R&D subsidies: wasted money or essential for firm growth?

A literature review of R&D subsidies for firms: the need for R&D subsidies, the empirical effects and the econometric challenges

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1. Introduction

Today, R&D is becoming more and more a crucial factor in the survival of a company. In a fast changing world, firms must continually revise their design and range of products to stay ahead of their competitors. R&D contributes to new knowledge and technological progress and is a key driver for economic growth. Thus, firms that try to stay ahead of their competitors would do well to invest enough in R&D activities.

However, firms reap only a share of the returns on R&D investments, since R&D has the characteristics of a public good. Therefore, government subsidies are needed for stimulating R&D investments. Currently, there are many different national, regional or EU-level R&D subsidy programs available. Today, the biggest innovation program in the EU is ‘Horizon 2020’, with a budget of €80 billion for the period of 2014-2020. (European Commission, 2014)

An important question for policy makers is how effective these R&D subsidy programs really are. For example: do the programs really increase private R&D spending and how is the firm performance affected by the subsidy? Which firms or projects should actually be funded and what is the best design for a subsidy program? In the past, many studies have focused on these questions but the results are ambiguous and there are still many open areas for future research.

To evaluate R&D subsidies, one would want to compare subsidized firms with non-subsidized firms. The hard thing when comparing these groups is finding a valid control group. Until now, different econometric methods have been used to overcome the so called selection bias. However, these methods not only differ from each other in their approach but also in their assumptions, which has consequences for interpreting the results.

This paper does not consider one typical subsidy but combines several papers made in the past, to see the recurrent difficulties in evaluating R&D subsidies. Part of these difficulties is to solve for endogeneity in the empirical estimations. This literature review is unique in the field of R&D subsidy literature because after presenting the theory behind giving R&D subsidies and stating the estimation problems, it presents several methods which are helpful for future evaluation research.

In chapter 2, the motivation for R&D subsidies is explained. In chapter 3, different empirical studies within the area of R&D subsidies are discussed and analyzed. Then, in chapter 4, several econometric methods are analyzed that are important for good policy making. Finally, some recommendations are given for future research into this topic.

2. Theoretical background

In this chapter, arguments for R&D subsidies are outlined. After that, the role of the government and the crowding versus additionality effects are explained. Finally, a general framework shows the complexity in estimating all the possible effects of a subsidy.

2.1 Arguments for R&D subsidies

The main reason for governments subsidizing private R&D projects is that the level of privately financed R&D activities is lower than socially desired. This is because R&D has the characteristics of a public good. Because of the incomplete appropriability of R&D investments, R&D generates positive external effects that cannot be internalized. (Arrow, 1962) Knowledge in itself is not subject to exhaustion or congestion because knowledge is a non-rival and partially excludable good. (Romer, 1990)

In other words: many firm R&D projects could have positive benefits to society, but do not cover the private costs. As a consequence, these projects are not carried out and there is underinvestment in R&D. Another argument for subsidizing R&D projects is the difficulty in financing R&D due to asymmetric information among borrowers and lenders. Because of the highly uncertain outcome of R&D investment, lenders often are reluctant to finance R&D. Especially for the small, young and cash-constrained firms, the cost of external capital is often too high, resulting in underinvestment in R&D. (Hall, 2002) Also, attention is given to the "systems approach to innovation", where the emphasis lies on the facilitating of knowledge diffusion and interactive learning among economic actors, such as firms, universities, suppliers and research institutes. (Lundvall, 2005)

2.2 Role of the government and crowding out versus additionality effects of public funding

The role of the government has been to close the gap between the private and the social rate of return to R&D investments, by offering subsidies to firms.[1] The subsidies help the firms overcome the externality problem and the financing difficulties. In this way, public funding reduces the price for private investors and more innovations are carried out.

[1] While also tax incentives count as a prevailing policy instrument in many countries, the advantage of direct funding of R&D programs is that government agencies have the freedom to target subsidies toward projects that have the highest perceived social marginal returns. For instance, the government funding could be concentrated in areas where there was a large gap between the social and the private rate of return.

