0.064	57.41	61.11
Axfood Others	135	94	87	73	84	82	37,052	20,017	0.003	0.013	40.34	42.86
Coop Nära	0	0	0	0	41	52	53,302	24,953	0.013	0.021	64.10	53.52
Coop Large	50	51	52	70	79	89	49,918	25,764	0.122	0.147	60.24	47.60
Coop Medium	240	255	254	244	232	219	23,947	12,820	0.026	0.056	49.64	46.36
OBS et al.	94	45	45	45	35	24	26,300	26,131	0.151	0.149	54.69	55.63
Vi	0	0	0	0	21	33	56,467	29,475	0.023	0.022	70.00	50.00
Bergendahls Others	33	37	42	47	52	55	33,494	19,868	0.020	0.055	41.20	45.00
Others	285	284	286	287	289	287	22,328	13,000	0.006	0.011	32.25	31.34

NOTES: *Repositionig* markets are those where at least one repositioning occurred during the year. *Non-Repositioning* markets are all others.

Table 5: Format repositioning from ICA, 2001-2006

	from ICA				
New Format (see Table 1)	Maxi	Kvantum	Supermarket	Nära	Rimi
ICA Maxi	-	8	0	0	0
ICA Kvantum	2	-	7	0	2
ICA Supermarket	0	8	-	7	100
ICA Nära	0	0	48	-	30
Willys et al.	0	0	0	2	0
Vivo	0	0	1	0	1
Handlarń	0	0	0	31	0
Tempo	0	0	0	21	0
Rimi	0	1	5	2	-
Axfood others	0	0	0	9	0
Vi	0	0	0	2	0
Bergendahls others	0	0	1	16	0
Others	0	2	1	220	1

NOTE: The figures represent the number of stores that switched format (see Table 1).

Table 6: Format repositioning from Axfood, 2001-2006

New Format (see Table 1)	Willys et al.	Vivo	Hemköp et al.	Handlarń	Tempo	AxFood Others
ICA Kvantum	0	2	0	0	0	0
ICA Supermarket	0	0	1	0	0	0
ICA Nära	0	1	4	0	1	1
Willys et al.	-	9	60	0	1	7
Vivo	0	-	0	0	1	1
Hemköp et al.	0	113	-	0	0	7
Handlarń	0	3	0	-	12	68
Tempo	1	19	45	3	-	14
Rimi	0	1	0	0	0	0
Axfood Others	0	5	4	8	4	-
COOP Medium	0	0	2	0	0	0
Vi	0	78	1	0	2	0
Bergendahls Others	0	4	3	0	6	4
Others	3	20	8	40	8	93

NOTES: The figures represent the number of stores that switched format (see Table 1).

Table 7: Format repositioning from Bergendahls, 2001-2006

Old Format (see Table 1)	ICA Supermarket	ICA Nära	Willys et al.	Hemköp et al.	Handlarń	Tempo	Axfood Others	COOP Medium	Vi	Others
Vi	0	0	1	3	1	2	0	0	0	1
Bergendahls Others	1	1	0	0	0	1	2	1	1	19

NOTES: The figures represent the number of stores that switch their format. One format contains one or more store concepts.

Table 8: Format repositioning from Coop, 2001-2006

Old Format (see Table 1)	ICA Nära	Willys et al.	Vivo	Handlarń	Tempo	Axfood Others	Coop Nära	Coop Large	Coop Medium	OBS et al.	Vi	Bergendahls Others	Others
Coop Large	0	1	0	0	0	0	0	0	43	0	0	0	0
Coop Medium	1	1	5	24	14	1	115	39	0	3	3	12	25
OBS et al.	0	0	0	0	0	0	0	53	38	0	0	0	1
Others	0	0	0	0	0	0	0	0	0	0	0	1	0

NOTES: The figures represent the number of stores that switched format.

Table 9: Demand model estimates

Format (see Table 1)	Std. Dev.	Distance	Pop. 0-14	Pop. 15-34	Pop. 65-100
ICA Maxi	0.1336	-0.6704	1.0289	0.6838	0.6420
	(1.0002)	(0.0274)	(0.0012)	(0.0358)	(0.0321)
ICA Kvantum	0.0272	-0.7171	-0.9031	0.4654	0.2201
	(2.0435)	(0.0902)	(0.0631)	(0.0002)	(0.0106)
ICA Supermarket	0.1822	-1.6194	2.4134	0.1637	0.8203
	(4.0305)	(0.0335)	(0.2648)	(0.0312)	(0.4253)
ICA Nära	0.7535	-0.4094	-0.2264	0.6900	0.2715
	(2.1431)	(0.2003)	(0.1231)	(0.0243)	(0.0155)
Willys et al.	0.6057	-0.8821	1.2520	0.3079	0.2587
	(3.0246)	(0.0548)	(0.324)	(0.1260)	(0.0332)
Vivo	0.3944	-0.9255	0.9616	0.7370	0.1189
	(3.257)	(0.1005)	(0.1946)	(0.0004)	(0.0282)
Hemköp et al.	0.9085	-0.7188	0.4967	0.4152	0.4151
	(0.0303)	(0.0332)	(0.0340)	(0.2112)	(0.0553)
Handlarń	0.1837	-0.0559	0.0886	0.2558	0.3278
	(4.566)	(0.0012)	(0.0394)	(0.0122)	(0.0134)
Tempo	0.1504	-0.4019	0.2046	0.7964	1.9868
	(0.0201)	(0.0141)	(0.0244)	(0.0432)	(0.0043)
Rimi	0.1333	-0.2393	0.1031	0.7484	-0.9531
	(0.0223)	(0.0030)	(0.1506)	(0.0003)	(0.0245)
Axfood Others	0.9813	-0.5016	0.5548	0.7413	0.4577
	(1.0033)	(0.0302)	(0.0232)	(0.0191)	(0.0126)
Coop Nära	0.6035	-1.0515	0.5386	1.9743	0.1485
	(5.0130)	(0.0004)	(0.0930)	(0.0023)	(0.0165)
Coop Large	0.2385	-0.6393	0.8863	0.4163	0.1556
	(3.0201)	(0.0221)	(0.0562)	(0.0646)	(0.0427)
Coop Medium	0.8516	-0.1116	0.2041	0.4366	0.1325
	(10.2374)	(0.0047)	(0.1041)	(0.0406)	(0.0256)
OBS et al.	0.3486	-0.6849	0.4394	0.3244	0.3012
	(4.0504)	(0.0257)	(0.0452)	(0.0757)	(0.0432)
Vi	0.9622	-1.0666	0.5819	0.6543	0.3114
	(8.0250)	(0.0303)	(0.0940)	(0.0043)	(0.0165)
Bergendahls Others	0.2408	-0.9030	0.0820	0.2175	0.3407
	(9.0031)	(0.0221)	(0.0322)	(0.0046)	(0.0047)
Age	0.6561				
	(0.0135)				
Sales space	0.0828				
	(0.0409)				
Quality transition	0.1718				
Repositioning	(0.0042)				
Quality transition	0.6232				
Non-repositioning	(0.0023)				
Number of observations	18,519				
GMM objective	28647				
Sargan p-value	0.184				

NOTES: Standard errors are in parentheses. Population is in logs at municipality level. Coefficients on market-format and year dummies are not reported.

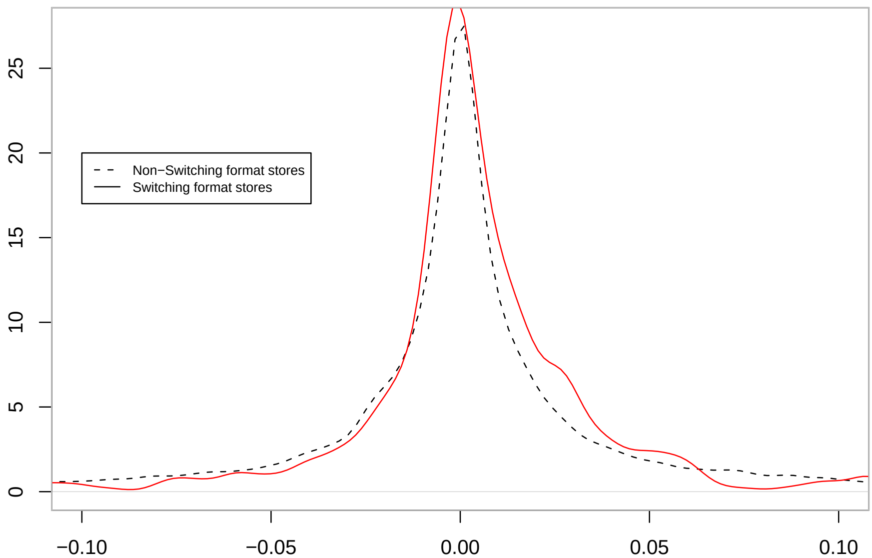

Figure 2: Quality kernel density estimates, repositioning and non-repositioning stores

Table 10: Sales function estimates

	Model 1	Model 2	Model 3	Model 4
Demographics				
Population (0-14 years)	0.0008	0.0007	0.0002	0.0009
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Population (15-34 years)	-0.0006	-0.0006	-0.0005	-0.0007
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Population (over 65 years)	0.0014	0.0014	0.0014	0.0017
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Store characteristics and competition				
Age	-0.0209	-0.0202	-0.0115	0.0002
	(0.0021)	(0.0021)	(0.0009)	(0.001)
Distance	-0.0282	-0.0282	-0.0165	-0.0011
	(0.0031)	(0.0031)	(0.0014)	(0.0006)
Store quality	0.0073	0.0074	0.0041	0.0004
	(0.0007)	(0.0007)	(0.0003)	(0.0001)
Store quality squared	-0.00005	-0.00005	-0.00003	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.000001)
Number of stores commonly owned in format			-0.0076	-0.0053
			(0.0007)	(0.0006)
Number of stores owned by other firms			-0.0065	-0.0043
			(0.0007)	(0.0005)
Format repositioning		0.0205	0.0594	0.0047
		(0.0069)	(0.0438)	(0.0023)
Revenue effects				
Store market share less than market average				-0.2174
				(0.1399)
Number of observations	18,519	18,519	18,519	18,519
Sales for non-repositioning				
actual mean	32,817	32,817	32,817	32,817
predicted mean	28,033	30,297	30,281	31,902
correlation of actual, predicted	0.10	0.42	0.42	0.45
Sales for repositioning				
actual mean	35,120	35,120	35,120	35,120
predicted mean	30,118	33,428	33,715	34,717
correlation of actual, predicted	0.16	0.44	0.44	0.46

NOTES: Estimation by non-linear least squares. Standard errors in parentheses. Specifications include market-year fixed effects. Sales are reported in thousands of 2001 SEK. Population is in logs at municipality level.

Table 11: Policy parameter estimates: repositioning format strategies

Format (see Table 1)	Pop. 0-14	Δ Pop. 0-14	Pop. 15-34	Δ Pop. 15-34	Pop. 65-100	Δ Pop. 65-100	Own quality	Rivals quality	No. own Formats	No. rivals	Stay	Switch	Stay	Switch	Stay	Switch
											$\times$Age		$\times$Dist.		$\times$ Market share	
ICA Maxi	345.30	-204.735	72.082	165.369	-271.604	430.359	0.100	0.003	-4.336	0.179	-0.358	-0.422	-0.670	-3.355	70.376	40.907
	(0.045)	(0.072)	(0.042)	(0.069)	(0.009)	(0.016)	(0.016)	(0.005)	(0.604)	(0.005)	(0.055)	(0.067)	(0.148)	(0.060)	(0.780)	(0.067)
ICA Kvantum	334.62	-135.473	-8.922	175.906	-248.186	363.985	-0.077	0.008	-1.334	0.167	0.269	0.225	-1.251	-14.282	70.164	42.078
	(0.028)	(0.040)	(0.023)	(0.052)	(0.008)	(0.013)	(0.010)	(0.003)	(0.057)	(0.004)	(0.035)	(0.039)	(0.228)	(0.007)	(0.539)	(0.156)
ICA Supermarket	191.30	-86.721	-16.503	110.571	-219.378	251.676	0.006	0.018	-0.472	0.139	0.018	-0.054	-0.057	0.021	59.126	21.203
	(0.030)	(0.035)	(0.086)	(0.122)	(0.029)	(0.040)	(0.006)	(0.002)	(0.012)	(0.004)	(0.021)	(0.023)	(0.032)	(0.058)	(0.463)	(0.013)
ICA Nära	188.20	-47.723	-11.604	85.374	-28.716	167.076	-0.022	0.020	-0.285	0.121	0.118	0.061	0.128	0.062	30.160	11.760
	(0.094)	(0.139)	(0.601)	(0.814)	(0.178)	(0.228)	(0.005)	(0.001)	(0.008)	(0.004)	(0.017)	(0.018)	(0.023)	(0.053)	(1.034)	(0.070)
Willys et al.	262.32	-79.790	16.858	150.910	-163.264	326.505	0.046	0.001	-0.660	0.155	-0.178	-0.180	-0.344	-0.449	59.507	36.648
	(0.034)	(0.036)	(0.051)	(0.089)	(0.024)	(0.033)	(0.009)	(0.003)	(0.022)	(0.004)	(0.030)	(0.031)	(0.064)	(0.142)	(0.722)	(0.709)
Vivo	307.40	-137.283	-146.102	188.723	-310.258	235.689	-0.016	0.017	-0.344	0.126	0.089	0.044	-0.050	-0.345	57.083	16.709
	(0.034)	(0.048)	(0.010)	(0.026)	(0.004)	(0.008)	(0.009)	(0.004)	(0.011)	(0.004)	(0.032)	(0.035)	(0.085)	(0.675)	(0.193)	(0.005)
Hemköp et al.	273.91	-94.412	9.804	112.722	-299.879	396.696	-0.028	0.014	-0.693	0.155	0.120	0.110	0.016	0.131	58.467	31.218
	(0.027)	(0.036)	(0.020)	(0.035)	(0.009)	(0.014)	(0.007)	(0.002)	(0.020)	(0.004)	(0.026)	(0.027)	(0.047)	(0.061)	(0.626)	(0.166)
Handlarń	52.60	-36.425	-83.106	99.222	-276.976	249.792	0.030	0.037	-1.094	0.161	-0.072	-0.094	-0.145	-0.166	-106.767	-95.908
	(0.021)	(0.037)	(0.020)	(0.034)	(0.006)	(0.014)	(0.008)	(0.002)	(0.030)	(0.004)	(0.027)	(0.028)	(0.039)	(0.062)	(0.017)	(0.006)
Tempo	105.18	-1.073	-68.863	143.067	-124.473	237.636	0.037	0.024	-1.037	0.164	-0.097	-0.125	-0.269	-0.297	-43.008	-8.110
	(0.024)	(0.041)	(0.015)	(0.028)	(0.005)	(0.013)	(0.009)	(0.003)	(0.032)	(0.004)	(0.031)	(0.031)	(0.053)	(0.076)	(0.024)	(0.022)
Axfood Others	139.22	-87.366	-204.179	164.845	-453.006	249.841	-0.300	0.036	-0.885	0.149	1.028	0.997	1.269	1.172	58.009	35.261
	(0.019)	(0.037)	(0.013)	(0.027)	(0.007)	(0.017)	(0.008)	(0.002)	(0.025)	(0.004)	(0.029)	(0.029)	(0.043)	(0.120)	(0.164)	(0.030)
Coop Nära	303.41	79.893	-154.035	105.144	-143.469	-157.724	-0.056	0.004	-0.742	0.153	-1.715	0.204	-0.432	0.207	-112.152	-3.120
	(0.046)	(0.083)	(0.011)	(0.034)	(0.011)	(0.028)	(0.017)	(0.009)	(0.033)	(0.004)	(0.335)	(0.058)	(0.072)	(0.099)	(0.000)	(0.104)
Coop Large	336.05	-165.777	49.670	116.421	-231.398	372.340	0.044	0.007	-1.702	0.173	-0.114	-0.123	-0.754	-0.851	61.088	39.154
	(0.037)	(0.044)	(0.041)	(0.070)	(0.019)	(0.026)	(0.011)	(0.003)	(0.094)	(0.004)	(0.037)	(0.037)	(0.145)	(0.277)	(0.734)	(0.765)
Coop Medium	176.85	-22.874	-27.587	105.563	31.821	118.183	-0.096	0.026	-0.294	0.126	0.366	0.312	0.431	-1.746	55.942	24.581
	(0.034)	(0.084)	(0.403)	(0.551)	(0.115)	(0.142)	(0.006)	(0.001)	(0.008)	(0.004)	(0.020)	(0.023)	(0.027)	(0.931)	(0.651)	(0.018)
OBS et al.	127.11	-94.328	-13.593	127.303	-117.759	211.679	-0.154	0.032	-1.040	0.148	0.553	0.484	0.573	0.742	66.521	38.113
	(0.023)	(0.053)	(0.014)	(0.048)	(0.016)	(0.036)	(0.015)	(0.003)	(0.069)	(0.005)	(0.051)	(0.055)	(0.087)	(0.100)	(0.845)	(0.087)
Vi	42.37	-20.972	-152.186	160.744	61.124	-114.585	0.223	-0.006	-0.426	0.141	-3.788	-0.737	-8.365	-0.989	1.324	3.136
	(0.051)	(0.082)	(0.029)	(0.047)	(0.006)	(0.018)	(0.024)	(0.011)	(0.047)	(0.006)	(0.575)	(0.081)	(0.065)	(0.148)	(0.000)	(0.121)
Bergendahls Others	341.73	-150.366	-26.270	151.784	51.350	218.054	-0.136	0.002	-0.697	0.142	0.480	0.479	0.531	0.599	60.461	26.389
	(0.046)	(0.055)	(0.029)	(0.056)	(0.015)	(0.021)	(0.012)	(0.004)	(0.029)	(0.004)	(0.041)	(0.041)	(0.067)	(0.086)	(1.100)	(0.121)
Number of observations	18,519															
Log-Likelihood	-70771.77															

NOTES: Estimated multinomial logit model for conditional choice probabilities. Standard errors are in parentheses. Population is percent.

