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Abstract

We propose two semiparametric estimators of the dose-response function based on spline techniques. Under uncounfoundedness, the generalized propensity score can be used to estimate dose-response functions (DRF) and marginal treatment effect functions. In many observational studies treatment may not be binary or categorical. In such cases, one may be interested in estimating the dose-response function in a setting with a continuous treatment. We evaluate the performance of the proposed estimators using Monte Carlo simulation methods. The simulation results suggested that the estimated DRF is robust to the specific semiparametric estimator used, while the parametric estimates of the DRF were sensitive to model mis-specification. We apply our approach to the problem of evaluating the effect on innovation sales of Research and Development (R&D) financial aids received by Luxembourgish firms in 2004 and 2005.

Keywords: Continuous treatment; Dose-response function; Generalized propensity score; Non-parametric methods; R&D investment

JEL classification codes: C13 ; J31 ; J70

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1 Introduction

Nonexperimental methods are important in economics and many other fields to evaluate the effects of policies or interventions in the absence of an experiment. In many applications the units under study may receive different levels of the treatment, in which case estimation of dose-response functions is of interest. In order to adjust for systematic differences in background characteristics occurring between groups with different levels of the treatment variable, a key identifying assumption is that selection into levels of the treatment is random conditional on a set of observable pre-treatment variables (unconfoundedness). Propensity score methods are usually employed for the estimation of causal effects under unconfoundedness in a binary treatment setting, where the propensity score is defined as the probability of receiving treatment conditional on the observable pre-treatment variables (Rosenbaum and Rubin, 1983). Over the last years, several extensions of propensity score-based methods have been developed. Imbens (2000) and Lechner (2001) extended propensity score matching to handle a categorical treatment variable. For an ordinal treatment variable, Joffe and Rosenbaum (1999) and Lu et al. (2001) developed and applied a method based on a scalar "balancing score", which is a variable that balances pre-treatment variables among different comparison groups. Hirano and Imbens (2004) introduced the concept of Generalized Propensity Score (GPS) and extended the results in Rosenbaum and Rubin (1983) to the case of a continuous treatment. The GPS is defined as the conditional density of the treatment level given the observed covariates. Under unconfoundedness, GPS methods can be used to estimate dose-response functions (DRF) and marginal treatment effect functions. Imai and Van Dyk (2004) introduced a similar concept to the GPS, the "propensity function", allowing for arbitrary treatment regimes.

Hirano and Imbens (2004) discuss estimation of dose-response functions based on employing the GPS as a balancing score, and implement their approach in a parametric framework. Flores et al. (2011) use the GPS within a weighting and introduce a semiparametric estimator of the DRF based on kernel techniques. In this paper we propose two new semiparametric estimators of the dose-response function based on spline methods and compare them with both the parametric method in Hirano and Imbens (2004) and the semiparametric estimator proposed by Flores et al. (2011).

The estimation strategy we follow for estimation of the DRF, which is based on the ap-

proach in Hirano and Imbens (2004), consists of the following two steps. The first step involves a parametric but flexible estimation of the GPS based on generalized linear models; and the second step estimates the DRF adjusting for the GPS using regression techniques. Most of the existing studies use a full parametric approach in the second step, employing a polynomial approximation for the conditional expectation of the outcome variable given the treatment variable and the estimated GPS (e.g., Hirano and Imbens, 2004; Kluve et al., 2007; Mattei and Bia, 2008). The estimators we propose in this paper employ semiparametric techniques in this second step using either a cubic spline estimator or a penalized cubic spline estimator.

We compare these estimators with the inverse-weighting (IW) estimator proposed by Flores et al. (2011), using Monte-Carlo simulation. In this exercise we consider different sample sizes and dose-response functions. To the best of our knowledge, this is the first simulation study comparing different GPS-based estimators of the DRF.

All the GPS-based estimators of the DRF considered in this paper will be also applied to the problem of evaluating the effect of Research and Development (R&D) financial aids received by Luxembourgish firms in 2004 and 2005 on innovation sales in 2006, where innovation sales are defined as sales linked to innovation processes set up between 2004 and 2005. A distinct feature of our empirical study is that we are interested in assessing the impact of the intensity of R&D subsidies, by using the amount of policy exposure as a continuous variable. We would expect that firms receiving different amounts of contribution will differ in their market outcomes. For this reason, we argue that it is important to go beyond estimation of the causal effects of public policies employing a binary discrete intervention (to be exposed or not to a policy), and instead to estimate dose-response functions and marginal treatment effect functions of receiving different levels of R&D financial aid, which also allow us to uncover heterogeneities in the effects of different contribution levels.

The rest of the paper is organized as follows: in Section 2 we first briefly review the parametric approach in Hirano and Imbens (2004) and the semiparametric IW estimator in Flores et al. (2011). Then we introduce spline-based estimators of the dose-response function. In this section we also compare each alternative approach by simulation. Section 3 describes the data set used in our empirical application and shows the evaluation results for the effects of R&D contributions to Luxembourgish firms on innovations sales. Section 4 concludes and discusses directions for future research.

