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Abstract

This dissertation investigates firms' incentives to engage in research and development (R&D). In particular, I investigate empirically the link between R&D, innovation and productivity. This allows me to evaluate costs and benefits of R&D from a firm's perspective.

Firms invest in R&D in order to raise the probability of developing new innovations. These innovations can be new processes that improve product quality or reduce the production costs for the firm. Alternatively, innovations can encompass the introduction of new products or an extension of the range of final goods that the firm supplies. Firm innovations generate improvements in a firm's performance, specifically they increases firm's productivity and profits.

There is significant heterogeneity in R&D spending across firms and industries. Positive R&D expenditures are not necessarily observed for every firm at any point in time. So, the question is: Why do some firms invest in R&D and others do not? Also, what are the factors that affect firms' R&D investment decision? As with any other kind of investment the rate of return of R&D investment and the cost of R&D investment determine the firms' incentives to engage in R&D. In this thesis I develop an empirical model to estimate these returns and costs in order to understand the incentives firms face when they make their R&D choices. This in turn helps us understand the heterogeneity in firms' R&D efforts and productivity performances.

Most studies on the effects of R&D assume a direct link between R&D and productivity, for example Lichtenberg and Siegel (1991), Hall and Mairesse (1995), and Doraszelski and Jaumandreu (2011). These studies treat the process between R&D and productivity as a black box, since the outcome of the R&D process, the innovation it produces, is not directly observable. This thesis extends these studies by modeling the link between R&D and productivity explicitly. In particular, I let R&D affect the realization of product and process innovation. Once realized, these two types of innovation are then treated as determinants of productivity.

By breaking the direct link between R&D and productivity into two links, i.e. the link between R&D and innovation and the link between innovation and productivity, I am able to account for the different types of uncertainties associated with each link separately. The first link from R&D to innovation largely captures the uncertainty regarding whether R&D investment actually leads to an innovation. This uncertainty is sometimes referred to as R&D risk. The second link from innovation to productivity captures a very different type of uncertainty. Product innovations are typically associated with the risk that the market might reject these products. Process innovations on the other hand, are typically associated with the risk that the higher efficiency might not lead to lower costs or difficulties in their implementation. In contrast to previous models which assume a one-step direct link between R&D and productivity, my model distinguishes both links. Knowing more about the uncertainty inherent in each of the linkages will allow for a better understanding of the determinants of firms' R&D decisions. This is important when evaluating public policies, such as subsidies to R&D which can be undertaken to promote productivity growth.

My model is based on the structure of Aw, Roberts, and Xu (2011) (ARX). They endogenize firm productivity by allowing the firm's investments in R&D to shift the future path of productivity. In contrast to ARX, I model the link between R&D and productivity in more detail by assuming that R&D can lead to process and product innovation which in turn can lead to productivity gains. My model features a single agent which makes a dynamic choice of whether or not to invest in R&D: The current R&D choice leads to a change in future productivity which in turn affects the future R&D choice. In that sense productivity is endogenous and the R&D choice is dynamic in my model.

The second distinctive feature of this thesis is that I exploit a unique new data set,the Mannheim Innovation Panel (MIP), a rich data set that provides information on the innovation success of German firms. The MIP contributes to the Community Innovation Survey (CIS) which is available for many countries. Therefore, empirical studies using the CIS data for various European countries can be compared to studies using the German MIP data. The uniqueness of the data set lies, among other things, in the presence of variables identifying whether or not the firm introduces an innovation during a certain time period. Furthermore, it distinguishes between product and process innovation which makes it possible to separate the effects of different kinds of innovation on firms' productivity. The MIP has the additional advantage that it contains information on innovation expenditures. This means that in contrast to previous studies, I do not only account for R&D expenditures but also for costs pertaining to the link between innovation and productivity such as the marketing costs of new products.

To my knowledge, this thesis presents the first model structurally formulating the links from R&D to innovation and from innovation to productivity that is applied to the CIS data. The key structural parameters estimated are those that describe the process of endogenous productivity evolution, including the effect of an innovation of the firms future productivity, and the costs of conducting R&D for both experienced firms and firms beginning their R&D investments. The empirical model includes an equation describing the firms dynamic demand for R&D investment and it allows me to measure both the benefits and costs of R&D.

My empirical model produces the following results. First, product innovation as well as process innovation increase productivity. This result corresponds to economic intuition. Second, participation in R&D leads to a higher probability of a product or process innovation, implying that engaging in R&D leads to higher productivity. This result is in line with the empirical findings of the literature. Third, the firm's current R&D decision depends on productivity and on past R&D decisions. The idea here is that R&D investments and the productivity process are mutually dependent over time. Fourth, fixed costs of R&D are significantly smaller than sunk costs of R&D. This means that the firm R&D history is an important determinant of current R&D behavior: a firm that has chosen to invest in R&D previously has a lower cost of continuing than a firm that did not chose to invest in R&D previously. The latter firm has higher costs of entering the R&D process. The fifth finding concerns firm size: larger firms have higher R&D costs than smaller firms. This corresponds to the empirical pattern in my data that larger firms have a higher probability of investing in R&D than smaller firms.

I use the empirical estimates to investigate two policy applications. The first policy simulation investigates the questions whether an R&D subsidy leads to an increase in productivity. This question is at the heart of many discussions regarding the costs and benefits of public subsidies. I find that a subsidy which leads directly to lower R&D costs leads to more innovation and higher productivity. The second policy experiment concerns the effect of competition on R&D investment. There are two schools of thought: The first states that only monopolies have an incentive to innovate in order to deter potential entrants whereas the second school of thought states that competition fosters R&D because market participants want "to escape competition." My results shows that when firms face less elastic demand for their output, as would occur when there are fewer substitute products available, the gain in average productivity and the demand for R&D both decline.

This thesis contains the following chapters. Chapter 1 presents an overview of the literature on R&D, innovation and productivity. This chapter contains also a discussion of the results in the empirical literature that uses the CIS data. Chapter 2 contains the model while chapter 3 provides a detailed description of the data. Chapter 4 presents the estimation strategy. Chapter 5 discusses the empirical results and chapter 6 contains the results of the policy experiments. Chapter 7 concludes the thesis with a summary.

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Dedication

For my dear parents, siblings, and my beloved husband who fill my life with happiness.

In loving memory of my grandfather.

Chapter 1

Related literature

The literature on the returns to R&D has grown substantially in the last couples of decades.[1] The literature can be divided broadly into two strands: One strand investigates the returns to R&D at the firm-level and the other strand investigates the economy-wide returns to R&D. The latter line of research is very much concerned with R&D and knowledge spillovers since these generate the more significant social returns to R&D. In contrast, the literature on firm-level returns to R&D is concerned with identifying the various channels through which R&D affects firm performance. The effect of R&D on firm performance is usually assumed to take place via two channels: R&D leading to improved production processes including cost reductions and product quality improvements and R&D leading to a broader firm product supply. There are a number of specific goals of the empirical literature, including the estimation of the return to R&D, the estimation of the output elasticity of R&D and the effect of R&D on firm productivity. Different econometric approaches have been developed over time which are discussed below in turn.

[1] See Hall, Mairesse, and Mohnen (2009) for a detailed description.

1.1 Returns to R&D and output elasticity

A first line of research pioneered by Grilliches (1979) estimates a production function with a stock of knowledge as an input in conjunction with the usual inputs of labor, capital stock and materials. The stock of knowledge is built up from the past R&D expenditures of the firm. A number of researchers have extended this approach and applied it to various data sets covering different regions and periods. Doraszelski and Jaumandreu (2011) for example, avoid approximating the stock of knowledge capital from past R&D expenditures by assuming productivity is an unobservable that follows a Markov process which is shifted by the firms current R&D expenditures. They apply their model to an unbalanced panel of 1.800 Spanish manufacturing firms during the 1990s and find a significant role for R&D to shift the distribution of future firm productivity. Griliches and Mairesse (1984) exploit significant within-firm variation and make use of data set with 133 U.S. firms during the late 1960s/early 1970s. They estimate a rate of return for R&D of 35% using the production function approach. Rogers (2010) applies a value added production function with R&D as input to data on 719 U.K. firms during the 1990s and finds the R&D rate of return to be between 17% and 25%. Building on earlier work Crepon, Duguet, and Mairesse (1998) develop a novel approach, discussed in detail below, which they apply to a data set of 6.145 French firms during the 1990s. The results for the output elasticity of R&D range from 0.01 to 0.23 and the returns to R&D range from 35% to 108%.

In contrast to starting out with an assumption about a particular production function, a second line of research uses assumptions about cost minimizing or profit maximizing firm behavior. These assumptions in conjunction with duality theorems allows the researchers to derive and estimate a system of equations capturing, for example, product demand, factor demand or technological restrictions. This approach has been applied in different versions to various data sets. Using a translog cost function and factor demand equations, Bernstein (1988) estimates a return to R&D of 12% by applying his model to 680 Canadian manufacturing firms during the late 1970s. Bernstein and Nadiri (1990) on the other hand, employ a quadratic cost function and factor demand functions with adjustment costs. They apply their model to 35 U.S. firms during the 1960s estimating returns to R&D ranging from 9% to 20%.

1.2 R&D and productivity

The research described above focuses mainly on the estimation of average returns to R&D. An analysis of the effect of R&D on the future distribution of productivity, on the other hand, provides information about the firm-specific and industry-specific stochastic processes that govern the innovation process and help to better illuminate the incentives firms face when making their R&D investment decision.[2]

One line of research looks at the various sources of productivity with one of these sources being R&D. In a theoretical paper, Buettner (2004) extends the structural model of Olley and Pakes (1996) by allowing firm R&D investment to affect productivity.[3] He identifies difficulties in extending the Olley-Pakes methodology to the cases where productivity evolution is endogenous and shows that data on firm R&D investment is necessary to apply their production function methodology. Muendler (2004) is another example of a model where the firm productivity level

[2]Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazier (2006) focus on the estimation of productivity as an exogenous process which the firm cannot affect. They model productivity as an unobserved and serially correlated output shock instead of constructing a measure for productivity as above.

[3]Ackerberg, Benkard, Berry, and Pakes (2007) discuss the case when productivity is a controlled process.

is endogenously affected by the firm's R&D investment choice. My work is similar to Buettner (2004) and Doraszelski and Jaumandreu (2011) in that I model the distribution of productivity to be endogenously affected by firm R&D spending. More specifically, productivity is affected by innovation outcomes which in turn are influenced by R&D spending.

Another strand of the literature models the dynamic R&D choice. Klette and Kortum (2004) construct a theoretical model linking innovation and R&D spending. They allow innovation success to be an endogenous stochastic process which can be affected by R&D investment. This stochastic process leads to firm heterogeneity, which explains the persistence in firm's heterogenous R&D spending. Aw, Roberts, and Xu (2011) develop a dynamic structural model linking the export decision, productivity growth and R&D. They find that more productive firms are more likely to self-select into the export market and invest in R&D which in turn has a feedback effect on future productivity.

1.3 Innovation data

Beyond the discussions regarding the most appropriate econometric approach to deal with the typical problems of endogenous R&D choice, endogenous input levels and unobserved productivity, there is also a lively discussion among researchers on how to measure innovation. One line of research uses patent statistics as proxy for innovation. There are several problems with using patent statistics. For example, some firms decide not to patent a certain innovation because patents are made public and might give competitors an advantage. Furthermore, patents differ in their economic value and capture limited inventive information since not every invention is patentable. Patents also differ widely across industries with the pharmaceutical industry being a patent-heavy industry while service-related industries are traditionally very patent-light.[4]

The CIS data on R&D output that I use avoid these problems. In particular, the CIS data contain variables that report the magnitude of the innovation. Also, firms report process and product innovations even though these innovations are only imitations of other firms existing innovations. This captures more information on actual innovation than patent statistics.

Some work has been done studying the relationship between R&D, innovation and productivity using the CIS data. Most work using the CIS data uses the model by Crepon, Duguet, and Mairesse (1998) (hereafter CDM-model) which links R&D, innovation and productivity. In order to review the findings of those studies I describe the CDM-model first. The CDM-model summarizes the three linkages of the R&D process in four equations. The first link of the R&D process describes the determinants and motivation for firms to invest in R&D. The second link describes the output of the R&D process as a function of the research intensity and the third link connects the outcome of the research process to the firms' performance. More specifically,

1. R&D equations:

   The firm's decision to engage in research is based on decision criteria g^*, that is for example, the expected present value of the firm's profit from doing R&D. Firm engages in R&D if g^* exceeds a certain threshold. In case the firm is doing research, the research intensity is a function of the firm and industry characteristics. The authors define in their study k^* to be the log of research capital per employee. The decision criteria g^* and the research

[4] See Griliches and Pakes (1984) for a good discussion.

intensity k^* for firm i is given by:

$$
\begin{aligned}
g_i^* &= x_{gi} b_g + u_{gi} \\
k_i^* &= x_{ki} b_k + u_{ki},
\end{aligned}
$$

where x_g, x_k are vectors of factors that explain g^* and k^*, that contain for instance the number of workers, the market share of the firm. Additionally, these variables include indicators regarding the influence of demand or technology on innovation activities, and industry dummies in the estimation. The error terms $(u_{gi}, u_{ki}$ are joint normally distributed with mean μ and covariance matrix σ^2.

2. Patent equation:

   Conditioning on its research intensity k^* and other factors such as number of workers, the equivalent number of industry segments, that are summarized in x_n, the outcome of the innovation process n^*, i.e. the expected number of patent applications, is expressed as follows:

$$
\begin{aligned}
n_i^* &= E(n_i | k_i^*, x_{ni}, u_{ni}; \alpha_k, b_n) \\
&= g(k_i^*, x_{ni}, u_{ni}; \alpha_k, b_n)
\end{aligned}
$$

   The CDM-model makes a functional assumption for $g(\cdot)$ and estimates b_n and α_k, i.e. the impact of research on innovation output.

