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

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Abstract

This article investigates how a firm's financial strength affects its dynamic decision to invest in R&D. We estimate a dynamic model of R&D choice using data for German firms in high-tech manufacturing industries. The model 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. Financially strong firms 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 equals 6.6 percent of firm value. It ranges from 11.6 percent for firms in a strong financial position to 2.3 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

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investment increases innovation outputs and these in turn are positively correlated with firm 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 that 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 resources. This affects 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 to 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

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

in the highest financial strength category have the largest productivity improvements following an innovation. A firm in the highest financial strength category that reports a new product innovation has a productivity increase of 8.6 percent on average, while a new process innovation leads to a 9.0 percent increase, and both types of innovations lead to an increase of 11.5 percent. In contrast, firms in the lowest credit-rating category have productivity increases of 0.8, 0.6, and 3.8 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 better credit ratings. Expecting a high level of benefits, firms will be willing to spend more on R&D. In fact, our estimates show the highest level of investment benefits and R&D expenditures for firms in the highest financial strength category. On average, R&D investment is estimated to increase the long-run value of the firm by 6.6 percent. More importantly, this gain in long-run value varies across industries and with firm financial strength. Across industries, the average gain varies from 5.5 percent in the electronics industry to 8.0 percent in chemicals. Across financial strength categories, it varies from 11.6 percent for firms in the highest category to 2.3 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, and (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 they have corroborated 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

[2] See Hall, Mairesse, and Mohnen (2010), Hall and Mohnen (2013), and Mairesse, Verspagen, and Notten (forthcoming) 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)).

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 (Alderson and Betker (1996)). The higher cost for external capital is likely to have a larger effct on the R&D decision of firms with low financial endowment. In the remainder of this section we introduce an indicator of the firm's overall financial strength into the PRVF model to account for the heterogeneity in financing ability and investigate how this affects the firm's incentives to invest in R&D.

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 in which the log of firm output is a function of an aggregate industry time effect, the log of 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 revenue in period t 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 and zero otherwise. 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_{it} is a measure of the firm's financial strength. We view a firm conducting R&D as investing in a portfolio of innovation projects. Firms with a high degree of financial strength are able to invest in more projects than firms with limited financial resources. How intensively firms choose to invest depends on how their financial strength affects the expected payoff from R&D. The next two components of the model specify this financial strength-expected payoff relationship.

PRVF model the innovation process by allowing the firm's R&D participation to alter the joint probabilities of receiving product and process innovations. The probability the firm realizes an innovation is likely to be increasing in the number of R&D projects or, more generally, the size of the firm's R&D portfolio. Firms with higher financial strength have the ability to undertake more projects, hence we expect the probability of innovation to be increasing in the firm's financial strength. We represent this innovation process by a cumulative joint distribution of innovation types conditional on the firm's R&D choices and their financial strength $F(d_{it+1}, z_{it+1}|rd_{it}, f_{it})$. This component of the model corresponds to the second equation in the CDM framework. Our specification of the innovation production process recognizes that firms may direct their R&D activity toward improving their production processes and/or developing new or improved products and that the innovation outcomes are affected by stochastic forces. Furthermore, it includes the firm's financial strength as a proxy for the size of their R&D project portfolio.

The next component of the model is the innovation-productivity linkage, which corresponds to the third equation in the CDM model. PRVF model productivity as a persistent stochastic variable whose distribution is shifted by the firm's past productivity and current realizations of product and process innovations. In addition, firms with a large R&D portfolio may realize multiple innovations or innovations of higher quality. Converting the innovation into future sales and profits may require investments in capital, worker training, hiring, or additional costs that noninnovating firms do not incur. These factors suggest that a firm's access to financial resources plays a crucial role for the size of productivity gains resulting from innovation outcomes. We model the evolution of the firm's productivity with the cdf $G(\omega_{it+1}|\omega_{it}, d_{it+1}, z_{it+1}, f_{it})$.[4] More specifically:

