Firm R&D, Innovation, and Productivity in German Industry

Bettina Peters
Center for European Economic Research (ZEW)

Mark J. Roberts
Pennyslvania State University and NBER

Van Anh Vuong
University of Cologne and Institute of Energy Economics (EWI)

Helmut Fryges
Center for European Economic Research (ZEW)

January 2013
PRELIMINARY DRAFT

Abstract

This paper investigates empirically firm investment behavior in research and development (R&D). Firms make investments in R&D in order to produce innovations. These innovations in turn improve the firm's future productivity level, profitability and incentives to invest in R&D. Using German firm-level data from the manufacturing sector, we estimate a dynamic, structural model of the firm's choice to invest in R&D and quantify the benefit and cost of engaging in R&D. We find that among firms that engage in R&D, process and product innovations create a significant improvement in their productivity. The cost for performing R&D differs across firms based on their size and R&D history. We compute the benefits of R&D investment to the firm and find that by taking the dynamic nature of the investment into account the real return to R&D is several times higher than the one time gain in firm productivity.

1 Introduction

This paper develops a dynamic, structural model of the the firm's decision to invest in R&D and estimates it using firm-level data from the German manufacturing sector. The model incorporates four aspects of the innovation process. First, we treat the firm as making a discrete decision to invest in R&D. Second, this investment decision has a one-time startup cost for firm's that are just beginning the R&D process and a per-period maintenance cost for firms that are continuing. Third, the R&D investment raises the probability the firm develops new innovations. These innovations can lead to the introduction of new products or improvements in product quality or can be process innovations that reduce the production costs for the firm. Fourth, these innovations can generate improvements in a firm's performance, specifically they increase a firm's productivity and profits. By quantifying each of these four components, we are able to measure the costs and long-run benefits of R&D investment to the firm.

There is significant heterogeneity in R&D spending across firms and industries. Positive R&D expenditures are typically observed for only a fraction of firms at any point in time and firm's may vary between positive and zero expenditures over time. One question we address in this paper 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 paper we develop an empirical model to estimate these returns and costs in order to understand the incentives firms face when they make their decision to invest in R&D. 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 **?**, **?**, and **?**. 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 paper extends these studies by modeling the link between R&D and productivity explicitly. In particular, we let R&D affect the probability of realizing product or process innovations. 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, we are 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, this 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.

Our empirical model is based on the dynamic discrete choice model of R&D developed by **?** (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, we 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. A second distinctive feature of this paper is that we exploit a unique data set, the Mannheim Innovation Panel (MIP), 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 key structural parameters estimated are those that describe the process of endogenous productivity evolution, including the effect of an innovation of the firm's 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 us to measure both the benefits and costs of R&D.

The main empirical findings can be summarized as follows. First, product innovation as well as process innovation increase future firm productivity. 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. 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 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 fifth finding is that larger and more productive firms have a larger expected benefit from R&D than smaller firms. This corresponds to the empirical pattern in the data that larger firms have a higher probability of investing in R&D than smaller firms.

The next section of the paper develops the theoretical model of R&D investment. The third section discusses some important features of the data and section 4 develops the empirical model and estimation strategy. Section 5 discusses the empirical results.

2 Theoretical Model

This section develops a theoretical model of a firm's decision to undertake R&D investment. This investment decision is treated as a discrete choice by the firm which involves a current cost, either a startup or maintenance cost, and generates future benefits to the firm in the form of improved productivity and profits. Consider a single firm with an infinite horizon and making input choices at discrete points in time. At the beginning of each period, the firm observes its current productivity level ω_{it} and its capital stock k_{it}. Based on this information the firm makes static choices for variables inputs (labor, materials, and energy) and output price in order to maximize the period profit. After this the firm observes the realization of R&D costs, either a sunk startup cost if it is not currently investing in R&D or a fixed maintenance cost if it is, and makes a decision to invest in R&D or not. We will treat the R&D decision as discrete and the firm's R&D choice will affect its future productivity level, and thus its future profits, through the product and process innovations it creates. The model will contain three main components. The first component is firm $i's$ period profit as a function of its state variable $\pi_{it}(\omega_{it}, k_{it})$. The second component is the effect of the firm's discrete R&D decision on the probability that the firm realizes either a product or process innovation in the future $\Pr(d_{it+1}, z_{it+1}|rd_{it})$ where d, z, rd are all discrete 0/1 indicators of a product innovation, process innovation, and R&D investment, respectively. The third component describes the process of productivity evolution, where process and product innovations affect by the firm's future productivity, $\omega_{it+1} = g(\omega_{it}, d_{it+1}, z_{it+1})$.

2.1 Productivity and the Firm's Short-Run Profits

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

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

where c_{it} is the log of marginal cost, k_{it} is the log of firm capital stock, and w_t is a vector of log prices for variable inputs 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.

Each firm is assumed to produce one product. The demand for firm i's product is given by

$$\begin{aligned} q_{it} &= Q_t(\frac{p_{it}}{P_{It}})^{\eta}\exp(\phi_{it}) \\ &= \Phi_t(p_{it})^{\eta}\exp(\phi_{it}), \end{aligned} \tag{1}$$

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

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

The first-order condition yields

$$p_{it} = \frac{\eta}{1+\eta}\exp(c_{it})$$

for all i and t. 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

$$
\begin{aligned}
r_{it} &= (1+\eta)\ln\left(\frac{\eta}{1+\eta}\right) + \ln\Phi_t \\
&\quad +(1+\eta)\left[\beta_0 + \beta_k k_{it} + \beta_w w_t - \omega_{it}\right]
\end{aligned} \tag{2}
$$

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) implies that for a given capital stock, heterogeneity in the firm's revenue is captured by production efficiency ψ and demand heterogeneity ϕ. From hereon for convenience we will refer to the revenue productivity ω_{it} as productivity.[1] This is a summary of the joint effect of production and demand heterogeneity on firm profits. Given the form of the firm's pricing rule there is a simple relationship between firm profits and firm revenue:

$$
\pi_{it} = -\frac{1}{\eta}\exp(r_{it}). \tag{3}
$$

2.2 R&D Investment and Firm Productivity

We model the evolution of the firm's productivity ω_{it+1} as a first-order Markov process which is shifted by past realizations of process and product innovations for the firm:

$$
\begin{aligned}
\omega_{it+1} &= E[\omega_{it+1}|\omega_{it}, z_{it+1}, d_{it+1}] + \varepsilon_{it+1} \\
&= g(\omega_{it}, d_{it+1}, z_{it+1}) + \varepsilon_{it+1} \\
&= \alpha_0 + \alpha_1\omega_{it} + \alpha_2\omega_{it}^2 + \alpha_3\omega_{it} \\
&\quad +\alpha_4 z_{it+1} + \alpha_5 d_{it+1} + \alpha_6 z_{it+1}d_{it+1} + \varepsilon_{it+1},
\end{aligned} \tag{4}
$$

where z_{it+1} and d_{it+1} are dummy variables that take the value 1 if firm i had a process or product innovation in year t and 0 if they did not. The firm's productivity is assumed to persist over time, with the degree of persistence captured by the coefficients α_1, α_2, and α_3. Innovations are allowed to systematically shift the mean of the distribution of future firm productivity and magnitude of this effect is captured by the coefficients α_4, α_5, and α_6. In particular the coefficient α_6 allows the possibility that the marginal effect of either a product and process innovation on future productivity will depend on whether the firm has the other type of innovation. We also allow productivity to be affected by stochastic shocks that reflect the inherent randomness in the productivity process. We assume the productivity shocks ε_{it+1} are i.i.d. across time and firms and are drawn from a normal distribution with zero mean and variance σ_ε^2. This specification captures the relationship between the innovations that the firm has and the economic return to those innovations in the form of higher future productivity. It also captures the fact that the evolution of productivity over time is a noisy process and, while innovations do alter the firm's future productivity, they may be offset by other random factors that affect the firms productivity and profits.

[1] Even though the firm's performance is driven by heterogeneity on the production and on the demand side we do not have the data needed to separate these two shocks. We have data on sales revenue for each firm but do not have price and quantity data which would be needed to separate ψ_{it} and ϕ_{it}. For our purposes we only need to quantify the effect of productivity ω_{it} on firm profit.

We do not assume that the firm chooses whether or not it has a product or process innovation. Instead, the firm chooses whether or not to invest in R&D spending and this affects the probability that the firm realizes a product or process innovation. We model this step in the linkage from R&D to productivity as a transition probability $Pr(d_{it+1}, z_{it+1}|rd_{it})$ where this represents the joint distribution of product and process innovations conditional on whether or not the firm invests in R&D. We expect that firms that invest in R&D will have higher probabilities of product and process innovations. This specification also captures the fact that firms can have product or process innovations even if they do not invest in R&D. The economic return to R&D investment will depend on how this innovation probability changes as a result of the firm's R&D activity.

