ESTIMATING THE BENEFITS OF TARGETED R&D SUBSIDIES

Tuomas Takalo, Tanja Tanayama, and Otto Toivanen*

Abstract—We study the expected welfare effects of targeted R&D subsidies using project-level data from Finland. We model the application and R&D investment decisions of firms and the subsidy-granting decision of the public agency in charge of the program. Our model and institutional environment allow us to identify different benefits and costs of the R&D subsidy program. We find that expected effects of subsidies are very heterogeneous and estimated application costs low on average. The social rate of return on targeted subsidies is 30% to 50%, but spillover effects of subsidies are smaller than effects on firm profits.

I. Introduction

IT is widely recognized that R&D and the distribution of benefits generated by it are crucial for economic growth (see Aghion & Howitt, 1998, 2009, for overviews). Economic theory has shown that markets typically generate a suboptimal amount of R&D.[1] Endogenous growth theory in particular has singled out public subsidies to R&D as one of the main policy tools (Aghion & Howitt, 1998; Howitt, 1999; Segerstrom, 2000). R&D subsidies have also become ubiquitous in practice. They are one of the largest and fastest-growing forms of industrial aid in developed countries (Nevo, 1998; Pretschker, 1998); the United States has several programs (Lerner, 1999) and spends $1.5 billion a year on one R&D subsidy program alone;[2] and the EU exempts R&D subsidies from its state aid rules. In Finland, where our data originate, R&D subsidies were drastically increased amid the deep economic recession of the early 1990s and are now the most important tool of innovation policy (Georghiu et al., 2003).

In theory, R&D subsidies should lower the marginal cost of R&D, increasing R&D investments and thereby firm profits and spillovers. At the same time, they generate costs through the shadow cost of public funds and time and effort spent in the application process. Evaluating the net welfare effects of R&D subsidies is challenging, since R&D subsidies are not a registration system: one needs to understand how firms make their application and R&D decisions, how government authorities allocate subsidies, and how the firms and the authorities interact.

Our goal is to provide a framework to assess the social value of R&D subsidies and use this framework to study the effects of R&D subsidies on a public agency allocating them and on firms investing in R&D. We first model the R&D subsidy process, incorporating the firms' and the agency's decisions and their strategic interaction. Then we estimate the parameters of the firms' and the agency's objective functions, and the parameters of the firms' application cost function using detailed R&D project-level data. Finally, we use these parameter estimates to quantify the different benefits and costs of the R&D subsidy program and thereby generate an estimate of the social rate of return to R&D subsidies. Our approach thus yields estimates of the expected effects of the subsidies accruing to the firms and to the agency and of the costs of applying for subsidies. We can then assess the expected welfare effects of individual subsidies and the whole subsidy program.

A. *The Model*

In our model, firms with R&D ideas first decide whether to apply for a subsidy. Conditional on this decision and the outcome of the application, they decide how much to invest in the R&D project. The public agency running the program decides the level of the subsidy rate, that is, the fraction of R&D cost that the agency pays, conditional on receiving and grading the application.

B. *The Data*

We have access to rich R&D project-level data from Tekes (the Finnish Funding Agency for Technology and Innovation), the main source of R&D subsidies in Finland. Finland provides an interesting case because innovation policy relying on R&D subsidies has been a central theme in government policy,[3] and the country rapidly emerged from the economic crisis of the early 1990s as a technology-intensive economy (Trajtenberg, 2001). The data contain all the subsidy applications with details of the planned R&D projects, the agency's internal ratings of the applica-

Received for publication June 26, 2009. Revision accepted for publication June 20, 2011.

* Takalo: Bank of Finland; Tanayama: National Audit Office of Finland; Toivanen: Katholieke Universiteit Leuven.

We thank two anonymous referees for detailed comments. We also thank Tim Bresnahan, David Card, Chiara Criscuolo, Ken Chay, Dirk Czarnitzki, Stefanie Franzke, Ari Hyytinen, Guido Imbens, Jordi Jaumandreu, Saul Lach, Phil Leslie, Ariel Pakes, Jim Powell, Petri Rouvinen, Paul Ruud, Chris Shannon, George Siotis, Javier Suarez, John Van Reenen, Reinhilde Veugelers, Frank Wolak, and numerous seminar audiences for discussions and suggestions. We are thankful to Tekes, Funding Agency for Technology and Innovation, for funding and data and for several Tekes employees for helpful comments and thorough discussions. Takalo and Toivanen also acknowledge, with thanks, the funding from the Yrjö Jahnsson Foundation. This paper was partly written while Takalo was visiting Toulouse School of Economics and University of Cambridge and Toivanen UC Berkeley, whose hospitality they gratefully acknowledge. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the National Audit Office of Finland.

A supplemental appendix is available online at http://www.mitpressjournals.org/doi/suppl/10.1162/REST_a_00280.

[1] See Nelson (1959) and Arrow (1962) for the seminal arguments.

[2] The Small Business Innovation Research Program (SBIR): "In FY (fiscal year) 2001, [the SBIR program] produced 3,215 Phase I awards and 1,533 Phase II awards for approximately $1.5 billion dollars." Phase I is the start-up phase. Awards of up to $100,000 for approximately six months' support exploration of the technical merit or feasibility of an idea or technology. Phase II awards of up to $750,000, for as many as two years, expand phase I results. During this time, the R&D work is performed and the developer evaluates commercialization potential. Only phase I award winners are considered for phase II. Quotation and information are from http://www.sba.gov/sbir/indexwhatwedo.html, visited on January 21, 2004.

[3] For example, there are no R&D tax benefits.

tions, and its decisions over a two and half year period (January 2000–June 2002).[4] The information on applications is matched to data on over 14, 000 Finnish firms that constitute a large proportion of potential applicants. To get acquainted with the actual decision-making process, one of us spent eleven months in Tekes. Among other things she participated in the decision-making meetings.

C. *Identification*

In the literature on the effect of R&D subsidies, the main concern has been the endogeneity of the subsidy, which can arise through different channels. Because we have a structural model, we need to explicitly take a stand on how the endogeneity in our model arises. We allow spillovers to be a function of the shock determining the private profitability of R&D, but assume that the spillover per dollar of R&D (the spillover rate) is independent of that shock. This allows us to treat the agency's decision as being uncorrelated with the firms' decision to apply. While restrictive, this assumption generates, in line with the existing literature, endogenous subsidies. This endogeneity leads in our data to a sample selection problem as we observe the project-level R&D plans for only those firms that apply for a subsidy, whereas the existing literature mostly uses (survey) data where firm-level R&D is observed for all firms. In solving the sample selection problem, we can take advantage of an exclusion restriction embedded in the Finnish R&D subsidy environment: the EU rules allow the Finnish agency to grant larger subsidies to small and medium-sized enterprises (SMEs) than larger firms. The SME definition is decided at the EU level, and we believe it can safely be viewed as exogenous.

Following the standard methods of structural industrial organization (see Reiss & Wolak, 2007, for a survey), we identify a number of objects by combining theory, functional form, and distributional assumption. For example, we identify application costs by a procedure similar to that used by Berry and Waldfogel (1999) and others in identifying fixed costs of entry. While the identification of our model rests on neither distributional nor unusual functional form assumptions, some of our interpretations are potentially controversial.[5] Prior literature unfortunately provides little help in modeling and interpreting the objective of the agency running the subsidy program.[6] We assume that the agency completely internalizes firm profits; that it may receive benefits (for example, consumer surplus, spillovers, and private benefits to civil servants) that the firm does not internalize (these are what we label, without implication, the *spillover effects*); and that it cares about the out-of-pocket cost of subsidies. Given these, we identify, at a minimum, how the agency expects to benefit from a given subsidy. At a maximum, if one is willing to assume that the agency acts as a benevolent social planner, we identify expected general equilibrium effects of subsidies. In this sense, our approach complements existing work on estimating general equilibrium treatment effects (see Heckman, Lochner, & Taber, 1998; Abbring & Heckman, 2007). The costs of applying, the agency's opportunity cost of finance, and its lack of ability to commit to a subsidy rate ex ante mean that the program's benefits may not cover all its costs even when all decisions are optimal, as dictated by our revealed preference approach.[7]

Our identification of general equilibrium effects is certainly debatable. However, most of our results are not affected by the interpretation of the agency's objective function. For example, the agency's objective function is irrelevant for our results on the level and heterogeneity of the effects of subsidies on firm profits and application cost estimates. Nor does the interpretation matter for our insights into how firm and project characteristics affect the decisions of an agency granting R&D subsidies. Given the importance of this policy tool, this information ought to be valuable for future research.

D. *Results*

We report four main findings. First, the expected effects of subsidies on both the firms' expected discounted profits and the agency's utility (the spillover effect) are very heterogeneous. Second, estimated application costs vary greatly, and shocks to application costs and marginal profitability of R&D are positively correlated. That is, the more profitable the project is, the less likely a firm is to apply for a subsidy. This is intuitive once one observes that a major part of the application costs that we identify comes from opportunity costs. Third, as one might expect, the spillover effects of subsidizing a given R&D project are somewhat smaller than their effect on firm profits. Fourth, we find that the expected rate of return on the subsidy program is of the order of 30% to 50%. In addition to the main findings, some of our parameter estimates are of independent interest, indicating, for example, economies of scale in the spillover rate.

[4] Since we observe firms' R&D plans, not their actual R&D investments, our data are different from those used in most ex ante and ex post evaluation studies (Heckman & Vytlacil 2006a; Todd & Wolpin, 2008). While this means that our study is certainly not the final word on the evaluation of the R&D subsidy programs, it also means that we have a unique window to the program evaluation: we use the data that form the basis of the firms' application and the agency's subsidy decisions. Our calculations are thus informative of the decision makers' preferences and the consequences of their decisions prior to uncertainty about project outcomes unfolding. A policy at this stage should (at least) exhibit benefits that are larger than costs.

[5] As will become clear, we make one key distributional (covariance) assumption, which provides a way of estimating the agency decision rule. It has no impact on our other results. We also estimate the model semiparametrically, and the functional form assumptions we need to impose are certainly no stronger than those commonly used. Like Heckman and Vytlacil (2005), we do not need to impose all the traditional exogeneity assumptions to be able to measure treatment effects or to calculate the rate of return on the program.

[6] Blanes and Busom (2004) and Feldman and Kelley (2006) discuss possible objectives of an agency, and Tanayama (2007) describes in detail the decision-making process used by the agency we study.

[7] McFadden (1975, 1976) represents early work using a related revealed preference approach to public sector decision making.

E. Literature

There is a large literature estimating the effect of R&D subsidies on private R&D investments ("additionality") and other measures of innovative performance (for surveys, see David, Hall, & Toole, 2000; Klette, Møen, & Griliches, 2000). The paper closest to ours is González, Jaumandreu, and Pazó (2005), who focus on the effectiveness of subsidies in stimulating private R&D when there are fixed costs of starting a project. Using Spanish data, they find that subsidies can encourage non-R&D-performing firms to start investing in R&D. They, like us, assume that firms act partly on expected subsidies. However, we cannot use their appealingly simple way of deriving expectations (González et al., 2005) because structural modeling of the application decision and the related incomplete information are the key ingredients of our model. Hence, we assume that the firms do not know with certainty what rate of subsidy they would receive if they applied. We view our approach as complementary to González et al. (2005) and to other work following a similar approach.[8]

Methodologically, our paper belongs to a small but growing literature using structural empirical models in the economics of innovation, originating in the seminal work of Pakes (1986) and Levin and Reiss (1988). Related to our study, structural modeling has been used to study R&D spillovers and technology diffusion (Eaton & Kortum, 2002; Jovanovic & Eeckhout, 2002; and Xu, 2008). But to the best of our knowledge, structural models have not been previously used to study R&D subsidies, although Ferrari, Verboven, and Degryse (2010) consider subsidization of investments in automatic teller machine technology as a counterfactual. From this methodological perspective, our paper is closest to research on regulator-firm interaction, in particular to Wolak (1994; see Reiss & Wolak 2007) and Gagnepain and Ivaldi (2002).[9]

We present our model in detail in section II. We explain the institutional background and data in section III and statistical assumptions, identification, and estimation in section IV. Econometric results are reported in section V. In section VI, we present estimates of the effects of subsidies and our estimate of the agency's return on the R&D subsidy program, exploring also their sensitivity to distributional assumptions. Conclusions are in section VII.

