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"An Evaluation of some Technology Programs executed by the Norwegian Government in the 80's and the 90's"

Preface

The Research Department, Statistics Norway has employed me to do some analysis that I have used in order to write both my thesis and this paper. My supervisor was Tor Jakob Klette.

I want to thank all the staff at the Division for microeconometrics for the help they have given me, and especially Jarle Møen, Jon Ivar Sjåberge and Andreas Benedictow. I also wish to thank Abdul Aziz Babakerkhail and Ole Sand that both read my thesis carefully. This paper would not have reached "the critical mass", had it not been for their help.

Contents

1. A summary of this paper

In the last 40 years the Norwegian government has executed many technology programs targeted at the national high-tech industries in order to help them become able to compete with foreign high-tech companies. Especially the Information Technology (IT) sector has been supported to a large extent with programs containing many different efforts. One of the largest programs was "The National Program for Information Technology" implemented in the period from 1988 to 1990 and involving the amount of 4.9 billion kroner. Klette and Møen (1999) evaluated some of the technology programs targeted at the IT and IT-related industry sectors in Norway and involving Research and Development (hereafter R&D) subsidies. They tried to establish the relationship between plant performance and R&D subsidies and expected it to be positive. Klette and Møen measured firm performance by the following variables: total factor productivity, labour productivity, growth in man-hours, growth in sales, investment intensity, return on assets and profit margin. There is, however, a missing-data problem for anyone that tries to evaluate programs mentioned above, because there is no way to unveil how the supported firms would have performed without R&D subsidies. Klette and Møen solved this problem by comparing supported firms with non-supported firms undertaking R&D. The results following from their analysis did not indicate any significant positive difference in firm performance between supported and non-supported firms. Within some of the models analysed, it seemed that the R&D subsidies worsened firm performance. This tendency became even more evident when fixed effects were included into the performance models. These findings can be due to self selection in the data that will result in a correlation between the subsidy variable and the stochastic term, causing the OLS estimator to be biased and inconsistent.

Self selection with resulting bias in the OLS estimator is a data problem that might lead to wrong conclusions if it is not discovered and eliminated. In this paper we will analyse the same technology programs as Klette and Møen, applying four of their seven performance models. These four models cover the effects of receiving R&D subsidies on firm growth and on productivity. We show how a variant of Heckman's two-step procedure can be applied in order to achieve consistent estimates of the coefficient for the subsidy variable. Blundell (1998) illustrates how the above-mentioned biasedness in the OLS estimator can be eliminated by a direct control of the part of the stochastic term that is assumed to correlate with the subsidy variable. After this control is implemented our new results do indicate a positive relation between R&D subsidies and plant performance in all OLS regressions without fixed effects. Furthermore, in all these performance models there is clear indication of a negative correlation between the subsidy variable and the stochastic term, meaning that firms with poor performance had a higher chance of receiving R&D subsidies than well-performing firms. Such a self selection will obviously cause the OLS estimator to be downward biased.

The firms in our sample are different in many aspects and by including fixed effects we manage to control firm heterogeneity. In the performance models with fixed effects we do not find an unambiguous indication of what kind of self selection we are dealing with in our data. The results detected in the firm growth models are in accordance with the OLS findings described above. There seems to be a negative self selection, which we know will cause the OLS estimator to underestimate the effect of receiving R&D subsidies. But opposite results are detected in the remaining two performance models covering information about the effect of R&D subsidies on productivity. Here the results indicate a positive self selection, meaning that firms with good performance had a higher possibility to receive R&D subsidies. Such a self selection causes the OLS estimator to be upward biased. After controlling the positive correlation between the subsidy variable and the stochastic term, the negative difference in firm growth level between supported and non-supported firms increases even more. In the last chapter we give some suggestions for further investigations and amendments that can be made in order to improve our performance models.

2. Information technology and government support

2.1. General purpose technology

Economists have for a long time been preoccupied by themes such as long run economic growth and external effects arising from economic activity. The latter one is often presented as market failure because of the spillover effects connected to it, and this sort of market failure might bring about market outcomes that can be improved upon in terms of Pareto optimality. Pollution and contamination are often presented as examples of negative externalities resulting from economic activity. On the other hand R&D activities are examples of economic activity with positive externalities connected to it. The article Bresnahan and Trajitenberg (1995) set focus on the technological progresses and innovations that take place from time to time, and try to analyse the importance of these new innovations concerning economic growth. No doubt the steam engine, the motor, the electric dynamo, the industrial modern factory system and the semiconductor are all examples of important innovations with great contributions to economic growth. Bresnahan and Trajitenberg name such innovations and technologies that play the role as important forces behind economic growth "General purpose technologies (GPTs)". Some of the significant characteristics of the GPTs are: i) pervasiveness and a wide applicability, ii) inherent potential for technical improvements, iii) innovative complementarities (ICs). Bresnahan and Trajitenberg show how a new GPT and the R&D motivated by the new GPT can create externalities and spillover effects. These externalities and spillovers will not be taken into consideration by the participators in R&D when deciding how much resources should be spent on R&D. Therefore the economy might be suffering from new technologies that will not be properly developed. The new GPT with its technological improvements do not take off because the necessary R&D are not undertaken.

The externalities associated with R&D, the potential expansions in application of the new GPT throughout the industry-learning by doing, all the technological improvements resulting from a new GPT and its subsequent innovative complementarities, might bring about multiple growth equilibria where one equilibrium corresponds to the new GPT never taking off. This is so because the R&D activities following the new GPT do not reach the critical mass due to the many problems mentioned above. All potential gains resulting from the new GPT and its ICs are not fully exhausted in the low scale equilibrium. This can serve as a good example of how lack of co-ordination and co-orporation in an industry sector can create low scale equilibrium[1]. There are possibilities for further increases in production, but in order to achieve it some kind of interference in the market must be carried out.

2.2. Information technology seen as a GPT

Information technology is characterised as a GPT in a study done by Klette and Møen (1999) of the Norwegian governmental IT programs executed in the 80's and 90's. Potential for technical improvement is often inherent in new IT-products. If the necessary R&D are undertaken, many industry sectors are enable to implement the new IT-products. As already mentioned above, some kind of interference and co-ordination might be needed in order for this to happen. Especially if all potential profits and gains are to be exploited. It is known in theory that taxes, legislation, subsidies, grants, public production and so forth, can correct externalities. But, for example, the optimal design of a technology policy is still a debated theme among economists. This explains why we witness

[1] David Romer (1996), chapter 6.14.

different practices of technology policies across countries[2]. Klette and Møen argue that the introduction of various parts of new information technology throughout the economy's different sectors, often involve innovative complementarities. This may create the before-mentioned information- and co-ordination problems among the participants in R&D-activities aiming to implement the new IT-products in various sectors of the industry. If the necessary R&D are not undertaken we have a situation where potential gains are not exploited and where firms might be under-investing in new developed technology and capital. Such a situation can lead to a weakening of the national high-tech firms and their ability to compete with foreign companies. This was exactly what happened with the American semiconductor industry in the early 80's. They lost large market shares to Japanese companies. The U.S. government responded to the weakening of American firms' abilities to compete with Japanese firms by initiating technology programs such as the Sematech consortium and The Small Business Innovation Research program (SBIR)[3].

The Norwegian government has recognised the many problems mentioned above that might occur in our high-tech industries, and it therefore launched different programs in the 80's and the 90's in order to secure that gains and profits were not spilt[4]. These programs had well defined goals and expectations. As for the National Program for Information Technology, this huge program contained the following amongst its objectives[5]:
1) A 15% annual increases in the IT-sector's sales.
2) A 20% annual increases in the IT-sector's exports.

After this short introduction of some of the important points concerning the GPT-literature and how IT can be seen as a GPT, it is now time to move on to the microeconometric analysis that are the main purpose of this paper.

3. Short run effects of public R&D subsidies

3.1. Evaluation methods

In their evaluation of the governmental IT-programs in Norway in the 80's and 90's, Klette and Møen chose certain performance variables and applied Ordinary Least Squares (OLS) -regressions in order to detect how R&D-subsidies affected firm performance. There is an obvious missing data problem confronting anyone that wants to assess how public funds and subsidies influence the receivers' performances. It is not possible to unveil how the subsidised firms would have performed if they were not supported. One way to solve this problem is to compare the performance of the high-tech firms that received R&D-subsidies with the performance of those high-tech firms in the different industry sectors that did not receive any kind of public support[6]. This is exactly what Klette and Møen did, and we shall apply the same strategy throughout this study as well. In our new analysis of how R&D subsidies influenced supported high-tech firms and their performances in Norway, we apply the same dummy variable method used by Klette and Møen (1999). In the first part of this paper we recapitulate some of their regressions. After that we try to solve a data problem due to a suspected correlation structure between the subsidy variable and the stochastic term in the regression models.

[2] See Mowery (1995).

[3] Klette, Møen and Griliches (2000).

[4] Klette and Møen (1999), page 7-11.

[5] See Harlem, L. et al. (1990), page 173-174 and chapter 4 for further information. It is not clear whether the increases in Harlem et al. are in nominal or real terms. As for this paper we are measuring growth in real terms.

[6] See Klette, Møen and Griliches (2000) for a discussion of problems connected to our approach.

3.2. Choosing a good measurement of performance

When trying to uncover the short run effects of receiving public R&D-subsidies, we are in need of performance measures. It is not possible to find one single variable that reflects the performance of a firm completely. We therefore take more than one performance variable into consideration. In this analysis of some of the governmental technology programs executed by the Norwegian government in the 80's and the 90's, we have chosen four different performance measures, all of them being applied by Klette and Møen in 1998. The two performance measures that shall inform us how the R&D subsidies affected firm growth are relative change in man-hours and relative change in sales. In order to investigate how R&D subsidies influence firm productivity we have chosen the last two performance measures to be total factor productivity and labour productivity. Klette and Møen also considered the following performance measures: relative change in return on assets, relative change in profit margin and relative change in investment intensity.

3.3. The data set we will apply in our analysis

We define the IT sector as consisting of the manufacture of office machinery and communication equipment, i.e. ISIC 3825 and 3832. We expect to find the main effects of the technology programs in these sectors since they were intensely promoted by the government. But because related sectors also received significant support, and due to possible spillovers and classification problems, we have chosen to use R&D data aggregated to the three-digit line of business level. This means that our main sample contains plant-year observations of manufacturers of machinery, electrical equipment and technical instruments, i.e. ISIC 382, 383 and 385. The observations were done within the period from 1982 to 1995. All the 860 firms included in our sample have at least five employees. On the basis of the time series files of the Norwegian manufacturing statistics we constructed the four performance variables to be applied later in our regression analysis as dependent variables. All the information about R&D has been merged in from the R&D survey conducted by the Royal Norwegian Council for Scientific and Industrial Research (NTNF) in the years 1982-1989 and by Statistics Norway in the years 1991-1995. We do not expect small subsidies to have significant influence on the receivers' performances. When we created our subsidy variable we took this into consideration by letting the subsidy variable be equal to one if and only if the share of subsidies to total R&D over the three years prior to the year of observation, was larger than five per cent. We did not distinguish between a zero and a less than five-per cent subsidy share and either did we investigate whether there is a difference between receiving a medium or a large subsidy share from the government. This last change was done in order to ease our new regression analysis following the OLS regressions. Investigations of the long run effects of R&D subsidies were also dropped in our analysis.

We want to distinguish between firms doing R&D and firms that seldom take part in R&D activity. Constructing a R&D variable that equals zero if the plant observation did not report to have undertaken R&D within the specific year and one otherwise is a possible way to distinguish between the two above-mentioned groups of firms. It is important to remember that there might be firms that did undertake R&D without reporting it, which means that our distinction between firms undertaking R&D and the rest of the firms in the sample is encumbered with measurement error. We cannot claim that the R&D variable is either all including or flawless. Nevertheless we believe that our constructed R&D variable can help us to control partially systematic differences between firms undertaking R&D and firms that rarely complete R&D.

Let $(dy/y)_{j,t}$ be the relative change in any of the two performance variables accounting for firm growth, where t denotes the years 83, 84,..,95 and where j denotes the firms 1, 2,..,M. More accurately $(dy/y)_{j,t} = [(y_{j,t} - y_{j,t-1})/(y_{j,t-1})]$. When constructing these growth rates we cannot calculate percentage changes for the first year 1982 and we subsequently loose some plant observations when calculating the firm specific growth rates. The dependent variable in the labour productivity model is measured as the log of value added per man-hour deflated by the consumer price index. The dependent variable in the total factor productivity model is a translog multilateral measure comparing output and the use of capital, labour and materials to a hypothetical reference firm producing the yearly median output using the yearly median of each input. Constant returns to scale is assumed and the elasticities of labour and materials are calculated using cost shares. This index is based on the work of Caves et al. (1982)[7]. Both the latter dependent variables give us the possibility to rank the plant-year observations according to their specific labour productivity- and total factor productivity index values. After we have constructed our performance variables, our sample contains 821 firms in total, constituting 5899 plant observations.