Overall the transition probability for productivity is a combination of equation (4) and the probability of an innovation:

$$Pr(\omega_{it+1}|\omega_{it}, rd_{it}) = Pr(\omega_{it+1}|\omega_{it}, d_{it+1}, z_{it+1})Pr(d_{it+1}, z_{it+1}|rd_{it}). \tag{5}$$

This specification captures the endogeneity of the productivity process. The firm will decide to undertake R&D investments which will alter the probability of getting a product or process innovation which in turn will alter the distribution of future productivity the firm faces. We will refer to the first step as the innovation process and the second step as the productivity evolution process. The specification will allow for randomness at each stage which captures the fact that R&D investment does not guarantee that the firm receives an innovation and the fact that an innovation does not guarantee an increase in firm productivity. These are both sources of uncertainty in the linkage between firm R&D and productivity and we will recognize these in the firm's investment decision.

The remaining state variable capital is assumed to evolve deterministically. The firm's capital stock evolves as $K_{it+1} = (1-\delta)K_{it} + I_{it}$. We do not attempt to model the firm's investment process but do assume that the firm observes its capital stock at the start of each period before making input or R&D choices.

2.3 The Firm's Dynamic Decision to Invest in R&D

We next develop the decision rule for the firm's decision on whether or not to invest in R&D. We assume that, at the start of period t, the firm observes its state variables $s_{it} = (\omega_{it}, k_{it}, rd_{it-1})$, where the last variable rd_{it-1} is the discrete indicator of whether or not the firm invested in R&D in year $t-1$. The firm also knows its profit function, equation (3), and the process for productivity evolution, equation (5). In addition it observes a fixed cost γ_{it}^{f} of conducting R&D investment and a sunk, startup cost γ_{it}^{s} of beginning an R&D program. Both costs are assumed to be i.i.d. draws from a known joint cost distribution G^{γ}. The firm will make a discrete decision $rd_{it} \in \{0, 1\}$ on whether or not to invest in R&D. Given its state vector, the firm's value function, before it observes the fixed and sunk cost, can be written as:

$$
\begin{aligned}
V(s_{it}) \;=\;& \pi(\omega_{it}, k_{it}) \\
& + \int_{\gamma} \max_{rd \in \{0,1\}} \Big\{ \beta E\big[V(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 1)\big] \\
& - \gamma_{it}^{f} rd_{it-1} - \gamma_{it}^{s}(1 - rd_{it-1}); \\
& \beta E\big[V(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 0)\big] \Big\} dG^{\gamma}, \qquad (6)
\end{aligned}
$$

The expected future value of the firm is defined as an expectation over the future levels of productivity and innovation outcomes:

$$
E\big[V(s'|\omega, k, rd)\big] = \sum_{(d',z')} \Big[\int_{\omega'} V(s')dF(\omega'|\omega, d', z')\Big] P(d', z'|rd)
$$

In this specification if the firm conducted R&D in year $t-1$, then it will pay the fixed cost γ_{it}^{f} if it conducts R&D in year t. If it did not invest in R&D in the previous year then it must pay the startup cost γ_{it}^{s} instead. This equation shows that the firm will choose to invest in R&D if the expected future profits from doing R&D $EV(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 1)$, net of the relevant fixed or sunk cost, are greater than the expected future profits from not doing R&D $EV(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 0)$. What makes these two expected future profits differ is the effect of R&D on the firm's future productivity. Using this specification we can define the marginal benefit of conducting R&D as:

$$
\Delta EV(\omega_{it}) = EV(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 1) - EV(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 0). \qquad (7)
$$

This will depend crucially on the effect of R&D on firm's future productivity. A major goal of the empirical model is to quantify ΔEV, the long-run payoff to investing in R&D.

Overall, this model endogenizes the firm's choice to undertake R&D investments as a comparison between the net expected future profits of the two alternatives. The optimal choice of whether or not to undertake R&D depends on whether the gains in expected future profits from conducting R&D outweigh the relevant startup or fixed cost. In the empirical model developed in section 4 we will estimate the distribution of sunk and fixed costs faced by the firm and calculate the long-run payoff to R&D.

3 Data

The data we use to analyze the role of R&D in the productivity evolution of German firms 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.[2] These are representative for firms with German headquarters 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.[3] The MIP contributes to the Community Innovation Surveys (CIS).[4]

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 percent.

For the empirical analysis we 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, we focus on 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, we exclude observations with extremely high capital−labor ratios, revenue−labor ratios and material cost −labor ratios to guarantee a minimum level of comparability.[5] Also, observations with very low levels of material cost, capital stock and revenue are excluded from the analysis.[6]

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. 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 we will aggregate the empirical analysis for the manufacturing sector as a whole but will allow some parameters to differ by industry. Table 1 shows the set of industry definition we use.

For the estimation we use data on firm revenue, capital stock, innovation expenditures,

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

[3] See **?**, **?**, **?**

[4] 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)

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

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

product and process innovation, and spending on labor and materials. 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 before 1999 we impute these missing years using linear interpolation.[7]

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 we 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.[8] 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 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. Analogously, a process innovation is a new or significantly improved production technology or a new method of supplying and delivering a product. The main 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. 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.

When a firm reports 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 the sample, $70-80$ percent of all firms introducing process innovations also introduce a new product and we cannot distinguish these two explanations. To account for this in the empirical analysis, we define process innovations to be ones that have a cost reduction effect. Across the sample, 64 percent of all process innovations have a cost reduction effect.

Table 2 reports the share of innovators and the share of successful product and process innovations reported by the firms in each industry. An innovator is defined 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 in our sample are innovators. Only one third of all firms do not have any innovations and about 60 percent of all firms report to have introduced

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

[8] 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.

a new or improved product. Cost reducing process innovations are less common in the sample as only 31 percent 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 percent of all firms in MPO instruments introduced a product innovation and 33 percent introduced a cost reduction process.

Table 3 reports the transition rates for firms' R&D activities between periods. Several patterns are present. There is a substantial pattern of movement of firms into and out of R&D activities over time. The rate at which firms begin conducting R&D varies from 17.6 to 33.7 percent depending on the firm's size class and this rate increases with the size class. The rate at which they leave varies from a high of 21.75 percent for the smallest size class to 6.77 percent for the largest firms. The transition patterns in the data are important for estimating the sunk and fixed costs of conducting R&D.

4 Empirical Model

4.1 Productivity Evolution

In this section we describe how we estimate the relationship between R&D and innovations and innovation and productivity. The first relationship $Pr(d_{it+1}, z_{it+1}|rd_{it})$ is very simple. Given that we observe data on the discrete process and product innovations of the firm, d_{it+1} and z_{it+1}, and the discrete indicator of the firm's prior investment in R&D, rd_{it}, we construct the innovation rates observed in the data for d and z for each manufacturing industry when $rd_{it} = 0$ and $rd_{it} = 1$.

The estimation strategy for the model of productivity evolution is more complex and combines the firm's revenue function, equation (2), with the process of productivity evolution, equation (4) . The key parameters to be estimated are 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 cannot be estimated consistently because the productivity level ω_{it}, which is not observed, is likely to be correlated with the firm's capital stock k_{it}. The capital stock depends on the prior period investment I_{it-1} which is partly determined by the prior year's productivity ω_{it-1}. The assumption that productivity is serially correlated implies that current productivity and capital stock are correlated which causes the OLS estimates to be biased and inconsistent.

