New Perspectives on the Evaluation of Public R&D Funding

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December 2010

Abstract

Any economic criteria for an efficient allocation of resources is based on marginal "thinking". Such criteria can equally be applied to the evaluation of the public allocation of R&D funds. Differently from the usual evaluation schemes - mainly dichotomous - this study implements the continuous treatment matching approach to investigate the optimality of the modulation of public funding. With this method, the marginal treatment effects can be identified and sub-optimal amounts of public funding determined. Although we can distinguish cases of input additionality, the substitutability outcome seems to prevail also when unobserved heterogeneity is accounted for.

JEL: C14, H50, 038
Key Words: Public R&D funding; optimal amount of R&D funds; substitutability outcome.

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Acknowledgements: the authors are grateful to Dominique Foray, Rafael Lalive, Valdemar Smith, Christopher Tucci, Dario Pozzoli, Julio Raffo and Lhuillery Stephane for their valuable comments and suggestions. We also thank the CEBR for the provision of the database on Danish patent applications at EPO.

1 Introduction

The positive relationship between R&D investment and economic growth is well rooted in economic theory and, on this nexus, policies fostering private R&D investments are regarded as growth-conducive and therefore as desirable from a social point of view.

But it is also on a mere efficient ground that these policies are viewed as necessary in a market economy. The incomplete appropriation of the returns to R&D that arises - a form of negative externality - inevitably leads to a deficient level of R&D investment - a market failure. The role of public policy is then to propel private R&D investment to a social optimal level.

This role could not be more apparent than in the recent economic crisis. As noted by the OECD (2009), many governments have adopted a number of measures aiming at supporting firms' innovation. These measures reflect the conviction of policy makers that an adequate level of innovation is not only crucial to business success, but it is also a decisive factor to recover from the downturn.

Yet - even if governments allocate public resources in favor of those projects that would not have been realized in absence of public support (crowding-in), it is plausible that eligible firms simply substitute R&D investments they originally planned to undertake with the public financial resources made available (crowding-out), undermining the argument for "additional" effects of public aid.[1] In our sample, for instance, firms which receive the largest subsidies are also those exhibiting a significant dependence on public financing, with the public grant amounting to almost half of the private R&D expenditure. And, interestingly, firms showing the highest R&D intensity have the least dependency on public support.[2]

To strike a balance between "crowding-in" effects and "crowding-out" effects that typically plague such public policies, policy makers are assigned the task of

[1] For the use of this terminology - "crowding-in" - see Diamond (1999), p. 424 .
[2] R&D intensity is defined as the ratio of R&D expenditure to sales.

the modulation of public intervention. Therefore, an overall assessment of public grant support to R&D activities should evaluate not only the advisability of public support, but also its modulation, an equally important aspect, yet under-studied in this literature.[3] The aim of our analysis is precisely to make a step toward this ultimate goal, proposing to investigate the modulation of public support by means of the continuous treatment evaluation scheme.

The employment of such an econometric technique, together with the categorical treatment evaluation scheme, allows us to introduce new perspectives on the evaluation of public R&D subsidies, not least the part of the distribution of the public subsidy to R&D where "crowding-in" or "crowding-out" effects are likely to emerge as well as the marginal effect of benefiting from larger sums for the recipient firms. To investigate the implications of the modulation of public support along different dimensions, we divide recipient firms into a number of groups defined in terms of the percentile of the public support received.

First, we simply consider how different amounts of R&D grants impact on the advisability of public support. In fact, it is reasonable that a significant positive overall ATT is just an algebraic sum of positive and negative (often even negligible) effects of different modulations of treatment. By comparing R&D outcomes between similar funded and not funded firms within each group, we can establish which groups of funded firms are mainly contributing to the aggregate growth of R&D investment in the economy.

Second, we study the adequacy of the allocation of subsidies to firms' R&D activities. Employing a categorical treatment evaluation scheme we compare publicly financed firms with similar characteristics across different groups. The policy relevance of these comparisons is hard to question, as it is needed to determine whether firms benefiting from the largest amounts of public funding are also investing (in research) similarly to less supported firms. In this case, public authorities can improve their policy target through funds re-allocation among recipients. We do not

[3] See Blundell and Costa Dias (2000) and Aerts and Schmidt (2008).

confine this type of our analysis to the short run, but, for the first time, we attempt to extend it to the medium-run horizon to accommodate sensible lag effects of such public policies.

Finally, we turn to the question of determining the proper modulation of R&D public financing. By means of the continuous treatment matching evaluation scheme, we can evaluate for every treated firm the causal effect of further increasing the public grant on a firm's R&D outcome, as this method can identify the marginal effects of subsidies and their optimal amounts. The amount at which the public support ceases to be beneficial can therefore be determined. The practical relevance of such an analysis is the possibility to scrutinize whether returns to public R&D support are aligned to the governmental target.

Our findings corroborate the view that both "crowding-in" and "crowding-out" effects can coexist depending on the modulation of the public support. In particular, "crowding-out" effects prevail - as to be expected - for grants higher than DKK 9 million (corresponding to 23% of the financed firms).

The recent work by Görg and Strobl (2007) is - in our opinion - closest related to ours, implementing first the categorical matching, but neglecting - what is our salient contribution - the continuous treatment approach in evaluating such policies and the medium-run effects of these policies.

The reminder of the paper is organized as follows. The next section discusses the state of the art in the evaluation of public R&D grants. Section 3 introduces briefly the methodology employed in this paper, section 4 describes the data, and section 5 presents and discusses our findings. Section 6 concludes.

2 Empirical Review

The empirical literature concerned with the evaluation of R&D policies has typically relied on the notion of additionality as an indicator of policy effectiveness.

The concept of "additionality" was introduced by Buisseret et al. (1995) and indicates the difference made by the state interference in the market play. The argument can be summarized as follows: economic theory and empirical findings robustly support the positive relationship linking R&D investment and economic growth. Then, assuming that public aid for technological developments induces private firms to undertake "additional" R&D investments (i.e. firms that would have not undertaken those R&D investments without public support), it is possible to infer that the policy intervention leads to economic growth and social welfare.

To address the inquiry of "additionality", evaluations of public financing programs typically present casual analyses based on counterfactuals, what would have occurred in absence of intervention. At the heart of this analysis is the recognition that neither firms which have received support nor firms which have not applied for funds can be considered random events. On the contrary, firms' behavior is the explicit consequence of the policy design, as firms are often aware of those criteria on the basis of which governmental authorities will decide funds allocation (i.e. self-selection).

In this respect, our study is no exception and follows this strand of literature, assessing the Danish R&D grant support system performing an "after the fact" analysis.

