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A Stata package for the application of semiparametric estimators of dose–response functions

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Abstract. In many observational studies, the treatment may not be binary or categorical but rather continuous, so the focus is on estimating a continuous dose–response function. In this article, we propose a set of programs that semiparametrically estimate the dose–response function of a continuous treatment under the unconfoundedness assumption. We focus on kernel methods and penalized spline models and use generalized propensity-score methods under continuous treatment regimes for covariate adjustment. Our programs use generalized linear models to estimate the generalized propensity score, allowing users to choose between alternative parametric assumptions. They also allow users to impose a common support condition and evaluate the balance of the covariates using various approaches. We illustrate our routines by estimating the effect of the prize amount on subsequent labor earnings for Massachusetts lottery winners, using data collected by Imbens, Rubin, and Sacerdote (2001, American Economic Review, 778–794).

Keywords: st0352, drf, dose–response function, generalized propensity score, kernel estimator, penalized spline estimator, weak unconfoundedness

1 Introduction

The evaluation process in economics, sociology, law, and many other fields generally relies on applying nonexperimental techniques to estimate average treatment effects.
Propensity-score methods (Rosenbaum and Rubin 1983) are attractive empirical tools to balance the distribution of covariates between treatment groups and compare the groups in terms of observed covariates. Under the unconfoundedness assumption, which requires that potential outcomes are independent of the treatment conditional on the observed covariates, propensity-score methods allow one to eliminate (or at least reduce) the potential bias in treatment-effects estimates in observational studies. Most applications aim to evaluate causal effects of a binary treatment. There is extensive literature on identifying and estimating causal effects of binary treatments (for example, Imbens and Wooldridge [2009]; Stuart [2010]; Angrist, Imbens, and Rubin [1996]), and many statistical software packages have built-in or add-on functions for implementing methods to estimate causal effects of programs or policies. For example, Becker and Ichino (2002) developed a set of programs (pscore.ado) for estimating average treatment effects on the treated using propensity-score matching by focusing on four matching estimators: nearest-neighbor, radius, kernel, and stratification matching. More recently, building on the work of Becker and Ichino (2002), Dorn (2012) proposed a routine that helps improve covariate balance, and so the specification of the propensity-score model, using data-driven approaches.

In many empirical studies, treatments may take on many values, implying that participants in the study may receive different treatment levels. In such cases, one may want to assess the heterogeneity of treatment effects arising from variation in the amount of treatment exposure, that is, estimate a dose–response function (DRF). Over the past years, propensity-score methods have been generalized and applied to multivalued treatments (for example, Imbens [2000]; Lechner [2001]) and, more recently, to continuous treatments and arbitrary treatment regimes (for example, Hirano and Imbens [2004]; Imai and van Dyk [2004]; Flores et al. [2012]; Bia and Mattei [2012]; Kluve et al. [2012]).

In this article, we build on work by Hirano and Imbens (2004), who introduced the concept of the generalized propensity score (GPS) and used it to estimate the entire DRF of a continuous treatment. Hirano and Imbens (2004) used a parametric partial-mean approach to estimate the DRF. Here we focus on semiparametric techniques. Specifically, we present a set of programs that allows users to i) estimate the GPS under alternative parametric assumptions using generalized linear models;\(^1\) ii) impose the common support condition as defined in Flores et al. (2012) and assess the balance of covariates after adjusting for the estimated GPS; and iii) estimate the DRF using the estimated GPS by applying either the nonparametric inverse-weighting (IW) kernel estimator developed in Flores et al. (2012) or a new set of semiparametric estimators based on penalized spline techniques.

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1. Guardabascio and Ventura (2014) proposed the routine gpscore2.ado to estimate the GPS using generalized linear models.
We use a dataset collected by Imbens, Rubin, and Sacerdote (2001) to illustrate these programs and to evaluate the effect of the prize amount on subsequent labor earnings of winners of the Megabucks lottery in Massachusetts in the mid-1980s. We implement our programs to semiparametrically estimate the average potential postwinning labor earnings for each lottery prize amount. The prize is obviously assigned at random, but unit and item nonresponse lead to a self-selected sample where the prize amount received is no longer independent of background characteristics.

This article is organized as follows: Section 2 describes the methodological approach we refer to in the analysis. Section 3 introduces the GPS model and the semiparametric estimators of the DRF. Sections 3 and 3.2 show, respectively, the syntax and the options of the `drf` command. Section 5 illustrates the methods and the program using data from Imbens, Rubin, and Sacerdote (2001). Section 6 concludes.

2 Estimation strategy

We estimate a continuous DRF that relates each value of the dose (for example, lottery prize amount) to the outcome variable (for example, postwinning labor earnings) within the potential-outcome approach to causal inference (Rubin 1974, 1978). Formally, consider a set of $N$ individuals, and denote each of them by subscript $i$: $i = 1, \ldots, N$. Under the stable unit treatment value assumption (Rubin 1980, 1990), for each unit $i$, there is a set of potential outcomes $\{Y_i(t)\}_{t \in T}$, where $T$ is a subset of the real line, $T \subset \mathcal{R}$. We are interested in estimating the average DRF, $\mu(t) = E\{Y_i(t)\}$.

For each individual $i$, we observe a vector of pretreatment covariates, $X_i$, the received treatment level, $T_i$, and the corresponding value of the outcome for this treatment level, $Y_i = Y_i(T_i)$.

The central assumption of our approach is that the assignment to treatment levels is weakly unconfounded given the set of observed variables, that is, $Y_i(t) \perp T_i | X_i$ for all $t \in T$ (Hirano and Imbens 2004). This assumption is described as weak unconfoundedness because it requires only conditional independence for each potential outcome $Y_i(t)$ rather than joint independence of all potential outcomes.