Following the proxy variable approach pioneered by **?**, which makes use of the firm's observable choice variables to control for unobserved productivity, we use the firm's observed expenditure on materials as suggested by **?** 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. The firm's choice of variable inputs is a function of the firm's state variables k_{it} and ω_{it}. Thus, the econometrician can infer information about productivity from observing the expenditure on materials or other variable inputs. Focusing on the choice of material spending, the firm's demand for its intermediate input can be written as follows:

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

where f_t is assumed to be strictly monotone in ω_{it} for a given k_{it}. Inverting the function f_t yields an equation for firm productivity

$$\omega_{it} = f_t^{-1}(k_{it}, m_{it}). \tag{8}$$

Substituting the expression for ω_{it} from equation (8) into the revenue equation we have:

$$\begin{aligned} r_{it} &= \underbrace{(1+\eta)\big(\beta_0 + \ln \frac{\eta}{1+\eta}\big)}_{\gamma_0} \\ &\quad + \underbrace{(1+\eta)\beta_w w_t + \ln \Phi_t}_{\sum \gamma_t D_t} \\ &\quad +(1+\eta)\big[\beta_k k_{it} - \underbrace{f_t^{-1}(k_{it}, m_{it})}_{\omega_{it}}\big] \\ &\quad + u_{it}, \end{aligned} \tag{9}$$

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. Given that the form of f_t^{-1} is unknown, it is not possible to separately identify the coefficients of f_t^{-1} from the parameter β_k in this equation. We can combine all the terms related to capital and productivity and define a function $h(k_{it}, m_{it})$ as:

$$h(k_{it}, m_{it}) = (1+\eta)[\beta_k k_{it} - f^{-1}(k_{it}, m_{it})].$$

The revenue equation can then be written as

$$r_{it} = \gamma_0 + \sum \gamma_t D_t + h(k_{it}, m_{it}) + u_{it}. \tag{10}$$

By approximating the function $h(k_{it}, m_{it})$ in a flexible way a revenue equation can be estimated. We assume that the function h can be approximated as a cubic function of its arguments:

$$\begin{aligned} h(k_{it}, m_{it}) &= \lambda_1 k_{it} + \lambda_2 k_{it}^2 + \lambda_3 k_{it}^3 \\ &\quad + \lambda_7 m_{it} + \lambda_8 m_{it}^2 + \lambda_9 m_{it}^3 \\ &\quad + \lambda_{10} k_{it} m_{it} + \lambda_{11} k_{it}^2 m_{it} + \lambda_{12} k_{it} m_{it}^2. \end{aligned}$$

This allows us to estimate the coefficients γ_0, γ_t, and $\lambda_1 ... \lambda_{12}$ using OLS on equation (10) and then obtain the fitted value $\widehat{h_{it}}$ which is an estimate of the joint effect of productivity, and capital on the firm's sales.

Using the estimated $\widehat{h_{it}}$ we can next recover the structural parameters η, β_k and the parameters of the productivity process $\alpha_0, ..., \alpha_6$. Since $\widehat{h_{it}}$ is the estimate for $(1+\eta)\big(\beta_k k_{it} - \omega_{it}\big)$, one can write

$$\omega_{it} = -\frac{1}{1+\eta} h_{it} + \beta_k k_{it}. \tag{11}$$

Substituting this into the equation for productivity evolution (4) and solving for $\widehat{h_{it}}$ yields

$$\begin{aligned}\widehat{h_{it}} &= \beta_k^* k_{it} - \alpha_0^* + \alpha_1(\widehat{h_{it-1}} - \beta_k^* k_{it-1}) \\ &\quad -\alpha_2^*(\widehat{h_{it-1}} - \beta_k^* k_{it-1})^2 \\ &\quad +\alpha_3^*(\widehat{h_{it-1}} - \beta_k^* k_{it-1})^3 \\ &\quad -\alpha_4^* z_{it-1} - \alpha_5^* d_{it-1} - \alpha_6^* d_{it-1} z_{it-1} - \varepsilon_{it}^* \end{aligned} \tag{12}$$

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 $\hat{\alpha_0}, .., \hat{\alpha_6}, \hat{\beta_k}$ of the structural parameters of the revenue function and productivity process. The estimate $\hat{\beta_k}$ is 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 $\widehat{h_{it}}, \hat{\beta_k}$ and $\hat{\eta}$ are needed in order to recover ω_{it} . The first and second stage of the estimation yielded $\widehat{h_{it}}$, and $\hat{\beta_k}$. In order to estimate the demand elasticity η, we follow ARX and estimate a simple markup equation which links the firm's total variable cost and revenue:

$$TVC_{it} = q_{it}\exp(c_{it}) = (1 + \frac{1}{\eta})\exp(r_{it}) + \upsilon_{it}, \tag{13}$$

where TVC_{it} is the total variable cost of firm i in period t. We construct it as the sum of the firm's expenditures on materials and labor. ARX show that if the firm's marginal cost is constant for all output levels, the total variable cost is the product of output and marginal cost.

Given estimates $\widehat{h_{it}}, \hat{\beta_k}$ and $\hat{\eta}$, the firm's productivity can be estimated from equation (11). The parameters $\hat{\alpha_0}, .., \hat{\alpha_6}$ also provide the information needed to construct the transition matrix for productivity $Pr(\omega_{it+1}|\omega_{it}, d_{it+1}, z_{it+1})$ which is needed to construct the firm's value function.

4.2 Value Function and R&D Choice

The firm bases its R&D investment decision on the investment benefit and its realized costs γ^f and γ^s. These costs depends on the firm R&D participation in previous period. The firm's R&D investment decision is a trade off between the marginal benefit of the investment activity and its cost. Hence, the observed investment behavior provides information about the cost distribution. We estimate the parameters of the cost distribution using the firms' discrete choices on R&D.

For the estimation we utilize information on firm capital stock, R&D activity, firm innovation success, and productivity. Firm productivity has been constructed in the previous stage.

In order to solve for the firm's optimal R&D investment decision the value function equation (6) has to be known. It will be approximated using value function iteration. We discretize the state space and compute $V(.)$ at discrete (k, ω) grid points for given R&D history. In the implementation we calculate $V(.)$ at 100 productivity and 100 capital grid points. Depending on the firm's R&D choice, we then interpolate between the grid points (ω_g, k_g) using a cubic spline to impute the firm value at observed data points $V(\omega_{it}, k_{it}, rd_{it-1})$.

The objective function in the dynamic estimation is the likelihood function for the observed pattern of discrete R&D choices. Recall equation (6). The net payoff for investing in R&D is

$$\beta E\big[V(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 1)\big] - \gamma_{it}^f rd_{it-1} - \gamma_{it}^s (1 - rd_{it-1}),$$

whereas the payoff for not investing is

$$\beta E\big[V(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 0)\big].$$

On the one hand, if the firm invests in R&D it increases its chances for a successful innovation, which will boost its future 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:

$$\begin{aligned}
Pr\big(rd_{it} = 1|s_{it}\big) &= Pr\Bigg(rd_{it-1}\gamma_{it}^{f} + (1 - rd_{it-1})\gamma_{it}^{s} \\
&\leq \beta\big\{E\big[V(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 1)\big] \\
&\quad -E\big[V(s_{it+1}|\omega_{it}, k_{it}, rd_{it} = 0)\big]\big\}\Bigg) \\
&= Pr\Bigg(rd_{it-1}\gamma_{it}^{f} + (1 - rd_{it-1})\gamma_{it}^{s} \leq \Delta EV(\omega_{it}, k_{it})\Bigg)
\end{aligned}$$

The fixed costs and sunk startup 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 the realized firm costs are:

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

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, we also allow the cost distributions to differ across firms depending on firm size. Large firms might have synergy effects from other inputs, e.g. assets and technology, they can access. 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 $s_{it} = (\omega_{it}, k_{it}, rd_{it-1})$ are independent, and that the costs are *iid* across all periods and all firms, the likelihood function can be expressed as

$$L(\gamma|rd, s) = \prod_{i}^{N}\prod_{t}^{T_i} P(rd_{it}|s_{it}; \gamma), \tag{14}$$

where $\gamma = (\gamma^F, \gamma^S)$. The vectors rd and s 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 their productivity or capital stock does not provide the firm with extra knowledge about the cost it will have to incur for a particular project. Furthermore, we also require the cost draws to be *iid*, 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. We 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.

5 Empirical Results

We will aggregate the 12 industry groupings in table 1 into two broad categories based on the ratio of industry level R&D expenditures to sales. Five of these, chemicals, machinery, electronics, instruments (MPO), and vehicles have an industry R&D sales ratio greater than 5 percent and are classified as high-tech industries. The remaining seven industries, food, textiles, paper, plastic, non-metalic minerals, basic metals, and furniture, are classified as low-tech industries. We estimate the complete model separately for the high-tech and low-tech groups and also allow for additional industry specific coefficients in many parts of the model.

In subsection 5.1 we report the results for the productivity model comparing cases both with and without the innovation outcome data. Section 5.2 reports estimates of the fixed cost and entry cost parameters and section 5.3 summarizes firm values and gains from R&D investment.

5.1 Estimates of the Productivity Process

Table 4 reports the estimates for the demand elasticities for each industry in the high-tech and low-tech sectors using equation (13). For instance, the estimate of $\widehat{(1+1/\eta)}$ in the chemicals industry is .708. This implies a demand elasticity $\widehat{\eta}$ of -3.42 which is reported in the second column. The demand elasticity varies substantially across industries ranging from -2.99 in the food industry to -7.94 in vehicles. The demand elasticity is important in converting productivity into profit as seen in equations (2) and (3). As $|\eta|$ increases a given productivity level translates into a lower level of profits. Thus industries with high $|\eta|$ will have less incentive to invest in R&D in order to improve profitability, other things held fixed.