Table 12: Policy parameter estimates: entry and exit

	Entry probit $P(entry\|X)$	Exit probit $P(exit\|X)$
Quality		-0.049
		(0.006)
Competitors's quality in the same format	0.028	0.002
	(0.014)	(0.001)
Age		0.163
		(0.026)
Distance	0.025	0.021
	(0.012)	(0.002)
Population	1.904	-0.199
	(0.903)	(0.046)
Number of stores commonly owned in format	-0.061	-0.002
	(0.017)	(0.001)
Number of stores owned by other firms	-0.049	-0.0001
	(0.023)	(0.0001)

NOTES: Standard errors are in parentheses. Specifications include format market-year fixed effects. Population is in logs at municipality level.

Table 13: Parameter estimates: sunk repositioning costs and sell-off values

Parameter	Market Size		
	Population < 20,000	Population 20,000-60,000	Population > 60,000
Repositioning costs (γ_1)	[78.73 390.41]	[403.00 637.13]	[490.02 738.35]
PPHI outer - 95%	[62.41 416.23]	[384.45 701.92]	[481.52 793.32]
Sell-off values (γ_4)	[680.34 990.98]	[736.02 1203.92]	[920.97 1890.37]
PPHI outer - 95%	[603.72 1010.39]	[701.83 1308.62]	[839.82 1983.08]
Median sales of repositioning stores	8,000	17,500	17,500
Median sales/upper bound of repositioning costs	21	27	24
Mean no. of repositionings per year-market	1	2	11

NOTES: Repositioning costs are in thousands of 2001 SEK. The Pakes et al. (2007b) estimator is used. 100 simulations are used to construct the outer intervals.

Table 14: Sunk entry costs distribution results

Parameter	Market Size		
	Population < 20,000	Population 20,000-60,000	Population > 60,000
Mean	5,405	20,357	37,985
Variance	5E4	7E4	10E4
Median Sales of Entrants	2,500	4,500	10,750

NOTES: Median sales and costs are in thousands of 2001 SEK. The parameters were estimated by matching the cumulative distribution function of a normal distribution to the empirical probability of entry. The expected value of entry was computed using 100 replications of each state.

Appendix A. Sources of DELFI's data. DELFI Marknadspartner AB includes daily covers data on retail food stores from: (1) public registers, trade press, and daily press; (2) the Swedish Retailers Association (SSLF); (3) Kuponginlösen AB (a firm that deals with customers coupons); (4) each chains' headquarters; (5) matching customer registers from suppliers (customers); (6) telephone interviews, (7) annual surveys; and (8) The Swedish Retail Institute (HUI). In addition, DELFI verifies location, store-type, owner, and chain affiliation in annual reports.

Each firm has an identification number linked to it address. There are 11 store-types, based on size, location, product assortment, etc.: hypermarkets, department stores, large supermarkets, large grocery stores, other stores, small supermarkets, small grocery stores, convenience stores, gas-station stores, mini markets and seasonal stores.

Appendix B. Forward simulation steps that used to compute expected payoffs. The steps each year are :

1. Given store characteristics and market demographics, estimate the store quality from the random-coefficients demand model. I use 20 Halton draws for each unobserved characteristics.

2. Using the estimated sales generating function, compute discounted revenues for each store. I assume that the store are independently owned.

3. Compute the competition and demographics variables, which change every year and affect the multinomial (nested) logit format choice. Again, I assume that the stores are independently owned.

4. Simulate a choice for each store, i.e., compute the multinomial (nested) logit choice probabilities and compare then with a random random draw from a uniform distribution. If the store repositions I count how many times it does.

5. Conditional on current and previous, simulate the evolution of store-quality using draws from the empirical distribution of observed quality-innovations for the random components. In addition, simulate the evolution of demographics.

6. Update store formats.

Appendix C. Alternative estimators of sunk repositioning costs. An alternative estimator for the second step is the minimum-distance estimator, constructed using the set of inequalities below. Due to linearity in the cost function, the optimality conditions (1) can be re-written as

$$(36)\quad [W_j(\boldsymbol{\omega}, \sigma_j, \sigma_{-j}) - W_j(\boldsymbol{\omega}, \sigma_j^{'}, \sigma_{-j})]\boldsymbol{\gamma} \geq 0$$

This can be written in terms of profitable deviations from optimal policy,

$$(37)\quad g(\sigma_j^{'}; \boldsymbol{\gamma}, \boldsymbol{\alpha}) = [W_j(\boldsymbol{\omega}, \sigma_j, \sigma_{-j}) - W_j(\boldsymbol{\omega}, \sigma_j^{'}, \sigma_{-j})]\boldsymbol{\gamma}$$

where $\boldsymbol{\alpha}$ represents parameterization of the policy functions. More specifically, alternative policies can be drawn to generate a set of inequalities indexed by x. The estimates of W_j, denoted $\tilde{W}_j$, are obtained using forward simulation, and I use them in the sample analog of the objective function

$$(38)\quad Q_n(\boldsymbol{\gamma}, \boldsymbol{\alpha}) = \frac{1}{n_I} \sum_{x=1}^{n_I} (min\{\tilde{g}(x, \boldsymbol{\gamma}, \boldsymbol{\alpha}), 0\})^2$$

I use the Nelder-Mead method to obtain the starting values. Then I plug the estimated parameters as started values in the Uncmin optimization routine.[18] The later gives me the final estimates and the standard errors. Another alternative is to use the Laplace-type estimator (Chernozhukov and Hong, 2003).

Table 15: Alternative parameter estimates: sunk repositioning costs

Parameter	Market Size		
	Population $< 20{,}000$	Population 20,000-60,000	Population $> 60{,}000$
Repositioning costs (γ_1)	353	637	718
Std.	(102.34)	(223.26)	(287.03)
Median sales of repositioning stores	8,000	17,500	17,500
Median sales/repositioning costs	22	27	24
Mean no. of repositioning per year	1	2	11

NOTES: Median sales and repositioning costs are in thousands of 2001 SEK. Standard errors are in parentheses. The standard errors are not corrected for first-stage estimation errors.

[18]Uncmin performs unconstrained nonlinear optimizations (http://www1.fpl.fs.fed.us/optimization.html).

Paper IV

From Boom to Bust: A Dynamic Analysis of IT Services*

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Abstract

Aggregate shocks in demand such as the burst of the 2001 dot-com bubble affect firms' behavior and, therefore, the market structure. This paper proposes a fully dynamic structural model to analyze the impact of the 2001 dot-com bust on the productivity dynamics and the cost structure for IT services. The empirical application builds on an eight year panel dataset that includes every IT service firm in Sweden and is representative for many other European countries. Entrants are found less productive than incumbents and net exit contributed the most to productivity growth in the IT services after the dot-com bust. The paper finds higher fixed investment and labor costs for software but lower for operational services after the dot-com bust. Finding the relative importance of fixed costs is a step closer to being able to link policies that affect adjustment costs in IT services.

Keywords: IT services; imperfect competition; dynamic estimation; industry dynamics; strategic interactions
JEL Classification: L86, L13, L44, L52, C1, C3, C5, C7

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1 Introduction

The IT industry contributes significantly to increased productivity and improved service quality in virtually all sectors of the economy (Jorgenson et al., 2005, 2008). IT markets confirm strong recovery from the 2001-2003 slowdown until 2008.[1] The IT services industry, including software, has the highest contribution to total IT growth (Figure 2), e.g., 5.8 percent for software and 5.3 percent for operational services, maintenance, and repair.[2] Being affected differently by negative aggregate shocks in demand, such as the 2001 dot-com bust, firms change their behavior. Changes in firms' behavior regarding investment and labor affect the market structure. Using a fully dynamic model, this paper investigates the impact of the 2001 dot-com bust on productivity dynamics and the cost structure in Swedish IT services — an industry characterized by substantial entry and exit. The created selection process, induced by the impact of the 2001 dot-com bust, affected competition and productivity dynamics.[3] The direct effect of the dot-com bust was a decrease in the labor productivity dispersion, which was caused by an increase in the 25th percentile and a decrease in the 75th percentile.

The IT services firms are clustered around large cities that are characterized by dynamic labor markets. Some IT services grow faster in some regions than in others, i.e., there are some sources of exogenous variation (from local markets) in firms' incentives to invest in labor and capital. IT services are considered sophisticated because the products are often highly user-specific and non-standardized. The industry is characterized by high heterogeneity where the services produced include more than one type of activity and the consumer is extremely important. Firms respond to aggregate shocks in demand such as the 2001 dot-com bust by improving the quality of their services. Adjustments in labor might be costly if IT firms have to invest in redesign or have to change their service practices to suit

[1] While Western European IT markets were expected to grow at an annual average rate of 6.1 percent until 2008, the Central and East European markets were expected to grow by 13 percent (EU ICT Task Force Report, 2006). Figure 1 presents the evolution of the Western European ICT market growth from 1997 to 2007.

[2] EU market growth in this sector is principally driven by computer services. The EU IT market growth by segment in 2007 was as follows: software 5.8 percent, IT services 5.3 percent, computer hardware 2.4 percent, telecommunications equipment 2.0 percent, and carrier services 1.6 percent. IT services are important because companies and organizations modernize their IT infrastructure, i.e., consumers get lower prices and higher quality. Furthermore, IT services are highly dynamic due to the outsourcing of IT functions. The security of IT systems remains an important sector segment.

[3] Bartelsman and Doms (2000) and Syverson (2010) survey empirical work on productivity changes using micro data.

new customers. The direct cost of hiring a new employee is likely smaller than the cost involved in direct work with a new environment, i.e., there is an unobserved cost when firms hire a new employee. For small tasks, IT firms might hire external consultants and therefore increase fixed labor costs.

The present paper uses a dynamic structural model where firms make optimal decisions on entry, exit, and investment given the strategies of their competitors.[4] In IT services, the types of services offered and their quality are important aspects and depend on location. Since prices and other more detailed data on the IT services are not available, an accurate estimation of the quality of firms' services can not be obtained from a demand model. Instead, this paper estimates firms' productivity and assumes that there is a direct link between productivity and quality, i.e., a highly productive firm offers high-quality services. Firm productivity is estimated using an extension of Olley and Pakes (1996) framework that allows for lumpy investment and controls for unobserved prices. Since labor is a key factor for service quality in the IT industry, productivity is backed out from labor demand (Doraszelski and Jaumandreu, 2009; and Maican and Orth, 2009).

I assume that all relevant features of the IT services industry can be en-counted into a state vector that includes firms' perceived levels of productivity, local market demographics, and private shocks to profits. Firms receive states that depend on the payoffs in the product market. The evolution of productivity is influenced by entry, exit, and investment decisions. Firms' actions are subject to idiosyncratic shocks that are treated as private information, and they choose strategies that maximize their discounted profits, given the expected strategies of their rivals.

Using 1996-2002 panel data of the Swedish IT services industry, the present paper estimates productivity, and recovers both revenues and optimal policy functions for investment and labor consistent with the underlying model. The theoretical model is then used to simulate market outcomes with the cost structures before and after the dot-com bust.[5] Jorgenson et al. (2005, 2008) find higher productivity

[4] The theoretical framework is based on the Markov Perfect Equilibrium (MPE) framework of Ericson and Pakes (1995). Ericson and Pakes' framework assumes that firms make competitive investments that increase their productivity. Ackerberg et al. (2008) and Pakes (2008) review recent methodological developments in the empirical literature of imperfectly competitive markets.

[5] By comparing the predictions of the model under the different cost structures, this paper recovers the changes mode to a number of relevant policy measures. A more detailed discussion on the counterfactual analysis will be presented in future versions of the paper. It is important to understand how different ways to obtain perturbed policy functions affect the market structure. For example, we might generate policies that imply negative investments that make firms exit

growth in IT-producing industries than in IT-using industries. The IT services analyzed include all firms in software, operational services, and maintenance and repair. About 25 percent and 12-18 percent entered and exited the market during the period, respectively. The Swedish IT services market is representative of a majority of all IT markets in the EU.

The paper contributes to the previous literature by recovering both investment and labor adjustment costs in an innovative service industry before and after an aggregate negative demand shock. To my knowledge, this is also the first paper that analyzes productivity in IT services and provides estimates for demand elasticities and mark-ups for the IT services sub-sectors. The findings give information about the cost differences across sub-sectors and size groups of IT services firms that can be used, e.g., when subsidies are allocated for different groups of firms in this industry.

This paper uses a two-step procedure to recover the costs structure (Bajari et al., 2007-BBL). Recent empirical literature uses the BBL approach in a similar context (Ryan, 2009; Beresteanu and Ellickson, 2006; Ryan and Tucker, 2006; and Sweeting, 2007).[6] Pakes et al. (2007a) (POB), Aguirregabiria and Mira (2007), and Pesendorfer and Schmidt-Dengler (2003) develop alternative extensions to the Hotz and Miller (1993) approach to estimate dynamic games where actions have a discrete choice structure. Using the POB estimator, Dunne et al. (2005) evaluate the costs of entry and exit in isolated markets in the US for dentists and chiropractors. Pakes et al. (2007b) and Pakes (2010) show how the inequalities generated by behavior choice models can be used as a basis in estimation.

By estimating firms' productivity controlling for possible unobserved demand shocks at the local market level, productivity is the only serially correlated state variable that helps for consistency in estimation of continuation values and policy functions in case of fully dynamic models. Controlling for selection when estimating productivity is important in the IT industry. The exit and entry in my data is based on organizational number. There is a high likelihood of sell-offs of small firms to large firms since small firms have been successful. IT services offer specialized product services, and improved use of IT tools can raise the average prices and therefore increase revenues and productivity. However, since price variation

early.