The number of plant-year observations (hereafter N) varies somewhat from regression to regression as some of the plant-year observations lack information about required variables. 69 of the 821 firms reported to have R&D in all the 13 years and these firms constitute 629 plant observations. Furthermore 230 firms reported to have R&D in some of the years between 1983 to 1995 and these firms constitute 2290 plant observations. Finally 522 firms never participated or completed R&D activities and these firms constitute the remaining 2980 plant observations. When it comes to the subsidy variable we find that 831 plant observations have a subsidy share larger than five per cent. Among these 831 plant observations, 350 had a subsidy share larger than twenty five per cent. Only 7 firms were subsidised in all the 13 years from 1983 to 1995. These firms constitute 52 plant observations. 656 firms never received any kind of R&D support from the government. These firms give rise to 4221 plant observations. Finally we find that 158 firms were subsidised in some of the years between 1983 and 1995 and these firms constitute the remaining 1626 plant observations. Further details of the sample and the variable constructions are given in appendix A.

4. The regression models

4.1. The first steps in building up a model to be estimated

As mentioned before we have almost 5900 plant-year observations and we apply the same explanatory variables in all the performance models. Notice that when we use the index i we treat our data as if it was a cross section sample. Observations done of firms at different years are deflated and therefore comparable. Whenever we need to distinguish between observations done by the different firms, we substitute the former index i with the indexes j and t where the faster index t is over time and the slower index j is over firms. Let DS_i denote the subsidy variable for plant-year observation i. DS_i equals one if the share of subsidies to total R&D over the three years prior to the year of observation is larger than five per cent. It is this variable and its effect on firm performance that is at the focus of our interest. We assume a linear relationship between the performance variables and the regressors in our performance models. As stated earlier our sample contains 821 firms from 16 different industry sectors and we have therefore included 15 industry dummies (IDs). More information about the industry dummies are given in appendix B. Together with 12 time dummies (TDs) and the subsidy variable, we also include the R&D variable that equals one for all the plant observations that have reported R&D activities within the specific year and zero otherwise. It follows from the above-mentioned information that we have totally 29 independent variables (15 industry dummies, 12 time dummies, the subsidy variable, the R&D variable and the constant term $\Rightarrow k = 30$). The observations done of firm i's 29 regressors are gathered in the row vector X_i with order (1x30). The first component in this vector is 1 corresponding to the constant term α. Relation 1) gives the assumed linear relationship between any of the two dependent variables covering firm growth and the constant term plus the 29 regressors:

[7] See also Griliches (1979) and Griliches (1986)

1) $(dy/y)_i = \alpha + \beta_1 DS_i + \beta_2 TD_{84,i} + \beta_3 TD_{85,i} + ... + \beta_{13} TD_{95,i} + \beta_{14} DR_i + \delta_1 ID_{1,i} + \delta_2 ID_{2,i} + ... + \delta_{15} ID_{15,i} + U_i$,
$\forall i \; \varepsilon \; (1,N)$

The compact matrix presentation of any of the two growth models to be estimated is given by relation 1'):

1') $Y_{Nx1} = (X_{Nxk}\beta_{kx1})_{Nx1} + U_{Nx1}$

As for the performance models covering total factor productivity and labour productivity, they are given by the following two relations:

2) $TFP_{Nx1} = (X_{Nxk}\beta_{kx1})_{Nx1} + U_{Nx1}$

3) $\log (LP)_{Nx1} = (X_{Nxk}\beta_{kx1})_{Nx1} + U_{Nx1}$

We assume that the stochastic terms are independent, identically normally distributed in all performance models:

4) $U_i \sim iiN(0,\sigma_u)$, $\forall i \; \varepsilon \; (1,N)$

As already mentioned we have made some changes in our performance models, compared to the models of Klette and Møen. A replication of some of their regressions is therefore necessary before we continue with the self selection problem and try to find a new estimator that manages to eliminate the selection bias in the point estimate on the subsidy variable coefficient.

4.2. The effect of R&D subsidies on our chosen performance variables

In the following we will focus on the parameter estimates for the subsidy variable and the R&D variable since these are the parameters of interest. Information about the estimates for the time- and industry dummies' coefficients is not reported for space reasons. Furthermore it is important to understand why we include the R&D variable into our models. If this dummy is excluded we end up with comparing subsidised firms with both firms not supported by the government and firms that do not take part in R&D at all (here we abstract from the above-mentioned measurement error in the R&D variable). This might result in a biasedness in the estimate on the subsidy variable coefficient due to possible systematic differences between high-tech firms and low-tech firms when it comes to highly qualified personnel with knowledge of scientific R&D methods, R&D equipment and the latest developed production technology and machinery. By including the R&D variable we try to eliminate this source of bias in the estimate on the subsidy variable coefficient. Table 4.1 reports the results of the OLS regressions of the four performance variables on the two above-mentioned variables plus the 27 time- and industry dummies. Notice that almost all the results given in table 4.1 are in accordance with the findings done by Klette and Møen in 1998. This goes for performance models with and without fixed effects. The only difference arises in the point estimate on the subsidy variable in the growth in sales model without fixed effects and this is commented bellow. We can therefore conclude that the replication of some of Klette and Møen's work presented in chapter 4 and 5 are satisfactory.

The effect of R&D subsidies on productivity

We start out by analysing how R&D subsidies affected firm productivity. As mentioned earlier we have constructed two performance variables that contain information about change in productivity as a result of receiving R&D subsidies. From the two first columns in table 4.1, we see that R&D subsidies did not have any statistically significant effect on either total factor productivity or on labour productivity. Starting with the total factor productivity model we find that the point estimate on the subsidy variable coefficient is 0.0005. This indicates that the R&D subsidies contributed to an increase of 0.0005 in the total factor productivity level for the supported high-tech firms compared to the non-supported high-tech firms. The point estimate is statistically insignificant[8].

Moving to the second productivity model, the statistically insignificant point estimate on the R&D coefficient is -0.0248. The immediate, naive interpretation of this estimate is that the effect of receiving subsidies is a 2.5 per cent reduction in labour productivity level for the supported firms relative to the high-tech firms doing R&D without public funding. So according to this finding, the subsidised high-tech firms did not gain at all from being supported by the government.

Finally we find that the firms taking part in R&D did on average have a statistically significant (one per cent level) higher productivity level than the firms that did not report R&D within both productivity models. According to the point estimates on the R&D variable coefficients given in table 4.1, the differences in productivity levels between the two groups of firms were found to be 0.06 within the total factor productivity model and 0.08 in the labour productivity model.

The effect of R&D subsidies on firm growth

The sign of the point estimate on the subsidy variable coefficient are positive within both firm growth models although we once more find that the point estimates are small. If we choose growth in sales as our point of departure, we find that the supported firms have a statistically insignificant 2.1 per cent higher growth rate level than the rest of the unsupported high-tech firms. Klette and Møen reported a negative point estimate on this specific subsidy variable coefficient. They found that the effect of receiving a small R&D subsidy was a reduction in the growth in sales level equal to -2.1 per cent. It is though important to remember that Klette and Møen included an extra R&D subsidy regressor into their performance models in order to estimate the effect of receiving substantial R&D support on firm performance. The statistically insignificant point estimate on this regressor's coefficient, indicated an 8.3 per cent increase in the level of growth in sales. Moving to the second model accounting for growth in man-hours, we find that the effect of receiving R&D subsidies is given by the statistically insignificant point estimate equal to 0.0061. This indicates that the R&D subsidies contributed to only a marginal 0.6 per cent extra growth in man-hours relative to the non-subsidised high-tech firms.

When we compare performance in terms of growth in man-hours between firms undertaking R&D with the performance of firms that do not take part in R&D, we find that the latter group of firms have a 3.9 per cent higher level of growth rate. This difference in level is statistically significant at one per cent level and seems reasonable when we take into consideration that firms not completing R&D also had a lower level of labour productivity than the R&D undertaking firms. As for the growth in sales model, we find the same result. The firms not doing R&D have a statistically insignificant 1.8 per cent higher level of growth rate than firms that have completed R&D. An explanation for this last result could be that R&D undertaking firms are operating in markets with harder competition from foreign firms than what is the case for firms not completing R&D. The Norwegian high-tech firms might have lost market shares to other foreign companies producing alternative products. Furthermore we know that the risk of failing with the ongoing R&D programs undertaken by some of the high-tech firms are substantial. Perhaps subsequent failures in R&D done by national firms also result in the national high-tech firms selling less of their products in both national- and international markets.

[8] Whenever we state that a point estimate is statistically insignificant, we apply a significance level of ten per cent.

Table 4.1. Effect of R&D-subsidies on our four firm performance variables

Dependent variables:	Total factor productivity	Labour productivity	Growth in man-hours	Growth in sales
Subsidy variable:	0.0005 (0.0083)	-0.0248 (0.0176)	0.0061 (0.0185)	0.0214 (0.0283)
R&D variable:	0.0585*** (0.0063)	0.0791*** (0.0135)	-0.0394*** (0.0143)	-0.0186 (0.0219)
No. of observations	5732	5899	5525	5525
R-squared	0.1279	0.3193	0.0270	0.0200
Root mean square error	0.1727	0.3792	0.3973	0.6081

***** indicates statistical significance at the one per cent level.**
**** indicates statistical significance at the five per cent level.**
*** indicates statistical significance at the ten per cent level.**

Klette and Møen (1999)[9] point out that the positive estimates on the coefficient belonging to the subsidy variable reported in table 4.1 might partially be explained by what they call a reversed causality. What they mean is that successful, or unsuccessful firms, might have had a significant higher possibility to receive R&D subsidies. The reason for why successful firms could have had a higher probability of receiving R&D subsidies might be that this would increase the probability for the different technology programs to be successful as well. Such an aspect is perhaps important for the public authorities in charge of the distribution of the financial funds connected to the programs and the succeeding evaluations of the programs' different efforts. By introducing fixed effects we try to control partially this reversed causality.

5. Linear performance models with fixed effects

5.1. Motivation for the inclusion of fixed effects

So far, we have assumed that the effects from independent variables not varying over time are identical for all firms and given by the constant term α. On the other side we know well that the firms in our sample are heterogeneous in many aspects. They operate in different industry sectors, some are high-tech firms (1946 plant observations out of 5899 plant observations in total) and some are low-tech firms. Some engage in R&D and are producing advanced technology equipment and machinery while others are not doing R&D at all. If we take firm heterogeneity seriously and believe it is proper to include this aspect into our performance models, one way of doing so is to add firm specific coefficients α_j (hereafter fixed effects) into relations 1) to 3). We assume that the fixed effects are constant for each firm over time and they are meant to capture the differences between firms. Inclusion of fixed effects into the performance variables comes at a cost, because the bias on the estimated coefficients due to measurement errors is likely to increase[10].

[9] Klette & Møen(1999), page 14.
[10] Cf. Griliches and Hausman (1986)

5.2. The models we estimate after the inclusion of fixed effects

After we have introduced firm specific fixed effects we now have the following firm growth models:

$$5)\ (dy/y)_{j,t} = \alpha + \sum_{r=1}^{M} D_{r,t}\alpha_j + \beta_1 DS_{j,t} + \beta_2 TD_{84,j} + \beta_3 TD_{85,j} + ... + \beta_{13} TD_{95,j} + \beta_{14} DR_{j,t} + \delta_1 ID_{1,j} + ... + \delta_{15} ID_{15,j} + U_{j,t},\ \forall j \ \varepsilon\ (1,M) \text{ and } t\ \varepsilon\ T_j$$

Here $D_{r,t}$ is a dummy that equals one whenever r = j and zero otherwise. T_j is the number of observations done by firm j. In order to estimate all the coefficients in relation 5) except from the M plant specific fixed effects, we first calculate the M different mean performance values:

$$6)\ \overline{(dy/y)}_j = \frac{1}{T_j}\sum_{q=1}^{T_j} (dy/y)_{j,q} = \alpha + \sum_{r=1}^{M} D_{r,t}\alpha_j + \beta_1 \overline{DS}_j + ... + \delta_{15} \overline{ID}_{15,j} + \overline{u}_j,\ \forall\ j\ \varepsilon\ (1,M)$$

Then we express all plant-year observations as deviations from their respective plant means, wiping out the fixed effects and the constant term at the same time. The plant-year observations expressed as deviations from plant means are denoted with a tilde on top. The firm growth models we now estimate applying the OLS estimator are as follows:

$$7)\ (dy\tilde{/}y)_{j,t} = \beta_1 \tilde{DS}_{j,t} + ... + \delta_{15} \tilde{ID}_{15,j,t} + \tilde{U}_{j,t},\ \forall j\ \varepsilon\ (1,M) \text{ and } t\ \varepsilon\ T_j$$

Relations 8) and 9) give the two productivity models with fixed effects included:

$$8)\ \tilde{TFP}_{j,t} = \beta_1 \tilde{DS}_{j,t} + ... + \delta_{15} \tilde{ID}_{15,j,t} + \tilde{U}_{j,t},\ \forall j\ \varepsilon\ (1,M) \text{ and } t\ \varepsilon\ T_j$$

$$9)\ \log(\tilde{LP})_{j,t} = \beta_1 \tilde{DS}_{j,t} + ... + \delta_{15} \tilde{ID}_{15,j,t} + \tilde{U}_{j,t},\ \forall j\ \varepsilon\ (1,M) \text{ and } t\ \varepsilon\ T_j$$

The results from the OLS regressions of our four performance models after including fixed effects are presented in table 5.1.