Table 5 and 6 report the estimates of the productivity evolution process using equation (12). The productivity process is allowed to differ between firms in the high-tech and low-tech sectors. The first table includes the discrete indicators for process and product innovations, d and z, in the productivity evolution equation while the second table replaces them with the discrete R&D indicator, rd.

Using the innovation data, the cost elasticity of capital in the high-tech sector is estimated to be $\hat{\beta}_k = -0.056$ and in the low-tech sector is -0.060. Negative values of β_k imply firms with a higher capital stock have lower production costs because they use less variable inputs. The effect of past productivity on the current productivity level is measured by the coefficients of ω_{-1}, its squared and cubic terms. Past productivity is highly persistent. There is a non-linear relationship between current and lagged productivity for high-tech firms as seen by the statistically significant effect of ω_{-1}^2 and ω_{-1}^3. These higher-order terms are not significant in the low-tech industries implying a linear relationship between the current and lagged productivity level.

The positive coefficient estimates for z and d indicate that firms adopting innovations have, on average, higher future productivity levels compared to those that do not have any kind of innovation. The marginal effects of adopting a new process or developing a new product is nearly identical for high-tech firms. A new process innovation z contributes on average 1.4 percent to productivity gain and a new product contributes 1.3 percent. It is interesting to note that there is no additional effect from having both a product and process innovation. The coefficient on the interaction term $d * z$ is -.014 which just outweighs the direct effect of the second innovation. Basically, firms with either or both types of innovation have 1.4 percent higher future productivity.

The difference in the effect of the two types of innovations is more pronounced in the low-tech sector. Firms that introduced a new product have on average 0.2 percent higher future productivity while a new process innovation raises productivity by 1.0 percent. The reason for the stronger effect of process innovation might be that process innovations have mainly cost reducing effects. Alternatively product innovation can widen the range of products supplied by the firm, or replace old products. This can have an offsetting effect on firm revenue such that they can cause the overall magnitude of the effect to be smaller. If a firm realizes both product and process innovation the estimated interaction term which is -0.002 partially offsets the marginal effect of the second innovation type. The three coefficients together imply that firms with a process innovation have 1 percent higher future productivity regardless of whether or not they also have a product innovation and firms with just a product innovation have very little effect on future productivity.

Table 6 reports estimates of the productivity process using only the discrete indicator of R&D investment. We observe very similar estimates for the capital and productivity parameters. On average in the high-tech sector, the productivity gain for firms that invest in R&D is estimated to be 1.5 percent, almost identical to the estimate of 1.3 to 1.4 percent for the effect of product and/or process innovation in 5. In the low-tech sector, the impact of R&D on productivity is 0.8 percent, slightly lower than the 1.0 percent for firms that report process innovations but greater than the negligible effect of product innovation in these sectors. If R&D always produced a product or process innovation and the only way to get an innovation was by investing in R&D there should be a strong similarity between the two sets of results but, in general, the two variables contain different information. If R&D produces gains such as marketing or organizational innovations that improve firm performance then this contribution is missed in a model which only allows product and process innovations to impact productivity. On the other hand, if R&D expenditure only occasionally produces product and process innovations, but the innovations are the drivers of productivity improvement, then there should be a weaker link between R&D and productivity than there is between innovation and productivity.[9]

There is a strong but not perfect relationship between R&D investment and innovation outcomes. An additional set of estimates needed to construct the firm's value function is the

[9] We conducted a sensitivity check on the specification of the productivity process by allowing separate industry intercepts in the productivity evolution equation (4). They were never statistically significant and this is not surprising given the strong effect of past productivity.

relationship between R&D investment and product and process innovations, $Pr(d_{it+1}, z_{it+1}|rd_{it})$ in equation (5). We construct nonparametric estimates of these probabilities using the observed rates of innovation for d and z conditioning on the firms' R&D history. The estimates are reported for each industry in Table 7.

The second through the fifth columns show the probability of realizing each combination of product and process innovation given that the firm does not engage in R&D. Columns (6) through (9) report these probability for firms that do conduct R&D. Focusing first on the firms that did not engage in R&D, we observe that they have a high probability of not realizing an innovation. Column 2 shows that these firms have approximately a 78 percent chance of not having either a product or process innovation in the next year. This estimate is very similar across industries varying only from a low of .716 in electronics to .822 in basic metals. It does not even differ significantly between the low tech and high tech industry groups. What is probably more important to note is that approximately 22 percent of the firms still realize innovations even if their R&D spending is zero and the most common outcome among the three combinations is that they have both product and process innovations ($d = 1, z = 1$). This indicates that prior period R&D is neither necessary or sufficient for the firm to report realizing an innovation. Our model recognizes this possibility in the link between R&D and future productivity.

Examining the firms that do invest in R&D we observe that they are much less likely to report no innovation. Column (6) shows that between 9.0 and 27.1 percent of the firms that conduct R&D report no innovations in the next year. This probability does vary between the industry groupings, being significantly higher for the low-tech industry group. This can reflect a combination of lower R&D effort in these industries, even when the firm reports conducting R&D, and fewer technological opportunities for innovations. Among the three possible combinations of innovation outcomes, the most common is that the firm reports both a product and process innovation ($d = 1, z = 1$) with between 44.8 and 63.8 percent of the R&D firms reporting both innovations. Among these firms the success rate for introducing a new product innovation is in general much higher than the rate for a new process. The two exceptions are the paper and basic metals industry where the two probabilities are similar. Both of these industries are ones where large scale production is important and this could give a strong incentive for firms to invest to improve their production efficiency.

The literature on the return to R&D has often constructed the elasticity of output, usually measured as firm revenue, with respect to R&D expenditure (see **?**, table 2 for a review of these estimates). Using the results reported above we can construct an analogous measure, the proportional gain in firm revenue resulting if the firm moves from not investing in R&D ($rd_t = 0$) to investing in R&D ($rd_t = 1$). Combining the estimates in Table 7, the parameter estimates in Table 5, and the demand elasticities we can trace through how a discrete shift in firm R&D affects the probability of an innovation, future productivity, and future revenue.

Table 8 provides estimates of this shift on the log of future revenue for each industry (column 1). We contrast this with estimates of the same elasticity constructed from the model (Table 6) which does not use the innovation data and instead maps discrete R&D directly to future productivity and revenue (column 2). For the five high-tech industries, the elasticity of revenue with respect to R&D varies from .021 to .058 when we use the innovation outcome data. When we use just the R&D indicator the elasticity varies from .046 to .104 and in each industry is larger than the corresponding estimate in the first column. The model with the innovation variables recognizes that firms that conduct R&D may not have an innovation and firms without R&D may have an innovation. Together these narrow the range of impact of R&D on future productivity and contribute to a reduction in the revenue elasticity. The same pattern is seen for the seven industries in the low-tech group but here the elasticities are lower than what we observe for the high tech industries. Using the innovation outcomes the elasticities range from .008 to .026 and with just the R&D indicator they range from .016 to .037. These estimates are generally similar to the elasticities reported in **?** for production function based models.

5.2 Estimates of the Cost of and R&D Program

The final set of parameters we estimate is the sunk and fixed costs of establishing and maintaining an R&D program. These are estimated using the dynamic programming model developed in section 4.2. To complete the dynamic model we assume that firms draw their fixed costs from an exponential distribution with mean γ_k^F and their sunk costs from an exponential distribution with mean γ_k^S, where $k \in \{s, m, l\}$ indicating firm sizes small, medium and large. We estimate the parameters $(\gamma_s^F, \gamma_m^F, \gamma_l^F, \gamma_s^S, \gamma_m^S, \gamma_l^S)$ by maximizing the likelihood function in equation (14)[10].

Tables 9 and 10 report the estimated means of the distribution of sunk (γ^S) and fixed costs (γ^F) for the models when using innovation outcomes and R&D expenditures, respectively. In each table, the first three rows report the results for the high-tech group distinguishing between firm sizes. The average costs for firms in the low-tech group are reported in rows 5 to 7.

A number of general patterns stand out across all specifications. First, fixed costs are smaller than sunk costs for all firm sizes in both models. 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.