However, the innovation level only rises when subsidies cause firms to undertake R&D projects that would be unprofitable in the absence of a subsidy (Jaffe, 2002) (Wallsten S. , 2000) It is not hard to imagine that many firms have an incentive to reduce R&D costs and thus automatically apply for subsidies, even if the private expected return is positive. This is called the crowding out effect. When a subsidy is granted, the firm might simply substitute public for private investment. (Czarnitzki & Hussinger, 2004) On the other hand, additionality effects may take place: public funding may lead to even more private R&D activities. In this context, additionality can be defined as the change in industry-financed R&D spending, company behaviour or performance that would not have occurred without the public program or subsidy. (Buisseret, 1995) This definition shows three types of additionality: input additionality, output additionality and behaviour additionality.

Most studies have focused only on input additionality, which concerns the amount of resources (for example, R&D investments) that firms would not have allocated to the innovation process in the absence of policy. Output additionality instead concerns the innovative outcomes that firms would not have achieved without the public support. The outcomes can be for example patents, sales, new products, processes and services. Output additionality can occur when scale effects take place, but also when activities like logistics and marketing improve, which are not direct attributable to R&D. In recent years, behaviour additionality has received more attention: this can be defined as the change in a company's way of undertaking R&D which can be attributed to policy actions" (Buisseret, 1995)

2.3 General framework: MRR & MCC curves

David, Hall and Toole concluded that the empirical studies about the effects of funding upon the level of private R&D spending were missing a general structural framework. The underlying channels of a possible crowding-out or additionality effect were just not conceptualized well. In an elementary model of firm-level investment behaviour, the authors analyzed the demand for and the cost of R&D. (David, Hall, & Toole, 2000)

In the model (Fig. 1), the demand for R&D is given by the marginal rate of return (MRR) and the cost of R&D is given by the marginal cost of capital (MCC). The MRR curve derives from sorting R&D projects according to their internal rate of returns, as in a usual investment plan. This curve is a decreasing function of R&D expenditures, since firms will first implement projects with higher internal rate of returns and then those presenting lower rates. The MCC curve, instead, reflects opportunity costs of investment funds, at any level of R&D. This curve is upward-sloping: as soon as the number of projects to implement increases, firms have to shift from financing them by retained earnings to the more costly equity or debt funding.

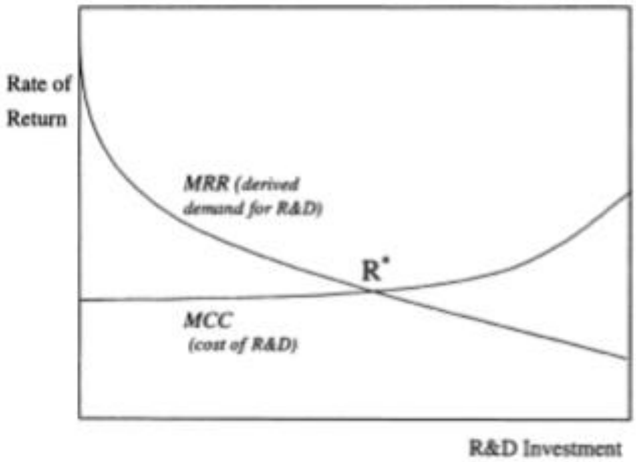

Fig. 1.

The MRR curve is a function of the level of R&D expenditure and the “X-variables”, that reflect the technological opportunities to generate innovations, the state of demand in its potential market area, plus the institutional and other conditions). The MCC curve is a function of the level of R&D expenditure and the “Z-variables”, that reflect the technology policy measures, macroeconomic conditions and expectations affecting the internal cost of funds, the bond market conditions affecting the external cost of funds and the availability of venture-capital finance. If the public funding is considered to be exogenous, the MRR curve or MCC curve will shift, or even both. For example, the MCC curve could shift to the right as a result of the lowering of the firm’s capital costs.

The MRR curve may also shift to the right: when public funds are made available for construction or research equipment, further R&D projects are conducted at a lower cost, thereby increasing the expected internal rates of return in R&D investments. Besides the examples of possible short-run effects, long-run effects of R&D subsidies may also take place. Informational spillovers from the advance of public science and engineering knowledge (which is made possible by government R&D activities) will likely shift the MRR curve outward over time. Also, it is possible that training of new engineers will lead to more qualified personnel in the long run.

