Dynamic R&D Choice and the Impact of the Firm's Financial Strength*

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August 2015

Abstract

This article estimates a dynamic model of firm R&D choice using data on German firms in high-tech manufacturing industries. It incorporates a measure of the firm's financial strength, derived from its credit rating, which is shown to lead to substantial differences in estimates of the costs and expected long-run benefits from R&D investment. Firms with high credit ratings have a higher probability of generating innovations from their R&D investment, and the innovations have a larger impact on productivity and profits. Averaging across all firms, the long run benefit of investing in R&D is 6.0 percent of firm value. It ranges from 10.8 percent for firms in a strong financial position to 2.0 percent for firms in a weaker financial position.

1 Introduction

The paper by Crépon, Duguet, and Mairesse (1998) (hereafter, CDM) provides an organizing framework linking firm data on research, innovation, and productivity. In the past 15 years it has become the basis for a large empirical literature analyzing the relationship between R&D investment, innovation outcomes such as new product introductions and patents, and productivity. The empirical studies built on this framework have established that firm R&D investment increases innovation outputs and these in turn are positively correlated with firm

*We are grateful to Eric Bartelsman, Bronwyn Hall, Jordi Jaumandreu, Hans Lööf, Florin Maican, Jacques Mairesse, Pierre Mohnen, Matilda Orth, and Hongsong Zhang for helpful comments and discussions. We thank the Center for European Economic Research (ZEW) for providing data access and research support. Contact information: Peters (b.peters@zew.de), Roberts (mroberts@psu.edu), Vuong (vananh.vuong@ewi.uni-koeln.de)

productivity. Firm productivity growth is not an exogenous nor purely random process but is rather systematically affected by the firm's R&D investment decision.

The process of a firm's endogenous investment in R&D is characterized by costs that are largely sunk, up-front expenditures and a payoff that is both uncertain and delayed in time. A recent paper by Peters, Roberts, Vuong, and Fryges (2013) (hereafter, PRVF) develops a dynamic, structural model of the firm's R&D investment decision which explicitly incorporates these characteristics and also the research-innovation-productivity linkage identified in the CDM literature.[1] In PRVF the firm's demand for R&D depends on its current cost and the expected payoff to the investment, where the latter depends on how R&D affects innovation outcomes, how these outcomes affect the firm's future productivity and profits, and how long-lived these effects are. Their analysis provides estimates of the expected benefits of R&D, that are defined as the increment to long-run firm value resulting from the R&D investment.

The PRVF model assumes that firms will choose to invest in R&D whenever the expected discounted stream of benefits is greater than the incurred cost. One further factor that can play a crucial role in the firm's investment decision is its financial ability. This includes the ability to finance the R&D outlays and to successfully develop and market the innovations. Financing of R&D can be done with a combination of current cash flow, retained past earnings, and borrowing. Firms that are in poor financial condition are not likely have access to these resources and may thus be constrained in their R&D decision. In this article we extend the PRVF model to recognize that firms differ in their ability to finance R&D investment. We construct a summary measure of a firm's financial strength, based on their credit rating, reflecting their ability to fund R&D investments. This measure depends on, among other things, information on the firm's sales, capital stocks, order history, growth, and history of bill payments.

The model is estimated using firm-level data for five high-tech industries in the German manufacturing sector. The results indicate significant differences in both the cost and the long-run expected benefits of R&D across firms with different levels of financial strength. Firms in the highest financial strength category have the largest productivity improvements following an

[1] Roberts and Vuong (2013) provide a nontechnical overview of the PRVF framework.

innovation. A firm that reports a new product innovation has a productivity increase of 8.4 percent on average, while firms with new process innovation have a 9.1 percent increase, and firms with both have a increase of 11.1 percent. In contrast, firms in the lowest credit-rating category have productivity increases of 0.4, 0.5, and 3.7 percent, respectively. Firms with higher credit ratings also have a higher probability of realizing a product or process innovation. Both of these factors lead to higher expected benefits from R&D investment for firms with higher credit ratings. These firms are also found to have higher costs of R&D investment but overall the higher expected payoff leads them to have higher rates of R&D investment. On average, R&D investment is estimated to increase the long-run value of the firm by 6.0 percent but this average varies across industries and with the firm's financial strength. Across industries, the mean varies from 4.7 percent in the electronics industry to 6.9 percent in chemicals. Across financial strength categories, the mean varies from 10.8 percent for firms in the highest category to 2.0 for firms in the lowest category.

The next section incorporates the role of financial strength into the PRVF model of dynamic R&D choice. The third section summarizes the data sample, which is drawn from the Mannheim Innovation Panel. The fourth and fifth sections present the empirical model and discuss the results.

2 A Model of R&D Investment and Financial Strength

Following Griliches (1979), a large empirical literature has estimated the impact of R&D on firm productivity, output, or profits using the knowledge production function framework. R&D creates a stock of knowledge or expertise within the firm that enters into the firm's production function as an additional input along with physical capital, labor, and materials. This framework was extended in several ways by Crépon, Duguet, and Mairesse (1998). In their analysis they distinguished between the inputs and outputs of the innovation process, included measures of innovation outputs such as patents and the share of firm sales devoted to new products in the empirical model, and utilized econometric methods that recognized the endogeneity of the R&D choice. Their basic setup incorporated three equations characterizing the stages of the innovation process: (i) R&D equation describing the determinants of research inputs, (ii) innovation function linking research inputs and innovation outputs, (iii) productivity equation linking innovations to productivity. This framework has been the basis for many empirical studies quantifying the impact of R&D on firm performance.[2]