2 Estimation Strategy

2.1 Reference Framework

Using the potential outcome approach to causal inference (Rubin, 1974, 1978), we estimate a continuous dose-response function that relates each value of the dose, i.e., incentive level, to the post-treatment level of firms' innovation sales. Formally, consider a set of N enterprises, and denote each of them by subscript i: $i = 1, \ldots, N$. For each firm i, we observe a vector of pre-treatment variables, X_i, the received incentive amount, T_i, and the value of the outcome variable associated with this treatment level, $Y_i = Y_i(T_i)$. In order to formally describe the econometric framework we adopt, extra notation is required. Let $Y_i(t)$ denote a random variable that maps a particular potential treatment, t, $t \in \mathcal{T} \subset R$, to a potential outcome. We are interested in the average dose-response function, $\mu(t) = E[Y_i(t)]$. Following Hirano and Imbens (HI) (2004), we assume that $\{Y_i(t)\}_{t\in\mathcal{T}}$, T_i, and X_i are defined on a common probability space, that T_i is continuously distributed with respect to Lebesgue measure on $\mathcal{T}$, and that $Y_i = Y_i(T_i)$ is a well defined random variable. Throughout this article, we make the Stable Unit Treatment Value Assumption (SUTVA, Rubin 1980, 1990), which implies that there is no interference between firms and that each level of the treatment defines a single outcome for each firm.

Our key identifying assumption in estimating the DRF is the weak unconfoundedness assumption, generalized to case of continuous treatment variables by Hirano and Imbens (2004). This assumption requires that the treatment assignment mechanism is independent of each potential outcome conditional on the pre-treatment variables: $Y_i(t) \perp T_i|X_i$ for all $t \in \mathcal{T}$. For instance, in our empirical study, this assumption implies that all variables that affect both the outcome (innovation sales in 2006) and the likelihood of receiving a given amount of financial aid are observed, and that all the others are perfectly collinear with the observed ones.

Given unconfoundedness, we can apply the methods based on the GPS with continuous treatments introduced by Hirano and Imbens (2004). The GPS is defined as the conditional density of the treatment given the observed covariates: $r(t, x) = f_{T|X}(t|x)$. Let $R_i = r(T_i, X_i)$ denote the conditional density at the treatment level actually received. The GPS is a balancing score (e.g., Rosenbaum and Rubin, 1983), that is, within strata with the same value of $r(t, x)$, the probability that $T = t$ does not depend on the value of X. In combination with the weak

unconfoundedness assumption, this balancing property implies that for every $t \in \mathcal{T}$

$$f_T\left(t|r(t,X_i),Y_i(t)\right) = f_T\left(t|r(t,X_i)\right).$$

As a result, the GPS can be used to eliminate any bias associated with differences in the covariates among groups receiving different levels of the treatment. Formally, Hirano and Imbens (2004) show that if the assignment to the treatment is weakly unconfounded given pre-treatment variables X_i, then

$$\beta(t,r) = E\left[Y_i(t)|r(t,X_i)=r\right] = E\left[Y_i|T_i=t,R_i=r\right]$$

and

$$\mu(t) = E\left[\beta(t,r(t,X_i))\right].$$

This result suggests that the dose-response function at t can be estimated using a partial mean approach (Newey, 1994), that is, averaging the regression function $\mu(t,r(t,X_i))$ over the covariates X_i, while holding fixed the treatment level t. Hence, the dose-response function can be estimated using the GPS by the following steps. In the first stage, we estimate the GPS using a parametric but flexible approach. Let $\widehat{R}_i$ denote the estimated GPS at the treatment actually received, and let $\widehat{R}_i^t = \widehat{r}(t,X_i)$ denote the estimated score at a specific treatment level, t. In the second stage, we estimate the dose-response function using the estimated GPS by following two steps. The first step involves estimating the conditional expectation of Y_i given T_i and the estimated GPS $\widehat{R}_i$, $E(Y_i|T_i,\widehat{R_i})$. The second step involves averaging this conditional expectation over $\widehat{R}_i^t$ to get the value of the dose-response function at t. Intuitively, we need to integrate over $\widehat{R}_i^t = \widehat{r}(t,X_i)$ in the second step because the potential outcomes at t are independent of T conditional on R_i^t.

In this paper, we apply both parametric and nonparametric partial mean estimators. Following HI, we implement a partial mean approach by assuming a (flexible) parametric form for the regression function of Y_i on T_i and $\widehat{R}_i$. Specifically,

$$E(Y_i|(T_i,\widehat{R_i}) = h(T_i,\widehat{R_i};\alpha)$$

and

$$\widehat{E[Y_i(t)]} = \frac{1}{N}\sum_{i=1}^{N} h(t,\widehat{R}_i^t;\widehat{\alpha}),$$

where $h(.)$ is a parametric function of its arguments, with parameter vector α.

We propose estimating the regression function $E(Y_i|T_i, \widehat{R_i})$ employing nonparametric techniques. Our spline estimator of the average dose-response can be defined as:

$$\widehat{E[Y_i(t)]} = \frac{1}{N}\sum_{i=1}^{N} g(t, \widehat{R}_i^t),$$

where $g(t, \widehat{R}_i^t)$ is a polynomial approximation of the conditional expectation $\beta(t, \widehat{R}_i^t)$. Specifically, $g(t, \widehat{R}_i^t)$ is a piecewise function of the form:

$$g(t, \widehat{R}_i^t) = \begin{cases} g_1(t, \widehat{R}_i^t) & \text{if} \quad k_1 \leq t < k_2 \\ g_2(t, \widehat{R}_i^t) & \text{if} \quad k_2 \leq t < k_3 \\ \vdots & \\ g_{p-1}(t, \widehat{R}_i^t) & \text{if} \quad k_{p-1} \leq t < k_p \end{cases}$$