It is undeniable that a plethora of studies implementing different approaches and overcoming database limitations in different ways has generated a vast mixed evidence, ranging from being in favor of "crowding-in" effects (Görg and Strobl, 2007; Aerts and Schmidt, 2008; Hussinger, 2008) to being unable to reject "crowding-out" effects (Lach, 2002; Heijs and Herrera, 2004).[4] Our study contributes to this literature proposing to assess the "additionality" question with yet another method within counterfactual analyis, namely the continuous treatment scheme. We ar-

[4] See also David et al. (2000), Garcia-Quevedo (2004), Aerts and Czarnitzki (2004, 2006), Almus and Czarnitzki (2003), Czarnitzki and Fier (2001), Duguet (2004), Gonzalez et. al (2005), Gonzalez and Pazo (2008), Lööf and Heshmati (2005), Busom (2000), Suetens (2002), and Wallsten (2000).

gue that this method, when implemented together with the categorical treatment scheme introduced by Görg and Strobl (2007), permits a sound assessment of a country R&D policy.

Finally, using Danish data, we are able to complement and extend existing analyses (Sørensen et. al., 2003; Kaiser, 2004; Bloch and Graversen, 2008) with a reacher data set.

3 Methodology

In this section, we briefly present the estimation methods implemented in our empirical assessment of public R&D funding policies.

Recent advances in the program evaluation analysis have regarded the overcoming of the notion of dichotomous treatment. Specifically, categorical and continuous treatment schemes have been proposed as promising alternatives to the traditional binary approach.[5] Because of their inclination to reduce biases arising from non-random assignments, these methods have been widely applied in empirical research about causal inference in observational studies. To provide some insights into the methodology as well as to discuss the strengths and the weaknesses of each method, we discuss them separately.

3.1 Continuous Treatment Matching

Although relevant enhancements have been carried out in the policy evaluation methods, to our knowledge the present work is the first study applying the continuous treatment matching in the literature on public R&D funding. Its implementation allows us to compare enterprises exposed to a specific level of public financing with "matched" less and more exposed ones, and then to identify marginal effects on firms' private R&D investment.

[5] Lechner (2001, 2004), Hirano and Imbens (2004).

The continuous treatment approach appears extremely useful when the number of treatment values is relatively large. In fact, by smoothing across treatment levels it is possible to improve the precision of the inferences (Imbens and Wooldridge, 2009). The key assumption behind this estimation strategy is the so-called weak unconfoundedness, introduced by Imbens (2000). Differently from the conditional independence assumption (CIA) made by Rosenbaum and Rubin (1983) in the binary case, here only the pairwise independence of the treatment with each (not joint) of the potential outcomes is required. Thus, the problems of bias removal and drawing causal inferences can be solved by adjusting for pre-treatment differences. In this setting, the computation of the conditional probability of receiving a specific level of treatment (not just receiving it) given the pre-treatment observables is called general propensity score (GPS). Since the weak unconfoundedness given all pre-treatment variables implies weak unconfoundedness given the GPS, the average treatment effects can be obtained by conditioning just on the GPS (Hirano and Imbens, 2004).

More formally, we define (a) a vector of pre-treatment characteristics $X_{i,t-1}$ for each firm i, (b) a set of continuously distributed treatment values $D_{i,t}$ and (c) the dose-response function $F_{i,t}(d)_{d\epsilon D}$. Moreover, we assume $X_{i,t-1}$, $D_{i,t}$ and $F_{i,t}(d)_{d\epsilon D}$ having common probability space. For the sake of simplicity, the subscripts will no longer be reported. Thus, the propensity to obtain the R&D subsidy is defined as the conditional density of the treatment given the covariates $r(d,x) = f_{D|X}(d|x)$, and the GPS is $R = r(D,X)$, with the function r defined up to almost everywhere equivalence.

Furthermore, the GPS is required to respect the following balancing property condition

$$X \perp 1(D = d)|r(d,x) \;,$$

where $1(\cdot)$ is the indicator function.

As explained in details by Bia and Mattei (2008), the implementation of the

GPS matching method mainly consists of three steps. In the first one, the score R is estimated and the treatment D (or a monotone transformation of it), given the covariates, is required to respect a normal distribution:

$$g(D)|X \approx N\left[(\gamma, X), \sigma^2\right] .$$

Here, $g(D)$ is a suitable transformation of the treatment variable and (γ, X) is a function of covariates with linear and higher-order terms, which depends on a vector of parameters γ. In the second step, the conditional expectation of the outcome variable Y, given D and R, is modelled as follows:

$$E(Y|D,R) = a_0 + a_1 D + a_2 D^2 + a_3 D^3 + a_4 R + a_5 R^2 + a_6 R^3 + a_7 DR ,$$

where the power of the arguments can be even higher than 3 and parameters are estimated by OLS. This procedure is useful to exclude that the explicative variables induce any bias while no direct meaning is attributed to their relative coefficients. Finally, the third step consists of averaging the estimated dose-response function $E(\hat{Y})$ over the estimated score function $\hat{R}$ evaluated at the desired level of treatment.

Although the longitudinal dimension of our unbalanced panel is quite short, it partially allows us to combine the GPS matching with DiD approach in order to make the unconfoundedness assumption less restrictive (Heckman et al., 1998). The basic idea is that, even if the unconfoundedness does not hold, it may be reasonable to assume that the evaluation bias is constant over time (or at least it is the same for a date before and after the treatment occurs). Thus, we evaluate the effect of the treatment on the change in the outcome variables rather than on its level, so correcting for time-invariant firm characteristics.

A general drawback of our matching analysis has roots in the almost impossible exact identification of the decision rule adopted by public authorities. Therefore, the typical omitted variable issue arises since we may miss variables (in our data set) that the public actor uses for the attribution of the subsidies. However, the richness of our data set allows us to include several key factors used in the evaluation process of grants, definitively a longer list than typically included in earlier studies.

3.2 Categorical Treatment Matching

It is tautological that the final private R&D spending will depend on the amount of the public subsidy received by a firm. But coupling the information on the R&D grant receipt by a firm with the information on the amount received opens the prospective of an analysis based on the categorical treatment matching. Mimicking the dichotomous propensity score matching, the categorical one evaluates the expected class of treatment a firm may receive given the pre-treatment variables. Consistent with the rationale of the continuous treatment matching, the estimation of the public intervention impact is based on the comparison of firms with similar scores, but belonging to two different classes or categories. These are defined in the present paper by looking at the terciles of the public funding distribution. It surely represents an objective rule and therefore it is not subject to fully arbitrary and potentially misleading categorization criteria. This estimation method is well suited for comparisons not only between two consecutive categories of treated groups, but also between treated and untreated (which is not allowed in the continuous treatment case) groups. It helps a lot in understanding whether a given effect obtained from the single-treatment framework is simply driven by a single category of treated or it is concretely confirmed for all categories (the homogeneity of treatment in the last case may be more acceptable).

Thus, we have the outcomes $\left\{Y^0, Y^1, .., Y^M\right\}$ of $M + 1$ different mutually exclusive treatment categories (the 0-category is exclusively composed of untreated). Obviously, we can observe only a realization of the potential outcome vector, the remaining M are counterfactuals. In order to estimate the different treatment effects, the unconfoundedness and common support assumptions have to be satisfied. Given the covariates, whereas the unconfoundedness requires the treatment indicator to be independent of the realized outcomes, the common support ensures to find a counterpart in the comparison group, which is addressed by the computation of the propensity score. In this regard, a practical suggestion is that the existence of differently treated units can be ignored in a given pairwise category comparison since they are not needed for identification.