The effect of R&D subsidies on productivity after including fixed effects

Starting out with total factor productivity we find that the estimated effect of receiving R&D subsidies is statistically significant (ten per cent level). The point estimate equal to -0.017 indicates a negative effect on total factor productivity from receiving R&D subsidies. When it comes to the distinction between firms undertaking R&D and firms that did not report any R&D activity, we see from the first column in table 5.1 that the former group of firms have a statistically significant (one per cent level) 0.03 higher total factor productivity level.

We have in all models with fixed effects, tested whether there is a significant difference between the firm specific fixed effects. The H_0 hypothesis is: $\alpha_1 = \alpha_2 = ... = \alpha_M$. We applied an F-test with significance level one per cent. On the basis of our sample we could just reject the H_0 hypothesis in the total factor productivity model. In the remaining three performance models we do not find significant support for the inclusion of fixed effects. The observed F-values are reported in the last row in table 5.1.

When we move to the labour productivity model we find that the estimated difference between R&D performing firms and firms not reporting R&D, is statistically insignificant. The point estimate indicates a 2.9 per cent higher labour productivity level for the former group of firms. Finally we find that there is a statistically significant (five per cent level) and negative difference of -5.6 per cent in labour productivity level between high-tech firms receiving R&D subsidies relative to the high-tech firms undertaking R&D without being supported by the government.

The effect of R&D subsidies on firm growth after including fixed effects
Once more we find only negative differences between subsidised and non-subsidised high-tech firms engaged in R&D. Choosing growth in man-hours as our point of departure, we see from column 3 in table 5.1 that the difference in growth level between the subsidised and non-subsidised high-tech firms is estimated to be -1.0 per cent. The point estimate is not significant. When comparing firms doing R&D with firms not completing any R&D, we find that the estimate on the R&D variable coefficient is statistically insignificant and equal to -0.023. This suggests a negative difference in the level of growth in man-hours between the two groups of firms equal to -2.3 per cent.

Moving to the growth in sales model we see from column 4 in table 5.1 that after controlling firm heterogeneity, the estimated difference in growth in sales level between R&D performing firms and firms not undertaking R&D is 1.4 per cent (this estimated difference equalled -1.8 per cent when fixed effects were not included). The negative and insignificant point estimate on the subsidy variable's coefficient suggests that the subsidised firms had a 2.2 per cent lower level of growth in sales compared to the rest of the high-tech firms in our sample that are engaged in R&D without public support.

Table 5.1. OLS estimates after including fixed effects into the performance models

Dependent variable:	Total factor productivity	Labour productivity	Growth in man-hours	Growth in sales
Subsidy variable:	-0.0170*	-0.0565**	-0.0101	-0.0221
	(0.0104)	(0.0246)	(0.0167)	(0.0248)
R&D variable:	0.0294 ***	0.0289	-0.0229	0.0135
	(0.0105)	(0.0209)	(0.0168)	(0.0343)
No. of observations	5732	5899	5525	5525
R-squared	0.6101	0.6823	0.2793	0.1860
R-squared adj.	0.5443	0.6300	0.1625	0.0542
Root mean square error	0.1246	0.2788	0.3676	0.5958
$F_{(\infty,\infty)}^{H_0:\ \alpha_1=\alpha_2=\ldots=\alpha_M}$ $(F_{(\infty,\infty)}^{one\ per\ cent\ level}=1)$	1.043	0.978	0.300	0.175

We expected to find a positive relationship between firm performance and R&D subsidies, meaning that public R&D support would lead to the subsidised firms having a higher level of productivity and a higher level of firm growth compared to the high-tech firms engaged in R&D without public support. But in the fixed effect models and in the labour productivity model without fixed effects, the statistically insignificant estimates of the subsidy variable coefficient were all negative. The immediate, naive interpretation of these findings is that R&D subsidies worsened the supported firms' performances. Furthermore in the remaining three OLS models without fixed effects we did not find significant, positive differences in performance between supported and non-supported high-tech firms engaged in R&D. The results achieved so far, especially in the fixed effect models, might indicate a downward bias when estimating the subsidy variable's coefficient applying the OLS estimator. We will investigate this suspicion further in chapter 6 where we also try to detect the source of the assumed downward biasedness and how it can be eliminated. This bias could for example originate in a violation of the assumptions concerning the stochastic term and the exogenous explanatory variables in our performance models given by relations 1) to 3). We know well from econometric theory that correlation between any of the explanatory variables and the stochastic term in our performance models, will cause the OLS estimator to produce inconsistent estimates. Consequently we must search for another estimator that solve the problem connected to the correlation between one of the regressors and the stochastic term. If the assumed correlation could be controlled in some manner, we also manage to eliminate the bias in our applied estimator. And more important, we are then able to produce consistent estimates on the vector β_{kx1}. This is the subject of the following chapter.

6. Correlation between the subsidy variable and the stochastic term

6.1. Self selection and inconsistent OLS estimates

When we analysed the results following from the OLS regression of the performance models with fixed effects, we found some surprising results. All the estimates of the subsidy variable coefficient were negative. This also accounts for the labour productivity model without fixed effects. In the remaining three models we found no evidence of any significant, positive difference between firms receiving R&D subsidies and other high-tech firms in our sample doing unsubsidised R&D. One reason for these negative or close to zero OLS point estimates on the subsidy variable coefficient in our two sets of models (with and without fixed effects), can be a negative correlation between the subsidy variable and the stochastic term. Such a correlation implies that the estimate on the subsidy variable coefficient is downward biased in all OLS regressions completed so far. To understand why it is plausible with a negative correlation between the subsidy variable and the stochastic term, it is important to be aware of the fact that the Norwegian IT sector faced many structural problems in the end of the 80's. If the R&D subsidies were distributed so as to help the high-tech firms most harmed by the restructuring of the IT sector in the end of the 80's and with poor firm performances due to the restructuring, this will lead to a negative correlation between the stochastic term and the subsidy variable. Formally the argument suggests that the following is true:

10) $p\lim_{N\to\infty}\left[\frac{1}{N}\sum_{i=1}^{\infty} DS_i U_i\right] = \psi \neq 0 \Rightarrow$

11) $Co\,\mathrm{var}(U, DS) \neq 0$

12) $p\lim \hat{\beta}_{kx1}^{OLS} \neq \beta_{kx1}$

It follows directly from 10) that the OLS estimator is not consistent in either set of models, after we have made the assumption of a negative correlation between the subsidy variable and the stochastic term. But it remains to find evidence of such a correlation in our data and to test a hypothesis concerning self selection.

In order to get consistent estimates of the subsidy variable coefficient we use a two-step procedure, the so-called "Heckit-estimator" due to Heckman (1979). A variant of his method will solve correlation problems similar to the one we believe that we are dealing with in our analysis. Heckman's procedure is one way to estimate the vector β_{kx1} consistently in both sets of models. The first step contains a probit model that helps us to calculate consistent estimates of the unknown firm specific inverse Mill's ratios denoted by λ_i^A and λ_i^B. These consistent estimates of the firm specific inverse Mill's ratios given by $\hat{\lambda}_i^A$ and $\hat{\lambda}_i^B$ are then included into the linear performance models. In this way we control directly the part of the stochastic term that is assumed to correlate with the subsidy variable. This is exactly how Heckman's two-step procedure deals with the selection problem we believe is apparent in our models. After the direct control of the above-mentioned correlation is implemented, we can test the H_0 hypothesis concerning self selection. More important, we are now able to estimate the parameters gathered in the vector β_{kx1} consistently by applying the OLS estimator. This follows from our assumption that the remaining part of the stochastic term does not correlate with any of the regressors included in the performance models. We have managed to eliminate the correlation between the stochastic term and the subsidy variable. Therefore the estimates of the coefficients following from the OLS estimations completed in the second step are consistent. In order to run our variant of Heckman's two-step procedure, we first have to make some strict assumptions.

6.2. Deciding who shall receive R&D subsidies

When the public authority decides who shall be granted R&D subsidies, we assume they apply a determination rule based on firm specific indexes. We believe that the index based rule takes into consideration the performance of the applicants of R&D support measured by for example relative change in profit margin or investment intensity. In addition to the applicants' performances, the public authority might also consider firm characteristics such as age, planned change in R&D activity, industry sector that the applicant belongs to, geographical location of the applicant, market position and so forth. We also included time dummies into the determination rule, because we know that the amount of money that the authorities spent on technology programs differed substantially from year to year. Finally, since some industry sectors were supported to a larger extent than others, we also included industry dummies into the index equation given by relation 13).

We will now illustrate how incorporating the before-mentioned firm characteristics into an index equation, can help us to parameterise the determination rule that we believe is decisive in the process where the public authorities determine who shall be subsidised. Let γ_{1xS} be a column vector of control variable coefficients with the intercept γ_0 as the first component. Here s denotes the number of right-side variables used in the index equation 13) and in the probit analysis model given by relation 16) bellow. The explanatory variables already described above, contains firm characteristics, time- and industry dummies and the intercept (hereafter we use control variables for all explanatory variables included in the index equation and the probit model). The row vector $Z^*_{i,1xS}$ contains the 41 control variable values for plant observation i plus the integer 1 as the first component in the vector corresponding to the intercept γ_0. Relation 13) gives the assumed regression relationship between the index values and the control variables:

13) $IN_i = (\gamma'_{1xS} Z_i^*)_{1x1} + V_i, \forall i \ \varepsilon \ (1, N)$

Notice that some of the control variables such as the IDs and the TDs are also applied in the two sets of performance models. Besides these dummies we included 14 other control variables covering firm characteristics (s = 42).