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

The function $g(\cdot)$ is the conditional expectation of future productivity and ε is an iid stochastic shock that is drawn from a $N(0, \sigma_\varepsilon^2)$ distribution. We parameterize the productivity evolution process as a cubic function of lagged productivity and interaction terms between product innovations, process innovations, and the firm's financial strength. Specifically, we classify each firm into one of three financial strength categories based on its credit rating. In this specification, the variable $z_{it+1}f_{it}$ 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 $d_{it+1}f_{it}$ and $d_{it+1}z_{it+1}f_{it}$. In addition to allowing the firm's financial strength to impact the evolution of the firm's productivity, the coefficients α_1, α_2, and α_3 capture the intertemporal persistence that is an important feature of firm-level data on productivity. Because productivity is persistent, the productivity shocks ε in any period are incorporated into future productivity levels rather than having a purely transitory effect.

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 expected benefits of investing, which depend on expected future improvements in productivity and profits, and the cost or investment expenditure needed to generate these improvements. We expect firms to be heterogenous in their innovation costs because of differences in the efficiency of their R&D labs, the experience or education of their workers, economies of scale in the innovation

[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 $G(\omega_{it+1}|\omega_{it}, d_{it+1}, z_{it+1})$.

process, and the nature of the specific innovation projects they are undertaking. We capture this heterogeneity by modeling R&D costs as depending on factors that lead to systematic differences in R&D expenditure and a stochastic component. The first source of systematic difference in the firm's R&D expenditure occurs because a firm that performs R&D continuously over time is likely to require a smaller expenditure to generate an innovation than a firm that begins to invest in R&D because it can rely on past expertise or synergy effects from previous projects. The second source is the size of the firm's R&D portfolio. If investment is profitable, firms with better access to financial resources can finance more projects at any time or finance higher quality projects, and we would expect to see higher R&D investments for these firms. We assume that a firm's R&D cost is a random draw from an exponential distribution,

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

with mean $\gamma^m(rd_{it-1} * f_{it})$ if firm i with financial strength f_{it} engaged in R&D in the previous year and $\gamma^s((1-rd_{it-1}) * f_{it})$ 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 the dummy variables measuring their financial strength f_{it}. The coefficient vector $\gamma = (\gamma^m, \gamma^s)$ captures differences in costs of maintaining ongoing R&D operations and start-up costs of beginning to invest in R&D for firms in each of the three 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 process for innovation F, and the process for 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 maintenance or startup cost, can be written

[5] Each firm is characterized by three exogenous variables, its capital stock k_{it}, which enters the profit function, its financial strength f_{it} 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.

as:

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

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, $\beta E_t V(s_{it+1}|\omega_{it}, rd_{it} = 1)$, net of the relevant maintenance or startup cost, are greater than the expected future profits from not investing, $\beta E_t V(s_{it+1}|\omega_{it}, rd_{it} = 0)$. 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 $\Delta EV(\omega_{it}) \geq C_{it}(rd_{it-1})$. This condition is used in the empirical model to explain the firm's observed R&D choice.

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 startup and maintenance costs 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 1200 firms and 3067 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 firm to one of three categories based on their credit rating. The Creditreform rating is a score between 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 assigned 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, 25.1 percent of the firms remain in the high-strength category over the whole period we observe them, 31.6 percent in the medium category and 20.6 percent in the low category. The remaining 22.7 percent of the firms switch at least once. In the dynamic model we will not attempt to model the transition process for

[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 used in Aghion, Askenazy, Berman, Cette and Eymard (2012).

[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.

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 (OECD (1992, 1997, 2005)) 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 or delivery costs. For instance, the introduction of automation 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.

Table 1 summarizes the proportion of firms in the sample 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 0.805 and this declines to 0.737 and 0.695 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 0.873 for the high strength category, 0.759 for the medium, and 0.707 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 as the financial position of the firm becomes weaker. 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, product and process innovation rates are much more similar in the low-tech industries.