One limitation of the existing CDM literature is that the equation describing the firm's choice of R&D in stage 1 has not been specified in a way that takes advantage of all the determinants of the firm's R&D choice. The dynamic model developed by PRVF takes advantage of the CDM structure to specify the firm's R&D investment decision as the solution to a dynamic optimization problem in which the firm weighs the costs incurred against the expected long-run benefit resulting from the investment. In their model, a firm's investment in R&D alters its probability of realizing product or process innovations. The realized innovations shift the distribution of firm's future productivity and profits. Productivity is allowed to be persistent over time, so that improvements in one period can lead to a stream of higher future profits. In this dynamic framework, the benefit of R&D investment is its impact on the firm's discounted sum of expected future profits. This impact depends on how R&D affects productivity and output in the subsequent period, which is the focus of the knowledge production function literature, but also on how the change in productivity impacts the discounted sum of future firm profits, including its effect on the firm's incentives to invest in R&D in the future.

A large empirical literature has quantified the role of financial resources in the funding of R&D. Studies have found that the firm's ability to generate funds internally is particularly important for financing innovation projects and show a positive correlation between R&D investment and changes in cash flow (Fazzari, Hubbard and Petersen (1988), Leland and Pyle (1977), Hall (1992), Bhagat and Welch (1995), Himmelberg and Petersen (1994), Bond, Harhoff and Van Reenen (2005), and (Bougheas, Görg and Strobl (2003)).[3] In addition, firms may be reluctant to use other forms of financing including issuing equity (Carpenter and Peterson (2002)) or using debt (Hall (2002)). Even when firms access credit markets, the fact that much of R&D investment is sunk and cannot be liquidated makes the investment a poor asset to use as security for the loans and increases the cost of external capital. The higher cost for

[2] See Hall, Mairesse, and Mohnen (2010) and Hall and Mohnen (2013) for recent reviews of the literature.

[3] A positive relationship between cash flow and R&D investment may simply result because both variables reflect common confounding factors, such as growing market demand, and the correlation is not sufficient to indicate financial constraints, (Kaplan and Zingales (1997)).

external capital is likely to have a larger effct on the R&D decision of firms with low financial endowment (Alderson and Betker (1996)). This paper utilizes an indicator of the firm's overall financial strength to account for the heterogeneity in financial ability and investigates how this affects the firm's incentives to invest in R&D.

In the next subsections we summarize the structural components of the PRVF model and discuss how the financial strength of the firm may be incorporated into the framework.

2.1 Productivity and the Firm's Short-Run Profits

We begin with a definition of productivity and its link to a firm's short-run profits. Following PRVF, we specify (i) a log linear short-run marginal cost function, which depends on variable input prices, capital stock, and a firm-specific cost shock, and (ii) a CES demand function that depends on the firm's output price and a firm-specific demand shifter. Assuming the firm operates in a monopolistically competitive market, the firm's revenue function is derived as:

$$r_{it} = (1+\eta)\ln\left(\frac{\eta}{1+\eta}\right) + \ln\,\Phi_t + (1+\eta)\,(\beta_0 + \beta_k k_{it} - \omega_{it}) + \upsilon_{it} \tag{1}$$

The log of the firm's revenue is r_{it}, the elasticity of demand is η, which is negative and assumed to be constant for all firms in the industry, Φ_t is a time effect that captures all market-level variables that are constant across firms including the level of aggregate demand for the product and variable input prices, k_{it} is the log of the firm's capital stock, ω_{it} is firm productivity, and υ_{it} is a transitory shock. The firm is assumed to know its revenue productivity ω_{it} which is unobserved to the researcher. Given the form of the firm's optimal pricing rule, which implies a constant markup over marginal cost, there is a simple relationship between the firm's short-run profits and revenue:

$$\pi_{it} = \pi(\omega_{it}) = -\frac{1}{\eta}\exp(r_{it}). \tag{2}$$

2.2 R&D Investment and Endogenous Productivity

In this article we treat R&D investment as a discrete variable rd_{it} equal to one if the firm spends money on innovation activities such as R&D. The outcomes of the innovation process are discrete variables z_{it+1} and d_{it+1} equal to 1 if the firm realizes a process or product innovation, respectively, in year $t+1$ and 0 otherwise. The variable f_i is a measure of the firm's financial strength, which we will treat as a firm characteristic that does not vary over time. Specifically, we will classify firms into one of three financial strength categories based on their credit rating.

The second component of our model specifies a stochastic innovation process that is summarized by a cumulative joint distribution of innovations conditional on the firm's prior R&D and financial strength $F(d_{it+1}, z_{it+1}|rd_{it}, f_i)$. This corresponds to the second equation in the CDM framework. This specification recognizes that firms may direct their R&D activity in different ways including improving their production processes and developing new or improved products. It also recognizes that the overall financial strength of the company can affect how many resources it is able to devote to starting and maintaining innovation projects and thus the likelihood that they generate innovations in the future.