For the implementation of the categorical matching, it is needed to run as many probit estimations as the number of effects we are interested in. So, once identified the probability of receiving a given subsidy size compared with the next larger one, conditional on the set of pre-treatment covariates, it is possible to compute the associated treatment effect. Counterfactuals are selected by using the caliper method (set at 0.01). That represents a scalar defining the boundary of the neighborhood in which matching is allowed. In this way, we seek to ensure the quality of matching, since "bad" matches are prevented to be included in comparison groups.

Analogously to the continuous treatment matching, to control for time-invariant firm-specific characteristics, it is appropriate to combine the multi-valued discrete matching with the DiD technique. Hence, the outcome variable which is the log private R&D expenditure will also be taken in first differences. Consequently, each treatment effect is nothing else than the difference in differences of the outcome variable: the pure treatment effect when time-varying factors (observed and unobserved) are balanced over categories.[6]

[6] Of course, we cannot completely rule out that there exist (firm-specific) time-varying unobservables affecting the receipt of public funding and private expenditure in research.

4 Data and Variables

Data for our empirical analysis are collected from four different data sources, three of them provided by Statistics Denmark. The first database is the Danish R&D Statistics, a survey conducted biennially from 1997 to 2005 by the Danish Centre for Studies in Research and Research Policy. Although this survey presents a longitudinal dimension (1997, 1999, 2001, 2003, 2005), only a subsample of firms is recorded over the entire time span. To use lagged values in the computation of the simple and general propensity score in our analysis, we retain only firms that are in the survey at least for two consecutive periods. Additionally, extremes values (i.e. 1st and 99th percentile of the distribution) in terms of private R&D intensity or received public R&D funds have been excluded to avoid pervasive influences of outliers.[7] From this survey we are interested in these variables: the amount of public funding, the private R&D expenditure and the presence of a R&D department within the firm.

The second data source is the "Integrated Database for Labor Market Research" (IDA). IDA is a longitudinal employer-employee database in which detailed information on individuals employed in the Danish firms is recorded every year on the 30th of November. From IDA it is possible to compute the firm's share of workers with vocational education and of employees with tertiary education. We proceed to classify firms into 18 industries and determine whether a firm has been established only within the three most recent years (dummy for entrepreneurship, "newentr").[8]

The third data-source we use is an accounting database from a Danish credit rating agency - "Købmandstandens Oplysningsbureau" (KØB) - containing information on firms' sales, value added, exports, total assets, and indebtedness.

[7] See also Wagner (2008).

[8] The industry classification is at the two-digit level. The different industries are business services, chemical products, construction, financial services, food - beverages and tobacco, hotels & restaurants, leather products, machinery & equipments, metal products, mineral products, paper products and petroleum products, plastic products, R&D services, textile products, transports, wholesale trade, wood products.

The last source has been provided by the Centre for Economic and Business Research (CEBR). It consists of a data set on patent applications and grants ascribed to Danish firms at the EPO in the period 1978-2003. From this data source we retrieve information on co-patents in order to proxy the firms' involvement in cooperation or other forms of collaboration with other economic actors. Co-patenting behavior - as captured by a co-patent dummy - is often related to the firm's ability to exploit external knowledge and generate beneficial spillovers as well. It would have been ideal to include the number of patent applications among the matching variables, but unfortunately that induces severe collinearity problems with the co-patent dummy variable.

Obviously, the treatment variable is the amount of the R&D subsidy received from the government or other public institutions.

The matching is defined on the basis of the following pre-treatment variables: log of total assets scaled to value added, indebtedness (log of loans), exports scaled to sales, R&D intensity indicator (private R&D expenditure over sales), a measure of public funding dependence (the ratio of public funds received to private R&D expenditure), shares of highly skilled employees and vocational workers, dummies for co-patent, size, industry and year.

Several among these covariates typically appear also in the related literature. The dummies account for potential macroeconomic fluctuations (business cycle effects), common demand or supply shocks or idiosyncratic shocks to a given company size or a given industry, while the other pre-treatment variables capture firm-specific and observable heterogeneity.

In this prospective, and a novelty in this literature, is the inclusion in the selection equation of the public funding dependence, to account for limited private resources that may constraint firms' private R&D initiative.[9] To account specifically for credit constraints, easy to envisage considered the relevant sunk costs

[9] Previous studies have typically used a dummy variable informing on whether the firm received the treatment or not.

associated to R&D activity, we also include indebtedness. Equally important, we add the dummy variable for entrepreneurship to our selection equation as innovative entrepreneurship and business potentials are key factors openly accounted by Danish authorities in the assignation of public R&D funding.

The ratio of firms' total assets over value added proxies for capital intensity: if the policy maker is more keen to favor support of labor-intensive production (employment promoting policies), capital-intensive firms may result disadvantaged vis-à-vis labor-intensive firms, so that a high capital intensity may be negatively associated with the propensity to be supported.

The inclusion of the shares of workers' categories is informative on the composition of the firm's workforce and accounts for the human capital embedded in the production process. The presence of an in-house R&D department is used in combination with the labor force composition to proxy firms' ability to properly exploit internal and external knowledge sources (absorptive capacity). Our aim is again to control for the creation of an internal and/or external center of knowledge and the promotion of workers' skills and competencies which are among the core factors for the allocation of public R&D funding. In this respect, the exports sales ratio might reveal a propensity by a policy maker to fund companies more active in international markets and characterized by higher productivity levels with larger potential for innovations.[10] Size dummies are defined as follows: firms with less than 20 employees, between 20 and 49, between 50 and 99, and equal or larger than a hundred. This classification finds justification in the Danish industrial structure, dominated by small and medium firms (enterprises with less than 50 employees account for more than 95% of the total firm population, e.g. OECD 2005).

Overall our strategy emerges clearly: each variable in the selection equation expresses our attempt to account at the best of our knowledge for the criteria that Danish public authorities declare to use for the targeting of their subsidies. Namely, cooperation, skill development, internationalization, entrepreneurship, high-tech

[10] Bernard and Jensen (1999) and Melitz (2003) among others.

projects, good business plans and performance.

4.1 Descriptive Statistics

Table 1 describes the main variables used in the analysis, favoring the comparisons across the four categories of firms. The first two variables listed are the two outcome variables (the dependent variables of our analysis); the other variables are all used in the selection equation and determine the matching between control and treated groups. Funded firms are divided into three groups (Cat 1, Cat 2 and Cat 3) corresponding to the first, second and third tercile of the public subsidy distribution respectively.[11] Cat 0 is the residual category including firms that were never granted public R&D support, but nevertheless are performing R&D. Cat 0 is by far the largest group of firms. It counts $12,566$ companies, while each tercile contains 147 funded enterprises. The number of observations shrinks notably when we account only for financed firms. This data limitation is ascribable to the design of the R&D survey characterized by a poor overlap of firms between-waves.