Table 1: Rate of R&D Investment and Innovation

	Financial Strength f_{it}		
R&D Investment Rate rd_{it}	High	Medium	Low
Chemicals	0.805	0.737	0.695
Machinery	0.900	0.743	0.616
Electronics	0.852	0.845	0.793
Instruments	0.948	0.835	0.792
Vehicles	0.864	0.531	0.722
Average across industries	0.873	0.759	0.707
Product Innovation Rate d_{it+1}			
Chemicals	0.715	0.674	0.621
. Machinery	0.834	0.683	0.550
Electronics	0.831	0.763	0.732
Instruments	0.903	0.795	0.682
Vehicles	0.727	0.508	0.611
Average across industries	0.805	0.703	0.627
Process Innovation Rate z_{it+1}			
Chemicals	0.581	0.536	0.505
Machinery	0.665	0.529	0.358
Electronics	0.634	0.586	0.463
Instruments	0.652	0.514	0.455
Vehicles	0.659	0.469	0.472
Average across industries	0.636	0.531	0.429

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 $F(d_{it+1}, z_{it+1} | \ rd_{it}, f_{it})$

nonparametrically using data on discrete innovation outcomes, discrete R&D, and the discrete 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 $C_{it}(rd_{it-1})$ is less than or equal to the expected payoff:

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

Using parameter estimates from the first-stage we solve the value function, equation (5), on a grid of values for the state variables ω_{it} and rd_{it-1}. The value function is solved and the payoff to R&D is constructed for each firm type which is defined on a grid of values for the capital stock, industry, and financial strength category. Subsequently, we interpolate the payoff to R&D, $\Delta EV(\omega_{it})$, for each data point using a cubic spline. The estimates of $\Delta EV(\omega_{it})$ are used to predict the probability of conducting R&D and 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 $F(d_{it+1}, z_{it+1}|rd_{it}, f_{it})$. 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 innovation probabilities for firms that have not incurred innovation expenditures in the previous year and the bottom half reports the probabilities for firms with positive innovation expenditure.

Among the firms that did not invest in R&D, the probability of not getting either a new product or process innovation is large and rises from 0.713 to 0.801 as the financial strength of the firm declines. Conversely, the probability of having both types of innovations declines from 0.164 to 0.104. For firms in the high and medium financial group, product innovations occur more frequently while process innovations are more likely for firms in the low financial group. Among the firms that invested in R&D in the previous year, the probability of realizing neither type of innovation is significantly lower, varying from 0.083 to 0.144 across groups, while the probability of both innovation types is substantially higher, ranging from 0.668 to 0.512. Overall, the estimates in table 2 indicate a positive correlation between the firm's financial strength and the probability of innovation. Firms with higher financial strength may have larger portfolios of R&D projects and thus be more likely to generate at least one innovation if they invest. Alternatively, if these firms do not invest they may still 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: $\Pr(d_{it+1}, z_{it+1} | \, rd_{it}, f_{it})$
(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	0.713	0.066	0.057	0.164
Medium	0.770	0.061	0.026	0.142
Low	0.801	0.054	0.041	0.104
		$rd_t = 1$		
High	0.083	0.220	0.029	0.668
Medium	0.094	0.260	0.045	0.601
Low	0.144	0.309	0.034	0.512

The expected benefits of R&D investment depend on the revenue/profit function and how the innovations impact their development, equations (1) and (3).[9] 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

[9] The benefits also depend on the industry demand elasticity. The elasticity estimates we construct are: chemicals -3.075, machinery -5.078, electronics -3.713, instruments -4.213, and vehicles -4.891.

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 hardly affected when the financial strength categorical variables are added to the productivity process.