3. Productivity equation:

   The last link explains the firm's productivity level q using the output of the innovation process n^* and a set of exogenous factors x_q such as number of workers, capital stock per worker or the ratio of engineers to total number of workers.

$$\ln q_i = \alpha_q \ln n_i^* + x_{qi} + u_{qi}$$

The authors estimate these equations using French firm level innovation data. They find that the probability of engaging in R&D increases with firm size, market share, market diversification, market demand and technological opportunities. They find the same relationships (except for firm size) for research effort, i.e. R&D intensity. The authors find a strong effect of R&D intensity on innovation output, here the expected number of patents and a positive effect of innovation output on productivity measure, logarithm of value added per employee.

1.4 CIS data

There are many studies that have estimated this structure with some of them applying it to the CIS data. These studies vary significantly regarding the definition of the variables and the way they use the data. For instance, some studies use reported firm profitability rather than factor productivity as the measure of economic performance. Other studies use innovation expenditures instead of R&D spending as the input variable. Some studies distinguish between different types of innovation, i.e. they distinguish between the effect of an innovation being new to the market and the effect of an innovation being new to the firm. In addition to product and process innovation, other studies distinguish between organizational innovation and marketing innovation. Below I give an overview of the literature based on the different modifications to the CDM-model and the different regional coverage.[5]

Janz, Lööf, and Peters (2004) assess the relationship between innovation and productivity in Germany and Sweden covering the period 1998-2000 using the CDM structure. The study uses cross-sectional data and the authors modify the traditional CDM-model by estimating the innovation elasticity of productivity only for innovators and by allowing productivity to affect innovation output. Furthermore, since the authors are conducting a cross-country analysis they focus on a comparable sub-group of firms, namely knowledge-intensive firms. They find that the innovation output elasticity with respect to innovation expenditure per worker and the elasticity of labor productivity with respect to innovation output are significant and not very different across Germany and Sweden.

Griffith, Huergo, Mairesse, and Peters (2006) conduct an European cross-country study using the CDM-model and the CIS 3 data.[6] The authors focus on manufacturing firms in France, Germany, Spain and the U.K. covering the period 1998-2000. The CDM-model is adjusted to allow firms to engage in innovation activities without reporting them. Hence, the model is not only applied to innovators but to all firms. The authors find that public subsidies, firm size and the ability to protect innovations have a positive effect on a firm's decision to perform R&D. R&D effort affects the probability of being an innovator positively and a higher investment per employee makes it more likely to be a process innovator. Interestingly, suppliers are an important source of information for process innovation while consumers are an important source for product innovation. These results are very similar across countries. There are, however, cross-country differences regarding labor productivity. The authors find a positive relationship between process

[5] See Hall (2011) for an excellent survey.
[6] The CIS 3 data is the third wave covering the years 1998 - 2000

innovation and labor productivity only for France. Product innovation affects labor productivity in France, Spain and the U.K. In Germany, however, no effect of product or process innovation on productivity can be established. The drawback of this study as well as the study mentioned above is that because of the cross-sectional nature of the data only correlations can be found.

Lööf and Heshmati (2006) conduct a sensitivity analysis on the relationship between innovation and productivity. They build on the Swedish CIS data for the period 1996 to 1998 and supplement it with additional data such as data on product life cycle, value added and human capital. Their data set contains a broad sample of manufacturing firms, service firms and utility firms. The authors modify the CDM-model by estimating the key equations separately and using an instrumental variables approach. The sensitivity analysis is carried out by employing various least square estimations to the system of key equations, by estimating the different models on sector-specific samples, by applying different measures of firm performance and by distinguishing between different types of innovations. They find significant evidence for the effect of innovation output on productivity and productivity growth. Interestingly, they show that the simultaneity problem is severe here. The relationship between innovation and productivity is found to be very homogenous across the manufacturing and service sector. However, employment increases with innovation output only for the service sector. Additionally, the authors find differences between different types of innovations. In the case of innovations new to the firm, there is an effect of innovation output on value added per employee, sales per employee and sales margin. In contrast, the growth rate of productivity increases only with innovations new to the market.

Lööf, Heshmati, Asplund, and Nåås (2001) investigate whether the aggregate productivity differences between Norway, Sweden and Finland can be explained by firm-level innovation and productivity differences. The CIS data cover manufacturing firms in the respective countries for the period 1994 to 1996. The authors modify the CDM-model by applying two-step and three-step least squares estimation procedures in conjunction with tobit and probit models. The regression models are applied separately to the three respective countries. In Finland, innovation intensity decreases with firm size but increases with export intensity and previous research. No significant correlation is found between innovation output and the intensity of innovation effort, and between innovation output and productivity. In Norway, innovation investment increases significantly with firm size, export intensity and previous R&D investments. While there is no significant relationship between innovation input and innovation output, there is a strong feedback effect from productivity to innovation output. In contrast to Finland and Norway, there is no significant effect of firm size and export intensity on innovation intensity. However, innovation intensity increases with previous research. Innovation output increases with innovation intensity whereas there is no feedback from productivity to innovation. The innovation elasticity of productivity is found to be significantly higher for radical innovations compared to the set of all innovations. The main conclusion for the authors is that the high aggregate productivity growth rates for Sweden and Finland compared to Norway cannot be explained by firm-level innovation behavior. In fact, the innovation elasticity of productivity is higher in Norway than in its neighboring countries.

Mairesse and Robin (2010) investigate the effect of innovation on labor productivity. They make use of the French CIS data for the manufacturing and service-related sector during the periods 1998 to 2000 and 2002 to 2004. The authors estimate the key equations of the CDM-model simultaneously with maximum likelihood thus relaxing the assumption that the various stages of the CDM-model are independent. They find that for the manufacturing sector the probability of performing R&D is increasing in firm size. Also, firms that are better able to protect their innovations are more likely to perform R&D. R&D intensity has a significant effect on product innovation but has no effect on process innovation. The main result is that product innovation has a strong effect on labor productivity while process innovation has no effect. The authors find essentially the same results for the service-related sector. One difference is that manufacturing firms are more likely to invest in R&D in case they receive public funding and another difference is that the ability to protect innovations has no effect on process innovations. While the main result that product innovation is the primary source of labor productivity growth is robust to various modifications the complementary result that process innovation has no effect on labor productivity growth is less robust. This leads the authors to suspect that process and product innovation might have a joint effect on labor productivity.

Masso and Vahter (2008) investigate the link between productivity and innovation for developing and transition economies. The authors adapt the CDM-model by using total expenditures on innovations instead of R&D expenditures, and by estimating a bivariate probit model for process and product innovation. The CIS data cover the Estonian manufacturing sector for the period 1998 to 2000 and 2002 to 2004. These data were amended with financial data from the Estonian Business Register for the period 1995 to 2005. They found that the results differ across the two periods under review. During the period 1998 to 2000, product innovation had a significant impact while no effect could be found for process innovation. The opposite result was established for the period 2002 to 2004: process innovation had a significant impact on labor productivity and no effect could be established for product innovation. The authors offer a macroeconomic explanation. During the period 1998 to 2000, the severe Russian crisis forced Estonian firms to adjust their product portfolio in order to access other export markets while during the second period from 2002 to 2004 growing labor costs forced firms to accelerate process innovations. In line with the literature, the authors find that higher innovation expenditures increases the probabilities of firms creating a process or product innovation. Additionally, export-oriented firms were found to be more likely to engage in innovation activities and spend more resources on innovation.

Siedschlag, Zhang, and Cahill (2010) investigate the effect of international linkages on firms' innovation behavior and productivity. The authors employ Irish CIS data for manufacturing and service related firms during the period 2004 to 2008 and add further data on number of employees, turnover and ownership collected by the Irish Central Statistics Office. The econometric model is an augmented version of the CDM-model which accounts for the selection bias by using the sample of all firms, adds explanatory variables accounting for international linkages and allows for various types of innovations. Furthermore, the model accounts for the omitted variable bias and endogeneity issues, i.e. innovation investment, innovation output and productivity might be determined endogenously. The authors find that firms with international linkages, i.e. foreign affiliates and exporters, are more likely to invest in innovation and are hence, more successful in generating innovation output such as product, process or organizational innovations. Innovation output is shown to be the most relevant explanatory variable for labor productivity. Therefore, a firm with international linkages is more likely to be a high productivity firm. Innovation expenditures, however, has no significant effect on innovation output.

Klomp and Van Leeuwen (2001) study the linkages between the innovation process and economic performance. The authors use Dutch CIS data for the period 1994 to 1996. The econometric approach uses a four-equation-model describing innovation intensity, innovation output, sales growth and employment growth. These equations are estimated separately and jointly using OLS, the Heckman two-step estimator and full maximum likelihood. The estimation produces a number of interesting results. The authors find that innovation output is more directly affected by the input from customers, suppliers and competitors than by available technological opportunities. In line with the literature they find that permanent R&D has a significant effect on the probability of innovation. Furthermore, implementing process innovation enhances innovation output and contributes directly to sales performance, employment growth and productivity. Also, permanent R&D has no effect on innovation intensity when controlling for age and size. Younger firms allocate more resources to innovation than older and larger firms.

Another investigation of the linkages between innovation and the usage of these innovations in the production process using the CIS data has been conducted by Parisi, Schiantarelli, and Sembenelli (2006). The authors use firm-level data from the manufacturing sector in Italy. They found positive effects of innovation on firms' productivity in the sense that the innovations explain some variation in the firms' output which cannot be explained by variation in inputs. In particular, the effect of process innovation on productivity is larger than the effect of product innovation on productivity. Another important finding is that R&D expenditures help to increase the probability of introducing a product innovation. However, the authors cannot find a similar effect for process innovation. This effect is more likely in firms which have a higher level of capital investment and this likelihood is then amplified by R&D spending. The authors argue that new technologies which facilitate the introduction of process innovations are embodied in new capital goods and R&D expenditures help to absorb these new technologies.

Overall, the review of the existing empirical studies that use the CIS data indicates that the linkages hypothesized by the CDM model are often present in the R&D, innovation, and productivity data. In particular the linkage from R&D expenditures to process and product innovation could widely be confirmed as the probability of having innovation success increases with R&D spending. The studies found an effect of innovation output on labor productivity, even though the results are mixed on whether this effect is from product or process innovation. Based on these results, in my model I also allow for the linkages that CDM hypothesized. That is, I model firm's investment decision as a dynamic discrete choice and allow for it to affect the outcome of the innovation process. The final link is to allow firm productivity level to be affected the by its innovation output.

Chapter 2

Model

In this chapter I develop a dynamic model of a firm's choice to invest in R&D. The R&D investment leads to an increase in knowledge which in turn increases the firms productivity and profits in the future. This future gain is balanced by a current period cost of the R&D investment.

The firm decides every period about its knowledge production input, i.e. its R&D activity. The gain in knowledge leads to an increase in productivity and results in higher profits for the firm.

I consider a single agent model in discrete time with an infinite horizon. At the beginning of each period, the firm observes the realization of its productivity level ω_{it}, its capital stock K_{it} and its age a_{it}. Based on this information the firm makes static input choices in order to maximize the period profit. Afterwards the firm observes the realization of factors on which it bases its dynamic R&D investment choice. R&D investment in turn will affect the firm's future productivity level.

I use different variations of the model to investigate the linkages between the firm's investment choice, innovation production and its effect on firm performance. Therefore, I model the firm's R&D choice as discrete allow for several sources of uncertainty affecting firm productivity and factors that affect the firm's investment choice. I start with a model where the firm makes a discrete R&D choice, i.e. whether or not to engage in R&D. This choice is subject to a cost realization shock that the firm can observe before making its decision. The R&D choice then will affect the productivity level in the next period. I allow for the productivity evolution process to be random and subject to a transitory shock that the firm cannot control. A modification of this setting is to have the firm produce innovations using R&D as input. Then, the productivity level is a function of the innovation output which is random. [1] In the next subsections I describe the models being used in the empirical analysis.

2.1 Product market competition - firms' static choice

The firm's short-run marginal cost function is given by

$$c_{it} = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_w w_t - \psi_{it}, \tag{2.1}$$

where c_{it} is the log of marginal cost, a_{it} denotes firm age, k_{it} is the log of firm capital stock, and w_t is a vector of log input prices which every firm faces in period t. The firm-specific production efficiency ψ_{it} is only observed by the firm but not by the econometrician. The variable ψ_{it} might capture the differences in firm-specific technology or managerial ability. Thus, there are two sources of cost heterogeneity; the capital stock and the unobserved production efficiency.

[1] An alternative modification is to consider a model in which the firm can choose the level of its R&D spending continuously. This modification is discussed in the appendix.

I assume each firm is producing one product. The demand for firm i's product is given by

$$\begin{aligned} q_{it} &= Q_t\big(\frac{p_{it}}{P_{It}}\big)^{\eta}\exp(\phi_{it}) \\ &= \Phi_t\big(p_{it}\big)^{\eta}\exp(\phi_{it}), \end{aligned} \tag{2.2}$$

where Q_t is the aggregate sector output in period t. P_{It} denotes the sector price index and p_{it} is the firm's output price in the market. The firm-specific demand shifter ϕ_{it} reflects product desirability or quality and is known by the firm. The elasticity of demand η is assumed to be constant.

The firm maximizes its short-run profit by setting the price for its output p_{it}. Assuming monopolistic competition in the market the firm's profit maximization problem is given by

$$\max_{p_{it}} p_{it} \underbrace{\Phi_t\big(p_{it}\big)^{\eta}\exp(\phi_{it})}_{q_{it}} - C_{it} \underbrace{\Phi_t\big(p_{it}\big)^{\eta}\exp(\phi_{it})}_{q_{it}}.$$

The first-order condition yields

$$p_{it} = \frac{\eta}{1+\eta} C_{it} \tag{2.3}$$

for all i and t.[2] The firm charges a constant markup $\frac{\eta}{1+\eta}$. Given the firm's optimal price, the revenue function of firm i can be written as

$$\begin{aligned} r_{it} &= (1+\eta)\ln\big(\frac{\eta}{1+\eta}\big) \\ &\quad +(1+\eta)\big[\beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_w w_t - \omega_{it}\big] + \ln\,\Phi_t, \end{aligned} \tag{2.4}$$

[2]If not otherwise specified capital letters represent levels and small letters represent logs.

where r_{it} is the firm's log revenue. Revenue productivity is denoted by ω_{it} and is defined to be $\omega_{it} = \psi_{it} - \frac{1}{1+\eta}\phi_{it}$. Equation (2.4) implies that for a given capital stock and age, heterogeneity in the firm's revenue is captured by production efficiency ψ and demand heterogeneity ϕ. From hereon for convenience I will refer to the revenue productivity ω_{it} as productivity. Even though the firm's performance is driven by heterogeneity on the production and on the demand side I do not have the data needed to separate these two shocks. I have data on aggregate sales of the firm but no price and quantity data for each firm product.[3] Furthermore, the goal is not to quantify each supply and demand shock effect. Rather, the goal is to quantify the effect a knowledge gain has on firm performance. The effect of gaining knowledge on firm performance serves as motivation for firms to engage in R&D. Therefore, I will only consider the effect of a knowledge gain on revenue productivity ω which is the combination of the two shocks mentioned above.