Both the average of private R&D expenditure and the level of indebtedness (reported in log of million DKK) are increasing along the defined categories. As expected, the share of larger firms also enlarges from the bottom to the top quartile. However, these patterns are not common for all other variables considered, which show non-monotonic relations between categories. For instance, the other dependent variable - the average private R&D growth - peaks in Cat 2, while it is on a quite low level in Cat 0.

Similarly, the share of new entrant firms is more similar between Cat 0 and Cat 3, but it grows from the first to the second category. The lowest average level of capital intensity is recorded for firms in Cat 0, while the highest is recorded for the least funded ones. The non-financed firms also show the lowest export intensity, but - on average - this variable is decreasing in accordance with the amount of

[11] Companies belonging to Cat 1 receive between DKK $0,003$ and $0,265$ million, those in Cat 2 between DKK $0,265$ and $1,350$ million and those in Cat 3 from DKK $1,350$ to $208,391$ million.

public funding provided.

It is worth noting that firms in Cat 2 show higher value in R&D intensity than firms in Cat 3, but nevertheless they are both considerably larger than those reported for the least and not funded categories. The most financed firms also exhibit a stronger dependence on public subsidies: on average the public support is almost half of the private R&D expenditure for Cat 3. However, such a group of firms largely dominates all other categories for fruitful cooperation or collaboration in research activities (proxied by co-patenting behavior) with other economic actors. Nevertheless, it appears extremely interesting that the category with higher R&D intensity (Cat 2) also presents the lowest dependence on public support among the categories of financed companies.

Every surveyed funded firm declares the presence of an internal R&D department, whereas only 23% of not financed businesses perform in-house R&D activities. That motivates the inclusion of this dummy in our analysis, which together with the labor force composition allows us to compare (financed with not financed) firms that presumably detain similar abilities to internalize knowledge and consequently turn it into innovations. Finally, the dummy indicating firms' partial or total foreign ownership does not turn out to be particularly informative: only the 0.1% of the untreated firms shows such a characteristic. However, its inclusion is useful to exclude foreign-owned firms from the sample, preventing eventual bias potentially induced by unobservables related to the legal status. A similar argument applies to five industries that are not represented in at least one category: financial sector, hotels & restaurants; paper products; petroleum products; transports.

It is plausible that these stylized facts partially reflect the targeting defined by public authorities (mentioned above), but the degree of dependence on public subsidies raises reasonable concerns about the optimality of the allocation and the social returns of R&D funds.

5 Results

This section presents the results based on our categorical and continuous matching evaluation. In the first approach, we divide financed firms into three categories reflecting the terciles of the distribution of the R&D support grant. This choice is clearly data-driven since it is not grounded on any a priori knowledge about optimal amount thresholds. Although the decision of partitioning the entire R&D subsidy distribution in three equally populated groups is to some extent arbitrary, it appears to us as the most sensible option given the size of our sample. In fact, one trades off the number of groups analyzed with the number of observation available in each group. If the number of available observations is not sufficient, not only estimates lose efficiency, but the estimation method also becomes unfeasible due to the lack of a common support. This limit does not affect the continuous matching method similarly, which approximates the distribution of public funds according to a normal density function.

We then turn to the medium-run evaluation and robustness checks.

5.1 Main Results

Table 2 summarizes the estimations obtained with the categorical matching method for our two outcome variables, namely the log-level of private R&D spending and the log difference of private R&D spending (i.e. growth rate of private R&D spending). While the first variable eases the interpretation of our treatment effect, the latter better accounts for unobserved heterogeneity and therefore constitutes our benchmark when we evaluate the significance of our effects.

The first row of Table 2 refers to the standard dichotomous matching method in which all categories of publicly financed firms (Cat 1, Cat 2 and Cat 3) are compared with untreated ones (Cat 0). This simple comparison shows a quite large positive and significant effect of public funds provision: on average the set of financed firms invests about 65% more than not financed ones. However, scrutinizing the pairs of differently funded versus unfunded companies, this result is not confirmed for the first tercile (Cat 1). In this case, the treatment effect is positive but insignificant. The interpretation of the results is unchanged if we consider the growth in private R&D expenditure: treated firms exceed of nearly 28% untreated ones and again Cat 1 does not significantly differ from Cat 0. Similarly for the comparison between Cat 3 and Cat 0 or Cat 1 when the private R&D growth is considered as outcome variable. However, the last two terciles of the treated firms show significantly positive effects with respect to the untreated or least treated firms for the log level of private R&D spending. Interestingly, when we only compare treated firms, we find that firms belonging to Cat 3 do not present any significant additionality effect with respect to those in Cat 2. Overall, Cat 2 is the only category that seems to show consistent additionality effects for both outcome variables, indicating that companies receiving the largest doses of treatment might substitute private R&D with public subsidies.

In line with this argument, we deepen our analysis to investigate the role that different amounts of public subsidy may have in determining a crowding- out effect of public R&D support.

Table 4 shows results from the continuous treatment matching evaluation. For a large number of treatment doses over the subsidy distribution, the marginal effects of R&D spending on the outcome variable are computed for a 1% variation in the amount of public subsidy received. For instance, a firm currently receiving approximately DKK 8.2 million subsidy would increase both its log level private R&D expenditure and its growth rate of private R&D of 0.2%, had the subsidy received increased of 1%.[12] The change at this threshold level (i.e, DKK 8.2 million) is statistically significant only for the outcome variable in first difference, while the threshold level for the outcome variable in levels is slightly superior (i.e. DKK 18.2

[12] Made 100 the initial level of R&D spending, the percentage increase in the level of spending corresponds in absolute terms rather than in log scale to an increase of $100^{(}0.0024) - 1 = 0,0111$ or 1.11%.

million). Overall, these results confirm the hypothesis of crowding-out between private expenditure and public financing for a considerably high level of treatment doses, and these negative treatment effects strengthen with the increase of the dose.

Finally, it is opportune to complement these results from the intra-tercile evaluation (i.e., continuous treatment evaluation) with those from the inter-tercile comparisons (i.e. categorical treatment evaluation). It emerges that crowding-in effects occur for several doses of treatment, mainly in the second tercile and in the last part of the first tercile, if the outcome variable is taken in log-levels. Although somewhat more restricted in the range, these findings are confirmed also for the rate of private R&D spending growth. Since differences in growth rates better account for firm-specific time-invariant effects, we are more confident in evaluations having such an outcome variable.

5.2 Robustness Checks

The sensitivity analysis corroborates our main findings. Specifically, increasing the treatment doses from 1% to 5 and 10%, we find stronger substitution effects: Table 5 clearly shows that increases of 5 or 10% lead to significant crowding-out effects for amounts already above DKK 4.5 million, as compared to the DKK $8,2$ million threshold arising with a 1% increase in the treatment dose. Therefore the firms are mainly in the highest tercile of the public funding distribution that tends to substitute between private and public funding. Moreover, the crowding-out behavior seems non-linear in the increase in the publicly provided funds: the substitution effect between private and public spending increases more than proportionally to the increase in the the funding received.