The third component of the model specifies the innovation-productivity linkage, which corresponds to the third equation in the CDM model. Productivity is a stochastic variable that is affected by the firm's past productivity, current realizations of product and process innovations, and its financial strength, distributed according to the cdf $G(\omega_{it+1}|\omega_{it}, d_{it+1}, z_{it+1}, f_i)$.[4] Specifically, we assume that firm productivity evolves as:

$$\begin{aligned} \omega_{it+1} &= g(\omega_{it}, d_{it+1}, z_{it+1,} f_i) + \varepsilon_{it+1} \qquad (3) \\ &= \alpha_0 + \alpha_1\omega_{it} + \alpha_2\omega_{it}^2 + \alpha_3\omega_{it}^3 + \alpha_4 d_{it+1}f_i + \alpha_5 z_{it+1}f_i + \alpha_6 d_{it+1}z_{it+1}f_i + \varepsilon_{it+1} \end{aligned}$$

The function $g(\cdot)$ is the conditional expectation of future productivity and ε is a zero mean stochastic shock. We parameterize the productivity evolution process as a cubic function of lagged productivity and a full set of interactions between product innovations, process innovations, and the dummy variables defining the firm's financial strength. In this specification, the variable $z_{it+1}f_i$ represents the set of interactions between the innovation outcome z_{it+1} and the three dummy variables defining the firm's financial strength, so α_4 is a vector of three coefficients. A similar definition is used for $d_{it+1}f_i$ and $z_{it+1}d_{it+1}f_i$. This specification captures several important aspects of productivity evolution. First, the firm's productivity is assumed to persist over time, with the degree of persistence captured by α_1, α_2, and α_3. This intertemporal

[4] Olley and Pakes (1996) specified productivity evolution as an exogenous stochastic process $G(\omega_{it+1}|\omega_{it})$. Aw, Roberts and Xu (2011) and Doraszelski and Jaumandreu (2013) endogenize the productivity evolution process by letting it depend on the firm's choice of R&D, $G(\omega_{it+1}|\omega_{it}, rd_{it})$ and PRVF reformulated it in terms of the firm's innovation outcomes $G(\omega_{it+1}|\omega_{it}, d_{it+1}, z_{it+1})$.

persistence is an important feature of firm-level data on productivity. Second, innovations are allowed to systematically shift the mean of the distribution of future firm productivity, and the magnitude of this payoff from each combination of product and process innovation depends on whether the firm is high, medium, or low financial strength. Implementing innovations is likely to require investments in capital, worker training, hiring, or additional costs that noninnovating firms do not incur and the financial strength of the firm can affect the level of resources available for implementation. Third, the specification recognizes that productivity change is affected by stochastic shocks ε_{it} that reflect the inherent randomness in the productivity process, and implies that the economic value of an innovation has a stochastic component. We assume the productivity shocks ε_{it+1} are *iid* across time and firms and are drawn from a normal distribution with zero mean and variance σ_{ε}^2. Due to the persistence in productivity, the shocks in any period are incorporated into future productivity levels rather than being transitory.

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

The firm's decision to invest in R&D results from a comparison of the benefits of investing, which depend on expected future improvements in productivity and profits, and the cost needed to generate these improvements. Innovation costs may vary across firms depending on their financial strength and R&D experience. Firms with different degrees of access to financial resources, either through their own retained earnings or through borrowing in capital markets, face different costs for capital. It is also likely that a firm that performs R&D continuously over time requires a lower expenditure to generate an innovation than a firm that is just beginning to invest in R&D because it can rely on past expertise or synergy effects from previous projects. To capture this heterogeneity in firm's innovation cost, we assume that a firm's cost is a random draw from an exponential distribution,

$$C_{it}\tilde{}\ \exp(\gamma^f(rd_{it-1} * f_i) + \gamma^s(1 - rd_{it-1}) * f_i)). \tag{4}$$

with mean $\gamma^f(rd_{it-1} * f_i)$ if the firm engaged in R&D in the previous year and $\gamma^s(1 - rd_{it-1}) * f_i)$ otherwise. The mean of the cost distribution depends on the full set of interaction terms between the firm's discrete R&D choice in the previous year rd_{it-1} and its financial strength

f_i, where $\gamma = (\gamma^f, \gamma^s)$ is a parameter vector to be estimated. The coefficient vector γ captures differences in fixed costs of maintaining ongoing R&D operations and start-up costs of beginning to invest in R&D for firms in each of the financial categories.

We assume that, at the start of period t, the firm observes its current productivity level ω_{it}, knows its short-run profit function, the processes for innovation F, and productivity evolution G. The firm's state variables $s_{it} = (\omega_{it}, rd_{it-1})$ evolve endogenously as the firm makes its decision to conduct R&D, $rd_{it} \in \{0, 1\}$.[5] Given its state vector and discount factor β, the firm's value function $V(s_{it})$, before it observes the fixed and sunk cost, can be written as:

$$\begin{aligned} V(s_{it}) &= \pi(\omega_{it}) + \\ &\int_{C_{it}} \max_{rd \in \{0,1\}} \left(\beta E_t V(s_{it+1}|\omega_{it}, rd_{it} = 1) - C_{it}; \beta E_t V(s_{it+1}|\omega_{it}, rd_{it} = 0)\right) dC, \end{aligned} \tag{5}$$

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

$$E_t V(s_{it+1}|\omega_{it}, rd_{it}) = \sum_{(d,z)} \int_{\omega} V(s_{it+1}) dG(\omega_{it+1}|\omega_{it}, d_{it+1}, z_{it+1}) dF(d_{it+1}, z_{it+1}|rd_{it}). \tag{6}$$

Equation (5) shows that the firm chooses to invest in R&D if the discounted expected future profits from investing, $\beta EV(s_{it+1}|\omega_{it}, rd_{it} = 1)$, net of the relevant fixed or sunk cost, are greater than the expected future profits from not investing, $\beta EV(s_{it+1}|\omega_{it}, rd_{it} = 0)$. What differentiates these two expected future profits 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:

$$\Delta EV(\omega_{it}) \equiv \beta E_t V(s_{it+1}|\omega_{it}, rd_{it} = 1) - \beta E_t V(s_{it+1}|\omega_{it}, rd_{it} = 0). \tag{7}$$

The firm chooses to invest in R&D if $\Delta EV(\omega_{it}) \geq C_{it}$. This condition is used in the empirical model to explain the firm's observed R&D choice.