II. The Model

We model the subsidy program as a four-stage game of incomplete information between a firm with an R&D project and the agency. We assume one project per firm and talk interchangeably of "firm," "project," and "applicant" in what follows. We postpone the discussion of the assumptions underlying the theoretical model to section IV.C.

In stage 0, the players' project-specific types are determined. The type of project i, $t_i^F = (\varepsilon_i, \nu_i) \in \Re^2$, and the agency's type pertaining to project i, $t_i^A = (\eta_i, \omega_{ic}, \omega_{im}) \in \Re^3$, are drawn from common knowledge (joint) distributions. As will become clear later, t_i^F and t_i^A affect the expected value of project i from the perspective of the firm and the agency. They also constitute the unobservables of the econometric model.

In stage 1, the firm decides whether to apply for a subsidy. We assume that symmetric but incomplete information regarding the agency's type prevails at this stage. In other words, the firm, when contemplating application, does not know exactly how the agency will value the proposed project. Without loss of generality, we assume that the firm's type is common knowledge.

In stage 2, the agency grades the proposed project and learns its type. It then decides the subsidy rate, s_i, $s_i \in [0, \bar{s}_i]$, which is the share of the R&D investment cost covered by the agency, and where $\bar{s}_i \leq 1$ is the applicant-specific upper bound for the subsidy rate. We assume that the agency cannot give subsidies to nonapplicants and that the agency's budget constraint does not bind.

In stage 3, the firm chooses the R&D investment, R_i, $R_i \in \Re_+$, with or without the subsidy. There are no fixed costs of R&D or any constraints on the investment of the firm. The subsidy is then $s_i R_i$— the subsidy rate times the R&D investment of the firm. Here we assume that the investment level R_i is nonverifiable but that the subsidy $s_i R_i$ cannot be misused.

We focus on perfect Bayesian equilibria where, in stage 1, a potential applicant correctly anticipates the agency's type-contingent strategies in stage 2 and the firm's and agency's strategies are sequentially rational. In this game, the firm's posterior belief concerning the agency's type after receiving a subsidy is inconsequential, so we start from the firm's maximization problem in stage 3. Because the goal of our theoretical model is to derive equations that can be taken to data, we model the players' payoffs by more specific functional forms than would be necessary from a purely theoretical point of view.

A. Objective Function of the Firm and Stage 3 of the Game

We specify the firm's expected discounted profits from project i as

$$\Pi(R_i, s_i, X_i, \varepsilon_i) = \exp(X_i \beta + \varepsilon_i) \ln R_i - (1 - s_i) R_i \qquad (1)$$

where X_i is a vector of observable firm characteristics and β a vector of parameters to be estimated. The marginal profitability is affected by a random shock, ε_i, (firm i's type), which is observed by the firm and the agency but unob-

[8] Other related contributions to the effects of subsidies include Wallsten (2000), Lach (2002), Czarnitzki and Licht (2006), and Criscuolo et al. (2007). Hall and Maffioli (2008) survey the evaluations of R&D subsidy programs in Latin America. See also Jaffe (2002).

[9] Since a subsidy can be viewed as a treatment, there is also a link to the literature on structural modeling of treatment effects, first advocated by Heckman and Robb (1985) and Björklund and Mofitt (1987), and subsequently summarized by Abbring and Heckman (2007), and Heckman and Vytlacil (2006a, 2006b).

served by the econometrician. As equation (1) shows, the firm's R&D technology exhibits decreasing returns to scale.

In stage 3, the firm chooses its investment R_i to maximize equation (1). Since the objective function is globally concave in R_i, the first-order condition,

$$R_i = \frac{\exp(X_i\beta + \varepsilon_i)}{1 - s_i}, \tag{2}$$

gives the firm's optimal investment $R_i(s_i)$ as a function of the subsidy rate. Equation (2) clearly shows how the subsidy rate in our model affects the intensive margin. Equations (1) and (2) also provide the economic interpretation of ε_i: a positive shock to the marginal profitability leads to a larger investment.[10]

B. *Agency Utility and Stage 2 of the Game*

The agency's expected utility from an applicant's project i is given by

$$\begin{aligned} U(R_i(s_i), s_i, X_i, Z_i, \varepsilon_i, \eta_i) =& V(R_i(s_i), Z_i, \eta_i) \\ &+ \Pi(R_i(s_i), s_i, X_i, \varepsilon_i) - g s_i R_i(s_i) - F_i, \end{aligned} \tag{3}$$

where F_i captures the fixed costs of applying and processing the application and g is the constant opportunity cost of agency resources, for example, the opportunity cost of tax funds. As equation (3) shows, the firm's profits enter directly and additively in the agency's utility function.

We label $V(\,)$, without implication, the *spillovers,* which captures the expected effect of the firm's project on the agency beyond the firm's profits and the direct costs of the subsidy and the application process. $V(\,)$ can include positive externalities from firm R&D, such as consumer surplus or technological spillovers to other firms. It can also contain idiosyncratic benefits to the decision maker, such as bribes or a revolving-door mechanism. This agency-specific part of the agency's utility can also be decreasing in R&D because of cost duplication, business-stealing effects, or negative environmental externalities, for example.[11] As emphasized in section I, the interpretation of $V(\,)$ in no way affects our results (for example, on the determinants of private returns to R&D and application costs).

In $V(\,)$, η_i constitutes part of the agency's type $t_i^A = (\eta_i, \omega_{ic}, \omega_{im})$, and it is defined as a random shock to the spillovers from project i. As mentioned, it is assumed to be observed by the agency at stage 2 after application and grading takes place, but unobserved by the potential applicant at stage 1 and by the econometrician too. In other words, the potential applicant is uncertain about how the agency, after grading the project proposal, sees the project and its potential to generate spillovers, consumer surplus, business stealing, or private benefits to the agency's civil servants.

The spillover $V(\,)$ also includes Z_i, a vector of observable firm characteristics, which contains the same elements as X_i. In our case, after receiving a proposal for an R&D project, the agency grades its quality in two dimensions, and Z_i thus also includes the two grading outcomes consisting of two grades on a Likert scale of 5 observed by the agency and by the econometrician but not by the firm.[12] The remaining parts of the agency's type, ω_{ic} and ω_{im}, are defined as random shocks to the grading outcome of project i in grading dimension c and m, respectively (with c and m standing for technical challenge and market risk as we explain in section III). We assume that the grading process, its parameters, and the distributions of ω_{ij}, $j \in \{c, m\}$, are common knowledge. That is, conditional on observables, the firm correctly assesses the probability of getting a particular grade in each grading dimension.

In stage 2, the agency chooses the subsidy rate s_i to maximize equation (3), taking equation (2) into account. To arrive at an estimable model, we need to specify the effect of R_i on $V(\,)$. We assume that

$$\frac{\partial V}{\partial R} = Z_i\delta + \eta_i, \tag{4}$$

where δ is a vector of parameters to be estimated. By equation (4), one can think of η_i as a shock to the spillover rate, that is, spillover per dollar of R&D.

Using the envelope theorem, equations (1), (2), and (4), the first-order condition for the agency's unconstrained problem can be written as

$$s_i^* = 1 - g + Z_i\delta + \eta_i. \tag{5}$$

We verify later that equation (5) characterizes the maximum. From equation (5), it is clear that the agency's unconstrained decision rule is decreasing in the shadow cost of public funds, g. It is also independent of the firm's type $t_i^F = (\varepsilon_i, \nu_i)$. Thus, even if the agency did not know the private shock to the marginal profitability of R&D, it would not matter. The optimal subsidy rate depends positively on the spillover shock η_i. As a result, the minimum constraint of $s_i = 0$ binds for $\eta_i \leq \underline{\eta}_i \equiv g - 1 - Z_i\delta$ and the maximum constraint of $\bar{s}_i$ binds for $\eta_i \geq \bar{\eta}_i \equiv \bar{s}_i + g - 1 - Z_i\delta$. These constraints and the first-order condition, equation (5), yield the optimal subsidy rate equation.

[10] Our functional form assumptions create a minor problem. For very small values of ε_i, the firm may prefer not investing at all to investing the amount suggested by equation (2). Since this would happen in our data only for extremely small values of ε_i—an R&D investment of slightly larger than 1 euro would be sufficient to generate positive expected profits—we ignore the problem in our empirical implementation.

[11] In the basic models of innovation in industrial organization and endogenous growth theory, the positive welfare effects of R&D, typically consisting of consumer surplus and spillovers besides innovators' profits, are balanced against its negative welfare effects such as business stealing and cost duplication (see Aghion & Howitt, 1992). It is perfectly plausible in theory that positive externalities of an R&D investment are more than offset by its negative effects.

[12] The grades cannot be included into other equations since they are given only to applicants.

C. The Firm's Beliefs and Application Costs and Stage 1 of the Game

In stage 1, a firm applies for a subsidy if the expected profits from applying are at least as large as those from not applying. The firm needs to calculate expected profits from submitting an application based on its beliefs about the agency's valuation of its project. As mentioned, the agency's valuation of project i depends on its type $t_i^A = (\eta_i, \omega_{ic}, \omega_{im})$, which is unknown to the firm prior to application. Let $\phi(\eta_i)$ define firm i's belief about η_i, and let $\Phi(\eta_i)$ be the corresponding cumulative distribution function. Moreover, let $p_{ijh}(\omega_{ij})$ denote the probability that a firm's application gets grade $h \in \{1, \ldots, 5\}$ in grading dimension $j \in \{c, m\}$.

The firm weights the expected profit increase from applying against its costs. We specify the application costs as

$$K_i = \exp(Y_i\theta + \nu_i), \tag{6}$$

where Y_i is a vector of observable firm characteristics, θ is a vector of parameters to be estimated, and ν_i is a random cost shock observed by the firm and the agency but not by the econometrician. Note that these application costs are included in F_i in equation (3).

Dropping the subscript i and the argument ω_{ij}, we can now write the application decision rule as

$$\begin{aligned} d = 1\Bigg\{ &\sum_{ch=1}^{5}\sum_{mh=1}^{5} p_{ch}p_{mh}\{\Phi(\underline{\eta}(ch,mh))\Pi(R(0),0) \\ &+ \int_{\underline{\eta}(ch,mh)}^{\bar{\eta}(ch,mh)} \Pi(R(s(ch,mh,\eta)), s(ch,mh,\eta))\phi(\eta)d\eta \\ &+ [1-\Phi(\bar{\eta}(ch,mh))]\Pi(R(\bar{s}),\bar{s})\} \\ &\qquad -\Pi(R(0),0) - K \geq 0 \Bigg\}, \end{aligned} \tag{7}$$

where d_i is an indicator function that takes the value 1 if a firm applies for a subsidy and is 0 otherwise. In equation (7) the summations are over the potential grading outcomes. The first term in the inner braces is the expected profit in case the application is rejected. A rejection occurs when $\eta_i \leq \underline{\eta}_i \equiv g - 1 - Z_i\delta$ (where Z_i includes the grades ch and mh), that is, with probability $\Phi(\bar{\eta}_i)$. Correspondingly, the third term is the expected profits with a maximal subsidy rate, which the firm obtains with probability $1 - \Phi(\underline{\eta}_i \equiv \bar{s}_i + g - 1 - Z_i\delta)$. The second term is then the expected profit when $\eta_i \in (\underline{\eta}_i, \bar{\eta}_i)$ in which case the firm receives the optimal interior subsidy rate given by equation (5). The two last terms capture the opportunity cost of applying. Besides the application costs K_i, the firm takes into account the possibility of executing the project without a subsidy, in which case the project yields $\Pi(R_i(0),0)$.