5.3 Medium-run Effects

Among the novelties of our study is the combination of a short-run analysis with a medium-run one. It is, in fact, sensible that crowding-out effects may not substantiate immediately after the treatment, but they rather spread over a number of years. To investigate this issue, we draw on the categorical matching evaluation again. Specifically, we partition again the firms into three categories based on the average subsidy received over the sample period. Clearly, the latter constitutes the average dose treatment and includes also amounts equal to zero. The non-treated are necessarily those firms that have never received funding. Both outcome variables are evaluated at the end of the sample period, while the variables in the selection equations - upon which firms will be merged - are evaluated at the beginning of our sample period, namely 1997. That is, like a one-period analysis where the treatment is just calculated as the average of the treatments over the entire sample span, the outcome is taken in the last period of the sample and the pre-selection variables are the values in the first period of the sample. A 8-year window between the matching and the final treatment status being a rather long period of time, the causality nature of the analysis weakens; our results should then be cautiously interpreted as causal effects.

Table 3 presents our results. The standard dichotomous matching shows no significant ATTs. On the contrary, as far as the growth of private R&D expenditure is concerned, public funding to R&D seems to promote private R&D expenditure for the last tercile of treated compared to the untreated and Cat 1. However, we do not find any evidence that such a public policy is more effective for firms in Cat 3 as compared to Cat 2. Thus, we conclude that average levels or growth rates of private R&D expenditure (for the period 1997-2005) are not significantly different between categories associated with firms in the last two terciles, confirming partially the absence of an additionality effect characterizing the short-run view.

6 Discussion and Conclusions

This paper introduces and discusses new perspectives in the evaluation of the public funding to R&D, extending current studies in this field to include an intra-group assessment of the outcome of these policies. Unlike an inter-group analysis directed to investigate a differentiated impact of R&D grants across differently funded firms, an intra-group analysis investigates the implications of the current modulation of public intervention for similarly funded firms. Implemented by means of a continuous treatment evaluation method, it allows us to investigate the likelihood of crowding-in and crowding-out effects within each tercile along the distribution of the public R&D support grant.

The inter-tercile comparison is also presented aside using the categorical matching method.

Both methods are coupled with the DiD approach to account for unobserved heterogeneity and result strengthened by a rich data set featuring comprehensive information on the pre-treatment variables.

Our results show that a notable substitution between private and public funds occurs for a high level of the public subsidy. Firms in the third tercile do not outperform those in second tercile. The substitution becomes more apparent when we analyze the intra-tercile distribution of public funds: we highlight a considerable reduction in growth of private R&D expenditure among the top beneficiary companies. Specifically, it emerges - on average - that funded firms receiving subsidies up to DKK 8,2 million exhibit a low private contribution with respect to their counterfactual units.

Overall these results indicate that an ex-post evaluation of the targets of a R&D policy is desirable, if not necessary in time of downturns. In fact, if R&D funding has to become a valid policy instrument to support companies hardly hit by a crisis and facing financial restrictions, it is inevitable that public resources should not be redirected away from risky and promising long-term research projects toward the big players who would perform equally well without these funding.

The continuous treatment evaluation design presented in this paper is a general methodology which can be fruitfully applied to assess other similar public policies or other sources of R&D support, especially in contexts where the modulation of the public intervention is of great interest. Indeed, generally R&D grants are nowadays not from a unique source, but rather from a complex system of sources ranging from private venture capitalists, to public venture companies and ministerial, national or supra-national innovation funds. We can therefore conceive that this method could be successfully applied to future research to investigate the relative effectiveness of each type of financing source in promoting R&D research. Unfortunately, we have to refrain from exploring this promising avenue on our data for objective observational limits of our data set, even if the current survey on innovation comprises information - although incomplete - on the types of financing received by each company.

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Table 1: Descriptive Statistics