Under weak unconfoundedness, we can apply the GPS techniques for continuous treatments introduced by Hirano and Imbens (2004). Let $r(t, x) = f_{T | X}(t | x)$ be the conditional density of the treatment given the covariates. The GPS is defined as $R_i = r(T_i, X_i)$. The GPS is a balancing score (Rosenbaum and Rubin 1983; Hirano and Imbens 2004); that is, within strata with the same value of $r(t, x)$, the probability that $T = t$ does not depend on the value of $X$. The weak unconfoundedness assumption, combined with the balancing score property, implies that assignment to treatment is weakly unconfounded given the GPS. Formally,

$$f_T \{t | r(t, X_i), Y_i(t)\} = f_T \{t | r(t, X_i)\}$$

for every $t \in T$ (theorem 1.2.2 in Hirano and Imbens [2004]). Thus any bias associated with differences in the distribution of covariates across groups with different treatment levels can be removed using the GPS. Formally, Hirano and Imbens (2004) showed that
if the assignment to the treatment is weakly unconfounded given pretreatment variables \(X_i\), then \(\mu(t) = E[\beta(t) | r(t, X_i)]\), where \(\beta(t, r) = E[Y_i(t) | r(t, X_i) = r] = E[Y_i | T_i = t, R_i = r]\) (theorem 1.3.1 in Hirano and Imbens [2004]).

3 Inference

We use two-step semiparametric estimators of the DRF. The first step is to parametrically model and estimate the GPS, \(R_i = r(T_i, X_i)\), and to assess the common support condition and the balance of the covariates. The second step is to estimate the average DRF, \(\mu(t)\), using either the nonparametric IW kernel estimator proposed by Flores et al. (2012) or a semiparametric spline-based estimator. Here we describe these two steps, implemented in the routine \texttt{drf}.

3.1 Estimation of the GPS

The first part of the \texttt{drf} program estimates the GPS, allows users to impose an overlap condition, and tests the balancing property of the GPS.

The GPS is estimated parametrically and alternative distributional assumptions can be specified. Specifically, we assume that

\[
g(T_i | X_i) \sim \psi \{h(\gamma, X_i), \theta\}
\]

where \(g\) is a link function, \(\psi\) is a probability density function, \(h\) is a flexible function of the covariates depending on an unknown parameter vector \(\gamma\), and \(\theta\) is a scale parameter. In the \texttt{drf} program, we consider the Gaussian, inverse Gaussian, and Gamma distributions using the identity function, the logarithm, and the power function as link functions. We also implement a two-parameter beta distribution to address evaluation problems where the treatment variable takes on values in the interval \((0, 1)\), representing, for instance, a proportion. We use maximum likelihood methods to fit these models by using the official Stata command \texttt{glm} (see \cite{R glm}) or the user-written package \texttt{betafit} (Buis, Cox, and Jenkins 2003).\(^2\)

An important issue in GPS applications is determining the “common support” or “overlap region”. The \texttt{drf} program allows users to do this by using the approach proposed by Flores et al. (2012). Specifically, the sample is first divided into \(K\) intervals according to the distribution of the treatment, cutting at the \(100 \times (k/K)\)th, \(k = 1, \ldots, K - 1\) percentiles of the treatment empirical distribution. Let \(q_k\), \(k = 1, \ldots, K\), denote these intervals, and let \(Q_i\) be the interval unit \(i\) belongs to: \(T_i \in Q_i\). For each interval \(q_k\), let \(\hat{R}_i^k\) be the GPS evaluated at the median level of the treatment in that interval for unit \(i\), which is calculated for all units. The common support region with respect to \(q_k\), denoted by \(CS_k\), is obtained by comparing the support of the distribution

\(^2\)\texttt{betafit} (version 1.0.0 at the time of this writing) is available from the Statistical Software Components archive (or \texttt{findit betafit}) and must be installed separately from \texttt{drf}.
Semiparametric estimators of dose–response functions

of \( \hat{R}^{k}_i \) for those units with \( Q_i = q_k \) with that of units with \( Q_i \neq q_k \) and is given by the subsample

\[
CS_k = \left\{ i : \hat{R}^{k}_i \in \left[ \max \left( \min_{j:Q_j=q_k} \hat{R}^{k}_j, \min_{j:Q_j\neq q_k} \hat{R}^{k}_j \right), \min \left( \max_{j:Q_j=q_k} \hat{R}^{k}_j, \max_{j:Q_j\neq q_k} \hat{R}^{k}_j \right) \right] \right\}
\]

Finally, the sample is restricted to units that are comparable across all the \( K \) intervals simultaneously by keeping only individuals who are simultaneously in the common support region for all \( k \) intervals. Therefore, the common-support subsample is given by

\[
CS = \bigcap_{k=1}^{K} CS_k.
\]

As in applications of standard propensity-score methods, in GPS applications, it is crucial to evaluate how well the estimated GPS balances the covariates. Several methods can be applied to evaluate the balancing properties of the GPS. The drf command implements two approaches: an approach based on blocking on the GPS and an approach that uses a likelihood-ratio (LR) test. The “blocking on the GPS” approach was proposed by Hirano and Imbens (2004), and it is implemented in the drf routine using two-sided \( t \) tests or Bayes factors (see also Bia and Mattei [2008]). The second approach was proposed by Flores et al. (2012), who suggested using an LR test to compare an unrestricted model for \( T_i \) that includes all covariates and the GPS (up to a cubic term) with a restricted model that sets the coefficients of all covariates equal to zero. If the GPS sufficiently balances the covariates, then the covariates should have little explanatory power conditional on the GPS.

3.2 Estimation of the dose–response function

We estimate the DRF by applying spline and kernel techniques. The first technique is implemented using a partial mean approach (Newey 1994). Specifically, for the penalized spline methods, we first estimate the conditional expectation of the observed outcome \( Y_i \) given the treatment actually received, \( T_i \), and the GPS previously estimated in the first stage, \( \hat{R}_i \), using bivariate penalized spline smoothing based on i) additive spline bases; ii) tensor products of spline bases; or iii) radial basis functions (for example, Ruppert, Wand, and Carroll [2003]). Mixed models provide a representation of the penalized splines that allows smoothing to be done using mixed-model methodologies and software. In our routine, we use the Stata routine xtmixed, renamed mixed in Stata 13, to fit penalized spline regressions. The average DRF at \( t \) is then estimated by averaging the estimated regression function over the estimated score function evaluated at the specific treatment level \( t \); that is, \( \hat{R}^{k}_i \equiv \hat{\tau}(t, X_i) \).