where g_j is a pre-fixed degree polynomial and $k_1 < \ldots < k_p$ are p distinct knots in the support of T, $\mathcal{T}$. The piecewise function g must interpolate all knots and be twice continuously differentiable on the interval $[k_1, k_p]$. In this paper, we use a natural cubic spline of the treatment variable, therefore

$$g_j(t, \widehat{R}_i^t) = a_j(t-k_k)^3 + b_j(t-k_j)^2 + c_j(t-k_j) + d_j + \delta\widehat{R}_i^t \quad \text{for } j = 1, \ldots, p-1$$

with $\partial^2/\partial t\, g_1(t, \widehat{R}_i^t) = 0$ and $\partial^2/\partial t\, g_{p-1}(t, \widehat{R}_i^t) = 0$. Since the curve $g(t, \widehat{R}_i^t)$ must be continuous across its entire interval, each sub-function must join at the knots, so $g_j(k_j, \widehat{R}_i^{k_j}) = g_{j-1}(k_j, \widehat{R}_i^{k_j})$ for $j = 2, \ldots, p-1$. Also, to make the curve smooth across the interval, the derivatives must be equal at the knots; that is, $\partial/\partial t\, g_{j-1}(k_j, \widehat{R}_i^{k_j}) = \partial/\partial t\, g_j(k_j, \widehat{R}_i^{k_j})$ and $\partial^2/\partial t\, g_{j-1}(k_j, \widehat{R}_i^{k_j}) = \partial^2/\partial t\, g_j(k_j, \widehat{R}_i^{k_j})$ for $j = 2, \ldots, p-1$.

In order to address overfitting problems, we also propose an estimator based on the penalized spline (Ruppert, Wand and Carroll, 2003; Jann and Gutierrez, 2008):

$$g(t, \widehat{R}_i^t) + \lambda \int \partial^2/\partial t\, g(t, \widehat{R}_i^t).$$

The parameter λ introduces a penalty for lack of smoothness. More specifically, if λ is small, the solution will be a spline, which almost interpolates the data points; conversely, if $\lambda = \infty$ then we get an OLS fit to the data. Penalized splines can be formalized in several ways; here we use a mixed model approach. In this paper, we focus on a penalized cubic spline.

In addition to the partial-mean based estimators above, we also consider the semiparametric Inverse-Weighting (IW) estimator based on the kernel method proposed by Flores et al. (2011). Instead of using the GPS as a balancing score, this approach uses the GPS to weight the observations in order to adjust for differences in the pre-treatment variables across groups receiving different treatment levels. We implement the IW estimator by choosing a global bandwidth based on the procedure proposed by Fan and Gijbels (1996). The unknown terms appearing in the optimal global bandwidth is estimated by employing a global polynomial of order p plus 3, where p is the order of the local polynomial fitted.

The IW Kernel Estimator of the average dose-response is given by:

$$\widehat{E[Y_i(t)]} = \frac{D_0(t)S_2(t) - D_1(t)S_1(t)}{S_0(t)S_2(t) - S_1^2(t)}$$

where

$$S_j(t) = \sum_{i=1}^{N} \tilde{k}_{hX}(T_i - t)(T_i - t)^j$$

$$D_j(t) = \sum_{i=1}^{N} \tilde{k}_{hX}(T_i - t)(T_i - t)^j Y_i$$

$$\tilde{k}_{h_X}(T_i - t) = K_h(T_i - t)/\widehat{R_i^t}$$

2.2 Monte Carlo Simulations: HI, IW and Spline Estimator

In this section we aim at comparing the alternative GPS-based estimation approaches of the DRF by simulation. We generate 100 samples of size $n = 50$ and $n = 500$ respectively, where the outcome (innovation sales in 2006) and the treatment (public R&D contributions) are randomly generated from reference populations. Specifically, we consider two different "true" unit-level dose-response functions; non linear and linear in the treatment parameter, respectively:

$$Y_i(t) = 10 + 0.005 \cdot t + 0.01 \left(\frac{t^2}{1000} \right) + 0.01 \cdot r(t, X_i) + 0.001 \cdot t \cdot r(t, X_i) + e_i$$

$$Y_i(t) = 5 + \frac{1}{400} \cdot t + \exp\left(-50 \cdot \left(\frac{t}{400 - 0.5}\right)^2\right) + r(t, X_i) + 10 \cdot r(t, X_i)^2 + 0.0075 \cdot r(t, X_i) \cdot t + e_i$$

where e_i is the error term normally distributed: $e_i \sim \mathrm{N}(0, 0.7^2)$, and the $r(t, X_i)$ is derived assuming the normality of the treatment variable (or of its transformation) conditional on the pre-treatment covariates. In our simulations, we assume that the logarithm of the treatment (amount of the financial aid) has a normal distribution, given the covariates:

$$\log(T_i)|X_i \sim \mathrm{N}\left(\beta_0 + \beta_1' X_i, \sigma^2\right).$$

As we can clearly see from Figure 1 (left panel), all techniques work very well when applied to estimating the linear dose-response function. Therefore we mainly focus on the non-linear case (Figure 1, right panel). Our simulation results show that both the IW estimator and the Spline estimators fit "reasonably well" the true non linear mean dose-response, although both the estimators underfit the true values for central treatment levels and overfit the tails of the true dose-response distribution.