[5] Each firm is characterized by three exogenous variables, its capital stock k_{it}, which enters the profit function, its financial strength f_i which enters the cost function for innovation and the innovation and productivity evolution processes, and its industry which enters all of the structural components. To simplify the notation, we suppress these exogenous characteristics and explain the dynamic decision to invest in R&D focusing on the endogenous variables in the model ω and rd. In the empirical model we treat the firm's capital stock, financial strength, and industry as defining an exogenous firm type and solve the firm's value function for each firm type.

Overall, in contrast to CDM, this model endogenizes the firm's choice to undertake R&D investments by explicitly characterizing the net expected future profits from the two alternatives. Following the approach developed in PRVF, we estimate the innovation function, productivity evolution process, and distributions of sunk and fixed costs of innovation faced by the firm, and quantify $\Delta EV(\omega_{it})$, the expected long-run payoff to investing in R&D.

3 Data

The data we use is drawn from the Mannheim Innovation Panel (MIP) survey of German firms collected by the Centre for European Economic Research (ZEW). The data covers the period 1993-2008 and follows the form of the Community Innovation Surveys (CIS) that are administered in many OECD countries (see Peters and Rammer (2013) for details on the MIP survey). We estimate the model for a group of high-tech manufacturing industries including (NACE Rev 1.1 codes): chemicals (23, 24), non-electrical machinery (29), electrical machinery (30, 31, 32), instruments (33), and motor vehicles (34,35).

The estimation requires data on firm revenue, variable costs, capital stock, innovation expenditures, product and process innovations, and financial strength. Firm revenue is total sales, total variable cost is the sum of expenditure on labor, materials, and energy, and the firm's short-run profit is the difference between revenue and total variable cost. The firm's value is the discounted sum of the future short-run profits. We restrict the sample to the firms that report all the necessary variables and have at least two consecutive years of data. This gives a total of 1208 firms and 3099 observations.

The financial strength variables are constructed from the firm's credit rating produced by the company Creditreform.[6] The rating is based on the likelihood that the borrower will be able to service their debts fully and on time. It takes into account the credit opinion of experts, the firm's business development strategy, past history of bill payments, growth, sales, capital, age, order history, industry, and legal form of organizaton among other things. We assign each

[6] Creditreform is the largest German credit rating agency. This information has been used as a measure of financial constraints in previous studies by Czarnitzki (2006) and Czarnitzki and Hottenrott (2009). A measure of credit constraints based on the repayment of trade credits has been Aghion, Askenazy, Berman, Cette and Eymard (2012).

firm to one of three categories based on their credit rating. The Creditreform rating is a score bewteen 100 and 600 with 100 being the best rating. We assign firms to the high financial strength category if their rating is 100 to 190. Firms with credit ratings between 191-228 are classified in the medium category and firms with ratings higher than 229 are asigned to the low category.[7]

In our sample, there is substantial persistence over time in a firm's financial strength. Between adjoining years, 95.5 percent of the firms that start in the high-strength category, 91.4 that start in the middle category, and 87.3 percent that start in the low category, remain in the same category in the next year. In addition, 24.2 percent of the firms remain in the high-strength category over the whole period we observe them, 32.0 percent in the medium category and 23.6 percent in the low category. The remaining 20.2 percent of the firms switch at least once. In the dynamic model we will not attempt to model the transition process for this variable, but rather assume that the firm treats its financial strength category as fixed when making the R&D decision.

A feature of the Community Innovation Surveys is that they provide measures of both innovation input and innovation output. Innovation input is measured by the firm's expenditure on a set of activities related to innovation, including R&D spending but also spending on worker training, acquisition of external knowledge and capital, marketing, and design expenditures for producing a new product or introducing a new production process. Innovation output captures the introduction of a new product or a new production process by the firm. The Oslo Manual defines a product innovation as a new or significantly improved product or service. A process innovation refers to new or significant changes in the way products are produced, delivered, or supplied. The main purpose of a process innovation is to reduce production costs or to improve the quality of a product. For instance, the introduction of automation concepts or IT-networking technology in production or logistics are process innovations. The innovation does not have to be new to the market but only to the firm. A firm could report an innovation if it adopted a production technology from a competitor or expanded its product line even if the product was already offered by other firms.

[7] In terms of Standard and Poor's rating system, the high category corresponds to ratings above BBB, the medium category to ratings above BB to BBB, and the low category to ratings BB and below.

Table 1 summarizes the proportion of firms in the sample in each industry that report positive innovation expenditures, successful product innovations, and successful process innovations for each industry and for the three discrete categories of financial strength. The first pattern to observe is that the rate of investment in innovation activities is always highest for the firms in the high financial strength category and declines as we move to the medium and low financial strength categories. For example, in the chemical industry the proportion of firms in the high strength category that invest is 0.787 and this declines to 0.768 and 0.719 with declines in financial strength. This monotonic reduction is present in every industry except the vehicle industry, where the medium category has the lowest investment rate. Averaging across the five industries, the investment rate is 0.864 for the high strength category, 0.772 for the medium, and 0.693 for the low category. This decline in the proportion of firms that invest can reflect either a decline in the expected benefits of innovation-related investments, an increase in the cost of innovation, or both. The structural model developed above is designed to distinguish these explanations.