[6]Ryan (2009) evaluates the welfare costs of the 1990 Amendaments to the Clean Air Act on the US Portland cement industry using a dynamic model of oligopoly in the tradition of Ericson and Pakes (1995). Benkard (2004) examines the wide-body aircraft industry but does not recover estimates of fixed costs.

can also be due to local market power or demand shocks, it is important to control for demand when estimating productivity in this industry.

I find that the estimated elasticity of demand for the software industry is about -4.6, i.e., a mark-up of 1.277. For grouped operational services and maintenance firms, the estimated demand elasticity is about -5.96, yielding a mark-up of 1.52. For software, the productivity growth was around 21 percent from 1997 to 2000, but only about 6 percent from 1997 to 2002. After the 2001 dot-com bust, exit firms contributed more to productivity growth (12 percent) than continuing firms (7.5 percent). For operational services and maintenance, the productivity growth was about 70 percent from 1997 to 2000 and about 32 percent from 1997 to 2002. In the period 1997-2000, almost all productivity growth came from continuing firms. However, exit firms contributed the most (50 percent) to productivity growth from 1997 to 2002. This emphasizes the importance of selection effect in this industry. Entrants are found less productive than continuing firms.

The results indicate that doubling the capital stock increases revenues slightly over 30 percent. For software and operational services, foreign IT firms have about 19 percent higher revenues than domestic IT firms. The geographical location of owing firm has been found to be more important for productivity growth than the location of IT firms (Bloom et al., 2009).[7] On average, the impact of the 2001 dot-com bust on revenues was a decrease of about 20 percent for software and operational services and of about 34 percent for maintenance and repair. Furthermore, firms reduced the number of employees by about 25 percent. After the dot-com bust, firms were more likely to exit in all sub-sectors. I also find that foreign IT firms were more likely to exit.

The impact of dot-com bust on investment and labor adjustment costs varies significantly depending on firm productivity and firm size. Lower adoption and smaller size IT investments in Europe are found to be responsible for the lower productivity growth in Europe than in the US over 1990s (van Ark et al., 2008). The present paper models fixed adjustment labor and capital costs to depend on the likelihood to adjust positively or negatively, and this propensity for adjustment depends on firms' state variables. My findings suggest that fixed and variable adjustment costs are important determinants of investment and labor decisions in the Swedish IT services industry. In addition to the lack of demand, they also

[7]They find that productivity from IT capital plays a key role in explaining higher productivity of US-based multinationals operating in the EU compared to EU firms. This advantage is explained by the evidence of complementarity between IT capital and human resources.

explain the downturn in productivity after the 2001 dot-com bubble. When there are fixed costs, a static evaluation ignores important economic penalties associated with the dot-com bust costs. The paper finds that, after the burst of the 2001 dot-com bubble, there was an increase in fixed (setup) investment costs for software but a decrease for operational services and maintenance and repair firms. From 2000 to the end of studied period, there were higher fixed costs for positive labor adjustment for software compared to 1996-1999 (about 4 times), lower for operational services (about 4 times), and about the same for maintenance and repair. For negative labor adjustment, the findings indicate higher fixed costs for software but lower for operational services after the dot-com bust. I find that the entry costs for software were six times lower than for operational services, which might explain the large number of entrants in software. In addition, while firms in software and operational services had higher scrap (sales-off) values after 2000, the maintenance and repair firms had lower scrap values.

The paper is organized as follows. Section 2 gives a brief overview of the Swedish IT services industry and relevant events over the last 10 years. It also includes a discussion on the data sources. Section 3 presents the theoretical model and Section 4 discusses the estimation details. The empirical results are presented in Section 5, whereas Section 6 concludes the paper.

2 Overview of the Swedish IT Services Industry

The Swedish IT industry is in better shape than it has been for many years. At the beginning of 2006, IT stocks had a 52 percent 12-month growth rate. The Swedish IT industry had 48 firms among Europe's 500 fastest growers in Deloitte's Technology European Fast 2006. In contrast to the late 1990s IT boom profit growth continues to rise due to better business models and high demand.

Data. This paper draws on a census of the Swedish IT services industry, provided by Statistics Sweden, Financial Statistics(FS) and Regional Labor Statistics (RAMS). The Swedish industrial classification code (SNI) for this industry is 72.[8] The IT services industry includes the following subgroups: hardware consultancy (code 7210); software consultancy (code 7220) - customized software and packages software; data processing (code 7230); database activities (code 7240);

[8]The SNI standard builds on the Statistical Classification of Economic Activities in the European Community (NACE).

maintenance and repair of office, accounting and computing machinery and data processing equipment (code 7250); and operational service activities (code 7260). Because it is difficult to divide IT consultancy services for hardware and software, I keep them in one group called software. In addition, there are few observations for hardware consultancy. On the other hand, data processing, database activities, and other computer-related services can be grouped into *operational service activities*.[9] New firms have appeared while others have exited or merged. FS contains information on firm input and output and RAMS contains information on employee education and wages. The dataset covers the period 1996-2002. A unit of observation is a firm with one or many establishments. The computer consultancy was affected by some major changes in the last few years of the period. It is important to note that large firms can have many subsidiaries in the same sector, although I cannot observe this in my data. Appendix A provides additional information on the data and variable definitions.

According to the Swedish Business Statistics 1999, the Swedish industrial classification group 72 consists of 19,045 establishments (5,625 firms in my data) and around 71,000 employees (Table 1). The total net turnover was SEK 83.3 billion and value added was SEK 38.3 billion (values are 1996 SEK). Table 1 presents characteristics of the Swedish IT services during 1996-2002. From 1996 to 2002 at the industry level, the number of firms grew by 60 percent, the industry value-added by 100 percent, the number of employees by around 100 percent as well, total wages by 147 percent, and investments by 99 percent. Most of the growth occurred from 1996 to 2000. From 2000 to 2001 at the industry level, the number of firms grew by 3 percent, value-added by 22 percent, wages by 15 percent, the number of employees by 10 percent, and investments by 8 percent. However, the burst of the 2001 dot-com bubble induced a negative growth of about 2 percent in number of firms, about 8 percent in value-added, about 7 percent in total wages and labor, and 10 percent in investment.

Software consultancy is the sub-sector with the largest share of firms, employees, turnover and value added in relation to the total value for each of these variables, e.g., there are about 10 times more firms active in software than in operational services (Panels B and C). Software has net entry over the study period and the largest numbers of entrants (1,532) and exits (1,017) in 2000. Operational services had net entry until the burst of the 2001 dot-com bubble. Maintenance and repair is the smallest sub-sector – about 110 firms.

[9] Statistics Sweden (SCB), a Swedish government office, also uses this grouping.

Table 2 shows the impact of the 2001 dot-com bust on the growth rates by sub-sector between 2000-2001 and 2001-2002. The IT sub-sectors were affected differently. Operational service firms were more affected between 2000-2001, e.g., the number of firms decreased by around 20 percent, sales by 27 percent, and investments by 19 percent. Software firms were most affected from 2001 to 2002, i.e., sales decreased by 18 percent and investments by 10 percent.

IT service firms are also found in the following sectors: retail trade in computers; office machinery and equipment wholesale; and telecom products and electronic components wholesale. It is hard to specify the activities of these firms. Therefore, they are not included in the study.[10] They represent 0.2 percent of the total number of companies and their net turnover represents 41 percent of the total net turnover in the industry. Apart from analyzing different sub-sectors, the paper also groups the firms into three classes according to number of employees: (i) small – 0-19 employees; (ii) medium – 20-99 employees; and (iii) large – over 100 employees.

In Sweden, IT services are concentrated to the three largest cities, i.e., Stockholm, Gothenburg, and Malmö. The Swedish government focuses on the IT sector and pays close attention to firm entry and exit.[11] Lundmark (1995) studies the patterns of growth and location of computer services in Sweden. More specifically, he analyzes location patterns of IT services in local markets. He emphasizes that the market structure of Swedish IT services is characterized by a large degree of local and regional sales, indicating the importance of proximity to customers. The Swedish IT industry is characterized by large heterogeneity. Most of the firms are small – around 90 percent of the firms in my data had fewer than 20 employees in 2000. Yet, despite the large proportion, small firms only generated about 25 percent of total employment and sales in 2000. Therefore, large firms that operate on both national and international markets are important for the overall performance.

Market definition. Information is what is demanded in the IT services industry. How much and from who depend on the type of activity carried out (in Sweden),

[10]However, the share of total turnover in the sectors that represents IT consultancy activities cannot be determined from the survey or from Swedish Business Statistics in 1999.

[11]The Swedish Agency for Economic and Regional Growth (NUTEK) contributes to the creation of new enterprises, more growing enterprises, stronger regions, and consequently to promote sustainable economic growth and prosperity throughout the country. Another Swedish government agency for innovation, Vinnova, elaborates strategies and forms reference groups with key players from the industry, government agencies, and universities to improve the competitiveness of the IT industry.

price, training effort, and the level of learning.[12] Statistics Sweden (SCB) conducted a survey about demand structure in the Swedish IT services industry in 2001. They found that the customers of Swedish IT services are as follows: firms and public utilities around 76 percent; central government and municipal authorities 14 percent; households and individuals 0.2 percent; and exports around 10 percent. Only firms that are in the SNI group 72 were included in the survey. The customers of small firms are households and private individuals. Large and medium IT firms commonly have business enterprises as customers. While large companies dominate the Swedish IT services in terms of market share, small and medium companies dominate the market with respect to number of firms.[13] Moreover, 50 percent of firms say that 75-100 percent of their sales come from neighboring municipalities and 35 percent of firms do not make sales in neighboring municipalities.

The paper uses Statistics Sweden's county definition to define markets. A county consists of a collections of municipalities. This classification groups the Swedish municipalities (290) into 25 markets that are mutually exclusive and exhaustive of the land mass of Sweden.[14] The county-based market definition is a compromise between contradictory requirements. The theoretical model assumes that IT service markets are isolated geographic units; firms in one market interact competitively only with other firms in the same county market. Firms placed in too large markets may not all respond to the same market forces (external or actions of industry competitors). Counties are a suitable compromise to resolve the tension between isolating markets yet ensuring that the IT service firms within them are interconnected. IT service firms should, however, be close to their customers. Large firms in this sector may face international competition if they sell for example software.

Tables 3 and 4 present the summary statistics at the local market level for the Swedish IT service industry from 1996 to 2002, for all firms (Table 3) and grouped by size (Table 4). An average local market (county) has about 255 IT service firms; 3,100 employees; 7,225 non-IT firms; and a population of about 400,000 people (Table 3). Table 4 shows that an average market has about 230 small, 22 medium, and about 7 large IT firms. The counties that include Stockholm, Gothenburg, or

[12]Bower (1973) discusses the specificity of demand in IT services.

[13]Firms that are in other SE-SIC 92 groups and provide IT services are not included in the survey due to the difficulties in measuring their activities. Cerda and Glanzelius (2003) provide more details about Swedish IT services.

[14]Statistics Sweden provides more detailed information, www.scb.se.

Malmö have about 10 times more firms than does an average county (Table 4).

Having access to detailed data on individual counties and information on demand based on surveys, demographic characteristics, population and number of firms (other than IT service firms) are good proxies for local demand.

3 The modeling approach

The model. To evaluate the impact of 2001 dot-com bust on cost structure it is necessary to have a theoretical model of the IT services industry. The model builds on the work of Ericson and Pakes (1995), who provide a theoretical framework of industry dynamics on imperfectly competitive markets. The IT industry is characterized by simultaneous entry, exit, investment, and production service decisions of firms in each local market (county). The structure within each county market is primarily determined by the distribution of capacities (IT labor) and the industrial structure of the market. The IT industry is characterized by heterogeneous firms, where skilled labor, demand, and the efficiency of using new technologies are the most important aspects. Investments in knowledge and technology change the quality of IT services tomorrow and firms pay both fixed and variable adjustment costs.

Timing. There is a number of firms in a set of markets in an infinite sequence of years. In each year, the timing of the game is as follows:

1. Each firm observes its current firm productivity and market demographics.

2. Each potential entrant receives a draw from the distribution of entry values and makes its entry decision; each incumbent firm makes its investment decision.

3. Each firm receives a private productivity shock and then firms compete in the product market.

4. Each incumbent that chooses to leave the market exits and receives its scrap payment; each entrant pays its entry fee. Firms decide on investments in labor and capital without knowing the decisions of their competitors.

5. The state vector adjusts and firms enter and exit.

Firms observe the state variables at the beginning of each period along with the entry, exit, investment, and production decisions of their rivals in the previous period. Private information shocks are drawn independently across periods from a known distribution. Firms do not update their expectations of future behavior after observing the actions of their rivals.

State space. All economically important characteristics of firms are incorporated into a state vector that includes productivity, market demographics, and a set of private information payoff "shocks" that affect firms' payoffs. Firms' state variables are grouped in the vector s. Firms receive state-dependent revenues from the product (service) market in each period. Entry, exit, and investments (labor and technology) influence the evolution of the state vector. The most important component of the state space is productivity, ω. Firm j's productivity in market m, ω_{jmt}, is not directly observable in the data, but is obtained by estimation of a value-added generating function model. The paper assumes that the productivity evolves stochastically according to the following Markov process:

$$(1) \quad \omega_{jmt} = \tilde{g}(\omega_{jmt-1}) + \xi_{jmt},$$

where $\xi_{jmt} \in N(0, \eta^{\omega})$ and $\tilde{g}(\cdot)$ is an unknown function. Thus, firms' actual productivity ω_{jmt} in period t can be decomposed into expected productivity $\tilde{g}(\omega_{jt-1})$ and a private productivity shock, ξ_{jt}. The private shock, ξ_{jt}, may be thought of as the realization of uncertainties that are naturally linked to productivity. The conditional expectation function $\tilde{g}(\cdot)$ is unobserved by the econometrician (though known to the firm) but can be estimated non-parametrically. Furthermore, I assume that ω_{jmt} evolves independently across markets.

Each market m is defined by its characteristics: the total number of firms (other than IT) in the market and population. Since population is highly correlated with number of firms (0.99), only the number of firms is used in the empirical part. The growth rates for population and number of non-IT firms evolve according to the following AR(1) process:

$$(2) \quad firms_{mt} = \delta_1^{firms} firms_{mt-1} + \delta_0^{firms} + \upsilon_{mt}^{firms}, \text{where} \quad \upsilon_{mt}^{firms} \sim N(0, \eta^{firms}).$$

Equilibrium concept. Equilibrium is obtained when firms follow strategies that maximize the expected discounted present value of their stream revenues given the expected strategies of their competitors. The paper assumes that firms' strategies depend only on the current state vector and generate a Markov Perfect Nash Equilibrium (MPNE). The MPNE consists of a set of best response strategies governing entry, services production, exit, and investment.

Firm j makes decisions regarding, e.g., entry, exit, and investments collectively denoted by Γ_j. Since the full set of dynamic Nash equilibria is unbounded, I restrict firms' strategies to be anonymous, symmetric, and Markovian. Therefore, a firm's strategy, σ_{jt}, can be written as a mapping from states to actions:

$$\sigma_{jt} : S_{jt} \rightarrow \Gamma_{jt}.$$

A vector of strategies is a mapping of the current state of the system for each firm's strategy. The time horizon is infinite, payoffs are bounded, firms have Markovian strategies, and the discount factor β is positive and less than one. The value of a firm in state $s \in S$ is

$$(3) \quad V_j(s|\sigma(s)) = \pi_j(\sigma(s)) + \beta \int V_j(s'|\sigma) dP(s'|\sigma(s), s),$$

where $\sigma(s)$ is the vector of strategies, $\pi_j(\sigma(s))$ is the per-period payoff function, and $P(\cdot)$ is the conditional probability distribution governing the transition between states. A strategy profile σ is an MPNE giving competitors profile σ_{-j} if each firm j prefers strategy σ_j to all Markov strategies $\sigma_j^{'}$:

$$(4) \quad V_j(s|\sigma_j^*, \sigma_{-j}) \geq V_j(s|\sigma_j^{'}, \sigma_{-j})$$

for all j, s, and $\sigma_j^{'}$. I assume that such an equilibrium exists and is unique. Doraszelski and Satterthwaite (2010) discuss the details on existence and uniqueness.

