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.

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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 investigates 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. (2008) (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. (2011) and Doraszelski and Jaumandreu (2011) 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 model it is unclear whether a framework with exogenous productivity process can

[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.

be applied. A further improvement to previous work is that the present paper explicitly models the effect of competitive pressure on productivity and its link to R&D and discusses 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 physical capital depends on the competitive pressure faced by firms.

[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 tends to reduce R&D spending-provided that the total market for varieties does not shrink; a larger 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.

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. (2011) provide a dynamic structural model of firms' decision to invest in R&D and to export.[6] My framework does not explicitly model the choice of R&D, it does it in an indirect way. Jones and Williams (1998) link the gap between the recent growth literature and the empirical productivity

[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.

literature by constructing a relationship between social rate of return to R&D and the estimated coefficients of the productivity literature. They show that the latter represent a lower bound.

I apply my structural model 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 R&D intensive 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 the productivity distribution in the MME and EOE industries. Therefore, my findings suggest that entrepreneurship policies can complement policies that promote R&D spending. Foreign market penetration has a positive impact on productivity

[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.

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, 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 discusses the

[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.

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 assume a stochastic dynamic single-agent model for the industry. A firm maximizes the expected discounted value of future net cash flows. 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. Firm's state variables are productivity $\omega \in \Omega$, capital stock $k \in \mathbb{R}_+$, and competitive pressure $\theta \in \mathbb{R}$.[11] I follow the common notation of capital letters for levels and small letters for logs.

The dynamic model is formulated by the following Bellman equation with the discount factor β ($\beta < 1$):[12]

$$\begin{aligned} V(\omega, k, \theta) = \;& max\left\{\phi, \sup_{\psi', i}\left[\pi(\omega, k, \theta) - c(i, k) - z(\psi', \omega) + \right.\right. \\ & \left.\left. \beta \int V(\omega', k', \theta') P(d\omega' | \psi', \theta)\right]\right\}, \end{aligned} \tag{1}$$

where (ω', k', θ') denotes the next-period state variables, where the probabilities associated with the next-period state are conditioned on the starting state (ω, k, θ) and choosing action (ψ', i). The action represents the choice of the next period's productivity through R&D spending ψ' and the decision to invest in capital i. $z(\psi', \omega)$ is the R&D spending function, and $c(i, k)$ is the cost of physical capital.

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 $r(\tilde{\psi}, \tilde{i}, \omega, k, \theta) = \pi(\omega, k, \theta) - c(\tilde{i}, k) - z(\tilde{\psi}, \omega)$ in state (ω, k, θ) when action $(\tilde{\psi}, \tilde{i})$ is selected.

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. An incumbent 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

[11] For simplicity of exposition, I consider that competitive pressures θ is a scalar variable in the theoretical part. In the empirical implementation, θ is a vector.

[12] See Ericson and Pakes (1995).

given by

$$K' = (1 - \delta)K + I,$$

where 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 periods, yet the outcome of the research process is 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 (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 advantage of the index is that we can study the properties of the policy functions of firm's dynamic problem when firm invests in R&D or has lumpy R&D spending.

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. I assume that the process of competitive pressure is completely static, i.e., that the current competitive pressure is a sufficient statistic for future values of competitive pressure and that firms do not form beliefs about future competitive pressure when making strategic choices. The assumption on how competitive pressure affects productivity relies on the X-inefficiency hypothesis, i.e., increased competition forces firms to improve their productivity, which induces reallocation and exit. The effect of competitive pressure on productivity can be linked to spillover effect. When θ measures the R&D investments of the competitors, the positive impact of competitive pressure on productivity indicates the presence of spillover effect.

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:

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

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

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

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 through ψ'. 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*** $\tilde{\tilde{i}}(\omega,k,\theta)=\tilde{i}(\tilde{\psi}(\omega,k,\theta),k,\theta)$ *is non-decreasing in* ω *and strictly non-decreasing in* ω *on the sets*

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

Proof: see appendix B.