Using revenue, firm profit can be expressed as

$$\pi_{it} = -\frac{1}{\eta} R_{it}. \tag{2.5}$$

2.2 Productivity process and firms' dynamic R&D choice

2.2.1 Discrete R&D choice with direct effect on productivity

At the beginning of period t the firm observes its past productivity level ω_{it-1}, its age a_{it-1}, its capital stock K_{it-1} and its past R&D choice rd_{it-1}. In particular, I

[3] Firm's aggregate sales are deflated by an industry output price index.

assume that the productivity level ω_{it} follows a first-order Markov process which is endogenous to the firm's past R&D choice and subject to a random shock:

$$\begin{aligned}
\omega_{it} &= E[\omega_{it}|J_{it-1}] + \epsilon_{it} \\
&= E[\omega_{it}|\omega_{it-1}, rd_{it-1}] + \epsilon_{it} \\
&= g(\omega_{it-1}, rd_{it-1}) + \epsilon_{it} \\
&= \alpha_0 + \alpha_1\omega_{it-1} + \alpha_2\omega_{it-1}^2 + \alpha_3\omega_{it-1}^3 \\
&+ \alpha_4 rd_{it-1} + \epsilon_{it},
\end{aligned} \tag{2.6}$$

where J_{it-1} denotes the information that is available to firm i at time $t-1$. The dummy variable rd_{it-1} indicates firm i's past R&D choice.[4] It takes the value 1 if firm i has engaged in R&D in $t-1$ and 0 otherwise. The firm can actively affect the evolution of its productivity level by investing in R&D. However, there are stochastic factors influencing productivity. These are captured by the random shock ϵ_{it} which is assumed to be i.i.d. with zero mean and variance σ_ϵ^2. Allowing for the productivity process to be stochastic takes the uncertain nature of knowledge production into account. Firms engaging in R&D with the same productivity level today do not necessarily have the same productivity level tomorrow. However, firms with R&D activity today are more likely to have higher productivity tomorrow. Current productivity depending on its previous level allows for high productivity firms to be more likely to have high productivity in the next period. It also captures the idea that knowledge gain can be accumulated over time. This is in part controlled by the firm via its R&D choice and in part stochastic via the random shock ϵ.

[4] I only make explicit assumptions about the evolution of ω and not about ψ and ϕ since the analysis is focused on the revenue productivity which consists of ψ and ϕ. In particular, I do not need ψ and ϕ to be independent.

Firm age in t is given by $a_{it} = a_{it-1} + 1$ and the capital stock in t is given by $K_{it} = (1-\delta)K_{it-1} + I_{it-1}$ follows a deterministic exogenous process. The reason is that I do not model firm investment choice in physical capital stock explicitly but assume instead that the investment level I_{it} is exogenous and known to the firm in period $t-1$.

In each period the firm chooses its R&D investment to maximize the expected present value

$$\begin{aligned} V(x_{it}) &= \int_{\gamma} \Pi(\omega_{it}, a_{it}, k_{it}, \Phi_t) + \max_{rd_{it}\in\{0,1\}} \Big\{ \beta E_t V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it} = 1) \\ &- rd_{it-1}\gamma^f_{it} - (1 - rd_{it-1})\gamma^s_{it}; \\ &\quad \beta E_t V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it} = 0)\Big\} dG^{\gamma}, \end{aligned} \tag{2.7}$$

where $x_{it} = (\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it-1})$ is the state vector for firm i in year t, γ denotes the cost vector $(\gamma^f_{it}, \gamma^s_{it})$ and β is the discount factor. $V(\cdot)$ is the firm's expected value before observing its fixed and sunk costs for engaging in R&D. More specifically, firm i's expected future value conditional on R&D choices is:

$$E_t V(x'|\omega, a, k, \Phi, rd) = \int_{\Phi'} \int_{\omega'} V(x') dF(\omega'|\omega, rd) dG(\Phi'|\Phi) \tag{2.8}$$

As described above, there is a trade-off for investing in R&D. The firm benefits by improving its productivity, which increases its future returns. However, there are certain costs to be incurred such as creating an R&D department, investing in research facilities or maintaining physical plant. This can also include the recruitment and training of staff and establishing links with universities and other research agencies. The firms previous R&D activities will determine whether it has to incur a fixed or a sunk cost in the current period. A fixed cost γ^f_{it} is incurred, if in the previous period the firm performed R&D. If it did not perform R&D activities then a sunk cost of γ_{it}^s is incurred. These costs are random draws from a known distribution and are realized before the firm makes its investment decision. The random nature of these costs highlights the fact that R&D is a long-term investment. The time to complete a R&D project is indefinite and the possible outcome may not be as originally planned. Hence, there are many uncertainties in the cost of R&D investment. Finally, the firm decides to invest in R&D if the marginal benefit in doing so exceeds the marginal costs.

I define the marginal benefit of conducting R&D as

$$E_t V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it} = 1) - E_t V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it} = 0). \tag{2.9}$$

Thus, the magnitude of the benefit depends on the impact of R&D on future productivity which is captured by α_4 in equation (2.6). All in all, firms in this model differ with respect to their level of productivity, capital stock and their R&D history. Firm productivity is endogenous in R&D investment. In other words, firms can improve their productivity by investing in costly R&D. The optimal firm R&D choice depends on the impact of R&D on future productivity and on the costs of R&D.

2.2.2 Discrete R&D investment choice and random realization of innovation output

The previous subsection introduced a model that examines the effect of R&D on productivity. In this section I introduce a variation of this model that explains in detail how R&D affects productivity. More specifically, I model the channel through which R&D affects productivity explicitly.

The structure of product market competition is the same as before. The difference is that the firm decides about its investment in R&D which in turn can result in innovation. This innovation can be a new product broadening the range of firm supply, creating additional demand and hence, resulting in an increase in firm revenue. It can also be a new process improving the production process helping to reduce production costs.

The time line is as follows. At the beginning of period t the firm observes its productivity level, age and capital stock $(\omega_{it}, a_{it}, k_{it})$. Based on this information it makes its static choices to maximize the period profit $\pi_{it} = \pi(\omega_{it}, a_{it}, k_{it,\Phi_t})$. Then, the firm receives a cost draw which determines its cost for R&D. Firm makes its R&D investment decision. At the end of that period, the firm observes the output realization of its innovation production meaning it observes whether or not it had created a new product or a new process. This innovation output together with a random shock which gets realized at the beginning of next period determine firm productivity level ω_{it+1}.

Thus, performing R&D creates new products and processes. These in turn affect productivity. Let the productivity ω_{it} follows a first-order Markov process which is endogenous subject to the firm's past innovation success and a random shock:

$$\begin{aligned}
\omega_{it} &= E[\omega_{it}|J_{it-1}] + \epsilon_{it} \\
&= E[\omega_{it}|\omega_{it-1}, z_{it-1}, d_{it-1}] + \varepsilon_{it} \\
&= g(\omega_{it-1}, d_{it-1}, z_{it-1}) + \epsilon_{it} \\
&= \alpha_0 + \alpha_1\omega_{it-1} + \alpha_2\omega_{it-1}^2 + \alpha_3\omega_{it-1}^3
\end{aligned}$$

$$+ \quad \alpha_4 z_{it-1} + \alpha_5 d_{it-1} + \alpha_6 z_{it-1} d_{it-1} + \varepsilon_{it}, \tag{2.10}$$

where z_{it-1} and d_{it-1} are dummy variables indicating firm i's past process and product innovation status.They take value 1 if firm i has a process or product innovation in the previous period and 0 otherwise. I also assume the stochastic factor in the productivity process ε_{it} to be i.i.d. with zero mean and variance σ_ε^2. Note that I do not model the decision of the firm to engage in product or process innovation explicitly, but allow for the realization of both types of innovation to be affected by the R&D choice. That is the firm cannot choose which innovation to have. There are two main motivations for this. The first is the uncertainty in the research process and second I do not have information about the firm's decision in their innovation spending. That means only the total amount of spending is available but not the allocation of these expenditures.

The variable ω is a combination of a cost side and a demand side shock. A process innovation can be associated with the cost side shock ψ since it helps to reduce production costs. On the other hand, a process innovation can also be intended to improve the quality of the existing product and therefore can be associated with the demand side shock ϕ as well. A product innovation widens the spectrum of final goods supplied by the firm which shifts the firm-specific demand. This can be captured by a change in ϕ. The introduction of a new product might increase the production cost and is hence captured by a change in ψ. As pointed out in the previous subsection I do not have the data needed to separate these two shocks and hence nothing can be said about how process and product innovations affect ψ and ϕ explicitly. Therefore, I will only consider the effect of product and process innovation on the revenue productivity ω.

Hence, the transition probability of ω can be written as

$$\mathcal{P}_\omega = \big\{Pr(\omega'|\omega, rd)|\omega \in \mathbb{R}, rd \in \{0,1\}\big\}.$$

The transition is determined by the probability of introducing a product innovation or process innovation $\mathcal{P}_{(d,z)} = \big\{Pr(d,z|rd)|rd \in \{0,1\}\big\}$ and the probability of the random shock $\mathcal{P}_\varepsilon = \big\{Pr(\varepsilon)|\varepsilon \in \mathbb{R}\big\}$. For the former, I assume that the firm can have a positive innovation outcome even if it does not choose to engage in R&D. However, engaging in R&D increases the probability of an innovation success. As noted above, in particular I assume $\varepsilon \sim N(0,\sigma_\varepsilon)$. The non-zero probability of experiencing innovations without an investment in the current period captures the idea that R&D is a long term project with innovations breaking through possibly because of previous investments in knowledge several periods a in the past.

The firm's value function given its productivity, age, capital stock, history and macroeconomic factors is

$$\begin{aligned} V(x_{it}) = {} & \pi(\omega_{it}, a_{it}, k_{it}, \Phi_t) \\ & + \int_\gamma \max_{rd\in\{0,1\}} \Big\{ \beta E_t\big[V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it}=1)\big] \\ & -\gamma^f_{it} rd_{it-1} - \gamma^s_{it}(1-rd_{it-1}); \\ & \beta E_t\big[V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it}=0)\big]\Big\} dG^\gamma, \end{aligned} \tag{2.11}$$

where

$$E_t\big[V(x'|\omega, a, k, \Phi, rd)\big] = \sum_{(d,z)} \Big[\int_{\Phi'}\int_{\omega'} V(x')dF(\omega'|\omega, d, z)dG(\Phi'|\Phi)\Big] P(d,z|rd) \tag{2.12}$$

with $(d, z) \in \{(1,0),(0,1),(1,1),(0,0)\}$. The expectation is taken over the transitory shock in the productivity evolution process, the realization of innovation success and future macroeconomic states.

The main difference between this framework and the one described in the previous subsection is the uncertainty in the innovation production process. In the previous case, an investment in R&D creates a positive effect on productivity to the amount of α_4, see equation (2.6). However, in the current framework, an investment in R&D merely increases the probability of innovation success $d = 1$, $z = 1$. In case the firm succeeds, the effect on productivity is a combination of $\alpha_4, \alpha_5, \alpha_6$ as defined in equation (4.1).

To sum up, in this model firms are heterogenous in their productivity level and capital stock. In each period firm maximizes its period profit and makes a decision about whether or not to undertake R&D. The investment in R&D affects future productivity, which determines its future profit. The effect of R&D on productivity can be modeled as a direct effect (model 1), or indirectly through the effect of innovation success on productivity (model 2). The decision to invest in R&D is also determined by a realized cost shock, which depends on firm's past investment status.

Chapter 3

Data

The purpose of the model and estimation strategy developed in the previous sections is to analyze the role of R&D in the productivity process of German firms.

The data are provided by the Mannheim Innovation Panel (MIP) survey collected on behalf of the German Federal Ministry of Education and Research. The survey is conducted every year for firms in the manufacturing, mining, energy, water, construction and service sector. The latter includes retail, wholesale, and telecommunication firms as well as consultancies. Samples are drawn from the Creditreform database according to the stratifying variables firm size, region, and industry.[1] These are representative for firms with German headquaters and at least 5 employees.

The survey started in 1993 for the manufacturing, mining, energy, water and construction sectors and added the service sector in 1995. The survey adheres to the Oslo Manual which provides guidelines for the definition, the classification and measurement of innovation.[2] The MIP contributes to the Community Innovation

[1]The Creditreform database is the largest credit-rating agency in Germany with the most comprehensive database of German firms.

[2]See OECD (1992), OECD (1996), OECD (2005)

Surveys (CIS).[3]

Every year the same set of firms are asked to participate in the survey and to complete the questionnaire sent to them via mail. The sample is updated every two years to account for exiting firms, newly founded firms and firms that developed to satisfy the selection criteria of the sample. Additionally a non-response analysis is performed via phone to check and correct for non-response bias. The participation in the survey is voluntary and the average response rate is about 25%.

For the empirical analysis I focus on the manufacturing sector for a number of reasons. First, it has overall the best coverage in the survey. Second, the questionnaires sent to firms differ from sector to sector which reduces the consistency of the panel. For instance, for the service sector there is no information on capital stock and material expenditures before 2001. Therefore, I favor the manufacturing sector for its data consistency, interpretation and the length of the panel.