I describe each component of the model in detail in the following sections by deriving the ex-ante value functions for potential entrants and incumbents. These value functions are important in the counterfactual simulations when the costs of the dot-com bust are evaluated.

4 Estimation

The estimation is made in two steps. In the first step, I estimate a value added generating function to obtain an estimate of firms' perceived productivity. Knowing how the state space evolves over time, the revenue generating function and the policy functions, which describe the optimal strategy profile for each firm, can be estimated. In the second step, I estimate the dynamic parameters governing investment, scrap values, and sunk costs.

Firm productivity. The present paper assumes a Cobb-Douglas technology where IT service firms sell a homogeneous product (at the subsector level) and that the factors underlying profitability differences among firms are neutral efficiency differences. Allowing for heterogeneity in the dynamic model makes this assumption not so restrictive. The services production function can be specified as

$$(5) \quad q_{jt} = \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + \omega_{jt} + u^p_{jt},$$

where q_{jt} is the log of service output sold by firm j at time t; l_{jt} is the log of labor input; and k_{jt} is the log of capital input. The unobserved factor, ω_{jt}, measures productivity, and u^p_{jt} is either measurement error (which can be serially correlated) or a shock to productivity that is not predictable during the period in which labor can be adjusted.

Specification (5) assumes that prices are constant across firms. When firms have some market power, prices set by individual firms influence their productivity. The negative correlation between input and prices leads to underestimation of the labor and capital parameters in the production function (Klette and Griliches, 1996; Melitz, 2000; and De Loecker, 2009). If the products are perfect substitutes, deflated sales are a perfect proxy for unobserved quality adjusted output. Following the recent literature, it is possible to correct for bias in elasticities by introducing the following downward sloping demand function:

$$(6) \quad p_{jt} = p_{It} + \frac{1}{\eta} q_{jt} - \frac{1}{\eta} q_{It} - \frac{1}{\eta}\lambda_{jt} - \frac{1}{\eta} u^d_{jt},$$

where p_{jt} is output price, p_{It} and q_{It} are IT service output price and quantity, λ_{jt} is demand shifters (observed and unobserved), and u^d_{jt} is simple i.i.d shock to demand.[15] The demand specification assumes that firms operate in a market with horizontal product differentiation, where η (< -1 and finite) captures the

[15]There is no price index for IT services from 1996 to 2002. From 2002, Statistics Sweden has started to construct a price index for IT services. In the empirical part, I use the consumer index price. For robustness, I have constructed a backward price index (1996-2002) from new IT services price index (2002-2009). Even if this construction is problematic (small sample errors) it can be informative. Because there are no substantial changes in the elasticities, the results are not reported.

elasticity of substitution among IT services. Due to data constraints, the demand system is quite restrictive, implying a single elasticity of substitution for all IT services and that there are no differences in cross price elasticities.

I decompose demand shifters into observed local market characteristics $z_m t$, i.e., number of non-IT firms and population, and unobserved demand shock ν_{jt}:

$$\lambda_{jt} = z'_{mt}\beta_z + \nu_{jt},$$

where ν_{jt} are either correlated unobserved shocks to demand or i.i.d. If ν_{jt} are correlated unexpected shocks, they enter into productivity measure. Therefore, it is not possible to use a more sophisticated demand model that allows for product differentiation (Berry, 1994; Berry et al., 1995; Nevo, 2001). Since the IT service prices of individual firms are unobserved, the deflated output is defined as $y_{it} = q_{it} - p_{It}$. Firm productivity follows a first order Markov process (equation 1) and takes the following form: $\omega_{jt} = \tilde{g}(\omega_{jt-1}) + \xi_{jt}$. Controlling for price and demand shocks in the value-added generating function (5) yields

$$\begin{aligned} y_{jt} = \; & \left(1+\tfrac{1}{\eta}\right)[\beta_0 + \beta_l l_{jt} + \beta_k k_{jt}] - \tfrac{1}{\eta} q_{It} - \tfrac{1}{\eta} z'_{mt}\beta_z + g(\omega_{jt-1}) + \left(1+\tfrac{1}{\eta}\right)\xi_{jt} \\ & -\tfrac{1}{\eta}\nu_{jt} - \tfrac{1}{\eta}u^d_{jt} + \left(1+\tfrac{1}{\eta}\right)u^p_{jt}, \end{aligned} \tag{7}$$

where $g(\cdot) = \left(1+\frac{1}{\eta}\right)\tilde{g}(\cdot)$. The value of k_{jt} is determined by previous investment i_{jt-1}. Labor l_{jt} is correlated with the random shock in productivity ξ_{jt}. The inverse labor demand helps us to recover unobserved productivity ω_{jt-1} rather than recovering from the unknown policy function of investment in capital and labor/materials (Olley and Pakes, 1996; Ackerberg et al., 2006). The main advantage is that zero investments are included in the analysis, which is important because IT firms often invest one year, followed by several years without investment. In year t-1, firms chose current labor l_{jt-1} based on current productivity ω_{jt-1}, which gives demand for labor as

$$l_{jt-1} = \frac{1}{1-\beta_l}[\beta_0 + ln(\beta_l) + \beta_k k_{jt-1} + \omega_{jt-1} - (s_{jt-1} - p_{jt-1}) + ln(1+\frac{1}{\eta})],$$

where w_{jt-1} is total wages paid. Solving for ω_{jt-1} yields

$$\begin{aligned} \omega_{jt-1} = \; & \tfrac{\eta}{1+\eta}\Big[\delta_0 + [(1-\beta_l) - \tfrac{1}{\eta}\beta_l]l_{jt-1} + w_{jt-1} - p_{It-1} - \left(1+\tfrac{1}{\eta}\right)\beta_k k_{jt-1} \\ & + \tfrac{1}{\eta} q_{mt-1} + \tfrac{1}{\eta} z'_{mt-1}\beta_z\Big], \end{aligned} \tag{8}$$

where $\delta_0 = -ln(\beta_l) - ln(1+1/\eta) - \beta_0(1+1/\eta) - lnE[e^{u^p_{jt}}] + \frac{1}{\eta}lnE[e^{u^d_{jt}}] + \frac{1}{\eta}lnE[e^{\nu_{jt}}]$. Appendix B presents the productivity estimation details.

Static firm payoffs. A firm's payoff in one period depends on its productivity, ω_{jmt}; competitors' productivity, ω_{-jmt} ; local market characteristics, x_{mt} ; and the firm's investment and labor decisions. Therefore, the payoff of firm j in market m in period t is

$$\begin{aligned}\pi_{jmt}(\omega_{jmt}, \omega_{-jmt}, x_{mt}, \varepsilon^r_{jmt}; \boldsymbol{\beta}, \boldsymbol{\theta}) = \; & r_{jmt}(\omega_{jmt}, \omega_{-jmt}, x_{mt}, \varepsilon^r_{jmt}) - c_i(i_{jmt}; \theta^i) \\ & -c_l(\Delta l_{jmt}; \theta^l),\end{aligned} \tag{9}$$

where ε^r_{jmt} denotes the private shocks to profits; $c_i(\cdot; \theta^i)$ the cost associated with investment in technology (machinery); and $c_l(\cdot; \theta^l)$ the cost of adjusting the number of employees. In the forward simulations, the revenue generating function $r_{jmt}(\cdot)$ is estimated using the following form:

(10)

$$\begin{aligned}r_{jmt} \; = \; & \beta_0 + \boldsymbol{\beta}_1'\mathbf{bs}_1(\omega_{jmt}) + \boldsymbol{\beta}_2'\mathbf{bs}_2(\textstyle\sum_{h\neq j}\omega_{hmt}) + \boldsymbol{\beta}_3'\mathbf{bs}_3(k_{jmt}) + \boldsymbol{\beta}_4'\mathbf{bs}_4(\textstyle\sum_{h\neq j}k_{hmt}) \\ & + \boldsymbol{\beta}_5'\mathbf{bs}_5(firms_{mt}) + \beta_6 after_{2000} + \beta_7 foreign_{jmt} \\ & + \beta_8 medium_{jmt} + \beta_9 large_{jmt} + \boldsymbol{\beta}_m + \varepsilon^r_{jmt},\end{aligned}$$

where $\mathbf{bs}(\cdot)$ is the basis function of cubic b-splines (Chen, 2007; Eubank, 1988; and Coppejans, 2004); $\boldsymbol{\beta}_m$ is the set of market effects introduced to capture differences in other unobserved factors that are common across all firms in a market; $firms_{mt}$ is the number of firms, other than IT, at the market level; and $medium_{imt}$ and $large_{imt}$ are dummy variables for medium and large firms.

Investment and labor costs. The cost function associated with investment in technology is:

$$\begin{aligned}c_i(i_{jmt}; \boldsymbol{\theta}^i) \; = \; & 1(i_{jmt} > 0)(\tilde{\theta}_0^{i,+} + \theta_1^{i,+} i_{jmt} + \theta_2^{i,+}(i_{jmt})^2) + 1(i_{jmt} < 0)(\tilde{\theta}_0^{i,-} + \theta_1^{i,-} i_{jmt} \\ & + \theta_2^{i,-}(i_{jmt})^2).\end{aligned}$$

Fixed and variable adjustment costs vary separately for positive and negative investments. Setup costs from installing new equipment are covered by the fixed costs, $\tilde{\theta}_0$. Fixed costs of investment are private information to the firm and are drawn each period from a known distribution, $F^{i,+}(\cdot; \gamma^{i,+})$. Since the firm can sell old IT equipment, sunk costs associated with negative investment can be positive. These costs are private information and drawn each period from a common distribution, $F^{i,-}(\cdot;\gamma^{i,-})$. The cost function associated with labor adjustment is given by:

$$c_l(\Delta l_{jmt};\boldsymbol{\theta}^l) = 1(\Delta l_{jmt} > 0)(\tilde{\theta}_0^{l,+} + \theta_1^{l,+}\Delta l_{jmt}) + 1(\Delta l_{jmt} < 0)(\tilde{\theta}_0^{l,-} + \theta_1^{l,-}\Delta l_{jmt}).$$

For example search and recruiting, training, explicit firing costs are covered by the $c^l(\cdot)$ function. Reorganization of services and consulting activities are also included. Fixed costs associated with positive and negative labor adjustment are drawn from the distributions $F^{l,+}(\cdot;\gamma^{l,+})$ and $F^{l,-}(\cdot;\gamma^{l,-})$.

Entry, exit, and fixed costs of operation. IT firms also have different costs that are not related to service production. To enter the market, firms pay an entry (sunk) cost, f_j^e. The entry cost is drawn from the common distribution, $F^e(\cdot;\gamma_e)$. Firms that exit the market receive the sell-off value associated with closing down the firm, f_j^x, which is commonly drawn from the common distribution, $F^x(\cdot;\gamma_x)$. Summarizing, the costs that depend on the status of the firm are:

$$f_j(\sigma(s)) = \begin{cases} f_j^e & \text{if the firm is an entrant,} \\ f_j^{in} & \text{if the firm is an incumbent,} \\ f_j^x & \text{if the firm exits the market.} \end{cases}$$

The ex-ante value functions for both potential entrants and incumbents can be written down. The value functions that give the expected discounted present value, in Swedish krona (SEK), of being at a given state vector, have two components:[16] (i) the per-period payoff function and (ii) the continuation value, i.e., the expected value of next period's state. Firms use their value function to find their optimal entry, exit, investment, and labor policies.

The value function for the potential entrant j who decides to enter in the next period conditional on the current state and the draw from the distribution of the sunk cost of entry, f_j^e, can be written as:

$$(11)\quad V_j^e(s, f_j^e) = \max_{i_j^e, l_j^e}\left\{-f_j^e - \tilde{\theta}_0^i - \theta_1^i i_j^e - \theta_2^i (i_j^e)^2 - \theta_1^l \Delta l_j^e + \beta E(V(s')|s)\right\}.$$

The value function for an incumbent has two parts. The first part corresponds to whether the firm decides to exit the industry. If it does, it receives its services-market payoffs $\pi_j(s)$ and its sell-off payment f_j^x. If it remains active, it receives

[16]At the beginning of the study period (1996), 1 USD=6.71 SEK and 1 EUR=8.63 SEK.

service-market revenues. Therefore, if firm j continues, it obtains the following payoff:

$$
\begin{aligned}
V_j^{stay}(s) = \ & \max_{i_j,l_j} -1(i_j > 0)(\tilde{\theta}_0^{i,+} + \theta_1^{i,+} i_j + \theta_2^{i,+}(i_j)^2) \\
& -1(\Delta l_j > 0)(\tilde{\theta}_0^{l,+} + \theta_1^{l,+} \Delta l_j) - 1(i_j < 0)(\tilde{\theta}_0^{i,-} + \theta_1^{i,-} i_j + \theta_2^{i,-}(i_j)^2) \\
& -1(\Delta l_j < 0)(\theta_0^{l,-} - \theta_1^{i,-} \Delta l_j) + \beta E(V(s')|s)
\end{aligned} \tag{12}
$$

The ex-ante value function for an incumbent is a combination of the payoffs if the firm stays or exits:

$$
V_j(s) = \int \pi_j(s_j) dS + (1 - p^x(s_j)) V_i^{stay}(s) + p^x(s_j) f_j^x. \tag{13}
$$

In (13), $p^x(s_j)$ is the probability that firm j exits the market. It is given by

$$
\begin{aligned}
p^x(s_j) &= Pr(f_j^x > V_j^{stay}(s)) \\
&= 1 - F^x(V_j^{stay}(s); \gamma^x).
\end{aligned} \tag{14}
$$

The continuation value, $V_j^{stay}(s)$, can be obtained by inverting equation (14), $V_j^{stay}(s) = (F^x)^{-1}(1 - p^x(s); \gamma^x)$. The expected sell-off value, $\tilde{f}_j^x$, conditional on exit is $E[f_j^x | f_j^x > (F^x)^{-1}(1 - p^x(s); \gamma^x)]$, i.e., it is a function of the probability of exit and the parameters of the exit distribution, γ^x. The recovered values $\tilde{\theta}_0^{i,+}$, $\tilde{\theta}_0^{i,-}$, $\tilde{\theta}_0^{l,+}$, $\tilde{\theta}_0^{l,-}$, and $\tilde{f}_j^x$ are the means of the distributions $F^{i,+}$, $F^{i,-}$, $F^{l,+}$, $F^{l,-}$, and F^x only when firms receive favorable draws. To avoid this problem, the fixed costs can be recovered using linear sieve (Ryan, 2009):

$$
\begin{aligned}
&\tilde{\theta}_0^{i,+}(p_j^{i,+}) = \boldsymbol{\delta}^{i,+} \boldsymbol{bs}(p_j^{i,+}(s)), \quad \tilde{\theta}_0^{i,-}(p_j^{i,-}) = \boldsymbol{\delta}^{i,-} \boldsymbol{bs}(p_j^{i,-}(s)), \\
&\tilde{\theta}_0^{l,+}(p_j^{l,+}) = \boldsymbol{\delta}^{l,+} \boldsymbol{bs}(p_j^{l,+}(s)), \quad \tilde{\theta}_0^{l,-}(p_j^{l,-}) = \boldsymbol{\delta}^{l,-} \boldsymbol{bs}(p_j^{l,-}(s)), \\
&\tilde{f}_j^x(p_j^x) = \boldsymbol{\delta}^x \boldsymbol{bs}(p_j^x(s)),
\end{aligned}
$$

where δ parameters are finite and $\mathbf{bs}(\cdot)$ are basis functions defined from the probability of positive investment, $p^{i,+}$; the probability of negative investment, $p^{i,-}$; the probability of positive labor adjustment, $p^{l,+}$; the probability of negative labor adjustment, $p^{l,-}$; and the probability of exit, p^x. The distribution of sunk entry-costs can be recovered by matching its cumulative distribution to the predicted probability of entry. A firm enters when the value of doing so, $EV^e(\boldsymbol{s})$, is larger than f_j^e. By simulating many forward paths of possible outcomes given that the firm entered, and averaging over those paths, I obtain the expected value of entry, which I then match against observed rates of entry. Therefore, the probability that a firm enters is given by

$$(15)\quad Pr(f_j^e \leq EV_j^e(\boldsymbol{s})) = F^e(EV^e(\boldsymbol{s});\gamma^e),$$

where $F^e(\cdot;\gamma^e)$ is the cumulative distribution of sunk entry-costs. The entry probability, estimated by logit, gives $Pr(entry|\boldsymbol{s})$. If ns is the number of simulated states from which EV^e is recovered, then the parameters of the distribution are estimated from the following optimization problem:

$$(16)\quad min_{\gamma^e}\frac{1}{ns}\sum_{k}^{ns}[Pr(entry|\boldsymbol{s}) - F^e(EV^e(\boldsymbol{s});\gamma^e)]^2.$$