A second pattern that is observed in Table 1 is that the rate of both new product and new process innovations declines with the financial strength of the firm. Again, the decline is monotonic across financial strength categories except for the vehicle industry. This decline could reflect higher levels of R&D spending by the financially stronger firms, so that they generate higher rates of innovation. A third pattern is that the investment rates in the top part of the table are always greater than the innovation rates for the corresponding category. This reflects the fact that some firms invest in R&D but do not realize any innovations. Finally, the product innovation rate is greater than the process innovation rate. This can reflect the fact that in this group of high-tech industries competition among firms is more strongly related to improving product quality through product innovation rather than reducing cost through process innovations.[8]

[8] PRVF compare innovation rates for these high-tech industries and a group of seven low-tech manufacturing industries that have much lower rates of R&D investment. They find that, while product innovations are still generally more common, the difference in product and process innovation rates are much smaller for the low-tech industries.

Table 1: Rate of R&D Investment and Innovation

	Financial Strength		
R&D Investment Rate	High	Medium	Low
Chemicals	0.787	0.768	0.719
Machinery	0.893	0.750	0.613
Electronics	0.865	0.851	0.780
Instruments	0.935	0.828	0.728
Vehicles	0.845	0.601	0.716
Product Innovation Rate			
Chemicals	0.713	0.684	0.596
Machinery	0.836	0.674	0.553
Electronics	0.837	0.759	0.732
Instruments	0.903	0.790	0.658
Vehicles	0.738	0.538	0.578
Process Innovation Rate			
Chemicals	0.579	0.539	0.506
Machinery	0.675	0.533	0.328
Electronics	0.624	0.598	0.445
Instruments	0.652	0.514	0.430
Vehicles	0.679	0.462	0.471

4 Empirical Model

In this section we briefly outline the key components and steps of the empirical model Details of the estimation procedure are provided in PRVF. Estimation is divided into two steps. In the first step, the profit function, equations (1) and (2), and the process of productivity evolution, equation (3), are jointly estimated using the methodology developed by Doraszelski and Jaumandreu (2013). Material expenditure is used as the control variable for the unobserved productivity level. Following estimation we construct an estimate of productivity for each observation. The data used at this stage are the firm's sales, capital stock, discrete innovation variables, variable input expenditures, and financial strength variables. We estimate the elasticity of demand by regressing the firm's total variable cost on firm sales (Aw, Roberts and Xu (2011)). At this stage we also estimate the innovation process $F(d_{it+1}, z_{it+1} | \ rd_{it}, f_i)$ nonparametrically using data on discrete innovation outcomes, discrete R&D, and the financial strength variables.

In the second step, the parameters of the cost function for R&D are estimated using the firm's discrete choice of R&D. The probability that a firm chooses to invest in R&D is given by the probability that its innovation cost $C_{it}(rd_{it-1}, f_i)$ is less than the expected payoff:

$$Pr\left(rd_{it} = 1 | s_{it}\right) = Pr\left[C_{it}(rd_{it-1}, f_i) \leq \Delta EV(\omega_{it})\right] \tag{8}$$

Using parameter estimates from the first-stage we solve the value function, equation (5), on a grid of values for the state variables and interpolate the payoff to R&D, $\Delta EV(\omega_{it})$, for each data point. These probabilities can then be used to construct the likelihood function for the discrete R&D choices in the data.

5 Empirical Results

5.1 Estimates of the Innovation and Productivity Processes

In this section we report the findings for the first step of the estimation. Table 2 reports estimates of the innovation probabilities conditional on prior year R&D and financial strength $F(d_{it+1}, z_{it+1}|rd_{it}, f_i)$. There are four possible outcomes for the discrete innovation variables. To simplify the results, we report the average across the five industries (the estimation recognizes the differences across the industries). The top half of the table reports the probabilities for firms that report no innovation expenditures in the previous year and the bottom half reports probabilities for firms that have positive investment expenditure. Among the firms that did not invest in R&D, the probability of no innovation is large and rises from 0.738 to 0.807 as the financial strength of the firm declines. Conversely, the probability of having both innovations declines from 0.162 to 0.096. For the firms that report one type of innovation, product innovations are more likely for the high and medium financial groups while process innovations are more likely for the low financial group.[9] Among the firms that invested in R&D in the previous year, the probability of no innovation is significantly lower, varying from 0.087 to 0.147 across groups, while the probability of both innovations is much higher, ranging from 0.676 to 0.506. Firms that invested in R&D report higher product innovation rates than

[9] Much of the reason that firms in the low financial category have a higher probability of reporting product innovations (.052) than the firms with higher financial strength can be traced to a single industry. Firms in the vehicle industry have a probability of 0.143 of reporting a process only innovation if they are in the low financial strength category.

firms without investment, while the probabilities of a process innovations are similar among these groups. Overall, the estimates in the table indicate that the financial strength of the firm is positively correlated with the probability of innovation. Investing firms with higher financial strength might be better able to devote more resources to innovations activities and enhance the innovation success rate. Alternatively, firms that do not invest but have greater financial strength may be better able to exploit opportunities that arise through learning-by-doing or other pathways that do not involve explicit R&D investment.

Table 2: Probability of Innovation Conditional on Past R&D: $\Pr(d_{it+1}, z_{it+1} | \ rd_{it}, f_i)$
(averaged across five industries)

Innovation Outcome	None	Product	Process	Both
	$d = z = 0$	$d = 1,\ z = 0$	$d = 0, z = 1$	$d = 1\ ,\ z = 1$
Financial Strength		$rd_t = 0$		
High	0.738	0.073	0.028	0.162
Medium	0.769	0.058	0.025	0.148
Low	0.807	0.044	0.052	0.096
		$rd_t = 1$		
High	0.087	0.209	0.028	0.676
Medium	0.096	0.243	0.048	0.613
Low	0.147	0.305	0.042	0.506

The expected benefits of R&D investment depend on the revenue/profit function and how the innovations impact their development, equations (1) and (3). Table 3 reports two sets of parameter estimates for two different specifications of productivity evolution. In the first case, productivity evolution does not depend on the firm's financial strength and the estimates of parameters α_4, α_5, and α_6 measure the average impact of product and process innovations on productivity improvement across all firms. The second case interacts dummy variables for the three financial strength categories with the innovation outcomes and allows the three innovation coefficients to vary across the financial categories.