In table 9 we estimate an average start-up cost for doing R&D for small firms of EUR 3.98 mln, more than six times higher than the fixed cost of EUR 0.65 mln. In the high-tech sector, the ratio of sunk costs to fixed costs is approximately 6 in both models for small, medium, and large firms. In the low-tech sector the ratio is between 4 and 5. The difference between fixed and sunk cost is crucial in explaining the pattern of R&D choice in the data. If the fixed cost is low relative to the sunk cost, continuing to do R&D is more attractive because it allows firms to avoid paying the sunk cost if it starts up again 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. A high sunk cost prevents firms from starting to do R&D which can contribute to the high persistence for non-R&D firms seen in table 3. On the other hand, reducing the gap between fixed and sunk cost would imply more switching between starting and quitting R&D. The magnitude of the cost estimates reflects the level of gain to R&D for given participation pattern in the data. The magnitude of the cost estimates in the low-tech sector ranges between half and one-third of the estimates in high-tech. Therefore according to the estimates low-tech industries have lower gain from research than high-tech industries.

[10] We estimated the cost parameters for small, medium and large firms. Firms with capital stock up to 33rd percentile of its industry are considered to be small. Large firms have capital stock exceeding the 66th percentile.

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 some low profit ones do engage. 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 both fixed and sunk costs increase with the firm's capital stock. This is driven by the fact that we observe a positive correlation in the data between capital stock and productivity level so that the payoff to conducting R&D is increasing with the capital stock. The model explains why not all large firms conduct R&D despite having high benefits by assigning them higher cost levels. 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 parameter that adjusts in the model, the cost of performing R&D, needs to increase.

5.3 Expected Benefits and Costs of R&D

Using these parameter estimates and equation (7), we can construct the expected marginal benefit to a firm from engaging in R&D. This measures the difference in the present value of expected future profits that accrue to the firm if it engages in R&D in a year versus does not engage in R&D. This benefit depends on the industry-level profit function, demand elasticity and innovation probabilities as well as the firm-level state variables, productivity and the capital stock, and will vary across firms in an industry as a result. It captures the randomness that arises in the relationship between R&D investment and a product or process innovation, captured in the model by $Pr\big(d', z'|rd\big)$, as well as the randomness between innovation outcomes and productivity, captured in the model by $dF(\omega'|\omega, d', z')$.

Tables 11 and 12 provides estimates of the expected payoff to the firm of conducting R&D $\Delta EV(\omega, k)$ using innovation outcomes at five different percentiles (5, 25, 50, 75, and 95) of the productivity distribution within each industry.[11] The first table covers the five high-tech

[11] The values in each cell are averaged over the discrete capital stocks

industries and the second table reports the values for the seven low-tech industries. The first five rows of Table 11 show that, as the productivity of a firm in the chemical industry increases from a low of -.299 to a high of 2.053, the $\Delta EV(\omega, k)$ rises from 0.965 million to 87.131 million euros. This reflects the impact of the higher productivity resulting from R&D on the firm's expected future profits. Every industry shows the benefit of R&D increasing with firm productivity but the level of the benefit differs across industries. Comparing the group of industries in Tables 11 and 12 we see that the marginal benefits of R&D are much larger in the high-tech industry group. At the upper end, in the electronics industry the high productivity firms have benefits from an R&D program averaging over 111 million euros. In contrast, the benefits of an R&D program in the low-tech industries is always less than four million euros and generally only exceeds one million euros for the highest productivity firms. This illustrates that the payoff to R&D is very specific to an industry reflecting, at least partly, differences in profit functions. If we rank industries by the expected marginal benefit at the median of the productivity distribution, the vehicle, chemical, and electronics industries have the highest expected payoffs to R&D, followed by machinery and instruments. Plastics and furniture have the lowest expected benefits.

In the model developed above, firm i will choose to do R&D if $\Delta EV(\omega_i, k_i) > \gamma_i$ where γ_i is the firm's cost draw from the relevant sunk or fixed cost distribution and $\Delta EV(\omega_i, k_i)$ is the marginal benefit of conducting R&D for a firm with (ω_i, k_i) = (productivity, capital) combination. The realized costs of firms that choose to do R&D will be described by a truncated exponential distribution where $\Delta EV(\omega_i, k_i)$ is the truncation point. For example, from the first row of Table 11, the benefit of R&D for the low productivity firms in the chemical industry is 0.965 million euros, so only firms that have R&D costs less than this value will conduct R&D. An alternative way to say this is that only firms that expect to be able to realize the benefit of R&D for less than an expenditure of $\Delta EV(\omega_i, k_i)$ euros will choose to conduct R&D. Because firms with the same observable state (ω_i, k_i) will spend different amounts on R&D in order to realize $\Delta EV(\omega_i, k_i)$ they have different net benefits from their R&D investment. In a later section of this paper we will report the distribution of net benefits to R&D across firms.

The third and fourth columns of Table 11 report the mean fixed and sunk costs among the firms in the five high-tech industries that choose to conduct R&D ($rd_t = 1$). For example, in the first row of the table, the low productivity firms in the chemical industry that conduct R&D will have an average R&D expenditure of 0.437 million euros if they had previously conducted R&D, and so were paying a fixed cost to maintain it, or 0.475 million euros if they were paying a sunk startup cost to begin an R&D program. The mean truncated expenditure on R&D rises with the level of productivity because the marginal benefit of R&D rises with productivity and thus high productivity firms are willing, on average, to invest more money in R&D programs than low productivity firms. The R&D expenditure differs across industries, reflecting differences in the distribution of productivity, capital stocks and profit function parameters but the differences are fairly small for fixed costs ($rd_{t-1} = 1$) and larger for sunk costs ($rd_{t-1} = 0$). The fixed costs for the median firm are almost always less than 3 million euros while the expenditure by the median firm starting up an R&D program can range as high as 12 million euros in the case of the vehicle industry.

Examining the patterns for the low-tech industry group in Table 12, we observe the same increase with productivity and higher costs for firms that were inexperienced ($rd_{t-1} = 0$). Not surprisingly, the R&D expenditures are lower for firms in these industries reflecting the fact that the industries were distinguished based on the R&D-sales ratio for the industry. The lower costs in these industries reflects the lower R&D expenditures in these industries and, even though the data on R&D expenditures by the firms was not used to estimate the model, this is not surprising.

The final two columns of Table 11 and 12 report the probability a firm conducts R&D based on its productivity, industry, and prior experience. Several patterns are evident. First, for the high tech industries the probability of maintaining an R&D program is generally above .90 for firms that have prior experience. This reflects the high benefits of conducting R&D seen in column (2). The probability of conducting R&D for firms that do not have prior experience is substantially lower reflecting the fact that the startup costs are significantly larger than the maintenance fixed costs. The gap between the probabilities in the last two columns is a measure of the effect of the higher startup costs, because the expected benefit of conducting R&D is the same for firms in both groups. Focusing on the R&D probabilities in the low-tech industries in Table 12 we observe the same pattern of higher probabilities with higher productivity, reflecting the higher marginal benefits seen in column 2, and with experience, reflecting the lower fixed costs relative to sunk startup costs. The primary difference between these industries and the ones in Table 12 are that the magnitudes of the estimates are substantially lower for the low tech industries. This reflects the fact that the payoff to R&D is substantially lower in these industries and that, while the cost distributions are lower (as seen in Table 9) they are not enough to compensate for the lower benefits accruing to R&D.

As discussed in the model section, an alternative framework ignores the information on the patterns of innovation and instead models productivity improvements as following directly from R&D expenditures. As seen in the comparison of Tables 5 and 6, this has little effect on the estimated pattern of productivity evolution. Prior R&D (Table 6) has a similar effect on current productivity as either a process or product innovation (Table 5). However, the inclusion of product and process innovation as an intermediate step between R&D investment and productivity outcomes does recognize an extra element of randomness in the process of endogenous productivity improvement. As seen in Table 2 there is, on average across industries, a probability of .22 that a firm with no R&D program will realize an innovation and a probability of .88 that a firm with R&D investment will not realize an innovation. This recognizes two realistic factors: first, that firms without R&D investments may still realize product or process innovations through luck so they are not completely shut out of the productivity improvements that can flow from innovations and, second, that even firms with R&D investments are not guaranteed to have innovations and so may actually enjoy smaller productivity gains than their competitors who do not invest. What this does is have the effect of lowering the benefit from doing R&D, because of the extra randomness due to the innovation process, but, at the same time, raising the benefit of not doing R&D, because the firm can still get innovations through luck. Together these will lower the expected benefit of R&D, ΔEV.