The results from Theorem 1 suggest that the data with zero R&D investment can be used when controlling for competitive pressure. Muendler (2005) finds a similar result for physical investment using a particular dynamic framework with a quadratic adjustment cost including fixed adjustment cost and without R&D data. My theoretical results indicate that the investment 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 U.S. 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; Doraszelski and Jaumandreu, 2011; Aw et al., 2011). 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 (2011) 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), Aw et al. (2003), Maican and Orth (2009), 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. The empirical framework is general and accommodates to different production function forms. For simplicity, I assume a Cobb Douglas production technology:[13]

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

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 component ω_{jt} is observed by the firm when it chooses inputs or makes exit deci-

[13]However, the framework can be applied to a general production function.

sions, and it is not observed by researcher. It represents *unobserved productivity*, and the endogeneity problems are consolidated into it and not into η_{jt}. The unobservable η_{jt} is neither observed nor predictable by the firm before its input and exit decisions at time t. 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.

Various approaches can be used to solve the bias problem in estimation of value-added generating function: fixed effects, the instrumental variable approach (Blundell and Bond, 2000), and the control function approach used in the OP framework (Ackerberg et al., 2008). 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; Levinsohn and Melitz, 2006; Maican and Orth, 2009; Foster et al., 2008; De Loecker, 2011; De Loecker and Warzynski, 2011). In the empirical section, the paper controls for this bias in an indirect way by accounting for competitive pressure.

4.1 Identification

This subsection discusses the identification using a control approach function to proxy for productivity. Ackerberg et al. (2008) provide a detailed discussion about the assumptions needed to estimate a production function using the OP framework (control function approach).

Timing assumptions. Three types of assumptions are important in this approach. First, there is an assumption that refers to the points in time when labor and capital 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 the intermediate inputs choice, i.e., investment or intermediate inputs functions are strictly monotonic in the scalar unobservable (productivity) for a firm whose investment or intermediate inputs choice are strictly positive.[14]

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. The production shock η_{jt} is realized after those choices are made. Thus, labor l_{jt} is a variable input and responds to the productivity ω_{jt}, but it is uncorrelated with the error term η_{jt}. The physical investment decision is made in period $t-1$ and investment affects the production process in period t.[15] In other words, actual

[14]To recover productivity, OP uses strict monotonicity of the investment demand function and Levinsohn and Petrin (2003) use strict monotonicity of intermediate inputs choice demand.

[15]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 in-

capital k_{jt} is a fixed dynamic input and is not affected by current productivity shocks ξ_{jt}. The competitive pressure θ_{jt} comes from static exogenous process. The actual competitive pressure θ_{jt} affects the choice of inputs, while θ_{jt-1} influences the productivity process. This assumption is also used in the productivity literature that controls for unobserved prices (De Loecker, 2011; Maican and Orth, 2009). In addition, η_{jt} is uncorrelated with l_{jt}, k_{jt}, and θ_{jt}.

Productivity process. The present paper assumes that productivity ω_{jt} follows a first-order endogenous Markov process. The innovation in productivity 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 previous R&D investment and productivity affect the distribution of ω_{jt} only through ψ_{jt}.

Control approach function and labor assumptions. The timing assumptions on labor are important for the whole identification strategy. If the investment demand function is not invertible in productivity, then materials or labor demand can be used to back out productivity. Based on Cobb-Douglas assumption, Doraszelski and Jaumandreu (2011) propose a model that endogenize the productivity by considering the effect of the R&D spending on productivity. Maican and Orth (2009) suggest a two-step approach that endogenizes productivity, controls for imperfect competition, and allows for a general production function. Doraszelski and Jaumandreu (2011) one-step estimation model relies on the assumption that labor is a static variable, i.e., it has 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. If we recover productivity from intermediate inputs m_{jt} (perfect variable input), labor is a part of the intermediate inputs function because it is more likely that firms adjust labor before materials

$$m_{jt} = \tilde{m}_t(\omega_{jt}, k_{jt}, \theta_{jt}, l_{jt}). \tag{7}$$

Because labor is a variable input, it is more likely to be chosen before the investment, i.e., it is part of the investment function

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

vestment decision affects the proxy's implementation. Current investment is ordered before the productivity shock in period t is known.