The first row of Table 3 reports the capital coefficient which implies that increases in capital reduce the firm's short-run marginal cost. The next three coefficients summarize the persistence of firm productivity over time and they indicate that productivity is highly persistent. These coefficient estimates are not affected when the financial strength categorical variables are added to the productivity process.[10]

The coefficients on the innovation variables exhibit a very interesting pattern. When the financial controls are not included the coefficients indicate that a new product innovation raises productivity, on average, by 3.7 percent, while a process innovation raises it by 3.5 percent. The coefficients are statistically significant at the .01 and .05 level, respecitively. Firms that report both innovations have an average productivity increase of 6.8 percent, which is basically the sum of the two individual effects, since the interaction coefficient α_6 is small and not statistically significant. When the productivity impact of innovation is disaggregated by the financial strength categories we observe that innovations have a larger effect for firms in the high strength category. For these firms, a product innovation raises average productivity by 8.4 percent, a process innovation raises it by 9.1 percent, and firms with both innovations will have productivity that is 11.1 percent higher. All three of the underlying coefficients are statistically significant. In contrast, for firms in the medium financial strength category the productivity impacts of innovation are more modest. They average 3.9 percent for product innovations, 2.6 percent for process innovations, and 5.4 percent for firms with both innovations, but only the product innovation effect is statistically significant. For the firms in the lowest financial strength category, the productivity effects are small: 0.4, 0.5, and 3.8 percent for product, process, and both innovations, respectively. None of the three coefficients, however, are statistically significant.

Overall, the productivity and thus, profit, impact of an innovation varies substantially across these groups of firms and will impact their expected benefits of R&D investment accordingly. In particular, the small productivity impact of the innovations for firms with low financial strength, gives them little incentive to invest in R&D. It takes financial resources to implement innovations. The path from development of a new product to actual sales and profits may require that the firm invest in legal, marketing, design, and testing processes that require financial resources. Firms in a strong financial position may also be able to invest in a larger number of research projects and thus have a larger number of innovations that they could potentially exploit. Overall, a strong financial position may enable firms to earn higher returns

[10] The demand elasticity estimates for each industry are: chemicals -3.075, machinery -5.078, electronics -3.713, instruments -4.213, and vehicles -4.891.

on their innovations.

Table 3: The Process of Productivity Evolution (standard errors)

Variable	Parameter	No Financial Controls	With Financial Controls
lnk	β_k	-.060 (.003)**	-.061 (.003)**
lagged ω	α_1	.739 (.020)**	.718 (.019)**
lagged ω^2	α_2	.188 (.012)**	.183 (.012)**
lagged ω^3	α_3	-.051 (.004)**	-.048 (.004)**
d	α_4	.037 (.008)**	
z	α_5	.035 (.015)*	
$d * z$	α_6	-.006 (.016)	
$d * f_{high}$	α_4		.084 (.012)**
$z * f_{high}$	α_5		.091 (.027)**
$d * z * f_{high}$	α_6		-.064 (.030)*
$d * f_{medium}$	α_4		.039 (.010)**
$z * f_{medium}$	α_5		.026 (.020)
$d * z * f_{medium}$	α_6		-.011 (.023)
$d * f_{low}$	α_4		.004 (.011)
$z * f_{low}$	α_5		.005 (.027)
$d * z * f_{low}$	α_6		.028 (.030)
intercept	γ_0	1.053 (.179)**	1.071 (.177)**
chemicals		.039 (.037)	.018(.037)
machinery		.021 (.031)	-.010(.031)
electronics		.048 (.035)	.037(.034)
instruments		.070 (.034)*	.042(.034)
observations		3099	3099
R^2		.937	.939

Both models contain time dummies as described in PRVF.
** significant at the .01 level, * significant at the .05 level.

5.2 Estimates of the Cost of Innovation

The cost function that is estimated in the dynamic model can be interpreted as the cost of purchasing a innovation. The economic value of the innovation depends on how it is translated into productivity and profits. The cost parameters estimated from the discrete R&D decision are the ones that rationalize the expected benefits of R&D and the observed rate of R&D investment. Given two groups of firms with the same investment rate, the group with the lower expected benefit from R&D must also have lower costs. Alternatively, if two groups of firms have the same expected benefit, then the group with the higher investment rate must have lower costs. The parameters characterizing the mean of the innovation cost function are reported in Table 4. We allow the estimated cost parameters to differ across industries and financial categories. The second column reports the cost parameters for firms starting new R&D investment and the third column the costs for firms maintaining their R&D program. In each case the startup cost is great than the fixed cost for the same industry or financial category, reflecting the fact that the observed investment rate is lower for firms that do not have previous R&D experience. With respect to the financial strength categories, the cost parameters decline moving from the high to low category. The higher costs for the high strength category reflects the higher expected benefits of R&D for firms in this category. Finally, there are also industry differences in the cost levels that reflect industry variation in the expected benefits and investment rates, the magnitudes, however, are small compared to the differences across financial categories.

