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Abstract:
We address the question of whether the returns to R&D differ between R&D projects funded by public grants and R&D in general. To answer this question, we use a flexible production function that distinguishes between different types of R&D by source of finance. Our approach requires no adjustment of the sample or data in order to include firms that never invest in R&D, in contrast to the standard Cobb-Douglas production specification. We investigate the productivity and profitability effects of R&D using a comprehensive panel of Norwegian firms over the period 2001−2009. The results suggest that the returns to R&D projects subsidized by the Research Council of Norway do not differ significantly from R&D spending in general. Our estimate of the average rate of return to R&D is about 10 percent. This estimate is robust with respect to whether firms with zero R&D are included in the estimation sample or not. In contrast, using a standard Cobb-Douglas specification and restricting the sample of firms to those with positive R&D, leads to implausibly high estimates of the rate of returns.

Keywords: eturns to R&D, public grants, public subsidies, productivity

JEL classification: C33, C52, D24, O38

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Sammendrag

Denne studien analyserer den privatøkonomiske avkastningen av offentlige FoU-subsidier, med et særlig fokus på rollen til Norges Forskningsråd (NFR). Vi adresserer spesielt spørsmålet om avkastningen av FoU er ulik for prosjekter som får prosjektstøtte fra NFR og FoU generelt. For å besvare dette, foreslår vi å bruke en fleksibel produktfunksjon som skiller mellom ulike typer FoU etter finansieringskilde. Vi undersøker virkningene på produktivitet og lønnsomhet av FoU ved å bruke et omfattende panel av norske foretak i perioden 2001−2009. Vår tilnærming krever ingen tilpasning av data for å kunne inkludere foretak som aldri investerer i FoU i analysen. Resultatene tyder på at avkastningen av FoU prosjekter støttet av NFR ikke er systemastisk forskjellig fra FoU prosjekter generelt. Våre estimater på den gjennomsnittlige avkstningsraten på FoU-investeringer foretatt av norske foretak i privat sektor er omtrent 10 prosent.

1 Introduction

Both economic theory and empirical evidence support the view that R&D plays an important role in raising productivity. The social returns to R&D investment is often found to be higher than the private returns to the investing firm. Thus, in the presence of market failure, policy intervention may be justified if a well-designed intervention scheme can be implemented. R&D incentives are designed in many different ways. Many countries offer tax credit schemes for R&D expenses and all countries in the OECD offer fiscal incentives in the form of grants to R&D. Although more countries have introduced tax incentives over time, there is no consensus on what is best practice. Evaluation of the incentives in various countries may provide some evidence on which policies or policy mixes work well.

Access to public grants may change a firm's incentives for carrying out R&D in several ways. One way is obviously by reducing the marginal cost of R&D and hence also the required returns. Thus, one may suspect that publicly funded R&D projects have lower private returns than internally funded projects in the absence of the grant. Another way is by improving the liquidity of the firm. In the latter case, the subsidy may finance R&D investments that would have been profitable also in the absence of subsidies (see Hall, 2002, and Cappelen et al., 2012, for discussions of the importance of financing constraints for R&D investments). The fact that there are arguments that publicly funded projects should have lower returns than privately funded R&D, but also for the opposite case, warrants a closer empirical investigation.

In the existing empirical literature, the most common way of estimating returns to R&D is to lump together all R&D spending for each firm or industry (or even country) without distinguishing between sources of finance. Thus, it is implicitly assumed that projects are perfect substitutes and have the same economic returns. A more flexible approach allows various projects to be perfect substitutes in terms of economic returns, but without imposing this as an a priori restriction.

In this study we analyze a panel of Norwegian firms in all industries from 2001 to 2009 and focus on the productivity effects of R&D grants given by the research Council of Norway (RCN) as opposed to privately funded R&D. To assess the productivity effects of R&D at the firm level, it is important to allow for the possibility of running a viable firm without ever undertaking R&D.[1] According to the Norwegian R&D surveys, most firms report that they do not undertake any R&D. Nevertheless, the most common way of specifying the underlying production function in the literature is to use a Cobb–Douglas function with R&D capital as a separate production factor (cf. the survey in Hall et al., 2010), which does not fulfill this requirement. The standard approach is to estimate the model using only firms with positive R&D. This creates a sample selection that may bias the results. Our results, based on a flexible production function that encompasses Cobb–Douglas as a special case, show that the bias may indeed be large.

According to our preferred model, R&D projects subsidized by the RCN do not have lower returns than R&D in general. To be more precise, we cannot reject the hypothesis that the productivity effects of RCN-funded projects are similar to that of ordinary R&D. Our estimate of the average rate of return to R&D spending by Norwegian firms is 10 percent. This estimate is low compared to the rate of return commonly observed in the international literature, cf. Hall et al. (2010).

The structure of the paper is as follows. Section 2 presents some studies relevant to our investigation. Section 3 describes our theoretical framework for analyzing the effect of R&D on productivity. Section 4 shows how the variables are constructed from various data sources, Section 5 presents the results and Section 6 offers some concluding comments.

2 Approaches to studying the relation between R&D and productivity

Several models of the relationship between R&D investment and productivity at the firm level have been proposed in the empirical literature. One general model structure was proposed in Pakes and Griliches (1984), was used in Crepon, Duguet and Mairesse (1998), and is usually referred to as the CDM model. Here firm output

[1] The proportion of firms reporting positive R&D in the survey varies from 25 percent to 37 percent during 2001–2009 with about 72 percent of firms never undertaking R&D. For firms with more than 50 employees, the corresponding shares vary from 37 percent to 48 percent with about 49 percent of these firms never undertaking R&D in 2001–2009.

is a function of input services and total factor productivity. Under the assumption of a standard neoclassical production function with constant returns to scale, labor productivity (net value added per man-hour) can be expressed as a function of capital intensity (capital per man-hour), K/L, and total factor productivity, A^*:

$$Y/L = A^* f(K/L). \tag{1}$$

The productivity level, A^*, in (1) is assumed to depend on several variables relating to R&D, market factors, industry, and possibly other variables. One way of specifying this model is to include an intangible factor – "knowledge capital" – explicitly in equation (1) to capture the effect of factors both internal and external to the firm (see the survey by Hall et al., 2010). In the CDM framework, R&D investment is not directly treated as the driving force of productivity, but is instead assumed to influence the productivity level – A^* in equation (1) – through product and process innovations. An extension of this model is found in Hall et al. (2012) where ICT investment is also included. A separate strand of literature looks at the impact of R&D expenditures on innovation separately, cf. Mairesse and Mohnen (2004), or Cappelen et al. (2012).

A common approach when specifying the effects of R&D on productivity is to link the productivity factor A^* in equation (1) to the R&D knowledge stock, R, by assuming that

$$A^* = AR^{\eta}, \tag{2}$$

where η is the elasticity of Y with respect to R, A is total factor productivity and the knowledge capital stock, R, accumulates according to

$$R_t = (1 - \delta)R_{t-1} + \widetilde{R}_{t-1}, \tag{3}$$

where δ is the depreciation rate of the knowledge stock and $\widetilde{R}$ is (real) R&D investment. If we assume the depreciation rate to be small, we can write

$$\Delta \ln(A_t^*) = \varrho(\widetilde{R}_{t-1}/Y_{t-1}) + \Delta a_t, \tag{4}$$

where ϱ is the rate of return to R&D, cf. Griffith et al. (2004), and $a_t = \ln A_t$. Equation (4) says that the growth rate of productivity depends linearly on R&D

investment divided by net value added, lagged one year. On the other hand, if an estimate (or qualified guess) of the depreciation rate is available, one can calculate the R&D capital stock, R, using (3), and estimate (1)-(2) directly. Unfortunately, little is known about the depreciation rate of R&D, although 0.15 is a value often encountered in the literature (see Hall et al., 2010). If one is uncertain about the depreciation rate of R&D, but is willing to assume that it is close to zero, model (4) is an alternative. Both approaches are well worth pursuing in empirical work.