The conclusion of the above is that theory does not predict either a crowding out effect or an additionality effect of R&D subsidies, both effects are consistent with the framework represented above. Depending on the magnitude of the (in)direct effects and the firm's elasticities, many different situations can occur where different subsidy effects can be produced.

After all, compared to private R&D investments, public subsidies can have a smaller effect (crowding out), an equal effect or a larger effect. (additionality) This means that empirical studies are needed to answer this question. In chapter 3, different empirical studies and their results are considered and analysed.

3. Empirical literature

3.1 Several papers concerning R&D subsidies

In the last decades, many studies have focused on the evaluation of the effects of R&D subsidies. In this chapter, the focus lies in particular on micro-level studies. To see the different results efforts has been done in the past, several empirical papers and its results are summarized.

3.1.1. The SEMATECH program

Irwin and Klenow (1996) made an effort to evaluate the SEMATECH program, which was a research consortium established in 1987. This program was set up to promote US manufacturing's role in the development of technology for production of semiconductor products. The consortium started with fourteen teams but it restructured somewhat after a while with few of the teams pulling out. About half of the consortium's annual budget (about US$200 million) was financed through government subsidies in the period 1987–1996. The regression analysis was in its basic form:

$$\mathrm{Y_{it}} = \alpha_\mathrm{i} + \beta_1 \mathrm{Y_{i,t-1}} + \beta_2 \mathrm{D_i^{SMT}} + \mathrm{Dummies} + \mathrm{e_{it}}$$

where $\mathrm{Y_{it}}$ stands for the private R&D to sales ratio for firm *i* in year t, while $\mathrm{D_i^{SMT}}$ is a dummy which is one if the firm was a SEMATECH member and zero otherwise. The dummies include time and firm age dummies, and firm fixed effects (α_i) were included as well.
Irwin and Klenow (1996) found that SEMATECH led to an elimination of excessive duplication of R&D, which was the major objective of the consortium. Also, SEMATECH firms experienced -on average- a faster growth in sales than non-member firms. The performance in terms of physical investment, returns on asset and sales, and labour productivity growth did not systematically differ from non-member firms.

3.1.2. Government support to commercial R&D projects in Norwegian high-tech firms

Klette and Møen (1999) have studied the impact of government support for commercial R&D projects in Norwegian high-tech firms. These projects were related to information technology and intended to stimulate complementary R&D activities in high-tech manufacturing. The impact of the program was very little: it turned out to be that the public financial support to R&D and innovation in the IT industry didn't create a substantial change to its performance.

Despite the large amounts of R&D support provided, only few significant differences showed up between the supported and non-supported firms in the same industries.

3.1.3. Japanese research consortia

Branstetter & Sakakibara (2002) have examined the impact of a large number of Japanese government-sponsored research consortia on the research productivity of participating firms. The research productivity (the patenting of the firms) is measured before, during and after the participation of the program. Different from the SEMATECH program, the econometric results of this consortium is that a membership in the Japanese research consortia stimulated private R&D spending. Also, research effort became more productive. Branstetter and Sakakibara (2002) used a slightly different model than Irwin and Klenow (1996):

$$\log(R\&D_{it}) = \alpha_i + \beta_1 \log(Capital_{it}) + \beta_2 S_{it} + Dummies + e_{it}$$

where the dependent variable is private R&D spending for firm *i* in year *t.* To control for size effects, the independent variable physical capital is included. S_{it} is the number of research consortia in which the firm is active in year *t,* and β_2 is the parameter of interest. The dummies include time and firm effects. The estimation is done on an unbalanced sample over the period 1983-1989: 141 firms participated in at least one research consortium in this period, 85 firms did not. The results revealed a positive and statistically significant value for β_2.

Branstetter and Sakakibara (2002) also examined whether the research effort became more productive, by estimating the following equation:

$$\log(P_{it} + 1) = \alpha_i + \beta_1 \log(R\&D_{it}) + \beta_2 \log(Capital_{it}) + \beta_3 S_{it} + Dummies + e_{it}$$

They found that being a member in an additional consortium led to an increase in patenting of 5%.