Table 4: Innovation Cost Parameters (standard errors)

	Startup Cost	Fixed Cost
High Financial Strength	31.891 (1.751)	5.852 (.197)
Medium Financial Strength	4.075 (.040)	0.381 (.049)
Low Financial Strength	0.168 (.006)	0.039 (.050)
Chemical	8.455 (.030)	0.125 (.048)
Machinery	2.726 (.018)	0.396 (.047)
Electronics	1.484 (.007)	0.121 (.049)
Instruments	0.626 (.309)	0.108 (.064)
Vehicles	1.379 (.079)	1.068 (.061)
log likelihood	-1682.0	

5.3 Expected Benefits and the Return to R&D

We construct the expected benefit of R&D investment, equation (7), as part of the estimation algorithm and it is a function of the firm's productivity, capital stock, financial strength, and industry. Following PRVF we construct a summary measure of the expected net benefit of R&D investment as:

$$NB_{it} = \frac{\Delta EV(\omega_{it}) - E(C_{it})}{V(s_{it})}$$

the expected benefit minus the mean cost for firms in the same industry and financial category, as a fraction of the firm's long-run value. Firms that have a negative value for NB would not invest in R&D if they faced the mean cost. Table 5 summarizes the mean of these variables over all firms and disaggregated by financial strength category.

Table 5: Expected Benefit of R&D Investment

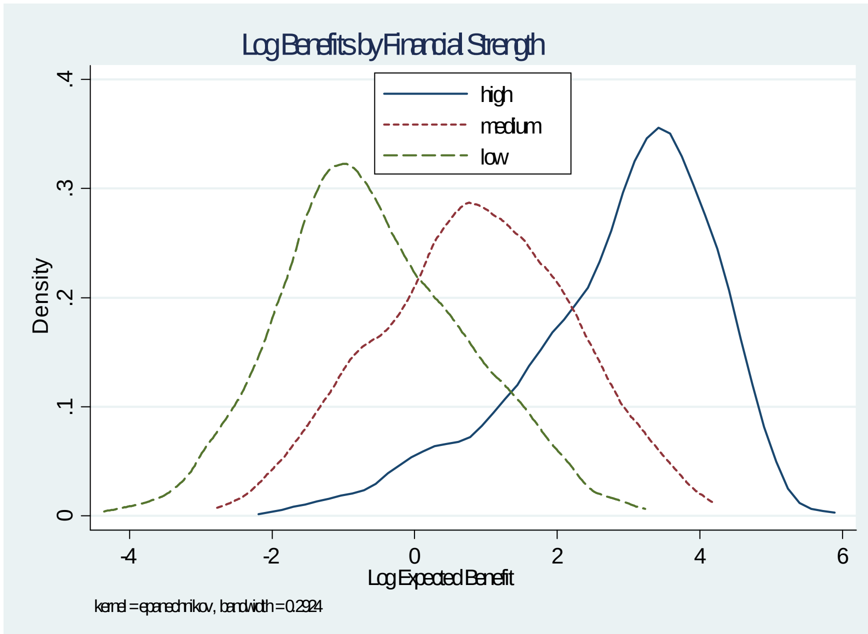
	All Firms	Financial Strength		
		High	Medium	Low
Mean $\Delta EV(\omega)$ *	12.69	32.09	5.42	1.36
Mean $\Delta EV(\omega)/V(s)$	0.060	0.108	0.049	0.020
Mean NB given $NB > 0$	0.053	0.087	0.044	0.017

* (millions of euros)

The first row of the table reports the mean value of expected benefits, which, over all observations in the sample, equals 12.69 million euros. This is the estimated difference in firm value that would result if a firm invested in R&D. The second row gives the proportional impact of R&D on firm value and it averages 6.0 percent across all observations. The third row summarizes the net benefits of R&D after the cost of innovation is factored in. Among the firms with positive net benefits, the average net benefit of R&D amounts to 5.3 percent of firm value.

The remaining columns of the table show how these statistics vary across firms with different financial strength. Moving from the high to low strength category, the mean of $\Delta EV(\omega)$ falls from 32.08 million to 1.36 million. The decline reflects the combined effects of fewer innovations and a smaller productivity impact of innovations for firms with less financial strength. To further illustrate the difference across the financial categories, Figure 1 graphs kernel density estimates of $log(\Delta EV)$ for the three groups and the difference in distributions across the financial categories is clear.

The second row in Table 5 shows that, as a proportion of firm value, firms in the high strength category have an average return of 10.8 percent and this declines to 4.9 and 2.0 percent in the medium and low strength categories, respectively. Finally, firms that find R&D investment profitable also have their expected net benefit declining. Firms in the high strength category that choose to invest have, on average, a firm value that is 8.7 percent higher than comparable firms that do not invest. This differential drops to 4.4 and 1.7 percent in the medium and



low categories. Overall, the benefits of R&D, in both euro magnitude and as a percentage of firm value are sensitive to the firm's financial position. Firms with higher credit ratings have greater benefits and are more likely to find R&D investment profitable.

An advantage of the PRVF model is that it provides a measure of the long-run expected benefit of R&D. However, the empirical model also provides a measure of the short-run payoff to R&D, which we define as the percentage gain in firm revenue resulting from R&D investment. This is a discrete analog to the elasticity of output (usually measured as revenue) with respect to R&D expenditure which is frequently estimated in the CDM literature. Using the estimation results on the effect of R&D on the innovations probability (Table 2) and innovation impact on productivity (Table 3), we construct this measure as:

$$\Delta r = (1+\eta) \sum_{(d,z)} [g(\omega, d, z, f) - g(\omega, 0, 0, f)] \left[\Pr(d, z|rd = 1, f) - \Pr(d, z|rd = 0, f)\right]$$

for all $(d, z) \in \{(1, 0), (0, 1), (1, 1)\}$. The top panel of Table 6 reports estimates of this revenue gain for each industry and financial category. The first column shows the average over all sample observations in each industry. Firms that invest in R&D have a revenue increase of between 7.5 (electronics) and 12.3 (machinery) percent. This range is similar to estimates of the elasticity of output with respect to R&D expenditure that are summarized in Hall, Mairesse, and Mohnen (2010).[11]

Given our framework, we can measure the short-run revenue gain across firms with different degrees of financial strength and we report these values in the last three columns of Table 6. We find that the estimates vary substantially in this dimension. For firms in the highest category, the revenue difference varies from 13.2 to 32.5 percent across industries, indicating substantially higher revenue gains from investing in R&D. In each industry, the proportional gain in revenue declines as we move to the medium and low categories. For firms in the low strength category, the gain from R&D varies in a narrow band between 3.0 to 3.8 percent across the industries. The results indicate substantial heterogeneity in the short-run return to R&D with differences in the firms' financial strength.