The paper uses logit approximation to estimate entry and exit probabilities.[17] To be more precise, I estimate the following entry and exit policies for all states:

$$\begin{aligned}
Pr(entry|s) = \quad & \phi(\alpha_0 + \alpha_1 \textstyle\sum_{h\neq j}\omega_{jmt} \\
& +\alpha_2 k_{jmt} + \alpha_3 \textstyle\sum_{h\neq j} k_{hmt} + \alpha_4 firms_{mt} + \alpha_5 after_{2000} \\
& +\alpha_6 foreign_{jmt} + \alpha_7 medium_{jmt} + \alpha_8 large_{jmt} + \boldsymbol{\alpha}_m) \\
Pr(exit|s) = \quad & \phi(\alpha_0 + \alpha_1\omega_{jmt} + \alpha_2 \textstyle\sum_{h\neq j}\omega_{jmt} \\
& +\alpha_3 k_{jmt} + \alpha_4 \textstyle\sum_{h\neq j} k_{hmt} + \alpha_5 firms_{mt} + \alpha_6 after_{2000} \\
& +\alpha_7 foreign_{jmt} + \alpha_8 medium_{jmt} + \alpha_9 large_{jmt} + \boldsymbol{\alpha}_m).
\end{aligned}$$

Both policy functions contain a dummy variable for before and after the dot-com bust.

Estimating structural parameters. The evolution process of the state vector and the level of payoff associated with each state are described by the first step estimation of productivity, policy functions, and evolution of demographic characteristics. In the second step of the estimation, I recover the rest of the parameters of cost functions by finding the set of parameters that make the firm's policy function optimal. Having the estimates from the first stage, I simulate the evolution of the market under different conditions. This is possible because the first stage estimates characterize what each firm would do in all possible situations. Using forward simulation, I find parameters of the optimal policy function that minimize the profitable deviations from these observed strategies.

[17] In many cases, entry and exit strategies take the form of simple cutoff rules in dynamic oligopoly models.

Firm behavior is simulated under two alternative strategies in order to identify the investment cost parameters. The first scenario implies that all firms use the optimal strategies recovered in the first stage; this strategy is denoted σ. The second scenario implies that a single firm deviates from the optimal strategy while all other firms use the optimal strategies. The strategy profile σ is an MPNE if and only if

$$(17) \quad V_j(s, \sigma_j, \sigma_{-j}; \theta) \geq V_j(s, \sigma_j^{'}, \sigma_{-j}; \theta)$$

for all states s, all firms j, and alternative profiles $\sigma_j^{'}$. The minimum distance estimator is constructed using this set of inequalities. Due to the linearity in the cost functions, the optimality conditions (17) can be re-written as $[W_j(s, \sigma_j, \sigma_{-j}; \theta) - W_j(s, \sigma_j^{'}, \sigma_{-j}; \theta)]\theta \geq 0$. The above equation can be written in terms of profitable deviations from the optimal policy

$$(18) \quad g(x; \theta, \alpha) = [W_j(s, \sigma_j, \sigma_{-j}; \theta) - W_j(s, \sigma_j^{'}, \sigma_{-j}; \theta)]\theta,$$

where α represents the parametrization of the policy functions. More specifically, alternative policies are drawn from a distribution F of all policies to generate a set of inequalities indexed by x. The estimates of W_j, denoted $\tilde{W}_j$, are obtained using forward simulation. They are used in the sample analog of the objective function

$$(19) \quad Q_n(\theta, \alpha) = \frac{1}{n_I} \sum_{k=1}^{n_I} (min\{\tilde{g}(x, \theta, \alpha), 0\})^2.$$

I use the Nelder-Mead method to obtain the starting values. Then I plug the estimated parameters as started values in the Uncmin optimization routine.[18] The later gives me the final estimates and the standard errors. Another alternative is to use the Laplace-type estimator (Chernozhukov and Hong, 2003). The present paper estimates the distribution of entry costs using a procedure that matches the observed entry rates to the simulated values of entering at each state.

Standard errors. The first-stage errors affect the standard errors in the second stage. The variance of the parameters is obtained directly from the Laplace estimator (equation 19). Due to the computation burden in forward simulations,

[18]Uncmin performs unconstrained nonlinear optimizations (http://www1.fpl.fs.fed.us/optimization.html).

I did not correct the second stage errors, i.e., the actual errors are downward biased. However, recent econometric literature suggests potentially easy computation alternatives to consider for future research. Ackerberg et al. (2009) propose a numerical equivalence between asymptotic variance for two-step semiparametric estimators when the sieves method is used in the first stage.

5 Results

This section presents the results of estimates of productivity, revenue-generating function, and optimal firm policies, i.e., in terms of entry, exit, investment in technology, and labor. The estimates of cost parameters are discussed in the second part of this section.

Before I discuss the estimated productivity results, I would like to summarize the results regarding labor productivity and capital intensity. Figures 3 and 4 present the evolution of the labor productivity distribution and capital intensity for the three IT services sectors. Labor productivity is measured as value added per number of employees. The firms in software and operational services with low labor productive (10th percentile) experienced a decrease in labor productivity in 2000, but then started to recover in 2001. The peak of median labor productivity occurred in 1999 for software and operational services and in 2000 for maintenance. While the labor productivity of median software and operational firms shows a weak but positive trend, the median maintenance firms had a negative trend after 2000. The highly labor-productive firms (90th percentile) increased their labor productivity from 1997 and 2000 (software and maintenance), but then those in software stagnated and remained fairly constant and those in operational services actually went down. The labor productivity dispersion decreased in all sectors after 2000 (particularly quickly in operational services). To avoid possible outliers, I measure productivity dispersion as the interquartile range over median. Software and operational services sectors have larger labor productivity dispersion than does the maintenance sector.

The next step is to look into capital intensity. Median firms and firms in the 90th percentile of capital intensity had an upward trend in all three sectors, but those at the 10th percentile decreased only in the maintenance sector after 2000

(Figure 4).[19] The capital intensity dispersion increased for maintenance and for software (small slope of the trend). For operational services, the capital intensity dispersion decreased until 2001 and then started to increase.

Productivity estimates. The theoretical model assumes that productivity is the state variable that captures all important aspects of an IT firm and that there is a direct link between productivity and quality. So, I assume that IT firms that offer high quality services have high productivity. Table 5 presents the results from estimating the value-added generating function using OLS and the semiparametric estimator presented in Section 4.[20] Firm productivity is recovered from the estimation of the value added generating function.

By using the OLS estimator, the coefficient of labor is around 1, suggesting presence of a simultaneity problem. Since firms productivity is positively correlated with labor, a large labor coefficient is not a surprise. Furthermore, it is expected that firms with large capital stock (large firms) stay in the market even if they have low productivity, i.e., the coefficient of the capital is downward biased for the OLS estimator (selection bias). Furthermore, the results show that the null hypothesis of constant returns to scale is accepted using the OLS estimator.

The last two columns of Table 5 show the estimates of the value-added generating function using the extended Olley and Pakes (1996) estimator (EOP) presented in Section 4. In addition to controlling for endogeneity and selection, the main advantage of this estimator is that it to some extent controls for a price bias by introducing a simple demand function. This allows me to estimate mark-ups for the IT services. Since we expect different demand elasticities for the different IT sectors, I make separate estimations for software and for operational services and maintenance. Column 3 (Table 5) presents the estimates for the software subsector. Compared to OLS, the labor coefficient goes in the right direction using EOP, i.e., it decreases to 0.680, and the capital coefficient increases to 0.374. The estimated elasticity of demand for software is about -4.6, implying a mark-up of 1.277. For grouped operational services and maintenance firms (column 5), the estimated labor coefficient decreases to 0.789 and the capital coefficient increases to 0.208 compared EOP and OLS. The estimated demand elasticity is about -5.96,

[19]Using UK data, Faggio et al. (2007) find that industries with high productivity growth have a large increase in IT capital intensity.

[20]The results using the Ackerberg et al. (2006) estimator (ACF) are available from the author. In the ACF estimator, I control for both endogeneity and selection. The ACF estimator controls for investment in the market threshold function that affects the likelihood of exit, but does not control for prices or wages.

yielding a mark-up of 1.52.[21] The estimated productivity using the EOP estimator is used in the rest of the paper.

Figure 5 shows the evolution of different parts of the productivity distribution for different size classes. It does not distinguish between what IT sector the firms belong to and type of firm, e.g., an entrant, an exit, or an incumbent. The results suggest that scale matters: large firms are the most productive, followed by medium-sized and small firms. This holds for the entire productivity distribution. Low productivity firms (10th percentile) increased their productivity (small positive slope) until 2001. For the median and the high productivity firms (90th percentile), there are three distinct periods. Their productivity was rather constant from 1997 to 1999, developed positively from 1999 to 2000, but negatively starting in 2001. These periods are also important for the dispersion trend, a decrease from 1999 to 2001 for large and medium firms. Medium-sized firms show the largest decrease in productivity dispersion. Small firms have a constant productivity dispersion over time. A decrease in productivity dispersion can be interpreted as an increase in competition, i.e., firms increase their quality and become closer to each other.

Summarizing, the paper finds that the 2001 dot-com bubble bust has affected firms differently depending on productivity and size. There is a smaller difference in productivity levels among large and median low productive firms (10th percentile) than among high productive firms (90th percentile). On the other hand, the gap between small and medium-sized firms decreases in the upper part of the productivity distribution (90th percentile).

Dynamic productivity decomposition. To analyze the productivity dynamics at the sector level, the present paper uses a dynamic productivity decomposition. Olley and Pakes (1996) propose a static decomposition of aggregate productivity where the weighted productivity for continuing stores, Ω_t, has two components: (1) unweighted contribution of productivity improvements, $\overline{\Omega}_t$ and (2) market share reallocations for the continuing firms $cov(ms_{jt}, \omega_{jt}) \equiv \sum_j (ms_{jt} - \overline{ms}_t)(\omega_{jt} - \overline{\Omega}_t)$. The change in the productivity index from period t to period t', $\Delta\Omega_{t,t'}$, can be written as

$$(20) \quad \Delta\Omega_{t,t'} = \Delta\overline{\Omega}_{t,t'} + \Delta cov_{t,t'}.$$

[21] It would have been more informative to estimate the mark-ups before and after the dot-com bust. Unfortunately, this is not possible due to data constraint.

Since the OP decomposition ignores entry and exit, Melitz and Polanec (2009) (MP) suggest a dynamic OP decomposition where there is a positive contribution for entering and exiting firms only when the aggregate productivity of these firms is larger than that of continuing firms in corresponding periods. The aggregate productivity in periods t and t' can be decomposed as

$$\begin{aligned} \Omega_t &= ms_{C_{t,t'},t}\Omega_{C_{t,t'},t} + ms_{X_{t,t'},t}\Omega_{X_{t,t'},t} \\ \Omega_{t'} &= ms_{C_{t,t'},t'}\Omega_{C_{t,t'},t'} + ms_{E_{t,t'},t'}\Omega_{E_{t,t'},t'}, \end{aligned} \tag{21}$$

where $ms_{C_{t,t'},t}$, $ms_{E_{t,t'},t'}$, and $ms_{X_{t,t'},t}$ are the aggregate market shares of incumbents in period t, of entrants in period t', and of exits firms in period t, respectively. Thus, the change in aggregate productivity can be written as

(22)

$$\Delta\Omega_{t,t'} = \Delta\overline{\Omega}_{C_{t,t'}} + \Delta cov_{C_{t,t'}} + ms_{E_{t,t'},t'}(\Omega_{E_{t,t'},t'} - \Omega_{C_{t,t'},t'}) + ms_{X_{t,t'},t}(\Omega_{C_{t,t'},t} - \Omega_{X_{t,t'},t}).$$

Table 6 presents the MP productivity decomposition from 1997 to 2002 for the software and operational services sub-sectors using 1997 as the base year. For software, the productivity growth is around 21 percent from 1997 to 2000 but only 6 percent from 1997 to 2002. The largest growth occurred from 1997 to 2001 (23 percent). Entrants contributed negatively to productivity growth, i.e., entrants were less productive than continuing firms. On the other hand, the exit firms contributed positively to productivity growth, and the contribution increased over time, e.g., from 5 percent in 1997 to around 18 percent in 2001. From 1997 to 2001, the continuing software contributed the most to growth: 35 percent (1997-2000) and 45 percent (1997-2001). From 1997 to 2002, the software firms that exited contributed more to productivity growth than did continuing firms (12 percent versus 7.5 percent).

For operational services and maintenance, the productivity growth was about 70 percent from 1997 to 2000 and about 32 percent from 1997 to 2002. Continuing firms accounted for almost all productivity growth from 1997 to 2000. Yet, exit firms contributed the most (50 percent) to productivity growth from 1997 to 2002.

Summarizing, the decomposition results emphasize the importance of net exit for productivity growth in the IT services after the 2001 dot-com bust. This suggests important changes in the market dynamics after the impact of aggregate shocks in the market, e.g., less productive firms exit.

Revenue-generating function. The estimated productivity is used to obtain a revenue-generating function, needed to evaluate the value functions, for each subsector. Table 7 presents two specifications. The first is a simple linear regression estimated by OLS. A flexible way to model firms' revenues as a function of the state variables is to use the method of linear sieves, i.e., a simple semi-nonparametric approach to estimate unknown functions. The second specification uses a non-parametric cubic b-splines approximation and is estimated by the OLS estimator. A nice feature of the linear sieves is their simple analytical form. This paper uses cubic b-splines as basis functions, denoted $bs(\cdot)$, which are finite dimensional piecewise polynomials (Appendix C provides a short description of the cubic b-splines).

The revenues are a function of firms' productivity, rivals' productivity, own capital, rivals' capital, number of non-IT firms in the local market, firm size (medium or large), and type of ownership (domestic or foreign). The variables are in log form. Rivals' productivity captures the effect of the competitive pressure on firms' revenues. The impact of rival size on revenues is captured by rivals' capital, which to some extent also captures competition, i.e., the number of IT firms. At the local market, number of non-IT firms measures demand for IT services.[22]

The OLS results (Panel A) show that doubling productivity increases revenues about 58 percent for software, and 53 percent for operational services and for maintenance and repair. Doubling the capital stock increases revenues by about 37 percent for software, 29 percent for operational services, and 33 percent for maintenance and repair firms. If the number of non-IT firms at the local market level doubles, then revenues go up about 12 percent for software, 33 percent for operational services, and 22 percent for maintenance and repair firms. Rivals' productivity and capital have a negative impact on software and operational firms' sales. For software and operational services, foreign IT firms have revenues about 19 percent higher than domestic IT firms. The dot-com bubble bust decreases revenues by about 20 percent for software and operational services and by 34 percent for maintenance and repair.