Using Italian data, Parisi et al. (2006) estimate the rate of return to knowledge capital to be 4 percent. This is rather low, but is an interesting result for a country with a relatively low R&D intensity in the business sector. Their results show that when both R&D intensity and an indicator for process innovation are included in the model, the R&D variable becomes insignificant. However, this result could be due to a simultaneity problem between R&D and innovation. In addressing this problem, Hall et al. (2012) found much higher returns to R&D for Italian firms.

There are few econometric studies using Norwegian firm data to estimate the rate of return to R&D at the micro level. Klette and Johansen (1998) estimate a model where the knowledge stock accumulates according to a log-linear process. Their assumption is based on the idea that old capital and investment in new knowledge capital are complementary, and therefore the more existing knowledge you have, the higher is the marginal return to investment. They estimate the rate of depreciation to be around 0.15 by imposing some identifying restrictions (no increasing returns to knowledge production). Their estimated mean net rate of return varies considerably across industries, with a mean value of 9 percent.

Griffith et al. (2004) develop a generalization of the model leading to equation (4). Based on theories of endogenous innovation and growth, technology transfer is seen as a source of productivity growth for countries or industries behind the technological frontier. Furthermore, R&D activities are seen as an important factor in creating an absorptive capacity for new knowledge and technology in line with the seminal paper by Cohen and Levinthal (1989). The specification chosen by Griffith et al. (2004) is

$$\Delta \ln (A_t^*) = \varrho \frac{\widetilde{R}_{t-1}}{Y_{t-1}} + \beta X_t + \mu \ln(\frac{A_{F,t-1}}{A_{t-1}}) + \kappa \frac{\widetilde{R}_{t-1}}{Y_{t-1}} \ln(\frac{A_{F,t-1}}{A_{t-1}}), \tag{5}$$

where A_F is the productivity level at the frontier (country or industry). The ratio A_F/A measures the distance to the technology frontier for each firm, and can be seen as a way of capturing "catch-up" effects. The last term on the right-hand side of (5) captures the interaction between the distance from the frontier and R&D intensity, $\widetilde{R}/Y$. The idea is that the further a firm/industry/country lags behind the frontier, the more it will benefit from investing in capacity to learn from or imitate others. Griffith et al. (2004) find that the technology gap variable, or "catch-up" variable, is not significant when entered alone ($\mu = 0$), whereas all the other terms enter significantly. Their conclusion is that disregarding the interaction term in (5) may lead to a potential misspecification, and hence produce a bias when estimating the effects of R&D investments on productivity growth.

An important feature of the (standard) approach is that the production function framework cannot be applied to all firms without modifications, as it predicts zero output for firms with zero R&D. In the literature using micro data, there are several options available to circumvent that problem. One "solution" is simply to study those firms that report positive R&D and neglect other firms. This strategy definitely creates a sample selection problem that may bias estimates of the returns to R&D, because selection depends on the *level* of R&D. The problem of sample selection can be solved ad hoc by adding a small amount of R&D investment to firms with zero reported R&D, which makes it technically possible to include them in the analysis. A refinement of this solution is suggested by Griffith et al. (2006) and Hall et al. (2012). Relying on the CDM approach, they replace observed R&D spending with imputed R&D using data for all firms. In this way, zero R&D investment is replaced by nonzero imputed R&D. While this approach may perhaps be justified for firms who report zero R&D in *some* years, it is clearly speculative to do so for the large proportion of firms (almost 50 percent in our sample) that *consistently* report zero R&D spending over time. For these firms, it is not justified to dismiss zero R&D as a mere measurement error. Finally, one may specify a more flexible functional form that allows zero R&D, as suggested already by Griliches (1979).

The advantage of this solution is that one avoids altering the data or the sample. This is the approach favored in the current paper.

3 Theoretical framework

Our starting point is a production function that is homogeneous of degree one in number of man-hours (L), real capital (K), and a measure of aggregate R&D capital (F). We assume

$$Y = AL^{\beta_0} K^{\beta_1} (\lambda L + F)^{\beta_2}, \tag{6}$$

where Y is production measured as net value added, i.e., net of depreciation, in constant prices, A is total factor productivity (unexplained "efficiency"), and F is an aggregate of two types of R&D capital, N and O;

$$F = (\alpha N^{\rho} + O^{\rho})^{\frac{1}{\rho}} . \tag{7}$$

In (7) we distinguish between RCN-funded R&D capital, N, and other R&D capital, $O = R - N$. N is obtained by using (3) with R and $\widetilde{R}$ replaced by N and $\widetilde{N}$, respectively. Note that the elasticity of substitution between the two types of R&D capital equals $s = 1/(1-\rho)$. If the distribution parameter $\alpha \neq 1$, N and O enter the aggregate *asymmetrically* with N being less productive (for given N and O), then α is lower. In particular, the marginal product of N is higher than that of O when $N/O < \alpha^s$. The special case $s = \infty$ ($\rho = 1$) is particularly important. Then $\alpha = 1$ implies that the two types of R&D capital have the same marginal productivity, whereas $\alpha < 1$ implies that the *lower* the share of RCN finance, the higher the marginal product of R&D. Note that F differs from R unless $s = \infty$ and $\alpha = 1$.

The specification (6), unlike (2), allows the (aggregate) R&D variable, F, to be zero without implying $Y = 0$. Two limiting cases are of particular interest: (i) $\lambda \to 0$, in which case (6) approaches a Cobb–Douglas production function in L, K, and F, and (ii) $\lambda \to \infty$, which we will analyze in more detail below. Note that the model is invariant with respect to choice of scale.[2]

[2] For example, replacing F by $F^* = F/k$, gives

$$Y = AL^{\beta_0} K^{\beta_1} (\lambda L + kF^*)^{\beta_2} = k^{\beta_2} AL^{\beta_0} K^{\beta_1} (\frac{\lambda}{k} L + F^*)^{\beta_2} = A^* L^{\beta_0} K^{\beta_1} (\lambda^* L + F^*)^{\beta_2},$$

which has the same form as (6).

We argued in the Introduction that RCN-funded projects may have either higher or lower returns than privately funded R&D. Thus our conjecture is that the decomposition of R into N and O, i.e., the ratio N/O, may not matter much for the marginal productivity of R&D. Hence our null hypothesis is that $s = \infty$ *and* $\alpha = 1$. Our alternative hypothesis is that $\alpha \neq 1$.

