Person-centered treatment (PeT) effects: Individualized treatment effects using instrumental variables

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Abstract

I describe a command, petiv, that uses a local instrumental variables (LIV) approach to estimate person-centered treatment (PeT) effects for a variety of specifications for the LIV estimand as outlined in Basu (2014). The petiv command creates a new variable in the dataset that contains the PeT effects for each individual in the dataset. However, the command takes the validity of the instrumental variables(s) and the specification of the LIV estimand as given. Appropriateness of these features of an LIV analysis should be determined prior to running the petiv command. The individual effects can be used to answer a variety of distributional questions and can also be easily aggregated to obtain mean treatment effect estimates.

Keywords: petiv, local instrumental variable methods, person-centered treatment effects, treatment effects heterogeneity.
1. Introduction

In the evaluation literature, nuanced treatment effects are most popularly characterized by conditional average treatment effects (CATE) where an average treatment effect is estimated conditional on certain values of observed covariates over which treatment effects vary. For example, if age is the only observed risk factor, one can establish a conditional effect of surgery versus active surveillance on mortality for patients of age 60 years diagnosed with clinically localized prostate cancer. This is an average effect for all 60 year olds in this condition. However, does this estimate apply to all men with clinically localized prostate cancer at age 60 years? Certainly not, as there may be many other factors that determine heterogeneity in treatment effects in this population. For example, clinical stage and grade of cancer not only determines overall survival but may also determine differential effects from alternative treatments. To the extent that all potential moderators of treatments effects are observed to the analyst of the data, a nuanced CATE can be established conditioning on values of all of these factors.

In most practical analyses, all moderators of treatment effects are not observed. Many of these moderators are yet to be discovered and hence remain unknown to scientific knowledge. They are typically represented by the pure stochastic error term in statistical analysis of data. However, there are some moderators that fall within the purview of scientific knowledge but remain unmeasured in the data at hand. For example, most randomized studies, which rely on randomization to equate the distribution of all these factors across the randomization arms, forgo measurement of several factors in the interest of time and expense.

In observational studies, these unmeasured moderators of treatment effects not only give rise to selection bias (Newhouse and McClellan 1998) but also play a vital role in generating essential heterogeneity as often they are observed by individuals and acted upon by some while making treatment selection (Heckman and Vytlacil 1999). An entire genre of methods, including methods based on local instrumental variable (LIV) approaches, have been developed to estimate policy-relevant and structurally stable mean treatment effect parameters in the presence of essential heterogeneity (Heckman and Vytlacil 2001; 2005). Basu and colleagues introduced these methods to the health economics literature where essential heterogeneity is widespread and instrumental variable methods are gaining popularity (Basu et al. 2007; Basu 2011).

LIV methods can seamlessly explore treatment effect heterogeneity across both observable characteristics and unobserved confounders and can be used to establish CATE
based on observed factors. Basu extended this literature in developing and presenting a new individualized treatment effect concept called **Person-Centered Treatment (PeT) effects**, which can also be estimated using LIV methods (Basu 2014). This new treatment effect concept is more personalized than CATE as it takes into account individual treatment choices and the circumstances under which people are making those choices in an observational data setting in order to predict their individualized treatment effects. There are several intuitive aspects about the PeT effects:

1. They help to comprehend individual-level treatment effect heterogeneity better than CATEs and can explain a larger fraction of the individual-level variability in treatment effects than the CATEs.
2. They are better indicators for the degree of self-selection than CATE. It has been shown that they are better predictors of true treatment effects at the individual level both in terms of the positive predictive value and the negative predictive value (Basu 2014).
3. All mean treatment effect parameters, such as the Average Treatment Effect and the Effect on the Treated can be easily computed from PeT effects.

2. PeT effects

**Intuitive ideas behind essential heterogeneity, marginal treatment effects and person-centered treatment (PeT) effects:**

To provide the intuition behind these concepts, we start with a stylized example. It is widely known that the effectiveness of surgery is heterogeneous across men with prostate cancer. Let us assume that surgery is more effective for younger men and for men with high baseline PSA values. Moreover, choice of treatment (surgery or watchful waiting) is influenced by age and baseline PSA of the patient.

However, if one obtains a sample of men diagnosed with prostate cancer from SEER-Medicare, “PSA values” will not be measured. Suppose the available dataset contains for each patient: age, treatment, whether the patient was cured, and a characteristic that all agree is a powerful and valid instrument. Let the instrument be a continuous variable (e.g. distance to hospital). Greater the distance to the hospital, less likely is the use of surgery. Moreover, distance is statistically independent of all risk factors that determine outcomes, a condition that
is met when the two underlying principles are met, i.e. distance does not directly affect outcomes and individuals do not select residences such that their distances from hospital are correlated with their risk factors. Note that one or more continuous instruments are necessary for the identification of PeT effects. In the absence of continuous instruments, only treatment effect bounds (Shaikh and Vytlacil 2011) and the average effects on some compliers (Frandsen et al. 2012; Frölich and Melly 2013) can be estimated.