The choice of control variables was done on the basis of a scheme used by the Norwegian Research Council (NFR) when they evaluated applications for R&D subsidies from high-tech firms. The inclusion of time- and industry dummies was done on the basis of our own reasoning. We believe all these control variables are important when the public authorities determine who is going to get R&D subsidies. The stochastic term V_i is assumed to be identically, independent normally distributed with a mean of zero and a standard deviation equal to σ_v:

14) $V_i \sim iiN(0,\sigma_v)$, $\forall i \; \varepsilon \; (1, N)$

So what we have at this point is firm specific index values that we assume are the basis for the determination of who will be subsidised by the government and who will not. As explained above we suspect that the close to zero and negative estimates on the subsidy variable coefficient reported in tables 4.1 and 5.1 are due to the fact that the public authorities were trying to support those high-tech firms in Norway that encountered troubles during the restructuring of the Norwegian IT sector in the end of the 80's. We formalise this by assuming that all firms with index values greater than a critical threshold value IN^* will receive R&D subsidies. This suggests that the public authorities are applying the following determination rule: "If $IN_i > IN^*$ then the firm i shall be subsidised". This decision rule can also be expressed formally as illustrated in relation 15):

$$15)\ IN_i > IN^* \Leftrightarrow (\gamma_{1xS}^{'} Z_{i,1xS}^{*})_{1x1} + V_i > IN^* \Leftrightarrow \gamma_{1xS}^{'} Z_i^{*} + V_i - IN^* > 0 \Leftrightarrow \gamma_{1xS}^{*'} Z_i^{*} + V_i > 0 \Rightarrow DS_i = 1,\quad \forall i \; \varepsilon \; (1, N)$$

Notice that the only difference between the two vectors γ'_{1xS} *and* $\gamma^{*'}_{1xS}$ is in the first component of the vectors. The first component equals γ_0 in the former vector and $\gamma_0 - IN^*$ in the latter one. The first step in our variant of Heckman's two-step procedure contains a maximum likelihood estimation of all the parameters in the vector $(\gamma^{*\prime}/\sigma_V)$ belonging to the control variables included in the probit model given by relation 16). We use the whole sample containing N plant observations in the estimation of these coefficients. The maximum likelihood estimates are then used to calculate consistent estimates of the inverse Mill's ratios. The unobserved firm specific index values are the underlying response variables in the probit model and the subsidy variable is the observed one:

$$16)\ DS_i = 1 \text{ if } (\gamma_{1xS}^{'} Z_{i,1xS}^{*})_{1x1} + V_i > 0 \text{ and}$$
$$DS_i = 0 \text{ otherwise, } \forall i \; \varepsilon \; (1, N).$$

Notice that the control variables in the index equation 13) are also the explanatory variables in the probit analysis model given by relation 16) where we explain the discrete subsidy variable and its variation between 0 and 1. From relations 12) to 16) it follows that:

$$17)\ \Pr[DS_i = 1] = \Pr[(\gamma_{1xS}^{*'} Z_i^{*} + V_i) > 0] = \Phi\left[\frac{\gamma_{1xS}^{*'} Z_i^{*}}{\sigma_v}\right],\ \forall i \; \varepsilon N$$

$$17')\ \Pr[DS_i = 0] = \Pr[(\gamma_{1xS}^{*'} Z_i^{*} + V_i) < 0] = 1 - \Phi\left[\frac{\gamma_{1xS}^{*'} Z_i^{*}}{\sigma_v}\right],\ \forall i \; \varepsilon N$$

Here $\Phi(.)$ is the normal cumulative function. It is obvious from relation 17) that we can only estimate the vector $(\gamma^{*\prime}/\sigma_V)$, and not $\gamma^{*'}$ and σ_V separately. More information about the results from the maximum likelihood estimation of the probit model is given in appendix B.

In order to apply Heckman's procedure we must make another strict assumption about the joint density of the stochastic terms (U_i,V_i). In the following we assume that the joint density of U_i and V_i is bivariate normal:

$$18)\begin{pmatrix} U_i \\ V_i \end{pmatrix} \sim iiN\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{UU} & \sigma_{UV} \\ \sigma_{UV} & \sigma_{VV} \end{pmatrix}\right],\ \forall i \; \varepsilon(1, N)$$

When the maximum likelihood estimation of the probit analysis model given by relation 16) is completed, we achieve consistent estimates of the coefficients in the vector $\left(\gamma^{*}{}'/\sigma_V\right)$. These estimates are then used to calculate consistent estimates of the firm specific inverse Mill's ratios. Given the set of assumptions about the stochastic terms in relation 18), it is then possible to estimate the vector β_{kx1} and the self selection coefficient (σ_{UV}/σ_V) consistently by OLS after we have included the estimated inverse Mill's ratios following from the probit model, into our performance models. This is the second step of Heckman's procedure. It contains OLS regressions of the two sets of performance models with the estimated inverse Mill's ratios included. Let N_1 be the number of firms subsidised by the public authorities and $N_2 = N-N_1$ the remaining firms in the sample. In the following we use some well-known results from the theory of truncated variables[11]:

19) $E[U_i\,|X_i\,, DS_i = 1] = E[U_i\,|X_i\,, V_i > -\gamma^{*}{}'_{1xS}Z_i^{*}\,] \Rightarrow$

19') $$E[U_i\,|X_i\,, DS_i = 1] = \left(\frac{\sigma_{UV}}{\sigma_V}\right)\left(\frac{\phi\left(\frac{\gamma^{*}{}'_{1xS}Z_i^{*}}{\sigma_V}\right)}{\Phi\left(\frac{\gamma^{*}{}'_{1xS}Z_i^{*}}{\sigma_V}\right)}\right), \forall i\ \varepsilon(1, N_1)$$

Here $\phi(.)$ is the normal density function and $\Phi(.)$ is the normal cumulative function.

20) $E[U_i\,|X_i\,, DS_i = 0] = E[U_i\,|X_i\,, V_i < -\gamma^{*}{}'_{1xS}Z_i^{*}\,]$, $\forall i\ \varepsilon(1, N_2)$

20') $$E[U_i\,|X_i\,, DS_i = 0] = \left(\frac{\sigma_{UV}}{\sigma_V}\right)\left(\frac{-\phi\left(\frac{\gamma^{*}{}'_{1xS}Z_i^{*}}{\sigma_V}\right)}{1-\Phi\left(\frac{\gamma^{*}{}'_{1xS}Z_i^{*}}{\sigma_V}\right)}\right), \quad \forall i\ \varepsilon(1, N_2)$$

The two different expressions for the inverse Mill's ratio plus their consistent estimates based on the maximum likelihood estimation of our probit analysis model, are given by relations 21) to 24):

21) $$\lambda_i^{A} = \left(\frac{\phi\left(\frac{\gamma^{*}{}'_{1xS}Z_i^{*}}{\sigma_V}\right)}{\Phi\left(\frac{\gamma^{*}{}'_{1xS}Z_i^{*}}{\sigma_V}\right)}\right), \forall i\ \varepsilon(1, N_1)$$

[11] Richard Blundell (1998) and William Greene (1997).

$$22)\quad \hat{\lambda}_i^A = \left(\frac{\phi\left(\left(\frac{\hat{\gamma}^{*'}_{1xS}}{\sigma_V}\right)Z_i^*\right)}{\Phi\left(\left(\frac{\hat{\gamma}^{*'}_{1xS}}{\sigma_V}\right)Z_i^*\right)} \right), \forall i\, \varepsilon(1, N_1)$$

$$23)\quad \lambda_i^B = \left(\frac{-\phi\left(\frac{\gamma^{*'}_{1xS}Z_i^*}{\sigma_V}\right)}{1-\Phi\left(\frac{\gamma^{*'}_{1xS}Z_i^*}{\sigma_V}\right)} \right), \forall i\, \varepsilon(1, N_2)$$

$$24)\quad \hat{\lambda}_i^B = \left(\frac{-\phi\left(\left(\frac{\hat{\gamma}^{*'}_{1xS}}{\sigma_V}\right)Z_i^*\right)}{1-\Phi\left(\left(\frac{\hat{\gamma}^{*'}_{1xS}}{\sigma_V}\right)Z_i^*\right)} \right), \forall i\, \varepsilon(1, N_2)$$

In order to see that we have omitted an independent variable when doing the OLS regressions reported in table 4.1 and table 5.1, we must calculate the conditional expectations of the performance variables under the assumption that the stochastic term and the subsidy variable are correlated. We will find that the conditional expectation is different from the expression we achieved in chapter 4.3, where we assumed that there was no correlation between the stochastic term U_i and any of the right-side variables in the performance models with and without fixed effects. In the following we use one of the growth performance models without fixed effects to illustrate some important properties of the performance models under the new set of assumptions made in chapter 6. The results achieved in the following are assumed to be identical for all the other performance models, with and without fixed effects. Let X_i^* denote a row vector with (k-1) columns consisting all the data we have for plant observation i except for the observation of the subsidy variable DS_i. We start out by calculating the conditional expectations of the performance variable $(dy/y)_i$ under the new set of assumptions:

$$25)\ E[(dy/y)_i \mid X_i^*, DS_i=1] = \alpha + \beta_1 + \beta_2 TD_{84,i} + ... + \beta_{13} TD_{95,i} + \beta_{14} DR_i + \delta_1 ID_{1,i} + ... + \delta_{15} ID_{15,i} + E[U_i \mid X_i^*, DS_i=1], \forall i\, \varepsilon\, (1, N_1)$$

$$26)\ E[(dy/y)_i \mid X_i^*, DS_i=0] = \alpha + \beta_2 TD_{84,i} + ... + \beta_{13} TD_{95,i} + \beta_{14} DR_i + \delta_1 ID_{1,i} + ... + \delta_{15} ID_{15,i} + E[U_i \mid X_i^*, DS_i=0], \forall i\, \varepsilon\, (1, N_2)$$

Using 25) and 26) together with relations 22) and 24) give us the following expressions for the conditional expectations of $(dy/y)_i$:

27) $E[(dy/y)_i \mid X_i^*, DS_i = 1] = \alpha + \beta_1 + \beta_2 TD_{84,i} + \dots\dots\dots + \delta_{15} + \left(\sigma_{UV}/\sigma_V\right)\lambda_i^A$, $\forall i \in (1, N_1)$

28) $E[(dy/y)_i \mid X_i^{**}, DS_i = 0] = \alpha + \beta_2 TD_{84,i} + \dots\dots\dots + \delta_{15} ID_{15,i} + \left(\sigma_{UV}/\sigma_V\right)\lambda_i^B$, $\forall i \in (1, N_2)$

Finally, in order to be able to use the whole sample in the OLS regressions on the second step of Heckman's two step procedure, we introduce the regressor λ_i together with its consistent estimate in relations 29) and 29'):

29) $\lambda_i = DS_i \lambda_i^A + (1 - DS_i)\lambda_i^B$, $\forall i \in (1, N)$

29') $\hat{\lambda}_i = DS_i \hat{\lambda}_i^A + (1 - DS_i)\hat{\lambda}_i^B$, $\forall i \in (1, N)$

By combining relations 27), 28) and 29), we find that the expectation of $(dy/y)_i$ conditioned on X_i equals (remember that the vector X_i also contains the observation of DS_i):

30) $E[(dy/y)_i \mid X_i] = \alpha + \beta_1 DS_i + \beta_2 TD_{84,i} + \dots\dots\dots + \delta_{15} ID_{15,i} + \left(\sigma_{UV}/\sigma_V\right)\lambda_i$, $\forall i \in (1, N)$

The conditional expectation of the growth performance variable $(dy/y)_i$ calculated in chapter 4 equalled:

31) $E[(dy/y)_i \mid X_i] = \alpha + \beta_1 DS_i + \beta_2 TD_{84,i} + \dots\dots\dots + \delta_{15} ID_{15,i}$, $\forall i \in (1, N)$

By comparing relation 30) with 31) we see that we omitted the inverse Mill's ratio from relation 31) when we completed the OLS regressions in chapter 4 and 5. We omitted the inverse Mill's ratio because we assumed there was no correlation between any of the right-side variables and the stochastic term. If the R&D subsidies were not distributed randomly but instead given to firms with certain qualities, this will cause the OLS estimator to be biased and inconsistent. A distribution of R&D subsidy funds favouring firms with poor performance due to the restructuring in the end of the 80's, will give rise to a downward biasedness in the OLS estimator. If on the other side the public authorities favoured well-performing firms, this will lead to an upward biasedness.

When we work with the productivity models we just exchange the left-side variable in relation 32) with the total factor productivity indexes or the labour productivity indexes. If we want to control firm heterogeneity, we just include the firm specific fixed effects together with the firm dummies into the performance models. The stochastic term in the modified performance models equals:

32) $W_i = U_i - \left(\frac{\sigma_{UV}}{\sigma_V}\right)\left[\lambda_i^A DS_i + \lambda_i^B (1 - DS_i)\right] = U_i - \left(\frac{\sigma_{UV}}{\sigma_V}\right)\lambda_i$, $\forall i \in (1, N)$

Since the inverse Mill's ratios are unknown we apply the consistent estimates of the firm specific inverse Mill's ratios following from the first step of Heckman's two step procedure. We show in relation 33) what growth performance models we are now estimating in order to get consistent point estimates on the subsidy variable coefficient plus the selection parameter belonging to the combined inverse Mill's ratio variable $\hat{\lambda}_i$:

$$33)\ (dy/y)_i = \alpha + \beta_1 DS_i + \beta_2 TD_{84,i} + \ldots\ldots\ldots + \delta_{15} ID_{15,i} + \left(\sigma_{UV} \big/ \sigma_V \right) \hat{\lambda}_i + W_i \ ,\ \forall i\ \varepsilon\ (1,N)$$

6.3. The results after including the inverse Mill's ratios

It now remains to check whether the inclusion of the estimated inverse Mills ratios will lead to more intuitive results regarding the sign and the magnitude of the estimate on the coefficient belonging to the subsidy variable. The results from including the estimated firm specific inverse Mill's ratios into our performance models without fixed effects are presented in table 6.1.