The manufacturing sector includes the NACE classes $15 - 37$. The sample is restricted to observations with complete answers on the variables of interest. Furthermore, I exclude observations with extremely high capital−labor ratios, revenue−labor ratios and material cost −labor ratios to guarantee a minimum level of comparability.[4] Also, observations with very low levels of material cost, capital stock and revenue are excluded from the analysis.[5]

Table A.1 on page 63 shows the industry classifications, the number of firms and the number of observations in each industry.[6] For instance, the sample on

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[3]1993 (CIS 1 - covering data from 1990-1992), 1997 (CIS 2: 1994-1996), 2001 (CIS 3: 1998 - 2000), 2005 (CIS 4: 2002 - 2004), 2007 (CIS2006: 2004 - 2006) and 2009 (CIS2008: 2006-2008)

[4]Capital−labor ratios of more than 100 Million Deutsch−Mark (DM), revenue−labor ratios and material cost −labor ratios exceeding 10 Million DM.

[5]Observations with capital stock less than 5000 DM or revenue less than 10000 DM are excluded.

[6]The sector definition is based on the classification system NACE Rev.1 as published by Eurostat (1992) using 2-digit levels.

the textile industry contains information on 408 firms with 1036 observations. Every firm is in the panel, on average, for 2 to 3 years. Due to cost reasons, starting in 1998 the full questionnaires were only sent out every other year to all firms in the full-sample. However, information on variables of interest are asked retrospectively for the previous year to ensure the annual coverage. In odd years only short questionnaires with core questions are sent to a subset of firms. Those are for instance firms that have answered at least once in previous years. Therefore, the number of firms in odd years in the panel is significantly lower than in even years. The response rate is low overall because participating in the survey is not mandatory for the firms, so that each year there are approximately 2000 firms answering the questionnaires. Usable observations vary across years. Table A.2 shows the number of firms in each year in the sample. On average in odd years there are 643 firms in the panel and in even years there are 1350 firms. Due to the low numbers of observations in each industry I perform the empirical analysis for the manufacturing sector as a whole and do not consider each industry separately.

For the estimation I use data on firm revenue, capital stock, innovation expenditures, product and process innovation, age of the firms as well as firm spending on labor and materials. Table A.3 shows the summary statistics for these variables.[7] The standard deviations for all variables are very large implying high cross-sectional variation, which is due to the fact that significantly different industries are grouped together into one sector. All distributions are skewed to the right indicating that larger firms account for a big share of revenue and expenditures.

Firm revenue consists of domestic and export sales. For 1999 and 2000 the panel does not contain information on the firms' capital stock. To make use of the data

[7]All spending is in million Euro. Age variable is in years.

before 1999 as well I account for these missing values by linear interpolation.[8]The age of the firm is not asked in the survey but this information can be taken from the Credit Reform Database and added to the panel.

The special feature of this data set is that it provides measures of both innovation input and innovation output. Innovation input is measured by firm expenditure on innovation. This measure not only contains R&D spending, which is understood as firm investment in its knowledge stock, but it also includes spending on acquiring external knowledge, licences, material, labor and investment expenditures made explicitly for the purpose of producing an innovation. For simplicity I refer to these expenses throughout the paper as the spending on R&D.

Innovation output captures the introduction of a new product or a new process.[9] An innovation only has to be new to the firm. That means an innovation by a firm can be an imitation from another firm. In the survey, the firms are asked whether they introduced new or significantly improved products or services during the years $(t-2)$ to t. The answer to this question creates the variable *product innovation*. For the process innovation variable *process innovation*, the firms are asked whether they introduced new or significantly improved internal processes during the years $(t-2)$ to t. Consequently, a product innovation in the panel describes a product or a service whose basic characteristics are either new or significantly improved. The variables *product innovation* and *process innovation* are dummy variables in the panel. They take the value 1 if the firm introduced an innovation and 0 otherwise.

Analogously, a process innovation is a new or significantly improved production technology or a new method of supplying and delivering a product. The main

[8]The estimates of the model are robust with respect to different imputation algorithm.

[9]The panel also includes organizational innovation and marketing innovation being innovation output. However, these innovations have been introduced in the survey in 2005. Using them would restrict the panel to a length of 3 years.

purpose of a process innovation is to reduce production costs or to improve the quality of a product. For instance, the use of lasers to increase the quality of products in metal processing or the introduction of automation concepts are process innovations.

When I observe a firm reporting both product and process innovations, it is impossible to tell whether the two innovations are related. In one case the firm could introduce a new product and at the same time introduce a new process to reduce production cost. Alternatively, the process innovation may be necessary to produce a new product. In this case, the process innovation is not an innovation in the traditional sense. In my sample, $70\% - 80\%$ of all firms introducing process innovations also introduce a new product. From looking at the data I cannot distinguish these two cases. To account for this in the empirical analysis, I consider only the processes that have a cost reduction effect as process innovations. Across the sample, 64% of all process innovations have a cost reduction effect.

Table A.4 reports the share of innovators and the share of successful product and process innovations reported by the firms in each industry. I define an innovator as a firm that engages in innovation activities implying it has non-zero innovation expenditures. The fourth and fifth columns report the share of firms that introduced a new product or new process.

In the manufacturing sector the majority of firms are innovators. Only one third of all firms do not have any innovations and about 60% of all firms report to have introduced a new or improved product. Cost reducing process innovations are less common in the sample as only 31% of all firms reported a new or improved process. Firms in the chemical, machinery, electrical engineering, MPO instruments, and vehicle industry engage in innovation more actively then firms belonging to other industries. They report more successful innovations for products and processes.

For instance 77% of all firms in MPO instruments introduced a product innovation and 33% introduced a cost reduction process.

The data also show that the participation in R&D as well as the success rate in introducing innovations increases with firm size. Table A.5 reports the innovation shares by number of employees and capital stock. It is worth noting that as we move to larger firm size categories the share of innovation success rises more quickly than their share of being an innovator, firms that have between 51 and 200 employees have approximately 31% more participation in R&D than firms with less than 50 employees, however their product innovation rate is 34% higher and process innovation rate is 65% higher. This pattern is true for all firm size categories. These statistics show a positive relationship between firm size and firm innovation behavior and innovation success. Furthermore, older firms tend to innovate more and have more innovation success than younger firms. For instance, successful innovators are on average 4 to 5 years older than non-innovators.

Table A.6 reports the transition rates for firms' R&D activities between periods. The overall pattern is that larger firms are more likely to perform R&D, because they are more likely to enter and less likely to exit R&D.

Chapter 4

Estimation of the model

4.1 Static empirical model

In this section I describe the estimation strategy for the model of firm productivity. To this end, I focus on model 2 where productivity evolution is affected by product and process innovations:

$$\begin{aligned} \omega_{it} &= \alpha_0 + \alpha_1 \omega_{it-1} + \alpha_2 \omega_{it-1}^2 + \alpha_3 \omega_{it-1}^3 \\ &+ \alpha_4 z_{it-1} + \alpha_5 d_{it-1} + \alpha_6 z_{it-1} d_{it-1} + \varepsilon_{it}. \end{aligned} \tag{4.1}$$

The key parameters to be estimated are the cost elasticity of age β_a, the cost elasticity of capital β_k, the parameters of the productivity process $\alpha_0, ..., \alpha_6$ and η the elasticity of demand. The revenue function in equation (2.4) cannot be estimated consistently because the productivity level ω_{it} is not observed. The capital stock K_{it} is a function of last period's capital stock K_{it-1} and investment level I_{it-1}. Furthermore, the firm making its investment choice depending on ω leads to the current capital stock K_{it} being correlated with ω_{it} through ω_{it-1} which causes the OLS estimates to be biased and inconsistent. Following the proxy variable approach pioneered by Olley and Pakes (1996), which makes use of the firm's observable choice variables to control for unobserved productivity, I use the firm's observed expenditure on materials as suggested by Levinsohn and Petrin (2003) as a proxy for its unobserved ω_{it}. The idea is that the firm observes its own productivity level before choosing the level of expenditure on materials. Thus, the econometrician can infer information about the productivity from observing the level of investment in R&D. The firm's choice of variable inputs is a function of the firm's state variable a_{it}, k_{it} and ω_{it}. Focusing on the choice of material spending the firm's demand for its intermediate input can be written as follows:

$$m_{it} = f_t(a_{it}, k_{it}, \omega_{it}),$$

where f_t is strictly monotone in ω_{it} for a given (k_{it}, a_{it}). Inverting the function f_t yields

$$\omega_{it} = f_t^{-1}(a_{it}, k_{it}, m_{it}). \tag{4.2}$$

Other input choices by the firm depend also on its productivity level and could serve as proxy variables, too. In particular, firm's labor choice depends on ω_{it}. While ω is written here as a function of material spending age and capital stock only, (4.2) will be generalized in the empirical section to allow for other variable inputs such as labor or investment.[1] From the revenue function in equation (2.4),

[1]On the other hand, similar to Ackerberg, Caves, and Frazier (2006), one can think of labor as a non-perfect variable input, i.e. l_{it} is chosen at (t-b) after observing ω_{it-b} which is sometime between periods $(t-1)$ and t. That means $l_{it} = g_t(a_{it}, k_{it}, \omega_{it-b})$. Productivity evolves between $(t-b)$ and t meaning $\omega_{it} = E[\omega_{it}|\omega_{it-b}] + \upsilon_{it}$. In period t the firm chooses m_{it} as a function of $\omega_{it}, a_{it}, k_{it}$ and l_{it}. Assuming m is strictly monotone in ω for a given a, k and l, one can invert the m function to back out ω depending on a,k,l and m.

we have

$$\begin{aligned} r_{it} &= \underbrace{(1+\eta)\big(\beta_0 + \ln \frac{\eta}{1+\eta}\big)}_{\equiv \gamma_0} \\ &\quad + \underbrace{(1+\eta)\beta_w w_t + \ln\, \Phi_t}_{\sum \gamma_t D_t} \\ &\quad + (1+\eta)\big[\beta_a a_{it} + \beta_k k_{it} - \underbrace{f_t^{-1}(a_{it}, k_{it}, m_{it})}_{\omega_{it}}\big] \\ &\quad + u_{it}, \end{aligned} \tag{4.3}$$

where u_{it} captures transitory shocks and measurement errors in firm revenue. The time dummy D_t contains the market level factor prices and aggregate demand. Estimating equation (4.3) by approximating f_t^{-1} with a polynomial in its arguments leads to the polynomial being collinear with the constant, a_{it} and k_{it}. Therefore, it would be impossible to identify the constant and the coefficients β_a and β_k. To avoid this problem, the term $(1+\eta)\big[\beta_a a_{it} + \beta_k k_{it} - f^{-1}(a_{it}, k_{it}, m_{it})]$ can be written as a function $h(a_{it}, k_{it}, m_{it})$ which captures the effect of age, capital and productivity on revenue, so

$$\begin{aligned} r_{it} &= \gamma_0 + \sum \gamma_t D_t \\ &\quad + \underbrace{(1+\eta)\big(\beta_a a_{it} + \beta_k k_{it} - f_t^{-1}(a_{it}, k_{it}, m_{it})\big)}_{h(a_{it}, k_{it}, m_{it})} \\ &\quad + u_{it}. \end{aligned} \tag{4.4}$$

I approximate the function $h(a_{it}, k_{it}, m_{it})$ by specifying it as a cubic function in its arguments, so

$$h(k_{it}, a_{it}, m_{it}) = \lambda_1 k_{it} + \lambda_2 k_{it}^2 + \lambda_3 k_{it}^3$$

$$+\lambda_4 a_{it} + \lambda_5 a_{it}^2 + \lambda_6 a_{it}^3$$
$$+\lambda_7 m_{it} + \lambda_8 m_{it}^2 + \lambda_9 m_{it}^3$$
$$+\lambda_{10} k_{it} m_{it} + \lambda_{11} k_{it}^2 m_{it} + \lambda_{12} k_{it} m_{it}^2$$
$$+\lambda_{13} k_{it} a_{it} + \lambda_{14} k_{it}^2 a_{it} + \lambda_{15} k_{it} a_{it}^2$$
$$+\lambda_{16} a_{it} m_{it} + \lambda_{17} a_{it}^2 m_{it} + \lambda_{18} a_{it} m_{it}^2.$$

Thus, in the first stage I estimate

$$r_{it} = \gamma_0 + \sum_{t=0}^{T} \gamma_t D_t + h(a_{it}, k_{it}, m_{it}) + u_{it} \tag{4.5}$$

and obtain the fitted value $\widehat{h_{it}}$. The second stage of the estimation model recovers the structural parameters η, β_a, β_k and the parameters of the productivity process $\alpha_0, ..., \alpha_6$. Since $\widehat{h_{it}}$ is the estimate for $(1+\eta)\big(\beta_a a_{it} + \beta_k k_{it} - \omega_{it}\big)$, one can write

$$\omega_{it} = -\frac{1}{1+\eta} h_{it} + \beta_a a_{it} + \beta_k k_{it}. \tag{4.6}$$

Substituting the productivity expression (4.6) into equation (4.1) and solving for $\widehat{h_{it}}$ yields

$$\begin{aligned}
\widehat{h_{it}} \quad = \quad & \beta_a^* a_{it} + \beta_k^* k_{it} - \alpha_0^* + \alpha_1(\widehat{h_{it-1}} - \beta_k^* k_{it-1} - \beta_a^* a_{it-1}) \\
& -\alpha_2^*(\widehat{h_{it-1}} - \beta_k^* k_{it-1} - \beta_a^* a_{it-1})^2 \\
& +\alpha_3^*(\widehat{h_{it-1}} - \beta_k^* k_{it-1} - \beta_a^* a_{it-1})^3 \\
& -\alpha_4^* z_{it-1} - \alpha_5^* d_{it-1} - \alpha_6^* d_{it-1} z_{it-1} - e_{it}^*
\end{aligned} \tag{4.7}$$

where $\alpha_2^* = \alpha_2 \frac{1}{(1+\eta)}$ and $\alpha_3^* = \alpha_3 \frac{1}{(1+\eta)^2}$. All other parameters with an asterisk denote the original parameter times $(1+\eta)$. Estimating this equation using NLLS yields the estimates $\hat{\alpha_0}, .., \hat{\alpha_6}, \hat{\beta}_a, \hat{\beta}_k$. The estimates $\hat{\beta}_a, \hat{\beta}_k$ are helpful in the next step for computing the productivity level. The other estimates $\hat{\alpha_0}, .., \hat{\alpha_6}$ show how the productivity is affected by its past values and by innovations.