D. Equilibrium

To complete the model, we show that there is a unique perfect Bayesian equilibrium, ensuring a meaningful econometric implementation of the model. Perfect Bayesian equilibria in our model consist of four components: (a) a firm's belief functions $p_{ijh}(\omega_{ij})$, $j \in \{c, m\}$, $h \in \{1, \ldots, 5\}$, and $\phi(\eta_i)$ that describe a (common) assessment of how the agency values the firm's project; (b) the firm's decision whether to apply for a subsidy, $d_i \in \{0,1\}$, given its beliefs; (c) the agency's subsidy rate decision rule $s_i = s_i^* d_i$, which determines the subsidy rate granted to the project i; and (d) the firm's investment rule $R_i^*(s_i)$.

Proposition. There is a unique perfect Bayesian equilibrium where d_i is given by equation (7), $s_i = s_i^* d_i$ with $s_i^* = 0$ for $\eta_i \leq \eta_i$, s_i^* is given by equation (5) for $\eta_i \in (\eta_i, \bar{\eta}_i)$, and $s_i^* = \bar{s}_i$ for $\eta_i \geq \bar{\eta}_i$, and $R_i^*(s_i)$ is given by equation (2).

Proof. For brevity of notation, we drop the subscript i. In stage 3, the firm has a well-defined best-reply function $R^*(s)$ given by equation (2). In stage 2, the agency maximizes its expected utility conditional on its type $t^A = (\eta, \omega_c, \omega_m)$ and receiving an application ($d = 1$). There is a unique type-contingent optimal subsidy rate s^* if the second-order condition for the agency's decision problem holds. Since we have linear constraints of minimum and maximum subsidies, it suffices to show that $U(R^*(s),s)$ is concave when evaluated at the interior solution given by equation (5). Differentiating equation (3) twice using the fact that $\partial\Pi/\partial R = 0$ shows that $U(R^*(s),s)$ is concave if

$$\begin{aligned} &\frac{\partial^2 V}{\partial R^2}\left(\frac{dR}{ds}\right)^2 + \frac{dR}{ds}\left(\frac{\partial^2\Pi}{\partial R\partial s} - 2g\right) \\ &\qquad + \frac{d^2R}{ds^2}\left(\frac{\partial V}{\partial R} - gs\right) + \frac{\partial^2\Pi}{\partial s^2} < 0. \end{aligned} \tag{8}$$

Since from equations (1) and (4) we see that $\partial^2\Pi/\partial s^2$ and $\partial^2 V/\partial R^2$ are 0, equation (8) simplifies to

$$\frac{dR}{ds}\left(\frac{\partial^2\Pi}{\partial R\partial s} - 2g\right) + \frac{d^2R}{ds^2}\left(\frac{\partial V}{\partial R} - gs\right) < 0.$$

Using equations (1), (2), and (4), we get

$$\frac{R}{1-s}(1-2g) + \frac{2R}{(1-s)^2}(Z\delta + \eta - gs) < 0,$$

which is equivalent to $1 - 2g + 2(Z\delta + \eta - gs)/(1 - s) < 0$. Evaluating this inequality at the interior solution given by equation (5) yields $-1 < 0$. Consequently, there is a unique maximum that solves the agency's decision problem. Because the optimal unconstrained subsidy rate, equation (5), is increasing in η, $s = 0$ for $\eta \leq \underline{\eta}$, s is given by equation (5) for $\eta \in (\underline{\eta}, \bar{\eta})$ and $s = \bar{s}$ for $\eta \geq \bar{\eta}$, given $d = 1$. If the agency does not receive an application ($d = 0$),

$s = 0$ by assumption, regardless of the agency's type. Thus, conditional on d, the type-contingent action of the agency in stage 2 is unique. In stage 1, the firm decides whether to apply given s^*, $p_{ijh}(\omega_{ij})$, and $\phi(\eta)$. Since in a perfect Bayesian equilibrium the choice of the firm must maximize the profits and the firm's beliefs must be consistent with the agency's strategy, $d = 1$ only if equation (7) holds and $d = 0$ otherwise. Clearly the agency's best response to $d = 1$ is $s = s^*$ so we have found a perfect Bayesian equilibrium. Since the utility-maximizing action in each stage of the game is unique, the equilibrium is also unique. ■

III. Finnish Innovation Policy, Tekes and Data

A. *Innovation Policy and Tekes's Subsidy Program*

In 2001 Finland invested 3.6% of GDP—5 billion euros—on R&D.[13] Several organizations provide public funding to private R&D in Finland, of which Tekes is by far the most important (see Georghiu et al., 2003, for a description of the Finnish innovation policy system). The primary objective of Tekes is to promote the competitiveness of the Finnish industry and service sector. To this end, Tekes strives to increase Finnish firms' R&D activities and risk taking by providing funding and advice to both business and public R&D. Tekes is also responsible for allocating funding for less-favored regions from European Regional Development Funds (ERDF). Finnish regions are heterogeneous: for example, most of the economic activity and R&D take place in the capital region in southern Finland where some 20% of the population lives.

Besides funding business R&D, Tekes finances feasibility studies and R&D by the public sector, including scientific research. In 2001 Tekes funding amounted to 387 million euros, and it received some 3,000 applications. The number of R&D funding applications by the business sector was 1820 and two-thirds of them were accepted. In monetary terms, the business sector applied for 577 million euros; 241 million euros were granted to it.

Business R&D funding consists of grants, low-interest loans, and capital loans. Tekes's low-interest loans not only have an interest rate below the market rate but they are also soft: if the project fails commercially, the loan may not have to be paid back. A capital loan granted by Tekes differs from the standard debt contract in various ways: it is included in fixed assets in the balance sheet, it can be paid off only when unrestricted shareholders' equity is positive, and the debtor cannot give collateral for the loan. The share of each instrument of the total funding allocated to business R&D in 2001 was 66%, 20%, and 14%. Subsidies covered 83% of the total amount applied.

The application process, which to our understanding is well known among potential applicants, proceeds along the lines of the model described in Section II. In practice, Tekes screens an application and grades it in several dimensions, not two, as we assume for simplicity. The two dimensions concerning the technical challenge of the project and its market risk that we use are, however, the most important ones.[14] Tekes's public decision criteria are the project's effect on the competitiveness of the applicant, the technology to be developed, the resources reserved for the project, the collaboration with other firms within the project, societal benefits, and the effect of Tekes's funding. Tekes takes into account whether the application comes from an SME. The funding also has a regional dimension through ERDF. Besides the regional aspect, the funding from ERDF is subject to the same general criteria as other Tekes funding.

An application has to include the purpose and the budget of the R&D project for which Tekes funding is needed and the applied amount of funding in euros. Tekes's final decision is based on the planned budget of the project before the R&D investments are made and a subsidy is granted as a share of to-be-incurred R&D costs. Decision making is constrained by the rules preventing negative subsidies and very large subsidies in both relative and absolute terms. If the firm fulfills the SME criterion determined at the EU level, the upper bound for the share of covered R&D costs is 0.6. Otherwise it is 0.5.[15]

Actual funding is given only after the R&D investments are made, covering the promised share of incurred costs up to a specified euro limit. The limit should allow the promised reimbursement of investment costs up to the profit-maximizing level but prevents Tekes from covering costs extraneous to the project proposal.[16] In terms of our model,

[13] Because our application data are from January 2000 to June 2002, we use 2001 figures to describe the environment. Public information about Tekes can be found at http://www.tekes.fi/en/, accessed May 20, 2009. Public information is supplemented by knowledge we acquired when one of us spent eleven months in Tekes to participate in the actual decision-making process.

[14] A loose translation of grades of technical challenge is 0 = no technical challenge, 1 = technical novelty only for the applicant, 2 = technical novelty for the network or the region, 3 = national state-of-the-art, 4 = demanding international level, and 5 = international state-of-the-art. For market risk, it is 0 = no identifiable risk, 1 = small risk, 2 = considerable risk, 3 = big risk, 4 = very big risk, and 5 = unbearable risk. Since only five grades are used in practice, we too use a five-grade Likert scale.

[15] According to the EU's definition, an SME should have fewer than 250 employees and either sales less than 40 million euros or a balance sheet less than 27 million euros.

[16] Tekes can adjust a proposed budget downward, as when an application includes costs that cannot be covered because of Tekes's institutional rules. The euro upper limit provides protection against subsidy misuses. There are also other reasons for the limit. Since Tekes has an annual budget, a practical decision rule is to cap the euro amount using the planned budget, the best available information at the time of the subsidy decision. Tekes is also monitored by both the press and politicians, and its civil servants may also want to avoid the accusations of granting larger subsidies than originally planned. At the same time, however, there may be a desire to make the limit high enough to allow the profit-maximizing behavior of applicants. Within the euro limit, an upward adjustment of the planned budget is also possible in principle but rare in practice, occurring virtually only if the project significantly changes character during the application process. Such upgrades can thus be taken as exogenous events that cannot be manipulated by Tekes to overcome the institutional limits on its subsidy allocation.

TABLE 1.—DESCRIPTIVE STATISTICS

	Mean	Median	S.D.	Minimum	Maximum
Age, years	12	10	9.3	1	97
Number of employees	35	5	257	1	13451
Sales per employee, (thousands of euros)	165	78	2,157	0	206,876
Exporter	0.22	0	0.41	0	1
SME	0.97	1	0.16	0	1
CEO also chairman	0.14	0	0.35	0	1
Board size	4.35	4	2.00	1	10
Parent company	0.22	0	0.41	0	1
Number of previous applications	0.57	0	3.49	0	146
Applicant	0.08	0	0.28	0	1

There are 10,944 observations. Sources: Tekes for applications, Asiakastieto Ltd. otherwise.

the rules governing feasible subsidies amount to the minimum constraint of $s_i = 0\ \forall i$, the maximum constraint $\bar{s}_i \in \{0.5, 0.6\}$, and a goal of setting the euro limit at $s_i R_i(s_i)$. Our understanding is that the firms are free to scale back their projects.

B. Data

Our data come from two sources. The project-level data come from Tekes, containing all applications to Tekes from January 1, 2000, to June 30, 2002. They consist of detailed information on the project proposals and Tekes's decisions. The firm-level data covering 14,657 Finnish firms come from Asiakastieto Ltd., a for-profit company collecting, standardizing, and selling firm-specific quantitative information.[17] Asiakastieto's data are based on public registers and on information that Asiakastieto itself collected. The data contain, for example, firms' official profit and balance sheet statements, and include all the firms that must file their data in the public register or submit the information to Asiakastieto. We also have information on the size of the board and on whether the CEO also acts as the chairman of the board of directors.[18]

We use the 1999 cross-section from Asiakastieto's data, that is, all firm characteristics are recorded earlier than the application data. The sample was drawn from Asiakastieto's registers in 2002 according to three criteria: the most recent financial statement of the firm in the register is from either 2000 or 2001, the firm is a corporation, and the industrial classification of the firm is manufacturing, information and communications technology, research and development, architectural and engineering and related technical consultancy, or technical testing and analysis. Firms in these industries are the most likely to apply for funding from Tekes. After cleaning the data of firms with missing values, we are left with 10,944 firms. These firms constitute our sample of potential applicants.

The firms in our sample account for roughly half of all applications. In case a firm had multiple applications within our observation period, we use the first one. This leaves us with 914 applications (or applicants, given one application per applicant). Of these applications, 722 were accepted, that is, they received a positive subsidy rate. There are three principal reasons for the exclusion of an applicant from our sample: the firm did not exist in 1999, the firm did not operate in the industries from which the sample was formed, and the firm was so small that it was not obliged by law to send its profit and balance sheets to the official registry.

