Evaluating the effects of subsidy intensity on future R&D investment using the generalized-propensity score. Evidence from a Tuscan small-business program

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Overlooked issues in R&D policy evaluation

In their recent review of the R&D subsidy literature, Zúñiga-Vicente et al. (2012) invoke research on:

- ❑ medium- or long-term relationship between R&D subsidies and private R&D spending,
- ❑ the effect of different amounts of subsidy on this spending

Why could subsidies have medium- or long-term effects?

- ❖ firms might face adjustment costs in the set-up or implementation of the R&D investment (Lucas, 1967), but overall…
- ❖ learning-by-doing changes the firms' profit opportunities in favor of more R&D-intensive products (Klette and Møen, 2012)
- ❖ behavioural effects (Buisseret et al.,1995)

What is the expected shape of the subsidy-investment relationship?

Lack of theory. Empirical hints suggest that it could be inverted-U shaped →

Empirical support in the economic literature

- non-immediate effects of R&D subsidies: e.g. Lach (2002), Guellec & Van Pottelsberghe (2003), Klette & Møen (2012)

- behavioural effects: recent review by Gök & Edler (2012)

- relation between subsidy intensity and R&D investment, an inverted-U shape?
  - Guellec & Van Pottelsberghe (2003), country-level autoregressive R&D investment model
  - Görg & Strobl (2007) and Aschoff (2009), micro-econometric "program-evaluation" approach with arbitrary discretization of a continuous treatment

We will try to estimate the shape of this relation, within a "causal" framework

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A novel approach in program evaluation

Basic idea: Hirano & Imbens (2004) show how to avoid discretization and evaluate the effects of a continuous treatment (e.g. subsidy, training duration) by means of a dose-response function (DRF), where a generalized propensity score is used for adjusting for differences in observed pre-treatment variables

Methodological and applied studies taking the dose-response approach

Methodology developments	**Applications [areas of economics]**
Hirano & Imbens (2004), flexible but parametric DRF	Kluve *et al.* (2012) [training]
	Bia & Mattei (2012) [investment subsidies]
	Becker *et al*. (2012) [EU funds & regional growth]
	Doyle (2011) [entry in higher education]
	Fryges (2008) [export-growth relationship in firms]
Flores et al. (2012), develop semi-parametric kernel estimators for the DRF	Flores et al. (2012) [training]
Egger & von Erhrlich (2013) extend parametric approach to multiple treatments	

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A closer look at methodology (1)

Under the potential outcomes approach and the usual stable unit-treatment value assumption, the main concepts of the binary-treatment literature are extended to the continuous treatment case (Imbens, 2000; Hirano & Imbens, 2004), such as:

Unconfoundedness: becomes *weak unconfoundedness* in a continuous treatment setting. That is, the level of treatment received is independent of the potential outcome conditional on observed covariates: $Y_i(t) \perp T_i \mid X_i \text{ for all } t \in \Im$

Propensity score: a *generalized* version of the *propensity score (GPS)* can be used to adjust for covariate unbalance in a continuous treatment setting.
The *GPS* $r(t,x) = f_{T|X}(t|X = x)$ is the conditional density of the treatment given the covariates and has the same balancing properties of the "classic" propensity score. For each unit, $R_i = r(T_i, X_i)$ denotes the "actual" GPS and $R_i^t = r(t, X_i)$ is a random variable indexed by *t.*

GPS balancing property: within strata with the same value of $r(t, X)$ the probability that $T = t$ does not depend on the value of *X:* $X \perp I\{T = t\} \mid r(t, X)$

Unconfoundedness + GPS $\Longrightarrow$ $f_T(t \mid r(t, X), Y(t)) = f_T(t \mid r(t, X))$

A closer look at methodology (2)

We want to estimate the average DRF on treated firms $\mu(t) = E[Y_i(t) \mid t > 0]$, by using the GPS to remove the selection bias (which would prevent us from finding a cause-effect relationship) or any other biases associated with differences in the covariates.

First, we estimate the GPS by considering a distribution for the treatment given the covariates $T_i \mid X_i \sim N(\beta_0 + \beta_1 X_i, \sigma^2)$:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left(-\frac{1}{2\hat{\sigma}^2} (T_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)^2 \right)$$

Then, we estimate the average DRF as function of T_i and $\hat{R}_i$.

In literature, two main approaches are presented :

- Partial mean (PM) approach (Hirano & Imbens, 2004)
- Inverse weighting (IW) approach (Flores et al. 2012)

A closer look at methodology (3)

Partial mean approach (Hirano & Imbens, 2004)

First, we estimate the conditional expectation of the outcome Y_i as a function of T_i and R_i

(i) $\beta(t,r) = E[Y_i(t) \mid r(t, X_i) = r] = E[Y_i \mid T_i = t, R_i = r]$

Then, we estimate the DRF for each level of *t* by averaging (i) over $R_i^t = r(t, X_i)$

(ii) $\mu(t) = E[\beta(t, R_i^t)]$

Usually, the conditional expectation (i) is formulated in a flexible but parametric way, such as, for example $E(Y_i \mid T_i, \hat{R}_i) = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 T_i^3 + \alpha_4 \hat{R}_i + \alpha_5 T_i \hat{R}_i$

so the PM estimator is obtained as:

$$\hat{\mu}(t) = \frac{1}{N} \sum_{i=1}^{N} \hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 t^3 + \hat{\alpha}_4 \hat{R}_i^t + \hat{\alpha}_5 t \hat{R}_i^t$$

Alternatively, we can use a non parametric formulation (see for example the Non-Parametric Partial Mean approach in Flores et al., 2012, that exploits kernel regressions)

A closer look at methodology (4)

Inverse Weighting approach (Flores et al. 2012)