Table 6: Average Short-Run and Long-Run Return to R&D

	All Firms	Financial Strength		
		High	Medium	Low
Short Run: Δr				
Chemicals	0.094	0.132	0.075	0.038
Machinery	0.123	0.281	0.063	0.030
Electronics	0.075	0.147	0.064	0.032
Instruments	0.105	0.234	0.071	0.037
Vehicles	0.122	0.325	0.069	0.031
Long Run: $\Delta \ln EV$				
Chemicals	0.084	0.120	0.064	0.031
Machinery	0.069	0.125	0.057	0.023
Electronics	0.054	0.100	0.048	0.023
Instruments	0.062	0.119	0.054	0.018
Vehicles	0.076	0.182	0.054	0.019

Using our framework, we construct an analogous measure of the long-run effect of R&D as the log difference in the expected future value of the firm: $\Delta \ln EV = \ln(EV(s_{it+1}|\omega_{it}, rd_{it} = 1)) - \ln(EV(s_{it+1}|\omega_{it}, rd_{it} = 0))$. This differs from the short-run difference in log revenue Δr because it captures the persistence of productivity on future profits and the optimal decision of the firm to invest in R&D in the future. The values are reported in the lower panel of Table 7

[11] In their review of the literature, Hall, Mairesse, and Mohnen (2010) report that production function-based estimates of this elasticity vary from .01 to .25 and are centered around .08. Doraszelski and Jaumendreu (2013, Table 5) report summary statistics of the distribution of firm-level estimates for ten Spanish manufacturing industries. The average over all firms is .015, and the average at the industry level varies from -.006 to .046 across the ten industries, with half of the industries falling between .013 and .022.

by industry and financial category. Focusing on all firms in the sample, the mean of $\Delta \ln EV$ varies from 5.4 to 8.4 percent across industries. This is an estimate of the average long-run difference in the value of firms that invest in R&D relative to ones that do not invest. This measure also varies across the financial strength categories, declining as we move from the high to low category. In the high category, the return varies across industries from 10.0 percent to 18.2 percent. In the low category, the returns are more similar across industries, varying from 1.7 to 3.1 percent.

6 Conclusion

In a recent paper, Peters, Roberts, Vuong, and Fryges (2013) develop a dynamic, empirical model of R&D choice. The firm's decision to invest in R&D is modeled as the solution to a dynamic optimization problem in which the firm weighs the costs of investment against the expected long-run benefit from conducting R&D. In their model, the benefits of the investment depend on the R&D-innovation-productivity linkage that was introduced by Crépon, Duguet, and Mairesse (1998). In this article, we use the PRVF framework to study the role of a firm's financial strength on its decision to invest in R&D. Using data for a sample of German manufacturing firms in five high technology industries, we construct a measure of financial strength based on the firm's credit rating and allow this to affect the R&D-innovation-productivity process at several points. The firm's financial strength can affect its R&D investment decision by affecting the cost of external funding for R&D projects, but also by affecting their ability to commercialize and exploit innovations they generate.

Our empirical findings indicate that the expected long-run payoff from investing in R&D increases with the firm's financial strength. This occurs because firms in a strong financial position have a higher probability of realizing product and process innovations. Besides being able to devote more resources to innovation, firms in a strong financial position may also be able to develop a portfolio of complementary projects. The empirical results also show that the impact of innovations on productivity and profits is larger for firms in a strong financial position. This higher economic return could reflect higher quality innovations or an ability to better develop and market the innovations. Finally, the results show that these firms have higher costs of R&D investment, suggesting they spend more on innovation activities. Overall, the higher expected net payoff gives firms with greater financial strength a larger incentive to invest in R&D.

The PRVF model provides a useful measure of the expected long-run benefit of R&D, defined as the increment to long-run firm value resulting from the R&D investment. In the five German industries we study in this article, this average benefit varies from 4.7 percent in the electronics industry to 6.9 percent in chemicals. Comparing across the financial strength categories, the average increase in firm value is 10.8 percent for firms in the highest category, 4.9 in the medium, and 2.0 in the lowest category.

While this article documents that the underlying factors that contribute to the firm's R&D investment choice are positively correlated with the credit rating of the firm, the distinct roles of internal cash flow, retained past earnings, and external funding as sources of investment funds cannot be identified with the data we use. In addition, the firm's credit rating may be a proxy for more than just the financial resources available to the firm. It reflects other factors including the overall quality of the firm's product line, its longevity, or quality of its management that are not directly related to its ability to fund R&D investment. The results indicate that there is an important source of firm heterogeneity explaining differences in firm R&D choice beyond its capital stock, productivity, industry, and R&D history. For this reason, we prefer to view our findings on the role of financial strength as likely reflecting a broader pattern of variation due to differences in firm quality, rather than more specific conclusions about the role of financial constraints in the firm's R&D investment decision.

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