Assuming $\beta_0 + \beta_1 + \beta_2 = 1$ (constant returns to scale), it follows from (6) that

$$\frac{Y}{L} = A\left(\frac{K}{L}\right)^{\beta_1}\left(\lambda + \frac{F}{L}\right)^{\beta_2}. \tag{8}$$

Taking logarithms of both sides of (8) and reformulating, we obtain

$$y = a + \beta_1 k + \beta_2 \ln(\lambda + f), \tag{9}$$

where

$$y = \ln(Y/L), \;\; a = \ln A, \; k = \ln(K/L) \text{ and } f = F/L.$$

From (8) and (9) it follows that

$$\begin{aligned} \mathrm{El}_F Y &= f\frac{\partial y}{\partial f} = \beta_2 (\lambda + f)^{-1} f \qquad (10)\\ \mathrm{El}_L Y &= 1 - \beta_1 - \mathrm{El}_F Y \\ \mathrm{El}_K Y &= \beta_1. \end{aligned}$$

To study the case where λ is large, we reformulate (9) as

$$y = a^* + \beta_1 k + \beta_2^* \ln\left(1 + \frac{f}{\lambda}\right) \tag{11}$$

where

$$\beta_2^* = \beta_2/\lambda \text{ and } a^* = a + \beta_2 \ln\lambda. \tag{12}$$

Where λ is large,

$$\ln\left(1 + \frac{f}{\lambda}\right) \simeq f/\lambda. \tag{13}$$

Then we can reformulate (11) as

$$y = a^* + \beta_1 k + \beta_2^* f, \tag{14}$$

It follows that

$$\begin{aligned} \mathrm{El}_F Y &= \beta_2^* f \\ \mathrm{El}_L Y &= 1 - \beta_1 - \beta_2^* f. \end{aligned} \tag{15}$$

Note that the parameter β_2^* in (14) has a different interpretation from β_2 in (9).

The limiting case of (14), i.e., when $s = \infty$, is particularly interesting because it allows an approximation when the depreciation rate of R&D capital, δ, is small, similar to Griffith et al. (2004). Then, as we show in Appendix A,

$$\Delta y_t \simeq \Delta a_t^* + \beta_1 \Delta k_t + \varrho \left(\frac{\widetilde{R}_{t-1}}{Y_{t-1}} \right) + \varrho(\alpha - 1) \left(\frac{\widetilde{N}_{t-1}}{Y_{t-1}} \right) - \eta \Delta \ln L_t, \tag{16}$$

where ϱ can be interpreted as the expected return to R&D: $\varrho \equiv E\left(\partial Y / \partial F\right)$ and η is the expected (mean) value of $\mathrm{El}_F Y$: $\eta \equiv E(\mathrm{El}_F Y)$.

4 Sample and variable construction

For our analysis, we have constructed a panel of annual firm-level data for Norwegian firms with at least three consecutive observations during 2001–2009. The base for the sample is the R&D statistics, which are survey data collected by Statistics Norway. These data comprise detailed information about firms' R&D activities, such as total R&D expenses (divided into internally performed R&D and externally purchased R&D), grants from the RCN, the number of employees engaged in R&D activities, and the number of man-hours worked in R&D. Each survey contains about 5000 firms. Only firms with more than 50 employees are automatically included in the survey. For smaller firms (with 5–49 employees) a stratified sampling scheme is employed. The stratification is based on industry classification (NACE codes) and firm size. However, these smaller firms are not representative of firms of their size and industry, because they have a higher probability of engaging in R&D. Hence, to reduce the problem of endogenous sample selection, we include only firms with more than 50 employees in our analysis. Currently, data are available for 1993, 1995, 1997, 1999, and *annually* from 2001 to 2009. The information from all available surveys is used for the construction of R&D capital stocks.

Table 1: Overview of variables and data sources

Variables	Definition	Data sources
Y	Output (net value added)	accounts statistics
$\widetilde{R}$	R&D investments	R&D statistics
$\widetilde{N}$	Grants from the RCN	R&D statistics
R	Total R&D capital stock	R&D statistics
N	RCN-financed R&D capital stock	R&D statistics
K	Total capital stock	accounts statistics
L	Man-hours	REE
h	Share of man-hours worked by high-skilled workers	REE, NED
Derived variables:		
y	Log of labor productivity: $\ln(Y/L)$	
k	Log of capital intensity: $\ln(K/L)$	
O	$R - N$	
F	$(\alpha N^{\rho} + O^{\rho})^{\frac{1}{\rho}}$	
f	F/L	

The data from the R&D statistics are supplemented with data from three different registers: The accounts statistics, the Register of Employers and Employees (REE), and the National Education Database (NED). Table 1 presents an overview of the main variables and data sources used in our study. The data sources are described in more detail in Appendix B.

Output, Y, is net value added at factor cost and computed as the sum of operating profits net of depreciation and labor costs and deflated by the consumer price index. R&D investment, $\widetilde{R}$, is yearly R&D investment and $\widetilde{N}$ are the grants from RCN as they are reported in the questionnaire, deflated by a price index for R&D investment based on the price indices from the national accounts for the various components making up total R&D. According to Hall et al. (2010) the choice of deflator for R&D expenditures usually does not matter much for the econometric results for the main parameters of interest.

The (real) R&D capital stock (R) at the beginning of a given year t is computed by the perpetual inventory method using (3) and a constant rate of depreciation $\delta = 0.15$ (for details, see Cappelen et al., 2012). Following Hall and Mairesse (1995), the benchmark for the R&D capital stock at the beginning of the observation period for a given firm, R_1, is calculated as if it were the result of an infinite R&D investment series, $\widetilde{R}_{-t}$, $t = 0, 1, 2, ...$, with a fixed presample growth rate $g = 0.05$ (cf. equation

(5) in Hall and Mairesse, 1995). A separate capital stock, N, is calculated in the same way, using $\widetilde{N}$ instead of $\widetilde{R}$ to accumulate the capital stock. Then $O = R - N$ is the R&D capital stock financed from *other* sources than RCN.

To construct the physical capital stock, K, we used information from the accounts statistics. The accounts statistics distinguish between several groups of physical assets. To obtain consistent definitions of asset categories over the whole sample period, all assets have been divided into only two types: equipment, denoted by e, which includes machinery, vehicles, tools, furniture and transport equipment, and buildings and land, denoted by b. The expected lifetimes of the physical assets in group e (of about 3–10 years) are considerably lower than those of the assets in group b (about 40–60 years). Total capital, K, is then an aggregate of equipment capital, e, and building capital, b. We use the book value as a measure of the capital stock. This is justified on the grounds of the short time series for each firm and corresponds to the approach taken by Power (1998) and Baily et al. (1992). When aggregating the two capital types, we use a Törnqvist volume index with time-varying weights that are common across firms in the same industry (see OECD, 2001).

Man-hours, L, is the sum of all individual man-hours worked by employees in the given firm according to the contract. For each firm, we distinguish between two educational groups, high- and low-skilled. High-skilled workers are those who have postsecondary education, i.e., persons who have studied for at least 13 years (for a description of the educational levels, see Table 6 in Appendix B). To construct h, man-hours worked by high-skilled persons are aggregated to the firm level and divided by the total number of man-hours worked in the firm.

As mentioned above, to avoid the problem of endogenous sample selection, only firms with more than 50 employees are included in our analysis. We further exclude from the sample firms with incomplete information or with extreme values for the variables of interest. We need to use the panel structure of the data in order to address the endogeneity problem that arises with respect to input choices and to be able to conduct a dynamic analysis. Hence, only firms with observations in at least three consecutive years are kept. The final sample contains about 1900 firms. Descriptive statistics for the main variables and firms in the final sample are presented in Appendix C.