Table 1 displays summary statistics of our explanatory variables for potential applicants, and table 2 conditions the statistics on the application decision and success. As table 1 shows, potential applicant firms are heterogeneous. They are on average twelve years old with 35 employees. A very high proportion of firms are SMEs according to the official EU definition (see note 15). Sales per employee, a measure of value added, are 165,000 euros. Some 22% are exporters. In some 14% of potential applicants, the CEO is also the chairman of the board, and the board of an average potential applicant has four to five members. Descriptive statistics for industry and region dummies are reported in online appendix 1.

From table 2 we see that applicants are larger than nonapplicants and successful applicants larger than rejected ones. The median number of employees for nonapplicants is 5, for applicants 26, and for rejected applicants 22. The applicants also tend to have larger boards. Quite naturally, applicants have more previous applications on average than nonapplicants.

Table 3 reports information about applications and Tekes's decisions (see online appendix 2 for more details). Some 21% of applications are rejected. The planned investments are on average 630,000 euros, the rejected proposals being smaller, with a mean of 386,000 euros. According to Tekes's ratings, the projects have on average a technical challenge of 2 (scale 0 to 5) with the rejected proposals having a lower average score of 1.5. The mean risk score is also 2, but it is the same for successful and rejected applications.

[17] More information about Asiakastieto can be found at http://www.asiakastieto.fi/en/, accessed May 20, 2009.

[18] The extensive empirical literature on the role of boards of directors in corporate governance (see Hermalin & Weisbach, 2003, for a survey) does not provide unambiguous predictions concerning these variables. Having the CEO as the chairman of the board can, for example, improve the information flow between the board and the executive but weakens the board's independence, and a larger board is costlier and more vulnerable to free-riding, but is more likely to bring in expertise either in conducting R&D (for example, choosing among competing projects, organizing management of current projects, monitoring) or in the application process itself.

TABLE 2.—CONDITIONAL DESCRIPTIVE STATISTICS

	Nonapplicants	Applicants	Rejected Applicants	Successful Applicants
Age	12	12	12	12
	(9)	(10)	(10)	(9)
	[10]	[10]	[9]	[10]
Number of employees	21	189	102	212
	(122)	(776)	(188)	(867)
	[5]	[26]	[22]	[27]
Sales/employee	169	122	105	126
	(2253)	(55)	(94)	(167)
	[76]	[90]	[83]	[92]
Exporter	0.19	0.57	0.53	0.59
	(0.39)	(0.50)	(0.50)	(0.49)
SME	0.99	0.85	0.85	0.85
	(0.12)	(0.36)	(0.35)	(0.36)
CEO also chairman	0.14	0.15	0.18	0.14
	(0.35)	(0.36)	(0.38)	(0.35)
Board size	4.2	6.2	5.9	6.3
	(1.9)	(2.4)	(2.3)	(2.5)
	[4]	[6]	[5]	[6]
Parent company	0.19	0.51	0.46	0.52
	(0.40)	(0.50)	(0.50)	(0.50)
Number of previous applications	0.25	4.16	3.23	4.41
	(1.28)	(10.66)	(10.96)	(10.58)
	[0]	[2]	[1]	[2]
N	10,030	914	192	722

Numbers reported are mean, standard deviations in parentheses, and, for other than {0,1} variables, the median in brackets. Sources: Tekes for applications, Asiakastieto Ltd. otherwise.

TABLE 3.—DESCRIPTIVE STATISTICS OF APPLICATION VARIABLES

	All Applicants	Successful Applicants	Rejected Applicants
Planned investment, (in euros)	634,294	700,378	385,790
	(1,254,977)	(1,363,460)	(657,540)
Applied for subsidy only	0.75	0.74	0.78
	(0.43)	(0.44)	(0.42)
Technical challenge	2.1	2.3	1.5
	(0.98)	(0.87)	(1.00)
	{582}	{426}	{156}
Risk	2.2	2.2	2.3
	(0.94)	(0.93)	(0.94)
	{422}	{326}	{96}
Granted subsidy rate	-	0.32	-
		(0.13)	
Granted subsidy only	-	0.42	-
		(0.49)	
Number of observations	914	722	192

Reported numbers are mean, standard deviations in parentheses, and number of observations in braces in case that number deviates from that reported in the last row. Source: Tekes.

Tekes grants low-interest and capital loans besides subsidies. Because it is hard to calculate the value of such nonstandard loans to the applicants, we pool the instruments. We thus define the subsidy rate as the sum of all three forms of financing, divided by "accepted investment."[19] Because subsidies cover some 84% of the total applied amount and 61% of the total granted amount within our sample, this seems a reasonable simplification. When the subsidy rate is measured in this way, 0.4% of applicants get the maximum subsidy rate.[20] Successful applicants receive on average a subsidy rate of 32%. We test the robustness of our results to the definition of a subsidy by using only pure subsidies (see section VE).

IV. Econometric Implementation

We first explain how the theoretical model of section II is linked to the data and the institutional environment described in section III. In section IV.B, we explain and discuss our statistical assumptions, and in section IV.C, we discuss the implications of the assumptions underlying the theoretical model of section II.

A. *The Econometric Model*

Equations (2), (5), and (7), which characterize the unique Bayesian equilibrium of the theoretical model, also yield the core of our econometric model, providing estimation equations concerning the firms' application and investment decisions and the agency's subsidy rate decision with minor modifications. The theoretical model, however, provides somewhat less guidance of how to empirically construct the beliefs of the firm regarding the type of the agency.

The set of explanatory variables and estimation samples differs among estimation equations. We include in all estimation equations firm age, the log of the number of employees, sales per employee, a dummy for a parent company, the number of previous applications, a dummy indicating if the CEO is the chairman of the board, board size, and a dummy for exporters. We also include industry and region dummies.[21] In other words, we project all dependent variables on these explanatory variables. We also use the squared terms of these explanatory variables but drop them from some equations so as to minimize computation time when bootstrapping the standard errors; our results are not driven by these choices. As mentioned (see note 12), the grades for risk and technical challenge are used only to estimate the subsidy rate decision, since they are given to applicants only after their applications are screened. As will be explained in more detail, our institutional environment and theoretical model suggest that an SME dummy and a term reflecting the profit effects of an expected subsidy rate should be excluded from some equations. These two restrictions are used in identification.

The reason for different estimation samples is twofold. First, the set of potential applicants is naturally larger than the set of actual applicants. We use the set of potential applicants to estimate the application decision and the set of actual applicants in the remaining estimations. Second, the availability of information on the dependent variables

[19] As mentioned in note 16, Tekes sometimes adjusts a planned budget, for example, when it includes costs that Tekes cannot cover.

[20] There is a cluster of firms right below the maximum subsidy rate: the shares of applicants getting a subsidy rate less than 1 and 5 percentage points below the maximum rate are 1.9% and 2.5%, respectively. At the lower end, there is no such clustering: no firm gets a subsidy rate that is less than 2.9%: however, 2.6% of applicants get a subsidy rate that is greater than 2.9% and less than 5%.

[21] As shown in online appendix 1, we divide Finland into five regions: southern, western, eastern, northern, and central Finland. Of these, eastern and northern Finland are the least developed. We did try interactions between firm characteristics and industry and region dummies, but these had no impact on the results and we therefore dropped them.

TABLE 4.—SPECIFICATIONS AND SAMPLES USED IN ESTIMATION

	Subsidy Rate Equation	Application Equation	R&D Investment Equation	Grading Equations
Explanatory variables				
Age	x	x	x	x
Age^2	-	x	x	-
Log of employment	x	x	x	x
Ln(emp.) squared	-	x	x	-
Sales/employee	x	x	x	x
Sales/employee^2	-	x	x	-
SME	x	x	-	-
Parent company	x	x	x	x
Number of previous applications	x	x	x	x
Number of previous applications^2	-	x	x	-
CEO also chairman	x	x	x	x
Board size	x	x	x	x
Exporter	x	x	x	x
Industry dummies	x	x	x	x
Region dummies	x	x	x	x
Risk	x	-	-	-
Technical challenge	x	-	-	-
Dependent variable	Granted subsidy rate: 0 if latent subsidy rate ≤ 0; $\bar{s}_i \in \{0.5, 0.6\}$ if latent subsidy rate $\geq \bar{s}_i$; latent subsidy rate otherwise	Dummy taking value 1 if the firm applies for a subsidy, and value 0 otherwise	Planned R&D investment when subsidy rate is $\bar{s}_i$	Grade for risk or technical challenge
Sample	Applicants with grades for both risk and technical challenge	Potential applicants (applicants and nonapplicants)	Applicants	Applicants with grade for risk or technical challenge
Number of observations	379	10,944	914	422 (risk), 582 (challenge)
Estimation	Two-limit tobit model	Application equation as a probit model. Coefficients of the application cost function are calculated from the estimated parameters of the application equation using the estimated parameters of the investment equation and the structure of our model.	Tobit type II selection model	Two ordered probit models

To speed up the computation of the bootstrap, we used likelihood ratio (LR) tests to narrow the set of explanatory variables.

among the actual applicants varies with the coverage of Tekes's databases. We detail the differences in explanatory variables and sample sizes among estimation equations in table 4, where we also summarize the estimation method and the definition of the dependent variable. We next explain the estimation equations in the order in which they are estimated.

The grading equations. To calculate the expected benefits from applying for a subsidy, we need to form an empirical counterpart to the firm's beliefs about the type of the agency. The grading equations provide the counterpart in the two grading dimensions, allowing us to uncover the relationship between observable firm characteristics and Tekes's grades. To estimate the grading outcomes, we assume that the agency gives each application i a grade $h \in \{1,\ldots,5\}$ in dimension $j \in \{c, m\}$ by using a latent regression framework. Denoting the latent value of grading dimension $j \in \{c, m\}$ for application i by w_{ij}^* and the observed value by w_{ij}, we get:

$$
\begin{aligned}
&w_{ij} = h \text{ if } \mu_{h-1} < w_{ij}^* = T_i\zeta_j + \omega_{ij} \leq \mu_h \\
&h = 1, \ldots, 5,\ \mu_0 \to -\infty,\ \mu_1 = 1,\ \mu_2 = 2, \ldots, \mu_5 \to \infty \\
&j \in \{c, m\}, \qquad (9)
\end{aligned}
$$

where T_i is a vector of observable firm characteristics and ζ_j is a parameter vector to be estimated. Grading equations are estimated as two ordered probit equations, which allow us to identify the coefficients up to scale. The dependent variables are the two main grades, market risk and technical challenge, and the explanatory variables are firm characteristics without the squared terms and the SME dummy. We have 421 observations in the case of market risk and 581 in the case of technical challenge. These observations form the estimation samples for the two grading equations. The difference in the sample size is explained by imperfect storing of the grades at Tekes.

Estimating equation (9) yields the ζ_j vector, which allows us to construct firms' expectations of the grades they would receive were they to apply. In other words, we assume that the firms, knowing this grading process, its parameters, and the distributions of ω_{ij}, use equation (9) to generate the probabilities $p_{ijh}(\omega_{ij})$ of getting grade h in dimension j.

The subsidy rate equation provides the final part in the construction of the empirical counterpart to the beliefs of the firm and the structural parameters of Tekes's decision rule. We estimate the first-order condition of the agency's optimization problem, equation (5), repeated here for convenience,

$$s_i^* = 1 - g + Z_i\delta + \eta_i, \tag{10}$$

with observations $s_i = s_i^* d_i$ for $s_i^* \in (0, \bar{s}_i)$, $s_i = \bar{s}_i d_i$ if $s_i^* \geq \bar{s}_i$, and $s_i = 0$ if $s_i^* \leq 0$. In words, the dependent variable in equation (10) is the subsidy rate granted by Tekes. It takes the value 0 if the optimal (latent) subsidy rate is nonpositive and the value of the maximum allowed subsidy rate $\bar{s}_i \in \{0.5, 0.6\}$ if the optimal (latent) subsidy rate is $\bar{s}_i$ or larger, and it is equal to the optimal subsidy rate between these two (censoring) values.