As already mentioned above the OLS estimates reported in table 6.1 are consistent but inefficient due to the fact that the stochastic term in the new linear model that we estimated after including the firm specific inverse Mill's ratios is heteroscedastic[12]. We have chosen to include the standard errors and the respective significant levels for the estimates. But it is very important to recognise that as long as we are dealing with models that are in fact contaminated with selection bias, this will give rise to downward biased standard errors even after we have controlled for the assumed negative correlation by including the estimated inverse Mill's ratios. Furthermore this also means that the standard statistical inference based on the t-statistic is not liable either since the standard errors are too small. These facts can to some extent be relaxed if there is no significant evidence of selection bias in the sample at hand. In order to test whether there is any trace of selection in the data one can apply the ordinary t-test. The H_0- and H_1-hypothesis are given by the following two expressions:

$$34)\ H_0 : \frac{\sigma_{UV}}{\sigma_V} = 0 \quad and \quad H_1 : \frac{\sigma_{UV}}{\sigma_V} \neq 0$$

On the basis of the prob-values given in table 6.1, we know the probabilities of observing the point estimates ($\frac{\hat{\sigma}_{UV}}{\sigma_V}$) under the H_o-hypothesis of no self selection within the different models. Following standard statistical procedures on hypothesis testing, we can reject the H_0-hypothesis of no self selection on the basis of our sample at the statistical level of five per cent, only in the models containing information about firm growth. In both productivity models we see from table 6.1 that the point estimate on the selection parameter has prob-values less than one per cent which means that we cannot, on the basis of our sample, reject the H_0-hypothesis within the two productivity models. Notice that all point estimates reported in table 6.1 are significant at the one per cent level in these two models where we know that the negative self selection makes the estimated standard deviations of the point estimates too small. Since we on the basis of our sample could not reject the H_0-hypothesis of no self selection in the firm growth models, we can treat the calculated standard errors as proper. This will also hold for the statistical inferences about the point estimates. But in any case we know that all parameter estimates reported in table 6.1 are consistent given the assumptions elaborated in the beginning of chapter 5.2 and they therefore deserve a comment.

The effect of R&D subsidies on productivity

Starting with the total factor productivity model we see that the effect of receiving public support is considerably higher than the result we found in our first OLS analysis reported in table 4.1. The new finding is now in accordance with our a priori expectations concerning the effect of receiving R&D subsidies on firm performance. The estimate of the subsidy variable coefficient is 0.05, which means that R&D subsidies contributed to a higher total factor productivity level. Comparing firms

[12] Hence it is possible to apply a standard GLS procedure in order to achieve the most efficient estimates on the regressors' coefficients and thereby also proper standard errors for all the estimated coefficients of the first model given by relation 1).

undertaking R&D with firms not completing any R&D, we once more find that the former group of firms have a statistically significant (one per cent level) 0.06 higher level of total factor productivity.

Within the labour productivity model we find that R&D performing firms have a 7.25 per cent higher productivity level relative to firms not completing R&D. Furthermore there is a large increase in the point estimate on the subsidy variable coefficient in the labour productivity model, after the inclusion of the inverse Mill's ratios. We now find that there is an important difference between the subsidised high-tech firms relative to the non-subsidised high-tech firms. The point estimate on the subsidy variable coefficient indicates that the estimated effect of receiving R&D subsidies is a rise in the labour productivity level of 14.1 per cent (remember the earlier OLS result reported in table 4.1 indicating a negative effect of -2.5 per cent from receiving R&D subsidies on the labour productivity level).

Table 6.1. Effect of R&D-subsidies on 4 firm performance after including the estimated inverse Mill's ratios

	Total factor productivity	Labour productivity	Growth in man-hours	Growth in sales
Subsidy variable:	0.0496***	0.1407**	0.0113	0.0789
	(0.0172)	(0.0373)	(0.0345)	(0.0559)
R&D variable:	0.0571***	0.0725***	-0.0292**	-0.0234
	(0.0065)	(0.0139)	(0.0129)	(0.0208)
Selection parameter:	-0.0328***	-0.1111***	-0.0065	-0.0368
	(0.0097)	(0.0211)	(0.0195)	(0.0314)
Prob-value of the selection parameter estimate:	0.001	0.000	0.740	0.241
No. of observations	4754	4891	4891	4891
R-squared	0.1334	0.3025	0.0258	0.0229
Root mean square error	0.1668	0.3685	0.3408	0.5483

The effect of R&D subsidies on firm growth

Starting with the growth in sales model the effect of receiving R&D subsidies is also now found to be considerably larger compared with our first OLS results given in table 4.1, although the new point estimate on the subsidy variable coefficient is not significant. We see from table 6.1 that the estimated effect of receiving R&D subsidies is an increase in sales of 7.9 per cent which is closer to the expected 15 per cent increase in sales due to the National program for the IT sector than our earlier finding equal to 2.1 per cent. Furthermore firms undertaking R&D have within this model a statistically insignificant (one per cent level) 2.3 per cent lower growth level than the firms not completing R&D. The point estimate on the R&D variable coefficient in the second firm growth model covering growth in man-hours is also negative, suggesting a 2.9 per cent difference between the two groups of firms. This point estimate is statistically significant at the five per cent level. Finally we see from column 3 in table 6.1 that the effect of being a subsidised R&D high-tech firm is given by the statistically insignificant point estimate of 0.011. This indicates that the subsidised high-tech firms were positively stimulated by the R&D support that resulted in an extra 1.1 per cent increase in the growth of man-hours for the supported high-tech firms relative to the non-supported firms.

Before moving to the other set of models where we control firm heterogeneity, we want to comment a little bit further on the considerable changes in some of the point estimates after including the inverse Mill's ratios. The change is especially large when investigating the effect of R&D subsidies on labour productivity where the point estimate moves from -0.02 to 0.14. How can we test the significance of this change? If we could assume that these two point estimates were independent, normally distributed then we could apply the ordinary t-test, had it not been for the self selection in our data that makes the estimated standard deviation of $\beta_1^{Heckman}$ downward biased. If the latter biasedness were close to zero this would make it possible to apply the reported standard deviations in table 6.1. One test-suggestion could be to test whether the two latent parameters β_1^{OLS} *and* $\beta_1^{Heckman}$ are different. The result of such a test would be to reject the H_0 hypothesis of no difference on the basis of our sample. The observed t-value would be 2.58. Notice also that the 90 per cent confidence intervals for these two point estimates are the only pair of confidence intervals that just overlap each other when we compare the 90 per cent confidence intervals of the OLS point estimates with the corresponding Heckman point estimates[13]. There is a continual and considerable overlapping in all other cases, with and without fixed effects.

It is though very important to remember that all these statements done above are based on the condition that downward biasedness in the estimated standard deviations are so small that it might be neglected such that the reported standard deviations in table 6.1 can be used in hypothesis testing. While the assumption of normality that makes the t-test appropriate can be defended from an asymptotically point of view, this cannot be said about the assumption of independence. When we remember that the two point estimates commented upon in this paragraph is based on exactly the same sample, it is like dropping the clanger to assume independence between them. Admitting this fact leaves us with the non-overlapping confidence intervals as the only indication of a significant large and positive change in point estimate.

6.4. Fixed effect models with inverse Mill's ratios

As in chapter 6.2, we now make a new set of assumptions about the stochastic term U_i that are in accordance with our presumption of self selection in the data. As explained earlier, we assume that the self selection results in a negative correlation between the subsidy variable and the stochastic term. This makes the subsidy variable endogenous and the OLS estimate on its coefficient inconsistent. In order to estimate all the regressor parameters in the vector β_{kx1} consistently we apply our variant of Heckman's two-step procedure. The results from these final regressions are presented in table 6.2. Before we start commenting on the point estimates presented in table 6.2, we first need to test the H_0 hypothesis of no self selection in the different performance models. As in chapter 5.2 the H_0 and H_1 hypothesis are given by the two following expressions:

$$35)\, H_0 : \frac{\sigma_{UV}}{\sigma_V} = 0 \quad and \quad H_1 : \frac{\sigma_{UV}}{\sigma_V} \neq 0$$

Type of self selection in the performance models with fixed effects

Using the prob-values of the point estimates on the self selection parameters (σ_{uv}/σ_v), we cannot on the basis of our last regression analysis reject the H_0-hypothesis within any of the fixed effect models with included inverse Mill's ratios. This means that we can treat the standard errors as proper and this also goes for the statistical inference about the point estimates. In both productivity models we find statistically insignificant evidence of a positive selection meaning that there was a higher probability for high-tech firms with relatively good performance measured by productivity, to receive R&D subsidies. A motivation for distributing the R&D support in ways that favours well-performing firms might be the higher possibility of achieving the technology programs' targets and thereby also being

[13] OLS model covering labour productivity. 90% C.I. for the 2 point estimates on the R&D coefficient within the lab.prod.model: 90% C.I. Without the inv.M.r. = [-0.0754 , 0.0257] and with the inv.M.r.= [0.0208 , 0.2563].

able to claim that the undertaken public technology programs and efforts were successful. Such a selection bias will lead to an upward biasedness in the point estimate on the subsidy variable within the fixed effects models without the estimated inverse Mill's ratios included. We see from table 5.1 and table 6.2 that after controlling the correlation between the stochastic term and the subsidy variable, the statistically insignificant negative difference in productivity level between supported and non-supported high-tech firms doing R&D increases considerably. This holds for both productivity models. Within the models covering firm growth, we find statistically insignificant negative point estimates on both selection coefficients. These two findings are in accordance with our earlier assumption explained thoroughly in chapter 5.2. By comparing the results reported in table 5.1 and table 6.2 we see that after controlling the negative correlation between the subsidy variable and the stochastic term, the effect from receiving R&D subsidies increases considerably. In order to say something about the significance of the changes in estimate values after controlling the assumed self selection, we compared 95 per cent confidence intervals belonging to the estimates on the subsidy variable coefficient with and without estimated inverse Mill's ratios included. We found a considerable overlapping in all four comparisons and it is therefore hard to draw conclusions concerning the significance of the changes in the estimates on the subsidy variable coefficient on the basis of these comparisons.

The effect of R&D subsidies on productivity after including fixed effects and inverse Mill's ratios
Starting out with the labour productivity model the negative point estimate suggests a 17.5 per cent negative difference in labour productivity level between supported and non-supported high-tech firms doing R&D. This point estimate is the only statistically significant (five per cent level) point estimate on the coefficient belonging to the subsidy variable. When we compare firms doing R&D with firms not undertaking R&D in order to see if there is any difference between the two groups of firms, we find that the former group of firms have a statistically insignificant 1.5 per cent higher level of labour productivity. Also in the total factor productivity model we find that firms completing R&D have a higher level of productivity. The difference equal to 0.0235 is statistically significant (five per cent level). Finally we see from column 1 in table 6.2 that the effect of R&D subsidies within the total factor productivity model, is a reduction in the productivity level of -0.05. The point estimate is statistically insignificant.

The effect of R&D subsidies on firm growth after including fixed effects and inverse Mill's ratios
The changes in the point estimate on the subsidy variable coefficient are considerable in both firm growth models, and the new findings indicate that there is a positive difference between subsidised and non-subsidised firms in growth level within both models, even though none of the two point estimates are statistically significant. According to table 6.2 we see that the effect of R&D subsidies on supported high-tech firms relative to non-supported high-tech firms doing R&D, is a 0.7 per cent higher level of growth in man-hours and a 4.5 per cent higher level of growth in sales. Furthermore we see from column 3 in table 6.2 that firms not undertaking R&D have a statistically insignificant 0.2 per cent higher level of growth in man-hours. Finally we find that firms completing R&D have a statistically insignificant 0.8 per cent higher level of growth in sales compared to the firms not taking part in R&D.

Table 6.2 OLS estimates after including fixed effects and the inverse Mill's ratios into the performance models

	Total factor productivity	Labour productivity	Growth in man-hours	Growth in sales
Subsidy variable:	-0.0520	-0.1753**	0.0068	0.0454
	(0.0378)	(0.0875)	(0.0783)	(0.1352)
R&D variable:	0.0235**	0.0149	-0.0015	0.0086
	(0.0105)	(0.0213)	(0.0143)	(0.0273)
Selection parameter estimate:	0.0188	0.0647	-0.0183	-0.0411
	(0.0207)	(0.0475)	(0.0434)	(0.0722)
Prob.value for selection parameter estimate:	0.364	0.173	0.673	0.569
No. of observations	4754	4891	4891	4891
R-squared	0.6433	0.6876	0.2003	0.1878
R-squared adj.	0.5802	0.6337	0.0625	0.0478
Root mean square error	0.1157	0.2663	0.3334	0.5396

7. Final conclusions

7.1. A short recapitulation of the regressions

We have in this thesis tried to evaluate some of the recent technology programs targeted at the high-tech industries in Norway and their effects on firm performance. The missing-data problem confronting anyone trying to evaluate and estimate the effect of public programs, can be solved by comparing the subsidised with the non-subsidised as long as the firms in the two groups are similar in all other aspects but the fact that some were supported by the public authorities and others not. After the first set of OLS regressions on our linear performance models, we found some devastating results from the public authorities' point of view. It seemed that the technology programs did not achieve the targets that were set in advance. In the fixed effect models we found that the R&D subsidies worsened firm performance. Since we know from similar evaluations of technology programs completed abroad[14] that R&D subsidies did in fact have positive and statistically significant effects on firm performance, we started to search for possible reasons that could cause downward biasedness in the point estimates on the subsidy variable coefficient.