This is also consistent with labor having possible dynamic implications (part of the state space) and avoids the collinearity problems discussed in Ackerberg et al. (2006) (ACF).[16] It is less probable that competitive pressure θ_{jt} impacts a firm's choice of l_{jt} but does not impact choice of investment i_{jt}. To estimate labor in the first-stage, i.e. labor is a static perfect variable input, 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 of investment or intermediate inputs to recover productivity. I assume 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. When investment or intermediate inputs data are not available (e.g., retail industry), productivity can be recovered from the labor demand function (Maican and Orth, 2009):

$$l_{jt} = \tilde{l}_t(\omega_{jt}, k_{jt}, \theta_{jt}). \tag{9}$$

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

$$\omega_{jt} = \tilde{\omega}_t(i_{jt}, k_{jt}, \theta_{jt}, l_{jt}), \tag{10}$$

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.[17] Rewriting the value-added generating function (6) yields:

$$y_{jt} = \phi_t(i_{jt}, k_{jt}, l_{jt}, \theta_{jt}) + \eta_{jt}, \tag{11}$$

where $\phi_t(i_{jt}, k_{jt}, l_{jt}, \theta_{jt}) \equiv \beta_0 + \beta_l l_{jt} + \beta_k k_{jt} + \tilde{\omega}_t(i_{jt}, k_{jt}, l_{jt}, \theta_{jt})$. 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 (11). 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.

[16] This assumption can be tested, however.

[17] If competitive pressure contains information at the firm level, another way to back out productivity is from the competitive pressure function and using the data with zero investment. Competitive pressure faced by firm j in the market is a function of its productivity, investment, and capital stock, i.e., $\theta_{jt} = \tilde{\theta}_{jt}(\omega_{jt}, k_{jt}, l_{jt}, i_{jt})$. If the competitive pressure is strictly monotonic in productivity, then productivity is given by $\omega_{jt} = \tilde{\theta}_t^{-1}(i_{jt}, k_{jt}, l_{jt}, \theta_{jt})$.

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 controlled Markov process, the value-added generating function can be written as

$$y_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + E[\omega_{jt}|\psi_{jt}, \theta_{jt-1}, \chi_{jt} = 1] + \xi_{jt} + \eta_{jt}, \tag{12}$$

where $E[\cdot]$ is the expected productivity conditional on survival and firms' information set at $t-1$.[18] $E[\cdot]$ is an unknown function and is estimated by a non-parametric approach. For any value of β_k and β_l, the conditional expectation $E[\omega_{jt}|\psi_{jt}, \theta_{jt-1}]$ can be computed. 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 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

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

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:

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

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}.[19] 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}: $\underline{\omega}_{jt} = f(\psi_{jt}, Pr_{jt}, \theta_{jt-1})$.

[18] The constant β_0 is included into the productivity.

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

In a model with R&D data, the survival probability is estimated from $Pr_{jt} = \tilde{pr}_{jt-1}(k_{jt}, k_{jt-1}, l_{jt-1}, z_{jt-1}, \theta_{jt}, \theta_{jt-1})$.

In Section 3, I demonstrate 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 is a function of k_{jt} and ω_{jt}, i.e., $z_{jt} = z_t(\omega_{jt}, k_{jt})$. If the R&D investment is strictly 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 $i_{jt}(\cdot)$ 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 investment function in k_{jt} does not hold. This paper shows the identification in a general framework that accounts for the competitive pressure faced by firms when making their investments.

Competitive advantage has key implications for innovation. Competition makes firms invest in reducing their costs, and hence improve their productivity. This aspect is ignored in both the Buettner (2004) and Doraszelski and Jaumandreu (2011) frameworks. The present paper fills this gap. It also puts forth additional evidence on the link between productivity and competition.

R&D investment data. First, I present the identification using observations with positive R&D investments. 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

$$\begin{aligned} y_{jt} = \;& \beta_k k_{jt} + \beta_l l_{jt} + g(\tilde{z}_{t-1}^{-1}(z_{jt-1}, \omega_{jt-1}, \theta_{jt-1}), f(\tilde{z}_{t-1}^{-1}(z_{jt-1}, \omega_{jt-1}, \theta_{jt-1}), \\ & Pr_{jt}, \theta_{jt-1}), \theta_{jt-1}) + \xi_{jt} + \eta_{jt} \\ = \;& \beta_k k_{jt} + \beta_l l_{jt} + \tilde{g}(\hat{\phi}_{jt-1} - \beta_k k_{jt-1} - \beta_l l_{jt-1}, z_{jt-1}, Pr_{jt}, \theta_{jt-1}) + \xi_{jt} + \eta_{jt}, \end{aligned} \tag{13}$$

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 (13). R&D investment and the error term are correlated if R&D investment is used in the construction of the value-added measure y_{jt}.