The estimated GPS for each level of *t*, $\hat{R}_i^t = \hat{r}(t, X_i)$, is used to weight the observations to adjust for covariate differences

The IW approach estimates $\mu(t)$ using a local linear regression of *Y* on *T* with weighted kernel function $\tilde{K}_{h,X}(T_i - t) = K_h(T_i - t) / \hat{R}_i^t$, where $K_h(\cdot)$ is a kernel function (that assign more weigth to observations closer to treatment level *t*) with bandwidth *h.*

Explicitly, the IW estimator of the average DRF take the following form:

$$\hat{\mu}(t) = \frac{D_0(t)S_2(t) - D_1(t)S_1(t)}{S_0(t)S_2(t) - S_1^2(t)}$$

where $S_j(t) = \sum_{i=1}^{N} \tilde{K}_{h,X}(T_i - t)(T_i - t)^j$ and $D_j(t) = \sum_{i=1}^{N} \tilde{K}_{h,X}(T_i - t)(T_i - t)^j Y_i$

Data from an Italian small-business program

The program "1.1.1B, Aids to pre-competitive development"…

- implemented in 2003 and 2004 in Tuscany
- very broad sectoral and technological focus (manuf & services)
- "selective" matching grants (35-40%) for investment projects up to 750,000 euros, projects had to last no longer than two years
- aimed at product innovation

The data…

- only those "treated" firms that were not subsidised also by other regional or national R&D-support programs [→ 134 firms]; we acquire balance sheets
- more than 600 untreated control firms identified by means of a matched sampling strategy (Rosenbaum & Rubin, 1985) based on a set of baseline and balance-sheet variables
- for both treated and untreated we performed telephone interviews in order to acquire further data (e.g. innovation)

The sofware… currently, no ready-to-use packages are available for the totality of our analysis. We implement our study in the R computing environment.

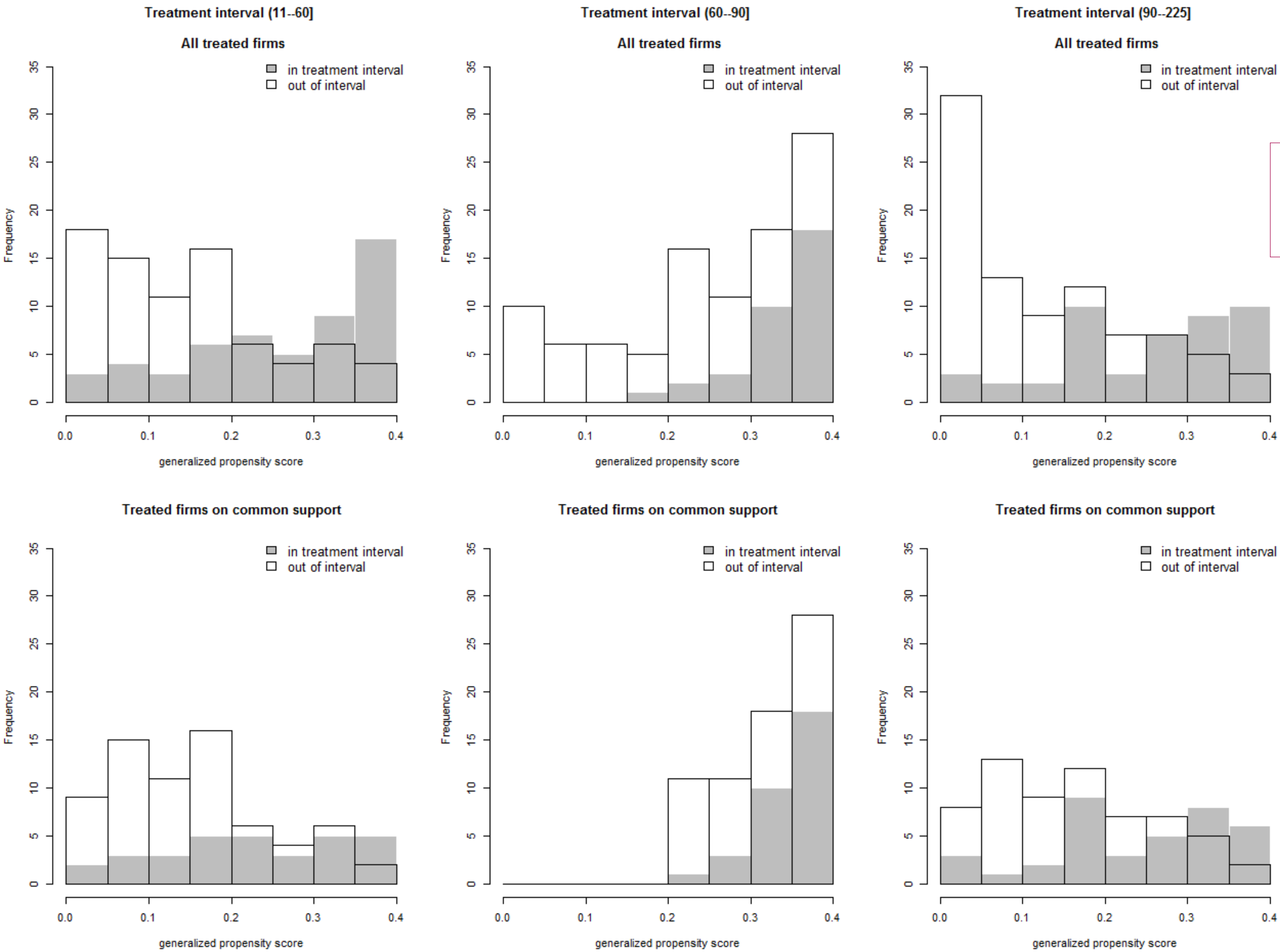
Outcomes and covariates

Outcome: average R&D investment over a two-years period after the end of the subsidized project