Panel B (Table 7) presents only a summary of the estimation results using b-splines with 6, 9, and 14 knots. For software and operational services, the adjusted R^2 increases, the root of mean squared errors (RMSE) and absolute mean errors (MAE) decrease using b-splines as basis functions for firms' own productiv-

[22]There is a high correlation (0.99) between number of firms and population at the county level.

ity, firms' own capital, rivals' productivity, and rivals' capital. This suggests that there is no need to use nonlinear approximation for operational services' revenues. Even if the simple linear regression does a good job estimating revenues, there is a significant increase in adjusted R^2, about 13 percentage points, and the RMSE decreases from 0.622 (OLS) to 0.599 when cubic b-splines are used for the software industry, for example. In the forward simulations, B-spline specification with 14 knots is used to estimate the value functions for software and operational services.

Policy functions. The next step is to estimate investment and labor policy functions for all firms. In addition, I estimate the entry and exit policies. All these policies are estimated for each IT sub-sector. Table 8 presents the logit estimates for the exit (Panel A) and entry (Panel B) policies. In my dataset, entry and exit are based on organization number.

For all sub-sectors, high productivity firms and firms located in markets with a large number of firms (only software and operational services) are less likely to exit. In all sub-sectors, firms are also more likely to exit after the 2001 dot-com bust. For software and operational services, firms are less likely to exit in markets where rivals have large capital stocks and high productivity. In the Swedish case, large firms are located in large markets and might have subsidiary (technology and innovation clusters). However, markets with large capital stocks imply high demand, i.e., there is still room to differentiate in these sub-sectors. For software and operational services, I find that firms with large capital are more likely to exit. There have been many technological innovations in this industry in recent years. Failing to update utilized technology has a negative impact on firm performance. Acquisitions were made during the studied period. This may explain the findings that software and operational service firms are more likely to exit if the firm has over 20 employees.

My findings indicate that IT firms are more likely to enter if rivals have high productivity, i.e., if there is sufficient demand. Software firms are less likely to enter markets where rivals have extensive capital, i.e., markets with large firms, but more likely to enter markets with a large number of firms. Hence, these markets offer sufficient demand and skilled labor. It is less likely to have foreign entrants (software and operational services) and to observe entry after the dot-com bust.

Table 9 shows the investment policy function estimates for all IT firms by subsector. Panel A presents the estimates from a simple linear investment specification. Panel B shows summary results from non-parametric regressions using cubic b-splines as basis functions for linear sieves approximations of unknown functions in own productivity, rivals' productivity, and rivals' capital. Both regression specifications use the OLS estimator. For software and operational services, productivity has a positive and significant effect on investment, i.e., firms with high productivity invest more in capital. For maintenance and repair, firms invest more if rivals reduce their capacity. For all IT sub-sectors, firms with large capital stock invest more, but they invest less after 2000. For software and operational services, increasing the business opportunities, i.e., increasing the number of non-IT firms, has a positive impact on investment. Allowing the marginal effects to depend on the size of the variables (b-splines specifications), the accuracy of recovering the observed investment increases. By using the non-parametric specification, the adjusted R^2 increases from 17 to over 86 percent for software, from 37 to 85 percent for operational services, and from 58 to 95 percent for maintenance and repair. Allowing for non-linearities in productivity and capital reduces the RMSE at least two times, and the correlation between observed and predicted investment increases from 0.41 to 0.93 for software, from 0.61 to 0.93 for operational services, and from 0.77 to 0.98 for maintenance and repair firms.

Table 10 presents the labor policy function results for all IT firms. A linear specification does a good job fitting the observed number of employees. For all IT sectors, the adjusted R^2 is about 90 percent. Allowing for non-linearities gives a better fit only for software and maintenance and repair labor policies.[23]

By doubling their productivity, the number of employees increases by about 52 percent for software and by about 48 percent for operational services and maintenance and repair firms. A double capital stock increases the number of employees about by 27 percent for software, by 20 percent for operational services, and by about 15 percent for maintenance and repair. If the number of firms doubles (double potential demand), operational services firms increase labor by about 33 percent and maintenance and repair firms by about 50 percent. On average, foreign firms have about 10 percent more employees than domestic ones in software. The corresponding numbers for operational services and maintenance and repair are around 8 percent and 37 percent, respectively. After the dot-com bust, IT firms reduced the number of employees by about 28 percent in software, by 24 percent in operational services, and by about 22 percent in maintenance and repair.

Recovering cost parameters. In the second step, I obtain the cost parameters

[23] A negative adjusted R^2 obtained for operational services regressions suggests that there is no need for non-linearities.

for each IT sub-sector before and after the IT dot-com bust. First, the value functions are estimated using the policy functions estimated in the previous subsection. The value functions are the expectations of discounted profits over current and future states, and profit shocks. In the estimation, 100 forward simulations are used and the discount parameter, β, is fixed to 0.95. For policy functions, the cubic b-spline estimates are used to extend the panel (forward simulations).

Since IT firms compete at the local market level, the order of generating the policy functions is very important. First, future productivity and capital stock are generated for each firm and year. To generate future productivity previous investment is also added as variable in the $g(\cdot)$ function. Second, the rivals' productivity and capital are computed for each market and year. Third, the revenues and required labor are generated knowing that the population and the number of other firms evolve as exogenous processes. Fourth, the exit estimates are used to simulate whether firms exit or continue. If a firm continues, the investment and setup cost components for investment and labor are generated using cubic b-splines with 14 knots. The setup cost components are the basis cubic b-splines in the estimated probability to invest, dis-invest, hire, or fire. The high setup costs might cause the observed lumpy investment and lack of adjustment in employment, i.e. the dynamics of investment and labor, to depend on the setup costs. Hamermesh (1989) finds empirical evidence that the adjustment labor costs, which are independent of the level changes, are determinants of lumpy adjustment.[24] I assume that employment dynamics in IT are generated by a process that distinguishes between hiring and firing costs.[25]

Table 11 shows the estimated cost parameters for each sub-sector before (1997-2000) and after (2001-2002) the 2001 dot-com bust. Panel A presents the estimated results for investment. The quadratic cost of adjustment implies that the future value of additional capital depends on the choice with respect to adjustment. I present only the results for positive investment. After 2003, IT firms started to invest again (Section 2). Therefore, to be close to how industry behave I use the investment policy function from 1996-2000 in the forward simulation after 2003. Since capital stock is a state variable, allowing for excessive negative investment

[24]Hamermesh and Pfann (1996) find evidence of asymmetric adjustment costs, e.g., the cost of advertising might be proportional to the number of hired employees but not firing cost (Pfann and Palm, 1993). Since the asymmetry implies non-linearity in the shape of the cost function, it would be impossible to estimate the cost parameters without additional approximations to reach linearity.

[25]In my case, I observe the number of employees in November.

makes smaller firms have a short life. For this reason, the results for negative investment are not significant. This paper finds that setup investment costs are higher for software but lower for operational services and maintenance after the dot-com bust. In the IT services case, the setup investment cost is associated with system and network configuration costs when firms change technology. Operational service firms have at least twice the setup costs of software and maintenance and repair. This sub-sector includes data processing and database activities, which require large costs in case of migration from one system to another even if the machines get cheaper due to technological innovations. However, the implied distribution of investment costs indicates higher investment costs, on average, for operational services after the dot-com bust even if the setup costs are lower (Panel B). During the study period, there was significant innovation with respect to on both hardware and software in the database management area, e.g., integration of Oracle (commercial product) and MySQL (free) on Linux. Fast access to information became very important at the same time as the complexity of the information stored increased. Therefore, firms had to invest in advanced technologies, which might explain the larger cost after the dot-com bust in this sub-sector. This contrasts the maintenance and repair sub-sector, where investment costs decreased after dot-com. Since advances in technology make hardware cheaper, firms prefer to buy rather than repair.

Panel C shows the estimates for labor adjustment costs. For software, the setup costs of positive labor adjustment are about 4 times larger after the dot-com bust. The variable marginal labor adjustment cost is about SEK 322,000 before and about SEK 271,000 after the dot-com bubble. The findings of larger setup costs and smaller variable adjustment labor costs after the dot-com bust suggest that firms face uncertainties regarding demand and might rather work with external consultants than hire new staff. The firing setup costs (about SEK 366,000) are about 2 times larger after the dot-com bust.

For operational services, the results indicate larger setup costs for positive labor adjustment before the dot-com bust. However, the setup costs are larger for negative than for positive adjustment. Here, setup labor costs might also include expenses in connection with employees' training, e.g., training to become a certified expert. This might explain the decrease in labor adjustment setup costs after the dot-com bust, when the firms were focused on reducing the costs due to the aggregate decrease in demand. Operational services has larger marginal cost of adjustment after the dot-com bust, i.e., about SEK 379,000 before and SEK

432,708 after. The marginal labor adjustment costs are larger for operational services than for software firms.

For maintenance and repair, the estimates indicate about the same positive labor adjustment setup cost (SEK 400,000) before and after the dot-com bust. Furthermore, the marginal cost of positive labor adjustment is with about SEK 50,000 less (SEK 245,000). The parameters for the negative adjustment costs could not be identified due to too few observations.

Having the estimated labor parameters, the implied distributions of cost for labor adjustment can be computed (Panel D). The 2001 dot-com bust implies higher positive labor adjustment costs for software but lower positive labor adjustment cost for operational services and maintenance and repair.

Distributions of exit and entry sunk costs. A median firm that exits has one employee for software and two employees for operational services and maintenance and repair. After the burst of the dot-com bubble, firms in software and operational services have higher (sell-off) while the maintenance and repair firms have lower scrap values (Table 11, Panel E).

To estimate entry cost, I assume that it follows a normal distribution. Using the minimum distance estimator, I recover mean and standard deviation for each industry before and after the dot-com bust. A median entrant in software or operational services has two employees, and a median entrant in maintenance and repair has three. The mean entry cost for software and operational services is estimated to be about SEK 19,000 and SEK 120,000, respectively. However, I find no significant difference between entry costs before and after the dot-com bust for software and operational services, i.e., demand uncertainty and large setup costs might explain the decrease in the number of entrants and their size. For maintenance and repair, the mean entry cost (about SEK 135,000) is not significant. One possible explanation to this is that this industry had few entrants. The low value of sunk entry costs for software firms – about 6 times lower than for operational services – explains the observed differences in the number of entrants; i.e., the yearly number of entrants in software was about 8 times the number of entrants in operational services.

6 Conclusions

This paper analyzes the impact of the 2001 dot-com bust on productivity and cost structure in the Swedish IT services. To understand the differences in productivity among the IT service sub-sectors and how the firms change their behavior when facing demand shocks, the paper analyses the possible changes in cost structure caused by the burst of the 2001 dot-com bubble. Since changes in the cost structure impact the market dynamics and therefore productivity growth, they are important both for market structure and agencies that support this industry, which is dominated by small firms (number of firms).

The results show that from 1997 to 2002, the productivity growth was about 6 percent for software and about 32 percent for operational services. After the dot-com bust, net exit contributed the most to productivity growth, suggesting important changes in the market dynamics after this aggregate shock.

Entrants are less productive than incumbent IT firms. Software firms invest more if there is an increase in business opportunities at the local market level. On average for the IT sub-sectors, firms with large capital stocks invest more. Yet, they invested less after the 2001 dot-com bust. This study finds that, among the low productivity IT firms, medium and large firms were affected the most by the dot-com bust.

The findings indicate that differences between setup (fixed) and variable costs help explain observed behavior in investment and labor policies in the IT services industry. Since the relative importance of setup and variable adjustment costs can not be measured directly from the observed data, they are inferred from the model. The downturn in productivity growth after the dot-com bubble can be explained not only by reduced demand but also by large adjustment costs.

Changes in cost structure cause changes in prices (and vice-versa), but this important aspect is not explicitly modeled here due to difficulties finding price data for IT services. Even if the paper controls for unobserved prices in an indirect way, there is still possible to have correlated unobserved demand shocks in estimated productivity (Ackerberg et al., 2008; Foster et al., 2008; and De Loecker, 2009). A detailed investigation of demand and a better understanding of the entry process would be interesting for future research.

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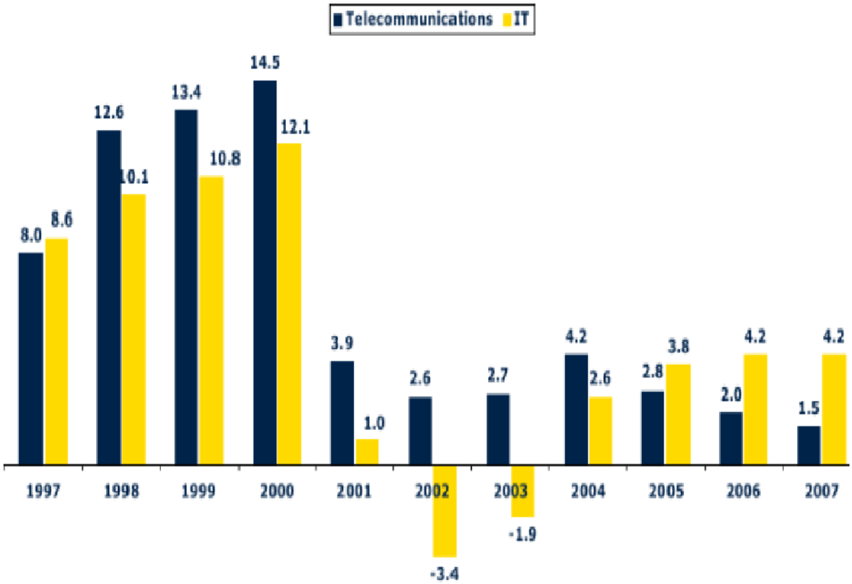

Figure 1: Western European ICT market growth, 1997-2007, in percent. Source: EITO 2006 in cooperation with IDC.

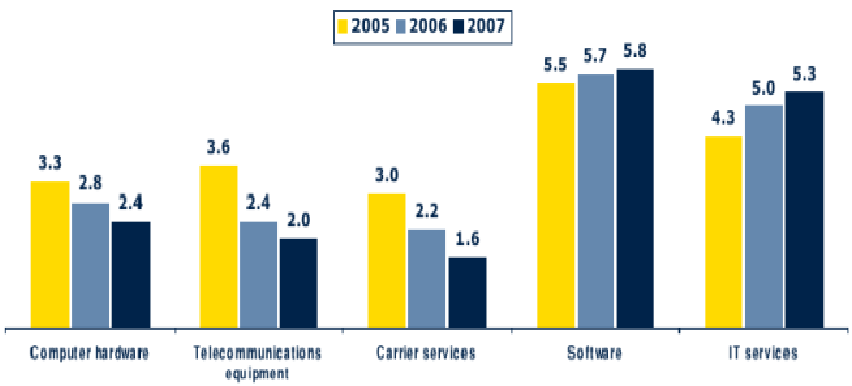

Figure 2: EU ICT, excluding Cyprus and Malta, market growth by segment, 2005-2007, in percent. Source: EITO 2006 in cooperation with IDC.

Table 1: Characteristics of the data for the Swedish IT service industry 1996-2002.