Second, when the firms reports no R&D investments the invertibility condition in $z(\cdot)$ does not hold. Therefore, we cannot back out ψ_{jt}, which might lead to identification problems for capital coefficient (Buettner, 2004). The threshold function combined with the fact that $\psi_t = \tilde{\psi}(\omega_{jt-1}, k_{jt-1}, \theta_{jt-1})$ yields the following equation for the second-stage:

$$y_{jt} = \beta_k k_{jt} + \beta_l l_{jt} + g(\tilde{\psi_t}(\omega_{jt-1}, k_{jt-1}, \theta_{jt-1}), \underline{\omega}_{jt}(k_{jt}, \theta_{jt}), \theta_{jt-1}) + \xi_{jt} + \eta_{jt}. \quad (14)$$

We need to proxy for k_{jt-1} in the ψ_{jt}. To get the identification of the coefficient of capital, I control whether firms invest in R&D. Using observed R&D investments ($\overline{z}_{jt}$) instead of k_{jt-1} solves the identification problems, i.e., we have

$$y_{jt} = \beta_k k_{jt} + \beta_l l_{jt} + \tilde{g}(\hat{\phi}_{jt-1} - \beta_k k_{jt-1} - \beta_l l_{jt-1}, \overline{z}_{jt-1}, Pr_{jt}, \theta_{jt-1}) + \xi_{jt} + \eta_{jt}. \quad (15)$$

This is also consistent with how index ψ_{jt} is defined, i.e., $\psi_{jt} = (\omega_{jt-1}, \overline{z}_{jt-1})$. Omitting the control for competitive pressure, this estimator is consistent with Doraszelski and Jaumandreu (2011) framework. This is my preferred model to estimate productivity in the empirical part of the paper. The advantage is that there is no need to do the inversion in the R&D spending function.

Estimation. The residuals $\xi_{jt}\hat{+}\eta_{jt}$ from equation (13) or (15) 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:

$$Q(\boldsymbol{\beta}^*) = \min_{\boldsymbol{\beta}^*} \sum_{h=1}^{\#\mathbf{w}} \left(\sum_j \sum_{t=T_{j_0}}^{T_{j_1}} \left(\xi_{jt}\hat{+}\eta_{jt}\right)(\boldsymbol{\beta}^*)\mathbf{w}_{jht} \right)^2, \quad (16)$$

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 $\mathbf{w}_{jt} = \{k_{jt}, k_{jt-1}, l_{jt-1}\}$.

The moments based on ξ_{jt} can be also used instead of of the sum of i.i.d shocks (ACF): $E[\xi_{jt}|k_{jt}] = 0$ and $E[\xi_{jt}|l_{jt-1}] = 0$. This might result in estimates with lower standard errors than those based on the sum of shocks. Based on one step estimation, the Doraszelski and Jaumandreu (2011) framework is more efficient than the two-step framework, but it comes with additional assumptions: static labor, Cobb-Douglas production function. Wooldridge (2009) also suggests a one-step formulation of the OP methodology, but it is difficult to apply it in my case because the state space is large which creates computational problems. Doraszelski and Jaumandreu (2011) discuss the relative merits of the parametric and non-parametric approaches (used here).

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.[20] 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 en-

[20]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).

dogenize 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 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., 2008; Doraszelski and Jaumandreu, 2011). 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.[21] 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.

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

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 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).[22] 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

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

R&D spending at the five-digits industry level, and foreign demand):

$$\Delta\hat{\omega}_{jt} = \mu + r^P(R\&D/ValueAdded)_{jt-1} + CompetitivePressure_{t-1}\boldsymbol{\beta} + \epsilon_{jt}, \quad (17)$$

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 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.[23] 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.[24] 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).[25]

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

[24]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.