To compare what happens in the estimated models, Tables 13 and 14 replicate the calculations reported in Table 11 and 12 but now using the model in which discrete R&D directly affects productivity improvement. To simplify the comparison we only report the values for the median productivity level in each industry. The most significant contrast this produces is that the expected benefit of R&D, ΔEV, is larger, as expected, for all industries when we model R&D as having a direct impact on productivity. For example, in the chemical industry, $\Delta EV(\omega = .849) = 20.506$ million euros in Table 11 and 24.742 million euros in the model that ignores innovation patterns (Table 13). This increase in the estimated benefit of R&D also translates into higher estimated fixed and sunk costs as seen in Tables 9 and 10. Together the higher benefit and higher cost of R&D will have an ambiguous effect on the probability of conducting R&D and we see that in the last two columns of Tables 13 and 14. Some industries have a higher probability of conducting R&D while other have a lower probability.

5.4 The Return to R&D

The patterns of benefits and costs reported in Tables 11- 14 are comparisons of predicted values from the estimated model across different values of the state variables and emphasize the role of productivity and past R&D experience. In this section we turn to the actual data and calculate the expected benefit of R&D, $\Delta EV(\omega_i, k_i)$, for each observation given its observed productivity and capital stock. Using the estimated fixed or sunk cost distribution we can then draw a value for the firm's R&D expenditure and calculate an expected net benefit if the firm makes this investment. Let γ_j be the fixed or sunk cost draw that the firm gets then the net benefit to the firm is $\Delta EV(\omega_i, k_i) - \gamma_j$ and the expected net benefit, prior to observing the cost draw, is $\Delta EV(\omega_i, k_i) - E(\gamma_j)$ where $E(\gamma_j)$ is the mean of the distribution of γ_j. We will normalize this by the value of the firm $V(s_i)$ given by equation (6) and define the summary measure:

$$NBV(s_i) = \frac{\Delta EV(\omega_i, k_i) - E(\gamma_j)}{V(s_i)}$$

This normalized expected net benefit of R&D will vary across firms and time depending on the state.

Firms will only choose to do R&D when $\Delta EV(\omega_i, k_i) - \gamma_j > 0$, and we can also describe the net benefit of R&D for all firms that choose to do R&D using the truncated mean of the distribution of γ. This gives rise to a measure of the expected net benefit of R&D when firms choose to do R&D:

$$TNBV(s_i) = \frac{\Delta EV(\omega_i, k_i) - E(\gamma_j | \Delta EV(\omega_i, k_i) - \gamma_j > 0)}{V(s_i)}$$

Both NBV and $TNBV$ summarize the long-run net payoff to R&D and they capture the fact that current R&D expenditure affects the future path of productivity and R&D choices. We can also calculate the short-run benefit of R&D as the increment to next period profits if the firm chooses R&D in the current period versus if it does not. We will express this as a ratio to the long-run benefit :

$$SNB(\omega_i, k_i) = (\pi(\omega_i^{'}, k_i^{'} | rd = 1) - \pi(\omega_i^{'}, k_i^{\prime} | rd = 0))/\Delta EV(\omega_i, k_i)$$

This measure recognizes that R&D spending will affect the state variables and profit in the next period.

In Table 15 we present the 25th, 50th, and 75th percentiles of the distributions of $NBV(\omega_i, k_i)$, and $TNBV(\omega_i, k_i)$ across observations in the data. We divide the firms by industry and by their prior R&D status because this affects whether they pay a fixed cost (continuing firm columns) to continue their R&D program or a sunk cost (startup firm columns) to begin one. In the case of the chemical industry the percentiles of the distribution of NBV for continuing R&D firms are .021, .031, and .037 indicating that the expected net benefit of R&D varies in a fairly narrow range relative to firm value. The median firm will have an expected long-run net payoff to an R&D program of 3.1 percent of firm value. When we truncate the payoffs to recognize that firms will choose not to do R&D in high cost situations, the distribution of net payoffs, $TNBV$, is not greatly affected. The truncated percentiles are .023, .033, and .037 indicating just a slight rightward shift in the lower tail of the distribution. This occurs because there is little difference between the truncated and untruncated means of cost for continuing firms.

The picture is different when we look at firms that were not previously conducting R&D. The distribution of NBV has percentiles equal to -.045, .001, and .016. In particular, a large percentage of the firms would have negative expected net benefits because the startup costs they would pay exceed $\Delta EV(\omega_i, k_i)$ and so would not choose to invest in R&D. The median firm would choose to do R&D but would have an expected payoff equal to one-tenth of one percent of the value of the firm. When we focus on the expected returns of the firms that would actual choose to invest we observe that the percentiles vary from .019 to .027. The distribution is less than the corresponding distribution for continuing firms because of the higher startup costs these firms have to pay.

Across the other 4 high-tech industries a similar pattern is observed. There are fairly small differences in the distribution of NBV and $TNBV$ for the continuing firms because the fixed costs they would pay tend to be small relative to the benefits and so most firms would choose to invest. There are more substantial differences in the two distributions for starting firms because many of these firms would not choose to do R&D. Even the median firm has a negative expected return in the machinery and instruments industries.

In the low tech industry group we see a very different picture reflecting much lower returns to R&D investment. For all of the industries the median of the distribution of NBV is negative and the 75th percentile is at its highest .001. The percentiles of the distribution of $TNBV$ lie between .001 and .003, indicating very small net benefits of R&D relative to firm value even for the firms that find it profitable to invest in R&D. The pattern is even stronger for the starting firms. The 75th percentile of NBV is always negative and the 75th percentile of $TNBV$ never exceeds .003.

The final summary statistic we report in Table 16 is the distribution of $SNB(\omega_i, k_i)$ across observations. In the case of the high-tech industry group, the table shows that the one period payoff from R&D is always small relative to the long-run payoff. For the median firm, the next period profit accounts for only between 0.9 and 2.7 percent of the total long-run payoff to R&D. Even at the 75th percentile the short run payoff is never more than 6.6 percent of the long-run payoff. In the low-tech sector, we observe that the short-run profit increase resulting from R&D investment accounts for a larger fraction of the total long-term benefit. At the 75th percentile, this fraction varies from 8.1 to 21.1 percent but the short run benefit is still small relative to the long-term payoff. This is not surprising because the one period change in profits captures only the immediate effect of R&D on productivity (a 1.4 percent increase as seen in Table 6) and firm revenue. It does not capture any of the payoff resulting from a permanently higher level of productivity in future periods or the increase this will have on the probability the firm continues to invest in R&D in the future. For at least 75 percent of the firms in these industries, these long run impacts account for over 79 percent, and often over 90 percent, of the payoff to current period R&D. This emphasizes the need to examine R&D choice and calculate the benefits to R&D in a dynamic framework.

6 Conclusions

This paper estimates a dynamic structural model of firm R&D investment using panel data from the German manufacturing sector. The four key components of the model are: the firm's profit function which relates productivity to profit, the evolution of firm productivity which depends upon product and process innovations realized by the firm, the probability of an innovation given that the firm invests in R&D, and the fixed and sunk costs of investing in R&D. After estimating these components we can construct the expected long-run payoff to the firm of investing in R&D. This payoff is the difference between the expected discounted sum of future profits if the firm undertakes R&D versus if it does not. It captures the fact that R&D investment raises the probability that the firm will be on a higher productivity path in the future. This long-run payoff varies across firms depending on their industry, productivity, and capital stock.

The data we use is derived from the Mannheim Innovation Panel which is part of the Community Innovation Survey. A novel aspect of the data is that it contains information on the the product and process innovations realized by the firm. Rather than modeling a direct link between R&D and productivity, this data allows us to separate the link into a component linking R&D investment to innovation rates in the firm and quantify the effect of innovation on productivity. We find that for a group of high-tech industries that includes chemicals, machinery and vehicles both linkages, R&D to innovation and innovation to productivity, are larger than for a group of low-tech industries such as food, textiles and furniture. These components combine to give a proportional difference in firm revenue between firms that undertake R&D investments and those that do not that varies from a high of 0.058 in vehicle, and .036 in machinery to a low of .008 to .010 in food, textiles, and paper.

We find that the benefit of conducting R&D increases with the firm's productivity and capital stock implying that large, productive firms will have a greater incentive to invest in R&D. This investment, in turn, will substantially increase the probability that they realize process and product innovations that will raise future productivity. Comparing the firm with the median productivity level in different industries we see that the expected benefit of investing in R&D varies from a high of 43 million euros in the vehicle industry and 20 million euros in the chemical industry to a low of about 350 thousand euros in the plastic, furniture and non-metallic mineral products industries. This difference in the benefit of R&D will lead to very different rates of R&D investment across industries.