3. An alternative approach, which is not implemented in our program, was proposed by Kluve et al. (2012). It consists of regressing each covariate on the treatment variable and comparing the significance of the coefficients for specifications with and without conditioning on the GPS.
The simplest bivariate penalized spline smoothing relies on additive spline bases, which can be formally defined in our setting as

$$E \left( Y_i | T_i, \hat{R}_i \right) = a_0 + a_t T_i + a_{tr} \hat{R}_i + \sum_{k=1}^{K^t} u_k^t (T_i - k^t_k)_+ + \sum_{k=1}^{K^r} u_k^r \left( \hat{R}_i - k^r_k \right)_+$$

where for any number $z$, $z_+$ is equal to $z$ if $z$ is positive and is equal to 0 otherwise, and $k^t_1 < \cdots < k^t_{K^t}$ and $k^r_1 < \cdots < k^r_{K^r}$ are $K^t$ and $K^r$ distinct knots in the support of $T$ and the estimated GPS, $\hat{R}_i$, respectively.

The additive models have many attractive features, one being their simplicity. However, an additive model may not provide a satisfactory fit, so more complex models including interaction terms are required. To this end, we consider tensor product bases, which are obtained by forming all pairwise products of the basis functions $1, T_i, (T_i - k^t_1), \ldots, (T_i - k^t_{K^t}), (\hat{R}_i, \hat{R}_i - k^r_1), \ldots, (\hat{R}_i - k^r_{K^r})$. Formally,

$$E \left( Y_i | T_i, \hat{R}_i \right) = a_0 + a_t T_i + a_{tr} \hat{R}_i + a_{tr} T_i \hat{R}_i + \sum_{k=1}^{K^t} u_k^t (T_i - k^t_k)_+ + \sum_{k=1}^{K^r} u_k^r \left( \hat{R}_i - k^r_k \right)_+ + \sum_{k=1}^{K^t} v_k^t T_i \left( \hat{R}_i - k^r_k \right)_+ + \sum_{k=1}^{K^r} v_k^r \left( T_i - k^t_k \right)_+ \left( \hat{R}_i - k^r_k \right)_+$$

Estimation problems may arise when the tensor product approach is applied, especially if the sample size is relatively small. When these problems arise, the `drf` program alerts users and suggests they adopt an additive model instead.

As an alternative to tensor product splines, we propose to use the so-called radial basis functions, which are basis functions of the form $C\{||(t, r)' - (k, k')||\}$ for some univariate function $C$. Here we consider the following function

$$C\left\{\left\| \begin{pmatrix} t \\ r \end{pmatrix} - \begin{pmatrix} k^t_k \\ k^r_k \end{pmatrix} \right\| \right\} = \left\| \begin{pmatrix} t \\ r \end{pmatrix} - \begin{pmatrix} k^t_k \\ k^r_k \end{pmatrix} \right\|^2 \log \left\| \begin{pmatrix} t \\ r \end{pmatrix} - \begin{pmatrix} k^t_k \\ k^r_k \end{pmatrix} \right\|$$

where $\| \cdot \|$ is the Euclidean norm, and we assume that

$$E \left( Y_i | T_i, \hat{R}_i \right) = a_0 + a_t T_i + a_{tr} \hat{R}_i + a_{tr} T_i \hat{R}_i + \sum_{k=1}^{K} u_k C \left\{ \left\| \begin{pmatrix} T_i \\ \hat{R}_i \end{pmatrix} - \begin{pmatrix} k^t_k \\ k^r_k \end{pmatrix} \right\| \right\}$$

where $u_1, \ldots, u_k$ are random variables with mean 0 and variance–covariance matrix $\text{Cov}(u) = \sigma_u^2 (\Omega_k^{-1/2} (\Omega_k^{-1/2})')$, with $\Omega_k = \left[ C \left\{ \left\| \begin{pmatrix} k^t_k \\ k^r_k \end{pmatrix} - \begin{pmatrix} k^t_{k'} \\ k^r_{k'} \end{pmatrix} \right\| \right\} \right]_{1 \leq k, k' \leq K}$.

Given the estimated parameters of the regression functions (1), (2), or (3), the average potential outcome at treatment level $t$ is estimated by averaging the estimated regression function over $\hat{R}_i^t$. 

Flores et al. (2012) proposed to estimate the DRF using a nonparametric IW estimator based on kernel methods. In this approach, the estimated scores are used to weight observations to adjust for covariate differences. Let $K(u)$ be a kernel function with the usual properties, and let $h$ be a bandwidth satisfying $h \to 0$ and $Nh \to \infty$ as $N \to \infty$. The IW approach is implemented using a local linear regression of $Y$ on $T$ with weighted kernel function $\tilde{K}_{h,X}(T_i - t) = K_h(T_i - t)/\tilde{R}_i$, where $K_h(z) = h^{-1}K(z/h)$. Formally, the IW kernel estimator of the average DRF is defined as

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

where $S_j(t) = \sum_{i=1}^{N} \tilde{K}_{h,X}(T_i - t)(T_i - t)^j$ and $D_j(t) = \sum_{i=1}^{N} \tilde{K}_{h,X}(T_i - t)(T_i - t)^jY_i$, $j = 0, 1, 2$.

We implement the IW estimator using a normal kernel. By default, the global bandwidth is selected using the procedure proposed by Fan and Gijbels (1996), which estimates the unknown terms in the optimal global bandwidth by using a global polynomial of order $p + 3$, where $p$ is the order of the local polynomial fitted. However, users can also choose an alternative global bandwidth.