The parameters $\widehat{h_{it}}, \hat{\beta}_a, \hat{\beta}_k$ and $\hat{\eta}$ are needed in order to recover ω_{it} . The first and second stage of the estimation yielded $\widehat{h_{it}}, \hat{\beta}_a$ and $\hat{\beta}_k$. In order to estimate the demand elasticity η, I follow ARX and estimate

$$TVC_{it} = q_{it}C_{it} = (1 + \frac{1}{\eta})R_{it} + \varepsilon_{it}, \tag{4.8}$$

where TVC_{it} is the total variable cost of firm i in period t. TVC is the sum of the firm's expenditures on materials, labor and workers training. ARX argue that since the firm's marginal cost is constant for all output levels, the total variable cost is the product of output and marginal cost. Equation (4.8) comes from equating marginal cost and marginal revenue.

The estimation strategy can be summarized as follows. In the first stage, I estimate equation (4.5) and construct $\widehat{h_{it}}$. In the second stage, I estimate β_a, β_k and the parameters of the productivity process $\alpha_0, ..., \alpha_6$ using equation (4.7). In addition, I estimate the elasticity of demand η, which together with $\widehat{h_{it}}$, $\hat{\beta}_a$ and $\hat{\beta}_k$ is necessary in order to construct the firm productivity level in equation (4.6).

4.2 Dynamic empirical model

As described in the previous section, the firm is subject to a random cost shock if R&D is performed in the current period. The costs depend on the firm's R&D history meaning that the cost draws come from different distributions. The goal in the dynamic estimation is to estimate the parameters of the firm's fixed and sunk cost distribution. To this end, I employ a maximum likelihood estimator.

For the estimation I utilize information on firm age, capital stock, R&D activity and productivity. Firm productivity has been constructed in the previous stage using the estimates on β_a, β_k and on α_i where $i = 0, .., 6$. As defined in the previous section the triple $(a_{it}, k_{it}, \omega_{it})$ characterizes firm i in time t and uniquely determines firm i's period profit. The firm's R&D investment decision is a trade off between the marginal benefit of the investment activity and its costs. Hence, the observed investment behavior provides information about the cost distribution.

The implementation of the dynamic estimation is outlined next. In order to solve for the firm's optimal investment choice as described in equation (2.11), the value function $V(\cdot)$ has to be known. It will be approximated by using value function iterations. $V(.)$ is computed at discrete grids for (a, k, ω).[2] The iteration rule is as follows. The start is an initial guess about the values. Then, there is a rule specifying how to update the values. The final ingredient is a convergence criteria which will terminate the iteration. More specifically,

1. it is assumed that the firm receives its period profit forever. So, let the initial guess be the discounted infinite sum of period profit

$$V^0(\underbrace{\omega, a, k, \Phi, rd_{-1}}_{x}) = \frac{\pi(\omega, a, k)}{1-\beta}.$$

2. The expected value function is given by equation (2.12). Hence, I compute

$$E\big[V^0(x'|\omega, a, k, \Phi, rd)\big] = \sum_{(d,z)} \left[\int_{\omega'} V^0(x')dF(\omega'|\omega, d, z)\right] Pr\big((d, z)|rd_{-1}\big),$$

[2] In the implementation I compute $V(.)$ at the average age level, 250 productivity and 8 capital grid points.

where $F(\omega'|\omega, d, z)$ is computed based on the functional form assumption in (4.1) using the estimates for α_i, $i = 0, .., 6$ from the first stage. The probability $Pr\big((d, z)|rd\big)$ is estimated from the data.

3. The value function is updated as follows:

$$\begin{aligned} V^1(x) &= \pi(\omega, a, k) + \Big[EV^0(rd = 1) - \gamma^f rd_{-1} - \gamma^s(1 - rd_{-1})\Big] \cdot \\ & \quad Pr\big(\gamma^f rd_{-1} - \gamma^s(1 - rd_{-1}) \leqq EV^0(rd = 1) - EV^0(rd = 0)\big) \\ & \quad + \Big[EV^0(rd = 0)\Big] \cdot \\ & \quad Pr\big(\gamma^f rd_{-1} - \gamma^s(1 - rd_{-1}) > EV^0(rd = 1) - EV^0(rd = 0)\big), \end{aligned}$$

where the first term is the period profit, and the second and third term are the expected payoffs from the optimal R&D choice.

4. The iteration will be carried out until $|V^{n+1} - V^n| < \epsilon$, for the tolerance level ϵ being a small number.

The main piece in the dynamic estimation is the likelihood function for the observed pattern in R&D investment behavior. Recall equation (2.11). The net payoff for investing in R&D is

$$\beta E_t\big[V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it} = 1)\big] - \gamma^f_{it} rd_{it-1} - \gamma^s_{it}(1 - rd_{it-1}),$$

whereas the payoff for not investing is

$$\beta E_t\big[V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it} = 0)\big].$$

On the one hand, if the firm invests in R&D it increases its chances for a successful innovation, which will boost its productivity level. Firms with higher productivity have higher period profit and hence a higher future return. On the other hand, the firm has to incur a cost for the investment. Therefore, the firm will invest in R&D if the cost does not exceed the benefit. The probability of firm i's R&D choice in time t conditional on its state variables is:

$$\begin{aligned} Pr\big(rd_{it} = 1|\omega_{it}, a_{it}, k_{it}, \Phi_t\big) \quad = \quad & Pr\Bigg(rd_{it-1}\gamma_{it}^f + (1 - rd_{it-1})\gamma_{it}^s \\ & \leq \beta\big\{E_t\big[V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it} = 1)\big] \\ & -E_t\big[V(x_{it+1}|\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it} = 0)\big]\big\}\Bigg). \end{aligned}$$

The costs of R&D investment are assumed to be distributed exponentially with mean γ^F and γ^S, respectively depending on the history of the firm:

$$\gamma_{it} \sim \begin{cases} G(\frac{1}{\gamma^F}), & \text{if } rd_{it-1} = 1 \\ G(\frac{1}{\gamma^S}), & \text{if } rd_{it-1} = 0 \end{cases}$$

This is a reasonable assumption since firms that perform R&D continuously might have different cost structures than firms that have to start the investment activity from scratch. It might be costly to set up and equip the research department or hire employees for the research unit. In the implementation, I also allow for firm's to have different cost distributions depending on their size. Large firms might have synergy effects from other inputs, e.g. assets and technology, they can co-use. Alternatively, they might have better access to credit, which is needed to set up or maintain a research unit.

Assuming the cost γ_{it} and other state variables $x_{it} = (\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it-1})$ are independent, and that the costs are i.i.d across all periods and all firms, the likelihood function can be expressed as

$$L(\gamma|rd, x) = \prod_{i}^{N} \prod_{t}^{T_i} P(rd_{it}|(\omega_{it}, a_{it}, k_{it}, \Phi_t, rd_{it-1}); \gamma), \tag{4.9}$$

where $\gamma = (\gamma^F \gamma^S)$. The vectors rd and x contain every firm's R&D choice, and state variables for each period respectively. The total number of firms is denoted by N and T_i is the number of observations for firm i.

The assumptions above are needed to develop the maximum likelihood estimator. They require that knowledge regarding the state variables might not provide the firms with additional knowledge about the future cost probability. This is reasonable since due to the random nature of R&D projects, knowing about firm productivity or age does not provide the firm with extra knowledge about the cost it will have to incur for a particular project. Furthermore, I also require the cost draws to be i.i.d, which means that knowing the cost of firm i in time t does not provide the firm with knowledge regarding its cost or other firm's cost at any other point in time. I recognize that this assumption is strong and can be violated if two firms are in the same industry or have the same location, or share the same contractors. Any shock to the costs that comes from those sources can affect several firms over several periods of time. It would also be violated if there was a source of persistence in cost over time for individual firms, after controlling for size and past R&D activities.

To sum up, I assume that the cost of R&D follows an exponential distribution with mean γ. The mean varies according to the firm's past R&D activities and their sizes. I use the maximum likelihood estimator to estimate the mean values of the cost distributions.

Chapter 5

Empirical results

5.1 Static results

The estimation of the static model proceeds in two steps. Step 1 is the estimation of the revenue equation and the construction of $\hat{h}$ which is a measure of revenue accounting for industry and time effects. In other words, the revenue equation captures the combined effect of age, capital and productivity on revenue. Step 2 uses $\hat{h}$ to estimate the structural parameters describing the evolution of productivity. First, I report the results for the revenue equation of step 1 using different input choices by the firm to back out the productivity level. Then, I report the estimates for the structural parameters for the two different innovation and productivity models, one depends just on R&D expenditure and the second depends on the realizes innovation outcome.

The main goal in the static stage of the estimation is to back out the productivity level using input choices by the firm. Under certain assumptions it is possible to use investment choices, labor or material spending to infer the level of productivity. Tables A.7, A.8 and A.9 report the results for the revenue equation (4.5).

Only positive values for observable inputs such as the firm's investment, labor and material choices can be used to back out the firm productivity level. I control for industry affiliation and time effects by adding industry and year dummies to the estimation equation. Overall, the estimates establish a significant correlation between revenue, firm age, capital stock, investment decisions, labor and material choices.

When using material spending to proxy for productivity, a significant and positive correlation between revenue, a, k and m can be established for this specification. The results are reported in table A.7. The relationship is non-linear and revenue is increasing in all arguments. The marginal effect of each of the variables on revenue is positive with the effect of age being the smallest and the effect of material on revenue being the largest. A positive marginal effect of age on revenue reflects that older firm have more ways to generate revenue. A positive marginal effect of material spending is natural since more material should translate into more output and hence, more revenue. For instance, for the median firm the marginal effect of age is .07 and the marginal effect of material is .76. The marginal effect of age and capital decreases in material spending and vice versa, which reflects the fact that these factors are not perfect substitutes in raising revenue.

The overall pattern and magnitude of coefficients are remarkably similar in all specifications. The additional specifications in tables A.8 and A.9 substitute labor l and investment i for material expenditures m as proxies for productivity while keeping capital and age as state variables. The result is that the k and a coefficients remain significant and have the same sign. Substituting other variables in place of materials lowers the goodness of fit of the equation and does not substantially alter the mean fitted value of h. The mean values for $\hat{h}$ are around 2.2. The variation in the $\hat{h}$ is also the highest when using material to proxy for ω. Overall, the first stage regressions indicate an important role for the proxy variables m, l and i. They capture well the effect of productivity, capital and age on revenue.

Given the data available I prefer the use of material spending to back out ω over physical capital investment and labor. There are several reasons for this. First, depending on the choice of input used to back out productivity, only observations with positive spending on investment, labor or materials are in the sample due to the invertibility of the input demand functions. Sharing the concerns raised by Levinsohn and Petrin (2003) that first, the estimation sample is reduced when using investment as proxy variable and that second, investment might not respond to the entire transmitted shock and hence, could fail to solve the simultaneity problem, I forgo the use of investment data as productivity proxy.

Second, the number of workers reported is the sum of full and part-time workers. Although the survey asked for the number of part time workers which can be used to construct an approximation for the number of full time equivalent workers, this information is not always provided by the firms leading to a more reduced sample. Hence, if using the number of workers to back out productivity it is important to recognize that the number of workers is overstated and might bias the effect of labor on revenue. Furthermore, it is likely that there are adjustment costs to labor such as firing and hiring costs which make labor a state variable rather than a variable input. Similar to investment, being a state variable raises doubts concerning labor's responsiveness to the transmitted shock and might violate the monotonicity condition.

Furthermore, as mentioned above I obtain the best fit when using material expenses to approximate for ω. The variation in the fitted value for h is the highest under this specification.

The estimates for the demand elasticity and the parameters of the productivity evolution process are reported in table A.10 for model 1 and table A.11 for model 2 with process and product innovation affecting productivity. The estimate of $(\widehat{1+1/\eta})$ is .7529. This implies a demand elasticity $\widehat{\eta}$ of -4.0479. More intense product market competition implied by higher demand elasticity gives firms more incentives to make cost reducing investments as pointed out by Bloom, Dorgan, Dowdy, Van Reenen, and Rippin (2005). The reason is as follows: a higher demand elasticity reduces firm profit as shown in equation (2.5). Recall that log firm revenue is given by

$$\begin{aligned} r_{it} &= (1+\eta)\ln\left(\frac{\eta}{1+\eta}\right) \\ &\quad +(1+\eta)\underbrace{\left[\beta_0+\beta_a a_{it}+\beta_k k_{it}+\beta_w w_t-\psi_{it}\right]}_{c_{it}}+\phi_{it} \\ &\quad +\ln\,\Phi_t. \end{aligned} \tag{5.1}$$

Thus, for any given η firm revenue is decreasing in its marginal cost, with the decrease being bigger with higher $|\eta|$. Hence, a change in the demand elasticity will alter the firm incentive to invest in R&D because it alters the link between R&D and profit.

First, I focus on the results for model 1 in table A.10 where productivity evolution is a function of past R&D activity. Column (3) displays the estimation results for the specification using a, k and m to proxy for ω. The cost elasticity of capital is $\hat{\beta}_k = -0.0765$. Negative values of β_k imply firms with a higher capital stock have lower production costs because they use less variable inputs. The estimate implies a 1% increase in capital stock increases revenue by about $= 0.0332\%$. The age coefficient is positive $\hat{\beta}_a = 0.0189$ implying that older firms have higher marginal cost and therefore lower revenue and profit. This result can be driven by the fact that older firms have older plants that operate inefficiently, are less reliable, and require high maintenance costs. Another reason, as discussed in Bloom *et al* (2005) is that older firms tend to have higher costs as they might suffer from bad management practices or older technologies. They also might have more difficulties adjusting to new conditions than younger firms. Even though they still learn and adopt new practices they do so at a slower rate than younger firms.

The parameters α_1, α_2 and α_3 measure the effect of past productivity on the current productivity level. Evidently, past productivity is persistent. A non-linear relationship between current and lagged productivity can be established because α_2 and α_3 are significant.