Combining estimates of the expected benefit of R&D with the cost of R&D we summarize the distribution of net benefits across firms in each industry. This net benefit differs substantially between firms that have already invested in R&D and those that are just starting R&D investments because the startup costs of beginning an R&D program are substantially higher than the costs of maintaining a program. Expressed as a proportion of long-run firm value, this net benefit for the median experienced firm in an industry varies from .024 to .032 across five high-tech industries but varies from -.046 to .001 for firms with no previous R&D experience. The negative value implies that the median firm would not find it profitable to invest in R&D. We can also examine the distribution of net benefits for firms that choose to invest in R&D because it is profitable. This distribution indicates a net benefit of .020 to .024 for startup firms in the high tech industries. These net benefits are substantially smaller, around .002 for the median firm, in the group of low-tech industries. Finally, we compare the expected short-run (one period) benefit that the firm gets from R&D with the expected long-run benefit and find that the long-run benefit is between five and 30 times larger depending on the industry.

The model we develop can also be used to conduct counterfactual experiment and we are currently in the process of investigating 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 and we can simulate different subsidy policies by changing the cost of R&D. 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." We can simulate different degrees of competition by varying the demand elasticity faced by the firms in our data and examining what this does to their incentive to invest in R&D.

Industries	NACE Rev.1	Description
Food	15, 16	Manufacture of food products, beverages and tobacco
Textiles	17, 18, 19	Manufacture of textile, textile products, leather and leather products
Paper	20, 21, 22	Manufacture of wood, wood products, pulp, paper, paper products, publishing and printing
Chemicals	23, 24	Manufacture of coke, refined petroleum products, nuclear fuel, chemicals, chemical products and man-made fibres
Plastic	25	Manufacture of rubber and plastic products
Mineral	26	Manufacture of non-metallic mineral products (glass, ceramic, bricks, cement, etc.)
Metals	27, 28	Manufacture of basic metals and fabricated metal products
Machinery	29	Manufacture of machinery and equipment n.e.c.
Electronics	30, 31, 32	Manufacture of electrical and optical equipment (office machinery, computers, electrical machinery, radio, television and communication equipment)
MPO	33	Manufacture of medical, precision an optical instruments, watches and clocks
Vehicles	34, 35	Manufacture of transport equipment
Furniture	36, 37	Manufacturing n.e.c (furniture, jewelry, musical instruments, sport goods, toys, recycling of metal waste, non-metal waste and scrap)

Table 1: Industry classification

Table 2: Innovation shares by industries - pooled over firms and years

Industries	Innovator	Product Innovation	Process Innovation
Food	0.5425	0.4732	0.2580
Textiles	0.5135	0.4643	0.2027
Paper	0.5174	0.3919	0.2453
Chemicals	0.7866	0.7081	0.3633
Plastic	0.6422	0.5915	0.3266
Mineral	0.5887	0.5257	0.3113
Metals	0.5938	0.4785	0.3164
Machinery	0.7702	0.7147	0.3609
Electronics	0.8053	0.7449	0.3977
MPO	0.8176	0.7706	0.3300
Vehicles	0.7309	0.6504	0.3955
Furniture	0.6060	0.5283	0.2697
Average	0.6596	0.5868	0.3148

Table 3: 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

Industry	$1+1/\eta$	N	Industry	$1+1/\eta$	N
Chemicals	0.708 (0.005)***	1361	Food	0.666 (0.008)***	1162
Machinery	0.803 (0.002)***	2644	Text./Leather	0.697 (0.003)***	990
Electronics	0.753 (0.005)***	1413	Paper	0.697 (0.003)***	1669
MPO	0.763 (0.006)***	1429	Plastic	0.798 (0.003)***	1396
Vehicles	0.874 (0.003)***	911	Mineral	0.675 (0.005)***	959
			Metals	0.822 (0.001)***	2773
			Furniture	0.765 (0.004)***	872

Table 4: Demand elasticity estimates (standard error)

	High-Tech Group	Low-Tech Group
k	-0.056 (0.002)***	-0.060 (0.002)***
ω_{-1}	0.961 (0.008)***	0.978 (0.005)***
ω_{-1}^2	0.030 (0.012)**	0.006 (0.008)
ω_{-1}^3	-0.008 (0.005)*	0.001 (0.004)
d	0.013 (0.005)***	0.002 (0.004)
z	0.014 (0.008)*	0.010 (0.005)*
$d*z$	-0.014 (0.009)	-0.002 (0.007)
const	0.010 (0.003)***	0.010 (0.002)***
SE(ε)	0.1010	0.1088
N	3337	4298

Table 5: Productivity evolution using innovation outcomes

	High-Tech Group	Low-Tech Group
ln k	-0.056 (0.002)***	-0.061 (0.002)***
(ω_{-1})	0.960 (0.008)***	0.978 (0.005)***
$(\omega_{-1})^2$	0.031 (0.012)**	0.006 (0.008)
$(\omega_{-1})^3$	-0.008 (0.005)*	0.001 (0.004)
rd	0.015 (0.004)***	0.008 (0.003)***
const	0.008 (0.003)**	0.010 (0.002)***
SE(ε)	0.101	0.109
N	3337	4298

Table 6: Productivity evolution using R&D choice

	$\mathbf{rd_{-1} = 0}$				$\mathbf{rd_{-1} = 1}$			
	$d=0, z=0$	$d=1, z=0$	$d=0, z=1$	$d=1, z=1$	$d=0, z=0$	$d=1, z=0$	$d=0, z=1$	$d=1, z=1$
High-tech Group								
Chemicals	0.779	0.048	0.048	0.124	0.112	0.214	0.045	0.629
Machinery	0.786	0.055	0.039	0.120	0.100	0.249	0.035	0.616
Electronics	0.716	0.092	0.028	0.163	0.100	0.262	0.029	0.609
MPO	0.779	0.044	0.035	0.142	0.090	0.317	0.010	0.582
Vehicles	0.783	0.058	0.050	0.108	0.139	0.172	0.052	0.638
Low-tech Group								
Food	0.767	0.047	0.043	0.142	0.243	0.170	0.047	0.540
Textiles	0.791	0.072	0.038	0.099	0.251	0.247	0.054	0.448
Paper	0.782	0.038	0.082	0.097	0.271	0.136	0.141	0.453
Plastic	0.786	0.079	0.020	0.115	0.148	0.171	0.045	0.636
Mineral	0.776	0.068	0.021	0.135	0.188	0.156	0.043	0.613
Metals	0.822	0.023	0.041	0.113	0.171	0.123	0.115	0.590
Furniture	0.775	0.085	0.035	0.106	0.170	0.258	0.066	0.507
Average	0.779	0.059	0.040	0.122	0.165	0.206	0.057	0.572

Table 7: Estimated probability of innovation

	with IO	without IO
High-Tech Group		
Chemicals	0.021	0.036
Machinery	0.036	0.061
Electronics	0.024	0.046
MPO	0.029	0.048
Vehicles	0.058	0.104
Low-Tech Group		
Food	0.008	0.016
Textiles	0.009	0.018
Paper	0.010	0.018
Plastic	0.022	0.032
Mineral	0.011	0.017
Metals	0.026	0.037
Furniture	0.015	0.037

Table 8: Elasticity of Revenue w.r.t R&D with and without innovation outcome indicators

		Fixed Cost	Startup Cost
High-Tech Group	Small Firms	0.655 (0.025)	3.980 (0.216)
	Medium Firms	1.933 (0.055)	12.215 (1.367)
	Large Firms	4.544 (0.154)	26.840 (1.009)
LLF	-1617.9		
Low-Tech Group	Small Firms	0.368 (0.018)	1.540 (0.300)
	Medium Firms	0.907 (0.037)	3.986 (0.372)
	Large Firms	1.675 (0.016)	8.262 (0.066)
LLF	-2670.2		

Table 9: Dynamic parameter estimates using innovation outcomes

		Fixed Cost	Startup Cost
High-Tech Group	Small Firms	1.149 (0.032)	7.129 (0.865)
	Medium Firms	3.340 (0.108)	19.612 (1.019)
	Large Firms	7.900 (0.407)	44.724 (1.423)
LLF	-1676.5		
Low-Tech Group	Small Firms	0.591 (0.003)	2.502 (0.031)
	Medium Firms	1.422 (0.063)	6.442 (0.18)
	Large Firms	2.732 (0.000)	13.200 (0.001)
LLF	-2706.7		