		Cat 0 : not financed firms					Cat 1 : first tercile of financed firms					Cat 2 : second tercile of financed firms					Cat 3 : third tercile of financed firms				
Variable	Description	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max
gr_privR&Dexp	growth of private R&D expediture	12566	0.019	0.897	-5.915	6.647	147	0.137	1.204	-3.352	2.802	147	0.291	1.169	-2.020	4.517	147	0.117	1.363	-3.955	4.633
ln_privR&Dexp	log private R&D expediture	12566	0.175	0.939	-4.711	7.610	147	0.573	1.828	-4.200	5.753	147	1.976	2.066	-3.381	6.424	147	2.846	1.185	-1.309	7.731
ln_loan	log amount of loans	12566	3.929	1.531	-0.001	11.278	147	4.661	1.500	1.310	7.943	147	5.559	1.787	0.229	9.707	147	5.818	1.971	0.474	9.012
ln_totassets_va	log (total assets/value added)	12566	0.498	0.692	-2.018	8.104	147	0.705	0.618	-0.656	2.236	147	0.685	0.701	-0.643	2.761	147	0.694	1.084	-0.883	5.033
R&D_int	R&D expenditure/sales	12566	0.071	1.006	0.000	0.853	147	0.056	0.126	0.000	0.774	147	0.484	1.580	0.000	1.685	147	0.283	0.632	0.000	3.093
Pfun_dep	public funding/private R&D	12566	0.007	0.115	0.000	0.736	147	0.167	0.741	0.000	2.267	147	0.151	0.393	0.000	2.364	147	0.472	1.198	0.000	8.133
exp_int	exports/sales	12566	0.329	0.350	0.000	1.000	147	0.652	0.314	0.000	1.000	147	0.553	0.327	0.000	1.000	147	0.460	0.351	0.000	1.000
copat	co-patenting dummy	12566	0.002	0.047	0.000	1.000	147	0.000	0.000	0.000	1.000	147	0.020	0.141	0.000	1.000	147	0.090	0.288	0.000	1.000
newentr	firm established less than 3 years ago	12566	0.016	0.125	0.000	1.000	147	0.020	0.140	0.000	1.000	147	0.040	0.196	0.000	1.000	147	0.017	0.129	0.000	1.000
sh_voc	share of vocational workers	12566	0.153	0.131	0.000	1.000	147	0.183	0.128	0.018	0.600	147	0.239	0.160	0.041	0.625	147	0.269	0.125	0.000	1.000
sh_hskill	share of highly educated workers	12566	0.073	0.127	0.000	1.000	147	0.104	0.153	0.000	0.800	147	0.146	0.161	0.000	0.646	147	0.226	0.177	0.000	1.000
foreing	foreign ownership dummy	12566	0.001	0.031	0.000	1.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000
R&D_d	R&D department dummy	12566	0.226	0.418	0.000	1.000	147	1.000	0.000	1.000	1.000	147	1.000	0.000	1.000	1.000	147	1.000	0.000	1.000	1.000
size_1_9	size dummy (1-9 employees)	12566	0.113	0.317	0.000	1.000	147	0.014	0.116	0.000	1.000	147	0.034	0.182	0.000	1.000	147	0.014	0.116	0.000	1.000
size_10_19	size dummy (10-19 employees)	12566	0.180	0.384	0.000	1.000	147	0.054	0.228	0.000	1.000	147	0.095	0.295	0.000	1.000	147	0.048	0.214	0.000	1.000
size_20_49	size dummy (20-49 employees)	12566	0.235	0.424	0.000	1.000	147	0.211	0.409	0.000	1.000	147	0.116	0.321	0.000	1.000	147	0.122	0.329	0.000	1.000
size_50_99	size dummy (50-99 employees)	12566	0.162	0.369	0.000	1.000	147	0.163	0.371	0.000	1.000	147	0.082	0.275	0.000	1.000	147	0.116	0.321	0.000	1.000
size_100	size dummy (more than 99 employees)	12566	0.334	0.472	0.000	1.000	147	0.558	0.498	0.000	1.000	147	0.673	0.471	0.000	1.000	147	0.701	0.460	0.000	1.000
y1	year 1997	12566	0.132	0.339	0.000	1.000	147	0.191	0.394	0.000	1.000	147	0.231	0.423	0.000	1.000	147	0.156	0.365	0.000	1.000
y2	year 1999	12566	0.258	0.437	0.000	1.000	147	0.054	0.228	0.000	1.000	147	0.327	0.471	0.000	1.000	147	0.408	0.493	0.000	1.000
y3	year 2001	12566	0.199	0.399	0.000	1.000	147	0.204	0.404	0.000	1.000	147	0.211	0.409	0.000	1.000	147	0.143	0.351	0.000	1.000
y4	year 2003	12566	0.206	0.405	0.000	1.000	147	0.238	0.427	0.000	1.000	147	0.143	0.351	0.000	1.000	147	0.184	0.389	0.000	1.000
y5	year 2005	12566	0.204	0.403	0.000	1.000	147	0.279	0.450	0.000	1.000	147	0.088	0.285	0.000	1.000	147	0.109	0.313	0.000	1.000
ind1	Business services	12566	0.201	0.401	0.000	1.000	147	0.177	0.383	0.000	1.000	147	0.245	0.431	0.000	1.000	147	0.340	0.475	0.000	1.000
ind2	Chemical products	12566	0.021	0.144	0.000	1.000	147	0.061	0.241	0.000	1.000	147	0.061	0.241	0.000	1.000	147	0.048	0.214	0.000	1.000
ind3	Construction	12566	0.039	0.194	0.000	1.000	147	0.007	0.082	0.000	1.000	147	0.007	0.082	0.000	1.000	147	0.000	0.000	0.000	0.000
ind4	Financial Services	12566	0.001	0.027	0.000	1.000	147	0.007	0.082	0.000	1.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000
ind5	Food, beverages and tobacco	12566	0.045	0.207	0.000	1.000	147	0.095	0.295	0.000	1.000	147	0.088	0.285	0.000	1.000	147	0.082	0.275	0.000	1.000
ind6	Hotels & Restaurants	12566	0.000	0.018	0.000	1.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000
ind7	Leather products	12566	0.002	0.039	0.000	1.000	147	0.014	0.116	0.000	1.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000
ind8	Machinery & equipments	12566	0.233	0.423	0.000	1.000	147	0.272	0.447	0.000	1.000	147	0.354	0.480	0.000	1.000	147	0.252	0.435	0.000	1.000
ind9	Metal products	12566	0.085	0.279	0.000	1.000	147	0.109	0.313	0.000	1.000	147	0.027	0.163	0.000	1.000	147	0.014	0.116	0.000	1.000
ind10	Mineral products	12566	0.021	0.143	0.000	1.000	147	0.020	0.142	0.000	1.000	147	0.014	0.116	0.000	1.000	147	0.027	0.163	0.000	1.000
ind11	Paper products	12566	0.058	0.234	0.000	1.000	147	0.020	0.142	0.000	1.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000
ind12	Petroleum products	12566	0.000	0.020	0.000	1.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000	147	0.000	0.000	0.000	0.000
ind13	Plastic products	12566	0.028	0.165	0.000	1.000	147	0.068	0.253	0.000	1.000	147	0.082	0.275	0.000	1.000	147	0.014	0.116	0.000	1.000
ind14	R&D services	12566	0.009	0.093	0.000	1.000	147	0.014	0.116	0.000	1.000	147	0.082	0.275	0.000	1.000	147	0.163	0.371	0.000	1.000
ind15	Textile products	12566	0.021	0.145	0.000	1.000	147	0.020	0.142	0.000	1.000	147	0.000	0.000	0.000	1.000	147	0.000	0.000	0.000	1.000
ind16	Transports	12566	0.040	0.196	0.000	1.000	147	0.014	0.116	0.000	1.000	147	0.000	0.000	0.000	0.000	147	0.020	0.142	0.000	1.000
ind17	Wholesale trade	12566	0.174	0.379	0.000	1.000	147	0.095	0.295	0.000	1.000	147	0.007	0.082	0.000	1.000	147	0.041	0.199	0.000	1.000
ind18	Wood products	12566	0.022	0.147	0.000	1.000	147	0.007	0.082	0.000	1.000	147	0.020	0.142	0.000	1.000	147	0.000	0.000	0.000	1.000

The first two rows in the list refer to dependent and contemporaneous variables, the others refer to values before treatment occurs.

Table 2 - Categorical Matching

Compared categories		*Log-level of private R&D expenditure*			*Growth of private R&D expenditure*		
Treated	Controls	ATT	Std. Dev	t-stat	ATT	Std. Dev	t-stat
Cat 1-3	Cat 0	0.653	0.258	2.531	0.282	0.156	1.808
Cat 1	Cat 0	0.056	0.377	0.149	0.090	0.245	0.367
Cat 2	Cat 0	1.018	0.373	2.729	0.542	0.303	1.789
Cat 3	Cat 0	1.148	0.424	2.708	0.130	0.163	0.798
Cat 2	Cat 1	1.108	0.591	1.875	0.686	0.359	1.911
Cat 3	Cat 1	0.870	0.732	1.189	0.072	0.300	0.240
Cat 3	Cat 2	0.180	0.487	0.370	-0.316	0.324	-0.975

Table 3 - Categorical Matching - Medium-run

Compared categories		*Log-level of private R&D expenditure*			*Growth of private R&D expenditure*		
Treated	Controls	ATT	Std. Dev	t-stat	ATT	Std. Dev	t-stat
Cat 1-3	Cat 0	0.076	0.445	0.171	0.295	0.288	1.024
Cat 1	Cat 0	0.054	0.346	0.156	-0.098	0.414	-0.237
Cat 2	Cat 0	0.629	0.392	1.605	0.299	0.416	0.719
Cat 3	Cat 0	1.271	0.971	1.309	1.287	0.607	2.120
Cat 2	Cat 1	0.745	1.057	0.705	0.028	0.489	0.057
Cat 3	Cat 1	1.282	1.555	0.824	1.039	0.603	1.723
Cat 3	Cat 2	0.308	1.032	0.298	-0.167	0.337	-0.496