Figure 3 shows the biases, the mean square errors and the coverage of nominal 95% confidence intervals, which are defined as the percentage of Monte-Carlo replications for which the corresponding nominal 95% confidence intervals include the true value of the dose-response function. The IW kernel, Spline and Penalized Spline estimators have coverage rates of 95% for most of the treatment values considered in the simulation. Concerning the parametric approach, the dose-response function is barely misspecified and the coverage is poor. Moreover, the IW and Spline estimators have lower bias and lower mean square error than the parametric-based estimator.

Needless to say the performance of all the techniques improves substantially considering a sample of bigger size ($n = 500$). Figures 4 and 5 clearly show the excellent performance for the IW estimator and the Spline estimators. They fit the non linear true mean dose-response very well; biases reduce significantly and mean square errors are very close to 0, coverage rates are high, in particular for treatment levels greater than 150,000 euro, and confidence intervals are very thin (see Figure 6). Note also that the highest bias and mean square as well as the lowest coverage rate for the true mean value of the dose-response function are again found in the parametric approach.

Figure 1: Linear and non linear Dose Response Function by HI, Kernel, Spline and Penalized Spline method ($n = 50$)

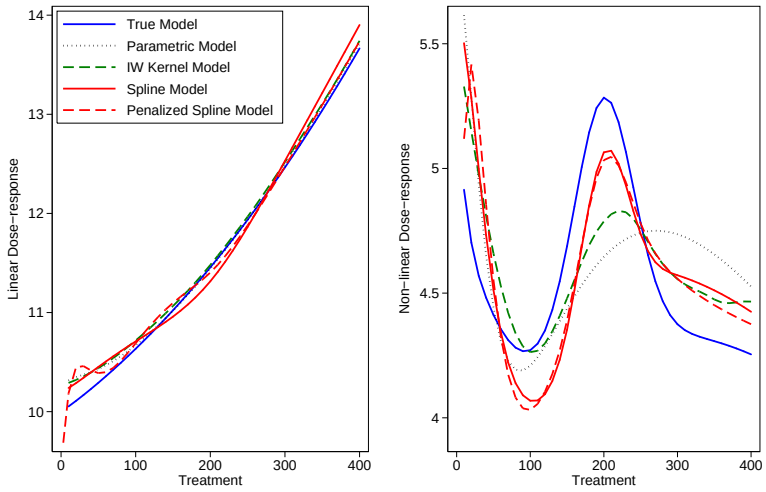


Figure 2: 95% confidence bands for the non linear Dose-Response Function by HI, Kernel, Spline and Penalized Spline method ($n = 50$)

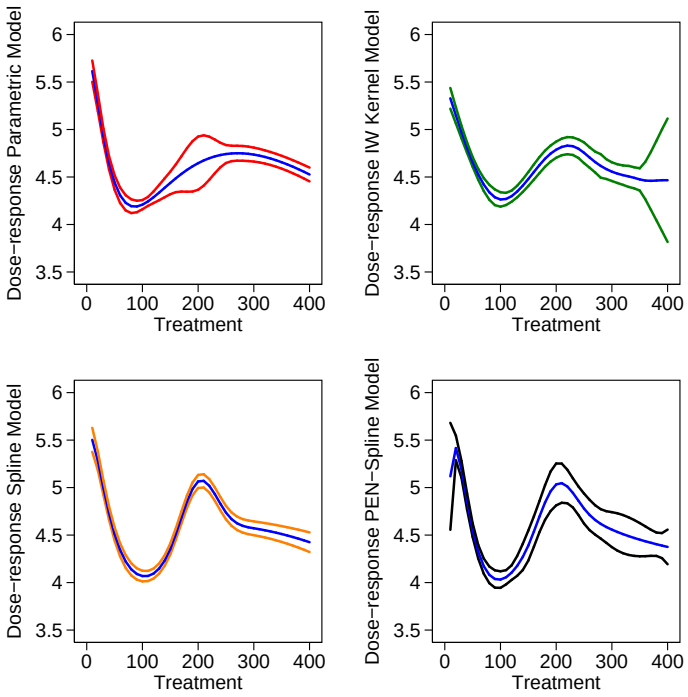


Figure 3: Bias, Mean Square Error (MSE) and Coverage Rates for the non linear dose-response function by HI, Kernel, Spline and Penalized Spline method ($n = 50$)

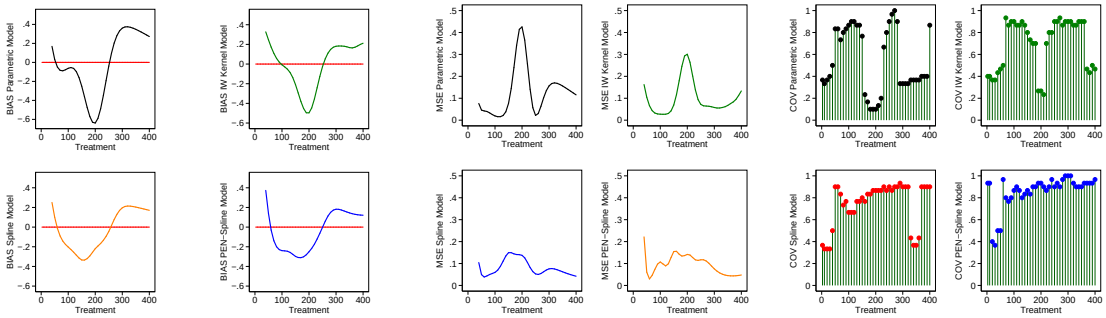


Figure 4: Linear and non linear Dose Response Function by HI, Kernel, Spline and Penalized Spline method ($n = 500$)