For the **estimation of the GPS**, we employ a wide set of pre-treatment variables, most of them are considered in *(t-1)* and in *(t-2)*

- General**:** age, limited company (1/0), n. of employees, turnover(log), exporter (1/0), is in a lagging-behind area (1/0), sector of activity (5 categories)
- Innovation drivers and experience: R&D investment, R&D department (1/0), % of graduated employees (0; up to the median; over the median), IPR applications (1/0), has R&D linkages with other firms (1/0), has R&D linkages with university (1/0), has product innovation experience (1/0)
- Availability of finance: credit score(log), cash flow/turnover(log)
- Productivity and profitability: value added per employee, ROI
- Structure of capital: tangibles, intangibles

Assessment of the estimated GPS: common support



out of 134 subsidized firms

100 are on common support, i.e. can be compared to each other

Assessment of covariate balance improvements

For each of the 36 covariates and 3 treatment intervals we assess the covariate balance by testing whether the mean in each treatment interval is different from the mean in the remaining intervals combined (two-sided t-test performed in 36 x 3 =108 cases).

 # unbalanced cases before and after restriction to common support and GPS-adjustment (# unbalanced / # balanced)

wider rejection area

narrower rejection area

	All treated, unadjusted	***On common support, unadjusted***	***On common support, GPS-adjusted***
10% confidence	**30** / 78	**6** / 102	**1** /107
5% confidence	**25** / 83	**1** / 107	**0** /108
# observations	134	100	100

Implementation choices (1)

- when implementing the Parametric Partial Mean approach, we estimate the conditional expectation of the outcome Y_i as a function of T_i and R_i by means of the following model: $E(Y_i \mid T_i, \hat{R}_i) = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 T_i^3 + \alpha_4 \hat{R}_i + \alpha_5 T_i \hat{R}_i$
- when implementing the IW approach, we use a Gaussian kernel function K(.) with bandwidth selected by the Silverman's rule of thumb

In the following slides, you will see DRFs and their derivatives…

- results are accompanied by 95% confidence intervals obtained with 1,000 bootstrap replications that account for all estimation steps (GPS, common support, DRF and derivative)

- the dashed line next to the DRFs represents what the average R&D investment would have been if our firms had taken no subsidy (*T=0*). This counterfactual scenario is analyzed stepping back to a binary treatment setting, estimating a balancing propensity score, and then employing a kernel matching estimator limited to the common support region. In doing so, we obtain a positive (statistically significant) average treatment effect on the treated (ATT)

Implementation choices (2)

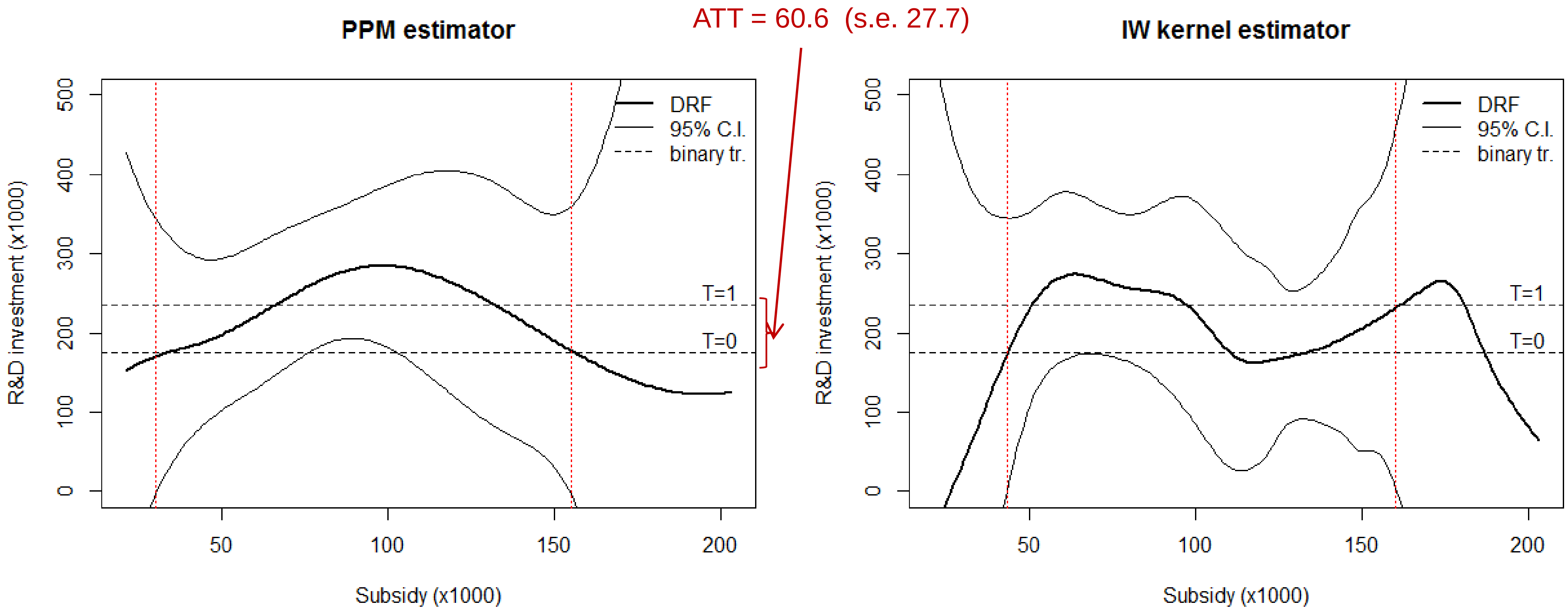
More about **derivative** estimation…

- for the PPM estimator, following Bia & Mattei (2008), the derivative of the DRF at *t* is "empirically" obtained as the forward change of 1,000 euros of subsidy:

$$\frac{\partial \hat{\mu}}{\partial t} = \frac{\hat{\mu}(t+1000) - \hat{\mu}(t)}{1000}$$