5 Implementations and results

5.1 Estimation

In addition to the variables in Eq. (9), our analysis includes the share of man-hours worked by high-skilled workers, h_{it}, dummies for the firm's age, industry, and location, whether the firm cooperates with other firms in their R&D activities, and whether the firm uses an external research institute for their R&D. The dummy variables are collected in the vector D_i. Then

$$y_{it} = \beta_1 k_{it} + \beta_2 \ln(1 + f_{it}/\lambda) + \beta_3 h_{it} + \beta_4' D_i + \nu_i + \zeta_{it}, \tag{17}$$

where the indices $i = 1, ..., N$ and $t = 1, ..., T$ denote firm and time, respectively, ν_i represents a fixed firm-specific effect and ζ_{it} is an error term. We allow the error term, ζ_{it}, in (17) to follow a first-order autoregressive process, i.e.,

$$\zeta_{it} = \phi \zeta_{i,t-1} + \varepsilon_{it}, \tag{18}$$

where

$$|\phi| < 1,\ E[\varepsilon_{it}] = 0,\ E[\varepsilon_{it}^2] = \sigma_\varepsilon^2$$

and

$$Cov[\varepsilon_{it}, \varepsilon_{jt}] = 0 \text{ if } t \neq s \text{ or } i \neq j.$$

Multiplying (17) by ϕ and quasi-differencing, we get a dynamic panel data equation:

$$\begin{aligned} y_{it} = {} & \phi y_{i,t-1} + \beta_1 k_{it} + \varphi_1 k_{i,t-1} + \beta_2 \ln(1 + f_{it}/\lambda) + \varphi_2 \ln(\lambda + f_{i,t-1}) \\ & + \beta_3 h_{it} + \varphi_3 h_{i,t-1} + \varphi_4' D_i + \varpi_i + \varepsilon_{it}, \end{aligned} \tag{19}$$

where

$$\begin{aligned} &\varphi_1 = -\phi\beta_1,\ \varphi_2 = -\phi\beta_2, \varphi_3 = -\phi\beta_3, \\ &\varphi_4 = (1-\phi)\beta_4,\ \varpi_i = (1-\phi)\nu_i. \end{aligned} \tag{20}$$

Equation (19) is a first-order difference equation, which can be solved by repeated substitution of lagged values $y_{i,t-1}$, $y_{i,t-2}$, and so forth. If we do this, we will see that every value of y_{it} depends on ω_i and all $\varepsilon_{i,t-s}$ for $s \geq 0$. Thus, $y_{i,t-1}$ is correlated with the firm-specific effect, ω_i, but not with ε_{it}. Moreover, we assume that k_{it}, f_{it} and h_{it} are predetermined endogenous variables, i.e., determined at the beginning of t, and hence correlated with ω_i and $\varepsilon_{i,t-s}$ for $s > 0$.

Even if the nonlinear parameters (λ, ρ, α) were known, the estimation of equation (19) by means of least squares will give inconsistent estimators. The usual method for addressing the endogeneity problem is to estimate equation (19) in first-differenced form in order to exclude ω_i from the equation and then use instruments for the endogenous variables.

To estimate the model, we performed a grid search in the (λ, ρ, α)-space, where, for each value of (λ, ρ, α), we estimate the remaining parameters in (19) using the generalized method of moments (GMM) estimator proposed by Arellano and Bond (1991), which uses lagged levels and first differences of the endogenous variables as instruments. Their method is implemented in STATA as *xtabond*. Our iterative estimation procedure converges when the GMM-criterion function of Arellano and Bond is minimized [3]. Table 10 in Appendix C shows the value of the criterion function for a wide range of (s, λ)-values when $\alpha = 1$. It turned out that $\widehat{s} = \infty$ $(\widehat{\rho} = 1)$ and $\widehat{\lambda} > 140$ for all $\alpha \in [0, 2]$, and hence for all reasonable values of α. For all practical purposes we can therefore assume also that $\widehat{\lambda} = \infty$. Inserting $\rho = 1$ in (7), we can write

$$\begin{aligned} f &= F/L = \alpha N/L + O/L \\ &= R/L + (\alpha - 1)N/L. \end{aligned} \tag{21}$$

Moreover, because λ is large, it follows from (13) that $\ln(1 + f_{it}/\lambda)$ can be replaced by f_{it}/λ. Using (12) and (21) in (17), we then obtain

$$y_{it} = \beta_1 k_{it} + \beta_2^* \frac{R_t}{L_t} + \beta_2^*(\alpha - 1)\frac{N_t}{L_t} + \beta_3 h_{it} + \beta_4' D_i + \nu_i + \zeta_{it}. \tag{22}$$

The corresponding dynamic regression equation can be expressed as

$$\begin{aligned} y_{it} &= \phi y_{i,t-1} + \beta_1 k_{it} + \varphi_1 k_{i,t-1} + \beta_2^* \frac{R_t}{L_t} + \beta_2^*(\alpha - 1)\frac{N_t}{L_t} + \\ &\varphi_2^* \frac{R_{t-1}}{L_{t-1}} + \varphi_2^*(\alpha - 1)\frac{N_{t-1}}{L_{t-1}} + \beta_3 h_{it} + \varphi_3 h_{i,t-1} + \varphi_4' D_i + \varpi_i + \varepsilon_{it}, \end{aligned} \tag{23}$$

[3] This is asymptotically equivalent to maximizing the Wald statistic provided by STATA as a goodness-of-fit test of the model against an alternative with only a constant term.

where $\varphi_2^* = -\phi\beta_2^*$ and ε_{it} is white noise.

Note that the parameters β_1, β_2^* and β_3, can be interpreted both as short- and long-run coefficients under the restrictions (20). For example, from (23) the long-run effect on y_{it} of a *permanent* unit change in k_{it} equals $(\beta_1 + \varphi_1)/(1-\phi)$, which is equal to β_1 under the restrictions (20). Similarly, the long-run coefficient of R/L, is $(\beta_2^* + \varphi_2^*)/(1-\phi)$, which is equal to β_2^*. There are several possible estimators of the long-run coefficients. One is the estimated coefficient of k_{it} in (23), $\widehat{\beta}_1$. However, this estimator is not robust against specification errors in (20). A more robust estimator is the long-term coefficient of k_{it} derived from (23): $\widehat{\beta}_1^{LR} = (\widehat{\beta}_1 + \widehat{\varphi}_1)/(1-\widehat{\phi})$. If the model is correctly specified, $\widehat{\beta}_1$ should be close to $\widehat{\beta}_1^{LR}$. A third method is to impose (20) a priori when estimating (23). We will pursue the first and second approach here and test whether the restrictions (20) are valid or not.

The final estimates are presented in Table 2. As a benchmark we also present fixed-effects (FE) estimators of (22). The FE estimator is a conventional within-estimator applied to equation (22). However, this method yields biased estimates due to the endogeneity of explanatory variables, as described above.

Both the FE and GMM estimators of the coefficient of the aggregate R&D capital stock variable, R_t/L_t, are positive and significant. However, the estimated (long-run) coefficient is notably smaller using FE (0.10) than GMM (0.29). Note that the estimated short-run coefficient of R_t/L_t (0.23) is close to the long-run coefficient (0.29). This gives support to the parameter restrictions (20). The estimates of $\beta_2(\alpha - 1)$ (the coefficient of N_t/L_t) are not significantly different from zero when using any of the methods. These results indicate that R&D capital subsidized by RCN adds no more or less to a firm's productivity than other R&D projects and that this is a robust finding.