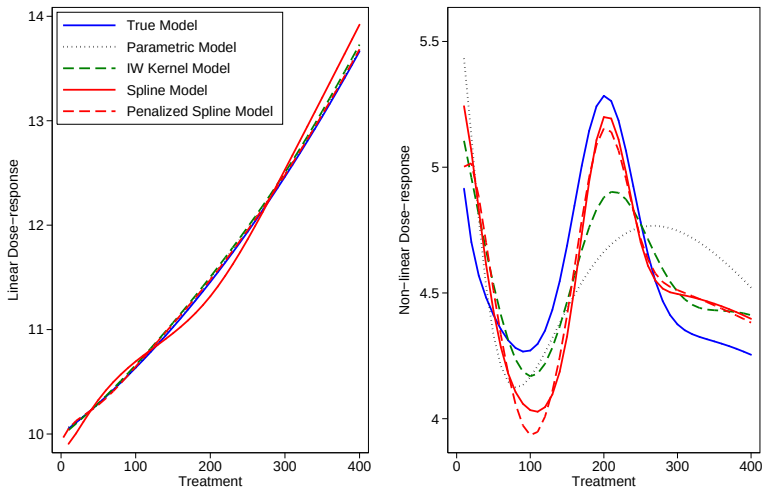


Figure 5: 95% confidence bands for the non linear Dose-Response Function by HI, Kernel, Spline and Penalized Spline method ($n = 500$)

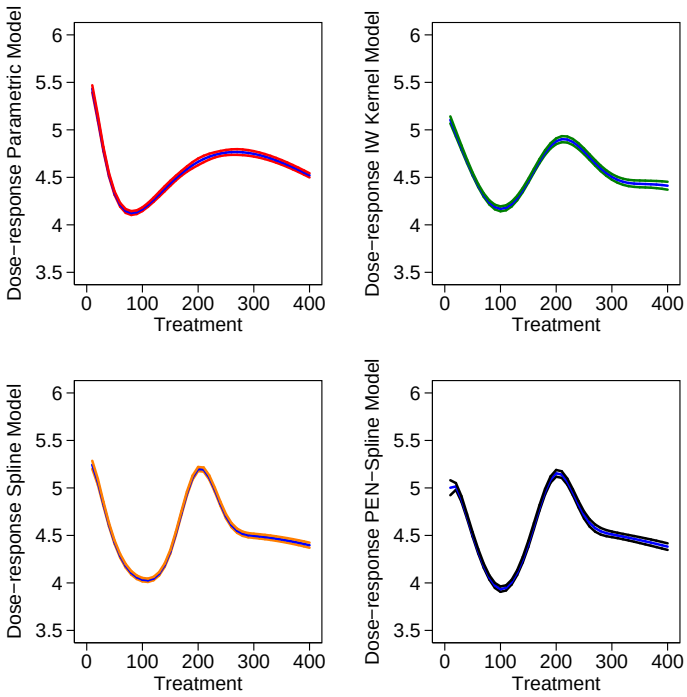
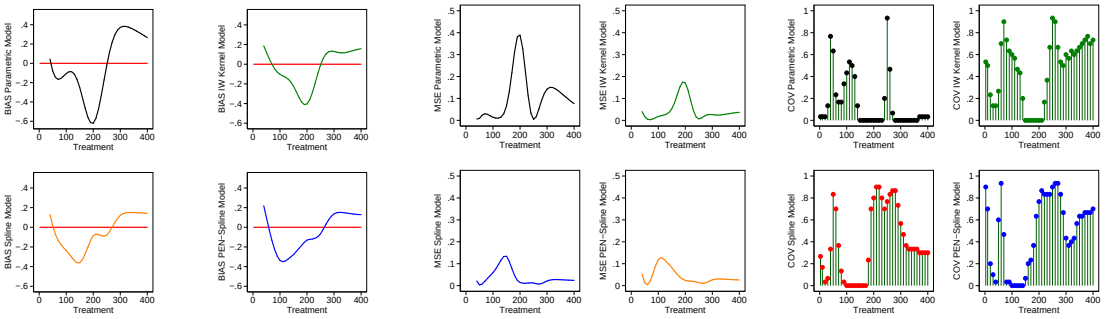


Figure 6: Bias, Mean Square Error (MSE) and Coverage Rates for the non linear dose-response function by HI, Kernel, Spline and Penalized Spline method ($n = 500$)



3 Application: The Effect of R&D contributions to Luxembourgish firms on Innovation Sales

Firms' innovation policies are an important feature to support local enterprises. Technological investments are considered an efficient strategy to guarantee competitiveness both at the firm-level and for the economy as a whole (Jones, 2005; Aghion and Howitt, 2005). Research & Development (R&D) investments fall in the class of interventions expected to set up technological progress and facilitate growth in the long-run (David et al., 2000; Cerulli, 2010). Many recent studies deal with public policies designed to encourage firms' investment in innovative activities, including public measures aimed at fostering innovation by strengthening and extending patent rights (Gallini, 2002) and R&D investments (David et al., 2000; Falk, 2004; Almus and Czarnitzki, 2003).