Table 10: Dynamic parameter estimates using R&D choice

Industry	ω	ΔEV	$E(\gamma\|\gamma < \beta(\Delta EV))$		$Pr(rd_t = 1)$	
			$rd_{t-1} = 1$	$rd_{t-1} = 0$	$rd_{t-1} = 1$	$rd_{t-1} = 0$
Chemicals	-0.299	0.965	0.437	0.475	0.378	0.088
	0.316	6.328	1.949	2.921	0.877	0.377
	0.849	20.506	2.921	8.136	0.998	0.731
	1.251	37.870	2.971	12.282	1.000	0.896
	2.053	87.131	2.972	16.702	1.000	0.990
Machinery	-0.227	1.685	0.709	0.819	0.587	0.154
	0.072	5.456	1.654	2.520	0.907	0.382
	0.301	9.572	2.112	4.191	0.980	0.548
	0.563	15.289	2.311	6.196	0.997	0.705
	0.886	19.616	2.347	7.476	0.999	0.785
Electronics	-0.296	3.367	1.273	1.610	0.724	0.231
	0.048	9.028	2.319	4.055	0.946	0.466
	0.332	16.882	2.766	6.950	0.994	0.669
	0.765	37.807	2.868	12.119	1.000	0.901
	1.445	111.846	2.869	16.709	1.000	0.997
MPO	-0.458	0.396	0.187	0.196	0.267	0.053
	-0.078	1.620	0.640	0.780	0.648	0.193
	0.204	3.499	1.135	1.630	0.849	0.343
	0.565	7.653	1.754	3.351	0.972	0.553
	0.944	10.773	1.948	4.500	0.992	0.660
Vehicles	-0.071	14.532	2.568	5.919	0.896	0.426
	0.090	28.995	2.959	9.607	0.983	0.632
	0.242	43.650	3.060	11.995	0.997	0.756
	0.391	56.940	3.081	13.433	0.999	0.824
	0.581	61.831	3.084	13.831	1.000	0.842

Table 11: Benefits and costs of conducting R&D for high-tech group (using innovation outcomes)

Industry	ω	ΔEV	$E(\gamma \vert \gamma < \beta(\Delta EV))$		$Pr(rd_t = 1)$	
			$rd_{t-1} = 1$	$rd_{t-1} = 0$	$rd_{t-1} = 1$	$rd_{t-1} = 0$
Food	-0.600	0.047	0.023	0.024	0.058	0.014
	-0.065	0.120	0.059	0.060	0.141	0.035
	0.590	0.409	0.187	0.200	0.399	0.115
	1.296	1.884	0.631	0.864	0.857	0.404
	2.031	4.009	0.913	1.687	0.978	0.632
Textiles	-0.569	0.040	0.020	0.020	0.058	0.014
	-0.190	0.096	0.047	0.048	0.132	0.032
	0.532	0.414	0.187	0.202	0.451	0.136
	0.957	1.074	0.407	0.506	0.759	0.307
	1.360	2.198	0.641	0.977	0.929	0.504
Paper	-0.554	0.045	0.022	0.022	0.059	0.014
	-0.108	0.122	0.059	0.061	0.152	0.038
	0.492	0.414	0.188	0.203	0.424	0.124
	0.983	1.250	0.467	0.587	0.778	0.320
	1.492	2.826	0.758	1.236	0.954	0.551
Plastic	-0.266	0.060	0.030	0.030	0.070	0.016
	-0.010	0.202	0.097	0.100	0.216	0.054
	0.204	0.358	0.166	0.176	0.349	0.094
	0.496	0.624	0.273	0.303	0.520	0.158
	0.761	0.594	0.262	0.289	0.503	0.151
Mineral	-0.653	0.048	0.024	0.024	0.059	0.014
	-0.129	0.111	0.054	0.055	0.132	0.032
	0.457	0.324	0.151	0.160	0.337	0.092
	0.906	0.824	0.343	0.396	0.624	0.217
	1.706	2.304	0.709	1.038	0.908	0.465
Metals	-0.250	0.130	0.063	0.065	0.115	0.027
	-0.007	0.476	0.216	0.233	0.352	0.094
	0.178	0.872	0.363	0.420	0.535	0.163
	0.397	1.504	0.547	0.707	0.719	0.262
	0.684	2.061	0.668	0.946	0.817	0.339
Furniture	-0.369	0.054	0.027	0.027	0.071	0.017
	-0.035	0.175	0.084	0.087	0.210	0.053
	0.277	0.356	0.164	0.175	0.377	0.106
	0.576	0.628	0.272	0.304	0.558	0.178
	0.954	0.631	0.273	0.306	0.559	0.179

Table 12: Benefits and costs of conducting R&D for low-tech group (using innovation outcomes

Industry	ω	ΔEV	$E(\gamma \mid \gamma < \beta(\Delta EV))$		$Pr(rd_t = 1)$	
			$rd_{t-1} = 1$	$rd_{t-1} = 0$	$rd_{t-1} = 1$	$rd_{t-1} = 0$
Chemicals	0.849	24.742	4.796	10.449	0.986	0.623
Machinery	0.300	10.578	3.034	4.829	0.925	0.418
Electronics	0.332	20.021	4.400	8.702	0.973	0.551
MPO	0.204	3.428	1.290	1.637	0.702	0.227
Vehicles	0.242	55.041	5.181	17.207	0.986	0.663

Table 13: Benefits and costs of conducting R&D for high-tech group (without innovation outcomes)

Industry	ω	ΔEV	$E(\gamma \mid \gamma < \beta(\Delta EV))$		$Pr(rd_t = 1)$	
			$rd_{t-1} = 1$	$rd_{t-1} = 0$	$rd_{t-1} = 1$	$rd_{t-1} = 0$
Food	0.590	2.127	0.788	0.996	0.761	0.319
Textiles	0.411	1.636	0.622	0.770	0.742	0.298
Paper	0.492	2.159	0.784	1.007	0.797	0.340
Plastic	0.204	1.627	0.649	0.776	0.685	0.242
Mineral	0.456	1.598	0.636	0.760	0.685	0.258
Metals	0.178	4.122	1.212	1.853	0.874	0.401
Furniture	0.278	1.630	0.641	0.774	0.721	0.271

Table 14: Benefits and costs of conducting R&D for low-tech group (without innovation outcomes

Industry		Continuing firms			Startup firms		
		25	50	75	25	50	75
High-Tech Group							
Chemicals	NBV	0.021	0.032	0.037	-0.045	0.001	0.016
	TNBV	0.023	0.033	0.037	0.019	0.024	0.027
Machinery	NBV	0.024	0.031	0.035	-0.042	-0.013	0.002
	TNBV	0.026	0.032	0.035	0.020	0.023	0.026
Electronics	NBV	0.027	0.032	0.037	-0.014	0.006	0.020
	TNBV	0.027	0.032	0.037	0.020	0.024	0.027
MPO	NBV	0.008	0.024	0.029	-0.095	-0.046	-0.019
	TNBV	0.018	0.026	0.030	0.015	0.020	0.023
Vehicles	NBV	0.020	0.028	0.031	-0.015	0.003	0.011
	TNBV	0.020	0.029	0.031	0.015	0.020	0.022
Low-Tech Group							
Food	NBV	-0.018	-0.007	0.001	-0.087	-0.044	-0.012
	TNBV	0.002	0.002	0.003	0.001	0.002	0.003
Textiles	NBV	-0.014	-0.006	0.001	-0.074	-0.040	-0.015
	TNBV	0.002	0.002	0.003	0.002	0.002	0.003
Paper	NBV	-0.014	-0.005	0.000	-0.074	-0.039	-0.019
	TNBV	0.002	0.002	0.003	0.002	0.002	0.003
Plastic	NBV	-0.011	-0.006	-0.003	-0.061	-0.041	-0.029
	TNBV	0.002	0.002	0.002	0.002	0.002	0.002
Mineral	NBV	-0.016	-0.008	-0.001	-0.081	-0.048	-0.022
	TNBV	0.002	0.002	0.003	0.002	0.002	0.002
Metals	NBV	-0.006	-0.002	0.000	-0.042	-0.029	-0.018
	TNBV	0.002	0.003	0.003	0.002	0.003	0.003
Furniture	NBV	-0.011	-0.006	-0.003	-0.063	-0.044	-0.028
	TNBV	0.002	0.002	0.002	0.002	0.002	0.002

Table 15: Long-run return to R&D given R&D history

	25	50	75
High-Tech Group			
Chemicals	0.015	0.017	0.023
Machinery	0.012	0.018	0.033
Electronics	0.007	0.009	0.014
MPO	0.015	0.020	0.030
Vehicles	0.014	0.027	0.066
Low-Tech Group			
Food	0.075	0.083	0.089
Textiles	0.059	0.069	0.081
Paper	0.065	0.077	0.087
Plastic	0.087	0.110	0.211
Mineral	0.087	0.103	0.113
Metals	0.063	0.079	0.129
Furniture	0.070	0.096	0.150

Table 16: Ratio short-run to long-run return on R&D