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 3.9 percent, while a process innovation raises it by 3.7 percent. The coefficients are statistically significant at the .01 and .05 level, respectively. Firms that report both types of 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 financial strength, we observe a larger effect of innovation for financially strong firms. For these firms, a product innovation raises average productivity by 8.6 percent, a process innovation raises it by 9.0 percent. Firms with both innovations have, on average, a productivity gain of 11.5 percent. All three coefficients are statistically significant. In contrast, firms in the medium financial strength category have more modest productivity gains from innovation. They average 3.9 percent for product innovations, 3.2 percent for process innovations, and 5.8 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: 0.8, 0.6, 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 affect their expected benefits from investing in R&D 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. Products and processes developed with limited resources and fewer inputs might be of lower quality or limited scope and hence yield low productivity gains for the investing firms. Furthermore, it takes financial resources to implement innovations. The path from developing a new product to actual sales and profits requires investments in legal, marketing, design, and testing processes that require financial resources. Firms in a strong financial position may also have invested in a larger number of research projects and thus have a larger number of innovations that they could potentially exploit. As a result, a strong financial position can help firms to earn higher returns on their innovations.

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

Variable	Parameter	No Financial Controls	With Financial Controls
lnk	β_k	-0.060 (0.003)**	-0.061 (0.003)**
lagged ω	α_1	0.741 (0.020)**	0.721 (0.019)**
lagged ω^2	α_2	0.190 (0.013)**	0.183 (0.012)**
lagged ω^3	α_3	-0.053 (0.004)**	-0.050 (0.004)**
d	α_4	0.039 (0.008)**	
z	α_5	0.037 (0.015)*	
$d*z$	α_6	-0.008 (0.016)	
$d*f_{high}$	α_4		0.086 (0.012)**
$z*f_{high}$	α_5		0.090 (0.027)**
$d*z*f_{high}$	α_6		-0.061 (0.030)*
$d*f_{medium}$	α_4		0.039 (0.010)**
$z*f_{medium}$	α_5		0.032 (0.020)
$d*z*f_{medium}$	α_6		-0.013 (0.023)
$d*f_{low}$	α_4		0.008 (0.011)
$z*f_{low}$	α_5		0.006 (0.025)
$d*z*f_{low}$	α_6		0.024 (0.028)
intercept	γ_0	1.064 (0.184)**	1.104 (0.183)**
chemicals		0.041 (0.037)	0.024 (.037)
machinery		0.024 (0.031)	-0.007 (.031)
electronics		0.050 (0.035)	0.039 (.034)
instruments		0.073 (0.034)*	0.046 (.034)
observations		3067	3067
R^2		0.937	0.939

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 we estimate in the second stage can be interpreted as the cost of purchasing the expected benefit $\Delta EV(\omega_{it})$. The economic value of undertaking R&D depends on how it is translated into innovations, productivity, and profits. The cost parameters estimated from firms' discrete R&D decisions rationalize the expected benefits of R&D and the observed R&D

investment rate. In particular, given two groups of firms with the same investment rate, the group with lower expected benefit from R&D must also have lower costs. With respect to firms' financial strength, the expected benefits of investment are smaller for firms in the lower financial strength categories, hence we will observe lower estimated costs for this group of firms. 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 greater than the maintenance 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 as we move from the high to low strength 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* (bootstrap standard errors)

	Startup Cost	Maintenance Cost
High Financial Strength	22.610 (6.060)	4.780 (0.602)
Medium Financial Strength	3.215 (1.162)	0.369 (0.103)
Low Financial Strength	0.166 (0.342)	0.034 (0.074)
Chemical	6.989 (4.024)	0.143 (0.077)
Machinery	2.760 (0.934)	0.420 (0.097)
Electronics	1.283 (0.875)	0.137 (0.076)
Instruments	0.580 (0.970)	0.092 (0.075)
Vehicles	1.678 (2.814)	1.096 (0.581)
log likelihood	-1636.92	