### 4 The drf command

#### 4.1 Syntax

```plaintext
drf varlist [if] [in] [weight], outcome(varname) treatment(varname) cutpoints(varname) index(string) nq_gps(#) method(type) [gps family(familyname) link(linkname) vce(vcetype) nolog(#) search common(#) numoverlap(#) test_varlist(varlist) test(type) flag(#) tpoints(vector) npoints(#) npercentiles(#) det delta(#) bandwidth(#) nknots(#) knots(#) standardized degree1(#) degree2(#) nknots1(#) knots2(#) knots1(#) knots2(#) additive estopts(string) ]
```

Note that the argument `varlist` represents the observed pretreatment variables, which are used to estimate the GPS. Note that `spacefill` must be installed (Bia and Van Kerm 2014).

#### 4.2 Options

**Required**

`outcome(varname)` specifies that `varname` is the outcome variable.

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4. `spacefill` requires the Mata package `moremata` (Jann 2005).
treatment(varname) specifies that varname is the treatment variable.

cutpoints(varname) divides the range or set of the possible treatment values, \( T \), into intervals within which the balancing properties of the GPS are checked using a “blocking on the GPS” approach. varname is a variable indicating to which interval each observation belongs. This option is required unless flag() is set to 0 (see below).

index(string) specifies the representative point of the treatment variable at which the GPS must be evaluated within each treatment interval specified in cutpoints(). string identifies either the mean (string = mean) or a percentile (string = p1, ..., p100). This is used when checking the balancing properties of the GPS using a “blocking on the GPS” approach. This option is required unless flag() is set to 0 (see below).

nq_gps(#) specifies that for each treatment interval defined in cutpoints(), the values of the GPS evaluated at the representative point index() have to be divided into # (# ∈ \{1, ..., 100\}) intervals, defined by the quantiles of the GPS evaluated at the representative point index(). This is used when checking the balancing properties of the GPS using a “blocking on the GPS” approach. This option is required unless flag() is set to 0 (see below).

method(type) specifies the type of approach to be used to estimate the DRF. The approaches are bivariate-penalized splines (type = mtspline), bivariate penalized radial splines (type = radialpspline), or IW kernel (type = iwkernel).\(^5\)

Global options

gps stores the estimated generalized propensity score in the gpscore variable that is added to the dataset.\(^6\)

family(familyname) specifies the distribution used to estimate the GPS. The available distributional families are Gaussian (normal) (family(gaussian)), inverse Gaussian (family(igaussian)), Gamma (family(gamma)), and Beta (family(beta)). The default is family(gaussian). The Gaussian, inverse Gaussian, and Gamma distributional families are fit using glm, and the beta distribution is fit using betafit.

The following four options are for the glm command, so they can be specified only when the Gaussian, inverse Gaussian, or Gamma distribution is assumed for the treatment variable.

link(linkname) specifies the link function for the Gaussian, inverse Gaussian, and Gamma distributional families. The available links are link(identity), link(log), and link(pow), and the default is the canonical link for the family() specified (see help for glm for further details).

---

5. The subroutines mtpspline and radialpspline are called, respectively, when estimators with penalized splines (type = mtspline) and radial penalized splines (type = radialpspline) are used.
6. This option must not be specified when running the bootstrap.
Semiparametric estimators of dose–response functions

\texttt{vce(vcetype)} specifies the type of standard error reported for the GPS estimation when the Gaussian, inverse Gaussian, or Gamma distribution is assumed for the treatment variable. \texttt{vcetype} may be \texttt{oim}, \texttt{robust}, \texttt{cluster clustvar}, \texttt{eim}, \texttt{opg}, \texttt{bootstrap}, \texttt{jackknife}, \texttt{hac}, \texttt{kernel}, \texttt{jackknife1} (see \texttt{help glm} for further details).

\texttt{nolog(#)} is a flag (\# = 0, 1) that suppresses the iterations of the algorithm toward eventual convergence when running the \texttt{glm} command. The default is \texttt{nolog(0)}.

\texttt{search} searches for good starting values for the parameters of the generalized linear model used to estimate the generalized propensity score (see \texttt{help glm} for further details).

**Overlap options**

\texttt{common(#)} is a flag (\# = 0, 1) that restricts the inference to the subsample satisfying the common support condition when it is implemented (\# = 1). The default is \texttt{common(1)}.

\texttt{numoverlap(#)} specifies that the common support condition is imposed by dividing the sample into \# groups according to \# quantiles of the treatment distribution. By default, the sample is divided into 5 groups, cutting at the 20th, 40th, 60th, and 80th percentiles of the distribution if \texttt{common(1)}.

**Balancing property assessment options**

\texttt{test(varlist)} specifies that the balancing property must be assessed for each variable in \texttt{varlist}. The default \texttt{test(varlist)} consists of all the variables used to estimate the GPS.

\texttt{test(type)} allows users to specify whether the balancing property is to be assessed using a “blocking on the GPS” approach employing either standard two-sided \texttt{t} tests (\texttt{test(t.test)}) or Bayes factors (\texttt{test(Bayes.factor)}) or using a model-comparison approach with an \texttt{LR} test (\texttt{test(L.\_like)}).

The “blocking on the GPS” approach using standard two-sided \texttt{t} tests provides the values of the test statistics before and after adjusting for the GPS for each pretreatment variable included in \texttt{test(varlist)} and for each prefixed treatment interval specified in \texttt{cutpoints()}. Specifically, let \(p\) be the number of control variables in \texttt{test(varlist)} and let \(H\) be the number of treatment intervals specified in \texttt{cutpoints()}. Then the program calculates and shows \(p \times H\) values of the test statistic before and after adjusting for the GPS, where the adjustment is done by dividing the values of the GPS evaluated at the representative point \texttt{index()} into the number of intervals specified in \texttt{mq.gps()}. (See Hirano and Imbens [2004] for further details.)

The model-comparison approach uses a \texttt{LR} test to compare an unrestricted model for \(T_i\), including all the covariates and the GPS (up to a cubic term), with a restricted model that sets the coefficients of all covariates to zero. By default, both the “blocking on the GPS” approach and the model-comparison approach are applied.
flag(#) allows the user to specify that drf estimates the GPS without performing the balancing test. The default is flag(1), which means that the balancing property is assessed.