Note that, despite a favourable economic framework, the Luxembourgish national R&D expenditures are lower than the European average. More than 80% of national R&D measures are undertaken by private firms (Nguyen, 2007) and only in the last years they have been considered as national priority, leading policy makers to invest more in innovation. Due to this 'peculiarity', there are specific sections in the Community Innovation Survey (CIS) designed to distinguish between internal and external R&D fundings. The formers are investments on research and innovation directly provided by the firm itself or by a group of two or more enterprises under common ownership[1]; the latters are external funds supplied by the Luxembourgish Ministry of Economy. This study focuses on this last aspect, analysing the impact of public financial aids on innovation sales in 2006.

3.1 Data: The Community Innovation Survey 2004-2006

The Community Innovation Survey (CIS) is carried out by "The Central Service for Statistics and Economic Studies" (STATEC) along with "The Centre for Population, Poverty and Public Policy Studies" of Luxembourg (CEPS/INSTEAD), and it collects information about product, process and marketing innovation for firms in Luxembourg. Most questions cover new or improved goods or services, the implementation of new or improved processes, and logistic

[1]Other sources can be also represented by economic supports from partner enterprises of a specific R&D project established in (or outside) Luxembourg or from European framework programmes on R&D.

and distribution methods.

In this section we aim at evaluating the impact of R&D contributions provided to the Luxembourgish firms in 2004 and 2005 by the Luxembourgish Ministry of Economy, using a panel dataset obtained by matching firms from the fourth and sixth Community Innovation Survey (CIS 2004 and CIS 2006)[2]. The outcome variable of interest is the amount of innovation sales in 2006, defined as sales linked to innovation processes set up between 2004 and 2005. No attrition problem occurred in assembling the CIS 2004 and 2006 samples: medium- and big-size firms were interviewed in both surveys. Our sample includes all the 22 CIS firms receiving R&D contributions. From this sample of firms we discarded 4 firms, which received very high economic supports from the Ministry between 2004 and 2005, focusing on firms receiving between 3,000 and 356,000 euro.

The observed pre-treatment characteristics include a dummy variable for the firms' size (equal to 1 for firms having more than 249 employees and 0 otherwise); a dummy variable for the sector (equal to 1 for firms operating in technological-manufacturing sector and 0 otherwise); the employment level in 2004; the percentage of employees with higher education; a dummy variable for the firms' domicile (equal to 1 for firms having domicile in Luxembourg and 0 otherwise); the amount of innovation sales in 2004; the total sales amount in 2004; a dummy variable for the type of private financial aid received in 2004 (equal to 1 if the firm receives in-house R&D contributions or R&D funds from a partner firm, 0 otherwise); a dummy variable for the reference market (equal to 1 if a firm is active in the international market and 0 otherwise); the amount of in-house R&D investment in 2004 and the level of public R&D contributions received in 2004. Some of these pre-treatment variables suffer from missing data: only 12 out 22 firms provide complete information. We address this issue using Multiple Imputation methods under the missing at random assumption. We assume that unconfoundedness holds conditional on all the pre-treatment variables listed in Section 3.1, arguing that these variables are good proxies of factors that might affect the intensity of the financial aid (Rubin, 2008).

Note that these data provide a unique opportunity to estimate the dose-response function of Luxembourgish enterprises to learn whether there exist differences in the returns to amount

[2]We are particularly grateful to Vincent Dautel, who run all the programs we developed and provided, as we did not have direct access to the data.

of financial aids. In addition, this analysis may inform policy makers about how to improve the efficacy of financial contributions provided to firms in Luxembourg.

Although many aspects of the effect of R&D subsidies have been investigated, there is a lack of empirical evidence on the analysis of research incentives provided by the Luxembourg Goverment. In addition, to the best of our knowledge, the existing studies on the impact evaluation of R&D measures in Luxembourg focus on the effect of receiving versus not receiving R&D subsidies (e.g., Nguyen, 2007; Czarnitzki and Lopes Bento, 2010; Dautel and Walther, 2010). Using data from CIS 2004, Nguyen (2007) finds that there are strong differences in the public fundings accross sectors and firms' sizes. Dautel and Walther (2010) analyse the local determinants of innovation in the Luxembourg Metropolitan Region, using the CIS 2006 innovation survey. They show space matters according to both spatial units and accessibility in the infra-regional context of Luxembourg. Czarnitzki and Lopes Bento (2010) focus on the effect of public incentives on internal R&D investment and total innovation intensity at a cross-country comparative level, finding that on average firms would have invested significantly less if they would not have received subsidies and that almost all the governments would benefit from an extension of their economic support policies to not financed firms.

3.2 Estimation Results

In our empirical study we focus on the impact evaluation of R&D financial aids (Euro per 1000) provided to Luxembourgish enterprises in 2004 and 2005. To be effective, innovation sales estimation should involve firms balanced with respect to their characteristics. The extent to which this has been achieved can be explored by comparing balance in the covariates among two groups before and after adjusting for the GPS.