Year	Firms	Entry	Exit	Sales	Value added	Total wages	Employees	Investment
A: All IT service firms								
1996	4,116		543	48,320,538	21,459,073	12,070,602	42,686	1,774,708
1997	4,581	1,166	551	53,209,942	25,707,591	14,506,458	49,883	2,038,902
1998	5,109	1,149	644	66,707,752	31,395,570	17,851,110	59,208	2,257,806
1999	5,625	1,185	820	83,369,434	38,282,741	22,787,128	71,133	3,022,545
2000	6,523	1,694	1,203	96,284,420	39,710,885	28,085,689	85,928	3,668,669
2001	6,749	1,336	1,326	112,979,488	48,588,640	32,312,569	94,096	3,947,814
2002	6,623	962		100,931,185	44,672,840	29,804,633	87,567	3,539,552
B: Software								
1996	3,474		445	35,638,817	16,448,024	9,376,162	32,580	1,110,581
1997	3,882	973	441	42,341,881	20,666,581	11,981,723	40,393	1,466,592
1998	4,398	1,022	536	56,348,497	26,907,847	15,241,528	49,657	1,741,355
1999	4,908	1,051	709	67,495,845	32,512,499	19,477,029	59,823	2,299,510
2000	5,742	1,532	1,017	76,266,817	32,079,924	23,499,892	70,792	2,937,217
2001	6,043	1,222	1,168	97,738,433	42,385,864	28,361,781	81,518	3,355,883
2002	5,932	856		80,063,479	36,335,808	24,621,346	71,526	3,007,020
C: Operational services								
1996	527		88	11,114,449	4,374,038	2,294,675	8,580	646,102
1997	583	174	100	9,435,368	4,379,401	2,139,978	7,996	549,014
1998	601	122	88	8,888,705	3,781,396	2,199,835	7,939	493,259
1999	616	124	102	13,227,458	4,896,611	2,774,268	9,497	678,515
2000	671	147	168	17,881,246	6,739,992	4,039,204	13,299	709,624
2001	602	101	141	12,969,458	5,325,738	3,305,638	10,298	574,791
2002	592	93		18,956,159	7,454,423	4,606,482	13,932	518,766
D: Maintenance and repair								
1996	115		10	1,567,272	637,011	399,765	1,526	18,025
1997	116	19	10	1,432,693	661,608	384,756	1,494	23,295
1998	110	5	20	1,470,551	706,326	409,747	1,612	23,191
1999	101	10	9	2,646,131	873,630	535,830	1,813	44,520
2000	110	15	18	2,136,357	890,968	546,592	1,837	21,828
2001	104	13	17	2,271,597	877,038	645,150	2,280	17,139
2002	99	13		1,911,548	882,608	576,804	2,109	13,764

NOTE: The data are from the merge between Financial Statistics(FS) and Regional Labor Statistics(RAMS) databases. Sales, value-added, wages, investment are measured in thousand 1996 SEK. 1 USD=6.71 SEK and 1 EUR=8.63 SEK.

Table 2: The 2001 dot-com bust: growth rates (percent) 2000-2001 and 2001-2002.

	Firms		Sales		Employees		Investment	
	2000-2001	2001-2002	2000-2001	2001-2002	2000-2001	2001-2002	2000-2001	2001-2002
Software	5	-2	28	-18	15	-10	14	-10
Operational services	-10	-2	-27	46	-25	58	-19	-10
Maintenance and repair	-5	-5	6	-16	17	-7	21	-20

NOTE: The data come from the merge between Financial Statistics(FS) and Regional Labor Statistics(RAMS) databases. The growth rates are computed at the sub-sector level.

Table 3: Summary statistics at the local market level for the Swedish IT service industry 1996-2002.

Variable	Minimun	Mean	Median	Maximum	Standard Deviation
Services production					
Sales	257	36,403	6,569	798,279	118,663
Value added	70	16,196	3,082	333,439	51,010
Capital	2,189	201,392	32,373	4,745,895	667,003
Employees	24	3,179.99	773	62,314	9,534
Wages	40	10,203	1,891	226,977	33,383
Demand					
Other firms	916	7,225	4,338	42,477	8,809
Population	57,313	399,814	269,699	1,838,882	416,484
Competition					
IT firms	6	255	87	3,490	593
Investment					
Investment	-4,307	1,068	168	23,349	3,594

NOTE: The data come from the merge between Financial Statistics(FS) and Regional Labor Statistics(RAMS) databases. There are 160 observations in 25 regional markets. The variables are aggregated at the county level. Sales, value-added, wages, capital, and investment are measured in thousand 1996 SEK. 1 USD=6.71 SEK and 1 EUR=8.63 SEK.

Table 4: Summary statistics of Swedish IT service grouped by size

A. Small size IT service firms: 0-19 employees					
Variable	Minimun	Mean	Median	Maximum	Standard Deviation
Services production					
Sales	164	8,908	2,389	137,769	23,116
Value added	70	3,721	1,102	52,299	9,324
Capital	1,263	47,820	14,169	739,642	118,627
Employees	17	799	273	10,861	1,855
Wages	40	2,259	627	37,211	5,989
Competition					
IT firms	6	230	81	3,061	527
Investment					
Investment	-234	249	75	4,771	660
B. Medium size IT service firms: 20-99 employees					
Services production					
Sales	29	8,616	2,280	145,898	23,682
Value added	-55	3,782	1,102	61,821	9,837
Capital	341	41,397	8,994	828,553	115,150
Employees	20	846	260	13,128	2,102
Wages	38	2,771	736	50,442	7,657
Competition					
IT firms	1	22	7	356	55
Investment					
Investment	-183	245	44	5,753	703
C. Large size IT service firms: over 100 employees					
Services production					
Sales	314	33,116	6,125	514,612	93,380
Value added	217	15,211	3,329	224,736	41,269
Capital	0	195,859	46,654	3,610,016	579,167
Employees	104	2,707	596	38,325	7,248
Wages	184	9,107	1,746	139,325	25,648
Competition					
IT firms	1	7	2	90	17
Investment					
Investment	-4,393	1,006	184	19,792	3,155

NOTE: The data are from the merge between Financial Statistics(FS) and Regional Labor Statistics(RAMS) databases. There are 160 observations in 25 regional markets. The variables are aggregated at the county level. Sales, value-added, wages, capital, and investment are measured in thousand 1996 SEK. 1 USD=6.71 SEK and 1 EUR=8.63 SEK.

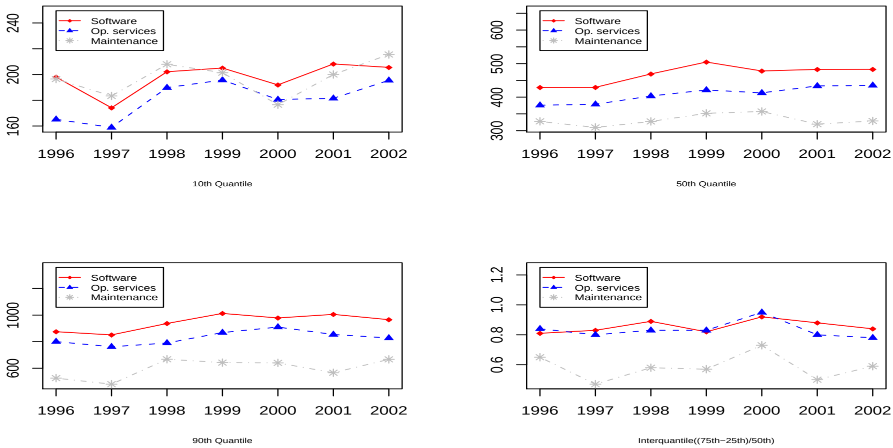

Figure 3: Evolution of the labor productivity percentiles and dispersion from 1996 to 2002.

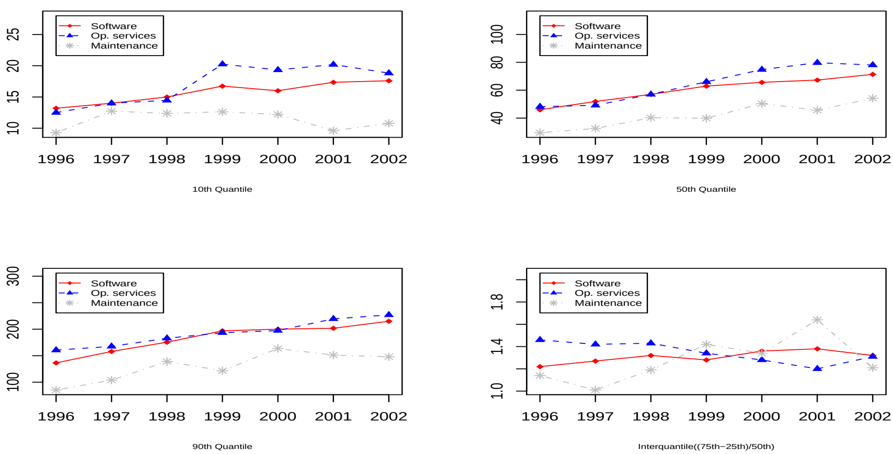

Figure 4: Evolution of the capital intensity percentiles and dispersion from 1996 to 2002.

Table 5: Estimates of value-added generating function parameters in Swedish IT services

	OLS software	EOP software	OLS Op. services and maintenance	EOP Op. services and maintenance
Log No Emp.	1.017	0.680	0.995	0.789
	(0.006)	(0.0004)	(0.0163)	(0.031)
Log capital	0.118	0.374	0.169	0.208
	(0.004)	(0.004)	(0.010)	(0.003)
Market output		0.217		0.168
		(0.004)		(0.010)
Scale	1.135	1.347	1.164	1.196
Demand		-4.609		-5.96
Mark-up		1.277		1.524
Sargan (p-value)		0.101		0.125
No. obs.	28,277	28,277	4,028	4,028

NOTE: OLS is ordinary least square regression including year dummies; EOP is the semi-parametric estimation of equation (23) specified in Section 4, including selection. Two-stage GMM is used in the EOP estimation. Reported standard errors (in parentheses) are robust to heteroscedasticity.

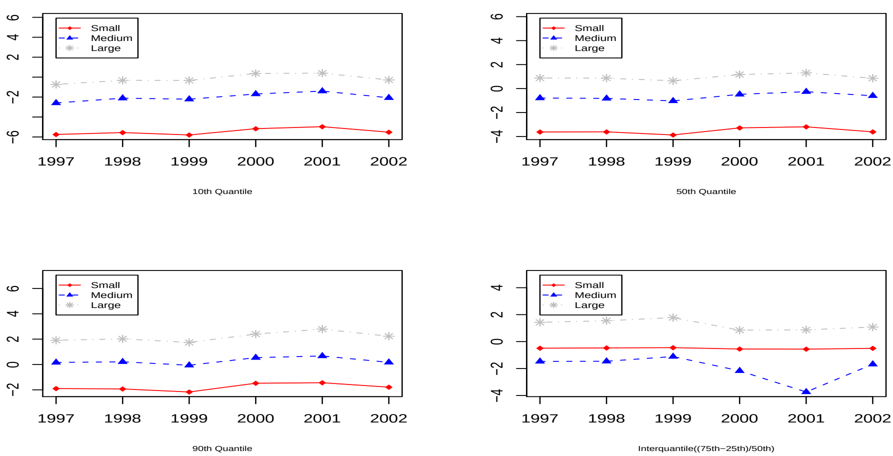

Figure 5: Evolution of the total factor productivity percentiles and dispersion for different size classes from 1996 to 2002.

Table 6: Dynamic Olley-Pakes productivity decomposition with entry and exit

Year	Prod. Growth (1)	Surviving firms change in weighted productivity Surviving firms $(\omega_{C_{t'}} - \omega_{C_t})$ (2)	Difference between entering and surviving in weighted productivity $s_{E_{t'}}(\omega_{E_{t'}} - \omega_{C_{t'}})$ (3)	Difference between surviving and exiting in weighted productivity $s_{X_t}(\omega_{C_t} - \omega_{X_t})$ (4)	Difference between surviving and exiting in unweighted productivity $(\overline{\omega}_{C_t} - \overline{\omega}_{X_t})$ (5)	Change in covariance for surviving firms $(cov_{C_{t'}} - cov_{C_t})$ (6)	Difference between entering and surviving in unweighted productivity $s_{E_{t'}}(\overline{\omega}_{E_{t'}} - \overline{\omega}_{C_{t'}})$ (7)	Difference between surviving and exiting in unweighted productivity $s_{X_t}(\overline{\omega}_{C_t} - \overline{\omega}_{X_t})$ (8)
A. Software								
1998	-0.005	0.062	-0.123	0.055	-0.020	0.083	-0.033	0.036
1999	-0.313	-0.205	-0.211	0.102	-0.284	0.078	-0.055	0.063
2000	0.208	0.353	-0.235	0.090	0.276	0.077	-0.024	0.087
2001	0.231	0.457	-0.401	0.175	0.318	0.139	-0.033	0.072
2002	0.063	0.075	-0.135	0.123	-0.049	0.124	-0.059	0.078
B. Operational services and repair								
1998	0.128	0.083	-0.189	0.234	0.171	-0.087	-0.031	0.199
1999	0.138	0.275	-0.108	-0.028	0.002	0.273	-0.074	0.102
2000	0.702	0.707	0.028	-0.033	0.461	0.246	-0.053	0.097
2001	0.663	0.990	-0.537	0.209	0.595	0.394	-0.017	0.031
2002	0.323	0.004	-0.186	0.505	-0.172	0.177	-0.013	0.062

NOTE: The reference period for calculation of the change of aggregate productivity index is 1997. Log of total factor productivity is used as measure of productivity.

Table 7: Revenues generation function estimates

A. Linear parametric specification			
Variable	Software	Operational services	Maintenance and repair
Intercept	6.371	5.956	7.075
	(0.102)	(0.345)	(0.686)
Own productivity	0.585	0.522	0.534
	(0.004)	(0.015)	(0.028)
Own capital	0.367	0.292	0.326
	(0.004)	(0.013)	(0.025)
Rivals' productivity	-6.63E-05	-1.85E-04	-3.45E-04
	(6.38E-06)	(7.86E-05)	(0.001)
Rivals' capital	-3.22E-08	-1.05E-08	-3.24E-06
	(4.57E-09)	(6.13E-08)	(3.79E-06)
Number of firms (other than IT)	0.119	0.327	0.222
	(0.011)	(0.039)	(0.083)
Foreign owner	0.186	0.198	0.389
	(0.032)	(0.088)	(0.276)
Medium size (20-99 employees)	0.199	0.042	-0.054
	(0.024)	(0.073)	(0.170)
Large size (over 100 employees)	0.458	0.304	-0.098
	(0.045)	(0.139)	(0.359)
After 2000	-0.202	-0.194	-0.335
	(0.017)	(0.052)	(0.090)
Adjusted R^2	0.821	0.814	0.808
Root of mean squares errors	0.622	0.708	0.583
Absolute mean errors	0.387	0.501	0.340
B. Linear non-parametric specification using cubic b-splines			
	Number of knots, $k_n = 6$		
Adjusted R^2	0.832		0.813
Root of mean squares errors	0.604		0.562
Absolute mean errors	0.365		0.316
	Number of knots, $k_n = 9$		
Adjusted R^2	0.833		0.822
Root of mean squares errors	0.600		0.524
Absolute mean errors	0.360		0.275
	Number of knots, $k_n = 14$		
Adjusted R^2	0.834		0.829
Root of mean squares errors	0.599		0.496
Absolute mean errors	0.359		0.246

NOTE: The dependent variable is the log of revenues. The independent variables are as follows: *Own productivity* measures the firm's productivity; *own capital* is the firm's capital stock; *rivals' productivity* is the log of sum of rivals' productivity at the county level; *rivals' capital* is the log of rivals' productivity at the county level; *Number of firms other than IT* is the log of the number of non-IT firms at the county level; *population* is the log of population at the county level; *foreign owner* is a dummy variable indicating whether the firm has foreign ownership; *medium size (20-99 employees)*, *large size (over 100 employees)*, and *after 2000* are dummy variables for the firm's size and the period following the 2001 dot-com bust. For Panel A, the standard errors are in parentheses.