We estimate equation (10) using a two-limit tobit specification. The explanatory variables are firm characteristics without the squared terms, but including the SME status, and the two grades mentioned above. Equation (10) is estimated using data on applicants for which we observe the grades for both market risk and technical challenge, yielding a sample of 379. For reasons explained below, this equation is not subject to selection biases emanating from the firms' application decision.

Estimation of equation (10) yields the spillover parameters δ and the variance of η_i. The δ vector measures how much the agency values each dollar of R&D by firm i in addition to the effect on firm profits. This is enough to identify $V(\ )$: integration of equation (4) yields $V(Z_i, \eta_i, R_i) = (Z_i\delta + \eta_i)R_i$ after noting that the constant of the integration must be 0 since a project generates spillovers only with positive R&D. The estimate of the variance of η_i completes the empirical construction of the firm's beliefs.

The application equation is given by equation (7), which can be simplified using equations (1), (2), (6), and some algebra (for example, taking logs of both sides) to

$$d_i = 1\{X_i\beta - Y_i\theta + \ln[-E(\ln(1 - s_i))] \geq \nu_i - \varepsilon_i\}. \tag{11}$$

The dependent variable is thus a dummy taking the value 1 if the firm applies for a subsidy and 0 otherwise. In the term $\ln[-E(\ln(1 - s_i))]$, the expectation is taken with respect to η_i, ω_{ic}, and ω_{im}, capturing the firm's expectations of the profit effects of the Tekes subsidy rate decision. This term is obtained by estimating the grading equations (9) and the subsidy rate equation (10). The explanatory variables used in estimating equation (11) are all firm characteristics and the expectation term $\ln[-E(\ln(1 - s_i))]$. The data we use to estimate equation (11) consist of all 10,944 firms.

As explained below, equation (11) forms the first stage of a traditional sample selection model (tobit type II), where the second stage is the firm's R&D investment decision. The investment equation enables us to identify estimated parameters β. Then the estimates of the application cost parameters θ can be obtained by noting that the estimated reduced-form coefficients for the variables that appear in both X_i and Y_i are of the form $(\beta - \theta)/\sigma_{\nu-\varepsilon}$, whereas the coefficients of those of variables only in Y_i are $-\theta/\sigma_{\nu-\varepsilon}$, and the coefficient of $\ln[-E(\ln(1 - s_i))]$ is $1/\sigma_{\nu-\varepsilon}$.[22] Note that the application cost parameters θ, and hence the costs of applying for subsidies, which are potentially crucial for welfare and counterfactual analyses, could not be identified without a theoretical model.

The R&D investment equation. The final stage of the game is the firm's R&D investment decision. Taking logs of both sides of the firm's first-order condition, equation (2), yields

$$\ln R_i^*(s_i) = X_i\beta - \ln(1 - s_i) + \varepsilon_i. \tag{12}$$

According to the theory, equation (12) specifies how much a firm will invest after knowing the subsidy rate. In the empirical implementation, we encounter a problem because we do not observe the actual R&D decisions of the firms that applied for a subsidy, only their plans. Hence we cannot estimate equation (12) as such.

To link firms' R&D plans to equation (12), we use our theoretical model. The model implies that an applicant strictly prefers proposing a budget based on a maximum subsidy rate over proposing any smaller amount and is indifferent between proposing that budget and any larger amount.[23] Thus, applicants propose to invest the amount they would invest were they to receive the maximum subsidy rate $\bar{s}_i$. Substituting $\bar{s}_i$ for s_i in equation (12) and rearranging gives

$$\ln[(1 - \bar{s}_i)R_i^*(\bar{s}_i)] = X_i\beta + \varepsilon_i. \tag{13}$$

The dependent variable in equation (13) is the (log of the) amount of own funds the firm plans to invest in the project (net of subsidies), and explanatory variables consist of all firm characteristics save the SME dummy. The use of planned instead of actual R&D as the dependent variable implies that we do not need to worry about the potential

[22] We can then identify the variance of the error term in equation (11), since following theory, the coefficient of the term $-E(\ln(1 - s_i))$ is constrained to unity. This implication of our theoretical model cannot be tested.

[23] To see this, recall first that the applicant does not know the agency's type, and the subsidy rate is bounded above at $\bar{s}_i$. As described in section III.A, there is also a euro limit to the ex post reimbursements based on the planned budget. Then, since $\partial\Pi_i/\partial s_i > 0$ by equation (1), the applicant wants as high a subsidy rate as possible. Therefore, it proposes an optimal project based on the maximum subsidy rate, $R_i^*(\bar{s}_i)$). Because of the euro limit, proposing anything less risks forgoing profits in cases where the actual subsidy turns out to be larger and the applicant subsequently reoptimizes. On the other hand, the applicant would never want to implement a project larger than $R_i^*(\bar{s}_i)$, and it is indifferent between announcing $R_i^*(\bar{s}_i)$ and any larger budget, given the assumption that it cannot misappropriate the funds.

endogeneity of subsidies in the investment equation (13). Even if the spillover shock η_i were correlated with ε_i, it would not affect estimates of equation (13).

Equations (11) and (13) form a traditional sample selection model with observation $\ln R_i(\bar{s}_i) = d_i \ln R_i^*(\bar{s}_i)$, as we only observe the R&D investment plans for the firms that apply for a subsidy. The model is identified by two exclusion restrictions. First, based on the theoretical model, the expectation term $\ln[-E(\ln(1 - s_i))]$ is excluded from the investment equation. The second exclusion restriction comes from the institutional environment. As explained in section III, SMEs have a higher maximum subsidy rate ($\bar{s}_i = 0.6$ if the firm is an SME, $\bar{s}_i = 0.5$ otherwise), with the criteria for qualifying as an SME being decided at the EU level. Because the SME status should affect the awarded subsidy rate but should have no effect on profitability of R&D, we include the SME dummy in the subsidy rate equation but exclude it from the investment equation. We also include the SME dummy in the application equation to allow the possibility that SMEs' opportunity costs are different (for example, because of different access to other types of subsidies).[24]

As mentioned, the sample for the first stage of the sample selection model covers the 10,944 firms that constitute our pool of potential applicants. The sample for the second stage comprises all 914 firms that apply for a subsidy and for which we observe the (planned) R&D investment. Equation (13) yields estimates of β, which measure the effect of firm characteristics on the marginal profitability of (log) R&D, and an estimate of the variance of the profitability shock ε_i.

B. *Statistical Assumptions*

We now explain our statistical assumptions, dropping the subscript i for brevity. The five unobservables (ε, η, ν and ω_j, $j \in \{c, m\}$), are assumed uncorrelated with observed applicant characteristics. This is necessary to obtain correct point estimates, but as in Heckman and Vytlacil (2005), the assumption can to a great extent be relaxed while still obtaining correct estimates of rate of return and the effects of subsidies.

We also impose an assumption:

Assumption. (*a*) $\nu = (1 + \rho)\varepsilon + \nu_0$, (*b*) $\eta \perp \varepsilon$, (*c*) $\eta \perp \nu_0$, (*d*) $\varepsilon \perp \nu_0$, (*e*) $\omega_j \perp \varepsilon$, $j \in \{c, m\}$, (*f*) $\omega_j \perp \eta$, $j \in \{c, m\}$, (*g*) $\omega_j \perp \nu_0$, $j \in \{c, m\}$, (*h*) $\omega_c \perp \omega_m$, (*i*) $\eta \sim N(0, \sigma_\eta^2)$, (*j*) $\varepsilon \sim N(0, \sigma_\varepsilon^2)$, (*k*) $\nu_0 \sim N(0, \sigma_{\nu_0}^2)$, (*l*) $\omega_j \sim N(0,1)$, $j \in \{c, m\}$.

As part a shows, the application cost shock ν and the profitability shock ε can be correlated with each other. We thus allow the possibility that firms with a high profitability shock have systematically different application costs than otherwise similar firms do.

While in line with the theoretical literature, parts b and c are probably our most controversial assumptions. The economic interpretation of part b is that η, the shock to the spillover rate (spillover per dollar of R&D), is uncorrelated with ε, the shock to the profitability of R&D. However, the spillover $V(\ )$ can be correlated with ε because $V(\ )$ is a (linear) function of the investment R. In other words, despite part b, spillovers are endogenous to the R&D shock ε. Part c in turn states that the spillover shock is uncorrelated with the application cost shock. From an econometric point of view, parts b and c rule out a selection problem from the subsidy rate equation (10), and, consequently, estimation can be broken into the three steps explained in section IV.A, which significantly reduces computational costs. In estimating the subsidy rate equation, we impose and test parts b and c and cannot reject the null.

Parts e to h imply that the grading equation shocks, ω_c and ω_m, are uncorrelated with all other shocks and with each other.[25] According to parts i to l, all shocks are normally distributed. The robustness of this distributional assumption is tested by semiparametric estimation methods (see section VE).

C. *Implications of Theoretical Assumptions*

Our theoretical model is built on a number of assumptions whose empirical implications we now discuss.

Information structure. We assume that symmetric but incomplete information regarding the agency's type prevails in the application stage, that the agency learns its type exactly after grading, and that the firm's type is common knowledge. While this may seem strong from the outset, we only need to assume that the firm, when contemplating application, does not exactly know how the agency values the proposed project. This ensures, in line with our data, equilibrium outcomes where a firm applies for a subsidy only to be turned down. We could make alternative informational assumptions.[26]

The agency's subsidy decision. We assume that the agency does not have a budget constraint. This is a strong

[24] Given our data, it is unlikely that firms deliberately keep themselves below the EU SME boundary (fewer than 250 employees and either sales less than 40 million euros or a balance sheet less than 27 million euros; see note 15). Most of the firms in our data are well below the boundary, as 95% them have fewer than 110 employees, less than 14 million euros in sales, and a balance sheet of less than 11 million euros. Because the SME criterion also maintains that large firms can hold at most 25% of an SME's equity and votes, it is unlikely that many of the SMEs are subsidiaries of large firms. We thus consider the SME status exogenous.

[25] At the request of a referee, we calculated the correlation of the (generalized) residuals of the two ordered probits in order to measure whether the shocks to grades are correlated. We found that the correlation coefficient (p-value) is 0.02 (0.73). We therefore maintain the assumption of no correlation in the structural model.

[26] For example, assuming that the firm's type is private information would not add much: due to our functional form assumptions, the agency does not care about it. See equation (5).

assumption that is motivated only by simplicity. Clearly it should be relaxed in future work. We do, however, impose a cost of financing on the agency. We also assume that the agency cannot give subsidies to nonapplicants because Tekes is prohibited from doing so by its institutional rules.

An important but potentially restrictive implication of equation (4) is that $V(\,)$ is proportional to R&D investment. That the theoretical literature on R&D spillovers often uses a similar formulation offers only a poor excuse. However, we test this assumption and do not reject it (see section VE).

The firm's investment decision. We assume that the firm's investment is nonverifiable to third parties. This prevents the firm and the agency from writing a binding contract specifying the amount the firm invests conditional on the subsidy rate. The alternative assumption would render the firm's investment behavior uninteresting. More controversial, we exclude moral hazard problems in the use of the subsidy.[27]

We assume that the firm's investment involves no constraints or fixed R&D costs. This assumption is clearly strong but ensures that the solution to the applicant's maximization problem in the last stage is interior. This greatly facilitates the estimation of our model. The assumption rules out credit rationing and other discontinuities that have been emphasized in the innovation policy literature (González et al., 2005). We do not dispute the importance of these phenomena, but this assumption is the price we need to pay to make progress in modeling the whole R&D subsidy program. Moreover, credit rationing and other similar nonlinearities might be less important at the project level than at the firm level. Our assumption means the firms have already made the fixed project-specific R&D investments, which is often realistic since the applicants are existing firms that submit plans for new projects.[28]

The firm's profit function. The firm's profit function specified by equation (1) is well behaving, but the functional form of its first part is admittedly ad hoc: it enables us to derive the estimation equations. We do test the assumption of logarithmic returns to R&D and do not reject it (see note 30). The functional form of the second part of the profit function, equation (1), is given by the agency's subsidy rate rules. It is also identical to that used in the industrial organization and in the endogenous growth literatures on R&D subsidies (Spencer & Brander, 1983; Leahy & Neary, 1999; Howitt, 1999; Segerstrom, 2000).