As expected, we find a significant positive relation between capital intensity, k, and labor productivity: the estimated elasticity of tangible capital is around 0.1 using GMM. The FE estimate is much smaller. Seen together, these results indicate that the FE estimator of the coefficients of both the physical capital stock (k) and the R&D capital stock (R/L) are biased downwards. With regard to the variable h (share of man-hours by high skilled workers), the results are ambiguous. GMM

Table 2: GMM estimates of the productivity equation. Robust standard errors in brackets

Dependent variable: y_t	GMM-estimates				FE (Within)	
Explanatory variables,$^{a)}$	short-run coeff.$^{b)}$		long-run coeff.$^{c)}$		estimates$^{d)}$	
y_{t-1}	0.38	[0.03]***	–		–	
k_t	0.09	[0.02]***	0.10	[0.03]***	0.03	[0.00]***
k_{t-1}	−0.03	[0.02]*	–		–	
R_t/L_t	0.23	[0.03]***	0.29	[0.06]***	0.10	[0.04]**
R_{t-1}/L_{t-1}	−0.05	[0.03]*	–		–	
N_t/L_t	−0.59	[0.38]	−1.00	[1.44]	−0.60	[1.26]
N_{t-1}/L_{t-1}	−0.02	[0.77]	–		–	
h_t	−0.09	[0.16]	0.14	[0.24]	0.16	[0.08]**
h_{t-1}	0.18	[0.14]				
Number of observations		7124			10976	
Number of firms		1886			1886	
R^2					0.17	

Notes: *significant at 10 percent **significant at 5 percent ***significant at 1 percent

$^{a)}$ Dummies for firm age, region, industry, cooperation, and time are included in the analysis, but not reported here

$^{b)}$ Estimates of coefficients of dynamic equation (23): $\widehat{\phi}$, $\widehat{\beta}_k$, $\widehat{\varphi}_k$, etc.

$^{c)}$ Derived long-run coefficients from (23): $(\widehat{\beta}_k + \widehat{\varphi}_k)/(1 - \widehat{\phi})$, etc.

$^{d)}$ Fixed-effects estimator of (22)

yields no significant coefficient estimates, whereas the FE estimator is positive, but significant only at the 10 percent level. The reason may be that both the FE and GMM estimator eliminate regressors that are constant over time, and poorly identify effects of variables that exhibit little within-firm variation, which is the case for h_{it}.

The estimate of ϕ in Table 2 – the coefficient of $y_{i,t-1}$ – is equal to 0.38 and is highly significant. Thus the error term in (19) exhibits strong serial correlation. Note that from (19) and (20) the coefficient, φ_2, of R_{t-1}/L_{t-1} should satisfy the constraint $\varphi_2 = -\phi\beta_2$. This constraint, and the other parameter restrictions in (20), are tested in Table 3. Neither of the restrictions is rejected by the statistical tests. As also seen from Table 3, the Arellano–Bond test of zero first-order autocorrelation in the error term ζ_{it} in (22) is rejected, but not for second-order autocorrelation. This confirms that ζ_{it} follows a first-order autoregressive process, as assumed in (18). We also applied a Sargan test to test the validity of the overidentifying restrictions with regard to the instrumental variables. With a χ^2-test statistic of 125.55 and 121 degrees of freedom, we cannot reject this hypothesis. All these specification tests, seen together, give strong support to our econometric specification.

Table 3: Test of parameter restrictions and significance of derived long-run coefficients

	Observed value (z) of test statistic (Z)	Level of significance $\Pr(Z > z)$
Test of parameter restrictions (20)*:		
$\varphi_1 = -\phi\beta_1$	0.32	0.75
$\varphi_2^* = -\phi\beta_2^*$	1.38	0.17
$\varphi_3 = -\phi\beta_3$	1.21	0.23
$(\alpha - 1)\varphi_2^* = -\phi\varphi_2^*(\alpha - 1)$	−0.32	0.75
Arellano–Bond test of zero autocorrelation in errors*		
order 1	−10.74	0.00
order 2	0.28	0.77
Sargan test of overidentifying restrictions**	125.55	0.10

Notes: *t-test **test statistics is distributed as $\chi^2(107)$

5.2 Return to R&D

GMM is the most appropriate method to handle the problem of endogeneity and autocorrelation in the residuals. From the GMM estimates in Table 2, we can calculate the elasticity of net value added with respect to R&D, $\mathrm{El}_F Y$, for any firm. Using (15),

$$\mathrm{El}_F Y = \beta_2^* \frac{F}{L},$$

whereas the marginal return to R&D capital, $\partial Y/\partial F$, equals

$$\frac{\partial Y}{\partial F} = \beta_2^* \frac{Y}{L}.$$

Using our long-run estimate of β_2^* ($= 0.29$) and the mean value of F/L for firms with positive R&D ($= 0.116$), we find that the estimated mean of $\mathrm{El}_F Y$ is 3.3 percent. The derived marginal returns have a mean value of 10.1 percent and median of 7.9 percent (see Table 4). Other percentiles are also depicted, e.g., the 10 percent and 90 percent percentiles are 5.1 and 15.3 percent, respectively. These figures are within the range of estimates obtained in the empirical literature.

To illustrate the robustness of these results, Table 4 shows the distribution of $\partial Y/\partial F$ when the model is estimated either on the full sample (superscript a) or the subsample of firms with positive R&D capital stock (superscript b), and also in the case when $\lambda = 0$ (i.e., a Cobb–Douglas production function). Both the mean value

Table 4: Distribution of marginal returns to R&D, $\partial Y/\partial F$, for different models

Model specification	Mean	Percentiles				
		10 %	25 %	50 %	75 %	90 %
Main model,[a] with $\lambda = \infty$						
All firms	0.101	0.051	0.062	0.079	0.108	0.153
Only firms with $R > 0$	0.108	0.051	0.063	0.083	0.114	0.160
Main model,[b] with $\lambda = \infty$						
Only firms with $R > 0$	0.123	0.059	0.072	0.095	0.130	0.183
Cobb–Douglas [b] ($\lambda = 0$)						
Only firms with $R > 0$	0.574	0.152	0.683	2.415	10.912	41.582

Notes: [a] Estimated on full sample of firms; [b] Estimated on subsample of firms having $R > 0$

and the percentiles in the distribution of $\partial Y/\partial F$ are shown in each case. The main findings from Table 4 are that for our estimated (main) model (i.e., $\lambda = \infty$), the distribution of $\partial Y/\partial F$ is not sensitive to whether we exclude firms with zero $R\&D$ or not, which is a strength of our model specification. On the other hand, if we assume a Cobb–Douglas production function ($\lambda = 0$), the distribution of $\partial Y/\partial F$ changes dramatically. The estimated mean return now becomes 57.4 percent and the median return becomes 241 percent, which are implausible numbers.