The effect of firms investing in R&D is estimated by $\hat{\alpha_4}$. The effect is statistically significant and positive. An $\alpha_4 = 0.0136$ implies that on average firms engaging in R&D have 1.36% higher productivity and 4.14% higher revenue.

The results of model 2 which assume that R&D investment creates product and process innovation which in turn boost productivity are reported in table A.11. The estimates indicates non-linear persistence in ω, as α_1, α_2 and α_3 are all statistically significant. The coefficient estimates, including β_a and β_k are almost identical to the estimates of model 1.

The marginal effect of a firm adopting a new process or developing a new product on the current level of productivity is captured by the coefficients α_4 and α_5. In particular, α_4 is estimated to be 0.0136. This implies that firms that introduce a new process have a 1.36% higher productivity and 3.66% higher revenue. The marginal effect of a product innovation is $\hat{\alpha_5} = 0.0133$ implying a gain in productivity of 1.33% compared to not having any kind of innovation. These estimates are virtually identical. This finding is somewhat surprising as often innovation studies have noted a stronger effect of process innovation. The reason for this might be that process innovations have mainly cost reducing effect whereas product innovation can widen the range of products supplied by the firm, can replace old products, is a substitute for existing product or quality improvement. All these versions have different or even offsetting effects on sales, such that they can cause the overall magnitude of the effect to be smaller.

Firms with both innovations have the highest productivity with 1.82% higher productivity than firms without innovations. Since the interaction term between the two types of innovation α_6 is negative and its magnitude is smaller than α_4 and α_5, the effect of introducing a new product given the firms already have a process innovations is less than the effect without the new process and vice versa. It is worth noting that the effect of R&D on productivity is lower than the joint effect of the two types of innovations. This is expected because uncertainty in the knowledge production process is incorporated in the coefficient of rd when modeling the linkage between R&D and productivity as one link. Not every firm engaging in R&D succeeds in introducing innovations and certainly not both types of innovations. The estimates for model 2 reflect the situation when the investment in R&D successfully created innovations.

The estimate of the cost elasticity of capital $\hat{\beta}_k$ is negative and significant in model 2 as well. The effect of age is also positive indicating higher costs for older firms.

Overall the estimates for the productivity evolution process show that lagged productivity plays an important role in explaining current productivity. Again, a non-linear relationship between ω_{it} and ω_{it-1} can be found for both models. The cost elasticities β_k and β_a have the same sign and similar magnitude in all model specifications, with higher cost for older firms and lower cost for firms with higher capital stock. There is a significant effect for R&D on future productivity, which is present if the linkage is modeled as the direct effect of R&D (model 1) or incorporates information on actual innovations (model 2).

5.2 Dynamic results

The descriptive results in table A.6 indicate that firms with a larger capital stock are more likely to perform R&D. In my model this reflects the effect of capital on the value of the firm for any given R&D choice and also the relationship between capital and the cost of R&D. To capture this latter effect I allow firms with a larger capital stock to draw their fixed and sunk R&D costs from different cost distributions.

Small firms draw their fixed costs from an exponential distribution with mean γ_s^F and their sunk costs from an exponential distribution with mean γ_s^S. Similarly, large firms draw their fixed costs from an exponential distribution with mean γ_l^F and their sunk costs from an exponential distribution with mean γ_l^S. I estimate the parameters $(\gamma_s^F, \gamma_l^F, \gamma_s^S, \gamma_l^S)$ by maximizing the likelihood function in equation (4.9).

Table A.12 reports for each industry the average probability of introducing an innovation depending on the firm's R&D history. This probability is estimated from the data using the observed rates of innovation for d and z given the firm conducts R&D and does not conduct R&D. The third and fourth columns show the probability of realizing a product and a process innovation given the firm does not engage in R&D. Columns (5) and (6) report these probability for firms conducting R&D. The overall pattern shows a substantial higher probability of receiving an innovation if the firm engage in R&D. It is worth noting that firms can still realize innovations even if their R&D spending is zero.

Table A.13 reports the estimated means of the distribution of sunk (γ^S) and fixed costs (γ^F) for various specifications. The first two rows report the results for the R&D model, i.e. the model specification where R&D has a direct effect on productivity. The last two rows report the results for the modification that incorporates the realization of innovation, i.e. R&D increases the probability of an innovation which in turn has an effect on productivity. For each of the two specifications I report the case where all firms draw their sunk and fixed costs from a single distribution (row one and three) and the case where large firms and small firms draw their costs from different distributions (row two and four).

A number of general patterns across all specifications stand out. First, fixed costs are smaller than sunk costs in all specifications. This means that firms that were previously engaged in R&D have to incur a smaller cost if they want to continue their R&D activities while firms that did not have any previous R&D activities will have to pay a higher amount to start their R&D activities.

The first specification estimates an average sunk cost for doing R&D of EUR 63mln, more than four times higher than the fixed cost of EUR 14mln. The ratio between fixed and sunk cost are approximately the same when distinguishing between small and large firms. The same is true when incorporating innovation in the R&D process even though the magnitude of the costs are lower. The difference between fixed and sunk cost is crucial in explaining the pattern of R&D choice in the data. If fixed cost is low relative to sunk cost, continuing to do R&D is more attractive in the sense of helping firms avoid possible sunk cost in the next period. Even facing negative shocks that lower the expected return of R&D would have less of an effect on the firm quitting R&D. High sunk cost prevent firms from starting to do R&D which corresponds to the high persistence for non-R&D firms seen in table A.6. On the other hand, reducing the gap between fixed and sunk cost would hence imply more switching between starting and quitting R&D.

In particular, the variation in R&D choice across firms cannot be fully explained by the variation in profit levels, since not all high profit firms engage in R&D and vice versa. There are a number of firms that have a high level of profit even though they did not perform R&D previously and choose not to engage in R&D currently. On the contrary, there is only a small number of firms with high profits that had previously performed R&D without choosing to perform R&D currently. This can be explained by a high cost of entry to R&D (high sunk costs) and low R&D continuation costs (fixed costs).

A second pattern that stands out is that firms with a larger capital stock have higher fixed costs and higher sunk costs than firms with a smaller capital stock. This is driven by the fact that we observe a positive correlation in the data between capital stock and productivity level. When deciding about R&D participation, firms compare the difference between the firm value when performing R&D and the firm value when not performing R&D (which is the benefit of performing R&D), with the costs of performing R&D. If the benefit of performing R&D is larger than the fixed or sunk costs, the firm is engaging in R&D. Since firm's profit is exponential in productivity level, high productivity firms have higher benefit from performing R&D. Given the probability of performing R&D we see in the data, higher benefit from R&D implies a high mean of the sunk and fixed costs distribution.

This means that large sunk and fixed costs for large firms compared to small firms are a result of a high net benefit of performing R&D. This however, is not surprising. The data show a significant persistence in performing R&D. Once a firm is engaged in R&D it typically continues to perform R&D. On the contrary, firms that have not performed R&D previously, are not very likely to engage in

R&D in the future. This persistence is much more pronounced for large firms than for small firms.

The third pattern that stands out is that the sunk and fixed costs are larger when R&D is assumed to affect productivity directly in contrast to the case when R&D affects the probability of innovation which in turn affects productivity. The reason is as follows: Incorporating product and process innovation and allowing both to affect productivity stochastically leads to an overall smaller effect of R&D on productivity than the direct effect of R&D on productivity. This means that the net benefit of performing R&D is higher for the model with the direct effect of R&D. When matching the empirical shares of firms performing R&D, this leads to higher sunk and fixed costs for this model. In other words, if the net benefit of performing R&D increases and the shares of firms performing R&D, i.e. the probability of a firm engaging in R&D, do not change, the variable that adjusts in the model is the cost of performing R&D, needs to increase.

Tables A.14 and A.15 show the firms' expected present values, costs and benefits, the probability of conducting R&D for different productivity levels and the R&D history for the two models. The mean productivity levels are nearly identical in the two models, 0.75 in model 1 and 0.74 in model 2. All values are average over capital stock k. For illustration I choose I will focus on the results of model 1 in table A.14 since the general pattern for both models is similar.

Columns (2) and (3) report the expected present value $V(\omega, rd_{-1})$ for the previous R&D performer and non-performer. The difference can be found in column (4). The value for $V(\cdot)$ is increasing in ω reflecting the fact that high productivity firms earn higher profits. Across all productivity levels, conducting R&D results in higher $V(\cdot)$ values. For instance, a firm with a productivity level of 1.20 has a $V(\cdot)$ value of EUR 1.79bln if it had performed R&D last period. Without having performed R&D, this value would have dropped by EUR 30.69mln. This is to be expected because a firm that conducted R&D in the previous period is more likely to have higher productivity, which leads to higher profits and hence higher values of $V(\cdot)$, as well as being able to avoid the sunk start up costs of R&D today.

Column (5) displays the marginal benefit of conducting R&D, defined as the difference between $EV(rd = 1)$ and $EV(rd = 0)$ in equation (2.9). In other words, it is the gain in firm's expected future value if the firm decides to perform R&D. Firms weigh this benefit against the costs they have to incur if they decide to participate in R&D. If the benefits exceeds the costs, firms will conduct R&D and stay idle otherwise. The magnitude of the marginal benefit of R&D depends on the productivity level with more productive plants having a higher return of engaging in R&D. For instance, the gain in expected future value for a firm with productivity level $\omega = 1.20$ is EUR 79.24mln but EUR 120.07mln if its productivity level is 1.53. Since the return to R&D is higher for high productivity firms, high productivity firms are more likely to engage in R&D. This is confirmed by the results reported in columns (8) and (9). They show that the probability of firms performing R&D consistently is increasing in ω irrespective of past R&D status.

The effect of history on the probability of conducting R&D is significant. For firms with a productivity level of 0.52 the probability of continuing to perform R&D is 71.96% while the probability of starting R&D activity is only 25.97%. For firms with a productivity level above the average, the difference is less striking as more than 80% of non-performers will start to conduct R&D. Firms that had participated in R&D in the previous period and have productivity levels above 1.53 have a probability of performing R&D of almost 1.

Among firms that conduct R&D I report their average fixed and sunk costs in columns (6) and (7), respectively. Firms that chose to be active in R&D received a cost draw which is lower than the marginal benefit of doing R&D. Hence, their average costs are computed as the mean of the truncated cost distribution with location parameters γ^F, γ^S as reported in Table A.13. As expected, firms that continuously perfomed R&D have lower cost than those that have started recently. For instance, at the productivity level 1.2 the continuation cost is on average EUR 14.43mln whereas firms that are new to R&D have to pay a startup cost amounting to EUR 30.78mln.

Summing up by virtue of an example: A firm with a productivity level of 1.20 has a marginal benefit of performing R&D of EUR 79.24mln. The probability of continuing R&D is 98.78% for previous performers and 67.18% for previous non-performers. This means 98.78% of the previous performers and 67.18% of the previous non-performers received a cost draw that is lower than EUR 79.24mln. This cost draw is on average EUR 14.43mln and EUR 30.78mln for previous performers and non-performers, respectively.

The corresponding firm values, the costs and benefits of conducting R&D and the probability of performing R&D in model 2 are shown in table A.15. Firms' expected values $V(\cdot)$ and $EV(\cdot)$ are smaller in model 2 for all productivity levels. This reflects the additional uncertainty in the innovation process captured in model 2.

In order to compare the two models, I use both models' estimated parameters and simulate firm productivity and R&D choice for each model separately. Then, I compare the simulated patterns of firms' productivity level and R&D decision. For the simulation, I use each firm's initial status $(\omega_{i0}, rd_{i0}, k_i)$, simulated random shocks for the productivity evolution process ϵ_{it} and simulated random fixed and sunk costs $\gamma_{it}^f, \gamma_{it}^s$ in order to compute the firm's productivity path according to equations (2.6) and (4.1). The firms' expected values $V(\cdot)$, $EV(\cdot)$ are computed as defined in equations (2.7), (2.8), (2.11) and (2.12). I use these values in combination with the random fixed and sunk costs draws to simulate the firm's investment decision. The firm's productivity path and investment choice is simulated for 20 time periods and repeated 100 times. The results are averaged for each time period over all simulations.

Table A.16 reports the average productivity and investment probabilities over all firms for both models after 5, 10, 15 and 20 years. Column (2) and (3) show the average productivity level in model 1 and 2, respectively. The initial productivity level is chosen as 0.6682. The simulated average productivity levels in both models are very similar. After 5 years, the average productivity level rises to 0.7355 in model 1 and to 0.7367 in model 2. The difference in the propensity of choosing R&D investment is negligible as well. Initially, the probability of investing in R&D is on average 66.98% and increases after 20 years to 74.33% in model 1 and 76.68% in model 2.

Chapter 6

Policy simulation

The estimates of the previous section are now used to explore practical policy implications. The first policy simulation investigates the extent to which public R&D subsidies affect firm-level innovations. The second policy experiment investigates the effect of product market competition on R&D investment.

6.1 Public R&D subsidies

R&D spending is a major concern for policy makers. In 2002 the Lisbon European Council called for the European Union to have 3% of GDP invested in R&D by 2010. The goal was to become

> "the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion."[1]

[1] http://cordis.europa.eu/era/3percent_en.html

There are a number of different channels through which OECD countries are trying directly to foster business R&D.[2] The direct channel of supporting business R&D consists of public funding in the form of grants, subsidies and loans. OECD (2010) reports that the USA, France and Korea with direct funding of around 0.15% of GDP have the highest direct funding among all OECD countries in 2008. The second channel consists of R&D tax incentives in the form of R&D tax credits, R&D allowances and depreciation allowances. Countries such as Korea and Canada have the highest R&D tax incentives among OECD countries in 2008 with values around 0.20% of GDP. The indirect way of fostering business R&D is by supporting public research centers, universities or public research organizations. For example, the federal institutions in Germany supported R&D activities with approximately EUR 10bln in 2008 of which approximately EUR 2bln were spent directly on private sector activities.[3] This shows that public R&D spending is a major focus of public policy. The various forms of public R&D spending and its effectiveness have been investigated extensively in the literature.

The literature on public R&D subsidies tackles a number of questions. First, researchers investigate whether R&D subsidies have an effect on firm R&D spending. The motivation here is to understand the social costs to R&D subsidies. A related second question is whether public R&D subsidies crowd out private R&D investment. A full crowding out of private R&D investment by public R&D subsidies would obviously imply a non-existing effect of R&D subsidies on R&D investment.