The restructuring of the IT sector in the end of the 80's might have caused the public authorities to distribute R&D subsidies so as to help those firms most harmed by the restructuring. Such a distribution of R&D subsidies will give rise to a self selection and a negative correlation between the subsidy variable and the stochastic term. In order to eliminate the biasedness caused by the self selection in our data, we applied a variant of Heckman's two step procedure that is thoroughly explained in Blundell (1998)[15]. This way of eliminating the biasedness and solving the inconsistency

[14] Klette, Møen and Griliches (2000)

[15] Richard Blundell (1998).

problem connected to the OLS estimator caused by the assumed self selection, resulted in new important findings. After including the estimated inverse Mill's ratios into our performance models without fixed effects, the point estimates indicating the effects of receiving R&D subsidies increased in all performance models. Furthermore, after including inverse Mill's ratios we found that the point estimates on the selection parameter were negative in all models without fixed effects. This means that firms with poor performance had a higher possibility of receiving R&D subsidies than well-performing firms had. This way of distributing R&D support will cause the OLS estimator to underestimate the effect of R&D subsidies on firm performance.

After completing the first set of model analysis, we wanted to control firm heterogeneity since we know that the firms are different in many aspects. The results from the fixed effect regressions were not so clarifying when it comes to what kind of self selection we are confronted with in our sample. After the direct control of the correlation between the subsidy variable and the stochastic term, the point estimates on the subsidy variable coefficient were found to be positive within the two firm growth models. In these two models, the estimate on the selection parameter indicated a negative correlation between the stochastic term and the subsidy variable. In the remaining two models covering productivity, we found negative effects of receiving R&D subsidies followed by positive estimates on the selection parameter.

In order to apply Heckman's two step procedure we made some crucial assumptions of how to model the authorities' decision rule when they decided which firms should be subsidised. Furthermore, in order to get consistent estimates on the firm specific inverse Mill's ratios we first completed a maximum likelihood estimation of the probit analysis using the whole sample of N plant observations in order to explain the variation of the discrete and dichotomous subsidy variable. In order to be able to complete the maximum likelihood estimation of the probit model we had to assume that the stochastic terms in the decision rule are independent, identically normally distributed. It has been shown that misspecification of distribution in two-step self selection estimators does not always lead to inconsistent estimates, which in our case means inconsistent estimates of the inverse Mill's ratios[16]. Finally we assumed that U_i and V_i are bivariate normally distributed. The goodness of fit-measure mostly applied when estimating variations in dichotomous variables, is the Pseudo-R^2 . The Pseudo-R^2 in our probit model equalled 0.25. The choice of control variables in the index equation and the probit model was based on an evaluation scheme used by the NFR and on our own reasoning.

7.2. Suggestions for improvements

In the future we will try to improve the probit analysis by including other reasonable regressors such as a dummy for receiving R&D subsidies in the past. The problem with such a dummy is that it might correlate too well with the subsidy variable that is the dependent variable in the probit analysis. Another difficulty is connected to our lack of knowledge about when the subsidies are starting to affect firm performance and three years is maybe not enough. Finally the efficiency of our estimates can be increased if we manage to improve the merge process of plant-year observations from the annual census of manufacturing statistics with the R&D statistics census, and in that way increase the number of plant-year observations in our sample. One could also try other estimators such as the propensity score and matching estimator in order to detect the influence of R&D subsidies on firm performance. The new results following from these regressions can then be compared to the results found here. We have in this paper found indications of self selection and a positive relationship between R&D support and plant performance. But further improvements need to be made in order for us to be sure of the success of the Norwegian technology programs executed in the 80's and the 90's

[16] Whitney K. Newey(1999).

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Appendix A

A.1 The sample and the construction of the variables used in our regressions

As explained earlier we have more than 6600 plant-year observations to start with stretching from 1982 to 1995 and all procedures concerning the sample - and variable construction, are identical with those applied in Klette and Møen (1999). We have used data from R&D surveys and times series files of the manufacturing statistics gathered by Statistics Norway. We only applied firms with more than 5 employees because the information available for the smaller firms with less than 5 employees are limited. See Halvorsen, Jensen and Foyn[17] for further information on this subject. More than 60% of the firms in our sample are single plant firms. If a firm contains more than one plant, the R&D expenditures are distributed according to sales.

Sale is measured as the value of gross production corrected for public taxes and subsidies. The labour productivity measure is the log of value added per man-hour deflated by the consumer price index. The total factor productivity measure is a multilateral measure comparing output and the use of capital, labour and materials to a hypothetical reference firm producing the yearly median output using the yearly median of each input. The R&D variable includes both intramural and extramural R&D expenditures. These expenditures consist mainly of labour costs and are deflated by an index based on the movements of average wages in ISIC 382, 383 and 385. For all the years without R&D surveys we imputed the R&D expenses plant by plant.

When we look upon the period from 1983 to 1995 we find 6448 plant-year observations of firms with more than 5 employees in ISIC 382, 383 and 385. 211 plant-year observations that lack sales, man-hours or capital have been removed entirely from the sample. Observations who lack less vital variables have only been removed from the particular analysis for which they miss necessary information. This causes the sample size to vary somewhat between the different regressions completed in this paper. When it comes to the trimming of the sample we have removed 258 outlying observations, which equals four percent of the sample with plant observations from 1983 to 1995.

R&D surveys are available for the yeas: 1982-85, 1987, 1989, 1991, 1993 and 1995. The Royal Norwegian Council for Scientific and Industrial Research (NTNF) first carried out the surveys until Statistics Norway took over in 1991. When we merged the data set from the time series files with the data set from the R&D surveys we lost a great number of R&D units due to matching problems. When we generated the age regressor to be applied in the probit analysis model, we lost more than 100 plant-year observations, evenly spread over industry sectors and years.

A.2 How we stacked our panel data sample

Since our data set contains time series for 821 firms over the period stretching from 1983 to 1995 constituting 5899 plant observations, there are many possible ways of stacking the sample. Our sample follows the conventional stacking that can be described in the following way: We first sorted the sample by plant specific numbers and by years. We started with the firm having the minimum plant number. We stacked this firm's observations in increasing time order. After that we continued with the plant having the second minimum plant number. We stacked this firm's observations in the same

[17] Halvorsen, Jensen and Foyn (1991)

manner as for the first firm. We continued this procedure for all the M firms in our sample. In this way we end up with a sample with N plant observations containing stacked groups of firm specific plant-year observations. It is very important to notice that our sample is not balanced and we do not necessarily have 13 observations of each plant. It is not common in our sample to have as much as 13 observations of the same firm.

A.3 The two indexes of plant observations used in this thesis

In our paper we use two different indexes that are somehow related to each other. The model given by relation 1) does not distinguish between the firms and their firm specific observations. The connection between the two indexes is demonstrated in table A.1.

Table A.1. Illustration of the connection between our two observation indexes

Index indicated by "i"	Index differing between firm specific observation groups. Firm counted by "j" :	Years counted by "t" :	The total number of observations done by each of the firms indexed by "n_j"
i = 1	j = 1	t = 82	
2	1	t = 83	
3	1	t = 84	$T_1 = 3$
4	j = 2	t = 82	
5	2	t = 83	
6	2	t = 84	
⋮	⋮	⋮	
⋮	j = 2	t = 91	$T_2 = 10$
⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮
N	j = M	t = 95	$T_{860} = 1$

Furthermore, we have given a short description in table A.2 of our sample with regards to the total number of firms included in our sample and how the number of observations are distributed between 1 up to the maximum amount of 14 observations stretching from the year 1982 up to 1995. Notice that this description is done before our performance variables are constructed. Therefore the number of firms equals 860 and they constitute more than 6600 plant-year observations.

Number of firms included in our sample = 860
Years are running from 1982 to 1995 $\Rightarrow$ T = 14

Table A.2. The most frequent patterns of how the firm specific observations appeared in our original sample

Frequency	Percent of total number of observations	Cumulative Percentage	The different patterns in which the observations are done
187	22.78	22.78	All the 14 years included
40	4.87	27.65	11111.........
31	3.78	31.43	1.............
23	2.80	34.23	1111..........
20	2.44	36.66	1111111111....
19	2.31	38.98	11............
19	2.31	41.29	1111111111111.
18	2.19	43.48	111...........
18	2.19	45.68	111
446	54.32	100.00	All the other patterns that appeared
Sum: 860	100.00	....	....

Appendix B

B.1 The probit analysis model

Let DS be the subsidy variable that equal 1 if the share of subsidies to total R&D over the three years prior to the year of observation is larger than five percent. The subsidy variable DS is the dependent variable in the probit model where we try to investigate the effects of the control variables on the subsidy variable and its variation between zero and one. Since it must be the past years' values of the different control variables that will influence the outcome of the subsidy variable we have chosen to lag the different control variables one year. We could alternatively have lagged the control variables more than one year or applied averages for the three last years' values of the control variables included in our probit model. Anyway we assume that the effect of doing so is marginal compared to the result we obtain following our procedure. And more important, we avoid the huge multicollinarity problems that arise when we include regressors that are lagged versions of the already included control variables. We believe that the part of the variation of the subsidy variable that can be explained by our control variables will be exhausted even with just lagging the control variables one year prior to the time of observation.

B.2 Maximum likelihood estimation of the control variables' coefficients

We have already stated in chapter 4.2 that we assume the government applies an index rule when they decide which firms are going to be subsidised. Relation B1) gives the linear relationship between the firm specific indexes and the control variables:

B1) $IN_i = (\gamma'_{1xS} Z^*_{i,1xS})_{1x1} + V_i$, i ε (1,N)

Furthermore we made another strict assumption about the two stochastic terms U_i and V_i that they are identically, independent bivariate normally distributed. Let $\Phi(.)$ be the standard normal cumulative function and $\phi(.)$ the standard normal density function. It follows from the assumptions about the stochastic term V_i in relation B1), that the likelihood function of our probit analysis model equals:

$$\text{B2) L } \left(\gamma^*{}_{Sx1} / \sigma_V\right) = \prod_{i=1}^{N} \Phi\left(\frac{\gamma^{*'}_{1xS} Z^*_{i,1xS}}{\sigma_V}\right)^{DS_i} \left[1 - \Phi\left(\frac{\gamma^{*'}_{1xS} Z^*_{i,1xS}}{\sigma_V}\right)\right]^{(1-DS_i)}$$

From this probit model we get consistent maximum likelihood estimates on the control variables' coefficients divided by the standard deviation of the stochastic term V_i. We cannot get separated estimates of both σ_v and the vector $\gamma^*{}_{Sx1}$. Notice that this does not matter for us since we are in need of consistent estimates of the firm specific Mills ratios that can very well be calculated after we have estimated the vector $\tilde{\gamma}^*_{Sx1} = \left(\frac{\gamma^{*'}}{\sigma_V}\right)_{Sx1}$ by a maximum likelihood procedure. The result of this M.L.E. of the coefficients in the vector $\tilde{\gamma}^*_{Sx1}$ is reported in table B.1.