Table 4 - Continuous Treatment Matching Evaluation

Change in public funding amount about 1%

Cat	*Public funding*	*Change in private R&D*	*Std. Dev.*	*t_stat*	*Change in private R&D growth*	*Std. Dev.*	*t_stat*
1	223.130	0.0067	0.0046	1.459	0.0039	0.0021	1.832
1	246.597	0.0070	0.0044	1.581	0.0038	0.0021	1.828
2	272.532	0.0071	0.0042	1.711	0.0037	0.0020	1.804
2	301.194	0.0073	0.0039	1.851	0.0035	0.0020	1.765
2	332.871	0.0074	0.0037	2.002	0.0033	0.0019	1.719
2	367.879	0.0075	0.0034	2.166	0.0031	0.0019	1.673
2	406.570	0.0076	0.0032	2.342	0.0029	0.0018	1.632
2	449.329	0.0076	0.0030	2.527	0.0027	0.0017	1.593
2	496.585	0.0077	0.0029	2.706	0.0025	0.0016	1.551
2	548.812	0.0079	0.0028	2.857	0.0023	0.0015	1.497
2	606.531	0.0080	0.0027	2.956	0.0021	0.0015	1.423
2	670.320	0.0081	0.0027	2.987	0.0019	0.0014	1.332
2	740.818	0.0083	0.0028	2.954	0.0017	0.0014	1.233
2	818.731	0.0084	0.0029	2.877	0.0016	0.0014	1.134
2	904.837	0.0085	0.0030	2.783	0.0014	0.0014	1.035
2	1000.000	0.0085	0.0032	2.693	0.0013	0.0014	0.931
2	1105.171	0.0084	0.0032	2.614	0.0011	0.0013	0.812
2	1221.403	0.0083	0.0033	2.544	0.0009	0.0013	0.671
2	1349.859	0.0080	0.0033	2.458	0.0007	0.0014	0.513
3	1491.825	0.0077	0.0033	2.324	0.0005	0.0014	0.346
3	1648.721	0.0072	0.0034	2.115	0.0003	0.0015	0.182
3	1822.119	0.0066	0.0036	1.841	0.0000	0.0016	0.027
3	2013.753	0.0060	0.0039	1.544	-0.0002	0.0017	-0.113
3	2225.541	0.0054	0.0042	1.269	-0.0004	0.0018	-0.232
3	2459.603	0.0047	0.0045	1.036	-0.0006	0.0020	-0.329
3	2718.282	0.0040	0.0047	0.846	-0.0009	0.0021	-0.408
3	3004.166	0.0033	0.0048	0.692	-0.0010	0.0022	-0.478
3	3320.117	0.0027	0.0048	0.562	-0.0012	0.0022	-0.547
3	3669.296	0.0021	0.0047	0.446	-0.0014	0.0022	-0.624
3	4055.200	0.0015	0.0045	0.337	-0.0015	0.0021	-0.717
3	4481.689	0.0010	0.0044	0.226	-0.0016	0.0020	-0.829
3	4953.033	0.0005	0.0042	0.109	-0.0018	0.0018	-0.962
3	5473.948	-0.0001	0.0041	-0.017	-0.0019	0.0017	-1.111
3	6049.647	-0.0006	0.0040	-0.152	-0.0020	0.0016	-1.267
3	6685.894	-0.0012	0.0039	-0.294	-0.0022	0.0015	-1.415
3	7389.056	-0.0017	0.0039	-0.443	-0.0024	0.0015	-1.551
3	8166.169	-0.0024	0.0040	-0.593	-0.0025	0.0015	-1.674
3	9025.014	-0.0030	0.0041	-0.743	-0.0027	0.0015	-1.787
3	9974.182	-0.0037	0.0042	-0.889	-0.0030	0.0016	-1.892
3	11023.177	-0.0044	0.0043	-1.027	-0.0032	0.0016	-1.989
3	12182.494	-0.0052	0.0045	-1.158	-0.0034	0.0017	-2.076
3	13463.737	-0.0060	0.0047	-1.279	-0.0037	0.0017	-2.153
3	14879.732	-0.0068	0.0049	-1.391	-0.0040	0.0018	-2.217
3	16444.646	-0.0076	0.0051	-1.491	-0.0042	0.0019	-2.269
3	18174.147	-0.0084	0.0053	-1.578	-0.0045	0.0020	-2.309
3	20085.537	-0.0093	0.0056	-1.649	-0.0048	0.0020	-2.336
3	22197.949	-0.0101	0.0059	-1.703	-0.0051	0.0022	-2.352
3	24532.531	-0.0109	0.0063	-1.739	-0.0054	0.0023	-2.359
3	27112.638	-0.0118	0.0067	-1.761	-0.0057	0.0024	-2.358
3	29964.103	-0.0127	0.0072	-1.770	-0.0060	0.0025	-2.350

Public funding is in 1000 DKK.

Standard errors are computed by bootstrapping (1000 repetitions).