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

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 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

$$\frac{s^{optimal}}{s^{actual}} = \hat{r}^P / (r - (1-\lambda) g_{output}). \tag{18}$$

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

$$\begin{aligned}\Delta\Omega_{t_0,t_1} = \; & \textstyle\sum_{j\in C_{t_0,t_1}} s_{jt_0}\Delta\omega_{jt_0,t_1} + \sum_{j\in C_{t_0,t_1}} \Delta s_{jt_0,t_1}(\omega_{jt_0} - \Omega_{t_0}) \\ & + \textstyle\sum_{j\in C_{t_0,t_1}} \Delta s_{jt_0,t_1}\Delta\omega_{jt_0,t_1} + \sum_{j\in E_{t_0,t_1}} s_{jt_1}(\omega_{jt_1} - \Omega_{t_0}) \\ & - \textstyle\sum_{j\in X_{mt_0,t_1}} s_{jt_0}(\omega_{jt_0} - \Omega_{t_0})\end{aligned} \tag{19}$$

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 (19) 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.[26] [27]

Table 9 shows the results of the productivity decomposition for the three industries 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.

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

[27] 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.

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).

References

ACKERBERG, D., L. BENKARD, S. BERRY, AND A. PAKES (2008): *Handbook of Econometrics,*vol. 6, chap. Econometric Tools for Analyzing Market Outcomes, pp. 4171–4276. Elsevier.

ACKERBERG, D., K. CAVES, AND G. FRASER (2006): "Structural Identification of Production Functions," Mimeo, UCLA.

AGHION, P., N. BLOOM, R. BLUNDELL, R. GRIFFITH, AND P. HOWITT (2005): "Competition and Innovation: An Inverted U Relationship," *Quarterly Journal of Economics*, 120(2), 701–728.

AGHION, P., R. BLUNDELL, R. GRIFFITH, P. HOWITT, AND S. PRANTL (2009): "The Effects of Entry on Incumbent Innovation and Productivity," *Review of Economics and Statistics*, 91(1), 20–32.

ATHEY, S. (2000): "Characterizing Properties of Stochastic Objective Functions," mimeo, MIT and NBER.

ATKESON, A., AND A. BURSTEIN (2007): "Innovation, Firm Dynamics, and International Trade," Discussion Paper 13326, NBER Working paper.

AW, B. Y., S. CHUNG, AND M. J. ROBERTS (2003): "Productivity, Output, And Failure: A Comparison Of Taiwanese And Korean Manufacturers," *Economic Journal*, 113(491), 485–510.

AW, B. Y., M. J. ROBERTS, AND D. Y. XU (2008): "R&D Investments, and the Evolution of Firm Productivity," *American Economic Review, Papers and Proceedings*, 98(2), 451–456.

——— (2011): "R&D Investment, Exporting, and Productivity Dynamics," *American Economic Review*, 101, 1312–1344.

BIESEBROECK, J. V. (2007): "Robustness of Productivity Estimates," *The Journal of Industrial Economics*, LV, 529–569.

BLOMSTRÖM, M., AND A. KOKKO (1994): chap. Home-country effects of Foreign-Direct Investment: Sweden', in Globerman, S. (ed.), Canadian-Based Multinationals, The Industry Canada Research Series, 4., Calgary: University of Calgary Press.

Blundell, R., and S. Bond (2000): "GMM Estimation with Persistent Panel Data: An Application to Production Functions," *Econometric Reviews*, 31(3), 549–569.

Blundell, R., R. Griffith, and J. Van Reenen (1999): "Market Share, Market Value, and Innovation in a Panel of British Manufacturing Firms," *Review of Economic Studies*, 66(3), 529–554.

Boone, J. (2000): "Competitive Pressure: The Effects on Investments in Product and Process Innovation," *RAND Journal of Economics*, 31(3), 549–569.

Buettner, T. (2004): "R&D and the Dynamics of Productivity," Mimeo, London School of Economics.

Costantini, J. A., and M. J. Melitz (2007): "The Dynamics of Firm-Level Adjustment to Trade Liberalization," Discussion paper, Mimeo, Princeton University.

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

De Loecker, J., and F. Warzynski (2011): "Markups and Firm-level Export Status," *American Economic Review (*forthcoming*)*.