An alternative approach to estimating the average return to R&D is provided by the model described in equation (16), which assumed a "small" depreciation rate δ, $s = \infty$ and $\alpha = 1$. Under the same assumptions regarding the error term ε_{it} and explanatory variables as above, we can rewrite (16) as

$$\Delta y_{it} = \beta_1 \Delta k_{it} - \eta \Delta \ln L_{it} + \varrho \left(\frac{\widetilde{R}_{i,t-1}}{Y_{i,t-1}} \right) + \varrho(\alpha - 1) \left(\frac{\widetilde{N}_{i,t-1}}{Y_{i,t-1}} \right) + \beta_3 \Delta h_{it} + \Delta \varepsilon_{it}, \quad (24)$$

where $\varrho \equiv E\left(\partial Y/\partial F\right)$ and $\eta \equiv E(\mathrm{El}_F Y)$ (cf. (16)).

The estimation results for (24) are presented in Table 5, together with an extended version of the model, which is similar to Griffith et al. (2004), i.e., when the productivity gap variable (A_f/A) is included as an explanatory variable as in (5). The dependent variable is the first-differenced log net value added per man-hour, Δy_t. In this model the assumed rate of depreciation of R&D capital is small so that R&D intensity is the relevant variable to include as discussed earlier. The advantage of this approach is that we do not need to assume any specific number for the depreciation rate (only that it is small), nor do we have to impute the initial R&D capital stock. Looking at the instrumental variable estimates in the first column of Table

Table 5: GMM estimates of productivity growth equation. Standard errors are shown in brackets

Dependent variable: $\triangle y_t$	Instrumental variable estimates			
Explanatory variables$^{a)}$	Basic model (24)		Extended model as in (5)	
Δk_t	-0.006	[0.006]	-0.004	[0.006]
$-\Delta \ln(L_t)$	0.244	[0.029]***	0.214	[0.028]***
$\widetilde{R}_{t-1}/Y_{t-1}$	0.063	[0.029]	0.132	[0.052]**
$\widetilde{N}_{t-1}/Y_{t-1}$	-0.550	[0.554]	-1.092	[1.334]
$\ln(A_f/A)_{t-1}$	–		0.105	[0.008]***
$\widetilde{R}_{t-1}/Y_{t-1} \times \ln(A_f/A)_{t-1}$	–		-0.059	[0.039]
$\widetilde{N}_{t-1}/Y_{t-1} \times \ln(A_f/A)_{t-1}$	–		0.348	[1.044]
Δh_t	-0.380	[0.183]**	-0.339	[0.181]*
Number of observations	7124		7124	
Number of firms	1886		1886	
R^2	0.048		0.086	

Notes: *significant at 10 percent **significant at 5 percent ***significant at 1 percent

$^{a)}$Dummies for firm age, region, industry, cooperation, and time are included in the analysis, but not reported here.

5 we obtain an estimate of the real rate of return to R&D (ϱ) of about 6 percent, whereas the estimate for the extended model (second column) is 13.2 percent. This latter estimate is almost significant at the 1 percent level, and close to the mean return derived from the model of Table 2 (estimated to be 10 percent).

The coefficient of $-\Delta \ln(L_t)$ in Table 5 can be interpreted as the (expected) elasticity of Y with respect to R&D capital, F, and is estimated as 24.4 percent. This is much higher than the estimated mean of $\mathrm{El}_F Y$ implied by the GMM estimates in Table 2 (3.3 percent). On the other hand, the estimate of the elasticity of tangible capital is negative, although insignificant. The effect on productivity of an increase in the share of employees with high education, Δh_t, is also estimated to be negative. More importantly, we have included a variable capturing the productivity effect of having R&D finance from RCN, $\widetilde{N}/Y$. The estimated coefficient is insignificant, implying that firms that receive finance from the RCN have the same returns on their R&D as firms that do not receive any funding from the RCN. Thus, in this case also our results support the view that we can add both kinds of R&D investments into a common aggregate, $\widetilde{R} = \widetilde{N} + \widetilde{O}$, because the rate of return to R&D is independent of the source of finance.

The second column of Table 5 shows the result of estimating equation (24) when we include the productivity gap variable (A_f/A) as in (5). This variable enters with a significant positive coefficient, meaning that firms that are far behind the frontier are "catching up" to firms that are close to the frontier. However, contrary to Griffith et al.'s (2004) findings, the estimated coefficient of the "absorptive capacity" term, i.e., R&D intensity $(\widetilde{R}/\widetilde{Y})$ interacting with the productivity gap variable (A_f/A), is insignificant. Again, we do not reject that RCN-funded projects have the same productivity effects as R&D in general.

6 Conclusions

In this paper, we have analyzed the effects of R&D on firm performance with a particular focus on R&D spending partly financed by the Research Council of Norway (RCN), using a comprehensive panel of Norwegian firms over the period 2001-2009. We have based our study on econometric models of the relationship between labor productivity and R&D. A number of specific assumptions need to be made to estimate the effects of R&D on productivity. In particular one must address whether or not to calculate the stock of R&D capital, or simply use R&D investment as an explanatory variable. We have specified several versions of our model to study the robustness of our results. An important issue is how to treat firms with zero R&D spending (about 50 percent of the firms in our sample). The model suggested in this study allows firms to have positive output without having a positive R&D capital stock, which contrasts with the classical Cobb–Douglas production model. Thus we have avoided manipulation of the data that would have been required to incorporate firms with zero R&D spending. Moreover, we distinguish between different types of R&D according to funding source and allow different projects to be imperfect substitutes in terms of economic returns.

The estimates of our preferred model yield results that are generally in line with the existing literature. R&D spending stimulates productivity growth at the firm level even after controlling for a number of possible effects relating to industries, common shocks, etc. We find that RCN-funded R&D spending generally has the same effect on productivity as total R&D spending and conclude that the source of finance of R&D matters little for the effects of R&D on productivity. To the extent that subsidies and grants from RCN increase R&D in the business sector, the effect is captured by a common R&D capital stock variable that includes all R&D spending, regardless of the source of finance. Based on our preferred model we estimate the returns to R&D to be roughly 10 percent and this rate of return applies both to RCN-funded and firm-funded R&D.

We have also found that when using our preferred specification of the production function at the firm level, it matters little for the estimated rate of return to R&D whether or not we include firms with zero R&D spending in the estimation sample; including only firms with positive R&D just marginally increases the estimated rate of return to R&D. On the other hand, when using a standard Cobb–Douglas production function and limiting the sample only to firms with positive R&D spending, the estimated returns to R&D becomes implausibly high.

The main argument for government subsidizes to R&D is usually that R&D creates spill over effects so that firms do not get all the returns from its own investment in R&D. Our finding suggests that this cannot be the only reason for public subsidies to R&D, since projects financed by the RCN earn a standard private rate of return. Instead, financing constraints or capital market imperfections seem to be the main obstacles for R&D in Norway. However, it may be the case the RCN has a tendency to select projects based on their internal rate of return supplemented by a statement by the applicant relating to additionality (that the project will not be carried out without the subsidy). If this is the case there is a possibility that current RCN practice to some extent neglects projects with low private returns but high social returns. Thus RCN should review its criteria in selecting R&D projects so that private returns are not emphasized too much compared to social returns.

References

[1] Arellano, M. and S. Bond (1991): Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies,* 58, 277–297.

[2] Baily, M., C. Hulten and D. Campbell (1992): Productivity dynamics in manufacturing plants, *Brookings Papers on Economic Activity, Microeconomics*, Vol. 1992, 187–249.

[3] Cappelen, Å., A. Raknerud and M. Rybalka (2012): The effects of R&D tax credits on patenting and innovations, *Research Policy*, 41, 334–345.