Table 8: Entry and exit policy functions estimation results

A. Exit policies			
Variable	Software	Operational services	Maintenance and repair
Intercept	14.292	-0.744	-0.431
	(0.479)	(0.948)	(2.32)
Own productivity	-0.321	-0.389	-0.285
	(0.014)	(0.036)	(0.087)
Own capital	0.027	0.084	0.021
	(0.012)	(0.032)	(0.086)
Rivals' productivity	-0.771	0.022	-0.350
	(0.022)	(0.042)	(0.179)
Rivals' capital	-0.646	0.093	-0.204
	(0.035)	(0.043)	(0.116)
Number of firms (other than IT)	-0.208	-0.496	-0.033
	(0.035	(0.120)	(0.268)
Foreign owner	0.628	0.730	1.122
	(0.102)	(0.226)	(0.635)
Medium size (20-99 employees)	0.015	0.795	0.687
	(0.088)	(0.200)	(0.601)
Large size (over 100 employees)	1.484	0.548	0.614
	(0.149)	(0.415)	(1.004)
After 2000	1.978	2.079	2.603
	(0.035)	(0.093)	(0.247)
Log-likelihood	-11851.188	-1635.361	-270.744
The likelihood ratio index	0.389	0.289	0.390
B. Entry policies			
Intercept	-1.051	-3.144	-4.822
	(0.353)	(0.860)	(1.931)
Rivals' productivity	0.068	0.184	0.434
	(0.015)	(0.036)	(0.150)
Rivals' capital	-0.192	-0.016	0.100
	(0.028)	(0.039)	(0.110)
Number of firms (other than IT)	0.265	0.177	0.134
	(0.028)	(0.116)	(0.232)
Foreign owner	-0.581	-0.468	0.334
	(0.115)	(0.287)	(0.744)
Medium size (20-99 employees)	-0.867	-0.902	-0.784
	(0.064)	(0.168)	(0.631)
Large size (over 100 employees)	-1.307	-1.665	-0.234
	(0.165)	(0.478)	(1.016)
After 2000	-0.760	-1.240	-1.416
	(0.034)	(0.107)	(0.282)
Log-likelihood	-15849.964	-1852.225	-330.732
The likelihood ratio index	0.184	0.194	0.255

NOTE: The estimations are done using logit estimator. The independent variables are as follows: *Own productivity* measures the firm's productivity; *own capital* is the firm's capital stock; *rivals' productivity* is the log of sum of rivals' productivity at the county level; *rivals' capital* is the log of rivals' productivity at the county level; *Number of firms other than IT* is the log of the number of non-IT firms at the county level; *population* is the log of population at the county level; *foreign owner* is a dummy variable indicating whether the firm has foreign ownership; *medium size (20-99 employees)*, *large size (over 100 employees)*, and *after 2000* are dummy variables for the firm's size and the period following the 2001 dot-com bust. The standard errors are in parentheses.

Table 9: Investment policy functions estimation results

A. Investment policies for IT services			
Variable	Software	Operational services	Maintenance and repair
Intercept	-1.565	-3.635	-0.778
	(3.682)	(5.385)	(0.543)
Own productivity	0.078	0.201	-0.003
	(0.032)	(0.179)	(0.019)
Own capital	0.474	0.947	0.105
	(0.027)	(0.165)	(0.017)
Rivals' productivity	-0.067	1.898	0.251
	(0.268)	(4.155)	(0.446)
Rivals' capital	-1.732	-4.728	-0.318
	(4.573)	(6.855)	(0.175)
Number of firms (other than IT)	0.108	0.245	0.041
	(0.057)	(0.425)	(0.039)
Foreign owner	0.632	1.940	0.631
	(0.212)	(1.059)	(0.192)
Medium size (20-99 employees)	-0.551	-2.328	0.373
	(0.157)	(0.881)	(0.118)
Large size (over 100 employees)	9.192	27.088	2.120
	(0.295)	(1.672)	(0.253)
After 2000	-0.188	-0.466	-0.127
	(0.089)	(0.553)	(0.061)
Adjusted R^2	0.174	0.367	0.583
Root of mean squares errors	4.085	8.501	0.405
Absolute mean errors	16.688	72.280	0.165
Correlation (observed,predicted)	0.418	0.609	0.770
B. Linear non-parametric specification using cubic b-splines			
Number of knots, $k_n = 6$			
Adjusted R^2	0.729	0.743	0.877
Root of mean squares errors	2.335	5.382	0.213
Absolute mean errors	5.451	28.966	0.045
Correlation (observed,predicted)	0.854	0.883	0.942
Number of knots, $k_n = 9$			
Adjusted R^2	0.836	0.767	0.945
Root of mean squares errors	1.818	5.075	0.136
Absolute mean errors	3.305	25.763	0.018
Correlation (observed,predicted)	0.915	0.887	0.976
Number of knots, $k_n = 14$			
Adjusted R^2	0.869	0.854	0.950
Root of mean squares errors	1.618	3.997	0.125
Absolute mean errors	2.619	15.982	0.015
Correlation (observed,predicted)	0.933	0.930	0.980

NOTE: The dependent variable is the investment expenditure in ten thousand Swedish krona. The independent variables are as follows: *Own productivity* measures the firm's productivity; *own capital* is the firm's capital stock; *rivals' productivity* is the log of sum of rivals' productivity at the county level; *rivals' capital* is the log of rivals' productivity at the county level; *Number of firms other than IT* is the log of the number of non-IT firms at the county level; *population* is the log of population at the county level; *foreign owner* is a dummy variable indicating whether the firm has foreign ownership; *medium size (20-99 employees)*, *large size (over 100 employees)*, and *after 2000* are dummy variables for the firm's size and the period following the 2001 dot-com bust. For Panel A, the standard errors are in parentheses.

Table 10: Labor policy functions estimation results

A. Labor policies for IT services			
Variable	Software	Operational services	Maintenance and repair
Intercept	1.012	1.603	1.620
	(0.423)	(0.619)	(0.824)
Own productivity	0.522	0.482	0.485
	(0.002)	(0.006)	(0.010)
Own capital	0.267	0.199	0.151
	(0.002)	(0.006)	(0.016)
Rivals' productivity	-1.261	-2.542	-1.069
	(0.174)	(0.387)	(0.568)
Rivals' capital	-1.224	-0.339	-0.302
	(0.725)	(0.680)	(0.151)
Number of firms (other than IT)	0.017	0.327	0.500
	(0.041)	(0.105)	(0.158)
Population	0.122	-0.025	-0.177
	(0.045)	(0.116)	(0.173)
Foreign owner	0.098	0.078	0.372
	(0.018)	(0.041)	(0.092)
After 2000	-0.278	-0.243	-0.219
	(0.009)	(0.022)	(0.036)
Adjusted R^2	0.899	0.929	0.939
Root of mean squares errors	0.351	0.329	0.245
Absolute mean errors	0.123	0.108	0.060
Correlation (observed,predicted)	0.949	0.964	0.970
B. Linear non-parametric specification using cubic b-splines			
Number of knots, $k_n = 6$			
Adjusted R^2	0.943	-1.272	0.960
Root of mean squares errors	0.069	1.865	0.193
Absolute mean errors	0.263	3.480	0.037
Correlation (observed,predicted)	0.971	0.584	0.981
Number of knots, $k_n = 9$			
Adjusted R^2	0.945	-8.892	0.963
Root of mean squares errors	0.067	3.858	0.178
Absolute mean errors	0.259	14.888	0.031
Correlation (observed,predicted)	0.972	0.507	0.984
Number of knots, $k_n = 14$			
Adjusted R^2	0.946	-2.010	0.964
Root of mean squares errors	0.065	2.112	0.169
Absolute mean errors	0.256	4.461	0.028
Correlation (observed,predicted)	0.973	0.475	0.985

NOTE: The dependent variable is the log of number of employees. The independent variables are as follows: *Own productivity* measures the firm's productivity; *own capital* is the firm's capital stock; *rivals' productivity* is the log of sum of rivals' productivity at the county level; *rivals' capital* is the log of rivals' productivity at the county level; *Number of firms other than IT* is the log of the number of non-IT firms at the county level; *population* is the log of population at the county level; *foreign owner* is a dummy variable indicating whether the firm has foreign ownership; *medium size (20-99 employees)*, *large size (over 100 employees)*, and *after 2000* are dummy variables for the firm's size and the period following the 2001 IT bubble burst. For Panel A, the standard errors are in parentheses.

Table 11: Cost estimates by sub-sector before and after the 2001 dot-com bust

Variable	Software		Operational services		Maintenance and repair	
	Before	After	Before	After	Before	After
A: Investment cost						
Setup investment	170.61	323.68	667.13	645.98	193.01	148.23
Std.	(9.60)	(7.63)	(5.81)	(9.51)	(8.59)	(5.27)
Variable investment	6.26	5.36	10.02	13.80	34.39	14.07
Std.	(0.16)	(0.60)	(0.33)	(0.70)	(4.57)	(9.36)
Variable investment squared	6.76e-6	295e-5	4.09e-5	8.60e-5	0.003	0.06
Std.	(8.03e-7)	(4.32e-6)	(2.10e-6)	(5.37e-6)	(0.0008)	(0.04)
B: Implied distributions of investment costs						
Investment - mean	4,293.81	4,673.79	3,015.53	3,491.63	1,043.34	787,17
Investment - std.	2,992.91	44.75	241.43	453.68	50.69	75.27
C: Labor adjustment cost						
Setup positive adjustemnt	141.89	666.67	413.50	89.63	400.47	404.28
Std.	(78.92)	(347.88)	(151.26)	(34.89)	(60.20)	(87.47)
Variable positive adjustment	322.58	271.27	379.26	432.708	294.36	245.14
Std.	(2.81)	(2.17)	(2.06)	(4.34)	(9.76)	(2.20)
Setup negative adjustment	167.12	366.72	562.01	210.55	337.74	
Std.	(67.37)	(89.02)	(87.50)	(93.33)	(99.74)	
Variable negative adjustment	285.14	285.82	324.05	279.41	262.132	
Std.	(1.47)	(4.57)	(3.959)	(26.38)	(2.01)	
D: Implied distributions of labor adjustment costs						
Positive adjustment - mean	2,587.32	2,890.39	2,000.37	1,515.04	2,534.41	2,089
Positive adjustment - std.	1,039.67	1,943.26	171.25	671.25	475.75	319.42
Negative adjustment - mean	1,262	1,429.50	1,650.87	927.97	1,003.73	
Negative adjustment - std.	478.26	631,68	287.41	150.04	66.98	
E: Exit costs						
Scrap (sell-of values)	170.01	175.01	230.00	255.15	260.11	248.04
Std.	(61.02)	(50.29)	(27.24)	(23.45)	(40.57)	(34.78)
F: Entry costs						
Sunk cost	18.69	19.92	120.61	120.33	135.96	117.14
Std.	(4.08)	(4.66)	(34.63)	(34.53)	(146.97)	(104.30)

NOTE: The estimates are obtained using 2,000 simulations with 100 years each, where the initial states are held constant across simulations. Standard errors in parentheses.

Appendix A: Data. This section describes the variables in the data. Value added is total shipments, adjusted for changes in inventories, minus the cost of materials. Real value added is constructed by deflating value added by a five-digit industry output deflater. The deflectors are taken from Statistics Sweden. The labor variable is the total number of employees. The total wages come from RAMS. I deflated sales, wages, and investment by the consumer price index (CPI) from IMF-CDROM 2005. The capital measure is constructed using a perpetual inventory method, $k_{t+1} = +(1-\delta)k_t + i_t$. Since the capital data distinguish between buildings and equipment, all calculations of the capital stock are done separately for buildings and equipment. As suggested by Hulten and Wykoff (1981), buildings are depreciated at a rate of 0.0361 and equipment at a rate of 0.1179. In the empirical part, the paper only uses machinery and equipment capital stock.

Appendix B: Productivity estimation. Considering the high turnover in the industry, it is important to control for selection. Olley and Pakes' (1996) approach to control for selection is to substitute the predicted survival probability into $g(\cdot)$. Thus, the final value-added generating function to be estimated is

$$
\begin{aligned}
y_{jt} = \; & \left(1+\tfrac{1}{\eta}\right)[\beta_0 + \beta_l l_{jt} + \beta_k k_{jt}] + -\tfrac{1}{\eta} q_{mt} - \tfrac{1}{\eta} z'_{mt}\beta_z + g(\mathscr{P}_{t-1}, \omega_{jt-1}) \\
& + \left(1+\tfrac{1}{\eta}\right)\xi_{jt} - \tfrac{1}{\eta}\nu_{jt} - \tfrac{1}{\eta}u^d_{jt} + \left(1+\tfrac{1}{\eta}\right)u^p_{jt},
\end{aligned}
\tag{23}
$$

where ω_{jt-1} comes from (8).[26]

The value-added generating function (23) is estimated using 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 $g(\cdot)$. To approximate $g(\cdot)$, a third order polynomial in ω_{t-1} is used.[27] A tensor product polynomial series of labor, capital, large entrants and local market conditions are used as instruments. To compute ω_{t-1} and, hence, to approximate $g(\cdot)$, I use the following instruments. This set of instruments is also used to estimate (23) using the optimal weighting matrix are the

[26]The condition for identification is that the variables in the parametric part of the model are not perfectly predictable (in the least square sense) by the variables in the non-parametric part (Robinson, 1988). Hence, there cannot be a functional relationship between the variables in the parametric and non-parametric part (Newey et al., 1999). Including additional variables that affect productivity guarantees the identification.

[27]For robustness, the expand $g(\cdot)$ using a 4th order polynomial was also used. Yet, the results were similar.

following: $\{1, l_{t-1}, s_{t-1}, k_{t-1}, p_{It-1}, w_{mt-1}, pop_{mt-1}, firms_{mt-1}, \}$. Using the specified GMM implementation, the parameter values $(\boldsymbol{\beta}, g_{K_T})$ are jointly estimated. The Nelder-Mead numerical optimization method is used to minimize the GMM objective function.

Appendix C: B-Splines. We consider a cubic spline, $f(x)$, $x \in [a, b]$, with q interior knots, ξ_i, $i = 1, \cdots, q$, that can be written as a sum of piecewise polynomials of order 4 (degree 3) on the any interval $[\xi_{i-1}, \xi_i]$,

$$f(x) = \sum_{m=0}^{3} \delta_{mi} x^m, \quad x \in [\xi_{i-1}, \xi_i), \quad i = 1, \cdots, q, \quad or \quad x \in [\xi_q, \xi_{q+1}], i = q+1.$$

The function $f(x)$ is assumed to be twice continuously differentiable. Collinearity is a potential problem when using cubic spline in regressions. For this reason, the b-splines are preferred because of their numerical properties. For b-splines, the basis is derived recursively.[28] To do this, additional knots, such as $\xi_{-3} = \xi_{-2} = \xi_{-1} = a$ and $\xi_{q+2} = \xi_{r+3} = \xi_{r+4} = b$, have to be added. The basis for b-splines, $\{B_{i,4}\}_{i=-3}^{q}$ is given by

$$B_{i,n} = \frac{x - \xi_i}{\xi_{i+n-1} - \xi_i} B_{i,n-1}(x) + \frac{\xi_{i+n} - x}{\xi_{i+n} - \xi_{i+1}} B_{i+1,n-1}(x), \quad \text{if} \quad \text{n=2,3,4},$$

where $B_{i,1}(x)$ is equal to 1 if $x \in [\xi_i, \xi_{i+1})$ and 0 otherwise. Having the basis, the cubic b-spline is given by

$$bs(x) = \sum_{i=1}^{q+4} \alpha_i B_{i-4,4}(x),$$

where α_i,$i = 1, \cdots, q + 4$ is the set of coefficients.

[28] Schumaker (1981) provides a detailed overview on spline theory. de Boor (1978) and Eubank (1988) provide detailed information on b-splines.

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