* millions of euros

5.3 Expected Benefits, Costs, and Probability of Investment

We use the parameter estimates from the structural model to construct three summary measures of the R&D investment process for each firm: first, the expected benefit of R&D investment, equation (7), which is a function of the firm's productivity, capital stock, financial strength, and industry; second, the mean R&D expenditure, given the firm chooses to invest in R&D, $E(C_{it}|C_{it}(rd_{it-1}) \leq \Delta EV(\omega_{it}))$; third, the probability the firm invests in R&D, equation (8). The second and third measures depend on the firm's prior R&D experience and the factors determining ΔEV. Table 5, column 2, reports the mean of each measure over all observations; similarly, columns 3, 4, and 5 report the mean of these measures over the observations in each financial category.

Table 5: R&D Benefits, Costs, and Investment Rates (mean over all observations)

	All Firms	Financial Strength		
		High	Medium	Low
ΔEV *	12.783	31.949	5.463	1.347
$E(C_t \| C_t \leq \Delta EV, rd_{t-1} = 1)^*$	1.557	4.053	0.523	0.204
$E(C_t \| C_t \leq \Delta EV, rd_{t-1} = 0)^*$	4.213	10.587	1.745	0.467
$\Pr(rd_t = 1 \| rd_{t-1} = 1)$	0.829	0.861	0.855	0.746
$\Pr(rd_t = 1 \| rd_{t-1} = 0)$	0.445	0.559	0.432	0.330

* millions of euros

In the top row we report the expected benefit of investing in R&D. It averages 12.783 million euros over the total sample. This number is the average addition to firm value resulting from R&D investment. Disaggregating this measure across the financial strength categories we see the average benefit falls from 31.949 million euros to 5.463 and 1.347 million euros as financial strength declines. This decline reflects the combined effects of fewer innovations, as seen in Table 2, and a smaller productivity impact of innovations for firms with weak financial position, as seen in Table 3. While not reported in the table, this fall in the expected benefits of investing in R&D is present in all five industries.

The second and third rows of Table 5 report the mean predicted R&D expenditure among those firms that find it profitable to invest in R&D. The expenditures differ between investing firms paying a maintenance cost ($rd_{t-1} = 1$) and those paying a startup cost ($rd_{t-1} = 0$) for their investment. Firms that continue their R&D investments spend, on average, 1.557 million euros, while those that are starting R&D spend more, 4.213 million euros, on average. The predicted expenditure also depends on the firm's financial strength, reflecting the variation in the expected benefits of R&D across these categories. We predict for financially strong firms, average expenditures of 4.503 and 10.587 million euros in the maintenance and startup cost categories, respectively. As the expected benefits of R&D decline with financial strength, the average expenditure does so as well. Firms in the lowest financial category have average predicted expenditures of 0.204 and 0.467 million euros.

The last two rows of Table 5 report the predicted probability of a firm investing in R&D, which depends on both the expected benefits and cost distribution of the investment. Averaging over all firms, the probability of investing is 0.829 for firms with previous investment. This probability declines from 0.861 for firms in the highest category to 0.855 and 0.746 for firms in the medium and low financial categories, respectively.[10] For those firms that are paying R&D startup costs, the probability of investing is much lower, 0.445 on average, and declines for all industries as financial strength declines. On average, this probability is 0.559, 0.432, and 0.330 for firms in the three financial groups. Overall, Table 5 demonstrates that our measure of firm financial strength captures a dimension of firm heterogeneity that is related to the benefits and the average expenditure on R&D across firms.

5.4 Long and Short-Run Returns to R&D

An advantage of the PRVF framework is that it provides measures of both the long-run and short-run benefits of R&D investment. The short-run gain captures changes in sales and profits in the subsequent period, while the long-run gain captures the changes in firm value due to the firm being on a higher productivity path. The latter includes both a higher profit stream and different optimal future R&D choices. Both of these effects are induced by the productivity gain resulting from R&D investment.

[10] The decline in investment probability, however, is not observed in all industries. Firms in the medium and low financial categories of the chemicals, electronics, and instruments industries, have a higher average investment probability than firms in the high financial category.