[4] Cohen, W. and D. Levinthal (1989): Innovation and learning: two faces of R&D, *Economic Journal*, 99, 569–596.

[5] Crepon, B., E. Duguet and J. Mairesse (1998): Research, innovation and productivity: an econometric analysis at the firm level, *Economics of Innovation and New Technology*, 7, 115–158.

[6] Griffith, R., E. Huergo, J, Mairesse and B. Peters (2006): Innovation and Productivity Across Four European Countries, *Oxford Review of Economic Policy*, 22, 483-498.

[7] Griffith, R., S. Redding and J. Van Reenen (2004): Mapping the two faces of R&D: productivity growth in a panel of OECD countries, *Review of Economics and Statistics*, 86, 883–895.

[8] Griliches, Z. (1979): Issues in assessing the contribution of research and development to productivity growth, *Bell Journal of Economics*, 10, 92-116.

[9] Griliches, Z. (1995): R&D and productivity: econometric results and measurement issues, in P. Stoneman (ed.): *Handbook of the Economics of Innovation and Technical Change*, NBER and University of Chicago Press.

[10] Hall, B. H. and J. Mairesse (1995): Exploring the relationship between R&D

and productivity in French manufacturing firms, *Journal of Econometrics*, 65, 263–293.

[11] Hall, B. H. (2002): The financing of research and development, *Oxford Review of Economic Policy*, 18, 35–51.

[12] Hall B. H., F. Lotti and J. Mairesse (2012): Evidence on the Impact of R&D and ICT investment on Innovation and productivity in Italian firms, NBER Working paper No. 18053.

[13] Hall, B. H., J. Mairesse and P. Mohnen (2010): Measuring the returns to R&D, in Chapter 24: *Handbook of the Economics of Innovation*, Vol. 2. North-Holland Publ. Comp., Amsterdam.

[14] Klette, T. J., and F. Johansen (1998): Accumulation of R&D capital and dynamic firm performance: A not-so-fixed effect model, *Annales de Economie et de Statistique*, 49/50, 389-419.

[15] Mairesse, J. and P. Mohnen (2004): The importance of R&D for innovation: A reassessment using French survey data, *NBER Working Paper 10897*, National Bureau of Economic Research, Cambridge, MA.

[16] Norges forskningsråd (2010): Det norske forsknings- og innovasjonssystemet - statistikk og indikatorer (The Norwegian research and innovation system – statistics and indicators), The Research Council of Norway, Oslo 2010.

[17] OECD (2001): *Measurement of Capital Stocks, Consumption of Fixed Capital and Capital Services*. OECD Manual 131, Paris, France, and Washington, DC.

[18] Pakes, A. and Z. Griliches (1984): Patents and R&D at the firm level in French manufacturing: a first look. In Z. Griliches (ed.): *Research and Development, Patents and Productivity*, The University Press of Chicago, Chicago, 55–72.

[19] Parisi, M. L., Schiantarelli, F. and Sembenelli, J. (2006): Productivity, innovation and R&D: micro evidence for Italy, *European Economic Review*, 50, 2037–2061.

[20] Power, L. (1998): The missing link: technology, investment, and productivity. *Review of Economics and Statistics*, 80, 300–313.

Appendix A: Derivation of (16)

By differencing (14), we obtain

$$\Delta y_t = \Delta a_t^* + \beta_1 \Delta k_t + \beta_2^* \Delta f_t. \tag{25}$$

If δ is small and $s = \infty$, then $F_t = R_t + (\alpha - 1)N_t$ and $\Delta F_t / F_{t-1} \simeq \widetilde{R}_{t-1}/F_{t-1} + (\alpha - 1)\widetilde{N}_t / F_{t-1}$. Now

$$\Delta f_t \simeq \frac{L_{t-1}\Delta F_t - F_{t-1}\Delta L_t}{L_{t-1}^2} = \frac{\Delta F_t}{F_{t-1}} f_{t-1} - \frac{\Delta L_t}{L_{t-1}} f_{t-1} \simeq f_{t-1}(\widetilde{R}_{t-1}/F_{t-1} + (\alpha - 1)\widetilde{N}_t/F_{t-1} - \Delta \ln L). \tag{26}$$

Thus

$$\Delta y_t \simeq \Delta a_t^* + \beta_1 \Delta k_t + \beta_2^* f_{t-1} \left(\frac{\widetilde{R}_{t-1}}{F_{t-1}} + (\alpha - 1)\frac{\widetilde{N}_t}{F_{t-1}} \right) - \beta_2^* f_{t-1} \Delta \ln L_t.$$

Defining $\eta = \mathrm{El}_F Y$ and $\varrho = \partial Y / \partial F$, then by definition $\eta = \varrho F / Y$, and from (15) $\eta = \beta_2^* f$. Finally, from (25) and (26),

$$\begin{aligned}
\Delta y_t &\simeq \Delta a_t^* + \beta_1 \Delta k_t + \eta \left(\frac{\widetilde{R}_{t-1}}{F_{t-1}} + (\alpha - 1)\frac{\widetilde{N}_t}{F_{t-1}} \right) - \eta \Delta \ln L_t \\
&= \Delta a_t^* + \beta_1 \Delta k_t + \varrho \frac{F_{t-1}}{Y_{t-1}} \left(\frac{\widetilde{R}_{t-1}}{F_{t-1}} + (\alpha - 1)\frac{\widetilde{N}_t}{F_{t-1}} \right) - \eta \Delta \ln L_t \\
&= \Delta a_t^* + \beta_1 \Delta k_t + \varrho \left(\frac{\widetilde{R}_{t-1}}{Y_{t-1}} \right) + \varrho(\alpha - 1)\frac{\widetilde{N}_t}{F_{t-1}} - \eta \Delta \ln L_t.
\end{aligned}$$

Appendix B. Data sources

Accounts statistics: All joint-stock companies in Norway are obliged to publish company accounts every year. The accounts statistics contain information obtained from the income statements and balance sheets of joint-stock companies, in particular, the information about operating revenues, operating costs and result, labor costs, the book values of a firm's tangible fixed assets at the end of a year, their depreciation, and write-downs.

The structural statistics: The term "structural statistics" is a general name for statistics of different industrial activities, such as manufacturing, building and construction, wholesale and retail trade statistics, etc. They all have the same structure and include information about production, input factors, and investments at the firm level. These structural statistics are organized according to the NACE standard and are based on General Trading Statements, which are given in an appendix to the tax return. In addition to some variables, which are common to those in the accounts statistics, the structural statistics contain data about purchases of tangible fixed assets and operational leasing. These data were matched with the data from the accounts statistics. As the firm identification number here and further we use the number given to the firm under registration in the Register of Enterprises, one of the Brønnøysund registers, which has operated from 1995.

R&D statistics: R&D statistics are the survey data collected by Statistics Norway every second year up to 2001 and annually from then on. These data comprise detailed information about firms' R&D activities, in particular, about total R&D expenses with division into internally performed R&D and externally performed R&D services, the number of employees engaged in R&D activities and the number of man-years worked in R&D. In each wave, the sample is selected with a stratified method for firms with 10–50 employees, whereas firms with more than 50 employees are all included. Strata are based on industry and firm size. Each survey contains about 5000 firms, although many of them do not provide complete information.