- for the IW estimator, the derivative estimate at *t* equals the slope coefficient of the linear term from a local quadratic regression of Y on T using the re-weighted kernel $\tilde{K}_h(T_i, X_i; t)$ (Flores et al., 2012)

Dose-response functions



Note to the figures: the function is significantly different from zero limited to the region where the confidence interval does not contain zero. This occurs in treatment interval:

[30,000---155,000] euros

[44,000---160,000] euros

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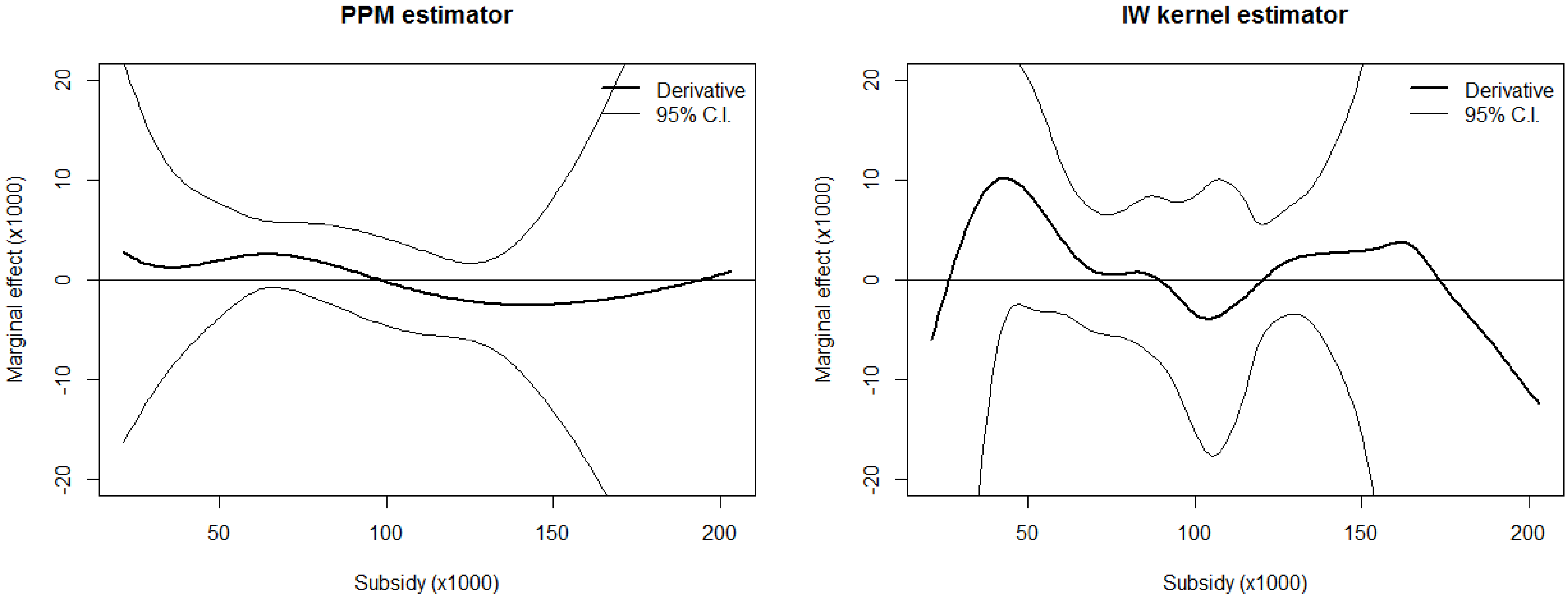
Marginal effects



Note to the figures: the derivative is significantly different from zero limited to the region where the confidence interval does not contain zero. This never happens in the figures

Brief discussion

Results suggest that the relationship between subsidy and future R&D investment has a roughly inverted-U shape

There is an intermediate region of subsidy amount (which corresponds to project size in a matching grant scheme where public aid is a fixed %) where some effects on future R&D can be appreciated (i.e. the aided R&D experience is more likely to have an unaided follow up)

This is not true if the subsidy (subsidized project) is…

- too small [insufficient to generate adequate learning in SMEs?]
- too large [too high management costs for SMEs offset the benefits of learning?]

Sensitivity analysis (1)

The validity of the previous results strongly relies on the plausibility of the unconfoundedness assumption. This is not directly testable, but it can be indirectly assessed in a variety of ways (Imbens & Wooldridge, 2009).

Following the work of Ichino et al. (2008) - extended to the continuous treatment case by Bia & Mattei (2012) - we investigate whether our estimates change substantially when unconfoundedness is assumed to fail in some way:

- We make assumptions about an unobserved binary covariate *U* that is correlated both with the potential outcome *Y* and with the treatment *T*.
- We relax the unconfoundedness assumption, assuming that the treatment assignment mechanism is unconfounded conditional on both the observable variables *X* and the unobserved covariate *U*: $Y_i(t) \perp T_i \mid X_i, U_i \text{ for all } t \in \Im$
- Then we derive estimates of the average dose-response function under different possible scenarios of deviations from unconfoundedness.
- If these estimated DRFs are similar to the original DRF, then our results could be considered reliable.