The long-run gain is defined as the proportional impact of R&D on firm value. It is measured as the log difference in the expected future value of the firm, equation (6), conditional on its R&D choice while holding fixed the firm's other characteristics:

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

The values are reported in the top panel of Table 6, disaggregated by industry and financial category. The second column of Table 6 reports the mean value of $EV(s_{it+1}|\omega_{it}, rd_{it} = 0)$, denoted $\overline{EV}$, which is the base to use for interpreting the proportional change in firm value.

Focusing on all firms in the sample, the mean of $\Delta \ln EV$ equals 0.066 with a standard deviation of 0.047. This means, across the whole sample, R&D investment increases the expected future value of the firm by 6.6 percent, on average. When compared against the base of 127.44 million euros for the expected future value of the firm in the absence of R&D investment, this equates to 8.38 million euros. The last three columns of the table show that this gain also varies across the financial strength categories, declining substantially as we move from the high to the low category. In the high category, the average return (standard deviation) is 0.116 (0.041) and this average return falls to 0.055 (0.025) and 0.023 (0.014) in the medium and low strength categories, respectively. The decline in average return reflects all factors underlying the differences between firms in the three financial categories. These factors include the probability of receiving an innovation, the impact of innovation on productivity, and the differences in firms' productivity and capital stocks. The reduction in the standard deviation of the long-run return in financial strength states that firms in the low strength group are more similar in their underlying productivity and size than firms in the other two financial groups.

The remaining rows in the top panel of Table 6 provide the average long-run returns disaggregated by industry. The decline in the mean and standard deviation of the long-run return in financial strength is present in every industry. Since the base $\overline{EV}$ varies across industries, the euro magnitude of the gains from R&D varies across industries as well. It is highest in the vehicle, chemical, and machinery industries.

Table 6: Proportional Return to R&D in the Long Run and Short Run (mean and standard deviation over all observations)					
			Financial Strength		
		All Firms	High	Medium	Low
Long Run:	$\overline{EV}$		$\Delta \ln EV$		
All Industries	127.44	0.066 (0.047)	0.116 (0.041)	0.055 (0.025)	0.023 (0.014)
Chemicals	134.12	0.080 (0.045)	0.111 (0.040)	0.065 (0.034)	0.032 (0.016)
Machinery	140.69	0.066 (0.041)	0.112 (0.030)	0.057 (0.020)	0.026 (0.015)
Electronics	114.67	0.055 (0.044)	0.108 (0.048)	0.045 (0.021)	0.023 (0.012)
Instruments	66.31	0.060 (0.046)	0.115 (0.046)	0.053 (0.021)	0.016 (0.009)
Vehicles	205.03	0.072 (0.062)	0.161 (0.034)	0.059 (0.029)	0.014 (0.011)
Short Run:	$\overline{\pi}$		Δr		
All Industries	29.48	0.134	0.234	0.113	0.057
Chemicals	51.82	0.097	0.129	0.081	0.043
Machinery	19.11	0.164	0.291	0.132	0.068
Electronics	38.41	0.093	0.163	0.082	0.049
Instruments	8.90	0.136	0.242	0.118	0.058
Vehicles	46.80	0.167	0.334	0.148	0.054

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 that is frequently estimated in the CDM literature. In our framework, since profits are proportional to revenue, equation (2), this percentage increase in revenue is equal to the percentage increase in profit. Using the estimation results on the effect of R&D on the innovation probability (Table 2) and innovation impact on productivity (Table 3), we construct this measure as:

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

for all $(d, z) \in \{(1, 0), (0, 1), (1, 1)\}$. The bottom panel of Table 6 reports the mean estimate of this revenue gain for each industry and financial category.[11] The second column reports the average level of short-run profits in each industry, denoted by $\overline{\pi}$.