**DRF options**

**tpoints(vector)** indicates that the DRF is evaluated at each level of the treatment in vector. By default, the drf program creates a vector with jth element equal to the jth observed treatment value. This option cannot be used with npoints() or npercentiles() (see below).

**npoints(#)** indicates that the DRF is evaluated at each level of the treatment belonging to a set of evenly spaced values \( t_0, t_1, \ldots, t_{\#} \) that cover the range of the observed treatment. This option cannot be used with tpoints() (see above) or npercentiles() (see below).

**npercentiles(#)** indicates that the DRF is evaluated at each level of the treatment corresponding to the percentiles \( t_{q0}, t_{q1}, \ldots, t_{q\#} \) of the treatment’s empirical distribution. This option cannot be used with tpoints() or npoints() (see above).

**det** displays more detailed output on the DRF estimation. When det is not specified, the program displays only the chosen DRF estimator: method(radialpspline), method(mtpspline), or method(iwkernel).

**delta(#)** specifies that drf also estimate the treatment-effect function \( \mu(t + \#) - \mu(t) \). The default is delta(0), which means that drf estimates only the DRF, \( \mu(t) \).

**Options for the IW kernel estimator (iwkernel)**

**bandwith(#)** specifies the bandwidth to be used. By default, the global bandwidth is chosen using the automatic procedure described in Fan and Gijbels (1996). This procedure estimates the unknown terms in the optimal global bandwidth by using a global polynomial of order \( p + 3 \), where \( p \) is the order of the local polynomial fitted.

**Options for the radial penalized spline estimator (radialpspline)**

**nknots(#)** specifies the number of knots to be selected in the two-dimensional space of the treatment variable and the GPS. The default is \( \text{nknots} \left( \max(20, \min(n/4, 150)) \right) \), where \( n \) is the number of unique \((T_i, R_i)\) (Ruppert, Wand, and Carroll 2003). When this option is specified, the subroutines radialpspline and spacefill (Bia and Van Kerm 2014) are called. This option cannot be used with the knots() option (see below).
**Semiparametric estimators of dose–response functions**

`knots(numlist)` specifies the list of knots for the treatment and the GPS variable. This option cannot be used with the `nknots()` option (see above).

`standardized` implies that the `spacefill` algorithm standardizes the treatment variable and the GPS variables before selecting the knots. The knots are chosen using the standardized variables.

**Options for the tensor-product penalized spline estimator (mtpspline)**

`degree1(#)` specifies the power of the treatment variable included in the penalized spline model. The default is `degree1(1)`.

`degree2(#)` specifies the power of the GPS included in the penalized spline model. The default is `degree2(1)`.

`nknots1(#)` specifies the number (#) of knots for the treatment variable. The location of the $K_k$th knot is defined as \( \{(k + 1)/(# + 2)\}^{th} \) sample quantile of the unique $T_i$ for $k = 1, \ldots, #$. The default is `nknots1(max(5, min(n/4, 35)))`, where $n$ is the number of unique $T_i$ (Ruppert, Wand, and Carroll 2003). This option cannot be used with the `knots1(numlist)` option (see above).

`nknots2(#)` specifies the number (#) of knots for the GPS. The location of the $K_k$th knot is defined as \( \{(k + 1)/(# + 2)\}^{th} \) sample quantile of the unique $R_i$ for $k = 1, \ldots, #$. The default is `nknots2(max(5, min(n/4, 35)))`, where $n$ is the number of unique $R_i$ (Ruppert, Wand, and Carroll 2003). This option cannot be used with the `knots2()` option (see below).

`knots1(numlist)` specifies the list of knots for the treatment variable. This option cannot be used with the `nknots1()` option (see above).

`knots2(numlist)` specifies the list of knots for the GPS. This option cannot be used with the `nknots2()` option (see above).

`additive` allows users to implement penalized splines using the additive model without including the product terms.

**Mutual options for the tensor-product and radial penalized spline estimators**

Mutual options for the tensor-product and radial penalized spline estimators involve either the `mtpspline` subroutine or the `radialpspline` subroutine, depending on which estimator is used.

`estopts(string)` specifies all the possible options allowed when running the `xtmixed` models to fit penalized spline models (see `help xtmixed` for further details).
5 Example: The lottery dataset

We illustrate the methods and the programs discussed by reanalyzing data from a survey of Massachusetts lottery winners (see Imbens, Rubin, and Sacerdote [2001] for details on the survey). We focus on evaluating how the prize amount affects future labor earnings (from social security records). This example is also considered in Hirano and Imbens (2004).

The sample we use consists of 237 individuals who won a major prize in the lottery. The outcome of interest is earnings six years after winning the lottery (year6), and the treatment is the prize amount (prize). The lottery prize is randomly assigned, but there is substantial unit and item nonresponse as well as heterogeneity in the sample with respect to background characteristics. Thus it is more reasonable to conduct the analysis conditioning on the observed pretreatment variables under the weak unconfoundedness assumption.

Pretreatment variables are age, gender, years of high school, years of college, winning year, number of tickets bought, working status at the time of playing the lottery, and earnings s years before winning the lottery, s = 1, 2, ..., 6. To avoid results driven by outliers, we drop observations belonging to the upper 5% of the treatment variable distribution.