Together with our assumption of no fixed costs or investment constraints, the form of the second part of equation (1) sets our work apart from the extensive empirical literature on the additionality of R&D subsidies. To allow a nonlinear effect of the subsidy rate, we could write the last part of equation (1) as $(1-s_i)^{\kappa}R_i$, as González et al. (2005), for example, do, where κ would measure additionality. We prefer our formulation for a number of reasons. First, the formulation $(1-s_i)^{\kappa}R_i$, while useful, is ad hoc and does not correspond to the way R&D subsidies are modeled in the theoretical literature or to the R&D subsidy rules in our data.[29] Second, the interpretation of κ is somewhat ambiguous. Using a Box-Cox transformation to model returns to R&D in equation (1) would yield the same estimation equation as the assumptions of logarithmic returns in R&D *and* $(1-s_i)^{\kappa}R_i$. Third, we cannot reject the null that $\kappa = 1$.[30] Finally, in contrast to most of the existing literature on additionality, our analysis is at the project level, not the firm level.

The profit function could also be modified to accommodate multiple projects per firm. For each firm with multiple project applications, we could treat each project as a separate observation. If the project-specific unobservables are uncorrelated, this will not materially affect estimation. The interpretation for nonapplicants would be that none of their projects resulted in an application.[31]

V. Estimation Results

As mentioned in section IV, the set of explanatory variables and estimation samples somewhat differ among estimation equations. Table 4 summarizes the details of each specification. We have verified that our results are not dependent on whether we include the squared terms. The results of the grading equations (9) and concerning the industry and regional dummies are reported in online appendix 3 and 6, respectively.

A. Subsidy Rate Equation and Spillovers

In table 5 we report the results concerning the subsidy rate equation. Based on our model the coefficients can be interpreted as the marginal effects of R&D on spillovers. We find that the more challenging a project is technically, the higher is its subsidy rate. A 1 point increase on the

[27] In practice, moral hazard temptations are certainly possible with monetary treatments. As a result, Tekes has several safeguards against expropriation. As mentioned, subsidies are paid only against receipts and there is a euro limit to a subsidy. Subsidized R&D projects are also randomly audited annually. The Finnish media are also quite attentive to potential misuses of R&D subsidies. Because Tekes's safeguards are common knowledge and the misuses found in the audits or otherwise are rare, we think that the assumption depicts equilibrium behavior.

[28] Although we make the assumption for simplicity, we also note that the revealed motivations for R&D subsidies have at least sometimes been based on spillovers rather than financial market failures. A study using Finnish data (Hyytinen & Pajarinen, 2003) and an evaluation of Finnish innovation policy (Georghiu et al., 2003) conclude that mainly small, R&D-intensive, growth-oriented firms face financial constraints. The situation is similar in many other industrialized countries, as the survey by Hall (2002) suggests. The absence of financial constraints also appears to be consistent with our data: although Tekes also grants low-interest loans, most firms were not interested in them.

[29] Theoretically justified ways to introduce nonlinear effects of subsidies, such as by financial frictions or fixed start-up costs at the project level, would greatly complicate the estimation of the model.

[30] Our point estimate of κ is 0.765 with a wide confidence interval (see table 7).

[31] We could also generalize equation (1) to include a reservation value from other projects, but this would not add much to the analysis.

TABLE 5.—SUBSIDY RATE EQUATION RESULTS

Variable	Dependent Variable Subsidy Rate
Risk	−.020*
	[−.043 .003]
Technical challenge	.100***
	[.076 .124]
Age	−.001
	[−.003 .002]
Log of employment	.019*
	[−.001 .039]
Sales/employee	.00005
	[−.0001 .0002]
SME	.083*
	[−.003 .169]
Parent company	.006
	[−.041 .052]
Number of previous applications	−.001
	[−.007 .004]
CEO also chairman	.001
	[−.054 .055]
Board size	−.007
	[−.017 .003]
Exporter	−.021
	[−.079 .038]
Constant	−.054
	[−.215 .107]
σ_η	.190***
	[.173 .206]
Number of observations	379
LogL.	−19.216
Joint significance	0.000
Linearity 1	0.659
Linearity 2	0.197
Sample selection	.030
	(.027)

Reported numbers are coefficients and, in brackets, 95% confidence interval. Joint significance is the p-value of a Wald test of joint significance of all explanatory variables. All specifications include industry and region dummies. Linearity 1 is the p-value of a LR test of including the planned R&D investment into the equation. Linearity 2 is the p-value of a LR test of including the planned R&D investment plus interactions between it and age, log employment, and sales per employee. Sample selection is the coefficient and (standard error) of the inverse Mills ratio term when the specification of the application equation is given by table 6. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

TABLE 6.—APPLICATION COST FUNCTION RESULTS

Variable	Dependent Variable: Applicant
Age	.019
	[−.016 .709]
Age^2	−.0001
	[−.007 .0003]
Log of employment	−.423**
	[−10.856 −.043]
Ln(emp.) squared	.069***
	[.022 1.382]
Sales/employee	.002***
	[.0007 .022]
Sales/employee^2	−7.97e−0.8
	[−8.53e−07 1.76e−06]
SME	.591
	[−.581 6.939]
Parent company	−.188
	[−4.164 .119]
Number of previous applications	−.236***
	[−5.383 −.077]
Number of previous applications^2	.002***
	[.0005 .037]
CEO also chairman	−.243
	[−1.575 .388]
Board size	−.098*
	[−2.486 .006]
Exporter	−.866***
	[−16.604 −.181]
Constant	13.449***
	[11.156 100.589]
Number of observations	10,944

Reported numbers are coefficients and, in brackets, the 95% confidence interval. Confidence intervals are estimated using a bootstrap with 400 repetitions. The specification includes industry and regional dummies. The dependent variable is 1 if the firm applies for a subsidy and 0 otherwise. ***, **, and * denote, respectively, that the whole 99%, 95%, and 90% confidence interval, respectively, has the same sign as the coefficient estimate.

5-point Likert scale leads to a 10 percentage point increase in the subsidy rate. In contrast, market risk carries a negative and significant (at 10% level) coefficient. Firm size is also significant at the 10% level. Moving an otherwise identical R&D project into a larger firm creates a larger spillover rate, for example, through higher employee rents. As against Tekes's stated preference that allows a 10 percentage point higher level of maximum subsidy for SMEs, it is unsurprising that SMEs are granted a higher subsidy rate, everything else equal: the difference is 8.3 percentage points. The rest of the firm characteristics have no effect.

B. *Application Equation*

The joint estimation of the application equation, (11), and the investment equation, (13), allows us to identify the parameters θ of the application cost function. They indicate, as reported in table 6, how the explanatory variables affect the application costs.[32] Age, CEO being chairman, and SME and parent company statuses have no statistically significant effect on application costs, but firm size nonlinearly decreases them. Sales per employee increase application costs. One interpretation is that because the opportunity costs of the effort of making and promoting an application are probably far greater than the direct monetary costs of filling in and filing it, firms with high-value current production have higher opportunity costs of applying. Firms with high-value-added products and services might also have more complicated R&D projects that are more laborious to write down. The size of the board decreases application costs, perhaps reflecting the role of external knowledge in lowering application costs. Exporters have lower costs, maybe because they are relatively more experienced in dealing with government bureaucracy than nonexporting firms or are better managed in general.

The number of past applications has a nonlinear effect, first decreasing and then, after 118 applications, increasing application costs. However, there are only few observations with more than 118 past applications. Increasing the number of past applications from nonapplicants' median of 0 to applicants' median of 2 decreases application costs by 37%. One prior application decreases costs by 21% and four by 60%. It seems that learning by doing is going on. Given that our data are cross-sectional, it is, however, possible that the results are generated by unobserved heterogeneity, and one should be cautious about a causal interpretation.

[32] Note that in table 6, we do not report the coefficients obtained from the (probit) estimation of a firm (not) applying, but the parameters θ of the application cost function.

TABLE 7.—R&D INVESTMENT EQUATION RESULTS

Variable	Dependent Variable: Planned R&D Investment
Age	−.005
	[−.024 .011]
Age^2	.0001
	[−.0001 .0004]
Log of employment	−.106
	[−.259 .069]
Ln(emp.) squared	.024**
	[.003 .046]
Sales/employee	.001**
	[.0001 .002]
Sales/employee^2	−7.42e−08
	[−5.59e−07 1.74e−06]
Parent company	−.023
	[−.184 .149]
Number of previous applications	−.043**
	[−.073 −.008]
Number of previous applications^2	.0002**
	[−7.26e−06 .0006]
CEO also chairman	−.097
	[−.274 .097]
Board size	.008
	[−.028 .050]
Exporter	−.190*
	[−.383 .043]
Constant	12.840***
	[11.638 13.674]
Number of observations	914
Joint significance	0.000
$\ln(1-\bar{s}_i)$	−0.765
	(0.780)

Reported numbers are coefficients and, in brackets, the 95% confidence interval. Confidence intervals are based on a bootstrap with 400 repetitions. The numbers are from an estimation where the coefficient of $\ln(1-\bar{s}_i)$ is constrained to be −1. In the last row, $\ln(1-\bar{s}_i)$ is the coefficient and the (p-value) of a χ^2 test of difference from minus unity. Joint significance is the p-value of a Wald test of joint significance of all explanatory variables. ***, **, and * denote, respectively, that the whole 99%, 95%, and 90% confidence interval has the same sign as the coefficient estimate.

TABLE 8.—COVARIANCE STRUCTURE RESULTS

Variable	Coefficient [95% confidence interval]
σ_ε	1.212***
Standard deviation of the investment equation shock	[1.010 1.351]
σ_η	.190***
Standard deviation of the spillover (=V( )) shock	[.173 .206]
$\sigma_{\upsilon 0}$	.791***
Standard deviation of the uncorrelated part of the application cost function shock	[.234 20.917]
$1+\rho$	1.673***
Measure of the variance share of ε in υ	[1.174 17.304]
$\rho_{\varepsilon\upsilon}$	−.718***
Correlation between ε and the application equation error term	[−.832 −.462]

For all but σ_η, the values are based on a bootstrap with 400 repetitions. For σ_η, the value is based on the estimated covariance matrix. ***, **, and * denote, respectively, significance at 1%, 5%, and 10% level.

C. *Investment Equation*

Our investment equation, (13), identifies the effects of exogenous variables on the marginal profitability of R&D investment. In view of the received literature, it is likely that unobserved heterogeneity accounts for a substantial part of the marginal profitability of R&D. This is also what we find, as table 7 shows. Firms with higher value-added production have a higher marginal profitability of R&D. Other findings are not robust (see online appendix 5).

In table 7, we also report the test of our assumption that the coefficient of $\ln(1-\bar{s}_i)$ is −1. When we estimate the coefficient, it obtains the value of −0.765. The chi square test value is 0.780, and we cannot reject the null hypothesis that the coefficient is −1.

D. *Covariance Structure*

As we explained in section IV, we are able to identify the variances of all error terms, and the covariance between the unobservables in the application and investment equations (table 8). The coefficient determining the variance share of profitability shock in the application cost shock (part a of the assumption) obtains a value of 1.7. Ceteris paribus, the higher the unobserved marginal profitability of the R&D project of a firm, the less likely the firm will apply. Like the firms with higher sales per employee (see section VB), projects with higher marginal profitability of R&D could have higher opportunity costs of applying, which probably constitute a major part of application costs. Such projects could also be more complicated and are therefore more difficult to describe in an application.