Hall and Van Reenen (2000) give an excellent overview regarding the first issue. The authors review econometric studies that have investigated the effect of tax credits on R&D spending. R&D tax credits are a wide-spread form of public

[2] As an excellent reference, see OECD (2010).
[3] See BMBF (2010).

subsidies because they are more market-oriented than direct R&D subsidies. The reason is that R&D tax credits still leave the decision which particular projects to pursue to private sector decision makers. The survey concludes that R&D tax credits have an effect of R&D spending. In particular, the authors show that the tax price elasticity can be assumed to be around a unity, i.e. a one dollar tax credit leads to a one dollar increase in R&D spending.

David, Hall, and Toole (2000) give a broad overview of the empirical literature on the substitution and complementary effects between publicly funded and privately funded R&D. Substitution effects refer here to a crowding-out of privately funded R&D while complementary effects refer to spillover effects from publicly funded R&D to private sector R&D. The authors do not find conclusive results when surveying the literature. They find that approximately half of all firm-level studies find a substitution effect while the other half reports a complementary effect between publicly and privately funded R&D. Relatively more studies using U.S. data find a substitution effect while non-U.S. studies report more often a complementary effect which might be a result of the particular design of U.S. R&D grants, awards, tax breaks and other forms of subsidies. The authors point to the broad range of methods used in the literature, the various levels of aggregation and the different forms of R&D subsidies that make a general conclusion on the results of the overall literature impossible.

My model allows me to simulate the effect of an R&D subsidy which lowers the cost of conducting R&D, such as a tax credit for R&D expenditures. To do this I shift the distributions of fixed or sunk costs and simulate the optimal firm R&D choices under the new regime.

The simulation is carried out as described in the previous section using cost parameter estimates reported in table A.13. For the simulation, I assume a reduction in average R&D fixed and sunk costs of 20%. This reduction can be the consequence of a direct government support such as a grant or a subsidy, or the consequence of an indirect government support such as a tax credit. The reduction is constant during all periods throughout the experiment. This leads to firms receiving their cost draws in every period from an exponential distributions with a lower mean. The experiment is simulated for 20 time periods. Table A.17 reports the results for both models. I compare the outcome of the experiment, i.e. firm productivity and R&D choice, with the corresponding outcome during the initial regime reported in table A.16 when the mean of R&D costs was given by γ as reported in table A.13.

Columns (2) and (4) show the change in average productivity level ($\bar{\omega}$) in model 1 and 2, respectively. After 20 years in model 1, due to the cost reduction, $\bar{\omega}$ is higher than in the baseline regime by 1.63%. The gain of 1.63% in average level of ω corresponds to a 4.7% difference in revenue. Columns (3) and (5) report the probability of participating in R&D $\overline{Pr(rd = 1)}$ for model 1 and 2. The probability of conducting R&D is 6.9 percentage points higher in model 1 after 20 years. Similar patterns can be seen for model 2, whereas the effect of the subsidy programm on $\bar{\omega}$ and on $\overline{Pr(rd = 1)}$ is slightly lower in model 2.

These results are broadly in line with the literature on public R&D support for businesses: Public R&D funding of private sector activities leads to an increase in productivity and revenue. Note however, that the overall quantitative magnitude of the subsidy appears to be rather small: A 20% cost reduction in each period leads to a 4.7% increase in revenue. However, there seems to be at least no full crowding-out effect: A reduction in R&D costs does lead to an increase in productivity and revenue. This in turn might create positive spillover effects. These however, are outside the scope of this model.

6.2 R&D and competition

There is an extensive literature on the interaction between competition and R&D or more broadly, innovation. The classic reference is Schumpeter (1942) who argues that increased competition leads to smaller returns on innovation. That view stipulates that monopolies might have larger incentives to invest in R&D since this might be an effective way to deter potential entrants. On the other hand, increased competition might lead to more investment in R&D since the market participants are trying to create a cost advantage via process innovations or might try to achieve higher returns by product differentiation via product innovation.

Recently, Aghion, Bloom, Blundell, Griffith, and Howitt (2005) have argued that there exists an inverted U-relationship between competition and innovation. The authors argue that the key factor is the difference between postinnovation and preinnovation rents of incumbent firms. An increased level of competition reduces incumbent firms' rents. However, innovating in such an environment leads still to reduced rents but preinnovation rents decrease more dramatically than postinnovation rents, thus creating an incentive on the margin to innovate for incumbent firms. "Escaping competition" is the dominating effect here. To the contrary, a decreased level of competition increases incumbents' rents. Innovating in such an environment leads to smaller additional postinnovation rents than additional preinnovation rents, thus reducing the incentive to invest in innovative behavior. Hence, the "Schumpeter-effect" described above dominates. The authors confirm their theoretical prediction empirically for a panel of U.K. firms between 1973 and 1984.

Blundell, Griffith, and Van Reenen (1999) provide a thorough empirical investigation of the relationship between innovation and competition for U.K. firms between 1973 and 1982. Innovation is measured in observable innovation headcount and patents. The authors find that less competitive industries produce fewer innovations. This finding is in line with the "escaping-competition-effect": The higher the level of competition the more innovative are incumbent firms because they need to gain an advantage over their competitors. However, within industries, the high-market-share firms have generated more innovations than small-market-share firms. This in turn is in line with "Schumpeter-effect": The more dominant an incumbent firm is, the higher is its ex-post benefit from an innovation. The last result is confirmed by incorporating data on firm stock market value. Within industries, the effect of innovation on stock market value is higher for higher for high-market-share firms.

In my model I can simulate the effect of decreased current market competition on the firm's R&D choice by decreasing the demand elasticity faced by the firms and constructing the optimal firm response when it faces a less elastic demand. This does not fully capture the tradeoff between competition and innovation because there is no impact on future competition. That is, since there is no direct competition between firms in my model, a firm that invests in R&D will not have any advantage in the ex-post competition among firms. However, by altering the demand elasticity I can affect the profit flow that will result from the firm's investment and innovation.

The simulation is similar to the cost-subsidy experiment and is implemented in the same manner as described previously. For this experiment, I assume a demand elasticity of $\widetilde{\eta} = -3$ in order to look at the effect of less competition on firms' R&D choice. This corresponds to a cost-revenue ratio of 0.67. Table A.18 reports the change in average productivity level and R&D choice resulting from a lower demand elasticity. I compare the results with those from the baseline regime reported in table A.16.

Columns (2) and (4) show the difference in average productivity level between the environments with different levels of η for model 1 and 2. Facing a lower demand elasticity results in a lower productivity level. After 20 years in model 1, the difference in productivity amounts to 16.33% when comparing the level of ω in a low-elasticity environment with the level of ω in a high-elasticity environment. This is a reflection of the impact of R&D on firm profits in the long run, absent any effect on competition between firms.

These results are confirmed when comparing the propensity to perform R&D. Columns (3) and (5) show the difference in firms' probability of performing R&D. The propensity to R&D investment is substantially lower in the environment with lower $|\eta|$. More specifically, the probability of conducting R&D declines by 56.88 percentage points after 5 years in model 1. Thus, the probability of conducting R&D declines to approximately 0.06 after 5 years. Note however, that these results do not account explicitly for the complex interactions assumed by the "Schumpeter-effect". That is, there are no potential entrants which might to be deterred, so that there is only limited room for such an effect in my model environment.

Chapter 7

Conclusion

This thesis presents the first work applying a structural econometric model of firm R&D investment to the micro data collected as part of the Community Innovation Survey (CIS).

On the theoretical side, I have contributed to the literature by replacing the direct link between R&D and productivity in the model developed by Aw, Roberts, and Xu (2011) with two links: The link from R&D investment to product and process innovation and the link from innovation to productivity. This presents a unique contribution since these two links provide more realistic channels through which R&D affects productivity.

On the empirical side, I have contributed to the literature by exploiting the rich information provided by the CIS data with a structural econometric model. In particular, I am able to exploit the rich intertemporal structure of the data as well as the unique data on product and process information.

Applying my model to the data yields five empirical results: First, product innovation and process innovation increase productivity. Second an increase in R&D spending leads to a higher probability of a product or process innovation, which in turn implies that higher R&D investment leads to higher productivity. Third, the firm R&D decision depends on productivity and on past R&D decisions. Fourth, fixed costs of R&D are significantly smaller than sunk costs of R&D. Fifth, larger firms have higher R&D costs than smaller firms.

I apply the empirical model estimates to two policy simulations. First, I show that public R&D subsidies which reduce firm R&D costs lead to an increase in firm productivity. This result has major policy implications. It states that public sector policy can foster private sector innovation and productivity by directly subsidizing private R&D costs. This however, does not imply that any sort of public sector subsidies would lead to higher innovation and productivity. To the contrary, this result is very restrictive: Only if the public subsidy is used to lower the direct costs to R&D, and is not channeled to fund other projects within the firm, the firm will experience an increase an innovation and productivity. Note too, that this analysis does not have any implications on the costs and benefits on an economy-wide level of R&D subsidies.

Finally, I have laid the ground for future research. I have developed a model where the firm R&D choice is continuous. This is indeed a very attractive road for future research since R&D investment decisions are certainly not binary but rather continuous. This model might be used to investigate the determinants for different levels of investing in R&D. This is particular interesting, when comparing firms from different industries since there are very different levels of R&D investments across industries.

Appendix A

Descriptive statistics and empirical results

Table A.1. Industries in manufacturing sector covered in the sample

	Industries	NACE	firms	observations
1	Food	15-16	525	1213
2	Textiles	17-19	408	1036
3	Wood/paper/printing	20-22	673	1720
4	Chemicals	23-24	554	1415
5	Plastic/rubber	25	517	1442
6	Glass/ceramics	26	387	1031
7	Metals	27-28	1080	2905
8	Machinery	29	1090	2815
9	Electrical engineering	30-32	668	1705
10	MPO instruments	33	576	1491
11	Vehicles	34-35	404	981
12	Furniture/recycling	36-37	389	901
			7271	18655

Table A.2. Number of firms in each year

year	1993	1994	1995	1996	1997	1998	1999	2000
N	1942	1953	1468	1526	779	1446	472	626
year	2001	2002	2003	2004	2005	2006	2007	2008
N	530	1165	575	1431	688	1486	813	1755

Table A.3. Descriptive statistics

Variables	Mean	Median	Std.Dev.	5%	95%
Revenue	143.79	9.00	1738.92	0.51	246.35
Capital stock	44.87	2.31	571.75	0.06	68.51
Labor	33.08	2.56	423.12	0.17	55.22
Material	77.91	3.74	1079.57	0.12	127
Age	35.55	17.00	44.42	3.00	123.00
Innovation Spending	8.62	0.12	129.78	0.00	9.2

Table A.4. Innovation shares by industries - pooled over firms and years

	Industries	Innovator	Product Innovation	Process Innovation
1	Food	0.5425	0.4732	0.2580
2	Textiles	0.5135	0.4643	0.2027
3	Wood/paper/printing	0.5174	0.3919	0.2453
4	Chemicals	0.7866	0.7081	0.3633
5	Plastic/rubber	0.6422	0.5915	0.3266
6	Glass/ceramics	0.5887	0.5257	0.3113
7	Metals	0.5938	0.4785	0.3164
8	Machinery	0.7702	0.7147	0.3609
9	Electrical engineering	0.8053	0.7449	0.3977
10	MPO instruments	0.8176	0.7706	0.3300
11	Vehicles	0.7309	0.6504	0.3955
12	Furniture/recycling	0.6060	0.5283	0.2697
	Average	0.6596	0.5868	0.3148

Table A.5. Innovation shares by number of employees and by capital stock

	Categories	Innovator	Product Innovation	Process Innovation
Labor	5-50	0.5260	0.4505	0.1849
	51-200	0.6891	0.6039	0.3058
	201-500	0.7926	0.7158	0.4513
	> 501	0.8814	0.8277	0.5876
Capital	[0, .15]	0.4452	0.3824	0.1134
	(.15, .42]	0.5334	0.4616	0.1622
	(.42, .92]	0.5961	0.5178	0.2479
	(.92, 1.75]	0.6264	0.5468	0.2557
	(1.75, 3.04]	0.6623	0.5861	0.3136
	(3.04, 5.49]	0.7160	0.6362	0.3522
	(5.49, 10.83]	0.7775	0.6968	0.4061
	> 10.83	0.8303	0.7538	0.5174

Table A.6. Transition rates

	no R&D	R&D	Capital
no R&D	81.25	18.75	[0, .15]
	82.37	17.63	(.15, .42]
	77.16	22.84	(.42, .92]
	74.51	25.49	(.92, 1.75]
	78.65	21.35	(1.75, 3.04]
	71.68	28.32	(3.04, 5.49]
	66.29	33.71	(5.49, 10.83]
	66.93	33.07	> 10.83
R&D	21.75	78.25	[0, .15]
	19.42	80.58	(.15, .42]
	21.46	78.54	(.42, .92]
	16.85	83.15	(.92, 1.75]
	17.23	82.77	(1.75, 3.04]
	14.34	85.66	(3.04, 5.49]
	8.08	91.92	(5.49, 10.83]
	6.77	93.23	> 10.83

Table A.7. Revenue equation $h(a, k, m)$ including time and industry dummies

Variables	Coefficients (Std. Error)	Variables	Coefficients (Std. Error)
const	1.0037 (0.0361)***		
a	-0.1102 (0.0338)***	km	-0.0673 (0.0061)***
a^2	0.058 (0.0114)***	k^2m	-0.0011 (0.0026)
a^3	-0.0061 (0.0013)***	km^2	0.005 (0.002)**
k	0.1955 (0.0213)***	ka	-0.0116 (0.0161)
k^2	0.0233 (0.0044)***	k^2a	0.0029 (0.001)***
k^3	-0.0006 (0.0012)	ka^2	0.0038 (0.0029)
m	0.685 (0.0236)***	am	-0.0068 (0.0173)
m^2	0.0763 (0.0038)***	a^2m	0.0007 (0.0032)
m^3	-0.0054 (0.0007)***	am^2	-0.0044 (0.0011)***
$\hat{h}$	2.2848	N	17811
	(-0.5378, 5.5014)	R^2	0.9511