The output from running `drf`, shown below, is organized as follows. First, the GPS model and summary statistics of the estimated GPS are shown, and the common support is determined. The results show that 31 observations were dropped after we imposed the common support condition. Second, the balancing property is assessed. We specify the `test(L_like)` option for the balancing test, so results from only the model-comparison approach using the LR test are reported. The LR test shows that the GPS balances the covariates: they have little explanatory power conditional on the GPS. Indeed, the restricted model for Ti that excludes the covariates cannot be rejected at the usual significance levels (p-value is 0.284), whereas the restricted model that excludes the GPS is soundly rejected (p-value is 0).

```
use lotterydataset.dta
* we delete the extreme values (1 and 99 percentile)
drop if year6==.  (35 observations deleted)
summarize prize, de

<table>
<thead>
<tr>
<th>Percentiles</th>
<th>Smallest</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>5.3558</td>
</tr>
<tr>
<td>5%</td>
<td>10.08</td>
</tr>
<tr>
<td>10%</td>
<td>11.246</td>
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<tr>
<td>25%</td>
<td>17.034</td>
</tr>
<tr>
<td>50%</td>
<td>32.1835</td>
</tr>
<tr>
<td>75%</td>
<td>71.642</td>
</tr>
<tr>
<td>90%</td>
<td>137.27</td>
</tr>
<tr>
<td>95%</td>
<td>171.73</td>
</tr>
<tr>
<td>99%</td>
<td>305.09</td>
</tr>
</tbody>
</table>

Percentiles Smallest Largest
1% 5.3558 1.139
5% 10.08 5
10% 11.246 5.3558 Obs 202
25% 17.034 6.844 Sum of Wgt. 202
50% 32.1835 Mean 57.36918
75% 71.642 270.1 Std. Dev. 64.84194
90% 137.27 305.09 Variance 4204.477
95% 171.73 323.32 Skewness 2.821964
99% 305.09 484.79 Kurtosis 14.18278
```
Semiparametric estimators of dose–response functions

.drop if prize >= r(p95)
(11 observations deleted)
.replace year6 = year6/1000
year6 was long now double
(92 real changes made)
.matrix define tp = (10 20 30 40 50 60 70 80 90 100)
.set seed 2322
.drf agew owmhs owncoll male tixbot workthen yearm1 yearm2 yearm3 yearm4
> yearm5 yearm6, outcome(year6) treatment(prize) gps test(L_like)
> tpoints(tp) numoverlap(3) method(radialpspline) family(gaussian)
> link(log) nknots(10) nolog(1) search det delta(1)
*****************************************************
Algorithm to estimate the generalized propensity score
*****************************************************

Estimation of the propensity score

Generalized linear models
Optimization : ML
No. of obs = 191
Residual df = 178
Scale parameter = 1365.58
Deviance = 243073.1517 (1/df) Deviance = 1365.58
Pearson = 243073.1517 (1/df) Pearson = 1365.58
Variance function: V(u) = 1
[Gaussian]
Link function : g(u) = ln(u)
[Log]
AIC = 10.12285
BIC = 242138.2
Log likelihood = -953.731889

|     | Coef.  | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|-----|--------|-----------|-------|-------|---------------------|
| agew| 0.0158337 | 0.0053884 | 2.94 | 0.003 | 0.0052727 - 0.0263947 |
| owmhs| 0.0585063 | 0.0742126 | 0.79 | 0.430 | -0.0869477 - 0.2039603 |
| owncoll| -0.0108263 | 0.0389408 | -0.28 | 0.781 | -0.0871488 - 0.0654962 |
| tixbot| -0.0174202 | 0.0188308 | -0.93 | 0.355 | -0.0543279 - 0.0194875 |
| workthen| 0.0680442 | 0.1819285 | 0.37 | 0.708 | -0.2885291 - 0.4246174 |
| yearm1| -0.0033454 | 0.0102149 | -0.33 | 0.743 | -0.0233662 - 0.0166754 |
| yearm2| 0.0018299 | 0.0151926 | 0.12 | 0.904 | -0.0279471 - 0.0316069 |
| yearm3| -0.0190244 | 0.0134829 | -1.41 | 0.158 | -0.0454505 - 0.0074016 |
| yearm4| 0.0451296 | 0.0194034 | 2.33 | 0.020 | 0.0070997 - 0.0831596 |
| yearm5| -0.0094795 | 0.0147496 | -0.64 | 0.520 | -0.0383882 - 0.0194293 |
| yearm6| -0.0056688 | 0.0084792 | -0.66 | 0.511 | -0.0221877 - 0.0110501 |
| _cons| 2.534394 | 0.489911 | 5.17 | 0.000 | 1.574186 - 3.494602 |

Note: The common support condition is imposed
31 observations are dropped after imposing common support

---

**Percentiles Smallest**

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Small Value</th>
<th>Large Value</th>
<th>Mean Value</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>.00000774</td>
<td>.00000308</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5%</td>
<td>.00118</td>
<td>.0000774</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10%</td>
<td>.0033023</td>
<td>.0003646</td>
<td>Obs 160</td>
<td></td>
</tr>
<tr>
<td>25%</td>
<td>.0077024</td>
<td>.0004499</td>
<td>Sum of Wgt. 160</td>
<td></td>
</tr>
<tr>
<td>50%</td>
<td>.0092675</td>
<td>.002953</td>
<td></td>
<td></td>
</tr>
<tr>
<td>75%</td>
<td>.0103387</td>
<td>.0107928</td>
<td></td>
<td></td>
</tr>
<tr>
<td>90%</td>
<td>.0107851</td>
<td>.0107956</td>
<td>Skewness -1.419599</td>
<td></td>
</tr>
<tr>
<td>95%</td>
<td>.0107956</td>
<td>.0107957</td>
<td>Kurtosis 3.908883</td>
<td></td>
</tr>
</tbody>
</table>

---

End of the algorithm to estimate the gspcure

---

Log-Likelihood test for Unrestricted and Restricted Model

---

Generalized linear models

**Optimization : ML**

Scale parameter = 383.389

Deviance = 55208.02303 (1/df) Deviance = 383.389

Pearson = 55208.02303 (1/df) Pearson = 383.389

Variance function: V(u) = 1 [Gaussian]

Link function : g(u) = ln(u) [Log]