Doraszelski, U., and J. Jaumandreu (2011): "R&D and Productivity: Estimating Production Functions when Productivity is Endogenous," (Mimeo, Harvard University).

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

EU (2009): "Monitoring Industrial Research: The 2009 EU Industrial R&D Investment Scoreboard," Discussion paper, European Commission.

Fors, G. (1997): "Utilization of R&D Results in the Home and Foreign Plants of Multinationals," *The Journal of Industrial Economics*, 45(3), 341–358.

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

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

Geroski, P. (1990): "Innovation, Technological Opportunity, and Market Structure," *Oxford Economic Papers*, 42(3), 586–602.

Greenstreet, D. (2005): "Exploiting Sequential Learning to Estimate Establishment Level Productivity Dynamics and Decision Rules," Mimeo, University of Michigan.

Griliches, Z. (1998): *R&D and Productivity*. The University of Chicago Press, Chicago.

Hall, B. H. (1995): "The Private and Social Returns to Research and Development: What Have We Learned?," mimeo, University of California at Berkley.

Hopenhayn, H. A. (1992): "Entry, Exit and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 60(5), 1127–1160.

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

Jones, C., and J. Williams (1998): "Measuring the Social Return to R&D," *The Quarterly Journal of Economics*, pp. 1119–1135.

Jovanovic, B. (1982): "Selection and the Evolution of Industry," *Econometrica*, 50(5), 649–670.

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

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

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

MacDonald, J. (1994): "Does Import Competition Force Efficient Production?," *Review of Economics and Statistics*, 76(4), 721–727.

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

Marschak, J., and W. H. Andrew (1944): "Random Simultaneous Equations and the Theory of Production," *Econometrica*, 12(3-4), 143–205.

Melitz, M. (2003): "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71(6), 1695–1725.

Melitz, M., and S. Polanec (2009): "Dynamic Olley-Pakes Decomposition with Entry and Exit," Mimeo, Princeton University.

Muendler, M. (2005): "Estimating Production Functions when Productivity Change is Endogenous," mimeo, University of California, San Diego and CESifo.

Nickell, S. J. (1996): "Competition and Corporate Performance," *Journal of Political Economy*, 104(4), 724–746.

Olley, S., and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, Vol. 64(No. 6), 1263–1297.

Pakes, A. (1994): chap. The Estimation of Dynamic Structural Models: Problems and Prospects Part II. Mixed Continuous-Discrete Control Models and Market Interactions, Laffont, J. J. and Sims, C. eds, Advances in Econometrics: Proceedings of the 6th World Congress of the Econometric Society, Chapter 5.

Porter, M. (1990): *The Competitive Advantage of Nations*. Macmillan Press.

Raith, M. (2003): "Competition, Risk, and Managerial Incentives," *American Economic Review*, 93, 1425–1436.

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

Schmidt, K. (1997): "Managerial Incentives and Product Market Competition," *Review of Economic Studies*, 64, 191–213.

Sivadasan, J. (2004): "Barriers to Entry and Productivity: Micro-Evidence from Indian Manufacturing Sector Reforms," mimeo, University of Chicago.

Smith, J. E., and K. J. McCardle (2002): "Structural Properties of Stochastic Dynamic Programs," *Operations Research*, 50(5), 796–809.

Svensson, R. (2008): "Growth through research and development," Discussion Paper 19, Vinnova.

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

——— (2004b): "Product Substitutability and Productivity Dispersion," *Review of Economics and Statistics*, 86(2), 534–550.

Vives, X. (2004): "Innovation and Competitive Pressure," mimeo, INSEAD and Centre for Economic Policy Research.

Wooldridge, J. M. (2009): "On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables," *Economics Letters*, 104(3), 112–114.