Table 5: Robustness Checks

Continuous Treatment Matching Evaluation with Different Treatment Doses

		Change in public funding amount about 5%						*Change in public funding amount about 10%*					
Cat	*Public funding*	*Change in private R&D*	*Std. Dev.*	*t_stat*	*Change in private R&D growth*	*Std. Dev.*	*t_stat*	*Change in private R&D*	*Std. Dev.*	*t_stat*	*Change in private R&D growth*	*Std. Dev.*	*t_stat*
1	223.130	0.0403	0.0326	1.238	0.0225	0.0201	1.118	0.0812	0.0654	1.242	0.0445	0.0402	1.1055
1	246.597	0.0415	0.0309	1.341	0.0215	0.0197	1.093	0.0834	0.0628	1.329	0.0425	0.0388	1.0940
2	272.532	0.0424	0.0291	1.461	0.0204	0.0191	1.070	0.0853	0.0598	1.426	0.0403	0.0372	1.0818
2	301.194	0.0433	0.0270	1.603	0.0192	0.0183	1.052	0.0869	0.0565	1.537	0.0379	0.0354	1.0693
2	332.871	0.0439	0.0248	1.771	0.0180	0.0173	1.041	0.0881	0.0528	1.668	0.0354	0.0335	1.0560
2	367.879	0.0444	0.0226	1.966	0.0167	0.0162	1.035	0.0891	0.0488	1.824	0.0328	0.0315	1.0406
2	406.570	0.0448	0.0205	2.185	0.0154	0.0150	1.033	0.0897	0.0447	2.007	0.0303	0.0296	1.0219
2	449.329	0.0450	0.0186	2.415	0.0142	0.0138	1.031	0.0901	0.0407	2.213	0.0278	0.0279	0.9992
2	496.585	0.0451	0.0171	2.635	0.0131	0.0128	1.023	0.0903	0.0372	2.426	0.0256	0.0263	0.9727
2	548.812	0.0452	0.0160	2.820	0.0120	0.0120	1.002	0.0903	0.0345	2.617	0.0236	0.0250	0.9436
2	606.531	0.0451	0.0153	2.948	0.0112	0.0116	0.964	0.0901	0.0327	2.759	0.0220	0.0240	0.9141
2	670.320	0.0450	0.0149	3.011	0.0105	0.0115	0.913	0.0898	0.0316	2.842	0.0206	0.0233	0.8868
2	740.818	0.0447	0.0148	3.018	0.0099	0.0115	0.859	0.0893	0.0310	2.884	0.0195	0.0227	0.8624
2	818.731	0.0443	0.0148	2.986	0.0094	0.0116	0.810	0.0885	0.0305	2.900	0.0186	0.0222	0.8377
2	904.837	0.0438	0.0150	2.927	0.0090	0.0117	0.765	0.0873	0.0302	2.889	0.0177	0.0220	0.8045
2	1000.000	0.0431	0.0151	2.846	0.0084	0.0117	0.720	0.0857	0.0303	2.828	0.0166	0.0220	0.7518
2	1105.171	0.0421	0.0154	2.736	0.0078	0.0117	0.662	0.0836	0.0311	2.689	0.0151	0.0225	0.6719
2	1221.403	0.0408	0.0158	2.588	0.0069	0.0118	0.581	0.0809	0.0327	2.472	0.0132	0.0234	0.5634
2	1349.859	0.0392	0.0164	2.391	0.0057	0.0121	0.468	0.0775	0.0352	2.204	0.0106	0.0246	0.4304
3	1491.825	0.0373	0.0173	2.148	0.0041	0.0126	0.326	0.0734	0.0382	1.923	0.0073	0.0261	0.2786
3	1648.721	0.0349	0.0186	1.874	0.0021	0.0132	0.161	0.0686	0.0415	1.654	0.0031	0.0276	0.1134
3	1822.119	0.0323	0.0203	1.594	-0.0002	0.0140	-0.016	0.0631	0.0449	1.406	-0.0018	0.0293	-0.0605
3	2013.753	0.0293	0.0221	1.328	-0.0030	0.0149	-0.199	0.0570	0.0482	1.182	-0.0074	0.0310	-0.2387
3	2225.541	0.0260	0.0239	1.088	-0.0060	0.0157	-0.382	0.0503	0.0514	0.980	-0.0136	0.0326	-0.4182
3	2459.603	0.0225	0.0257	0.877	-0.0093	0.0166	-0.561	0.0433	0.0542	0.798	-0.0204	0.0341	-0.5976
3	2718.282	0.0189	0.0272	0.693	-0.0128	0.0174	-0.736	0.0358	0.0565	0.634	-0.0274	0.0353	-0.7766
3	3004.166	0.0150	0.0283	0.531	-0.0164	0.0182	-0.905	0.0281	0.0582	0.483	-0.0347	0.0363	-0.9553
3	3320.117	0.0111	0.0290	0.383	-0.0201	0.0188	-1.072	0.0203	0.0592	0.342	-0.0421	0.0371	-1.1334
3	3669.296	0.0072	0.0292	0.245	-0.0238	0.0192	-1.239	0.0123	0.0594	0.207	-0.0495	0.0377	-1.3108
3	4055.200	0.0032	0.0291	0.109	-0.0275	0.0195	-1.411	0.0043	0.0590	0.074	-0.0567	0.0381	-1.4878
3	4481.689	-0.0008	0.0287	-0.028	-0.0310	0.0195	-1.591	-0.0036	0.0581	-0.062	-0.0638	0.0383	-1.6659
3	4953.033	-0.0048	0.0282	-0.170	-0.0345	0.0194	-1.781	-0.0116	0.0568	-0.203	-0.0706	0.0382	-1.8473
3	5473.948	-0.0087	0.0277	-0.315	-0.0378	0.0191	-1.978	-0.0195	0.0554	-0.351	-0.0772	0.0380	-2.0335
3	6049.647	-0.0127	0.0273	-0.465	-0.0410	0.0188	-2.176	-0.0273	0.0541	-0.505	-0.0836	0.0376	-2.2237
3	6685.894	-0.0166	0.0269	-0.617	-0.0441	0.0186	-2.368	-0.0352	0.0532	-0.661	-0.0897	0.0371	-2.4140
3	7389.056	-0.0205	0.0267	-0.771	-0.0470	0.0185	-2.545	-0.0431	0.0528	-0.816	-0.0955	0.0368	-2.5972
3	8166.169	-0.0245	0.0265	-0.926	-0.0499	0.0184	-2.704	-0.0510	0.0528	-0.966	-0.1011	0.0366	-2.7659
3	9025.014	-0.0285	0.0264	-1.081	-0.0526	0.0185	-2.843	-0.0590	0.0531	-1.111	-0.1065	0.0365	-2.9153
3	9974.182	-0.0326	0.0263	-1.236	-0.0552	0.0186	-2.965	-0.0672	0.0537	-1.251	-0.1118	0.0367	-3.0451
3	11023.177	-0.0367	0.0264	-1.390	-0.0578	0.0188	-3.072	-0.0754	0.0543	-1.389	-0.1168	0.0370	-3.1588
3	12182.494	-0.0409	0.0265	-1.541	-0.0603	0.0190	-3.167	-0.0838	0.0549	-1.527	-0.1218	0.0373	-3.2609
3	13463.737	-0.0451	0.0267	-1.693	-0.0627	0.0193	-3.254	-0.0924	0.0555	-1.666	-0.1265	0.0377	-3.3546
3	14879.732	-0.0494	0.0268	-1.845	-0.0650	0.0195	-3.333	-0.1011	0.0559	-1.807	-0.1310	0.0381	-3.4408
3	16444.646	-0.0538	0.0269	-1.998	-0.0671	0.0197	-3.402	-0.1098	0.0564	-1.948	-0.1353	0.0385	-3.5176
3	18174.147	-0.0582	0.0271	-2.148	-0.0692	0.0200	-3.460	-0.1187	0.0568	-2.089	-0.1392	0.0389	-3.5810
3	20085.537	-0.0626	0.0273	-2.292	-0.0710	0.0203	-3.501	-0.1275	0.0573	-2.225	-0.1428	0.0394	-3.6264
3	22197.949	-0.0670	0.0277	-2.421	-0.0726	0.0206	-3.519	-0.1363	0.0579	-2.352	-0.1459	0.0400	-3.6484
3	24532.531	-0.0714	0.0282	-2.530	-0.0740	0.0211	-3.510	-0.1450	0.0589	-2.463	-0.1486	0.0408	-3.6431
3	27112.638	-0.0757	0.0290	-2.614	-0.0751	0.0216	-3.472	-0.1536	0.0602	-2.551	-0.1507	0.0418	-3.6082
3	29964.103	-0.0800	0.0300	-2.671	-0.0760	0.0223	-3.404	-0.1621	0.0620	-2.613	-0.1524	0.0430	-3.5442

Public funding is in 1000 DKK.

Standard errors are computed by bootstrapping (1000 repetitions).