Register of Employers and Employees (REE): The REE contains information obtained from employers. All employers are obliged to send information to the REE about each individual employee's contract start and end, working hours, overtime and occupation. An exception is made only if a person works less than four hours per week in a given firm and/or was employed for less than six days. In addition, this register contains identification numbers for the firm and the employee, hence, the data can easily be aggregated to the firm level.

National Education Database (NED): The NED gathers all individually based statistics on education from primary to tertiary education and has been provided by Statistics Norway since 1970. We use this data set to identify the length of education. For this purpose, we utilize the first digit of the NUS variable. This variable is constructed on the basis of the Norwegian Standard Classification of Education and is a six-digit number, the leading digit of which is the code for the educational level of the person. According to the Norwegian standard classification of education (NUS89), there are nine educational levels in addition to the major group for "unspecified length of education". Education levels are given in Table 6.

Table 6: Educational levels

Tripartition of levels	Level	Class level
	0	Under school age
Primary education	1	1st – 7th
	2	8th – 10th
Secondary education	3	11-12th
	4	12th – 13th
	5	14th – 17th
Postsecondary education	6	14th – 18th
	7	18th – 19th
	8	20th+
	9	Unspecified

Appendix C: Tables with descriptive statistics

Table 7: Descriptive statistics for the main variables used in the final sample

Variable	Obs	Mean	Std.	Min	Max
$Y^{a)}$	10976	234071	2518593	3953	1.48E+08
$\widetilde{R}^{a)}$	10976	6444	41758	0	1551539
$R^{a)}$	10976	38182	231021	0	6982151
$\widetilde{N}^{a)}$	10976	70	667	0	32311
$N^{a)}$	10976	371	2285	0	51769
$K^{a)}$	10976	47449	642380	1.5	2.88e+07
$L^{b)}$	10976	475042	1033602	42862	3.40E+07
$h^{c)}$	10976	0.262	0.218	0	0.937
y	10976	-1.233	0.509	-3.644	1.766
k	10976	-4.313	1.623	-11.566	2.198
f	10976	0.133	0.379	0	6.94
$\widetilde{R}/Y$	10976	0.045	0.146	0	0.937

Notes: $^{a)}$- in 1000 NOK; $^{b)}$- in man-hours; $^{c)}$- in shares

Table 8: Firms' description in the final sample, 1886 firms

Firm characteristics	Share of firms (in %)	$\widetilde{R}/Y$	R/L	N/L	h (in %)
All firms	100	0.049	0.079	0.0011	25.8
50–99 employees	41.6	0.066	0.108	0.0018	26.3
100–249 employees	36.9	0.037	0.071	0.0008	26.0
250+ employees	21.5	0.028	0.065	0.0005	26.2
age 0–2	13.8	0.057	0.088	0.0018	27.1
age 3–5	13.2	0.055	0.089	0.0013	28.4
age 6–9	13.4	0.049	0.087	0.0012	30.4
age 10–14	15.9	0.046	0.092	0.0013	27.4
age 15+	40.6	0.042	0.078	0.0009	23.9
Capital region	29.8	0.051	0.114	0.0014	37.1
East coast	15.8	0.045	0.077	0.0005	20.2
East innland	6.5	0.039	0.071	0.0014	16.0
South	17.4	0.051	0.090	0.0015	24.8
West	16.9	0.035	0.045	0.0006	20.9
Central Norway	7.2	0.047	0.078	0.0010	22.5
North	6.4	0.029	0.041	0.0010	21.2
Manufacturing	50.0	0.049	0.082	0.0009	18.8
Construction	6.9	0.003	0.005	0.0001	14.3
Retail trade	8.1	0.029	0.063	0.0001	27.0
Transport	14.1	0.009	0.029	0.0003	21.2
Services	10.8	0.126	0.225	0.0048	65.6
Other industries	10.0	0.041	0.094	0.0013	40.6

Note: Based on the first firm-year observations

Table 9: Description of main variables by time period

	2001–2003	2004–2006	2007–2009
Number of firms	1351	1652	1416
$\widetilde{R}/Y$	0.052	0.044	0.039
R/L	0.070	0.085	0.086
N/L	0.001	0.001	0.001
h	24.8 %	26.2 %	26.8 %
Share of firms (R&D_$av > 0$)	54.4 %	54.7 %	49.6 %
$\widetilde{R}/Y$ | R&D_$av > 0$	0.095	0.080	0.078
R/L | R&D_$av > 0$	0.123	0.145	0.156
N/L | R&D_$av > 0$	0.002	0.002	0.002
h | R&D_$av > 0$	26.8 %	29.4 %	31.4 %
Share of firms (*all* R&D > 0)	37.2 %	38.9 %	36.0 %
$\widetilde{R}/Y$ | *all* R&D > 0	0.128	0.104	0.104
R/L | *all* R&D > 0	0.166	0.192	0.204
N/L | *all* R&D > 0	0.003	0.003	0.003
h | *all* R&D > 0	28.6 %	31.4 %	32.7 %
Share of firms (RCN_$av > 0$)	7.8 %	5.9 %	6.4 %
N/L | RCN_$av > 0$	0.008	0.011	0.014
Share of firms (*all* RCN > 0)	1.5 %	2.0 %	2.5 %
N/L | *all* RCN > 0	0.027	0.023	0.023

Note: R&D_$av > 0$ when $\widetilde{R} > 0$ in at least one year in the given period, *all* R&D > 0 when $\widetilde{R} > 0$ in all years in the given period (the same for RCN).

Table 10: Value of criterion function to be maximized in grid search over different (s, λ)-values when $\alpha = 1$

$s \backslash \lambda$	0.01	...	0.09	0.1	0.2	...	1	...	130	140	150
1.001	1061.19	...	1149.16	1150.19	1145.59	...	1129.76	...	1121.67	1121.66	1121.66
...	...	...	...	...	...	...	...	...	...	...	...
1.01	1056.74	...	1145.17	1146.60	1144.44	...	1130.74	...	1119.10	1118.98	1118.87
...	...	...	...	...	...	...	...	...	...	...	...
1.05	1047.34	...	1128.91	1130.69	1135.58	...	1138.58	...	1102.59	1102.09	1101.64
1.1	1050.79	...	1121.44	1121.83	1122.32	...	1116.78	...	1083.55	1083.52	1083.44
1.15	1050.27	...	1115.37	1114.27	1105.71	...	1066.65	...	1077.65	1078.18	1078.78
1.2	1042.46	...	1104.13	1103.25	1098.44	...	1057.50	...	1093.67	1095.16	1096.55
1.25	1032.06	...	1093.33	1093.39	1095.06	...	1054.19	...	1104.66	1105.82	1106.87
1.3	1022.13	...	1082.66	1083.44	1090.60	...	1052.29	...	1110.79	1111.64	1112.40
...	...	...	...	...	...	...	...	...	...	...	...
5	969.93	...	1008.55	1009.35	1038.12	...	1061.74	...	1330.03	1349.04	1348.84
...	...	...	...	...	...	...	...	...	...	...	...
90	968.21	...	1006.52	1007.18	1036.16	...	1063.40	...	1344.17	1350.53	1350.37
100	968.20	...	1006.51	1007.17	1036.15	...	1063.40	...	1344.23	1350.58	1350.39
$s = \infty$	968.14	...	1006.44	1007.09	1036.08	...	1063.46	...	1344.66	1350.60	1350.40

B

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