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

Estimation procedure	OLS (1)	OP (2)	LP-m (3)	ACF-i (4)	ACF-m (5)	Buettner (2004) procedure: B-1 (6)	B-2 (7)	B-3 (8)	Endogenous productivity: EP-i (9)	EP-all (10)
A. Machinery and equipment industry										
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	Percentage of growth from: Within firms (1)	Between firms (2)	Cross firms (3)	Entry (4)	Exit (5)	Net Entry (4) - (5)
A. Machinery and equipment industry								
1996-2000	Labor	11.27	2.80	-0.50	6.28	-0.18	-2.33	2.15
1996-2000	OP	7.10	-3.30	1.42	5.77	3.19	-0.01	3.20
1996-2000	ACF-i	6.60	-2.15	0.17	6.27	1.48	-0.83	2.31
1996-2000	EP-i	4.19	-2.84	-1.42	7.27	-1.18	-2.07	0.88
1996-2000	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	OP	8.87	-2.38	0.55	5.25	6.89	1.47	5.42
1996-2002	ACF-i	8.58	-1.19	-0.39	5.84	4.89	0.57	4.32
1996-2002	EP-i	7.00	-2.47	-2.26	7.23	1.16	-3.33	4.49
1996-2002	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	OP	57.61	23.40	-0.69	27.44	3.28	-4.17	7.46
1996-2000	ACF-i	57.41	22.51	0.69	27.43	2.82	-3.95	6.78
1996-2000	EP-i	59.18	23.61	1.09	27.78	2.65	-3.98	6.63
1996-2000	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	OP	21.41	-1.12	0.52	9.91	9.20	-2.92	12.12
1996-2002	ACF-i	17.68	-1.42	-0.99	10.17	8.38	-1.54	9.92
1996-2002	EP-i	16.79	-0.92	-1.59	10.60	7.56	-1.14	8.71
1996-2002	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	OP	47.26	27.38	-6.40	23.00	7.12	-3.84	3.28
1996-2000	ACF-i	51.68	28.29	2.90	24.44	-0.03	4.32	-4.35
1996-2000	EP-i	52.27	28.06	4.06	24.91	-0.47	4.29	-4.76
1996-2000	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	OP	25.42	13.02	-0.87	5.73	11.28	3.78	7.54
1996-2002	ACF-i	22.54	13.05	-1.73	7.43	0.16	-3.63	3.79
1996-2002	EP-i	21.81	12.78	-1.72	7.54	-1.35	-4.57	3.22
1996-2002	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 number of 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 investment 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

$$
\begin{aligned}
&V(\omega,k,\theta) = max\{\phi, \pi(\omega,k,\theta) - c(\tilde{i}(\omega,k,\theta),k) - z(\tilde{\psi}(\omega,k,\theta),\omega)\\
&+\beta \int \chi(\omega',k',\theta') \left[\pi(\omega',k',\theta') - c(\tilde{i}(\omega',k',\theta'),(1-\delta)k + \tilde{i}(\omega,k,\theta))\right.\\
&\left.-z(\tilde{\psi}(\omega',(1-\delta)k + \tilde{i}(\omega,k,\theta),\theta'),\omega',\theta')\right] P(d\omega'|\tilde{\psi}(\omega,k,\theta),\tilde{i}(\omega,k,\theta),\theta)\\
&+\beta\phi \int [1-\chi(\omega',k',\theta')] + \beta^2 \int \chi(\omega",k",\theta")V(\omega",k",\theta")\\
&P(d\omega"|\tilde{\psi}(\omega',k',\theta'),\tilde{i}(\omega',k',\theta'),\theta')P(d\omega'|\tilde{\psi}(\omega,k,\theta),\tilde{i}(\omega,k,\theta),\theta).
\end{aligned}
\tag{20}
$$

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

$$\begin{aligned}
&\int_{\omega'} P(\omega" > \tilde{\omega}|\psi", i(\omega', k', \theta'), \theta')P(d\omega'|\psi', i(\omega, k, \theta), \theta) = \\
&\int_{\omega'} P(\omega" > \tilde{\omega}|\psi" + \Delta(\psi", \omega', \theta', \epsilon), i(\omega', k', \theta') + \Delta(\psi", \omega', \theta', \epsilon), \theta')\cdot \\
&P(d\omega'|\psi' - \epsilon, i(\omega, k, \theta) - \epsilon, \theta),
\end{aligned} \tag{21}$$

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***

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

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

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

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' (e.g., spillover effect). 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

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

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

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

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

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

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), $i^*(\omega',k',\theta')=\tilde{i}(\omega',k',\theta'-\Gamma(\epsilon))$, $\psi^*=\tilde{\psi}(\omega,k+\epsilon,\theta)$, 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.■