3.2 Interpretation of the results

The studies discussed in 3.1 all evaluated the government funding to stimulate R&D activities. Despite the serious efforts of the government in these three programs, the impact appeared to vary considerably. David et. al (2000) rightly concluded that the ambiguous results of the empirical studies were caused by the use of different estimators, as well as the application for a broad range of countries, each with their own specific science and technology policy. Nevertheless, there is more to say about the interpretation of the results. What is missing in the discussed papers, which are just examples of many more, is the consideration of endogeneity in the model, which will be explained in the next paragraphs.

3.2.1 Endogeneity at the firm level

At the firm level, it is a mistake to assume that public R&D subsidies may be viewed as exogenous in a model of company R&D determination. Federal R&D contracts are namely not distributed randomly among firms in an industry, independently of firm characteristics. (Lichtenberg, 1984) According to Lichtenberg (1984), “federal contracts do not descend upon firms like manna from heaven; firms must actively solicit and often compete for contracts.”

More technically spoken, OLS and other methods that are based on the assumption that the support is randomly assigned, conditional on observed factors, are likely to yield biased estimates of the causal effect of the program because it seems unlikely that conditioning on the observable attributes is sufficient to avoid differences in the expected performance between the supported and unsupported groups in the absence of the treatment. (Jaffe, 2002)

It could very well be that in a certain program, the government subsidizes projects with the highest returns, which is described by the so called “cherry-picking” strategy. Of course, the government’s task is to subsidize R&D projects with the biggest gap between the social and private returns. However, is not unimaginable that program managers who award the subsidy choose for the most promising projects, in order to convince others about the relevance about the subsidy. In this case, the possibility exists that subsidies and firm growth are correlated with each other because growing firms receive the subsidies, not because subsidies cause firms to grow. (Wallsten S. J., 2000)

Self-selection is not likely to come from the side of the government alone. For instance, the firms which received a subsidy may have had an information advantage or may be better acquainted with policy measures they qualify for. (Aerts & Thorwarth, 2008) Also, firms that discovered particularly promising R&D projects, are more likely to apply for support. (Klette, Møen, & Griliches, 2000) More generally, there may be more (unobserved) permanent differences across firms. Subsidies are distributed between applicants, and these applications for financial support are highly dependent on the firm’s intentions to invest in R&D. These intentions are strongly dependent on many factors not included in the explanatory variables of any regression analysis. (Kauko, 1996)

This is not taken sufficiently in account by Irwin and Klenow (1996), in the evaluation of the SEMATECH program. When a comparison is made of the SEMATECH firms and the non-member firms, it is evident that the SEMATECH members are the leading US manufacturers in the electronic components industry.[2] Irwin and Klenow (1996) indeed try to account for this by incorporating fixed effects, but even when there is controlled for these permanent differences, it remains questionable whether the non-member firms in the same industry reveal what the members would have experienced without the SEMATECH program.

The same problem is found in Branstetter and Sakakibara's study, but the selection bias is negative here. In their analysis, they find that firms with the most promising technological projects were unwilling to participate in research consortia, because they were afraid to lose competitive advantage.

Behind comparing the supported and unsupported firms to evaluate the effect of a subsidy is the assumption that there are no spillover effects of the R&D support scheme to the non-supported firms. This is a strong assumption; the question is whether the performance of the non-supported firms can be considered independent of the support given to the supported firms. When estimating the impact of a R&D subsidy, one will underestimate the effect of the subsidy if the non-supported firms benefit from pure knowledge spillovers from R&D in the supported firms. On the other hand, one will overestimate the effect of the subsidy if the non-supported firms are hurt as they lose relative competitiveness to the supported firms. (Klette, Møen, & Griliches, 2000)

3.2.2 The industry level

While at the industry level, the exogeneity assumption is much more acceptable, because supported and non-supported industries can be better compared, (Capron & Van Pottelsberghe, 1997) other problems may arise in empirical analyses. Both private and public investment decisions may respond to the inter-industry variation in the "technological opportunity set". Some industries just have greater technological opportunities than others. The government may allocate its support partly in line with the technological opportunities. These technological opportunities may differ across industries and affect R&D investment

[2] This was also the case before the SEMATECH program started

decisions. Variation in R&D support funding across industries is likely to be endogenous as a result (David, Hall, and Toole, 2000).