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Sensitivity analysis (2)

How it works:

- Assume that the conditional distribution of *U* given *T* and *Y* does not depend on the covariates *X*: $\Pr(U=1|T,Y,X)=\Pr(U=1|T,Y)$
- Assume that the conditional distribution of *U* given *T* and *Y* follows the logit model:
$$p_u(t,y)=\Pr(U=1|T=t,Y=y)=\frac{\exp(\alpha_0+\alpha_1 t+\alpha_2 y+\alpha_3 ty)}{1+\exp(\alpha_0+\alpha_1 t+\alpha_2 y+\alpha_3 ty)}$$
- Fix the *α* parameters and draw a value U_i for each firm, according to the corresponding T_i and Y_i values, with a Bernulli experiment with $p_u(t,y)$
- Include *U* in the set of variables used to estimate the GPS and the average DFR.
- For each given set of parameters *α*, repeat all steps of the analysis *m = 100* times and obtain an estimate of the average DRF by means of the average DRFs over the distribution of the simulated *U*.

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Sensitivity analysis (3)

How to choose the α parameters?

Assume that the distribution of *U* is in turn comparable to the distribution of the observables, in particular those related to innovation and R&D.

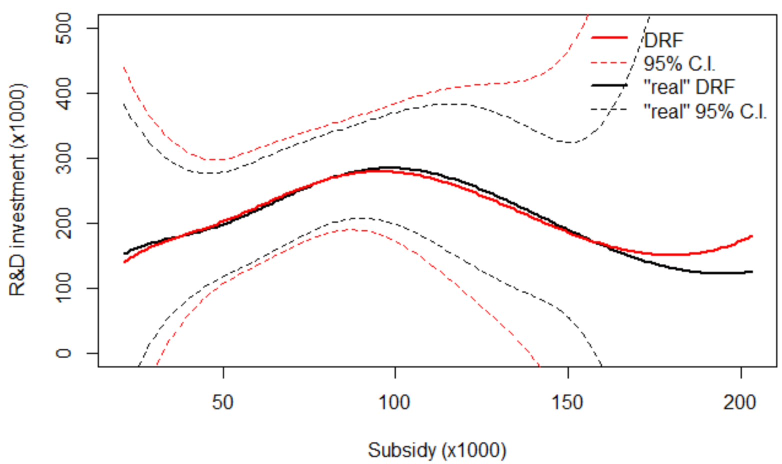
Specifically, for each observed covariate *X* (binary or transformed in binary) we estimate of a logit model linking the probability that the covariate takes value 1 to the treatment variable *T*, the outcome *Y* and their interaction. The estimated model coefficients are then used as α parameters.

This allows us to investigate the extent to which our results are robust to deviations from the unconfoundedness assumption induced by the impossibility of observing factors similar to the ones used to calibrate the distribution of *U*.

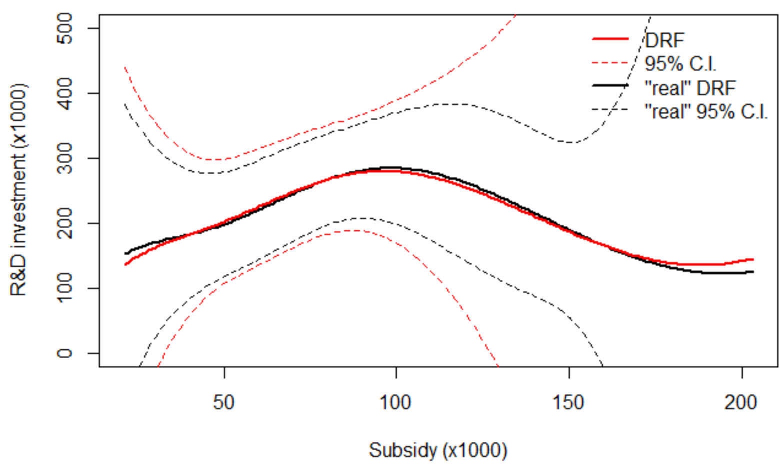
The results provide valuable evidence on the reliability of our estimates with respect to reasonable failures of the unconfoundedness assumption.

Sensitivity analysis – results (1)

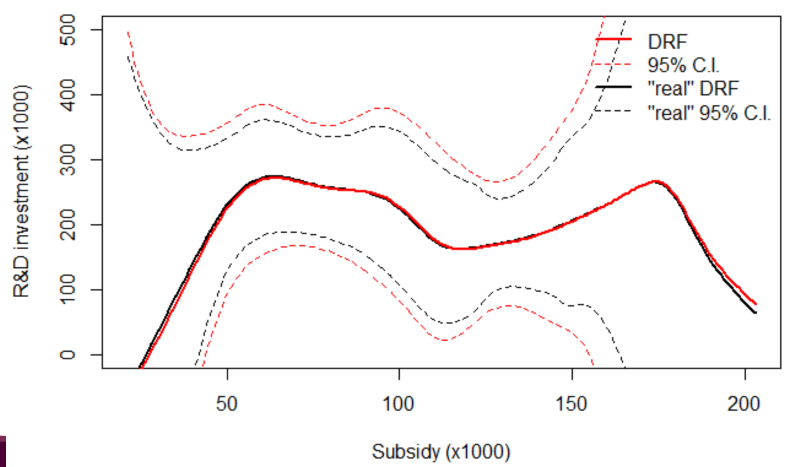
PPM est. -- 'R&D investment in (t-1)'-like confounder



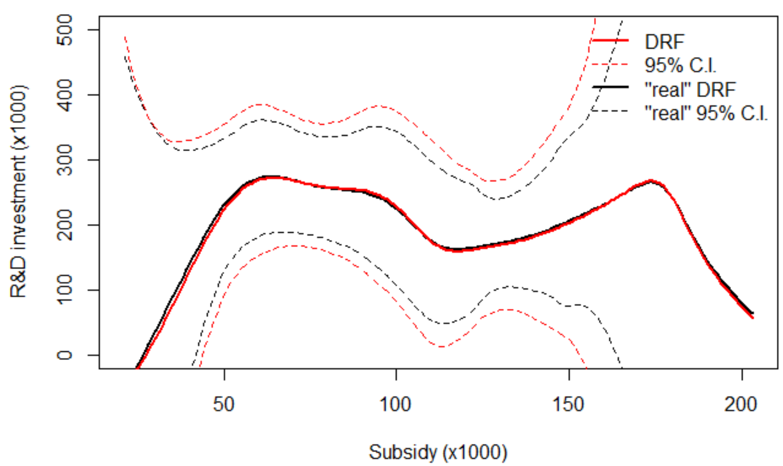
PPM est. -- 'R&D department in (t-1)'-like confounder