AIC = 8.881567

Log likelihood = -694.5253454 BIC = 54477.2

---

**GIM**

| Prize | GIM               | Coef. | Std. Err. | z    | P>|z|  | [95% Conf. Interval] |
|-------|-------------------|-------|-----------|------|------|----------------------|
| drf_gpscore | -139.9919 | 107.5174 | -1.30 | 0.193 | -350.7222 | 70.73837 |
| drf_gpscore2 | -46688.7 | 24107.57 | -1.90 | 0.058 | -92938.68 | 1561.268 |
| drf_gpscore3 | 4263995 | 1464344 | 2.90 | 0.004 | 1373634 | 7114055 |
| agew | .0067685 | .0036542 | 1.85 | 0.064 | -0.003935 | .139306 |
| ownhs | .0159357 | .034813 | 0.46 | 0.647 | -.0522974 | .0841687 |
| owncoll | .0146014 | .028585 | 0.51 | 0.609 | -.041463 | .0706192 |
| male | -.0071926 | .0945985 | -0.08 | 0.939 | -1.926022 | .178217 |
| tixbot | -.0120352 | .0108077 | -1.11 | 0.265 | -.033218 | .0091475 |
| workthen | -.0411355 | .122624 | -0.34 | 0.737 | -.2814743 | .1992032 |
| year1 | .0042786 | .0090239 | 0.53 | 0.594 | -.011448 | .0200852 |
| year2 | -.0129785 | .0123375 | -1.05 | 0.293 | -.0371595 | .0112024 |
| year3 | .0191091 | .015091 | 1.27 | 0.205 | -.0104687 | .048687 |
| year4 | .001562 | .0113064 | 0.14 | 0.890 | -.0205982 | .0237222 |
| year5 | -.008559 | .0116933 | -0.73 | 0.464 | -.0314774 | .0143595 |
| year6 | .0002114 | .00695 | 0.03 | 0.976 | -.0134105 | .0138332 |
| _cons | 4.74533 | .2786597 | 17.15 | 0.000 | 4.203088 | 5.287673 |
Semiparametric estimators of dose–response functions

---

### Restricted Model: Pretreatment variables are excluded

\[ \text{link}(E[T]) = \text{GPSCORE} + \text{GPSCORE}^2 + \text{GPSCORE}^3 \]

---

**Generalized linear models**

- **No. of obs**: 160
- **Residual df**: 156
- **Scale parameter**: 386.9127
- **Deviance**: 60358.37384 (1/df) Deviance: 386.9127
- **Pearson**: 60358.37384 (1/df) Pearson: 386.9127
- **Variance function**: \( V(u) = 1 \) [Gaussian]
- **Link function**: \( g(u) = \ln(u) \) [Log]
- **AIC**: 8.820758
- **Log likelihood**: -701.6606578
- **BIC**: 59566.65

| Coef.   | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|---------|-----------|-------|-------|---------------------|
| df_gscore | -84.75421 | 83.03918 | -1.02 | 0.307   | -247.508 | 77.99585 |
| df_gscore2 | -53755.36 | 20238.49 | -2.66 | 0.008   | -93422.08 | -14088.64 |
| df_gscore3 | 4533115 | 1287859 | 3.52 | 0.000   | 2008958 | 7057273 |
| _cons   | 5.034825  | 0.0706282 | 71.29 | 0.000   | 4.896396 | 5.173253 |

### Restricted Model: GPS terms are excluded \((\text{link}(E[T]) = X)\)

---

**Generalized linear models**

- **No. of obs**: 160
- **Residual df**: 147
- **Scale parameter**: 1311.924
- **Deviance**: 192852.8661 (1/df) Deviance: 1311.924
- **Pearson**: 192852.8661 (1/df) Pearson: 1311.924
- **Variance function**: \( V(u) = 1 \) [Gaussian]
- **Link function**: \( g(u) = \ln(u) \) [Log]
- **AIC**: 10.09489
- **Log likelihood**: -794.5908861
- **BIC**: 192106.8

| Coef.   | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|---------|-----------|-------|-------|---------------------|
| age     | 0.0196754 | 0.0078967 | 2.49 | 0.013   | 0.0041982 | 0.0351255 |
| ownhs   | 0.0445558 | 0.0879733 | 0.51 | 0.613   | -0.1278687 | 0.2169802 |
| owncoll | 0.0102703 | 0.0484571 | 0.21 | 0.832   | -0.0847039 | 0.1052455 |
| male    | 0.380062  | 0.1676205 | 2.27 | 0.023   | 0.051476 | 0.7085364 |
| tixbot  | -0.0179112 | 0.0212375 | -0.84 | 0.399   | -0.0595359 | 0.0237135 |
| workthen | 0.1593496 | 0.2189032 | 0.73 | 0.467   | -0.2696929 | 0.5883921 |
| yearm1  | 0.018368  | 0.0119526 | 1.52 | 0.128   | -0.0075090 | 0.0392624 |
| yearm2  | -0.0347405 | 0.0256188 | -1.36 | 0.175   | -0.0849524 | 0.0154713 |
| yearm3  | -0.0074285 | 0.0246222 | -0.30 | 0.763   | -0.0575656 | 0.0409086 |
| yearm4  | 0.0487374 | 0.0278511 | 1.75 | 0.080   | 0.0058497 | 0.1033245 |
| yearm5  | -0.013943  | 0.018552 | -0.75 | 0.452   | -0.0503042 | 0.0224183 |
| yearm6  | 0.000416  | 0.0150639 | 0.03 | 0.978   | -0.0291088 | 0.0299408 |
| _cons   | 2.285246  | 0.6383848 | 3.58 | 0.000   | 1.034035 | 3.538457 |
Then we estimate the DRF and the treatment-effect function, which represents the marginal propensity to earn out of the yearly prize money, using both penalized spline techniques and the \( \text{IW} \) kernel estimator. Following Hirano and Imbens (2004), we obtain the estimates of these functions at 10 different prize-amount values, considering increments of $1,000 between $10,000 and $100,000 for the estimation of the treatment-effect function. Note that we scaled the prize amount by dividing it by $1,000. To avoid redundancies, we show details on the output from running \texttt{drf} for only the radial penalized spline estimator (\texttt{method(radialpspline)}). Note that the \texttt{det} option is specified, so details on estimating the DRF are shown.