The variation in the technological opportunity set may explain the fact that there were hardly any differences between the supported and non-supported Norwegian high-tech firms in Klette and Møen's study.

Klette et. al (2000) stated that this might have been due to the government supporting the firms with severe problems, during the period of restructuration of the IT industry in the 80's. In this case, the effect of the government support is underestimated since there exists a positive relationship between receiving R&D support and the expectation of growing more slowly than average.

4. Econometric methods

In the previous chapter, some empirical studies were described to sketch the difficulties in measuring the impact of R&D subsidies. Klette et. al (2000) stated that evaluating subsidy programs has always been an exercise in counterfactual analysis and they stressed the need for better econometric methods to deal with this. In this chapter, some recent helpful econometric methods are outlined: Instrumental Variables, Matching and Difference-in-differences. Also, several papers are considered that make use of these methods.

4.1.1. Instrumental Variables

Instrumental Variables estimation (IV) is a well-known method to solve the problem of selection on unobservables. IV can be used to address several important threats to internal validity, namely omitted variable bias, simultaneous causality bias and measurement error. IV regression is thus meant to eliminate bias from these sources. Typically, the researcher needs to know a full set of exogenous variables (the instruments) correlated with the treatment variable (e.g. the amount of subsidy) and uncorrelated with the outcome y, in order to build a 2SLS estimation of the evaluation equation. Although IV can be helpful to solve bias in the estimation, its drawback is that finding appropriate instruments is not easy. Even if longitudinal data are available, the common practice to use lagged values does not necessarily solve the problem as lags are often highly correlated with future values of the variable. (Aerts, Czarnitzki & Fier 2006)

Cerulli (2008) described these several sources of bias, and he derived the following OLS equation:

$$\frac{\partial PRD}{\partial SUB} = \beta_1 + \frac{\partial u}{\partial SUB}$$

where *PRD* is the private R&D expenditure, *SUB* the subsidy received and *u* the unobservable variables affecting *PRD.* This OLS estimation shows a direct effect of *SUB* on *PRD* (β_1) and an indirect effect of *SUB* on *PRD* ($\frac{\partial u}{\partial SUB}$) . The latter indirect effect is passing through the link between *SUB* and *u*. The level of *SUB* is correlated to unobservable factors determining the level of *PRD*.

When the policy variable *SUB* is supposed to be endogenous for the reasons explained above, it is no longer a reduced form but part of a larger structural model that needs to be uncovered. Cerulli (2008) stated that it was Lichtenberg (1988) who recognized this need by considering the variable *SUB* as endogenous, in his analysis of whether non-competitive and competitive R&D contracts would stimulate private spending in the USA. Lichtenberg (1988) proposed a two-stage least squares (2SLS) estimation (basically the IV estimation) by instrumenting *SUB* with the "value of competitive contracts that were *potentially* awardable" to each firm. He supposes that this variable is correlated with SUB, but uncorrelated with the unobservables (*u)*.

4.1.2. Matching

Matching is in summary the balancing of the sample of program participants and comparable non-participants. The idea behind matching is to estimate the counterfactual using non-treated units that are "similar" to treated units. When a similar non-treated unit is matched with a treated unit, the counterfactual is estimated as the outcome of the non-treated unit. As a result, the remaining differences in the dependent variable are then interpreted as the effect of the treatment.

Rubin (1977) introduced the idea of conditional independence assumption (CIA). This condition implies for the evaluation of R&D subsidies that the receipt of subsidies and potential outcome are independent for firms with the same set of exogenous characteristics. However, the CIA is only fulfilled if all variables influencing the dependent variable and the subsidy variable are known and available. Matching can thus be difficult due to high dimensionality of the pre-treatment variables (X). Few years later, Rosenbaum & Rubin (1983) reduced this "curse of dimensionality" by conditioning the matching on the propensity score Pr(X) instead of X. The propensity score is the probability for an individual to get treated, conditional on a certain numbers of observable characteristics. This score reflects the wide set of observable characteristics affecting the probability of becoming treated. (Cerulli, 2008) Until today, this has been accepted as a valid method and it is the most applied type of matching.