KIW est. -- 'R&D investment in (t-1)'-like confounder



KIW est. -- 'R&D department in (t-1)'-like confounder



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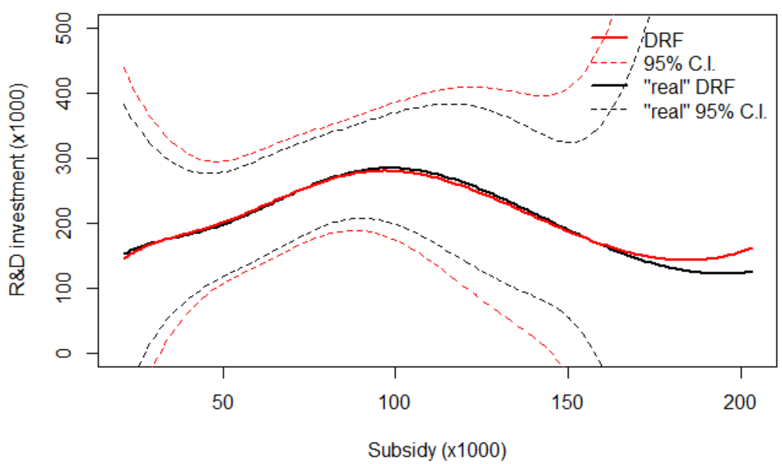
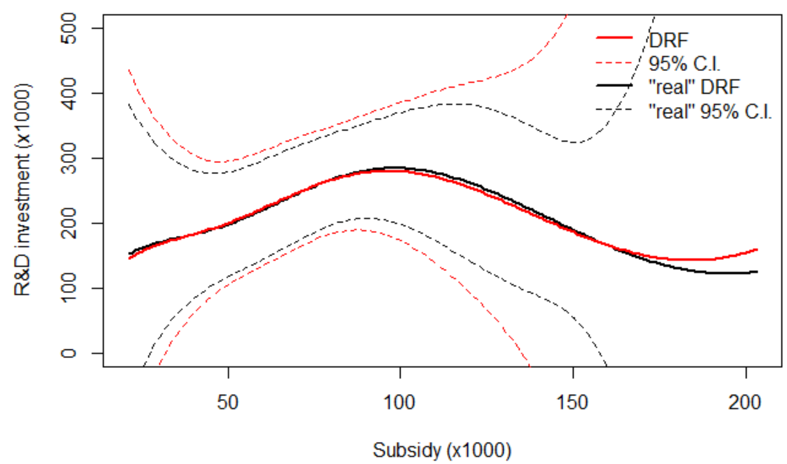
Sensitivity analysis – results (2)

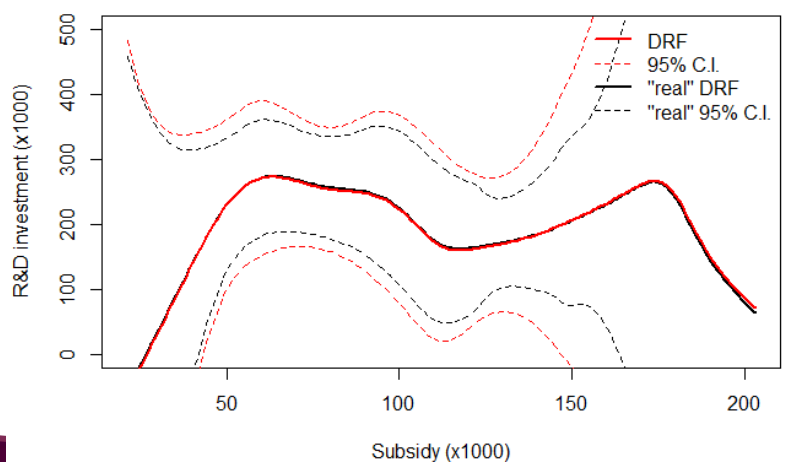
PPM est. -- 'IPR applications'-like confounder



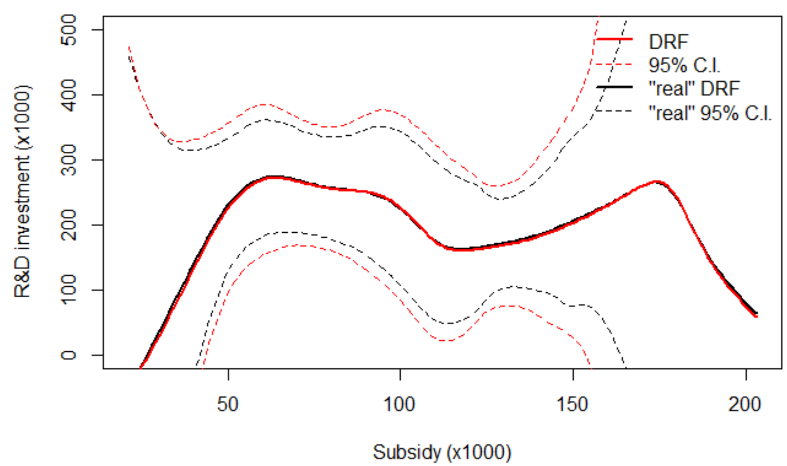
PPM est. -- 'Product innovation experience'-like confounder