E. *Robustness of the Estimation Results*

The estimation results so far rely on the assumption of normally distributed shocks parts i to k of the assumption. To test the assumption, we estimated the subsidy rate equation, (10), nonparametrically by a two-limit version of Powell's (1984) censored least absolute deviations (CLAD) estimator; the R&D investment equation, (13), using a semiparametric variant of the approach suggested by Das, Newey, and Vella (2003); and the application equation, (11), using the seminonparametric estimator of Gallant and Nychka (1987).[33] The estimation results, reported in online appendixes 4 to 7, suggest that the distributional assumptions of shocks do not affect the majority of our parameter estimates. However, our cross-validation results (see online appendix 5) reject the double normality assumption (parts j and k of the assumption) of the investment and application cost shocks. This is taken into account when assessing our results concerning the effects of subsidies in section VI.

To test parts b and c of the assumption, which maintain that the error in the subsidy rate equation is uncorrelated with the errors in the investment and application equations, we first estimated a probit application equation and then reestimated the subsidy rate equation by inserting the inverse Mills ratio into it.[34] This allows us to tackle the potential selection into the sample of applicants. The inverse Mills ratio obtained imprecisely estimated coeffi-

[33] Manski (1989) compares the merits of the parametric and nonparametric approaches and argues that although the nonparametric approach appears to be more flexible, it involves arbitrary exclusion restrictions.

[34] Naturally, the probit was run without the expected subsidy term, but both with and without added interactions to improve identification.

TABLE 9.—EFFECTS OF SUBSIDIES, IN EUROS

	Integration over the Domains of ε_i and ν_{0i}		Estimated ε_i and Integration over the Domain of ν_{0i}	
	Median	Mean	Median	Mean
Gross firm effect on applicants that received a subsidy	81,871	107,461	49,706	108,902
Net firm effect on applicants that received a subsidy	43,916	64,896	46,253	103,689
Application costs, applicants	35,533	41,827	2,431	4,762
Spillover effect generated by applicants that received a subsidy	56,331	79,990	33,565	75,720

cients with values close to 0 in all of our specifications, validating our assumptions of no correlation. Recall that this does not imply that spillovers are independent of profitability shocks, but rather that profitability shocks are transmitted to spillovers entirely through R&D investments.

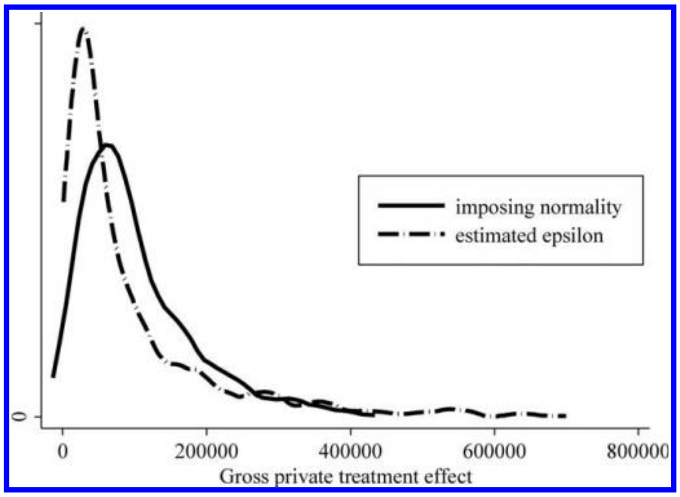
As explained in section III, our dependent subsidy variable pools subsidies and loans granted by Tekes. Thus, we also estimated the subsidy rate equation using pure subsidies as a dependent variable. The results, reported in online appendix 4, are in line with those reported in the main text. We also tested our assumption that $V(\,)$, the spillovers from a project, is linear in the firm's R&D investment as implied by equation (4). Were $V(\,)$ nonlinear in the firm's R&D, the subsidy rate equation would contain an investment term R_i or its interactions with observable applicant characteristics. We included these and could not reject the null of (joint) insignificance of them.[35] In addition, we have estimated the model (by maximum likelihood with normality assumptions) by excluding the observations in the 99th sales percentile, with essentially identical results to those reported.

VI. Effects of Subsidy

Our model allows us to calculate the effects of the subsidies on firms' expected discounted profits (the firm effect), and the expected benefits captured by the agency but not the firms (the spillover effect). If one is willing to believe that the agency acts as a benevolent social planner, the sum of the firm and spillover effects constitutes the general equilibrium effect of subsidies.

To calculate the firm effect, we plug our estimated coefficients and granted subsidy rates into equations (1), (2), and (6). To calculate the spillover effect, we first use equations (4) and (5) to obtain $V(Z_i,\eta_i,R_i) = (Z_i\delta + \eta_i)R_i = (s_i - (1 - g))R_i$, into which we insert the estimated coefficients and granted interior subsidy rates.[36] In addition, we need to take into account the shocks, ε_i and ν_i, which can be correlated with each other by part a of the assumption. We do this in two ways, explained in detail in online appendix 8. First, we integrate with respect to ε_i and ν_{0i} (the orthogonal part of ν_i) by using information provided by the application

FIGURE 1.—DISTRIBUTION OF THE GROSS FIRM EFFECT (IN EUROS) FOR APPLICANTS THAT RECEIVED A SUBSIDY



equation to restrict the domain of integration. Second, we use the estimated value of the profitability shock (the residual of the estimated investment equation) and integrate only over the domain of ν_{0i}.

In table 9 we report the median and mean effects of subsidies, calculated in two ways. Application costs are calculated for all the applicants, while other figures are calculated for successful applicants. Recall that all effects are measured prior to the launch of the R&D projects (but after the subsidy decisions).

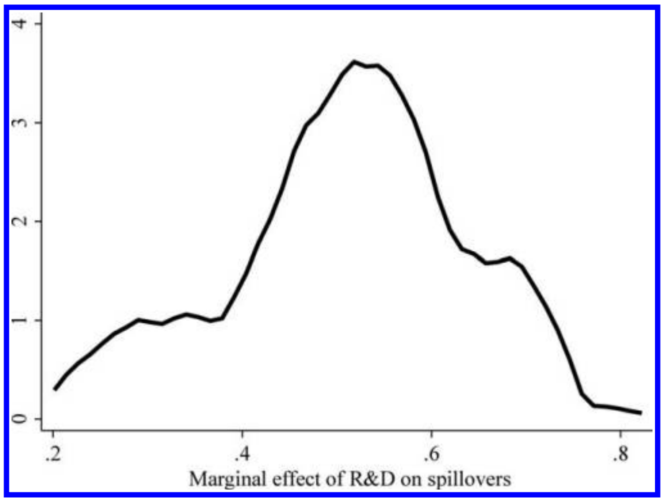
The first row of table 9 presents the gross firm effect that ignores the application costs. The figures reveal that using the estimated value of the profitability shock ε_i instead of integrating over its (imposed) normal distribution lowers the median by some 40% to 45%, but means are close to each other. The mean gross firm effect is of the order of 100,000 euros. Regardless of the way we calculate the shocks, the gross firm effect on successful applicants involves substantial heterogeneity, as shown by figure 1.

The second row of table 9 presents the net firm effect taking into account the application costs, which are reported in the third row. Integrating over the restricted domain of ε_i yields a clearly lower mean of the net firm effect than using the estimated value of ε_i, while the medians are fairly close to each other. Using the estimated value of ε_i reduces the mean application costs by 37,000 euros. Our robustness checks below indicate that application cost figures based on

[35] This is a valid test under parts b and c of the assumption because our investment variable is the amount the firm plans to invest in case it gets the maximum subsidy rate and it is therefore uncorrelated with η.

[36] Naturally, the calculation of $V()$ is adjusted for observations at the lower or upper bound of the subsidy rate.

FIGURE 2.—DISTRIBUTION OF MARGINAL EFFECT OF R&D ON EXPECTED SPILLOVERS, PER 1 EURO OF R&D INVESTED



The sample is trimmed at the 99th percentile.

the estimated value of ε_i are preferred over the figures based on integration of ε_i. With the mean application costs of 4,700 euros, the mean net firm effect remains close to that of the gross firm effect at around 100,000 euros.

Overall it seems that for an evaluation of the actual policy, application costs may not be of first-order importance. Nonetheless, our results from section VD suggest that any counterfactual policy analysis may critically depend on application costs since investment and application cost shocks may be positively correlated, indicating that nonapplicants could have higher application costs.

We then turn to the spillover effect (the fourth row of table 9). If the agency is a benevolent social planner caring only about domestic welfare, the spillover effect should reflect the anticipated change in, for example, domestic R&D spillovers, consumer surplus, and business stealing due to a subsidy. Using the estimated value of ε_i yields lower estimates of spillovers than integrating over its restricted domain. Comparing the second and the fourth rows of table 9 suggests that firms appropriate some 60% of the total effect. We have also calculated the expected rate of return on the subsidy program.[37] Integrating over the restricted domain of ε_i yields a figure of 1.45, while using the estimated ε_i gives a figure of 1.51.

Figure 2 shows the distribution of $Z_i\hat{\delta} + \hat{\eta}_i$ (for a sample trimmed at the 99th percentile). This is the marginal effect of R&D on expected spillovers (recall that $V(Z_i, \eta_i, R_i) = (Z_i\delta + \eta_i)R_i$). The expected spillovers are increasing in R&D investments and hence in the subsidy rate for most of the projects in our data. The expected increase in spillovers is typically between 0.25 and 0.5 per 1 euro of R&D and for 99% of firms, a 1 euro increase in R&D leads to less than a 0.85 euro increase in spillovers.

The calculations on the effects of subsidies are based on the assumption that the shocks are normally distributed (parts i to k of the assumption). As mentioned in section VD, our cross-validation results reject some of the normality assumptions (see online appendix 5). To explore the robustness of our results obtained under the normality assumptions, we calculate the effects of subsidies also based on semiparametric estimation (see online appendix 8). This allows us to recover the distribution of the shock term ($v_i - \varepsilon_i = \rho\varepsilon_i + \nu_{0i}$) in equation (11) without imposing a distributional assumption on ε_i or ν_{0i}. The results, presented in table A.8, remain close to those reported here.

Our welfare calculations may also be affected by our inability to identify the agency's screening costs ($F_i - K_i$). If they were large, our welfare calculations would be biased. Nor do we identify the opportunity cost of public funds (g) and the social rates of return we estimate need to be compared against different values of g to evaluate the program. For plausible values, say, $g = 1.2$, it appears that the estimated rates of return on the subsidy policy exceed the opportunity cost of public funds.[38]

VII. Conclusion

We study the effects of targeted R&D subsidies, one of the most widely used innovation policy tools. We complement the existing literature by building a structural model of the R&D subsidy process and show how the selection of the subsidy by the agency and "self-rejection" by the firms—the decision whether to apply—provide information on hitherto unmeasured objects: the spillover effect of subsidies and the application costs. Our model generates an R&D equation through firms' first-order condition that is close to those derived in theoretical industrial organization and endogenous growth literatures and those estimated in empirical work. More important, identification of our model does not depend on distributional or functional form assumptions, and identification of the effects of the subsidy is obtained under weak assumptions, for example, allowing the explanatory variables to be correlated with the error terms.

Taking the model to project-level data from Finland, we find that large firms generate a larger spillover rate (spillover per dollar of R&D), as do technically more challenging projects. Firms with higher-value-added current production have higher marginal returns to R&D and higher application costs. Profitability and application cost shocks are positively related, implying that firms do not apply for subsidies for the privately most profitable projects.