Czarnitzki and Bento (2013) used matching when examining the impact of the IWT, which is a governmental agency for Innovation by Science and Technology, founded by the Flemish

Government in 1991. It was created as the key organization for support and promotion of R&D and innovation in Flanders. Czarnitzki and Bento (2013) used caliper matching (a variant of nearest neighbour propensity score matching) for looking at the question of input additionality for a Belgian subsidy program. They did this by pairing each subsidy recipient with the single closest non-recipient. The estimated probability of receiving a subsidy was decisive for the creation of pairs. The propensity score was made by making a probit estimation on the dummy indicating the receipt of subsidies.

For matching, it is necessary that there is a sufficient overlap between the control and the treatment group, which is called the region of common support.[3] Thus, Czarnitzki and Bento (2013) calculated the minimum and the maximum of the propensity scores of the potential control group, and deleted observations on treated firms with probabilities larger than the maximum and smaller than the minimum in the potential control group. Also, to avoid bias in the estimation, they set up a certain threshold ("caliper") to the maximum distance between the treated and control firm. If the distance were above this caliper, the treated observation would be deleted from the sample. After removing 40 observations, (14 observations that are not in the region of common support and 26 observations because of the caliper), Czarnitzki and Bento (2013) found that all the covariates were well balanced and hence they concluded that their matching was successful. Only in the dependent variables are significant differences after the matching, but these differences can be attributed to the subsidy. As a result, the null hypothesis of crowding out effects is rejected: IWT grants indeed trigger investment into R&D.

In estimating the impact of R&D subsidies, matching seems preferable to OLS at least for three reasons. First, it does not need to specify a particular parametric relation between the dependent variable and its regressors, while in the case of OLS, a linear form is assumed. Second, only the common support group, with subsidized and non-subsidized firms, is considered. Third, matching reduces the amount of non-subsidized firms to a sub-sample with characteristics more homogenous to the treated units. Thus, the matching method prevents biases in the impact parameter that simple OLS estimation cannot solve. The drawback of using matching is that it only controls for selection on observables. Despite this limit, the

[3] If the samples of the subsidized and non-subsidized firms have no or only little overlap in X, matching is not applicable to obtain consistent estimates (Aerts, Czarnitzki & Fier 2006)

problem of unobservables should be attenuated when there are many observed variables available.

4.1.3. Difference-in-Differences (DiD) estimation

In the difference-in-differences model, the counterfactual outcome of a subsidized firm in a particular period is estimated by the outcome of that subsidized firm in an earlier period where it did not receive a subsidy. To control for changes over time, DiD relates the development of subsidized firms to a control group of non-subsidized firms and compares them before and after the moment of subsidy. (Aerts & Schmidt, 2008)

For DiD estimation, no functional form is required for the outcome measure. The disadvantage, however, is that panel data is required for DiD. Panel data is needed so that the same firm before and after the receipt of a subsidy can be observed. As subsidies often are awarded for longer term research projects, and firms may receive more than one grant over time, it is difficult to construct a database that is suited for an appropriate application of DiD. Also, the parallel trend assumption is often not likely to hold: this assumption suggests that subsidized and non-subsidized firms react similar to shocks that occur over time. To overcome this bias, Blundell & Costa (2000) suggested the conditional difference-in-difference estimator (CDiD), which is basically a combination of matching and DiD. Not a general control group is needed here, but a matching of comparable firms to subsidized firms in the period before the treatment, and a comparison of the evolution of the two groups over time. The great advantage of the CDiD method is that after it has controlled for selection on observables, it is also able to remove firm-level fixed effects and trend effects, so that the treatment effect can be estimated precisely. (Lach, 2002) and (Aerts & Schmidt, 2008) used CDiD for their estimation.