KIW est. -- 'IPR applications'-like confounder



KIW est. -- 'Product innovation experience'-like confounder



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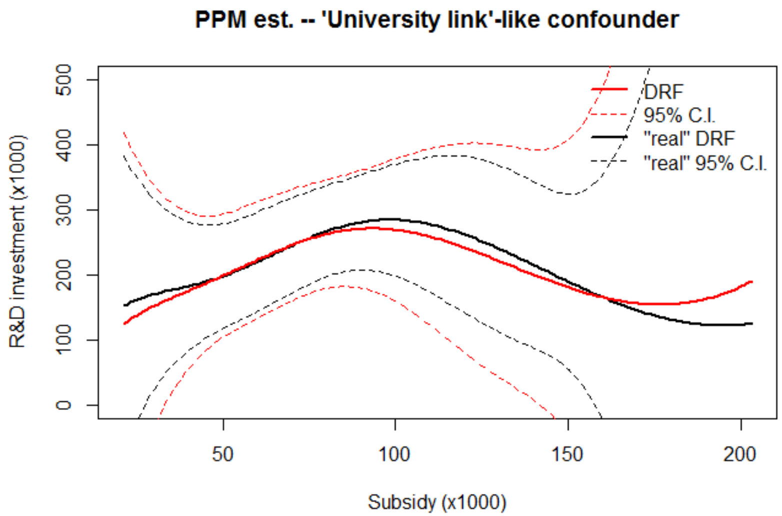
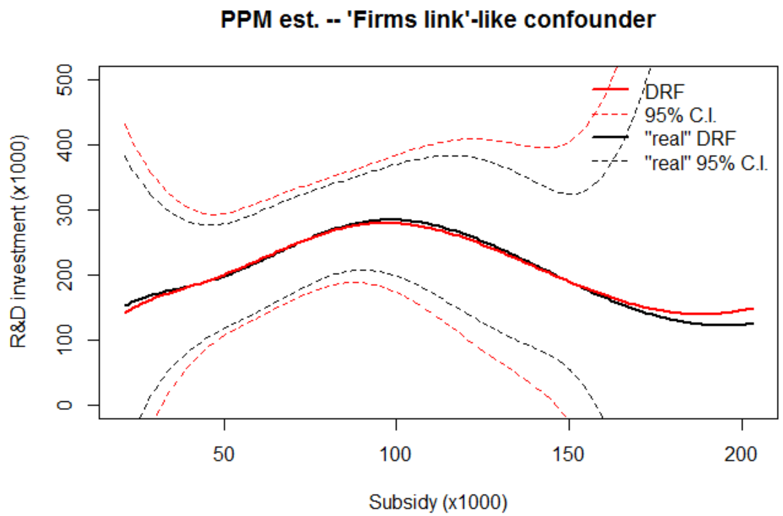
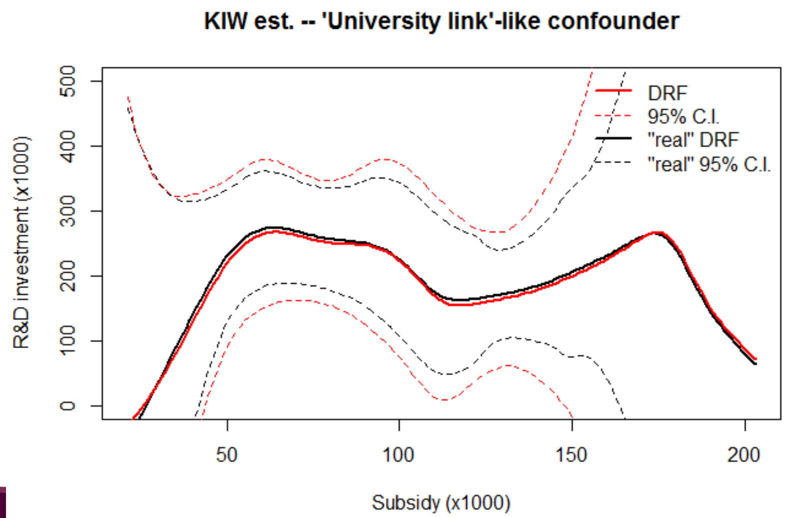
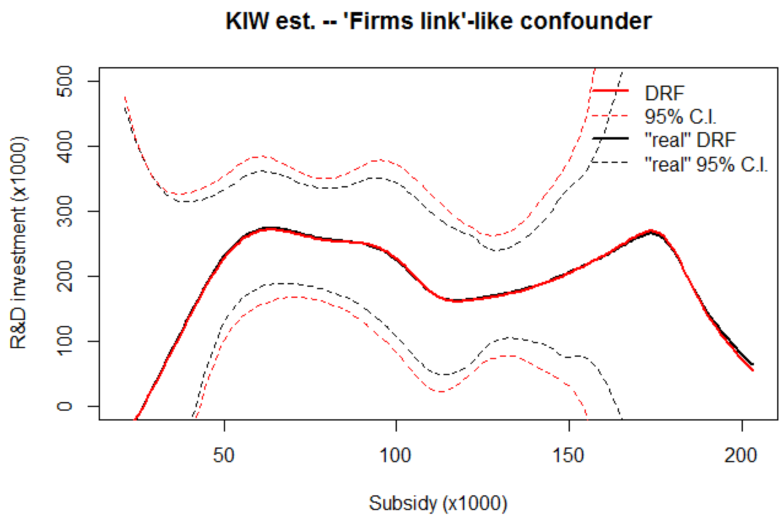
Sensitivity analysis – results (3)