We estimate expected effects of subsidies that reflect the revealed preferences of firms and the agency at the time the

[37] The rate of return on the subsidy program is the total benefits due to subsidies (the net firm effect plus the spillover effect) divided by the total amount of subsidies (granted subsidy rates multiplied by the investments given by the granted subsidy rates), ignoring the shadow cost of taxes, and taking all applicants into account.

[38] Kuismanen (2000) estimates the dead-weight loss of existing Finnish taxation to be 15% using a labor supply model.

firms make their application decision and the agency decides on the subsidy rate. The estimated effects thus embody the perceived benefits and costs of the subsidy program prior to the actual R&D investments. We find considerable heterogeneity in the subsidy effects. Our estimate of the mean net firm effect on the applicants that received a subsidy is around 100,000 euros, and the mean gross spillover effect is approximately 76,000 euros. These numbers suggest that treated firms internalize 60% of the total effect.

To produce a welfare analysis, we use strong but standard assumptions. Our spillover effect can be interpreted as (domestic) externalities and our calculated rate of return on subsidies as a social rate of return if one is willing to assume that the agency giving subsidies is a benevolent social planner. In that case, our estimates suggest that the expected program benefits exceed the opportunity cost of public funds.

In our desire to model the whole R&D subsidy program with explicit application, allocation, and investment decisions, we have overlooked some important issues that have been highlighted in the previous literature, such as fixed costs of R&D projects and financial market imperfections. These should clearly be incorporated in future work, which should also regard within-firm effects between individual R&D projects as a possible source of additionality. Another difference between our work and existing work is that we use firms' R&D plans. Our results are therefore informative of the expected returns to the policy and the agents prior to actual execution of the projects. While this provides a new perspective to the effects of R&D subsidies, in the future we hope to explore the differences between planned and realized R&D investments.

REFERENCES

Abbring, Jaap, and James J. Heckman, "Econometric Evaluation of Social Programs Part III: Distributional Treatment Effects, Dynamic Treatment Effects, Dynamic Discrete Choice, and General Equilibrium Policy Evaluation" (pp. 5145–5303), in James J. Heckman and Edward Leamer (eds.), *Handbook of Econometrics*, Vol. 6B (Amsterdam: Elsevier, 2007).

Aghion, Philippe, and Peter Howitt, "A Model of Growth through Creative Destruction," *Econometrica* 60 (1992), 323–351.

——— *Endogenous Growth Theory* (Cambridge, MA: MIT Press, 1998).

——— *The Economics of Growth* (Cambridge, MA: MIT Press, 2009).

Arrow, Kenneth J., "Economic Welfare and the Allocation of Resources for Invention" (pp. 609–626), in Richard R. Nelson (ed.), *The Rate and Direction of Inventive Activity* (Princeton, NJ: Princeton University Press, 1962).

Berry, Steven, and Joel Waldfogel, "Free Entry and Social Inefficiency in Radio Broadcasting," *RAND Journal of Economics* 30 (1999), 397–420.

Björklund, Anders, and Robert Moffitt, "The Estimation of Wage Gains and Welfare Gains in Self-Selection Models," this REVIEW 69 (1987), 42–49.

Blanes, Jose Vicente, and Isabel Busom, "Who Participates in R&D Subsidy Program? The Case of Spanish Manufacturing Dirms," *Research Policy* 33 (2004), 1459–1476.

Criscuolo, Chiara, Ralf Martin, Henry Overman, and John Van Reenen, "The Effect of Industrial Policy on Corporate Performance: Evidence from Panel Data," London School of Economics working paper (July 2007).

Czarnitzki, Dirk, and Georg Licht, "Additionality of Public R&D Grants in a Transition Economy: The Case of Eastern Germany," *Economics of Transition* 14 (2006), 101–131.

Das, Mitali, Whitney K. Newey, and Francis Vella, "Nonparametric Estimation of Sample Selection Models," *Review of Economic Studies* 70 (2003), 33–58.

David, Paul A., Bronwyn H. Hall, and Andrew A. Toole, "Is Public R&D a Complement or a Substitute for Private R&D? A Review of the Econometric Evidence," *Research Policy* 29 (2000), 497–529.

Eaton, Jonathan, and Samuel Kortum, "Technology, Geography, and Trade," *Econometrica* 70 (2002), 1741–1779.

Feldman, Maryann P., and Maryellen R. Kelley, "The Ex Ante Assessment of Knowledge Spillovers: Government R&D Policy, Economic Incentives and Private Firm Behavior," *Research Policy* 35 (2006), 1509–1521.

Ferrari, Stijn, Frank Verboven, and Hans Degryse, "Investment and Usage of New Technologies: Evidence from a Shared ATM Network," *American Economic Review* 100 (2010), 1046–1079.

Gagnepain, Philippe, and Marc Ivaldi, "Incentive Regulatory Policies: The Case of Public Transit Systems in France," *RAND Journal of Economics* 33 (2002), 605–629.

Gallant, A. Ronald, and Douglas W. Nychka, "Semi-Nonparametric Maximum Likelihood Estimation," *Econometrica* 55 (1987), 363–390.

Georghiou, Luke, Kenneth Smith, Otto Toivanen, and Pekka Ylä-Anttila, "Evaluation of the Finnish Innovation Support System," Finland's Ministry of Trade and Industry publications no. 5/2003 (2003).

González, Xulia, Jordi Jaumandreu, and Consuelo Pazó, "Barriers to Innovation and Subsidy Effectiveness," *RAND Journal of Economics* 36 (2005), 930–950.

Hall, Bronwyn H., "The Financing of Research and Development," *Oxford Review of Economic Policy* 18 (2002), 35–51.

Hall, Bronwyn H., and Alessandro Maffioli, "Evaluating the Impact of Technology Development Funds in Emerging Economies: Evidence from Latin America," *European Journal of Development Research* 20 (2008), 172–198.

Heckman, James J., Lance Lochner, and Christopher Taber, "General-Equilibrium Treatment Effects: A Study of Tuition Policy," *American Economic Review, Papers and Proceedings* 88 (1998), 381–386.

Heckman, James J., and Richard Robb, "Alternative Methods for Evaluating the Impact of Interventions," in James J. Heckman and Burton Singer (eds.), *Longitudinal Analysis of Labor Market Data* (Cambridge: Cambridge University Press, 1985).

Heckman, James J., and Edward Vytlacil, "Structual Equations, Treatment Effects, and Econometric Policy Evaluation," *Econometrica* 73 (2005), 669–738.

——— "Econometric Evaluation of Social Programs Part I: Causal Models, Structural Models, and Econometric Policy Evaluation" (pp. 4779–4874), in James J. Heckman and Edward Leamer (eds.), *Handbook of Econometrics*, Vol. 6B (Amsterdam: Elsevier, 2006a).

——— "Econometric Evaluation of Social Programs Part II: Using the Marginal Treatment Effect to Organize Alternative Econometric Estimators to Evaluate Social Programs, and to Forecast Their Effects in New Environments" (pp. 4875–5143), in James J. Heckman and Edward Leamer (eds.), *Handbook of Econometrics*, Vol. 6B (Amsterdam: Elsevier, 2006b).

Hermalin, Benjamin, and Michael Weisbach, "Boards of Directors as an Endogenously Determined Institution: A Survey of the Economic Literature," *Economic Policy Review* 9 (2003), 7–26.

Howitt, Peter, "Steady Endogenous Growth with Population and R&D Inputs Growing," *Journal of Political Economy* 107 (1999), 715–730.

Hyytinen, Ari, and Mika Pajarinen, *Financial Systems and Firm Performance: Theoretical and Empirical Perspectives* (Helsinki: Taloustieto, 2003).

Jaffe, Adam B., "Building Programme Evaluation into the Design of Public Research-Support Programmes," *Oxford Review of Economic Policy* 18 (2002), 22–34.

Jovanovic, Boyan, and Jan Eeckhout, "Knowledge Spillovers and Inequality," *American Economic Review* 92 (2002), 1290–1307.

Klette, Tor Jakob, Jarle Møen, and Zvi Griliches, "Do Subsidies to Commercial R&D Reduce Market Failures? Microeconomic Evaluation Studies," *Research Policy* 29 (2000), 471–495.

Kuismanen, Mika, "Labour Supply and Income Tax Changes: A Simulation Study for Finland," Bank of Finland discussion paper 5/2000 (2000).

Lach, Saul, "Do R&D Subsidies Stimulate or Displace Private R&D? Evidence from Israel," *Journal of Industrial Economics* 50 (2002), 369–390.

Leahy, Dermot, and J. Peter Neary, "R&D Spillovers and the Case for Industrial Policy in an Open Economy," *Oxford Economic Papers* 51 (1999), 40–59.

Lerner, Josh, "The Government as a Venture Capitalist: The Long-Run Impact of the SBIR Program," *Journal of Business* 72 (1999), 285–318.

Levin, Richard, C., and Peter C. Reiss, "Cost-Reducing and Demand-Creating R&D with Spillovers," *RAND Journal of Economics* 19 (1988), 538–556.

Manski, Charles, "The Anatomy of the Selection Problem," *Journal of Human Resources* 24 (1989), 343–360.

McFadden, Daniel, "The Revealed Preferences of a Government Bureaucracy: Theory," *Bell Journal of Economics* 6 (1975), 401–416.

——— "The Revealed Preferences of a Government Bureaucracy: Empirical Evidence," *Bell Journal of Economics* 7 (1976), 55–72.

Nelson, Richard R., "The Simple Economics of Basic Scientific Research," *Journal of Political Economy* 67 (1959), 297–306.

Nevo, Risaburo, "Trends and Patterns of Public Support to Industry in the OECD Area," *STI Review* 21 (1998), 12–24.

Pakes, Ariel, "Patents as Options: Some Estimates of the Value of Holding European Patent Stocks," *Econometrica* 54 (1986), 755–784.

Powell, James, "Least Absolute Deviations Estimation for the Censored Regression Model," *Journal of Econometrics* 25 (1984), 303–325.

Pretschker, Udo, "Public Support to Industrial R&D Efforts," *STI Review* 21 (1998), 91–104.

Reiss, Peter C., and Frank Wolak, "Structural Econometric Modeling: Rationales and Examples from Industrial Organization" (pp. 4277–4415), in James J. Heckman and Edward Leamer (eds.), *Handbook of Econometrics*, Vol. 6A (Amsterdam: Elsevier, 2007).

Segerstrom, Paul S., "The Long-Run Growth Effects of R&D Subsidies," *Journal of Economic Growth* 5 (2000), 277–305.

Spencer, Barbara J., and James A. Brander, "International R&D Rivalry and Industrial Strategy," *Review of Economic Studies* 50 (1983), 707–722.

Tanayama, Tanja, *Allocation and Effects of R&D Subsidies: Selection, Screening and Strategic Behavior*, Helsinki School of Economics Academic Dissertations A-309 (Helsinki: HSE Print, 2007).

Todd, Petra E., and Kenneth I. Wolpin, "Ex-Ante Evaluation of Social Programs," *Annals of Economics and Statistics, no. 91/92* (2008), 263–291.

Trajtenberg, Manuel, "Innovation in Israel 1968–1997: A Comparative Analysis Using Patent Data," *Research Policy* 30 (2001), 363–389.

Wallsten, Scott J., "The Effects of Government-Industry R&D Programs on Private R&D: The Case of the Small Business Innovation Research Program," *RAND Journal of Economics* 31 (2000), 82–100.

Wolak, Frank A., "An Econometric Analysis of the Asymmetric Information Regulator-Utility Interaction," *Annals of Economics and Statistics* 34 (1994), 13–69.

Xu, Daniel, "A Structural Empirical Model of R&D, Firm Heterogeneity and Industry Evolution," New York University working paper (March 2008).

This article has been cited by:

1. Dirk Czarnitzki, Cindy Lopes-Bento. 2013. Value for money? New microeconometric evidence on public R&D grants in Flanders. *Research Policy* **42**:1, 76-89. [CrossRef]