4.1.4. Regression Discontinuity Design

In the last decade, the regression discontinuity design (RDD) has received more attention. This design elicits causal effects of interventions by assigning a cutoff above or below which an intervention is assigned. The idea behind RDD is that assignment to the treatment is determined, either completely or partly, by the value of a predictor (the covariate Xi) being on either side of a fixed threshold. (Imbens & Lemieux, 2008) This approach is well-suited for the evaluation of programs where subsidies are awarded to firms based on a certain score. A subsidy is awarded when a firm has a score above the cutoff point, while a subsidy is not awarded when a firm has a score under the cutoff point (or vice versa). Because firms just below and just above the cutoff point are assumed to be quite similar, jumps in firm performance at the cutoff point is attributed to treatment. (Grilli & Murtinu, 2011) The downside of using RDD is that the estimated effect is confined to values of the variables that determines the threshold around the threshold. For instance, suppose that the government would create a measure of firm quality which ranges from 0 to 100, and all firms above 70 would receive a subsidy. Then, RDD can be used to compare firm growth around that threshold of 70. However, it is not certain that that is also the effect of providing a subsidy to firms with score 90 or 50.

4.1.5. The ideal situation + recommendations

There is not one simple answer to give when it comes down to the question what the best method is for the evaluation of R&D subsidies. This is at least dependent on the available data and the type of the specific subsidy program.

The most promising method seems to be the conditional difference-in-differences estimator (CDiD), since this method both uses matching and DiD and as a result controls for both observables and unobservables. Our recommendation is to take this into account for future evaluation research of R&D subsidies. For DiD, longitudinal data is needed and the conditions for matching must also be satisfied, such as enough overlap between the control group and treatment group. When there are scores available, one could surely make an attempt to use the Regression Discontinuity Design (RDD). For the research, it is desirable that the exact scores and explanation of the program are made available.

Another recommendation is to create ways to include the behaviour additionality into the model. While most empirical studies only consider the short run effects of a subsidy, the vision of the government is probably more targeted to the long run. Future research could focus on the long run, by for example taking spillovers into account. It is important here that there is a good framework for including the spillover effects in the model, so that there is no under- or overestimation.

5. Conclusion

In this literature review, we described the effects of R&D on firms and several evaluation methods. In chapter 2, the theoretical background has been discussed. Arguments that support the need for R&D subsidies are underinvestment in R&D because R&D bears the characteristics of a public good, the asymmetric information among borrowers and lenders, and interactive learning. The goal of government R&D subsidies is to increase the level of R&D innovations (additionality), but there is the risk of crowding out. David, Hall and Toole put the underlying channels of additionality versus crowding out in a framework.

In chapter 3, several empirical studies are outlined. Irwin and Klenow (1996) and Branstetter & Sakakibara (2002) both found additionality effects whereas Klette and Møen (1999) found crowding out effects. The problem of estimating the impact of a subsidy with OLS is that subsidies are not randomly assigned, which leads to endogeneity in the model. Instead of randomness, there is selection bias, which is caused by the intentions of the government and differences across firms.

In chapter 4, several econometric methods are outlined that correct for endogeneity in the model. Instrumental Variables (IV) estimation uses exogenous variables that are correlated with the treatment variable and uncorrelated with the outcome. While IV can help to solve bias in the estimation, it is hard to find good instruments. Matching derives the treatment effect from balancing program participants and comparable non-participants, while controlling for observables. The Difference-in-Difference (DiD) method is useful when longitudinal data is available, while Regression Discontinuity Design is suitable when scores are available.

In general, R&D subsidies can serve as great instruments for more innovations and more growth. Still, the challenge for policy makers is to find those projects where the gap between the private and the social level of financed R&D activities is the greatest. Therefore, it is important that firms can show that the projects to be subsidized are not (sufficiently) profitable in the absence of a subsidy.

Case studies (with for example interviews with the managers of the subsidized firms) can bring additional and useful information to the evaluation of the program, when the managers have to report a payoff for the projects. The danger with this is that there is likely an upward bias in the payoff, since a high estimate increases the chance that the R&D program will be regarded as successful and is continued. From empirical evidence, it seems that the relatively smaller firms benefit the most from R&D subsidies. This is probably so because the smaller firms have a higher cost of external capital and higher fixed costs than the bigger firms. More attention in the future for the “smaller firms” is thus desirable.

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