We first estimate the GPS, that is, the conditional distribution of the logarithm of the amount of R&D contribution given the covariates, and check its balancing property. Adjusting for the GPS seems to improve the balance, especially when the unadjusted differences are high (See Table 1). Next, we estimate the dose-response function using the estimators previously described. The results are shown in Figures 7 and 8. Figure 7 shows the DRF estimates of the amount of R&D contribution on innovation sales: although all the estimators suggest that there exists a positive relationship between innovation sales and amount of R&D contribution, the IW Kernel and Spline estimators show a non-linear relationship, while the parametric es-

timator reveals a linear and smooth shape of the dose-response function. In Figure 8, each estimate of the DRF derivative is accompanied by 95% confidence bands obtained using bootstrap methods that account for all estimation steps, including the estimation of the GPS. As we can see in Figure 8, the IW Kernel and Spline estimators suggest that financial aid has a positive and highly significant marginal effect on innovation sales for treatment levels of medium or high intensity. The HI technique reveals linear and positive (although negligible) effects of financial aid on innovation sales. The IW and PEN-Spline estimates are very similar to each other, whereas there are important differences between these semiparametric DRF estimates and the HI parametric estimates, especially in terms of standard errors significantly higher in the HI model than in the nonparametric methods (see Table 2). Table 3 highlights this aspect showing very high standardized mean differences for the HI versus IW and PEN-Spline techniques, but also for the Cubic Spline versus IW and PEN-Spline estimators. Most of the standardized mean differences between the Kernel and PEN-Spline models are lower than 3.5.

Table 1: Mean differences among covariates [a]

Pre-treatment variable	Unadjusted		Adjusted for the GPS	
	[0, 40]	[40, 356]	[0, 40]	[40, 356]
Sector 2004	0.333	-0.333	0.243	-0.267
	[0.236]	[0.236]	[0.248]	[0.249]
Size 2004	-0.333	0.333	-0.283	0.298
	[0.229]	[0.229]	[0.241]	[0.243]
International market 2004	0.000	0.000	-0.010	-0.089
	[0.157]	[0.157]	[0.170]	[0.186]
Domicile 2004	0.111	-0.111	0.101	**-0.089**
	[0.184]	[0.184]	[0.195]	[0.192]
In-house or group investment 2004	-0.222	0.222	-0.132	0.227
	[0.242]	[0.242]	[0.255]	[0.252]
Employees with high education 2004	0.161	-0.161	0.163	-0.162
	[0.080]	[0.080]	[0.096]	[0.082]
Log Innovation Sale 2004	0.483	-0.483	0.923	**-0.034**
	[3.145]	[3.145]	[2.780]	[3.171]
Log turnover 2004	-1.159	1.159	**-0.781**	1.247
	[0.653]	[0.653]	[0.654]	[0.699]
Log employment 2004	-1.098	1.098	**-0.846**	1.140
	[0.510]	[0.510]	[0.508]	[0.556]
Log public R&D contributions 2004	23.355	-23.355	**0.285**	-24.118
	[37.245]	[37.245]	[3.047]	[33.453]
Log private R&D contributions 2004	2.195	-2.195	-3.410	-3.224
	[11.699]	[11.699]	[7.241]	[10.617]

[a] (Standard erros in brackets)

Table 2: Dose response estimates by model[a]

Treatment values[b]	Parametric	Kernel	Splines	PEN$_{Splines}$
8	15.521	14.875	15.445	14.845
	[0.231]	[0.195]	[0.159]	[0.069]
16	15.521	14.875	15.445	14.845
	[0.133]	[0.147]	[0.198]	[0.087]
24	15.521	14.875	15.445	14.845
	[0.068]	[0.156]	[0.296]	[0.300]
32	15.521	14.875	15.445	14.845
	[0.053]	[0.215]	[0.428]	[0.321]
40	15.521	14.875	15.445	14.845
	[0.067]	[0.446]	[0.510]	[0.238]
88	15.521	14.875	15.445	14.845
	[0.262]	[0.393]	[0.064]	[0.025]
104	15.521	14.875	15.445	14.845
	[0.327]	[0.383]	[0.151]	[0.153]
128	15.521	14.875	15.445	14.845
	[0.430]	[0.195]	[0.416]	[0.334]
192	15.521	14.875	15.445	14.845
	[0.789]	[0.162]	[0.240]	[0.037]
320	15.521	14.875	15.445	14.845
	[2.099]	[0.216]	[0.567]	[0.410]
344	15.521	14.875	15.445	14.845
	[2.440]	[0.063]	[0.768]	[0.406]
352	15.521	14.875	15.445	14.845
	[2.561]	[0.141]	[0.837]	[0.378]

[a](Standard errors in brackets)
[b](We reported a grid of treatment values considered in the empirical study)

Table 3: Standardized Mean Differences by model

Treatment[a]	HI vs IW	HI vs Sp	HI vs PEN	IW vs Sp	IW vs PEN	Sp vs PEN
8	-0.400	-2.365	-1.700	-2.154	-1.395	1.461
16	0.974	2.891	**4.926**	2.011	3.436	0.418
24	**4.015**	**4.261**	**5.257**	1.831	2.762	0.760
32	**5.800**	1.224	3.098	-1.576	-0.713	0.896
40	**4.061**	-0.799	0.218	-3.311	-3.417	0.826
88	0.549	1.187	0.140	0.152	-0.564	**-4.103**
104	0.248	-0.970	0.552	-1.153	0.180	2.548
128	0.397	-3.034	-0.316	**-4.354**	-0.928	3.077
192	-1.804	-0.262	-1.955	**4.266**	-0.547	**-5.464**
320	1.369	0.382	1.168	-3.393	-0.844	2.382
344	0.542	0.164	0.898	-1.172	2.189	2.075
352	0.213	0.104	0.706	-0.314	3.177	1.686

[a]Euro per 1000

Figure 7: Evaluation of the amount of public R&D aids on the logarithm of Innovation sales: Dose-response function