Firms that invest in R&D have a revenue increase of between 9.3 (electronics) and 16.7 (vehicles) percent. These estimates are at the upper end of the range of output elasticity

[11] There are no standard deviations in these cells because the estimate does not vary within a cell because it does not depend on firm productivity or capital stock. In the model it only varies across firms with differences in industry and financial strength category.

estimates with respect to R&D expenditure that are summarized in Hall, Mairesse, and Mohnen (2010).[12] Their reported measures generally come from studies measuring the percentage change in revenue for an additonal monetary unit of R&D spending, while our proportional gain in revenue comes from a zero-one R&D choice. If the marginal revenue gain declines with additional spending, then our measure, the discrete impact of R&D investment, is likely to be larger.

The last three columns of Table 6 report the short-run revenue gain across firms with different degrees of financial strength. The estimates vary substantially in this dimension. For firms in the highest category, the revenue difference averages 23.4 percent and varies from 12.9 to 33.4 percent across industries. These numbers translate into absolute gains of 6.89, 6.68, and 15.63 million euros, respectively. 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 averages 5.7 percent and varies in a narrower band between 4.3 to 6.8 percent across the industries.

6 Conclusion

In a recent paper, Peters, Roberts, Vuong, and Fryges (2013) develop a dynamic, structural 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

[12] In their review of the literature, Hall, Mairesse, and Mohnen (2010) report that production function-based estimates of this elasticity vary from 0.01 to 0.25 and are centered around 0.08. 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 0.015, and the average at the industry level varies from -0.006 to 0.046 across the ten industries, with half of the industries falling between 0.013 and 0.022.

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. In addition to 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 that enhances their innovation success. The empirical results further 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, an ability to better develop and market the innovations, and the return on a larger number of R&D projects that they are able to sustain. Finally, the results show that these firms have higher expenditures on R&D investment but, 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 5.5 percent in the electronics industry to 8.0 percent in chemicals. Comparing across financial strength categories, the average increase in firm value is 11.6 percent for firms in the highest category, 5.5 in the medium, and 2.3 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 financial strength of the firm as indicated by its credit rating, 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.

References

[1] Aghion, Philippe, Phillipe Askenazy, Nicolas Berman, Gilbert Cette and Laurent Eymard (2012), "Credit Constraints and the Cyclicality of R&D Investment: Evidence from France," *Journal of the European Economic Association*, Vol. 10, No. 5, pp. 1001-1024.

[2] Alderson, Michael J. and Brian L. Betker (1996), "Liquidation Costs and Accounting Data," *Financial Management,* Vol 25, No.2, pp. 25-36.

[3] Aw, Bee Yan, Mark J. Roberts, and Daniel Yi Xu (2011), "R&D Investment, Exporting and Productivity Dynamics," *The American Economic Review*, Vol. 101, No. 4 (June), pp. 1312-1344.

[4] Bhagat, Sanjai and Ivo Welch (1995), "Corporate Research and Development Investments - International Comparisons," *Journal of Accounting and Economics*, Vol. 19, pp. 443-470.

[5] Bond, Steven, Dietmar Harhoff and John Van Reenen (2005), "Investment, R&D and Financial Constraints in Britain and Germany," *Annales d'Economie et de Statistique*, ENSEA, Vol. 79-80, pp. 433-460.

[6] Bougheas, Spiros, Holger Görg and Eric Strobl (2003), "Is R&D Financially Constrained? Theory and Evidence from Irish Manufacturing," *Review of Industrial Organization*, Vol. 22, No. 2, pp. 159-174.

[7] Carpenter, Robert E. and Bruce C. Petersen (2002), "Capital Market Imperfections, High-Tech Investment, and New Equity Financing," *The Economic Journal*, Vol. 112, No. 477, pp. 54-72.

[8] Crépon, Bruno, Emmanuel Duguet, and Jacques Mairesse (1998), "Research Innovation and Productivity: An Econometric Analysis at the Firm Level," *Economics of Innovation and New Technology*, Vol. 7, No. 2, pp. 115-158.