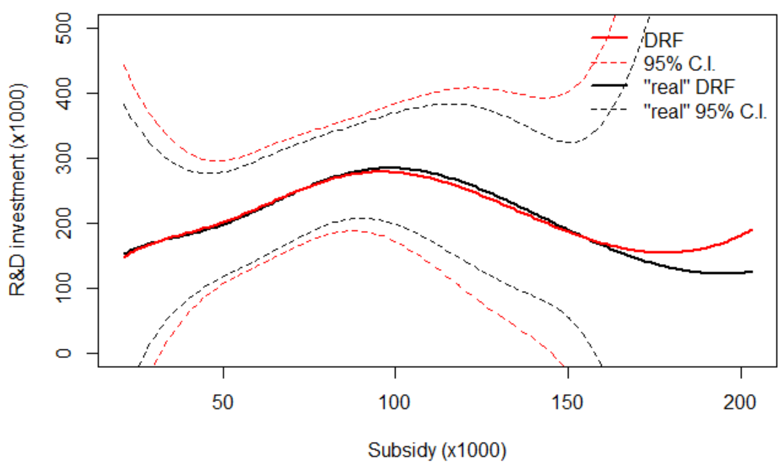




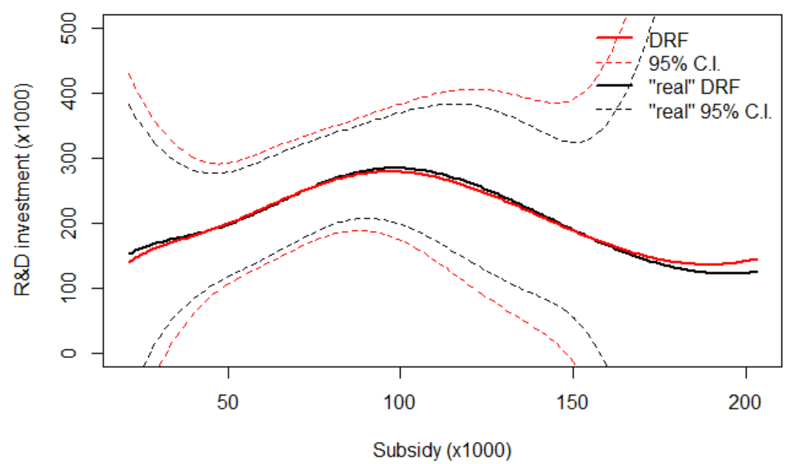


Sensitivity analysis – results (4)

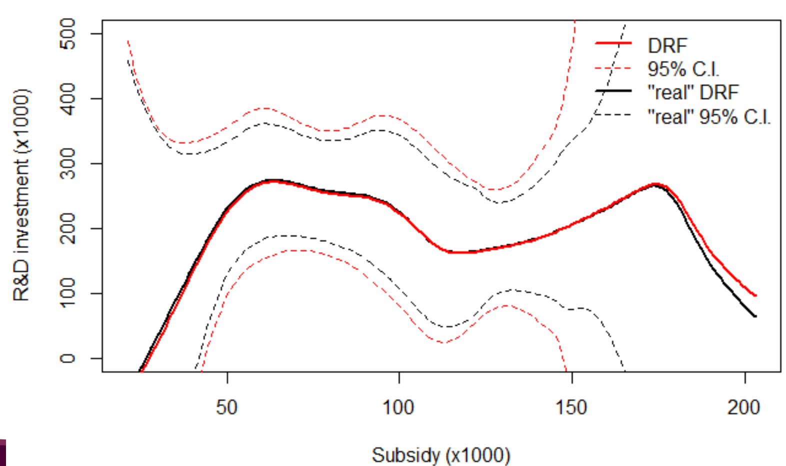
PPM est. -- 'Graduated employees in (t-1)'-like confounder



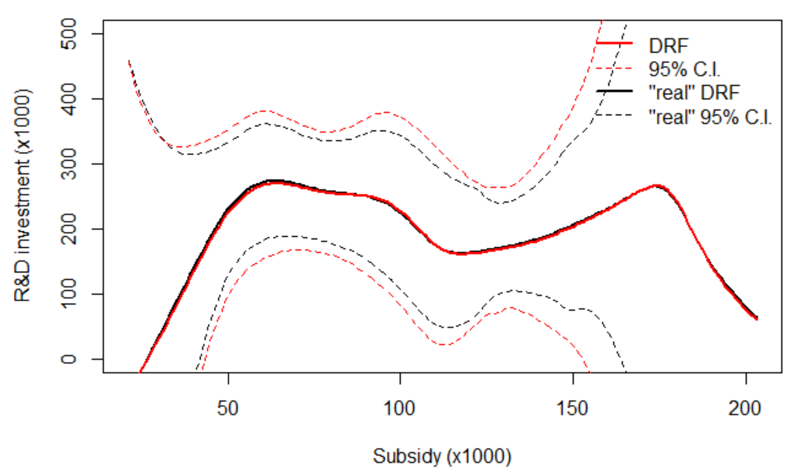
PPM est. -- Neutral confounder



KIW est. -- 'Graduated employees in (t-1)'-like confounder



KIW est. -- Neutral confounder



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Concluding remarks

We can say that a subsidy size in the range of 50-150,000 euros (corresponding to a project size approximatively in the range of 120-400,000 euros) is more likely to bring SMEs to an unaided follow up

If subsidy size lies between 60-100,000 euros (project size in the range 150-250,000 euros), its effect is presumably positive with respect to a no-subsidy situation

Within this region the effect of increasing the aid (size of project) tends to be positive (point estimates of the derivative > 0), albeit it mostly shows a marginally decreasing trend

Despite positive point estimates, derivatives are not statistically different from zero. This implies that we are not able to say for sure where the maximum/optimum point lies. However, as none of the estimates are statistically negative (confidence bands are not both below zero), nonnegative effects cannot be ruled out throughout

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