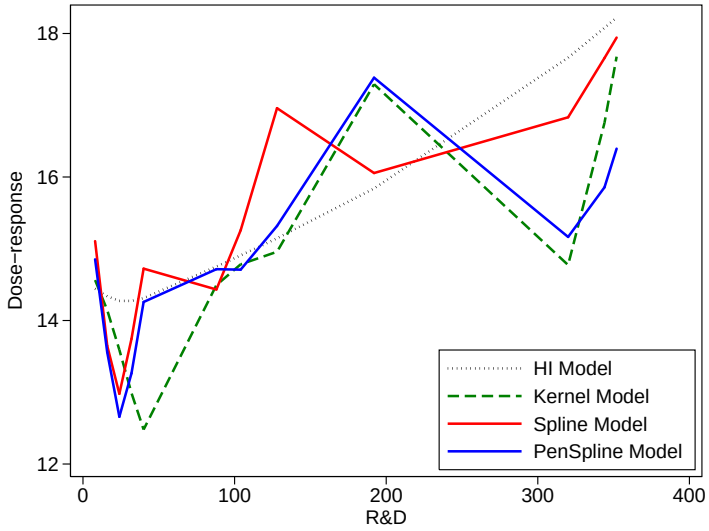
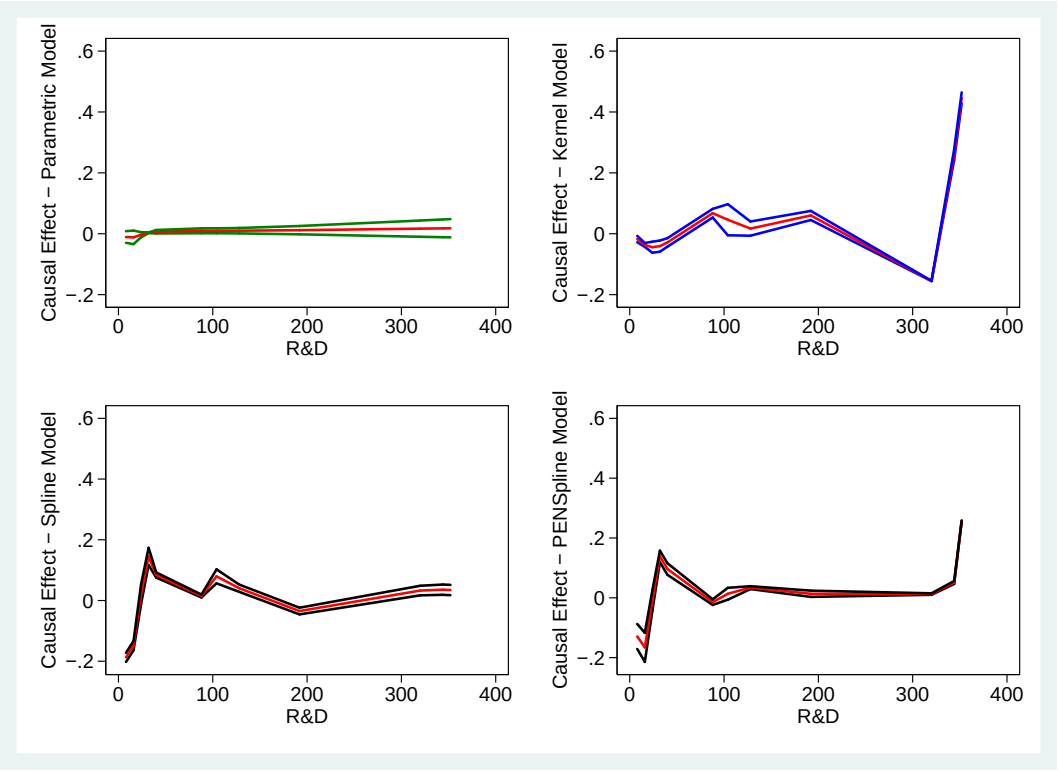


Figure 8: Evaluation of the amount of public R&D aids on the logarithm of Innovation sales: Estimated derivatives (95% confidence bands)



4 Conclusion

Severe model misspecification can lead to biased results. We address this issue proposing two new semiparametric estimators of the DRF based on spline methods, in the framework of continuous treatment regimes.

We conduct simulation exercises to investigate the performance of our techniques. We can argue that we get reliable estimates given the high performance of both the IW kernel and Spline estimators in the simulation. The coverage rates are often very high (95% for almost all treatment values), and both mean square errors and bias levels are very low if compared with the parametric technique. This is also more important if considering very small sample sizes. These results highlight the potential advantages of using nonparametric techniques, which allow one to avoid mis-specification problems.

In our application, we also provide empirical evidence on the impact of public R&D contributions on Luxembourgish firms' performances. We address these issues focusing on the causal effect of receiving different amounts of financial aid on innovation sales. We argue that estimating marginal effects of the intensity of economic supports provide more information regarding the effectiveness of the public interventions and might help policy makers in an effective allocation of public resources. Specifically, the nonparametric estimators show a non-linear relationship between innovation sales and amount of R&D contribution.

There are many directions for future research. The first is to extend this study by implementing a nonparametric specification of the GPS. Second, it could be of considerable interest to check the presence of unobservable heterogeneity sources and analyze the robustness of our results with respect to the underlying identifying assumptions, through appropriate sensitivity analyses.

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