Table B.1. The result from the maximum likelihood maximation of the probit analysis model

Regressor	Estimate	Robust Stand. Dev.	Prob.value	Mean Elasticity *
All these regressors are lagged one year:				
Capital intensity	0.00018	0.00007	0.008	0.1347
Number of workers	0.00055	0.00014	0.000	0.0816
Number of Ph.D man-labour years connected to R&D	0.23824	0.1106	0.031	0.0075
Profitmargin per worker	-1.21883	0.83663	0.145	-0.0056
Planned change in R&D	0.00004	6.97x10exp(-6)	0.000	-0.0406
Last Years total R&D	-0.00001	0.00003	0.716	-0.0252
Total costs connected to R&D	0.00005	0.00003	0.076	0.1104
Part of R&D bought from national firms	0.00021	0.00006	0.001	0.0538
Part of R&D bought from international firms	0.00006	0.00014	0.684	0.0020
Part of R&D connected to national R&D Consortiums	0.00011	0.00005	0.020	0.0045
Part of R&D connected to international R&D Consortiums	-0.00014	0.00002	0.000	-0.0648
Age	0.01859	0.00467	0.000	0.4205
Dummy for public capital ownership exceeding 50%	0.91524	0.21886	0.000	0.0096
Dummy for foreign capital ownership	-0.24675	0.10190	0.015	-0.0380

Regressor	Estimate	Robust Stand.Dev.	Prob.value	Mean Elasticity
Time dummies: (1983 dropped, 1995 dropped due to collinarity)				
TD_{84}	-0.51477	0.22494	0.022	-0.0854
TD_{85}	-0.39363	0.22219	0.076	-0.0614
TD_{86}	-0.42513	0.22171	0.055	-0.0692
TD_{87}	-0.28895	0.21947	0.188	-0.0426
TD_{88}	-0.30801	0.21952	0.161	-0.0420
TD_{89}	0.32967	0.12508	0.008	0.0422
TD_{90}	0.02818	0.12834	0.826	0.0046
TD_{91}	0.25251	0.12391	0.042	0.0344
TD_{92}	-0.02071	0.13019	0.874	-0.0031
TD_{93}	0.12640	0.12766	0.322	0.0155
TD_{94}	-0.06304	0.13263	0.635	-0.0091
Industry dummies: (Industrial sector 38210 is dropped)				
ID_{38220}	-0.32613	0.20705	0.115	-0.0183
ID_{38230}	-1.12398	0.39253	0.004	-0.0364
ID_{38241}	-0.75319	0.19147	0.000	-0.1627
ID_{38249}	-0.86969	0.20511	0.000	-0.1520
ID_{38250}	-0.37365	0.26321	0.156	-0.0126
ID_{38291}	-0.07596	0.29277	0.795	-0.0009
ID_{38292}	-1.36702	0.23714	0.000	-0.3069
ID_{38299}	-0.37637	0.17421	0.031	-0.1388
ID_{38310}	0.01392	0.17881	0.938	0.0023
ID_{38320}	0.24134	0.17576	0.170	0.0393

Regressor	Estimate	Robust Stand.Dev.	Prob.value	Mean Elasticity
Industry dummies: (Industrial sector 38210 is dropped)				
ID_{38330}	-0.47361	0.21684	0.029	-0.0239
ID_{38391}	-0.35117	0.25029	0.161	-0.0067
ID_{38399}	-0.59504	0.19998	0.003	-0.0761
ID_{38510}	-0.09048	0.19308	0.639	-0.0063
ID_{38520}	-0.99253	0.30669	0.746	-0.0010
Regional dummies (Regional dummy 1 is dropped. Regional dummy 6 is dropped due to collinarity)				
RD_2	-0.53848	0.18831	0.004	-0.2623
RD_3	-0.72524	0.20335	0.000	-0.1649
RD_4	-0.61546	0.20479	0.003	-0.1110
RD_5	-0.43943	0.21792	0.044	-0.0237
The Intercept	-0.87301	0.27479	0.001	....

In order to calculate the mean elasticities for the different control variables included in this probit model, we first calculated the elasticity with regards to control variable Z_p for every firm:

$$EL_{\left(Z_p/\sigma_V\right)}(\Pr ob\ DS_i = 1) = \left(\frac{\partial \Phi_i \left(\dfrac{\gamma^{*'}_{(1xS),\,i} Z^*_i}{\sigma_V} \right)}{\partial H_i} \right) \left(\frac{\partial H_i}{\partial (Z_p / \sigma_V)} \right) \left(\frac{(Z_{p,i} / \sigma_V)}{\Phi\left(\dfrac{\gamma^{*'}_{(1xS),\,i} Z^*_i}{\sigma_V} \right)} \right) \Rightarrow$$

$$EL_{\left(Z_p/_{\sigma_V}\right)}(\Pr ob\ DS_i = 1) = \left(\phi\left(\frac{\gamma^{*'}_{(1xS),\ i} Z^*_i}{\sigma_V}\right)\right)\left(\frac{\gamma_p (Z_{p,i} / \sigma_V)}{\Phi\left(\frac{\gamma^{*'}_{(1xS),i} Z^*_i}{\sigma_V}\right)}\right) = \left(\phi\left(\frac{\gamma^{*'}_{(1xS),\ i} Z^*_i}{\sigma_V}\right)\right)\left(\frac{\gamma_p (Z_{p,i})}{\Phi\left(\frac{\gamma^{*'}_{(1xS),i} Z^*_i}{\sigma_V}\right)}\right) \Rightarrow$$

$$EL_{\left(Z_p/_{\sigma_V}\right)}(\Pr ob\ DS_i = 1) = \lambda_i^A \left(\frac{\gamma_p Z_{j,p}}{\Phi(\gamma^{*'}_{1xS} Z^*_j)}\right)$$

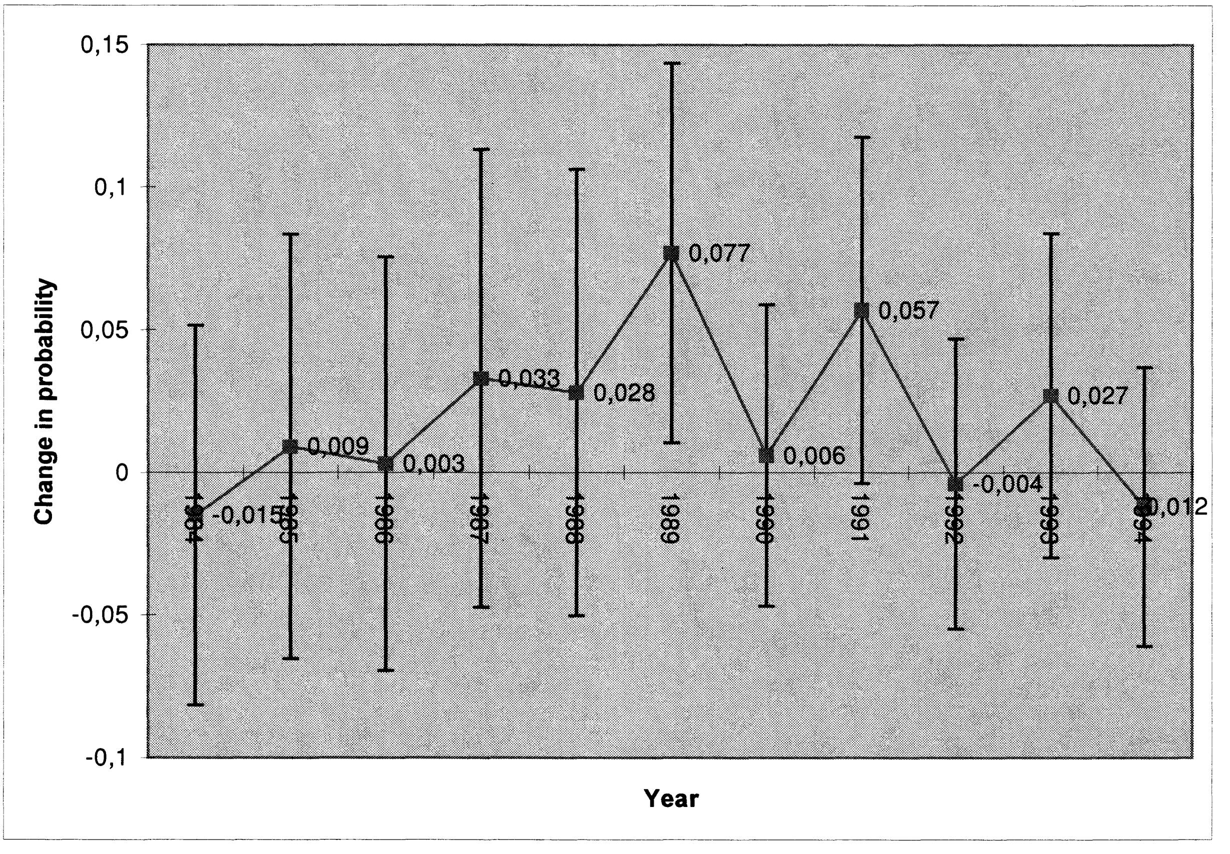
Here $H_i = \left(\frac{\gamma^{*'}_{(1xS),\ i} Z^*_i}{\sigma_V}\right)$ *and* Z_p *denotes a scalar whereas* Z^*_i *is the transposed of plant observation i's data vector.*

i= 1,2,...N. and p= 1,2,...,S, where N is the total number of plant observations ($N^{Probit} = 4901$) and S is the total number of control variables in the probit model. These elasticities are measured in units of standard deviation since we all the way are working with the standard normal density- and cumulative function. Notice also that Z_i is a control variable whereas Z_i^* is a vector of all the control variable values for plant observation i. We then calculate the estimated elasticities for each plant-year observation by using the maximum likelihood estimates. After doing this for every observation i and for all the control variables, we finally calculated the mean estimated elasticities for each control variable and they are presented in table B.1's last column.

B.3 How the probability of receiving R&D subsidies changes with time.

The public authorities had different R&D subsidy budgets from year to year and the number of programs and efforts varied over time as well. In figure C.1 we illustrate how the probability of receiving R&D subsidies changes when moving from 1983 to any of the years between 1984 to 1994. Notice that Stata 5.0 dropped the year 1994 completely from the analysis due to correlation problems. We use the estimates of the time dummies following from the maximum likelihood estimation of the probit model in order to calculate the changes in the probability of receiving R&D subsidies when comparing 1983 with another year between 1984 to 1994. Together with the estimated changes in the probability of receiving R&D, we also included the 95 per cent confidence intervals in figure B.1. We see that all years between 1985 and 1991 contributed to a rise in the probability of receiving R&D subsidies, compared with 1983. But we also notice that all the confidence intervals include both negative and positive numbers except for the year 1989. There is a statistically significant rise (one per cent level) in the probability of receiving R&D subsidies in 1989, the second year of The National Program for Information Technology lasting from 1988 to 1990.. The point estimate for 1989 equal to 0.077 indicates that the probability of receiving R&D subsidies increased with 8 per cent. Also the increase in the probability when comparing 1991 with 1983 is statistically significant (five per cent level) and the point estimate for this year equal to 0.057 indicates that the probability of receiving R&D subsidies increased with 6 per cent.

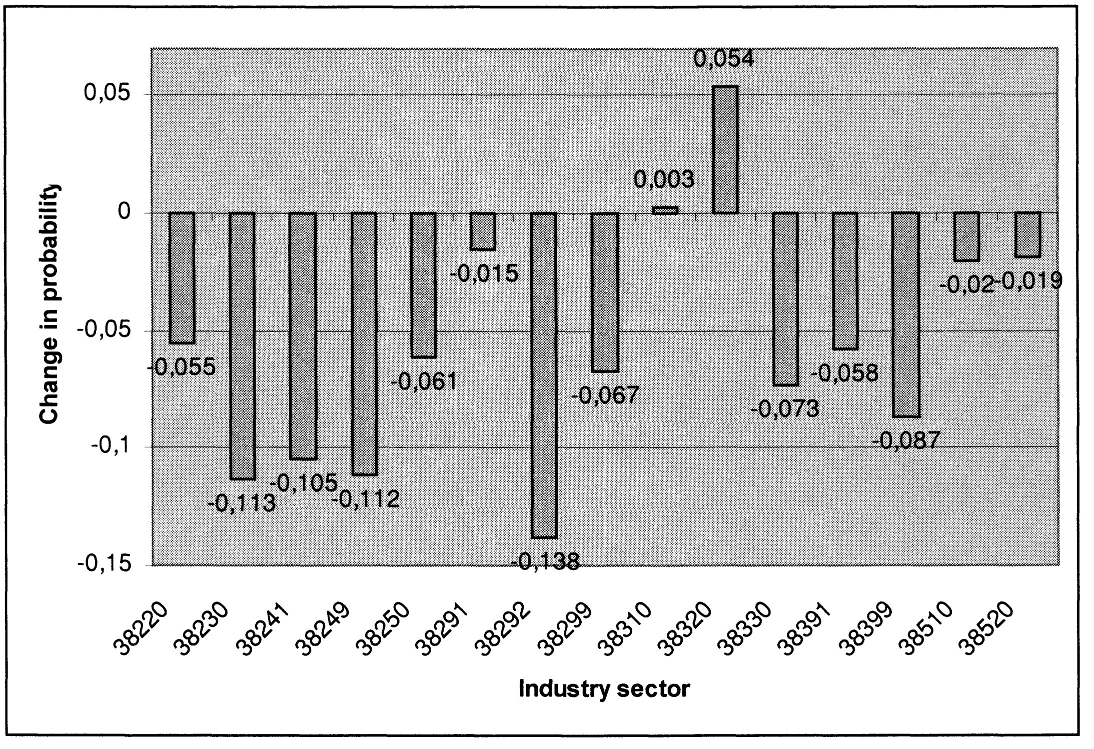
Figure B.1 How the probability of receiving R&D subsidies changes when moving from 1983 to any of the years between 1984 and 1994



B.4 How the probability of receiving R&D subsidies changes with industry sectors

When we want to learn about the differences between industry sectors when it comes to the probability of receiving R&D subsidies, we compare all industry sectors with the manufacturing of engines and turbines. In table B.2 we have given a description of the industry codes used for the different industry sectors. In order to calculate these changes in the probability of receiving R&D subsidies we use the point estimates of the industry dummies. From figure B.2 we see that there are only two sectors that have higher probabilities of receiving R&D subsidies than the manufacturing of engines and turbines. These are the manufacturing of electric motors and equipment for electricity production (ISIC 38310) and the manufacturing of radio, television and communication apparatus (ISIC 38320). The former sector has a statistically insignificant 0.3 per cent higher possibility of receiving R&D subsidies than the manufacturing of engines and turbines. When it comes to the manufacturing of radio, television and communication apparatus this sector has a statistically insignificant 5.4 per cent higher probability. The rest of the sectors have less chance to receive R&D subsidies than the manufacturing of engines and turbines. Repair of machinery has a statistically significant (one per cent level) 13.8 percent smaller chance of receiving R&D subsidies. Also the manufacturing of metal and wood machinery, oil and gas well machinery and tools and other industrial machinery, have statistically insignificant smaller probabilities of receiving R&D subsidies.