[9] Czarnitzki, Dirk (2006), "Research and Development in Small and Medium-Sized Enterprises: The Role of Financial Constraints and Public Funding," *Scottish Journal of Political Economy,* Vol. 53, No. 3, pp. 257-335.

[10] Czarnitzki Dirk and Hanna Hottenrott (2011), "R&D Investment and Financing Constraints of Small and Medium-Sized Firms," *Small Business Economics, Vol* 36, pp. 65-83.

[11] Doraszelski, Ulrich and Jordi Jaumandreu (2013), "R&D and Productivity: Estimating Endogenous Productivity," *Review of Economic Studies*, Vol. 80, pp. 1338-1383.

[12] Fazzari, Steven M., R. Glenn Hubbard and Bruce C. Petersen (1988), "Financing Constraints and Corporate Investment," *Brooking Papers on Economic Activity*, Vol. 1, pp. 141-206.

[13] Griliches, Zvi (1979) "Issues in Assessing the Contribution of Research and Development to Productivity Growth," *Bell Journal of Economics*, Vol. 10, No. 1 (Spring), pp. 92-116.

[14] Hall, Bronwyn H. (1992), "Research and Development at the Firm Level: Does the Source of Financing Matter?," NBER Working Paper No. 4096.

[15] Hall, Bronwyn H. (2002), "The Financing of Research and Development," *Oxford Review of Economic Policy,* Vol. 18, No. 1, pp. 35-51.

[16] Hall, Bronwyn H., Jacques Mairesse, and Pierre Mohnen (2010), "Measuring the Returns to R&D," in *Handbook of the Economics of Innovation,* Bronwyn H. Hall and Nathan Rosenberg (eds.), Vol. 2, Chapter 22, Elsevier, pp. 1033-1082.

[17] Hall, Bronwyn H. and Pierre Mohnen (2013), "Innovation and Productivity: an Update," Eurasian Business Review, Vol. 3, No. 1, pp. 47-65.

[18] Himmelberg, Charles P. and Bruce C. Petersen (1994), "R&D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries," *Review of Economics and Statistics*, Vol. 76, pp. 38-51.

[19] Kaplan, Steven and Luigi Zingales (1997), "Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?" *Quarterly Journal of Economics*, Vol. 115, pp. 707-712.

[20] Leland, Hayne E. and David H. Pyle (1977), "Informational Asymmetries, Financial Structure, and Financial Intermediation," *Journal of Finance*, Vol. 32, No. 2, pp. 371-387.

[21] Mairesse, Jacques, Bart Verspagen, and Ad Notten (forthcoming), "The Origins of the CDM Framework: Knowledge Recombination from Genetics Viewpoint," *Economics of Innovation and New Technology.*

[22] OECD (1992, 1997, 2005), *Oslo Manual: Proposed Guidelines for Collecting and Interpreting Technological Innovation Data, 1st, 2nd and 3rd edn.*, Paris.

[23] Olley, G. Steven and Ariel Pakes (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica,* Vol. 64, No. 6 (November), pp. 1263-1297.

[24] Peters, Bettina and Christian Rammer (2013), "Innovation Panel Surveys in Germany," in *Handbook of Innovation Indicators and Measurement* Fred Gault (ed.), Edward Elgar: Cheltenham, UK and Northampton, MA, USA, pp. 135-177.

[25] Peters, Bettina, Mark J. Roberts, Van Anh Vuong, and Helmut Fryges (2013), "Estimating Dynamic R&D Choice: An Analysis of Costs and Long-Run Benefits," NBER Working Paper No. 19374.

[26] Roberts, Mark J. and Van Anh Vuong (2013), "Empirical Modeling of R&D Demand in a Dynamic Framework,"*Applied Economic Perspectives and Policy,* Vol. 35, No. 2 (June), pp. 185-205.