Table A.8. Revenue equation $h(a, k, i)$ including time and industry dummies

Variables	Coefficients (Std. Error)	Variables	Coefficients (Std. Error)
const	1.9418 (0.0913)***		
a	-0.2376 (0.0821)***	ki	0.0312 (0.0154)**
a^2	0.1827 (0.0261)***	k^2i	0.0054 (0.0027)**
a^3	-0.0219 (0.0028)***	ki^2	0.0058 (0.0028)**
k	0.5726 (0.0364)***	ka	-0.0685 (0.0255)***
k^2	0.0498 (0.0077)***	k^2a	-0.0041 (0.0014)***
k^3	-0.009 (0.0012)***	ka^2	0.0082 (0.0044)*
i	0.1972 (0.0406)***	ai	0.0518 (0.026)**
i^2	-0.0322 (0.0104)***	a^2i	-0.0038 (0.0043)***
i^3	-0.0048 (0.0012)***	ai^2	0.0009 (0.0013)***
h	2.4538	N	16612
	(-0.0299, 5.3525)	R^2	0.7985

Table A.9. Revenue equation $h(a, k, l)$ including time and industry dummies

Variables	Coefficients (Std. Error)	Variables	Coefficients (Std. Error)
const	-1.587 (0.2243)***		
a	-0.3314 (0.1021)***	kl	-0.0414 (0.0408)
a^2	0.1023 (0.0219)***	k^2l	0.0004 (0.0035)
a^3	-0.009 (0.0021)***	kl^2	0.0027 (0.0052)
k	0.2847 (0.0844)***	ka	-0.0267 (0.0183)
k^2	0.0166 (0.0143)	k^2a	-0.0004 (0.0009)
k^3	-0.0013 (0.0009)	ka^2	0.006 (0.0031)*
l	0.4892 (0.1331)***	al	0.0795 (0.0248)***
l^2	0.0826 (0.0319)**	a^2l	-0.0094 (0.0042)**
l^3	-0.0047 (0.0027)*	al^2	-0.0036 (0.0014)**
h	2.1074	N	17811
	(-0.6655, 5.2029)	R^2	0.906

Table A.10. Productivity parameters and cost elasticities, $g(\omega, rd)$

Variables	Parameters	Coefficients (Std. Error)
const	α_0	0.0304(0.004)***
a	β_a	0.0183 (0.0077)**
k	β_k	-0.0761 (0.0017)***
ω	α_1	0.9234(0.0125)***
ω^2	α_2	0.0688(0.0139)***
ω^3	α_3	-0.0221(0.0045)***
rd	α_4	0.0144(0.0026)***
$SE(\varepsilon)$		0.1032
Adj. R^2		0.9715
$(1 + 1/\eta)$		0.7529(.0014)***
N		7845

Table A.11. Productivity parameters and cost elasticities, $g(\omega, d, z)$

Variables	Parameters	Coefficients (Std. Error)
const	α_0	0.0303 (0.004)***
a	β_a	0.0189 (0.0078)**
k	β_k	-0.0765 (0.0017)***
ω	α_1	0.9243 (0.0128)***
ω^2	α_2	0.069 (0.0143)***
ω^3	α_3	-0.0229 (0.0046)***
z	α_4	0.0136 (0.0069)**
d	α_5	0.0133 (0.003)***
zd	α_6	-0.0087 (0.0076)
$SE(\varepsilon)$		0.1032
Adj. R^2		0.9715
$(1+1/\eta)$		0.7529 (.0014)***
N		7503

Table A.12. Innovation realization

		$rd_{t-1}=0$		$rd_{t-1}=1$	
	Industries	$d=1$	$z=1$	$d=1$	$z=1$
1	Food	0.1897	0.1853	0.7101	0.587
2	Textiles	0.1711	0.1369	0.6951	0.5022
3	Wood/paper/printing	0.1359	0.1795	0.5882	0.5934
4	Chemicals	0.1724	0.1724	0.8428	0.6739
5	Plastic/rubber	0.1944	0.1349	0.8067	0.6809
6	Glass/ceramics	0.2031	0.1563	0.7695	0.656
7	Metals	0.1364	0.1544	0.7134	0.7055
8	Machinery	0.1753	0.1591	0.8651	0.6512
9	Electrical engineering	0.2553	0.1915	0.8708	0.638
10	MPO instruments	0.1858	0.177	0.8995	0.5927
11	Vehicles	0.1667	0.1583	0.8091	0.6893
12	Furniture/recycling	0.1901	0.1408	0.7642	0.5721
	Manufacturing	0.1713	0.1608	0.7959	0.6415

Table A.13. Dynamic estimates

	Fixed cost		Sunk cost	
R&D	γ^F		γ^S	
	14.6335		63.0140	
	(0.1194)		(1.9566)	
	γ_s^F	γ_l^F	γ_s^S	γ_l^S
	6.9272	23.8387	36.0166	109.503
	(0.1462)	(0.4446)	(1.9708)	(5.0687)
R&D and Innovation	γ^F		γ^S	
	8.9531		38.4007	
	(0.1334)		(1.2823)	
	γ_s^F	γ_l^F	γ_s^S	γ_l^S
	4.2122	14.4707	21.745	66.8554
	(0.0942)	(0.2815)	(1.2188)	(3.2317)

Table A.14. Model 1: Firm expected discounted values, policy functions and marginal benefit of R&D

ω	$V_1{}^a$	$V_0{}^b$	$V_1 - V_0$	$EV_1 - EV_0{}^c$	$E(\gamma\|\gamma < \delta(EV_1 - EV_0))$		$Pr(rd_t = 1)$	
					$rd_{t-1} = 1$	$rd_{t-1} = 0$	$rd_{t-1} = 1$	$rd_{t-1} = 0$
-0.16	187.82	187.66	0.16	2.35	1.08	1.11	0.1696	0.0373
0.18	263.57	262.37	1.20	7.00	2.99	3.26	0.4105	0.108
0.52	455.09	449.23	5.86	19.15	6.85	8.61	0.7196	0.2597
0.86	899.38	882.18	17.20	44.29	11.71	18.73	0.9282	0.4776
1.20	1785.41	1754.72	30.69	79.24	14.43	30.78	0.9891	0.6718
1.53	3336.20	3295.07	41.13	120.07	15.21	41.97	0.9987	0.8078
1.87	5918.36	5869.81	48.55	171.38	15.36	52.22	0.9999	0.9001
2.21	10331.20	10277.65	53.55	244.77	15.38	61.44	0.9999	0.959
2.55	18469.79	18413.55	56.24	357.17	15.38	68.28	0.9999	0.9885
2.89	34109.59	34053.29	56.30	362.16	15.38	68.48	0.9999	0.9892

[a] V_1: $V(\omega, rd_{-1} = 1)$
[b] V_0: $V(\omega, rd_{-1} = 0)$
[c] Marginal benefit of R&D, the difference between expected future values of conducting and not conducting R&D.

Table A.15. Model 2: Firm expected discounted values, policy functions and marginal benefit of R&D

ω	V_1[a]	V_0[b]	$V_1 - V_0$	$EV_1 - EV_0$[c]	$E(\gamma\|\gamma < \delta(EV_1 - EV_0))$		$Pr(rd_t = 1)$	
					$rd_{t-1} = 1$	$rd_{t-1} = 0$	$rd_{t-1} = 1$	$rd_{t-1} = 0$
-0.16	184.23	184.1	0.13	1.68	0.77	0.79	0.1924	0.0429
0.18	256.98	256.11	0.87	4.80	2.03	2.23	0.4428	0.1189
0.52	433.10	429.14	3.96	12.60	4.45	5.65	0.745	0.2745
0.86	824.90	813.97	10.93	27.95	7.28	11.79	0.9358	0.4883
1.20	1585.75	1566.87	18.88	48.74	8.80	18.90	0.9898	0.6753
1.53	2905.91	2880.85	25.06	73.10	9.24	25.55	0.9987	0.8079
1.87	5115.45	5085.9	29.55	104.14	9.33	31.76	0.9999	0.8997
2.21	8954.50	8921.88	32.62	149.02	9.34	37.40	0.9999	0.959
2.55	16214.67	16180.39	34.28	219.00	9.34	41.62	0.9999	0.9888
2.89	30898.75	30864.21	34.54	247.55	9.34	42.49	0.9999	0.9932

[a] V_1: $V(\omega, rd_{-1} = 1)$
[b] V_0: $V(\omega, rd_{-1} = 0)$
[c] Marginal benefit of R&D, the difference between expected future values of conducting and not conducting R&D.

Table A.16. Productivity and investment choices under model 1 and 2

	Model 1		Model 2	
year	ω	$Pr(rd=1)$	ω	$Pr(rd=1)$
1	0.6682	0.6698	0.6682	0.6698
5	0.7355	0.6298	0.7367	0.6474
10	0.8116	0.6727	0.8148	0.6949
15	0.8831	0.7112	0.8874	0.7343
20	0.9491	0.7433	0.9529	0.7668

Table A.17. Policy experiment: 20% cost reduction

	Model 1		Model 2	
year	$\%\Delta\omega$	$\Delta Pr(rd=1)^a$	$\%\Delta\omega$	$\Delta Pr(rd=1)^b$
5	0.3263	0.0778	0.3217	0.0759
10	0.914	0.0785	0.7015	0.0744
15	1.2998	0.0739	0.9211	0.0706
20	1.6264	0.0694	1.1279	0.0658

[a]Changes are in percentage points
[b]Changes are in percentage points

Table A.18. Policy experiment: lowering demand elasticity

	Model 1		Model 2	
year	$\%\Delta\omega$	$\Delta Pr(rd=1)^a$	$\%\Delta\omega$	$\Delta Pr(rd=1)^b$
5	3.1866	-0.5688	2.1098	-0.5497
10	8.1959	-0.6092	5.4572	-0.5891
15	12.638	-0.6404	8.3222	-0.6162
20	16.3333	-0.6644	10.8024	-0.6375

[a]Changes are in percentage points.
[b]Changes are in percentage points

Appendix B

Continuous R&D choice and random realization of innovation output

The next step towards a more realistic model framework is to allow for the firm to choose the level of its R&D spending continuously.

As described above, the firm starts each period receiving the information $(\omega_{it}, a_{it}, k_{it})$. Based on this information it maximizes $\pi(\omega_{it}, a_{it}, k_{it}, \Phi_t)$. Subsequently, the firm innovates by using R&D spending as input and producing new products or processes as output of the innovation production process. If the firm did not perform R&D in the previous period it has to pay a startup cost in the current period.

Innovations embody a knowledge gain which can be a result of learning in the course of production, receiving direct or indirect feedback from competitors, customers or contractors, or other ways not directly involving active spending. In order to capture this feature, I allow for firms to have an exogenous probability of being exposed to innovations.

An increase in R&D expenditure results in an increased probability of receiving a product or a process innovation if the level of spending exceeds a given threshold. This captures the idea that not any arbitrarily small amount of R&D spending has an effect. Otherwise, in order to avoid the startup costs firms would always spend a small amount in every period. The startup costs and the spending thresholds are random draws from a known distribution and are realized before the firm makes its R&D choice. The R&D costs are given by

$$C(rd_{it-1}, rd_{it}) = \begin{cases} \gamma^s(1 - I(rd_{it-1} > 0)) + rd_{it}, & \text{if } rd_{it} > 0 \\ 0, & \text{if } rd_{it} = 0 \end{cases}$$

where I is an indicator function and $\gamma^s \sim G^{\gamma^s}$ denotes the startup costs.

Assuming the functional form for the productivity evolution as in equation (4.1), the transition probability of ω is therefore given by

$$\mathcal{P}_\omega \quad = \quad \big\{Pr(\omega'|\omega, rd)|\omega \in \mathbb{R}, rd \in \{0,1\}\big\},$$

which is again determined jointly by the probability of innovation success

$$Pr(dz_{+1}|rd, \gamma^f) = \begin{cases} \alpha_0, & \text{if } rd < \gamma^f \\ 1 - (1-\alpha_0)\exp\left(-\big(\frac{rd-\gamma^f}{\alpha_{dz}}\big)^{\rho_{dz}}\right), & \text{if } rd \geq \gamma^f \end{cases}$$

and the probability distribution of the random shock $\varepsilon \sim N(0, \sigma_\varepsilon^2)$with $\gamma^f \sim G^{\gamma^f}$ being the threshold for minimum R&D spending. The parameter α_0 is the exogenous probability of receiving an innovation.

Before observing the startup cost and the threshold for investment spending, the firm's expected value is given by

$$V(x_{it}) \quad = \quad \pi(\omega_{it}, a_{it}, k_{it}) \tag{B.1}$$

$$
\begin{aligned}
&+ \quad \int_{\gamma^s} \int_{\gamma^f} \max_{rd \in \mathbb{R}_+} \Big\{ -C(rd_{it-1}, rd_{it}) \\
&+ \quad \beta E_t[V(x_{it+1}) | \omega_{it}, a_{it}, k_{it}, rd_{it}] \Big\} dG^{\gamma^s} dG^{\gamma^f},
\end{aligned}
$$

where

$$
\begin{aligned}
& E_t[V(x_{it+1}) | \omega_{it}, a_{it}, k_{it}, rd_{it}] \\
= \quad & \sum_{dz_{+1}} \underbrace{\left[\int_{\omega'} V(x_{it+1}) dF(\omega' | \omega, dz) \right]}_{\equiv W(dz|\omega,k)} Pr(dz_{+1} | rd, \gamma^f)
\end{aligned}
\tag{B.2}
$$

Firm's optimal R&D spending satisfies the Kuhn-Tucker Conditions

$$
\left[-\frac{\partial C(rd_{-1}, rd)}{\partial rd} + \beta \sum_{dz_{+1}} W(dz|\omega, k) \frac{\partial Pr(dz_{+1} | rd, \gamma^f)}{\partial rd} \right] = 0 \tag{B.3}
$$

In this framework the goal is to estimate the exogenous probability level α_0 and also the parameters of the distribution function G^{γ^s} and G^{γ^f}.

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