\begin{verbatim}
********************
DRF estimation
********************
Radial penalized spline estimator
  Run 1 .. (Cpq = 383.37)
  Run 2 .. (Cpq = 427.99)
  Run 3 ... (Cpq = 388.19)
  Run 4 .. (Cpq = 365.61)
  Run 5 ... (Cpq = 399.08)
Performing EM optimization:
Performing gradient-based optimization:
  Iteration 0: log restricted-likelihood = -509.60164
  Iteration 1: log restricted-likelihood = -509.60164
  Iteration 2: log restricted-likelihood = -509.60164
  Iteration 3: log restricted-likelihood = -509.60164
\end{verbatim}
Semiparametric estimators of dose–response functions

Computing standard errors:
Mixed-effects REML regression
Group variable: _all
Number of obs = 129
Number of groups = 1
Obs per group: min = 129
avg = 129.0
max = 129
Wald chi2(2) = 5.01
Log restricted-likelihood = -509.58286
Prob > chi2 = 0.0818

|         | Coef. | Std. Err. | z    | P>|z| | [95% Conf. Interval] |
|---------|-------|-----------|------|-----|----------------------|
| prize   | -.2582684 | .215657  | -1.20 | 0.231 | -.6809484 .1644115   |
| drf_gpscore | -1355.627 | 897.2735 | -1.51 | 0.131 | -3114.25 402.997 |
| _cons   | 34.56937  | 11.09994 | 3.11 | 0.002 | 12.8139   56.32485 |

Random-effects Parameters
<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Err.</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>_all: Identity</td>
<td>.0285723</td>
<td>.0584111</td>
</tr>
<tr>
<td>sd(Residual)</td>
<td>13.36947</td>
<td>.8725761</td>
</tr>
</tbody>
</table>

LR test vs. linear regression: chibar2(01) = 0.06
Prob >= chibar2 = 0.4072

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. Err.</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>c1</td>
<td>15.131775</td>
<td>12.106819</td>
<td>5.376398 5.2519104 6.0217689 5.5866336</td>
</tr>
<tr>
<td>c2</td>
<td>9.376398</td>
<td>7.2519104</td>
<td>6.0217689 5.5866336</td>
</tr>
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. matrix C = e(b)
. drop gpscore
. set seed 2322
Figures 1 and 2 show the estimates of the DRF and the treatment-effect function by using the semiparametric techniques implemented in the `drf` routine and a parametric approach. The parametric estimates are derived using the `doseresponse` routine (Bia and Mattei 2008), which follows the parametric approach originally proposed by Hirano and Imbens (2004). As can be seen in figures 1 and 2, the two penalized spline estimators and the $IW$ kernel estimator lead to similar results: the DRFs have a $U$ shape (which is more tenuous in the case of the radial spline method) and the treatment-effect functions have irregular shapes increasing over most of the treatment range and decreasing for high treatment levels. The parametric approach shows quite a different picture. The DRF goes down sharply for low prize amounts and follows an inverse $J$ shape for prize amounts greater than $20,000. The treatment-effect function reaches a maximum around $30,000, and then it slowly decreases.

7. The code to derive the graphs is shown here for only the radial penalized spline estimator.
Semiparametric estimators of dose–response functions

Figure 1. Estimated dose–response functions
Figures 3 and 4 show the DRFs and the treatment-effect functions estimated using the semiparametric and parametric techniques, now accompanied by pointwise 95% confidence bands. The confidence bands are based on a normal approximation using bootstrap standard errors, which are computed calling the `drf` program (or `doseresponse` program) in the `bootstrap` command.\footnote{The radial spline-based models may produce slightly different estimates in different runs and when using the `bootstrap` command. This happens because within those models, an optimal set of “design points” is chosen via random selection of the knot values using the `spacefill` algorithm (see Bia and Van Kerm [2014] for further details). Some selected sets of knots may raise convergence issues depending on the data. Thus we recommend that users set a seed before running the `drf` code to make the results replicable.}
Figure 3. 95% confidence bands for the dose–response functions
Figure 4. 95% confidence bands for the treatment-effect functions

The example allows us to highlight two important points. First, figures 3 and 4 show that differences in the point estimates and their precision among the three semi-parametric estimators are more pronounced for low and high treatment levels. This is because our data are sparse for lower and higher values of the treatment. Because of the nonparametric methods we use, estimation becomes noisier and the parameters are estimated less precisely in regions of the data with few observations, which is reflected in the wider confidence intervals. This is particularly evident for the radial spline approach, which seems to be more sensitive to the sample size than the IW and penalized splines estimators are. Second, it is clear from figures 3 and 4 that the parametric estimator produces much tighter confidence bands relative to the semiparametric estimators. This is due to the additional structure imposed by the parametric estimator, which allows extrapolation from regions where data are abundant to regions where data are scarce. However, if the assumptions behind the parametric structure are incorrect, the results, including their precision, are likely misleading.

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9. In particular, there are very few observations for prizes lower than $15,000 and greater than $40,000.
6 Conclusion

We develop a program where we implement semiparametric estimators of the DRF based on the GPS, assuming that assignment to the treatment is weakly unconfounded given pretreatment variables. We propose three semiparametric estimators: the IW kernel estimator developed in Flores et al. (2012) and two estimators using penalized spline methods for bivariate smoothing. We use data from a survey of Massachusetts lottery winners to illustrate the proposed methods and program. We find that the semiparametric estimators provide estimates of the DRF and the treatment-effect function that are substantially different from those obtained when using the parametric approach originally proposed in Hirano and Imbens (2004). All the semiparametric estimators agree on a U-shaped DRF, which contrasts with the estimated inverse J shape uncovered by the parametric estimator. Although we cannot draw a firm conclusion about the relative performance of the estimators based on one dataset, we argue that a misspecification of the conditional expectation of the outcome given treatment and GPS could result in inappropriate removal of self-selection bias and in misleading estimates of the DRF. Therefore, it is advisable to also use semiparametric estimators that account for complicated structures that are difficult to model parametrically. Conversely, semiparametric estimators can be sensitive to the sample size and might not perform well in regions with few observations.

7 Acknowledgments

This research is part of the “Estimation of direct and indirect causal effects using semiparametric and nonparametric methods” project supported by the Luxembourg “Fonds National de la Recherche”, which is cofunded under the Marie Curie Actions of the European Commission (FP7-COFUND).

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