Figure B.2 How the probability of receiving R&D subsidies varies over the different industry sectors



B.5 How the probability of receiving R&D subsidies changes with the other firm characteristics

When we want to learn about how the possibility of receiving R&D subsidies is influenced by firm characteristics, we apply the calculated elasticities reported in the last column of table B.1. The only performance variable we applied in the probit model as a regressor, was percentage growth in profit margin. We see from table B.1 that a high profit margin reduces the chance of receiving R&D subsidies. If the profit margin increases with ten per cent, this will lead to a reduction in the probability of receiving R&D subsidies of -0.06 per cent on average. Moving to factors of production, we see from table B.1 that both number of workers and capital have statistically significant (one per cent level) effects on the possibility of receiving R&D subsidies. If the amount of capital increases with ten per cent, this will lead to a 1.3 per cent increase in the possibility of receiving R&D support on average. Also age has an important and positive effect. An increase in age of one per cent results in a 4.2 per cent higher possibility of receiving R&D subsidies. When it comes to the input of labour, the effect of a ten per cent increase, is an 0.8 per cent higher possibility of receiving R&D subsidies. Ownership influences the chance of receiving R&D subsidies significantly according to the results reported in table B.1. In the probit analysis we included a dummy for public ownership exceeding 50 per cent and we found that this kind of public ownership increases the possibility of receiving R&D support, while foreign ownership has the opposite effect. Human capital formation is widely promoted by the national authorities and not surprisingly, the number of Ph.D. man-labour years connected to R&D activities has a positive effect on the chance of receiving R&D subsidies as well, even though the point estimate on the Ph.D. variable's coefficient is small and statistically insignificant. The mean elasticity for the Ph.D. variable indicates that a ten per cent increase in Ph.D. man-labour years will lead to a 0.1 per cent higher possibility of receiving R&D support. Joining international R&D consortiums is found to reduce the chance of receiving R&D subsidies and this effect is statistically significant at the one per cent level. If the part of total R&D activities connected to international consortiums increases with ten percent, this results in a -0.6 per cent reduction in the possibility of receiving R&D subsidies. Notice that the opposite result is found concerning the effect of joining national consortiums. An increase in the part of total R&D activity connected to national consortiums equal to ten per cent will contribute to a 0.1 per cent increase in the probability of receiving R&D support. When it comes to whom one buys R&D services from, there does seem to be a difference whether a national firm engaged in R&D activities buys from a national or an international firm. If there is an increase of ten per cent in the buying of R&D services from national firms this results in a one per cent increase in the possibility of receiving R&D support. The effect of this variable is significant at the one per cent level. The similar effect concerning buying of R&D services from international firms is not statistically significant and equal to 0.02 per cent. Planned change in R&D activity has a statistically significant effect at the one per cent level. A planned increase in future R&D activities of ten per cent will lead to a 0.4 per cent increase in the possibility of receiving R&D support. Furthermore, a ten per cent increase in total costs connected to R&D will lead to 1.1 per cent increase in the chance of receiving R&D support. We expected to find a positive effect of the last year's completed R&D, and we believe that our opposite finding is due to the fact that the variable covering last years completed R&D correlates too well with total costs connected to R&D. We have done another M.L.E. without the latter variable. We then found that the effect of Last years completed R&D had a statistically significant (five per cent level) and positive effect on the probability of receiving R&D subsidies.

B.6 Some higher-order moments of the stochastic term W_i

It still remains to derive the equation we will use in order to get consistent estimates of the selection bias term $\left(\frac{\sigma_{UV}}{\sigma_V}\right)$ and the parameters gathered in the vector β_{kx1}. The performance models we are going to estimate after we have calculated the consistent firm specific inverse Mill's ratios are given by the following relation:

$$\text{B3)}\ (dy/y)_i = \beta' X_i + \left(\frac{\sigma_{UV}}{\sigma_V}\right)\left[\lambda_i^A DS_i + \lambda_i^B (1 - DS_i)\right] + W_i \quad, i \ \varepsilon\ (1,N)$$

The stochastic terms in our new variant of the performance models are equal to:

$$\text{B4)}\quad W_i = U_i - \left(\frac{\sigma_{UV}}{\sigma_V}\right)\left[\lambda_i^A DS_i + \lambda_i^B (1 - DS_i)\right],\ i \ \varepsilon\ (1,N)$$

Given all the assumptions thoroughly explained in chapter 4.2 and especially the assumption of the two stochastic terms U_i and V_i being bivariate normally distributed, it is possible to express U_i as a linear combination of V_i. This is demonstrated in relation B5):

$$\text{B5)}\ U_i = (\sigma_{uv} / \sigma_{vv})V_i \quad, i \ \varepsilon\ (1,N)$$

Using B4) together with B5) gives us B6):

$$\text{B6)}\quad W_i = \left(\frac{\sigma_{UV}}{\sigma_{VV}}\right)V_i - \left(\frac{\sigma_{UV}}{\sigma_{VV}}\right)\left[E[V_i \mid V_i > -\delta_i^{*'} Z_i] DS_i - E[V_i \mid V_i < -\delta_i^{*'} Z_i](1 - DS_i)\right],\ i \ \varepsilon\ (1,N)$$

Furthermore it can be shown that W_i has the following properties:[18]

[18] Heckman (1979), pages 4 & 5, relations (4a) to (4h) and Greene (1997).

B7) $E[W_i \mid X_i^*, \mathrm{DS_i}=1, \lambda_i^A] = \left(\frac{\sigma_{UV}}{\sigma_{VV}}\right) E[V_i \mid V_i > -\delta_i^{*'} Z_i] - \left(\frac{\sigma_{UV}}{\sigma_{VV}}\right) E[V_i \mid V_i > -\delta_i^{*'} Z_i] = 0$, i ε (1,N)

B8) $E[W_i \mid X_i^*, \mathrm{DS_i}=0, \lambda_i^B] = \left(\frac{\sigma_{UV}}{\sigma_{VV}}\right) E[V_i \mid V_i < -\delta_i^{*'} Z_i] - \left(\frac{\sigma_{UV}}{\sigma_{VV}}\right) E[V_i \mid V_i < -\delta_i^{*'} Z_i] = 0$, i ε (1,N)

B9) $E[W_i^2 \mid X_i^*, \mathrm{DS_i}=1, \lambda_i^A] = \sigma_{UU}\left[\,1-\rho_{UV}^2 \lambda_i^A\left(\lambda_i^A - H_i\right)\right]$, i ε (1,N)

B10) $E[W_i^2 \mid X_i^*, \mathrm{DS_i}=0, \lambda_i^B] = \sigma_{UU}\left[\,1-\rho_{UV}^2 \lambda_i^B\left(\lambda_i^B - H_i\right)\right]$, i ε (1,N)

where $\rho_{UV}^2 = \left(\frac{\sigma_{UV}^2}{\sigma_{VV}\sigma_{UU}}\right)$ *and* : $0 \le \ (1 + H_i\lambda_i^q - (\lambda_i^q)^2) \ \ge 1$, q = A,B.

$B11)\ \ E[U_i \mid X_i^*, DS_i] = \frac{\sigma_{UV}}{\sigma_V}\left[\lambda_i^A DS_i + \lambda_i^B(1-DS_i)\right] \ \Rightarrow$

$B12)\ \ E[W_i \mid X_i^*, DS_i] = \frac{\sigma_{UV}}{\sigma_V}\left[\lambda_i^A DS_i + \lambda_i^B(1-DS_i)\right] - \frac{\sigma_{UV}}{\sigma_V}\left[\lambda_i^A DS_i + \lambda_i^B(1-DS_i)\right] = 0,\ \ i \in (1,N)$

$B13)\ \ E[U_i^2 \mid X_i^*, \lambda_i^A, \lambda_i^B, DS_i] = \left\{\left[\sigma_{UU}\left[\,1-\rho_{UV}^2\lambda_i^A\left(\lambda_i^A - H_i\right)\right] DS_i\right] + \left[\sigma_{UU}\left[\,1-\rho_{UV}^2\lambda_i^B\left(\lambda_i^B - H_i\right)\right](1-DS_i)\right]\right\},\ \ i \in (1,N)$

$B14)\ \ E[W_i^2 \mid X_i^*, \lambda_i^A, \lambda_i^B, DS_i] = E[U_i^2 \mid X_i^*, \lambda_i^A, \lambda_i^B, DS_i] \Rightarrow$

$B15)\ \ E[W_i^2 \mid X_i^*, \lambda_i^A, \lambda_i^B, DS_i] = \left\{\left[\sigma_{UU}\left[\,1-\rho_{UV}^2\lambda_i^A\left(\lambda_i^A - H_i\right)\right] DS_i\right] + \left[\sigma_{UU}\left[\,1-\rho_{UV}^2\lambda_i^B\left(\lambda_i^B - H_i\right)\right](1-DS_i)\right]\right\},\ \ i \in (1,N)$

We see from relation B15) that the stochastic term in the model given by relation 43) is heteroscedastic. This means we are able to estimate the vector most efficiently by applying the General Least Squares estimator instead of the OLS estimator. All the results from the OLS regressions completed on the last step of Heckman's two step procedure are reported in table 6.1 and table 6.2.

Finally we must also inform the reader of the different industries that are hiding beside the industry dummies, and this is done in table B.2.

Table B.2. The different Industrial sectors in our sample

Isic code	Frequency	Percent	Description of Isic code
38210	66	1.12	Manuf. of engines & turbines
38220	191	3.24	Manuf. of agricultural machinery
38230	83	1.41	Manuf. of metal & wood working machinery
38241	672	11.39	Manuf. of oil & gas well machinery & tools
38249	446	7.56	Manuf. of other industrial machinery
38250	134	2.27	Manuf. of office machinery

Isic code	Frequency	Percent	Description of Isic code
38291	46	0.78	Manuf. of household machinery
38292	527	8.93	Repair of machinery
38299	1253	21.24	Manuf. of other machinery
38310	698	11.83	Manuf. of electric motors & equipment for electricity production
38320	797	13.51	Manuf. of radio, television & communication apparatus
38330	166	2.81	Manuf. of electric household appliance
38391	126	2.14	Manuf. of insulated cables & wires
38399	394	6.68	Manuf. of other electrical apparatus & equipment
38510	263	4.46	Manuf. of professional & scientific nstruments not elsewhere classified
38520	37	0.63	Manuf. of photographic & optical goods
Total	5899	100%	....

In table B.3 we describe the different regional dummies applied in our probit model.

Table B.3. A description of the regional dummies

Regional Dummy	Description	Frequency	Percent
RD_1	Østfold, Akershus, Oslo, Hedmark, Oppland, Buskerud, Vestfold,Telemark	2958	44.64
RD_2	Agder and Rogaland	1940	29.28
RD_3	Hordaland, Sogn og Fjordane, Møre og Romsdal	763	11.52
RD_4	Trøndelag	624	9.42
RD_5	Nord-Norge	229	3.46
RD_6	Svalbard	112	1.69
Total	....	6626	100%

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