In this case, a traditional naïve regression would produce biased estimate of the average treatment effect (ATE) and also the conditional average treatment effects (CATEs) for old and young groups due to the endogeneity of the treatment status caused by the missingness of PSA values in the analysis.

A traditional instrumental variable analysis, using a strong and valid IV, will also produce biased estimates for ATE and CATEs due to the presence of essential heterogeneity, which suggests that the treatment effects vary over unobserved confounders, which in this case are the PSA values.

A local instrumental variable (LIV) approach can be used to overcome these issues when a continuous instrument is available. LIV methods are used to estimate the marginal treatment effects (MTEs) parameters. MTEs are the effects for individuals for whom the influence of the observed characteristics (old age and distance to hospital) balance with the influence of the unobserved confounders (PSA level) on treatment choice such that they are indifferent to choosing between using surgery or watchful waiting. To estimate an MTE, LIV methods compare the outcomes of two groups of, say, young patients, where one group is staying at a distance $d$ from the hospital and the other at a distance $d+\epsilon$, $\epsilon$ representing an epsilon (very small) change in distance. These two group of patients should be identical with respect to the distribution of their risk factors (observed and unobserved to the analysts). This is because if distance is a valid instrumental variable, then by definition, it is independent of all risk factors affecting outcomes. Treatment choices are affected differentially between these two groups only through the costs of traveling the extra distance. Therefore any difference between the average outcomes between these two groups must be driven by the fact that some people in these groups, who are identical in their risk factor distributions, have different treatment choices brought about by the difference in distance. However, since the difference in distance is very small, this difference in outcomes can be attributed to the effect of treatment on a margin of patients who were indifferent between two treatment options but made different treatment choices only due to the small perturbation of the instrumental variable, i.e., distance. For this
margin of patients, we can quantify a normalized level of unobserved confounders as they must balance the observed levels for the patients to be indifferent between treatment choices.

Here, normalized means a scalar score that represents a balancing score for unobserved risk factors, irrespective of their empirical distributions. Technically, equation 3 below shows that such a scalar score is always distributed Uniform(0,1). The conceptualization of this scalar score is in the spirit of constructing a scalar propensity score with many observed risk factors with varying empirical distributions.

Similarly, for another dyad of distances, $d'$ and $d'+\epsilon$, one can estimate another MTE, which reflects the causal treatment effect of patients at another level of unobserved confounder. In this way, a full schedule of MTEs can be estimated that vary over the unobserved confounder levels (i.e. PSA values) given any level of the observed confounder (i.e. age). Intuitively, LIV methods estimates these MTEs by first estimating a control function, which models how the observed outcome varying over observed risk factors, IV-dependent estimated propensity to choose treatment, interactions between them and non-linear polynomials of the propensity score. The partial derivate of the outcome, as characterized by the control function, with respect to the IV-dependent propensity score (reflecting epsilon changes) estimates the marginal treatment effect evaluated at specific values of the scalar unobserved risk factor levels.

Once MTEs are estimated over the range of observed and unobserved levels, they can then be easily aggregated to form meaningful treatment effect parameters such as the ATE, CATEs, TT and TUT and also study heterogeneity in effects using person-centered treatment (PeT) effects. The PeT effect for a patient in this stylized sample is conditioned not only on that individual’s age but his age-specific MTEs are also averaged over a distribution of PSA levels that conforms with the individual’s observed choice of surgery or watchful waiting. Thus these are deemed to be personalized effect for this patient.

Formal models behind essential heterogeneity, marginal treatment effects and person-centered treatment (PeT) effects:

We will restrict our discussion to two treatment states – the treated state denoted by $j = 1$ and untreated state denoted by $j = 0$, as petiv is designed only for binary treatments. However, theoretical extensions to multiple ordered treatments is possible (Heckman et al.)
The corresponding potential individual outcomes in these two states are denoted by $Y_1$ and $Y_0$. We assume,

$$Y_1 = \mu_1(X_0, X_U, \vartheta) \text{ and } Y_0 = \mu_0(X_0, X_U, \vartheta),$$

(1)

where $X_0$ is a vector of observed random variables, $X_U$ is a vector of unobserved random variables which are also believed to influence treatment selection (they are the unobserved confounders) and $\vartheta$ is an unobserved random variable that capture all remaining unobserved random variables. $(X_0, X_U) \perp \vartheta$ and $X_0 \perp X_U$ where $\perp$ denotes statistical independence.

We assume individual choose to be in state 1 or 0 (prior to the realization of the outcome of interest) according to the following equation:

$$D = 1 \text{ if } \mu_0(X_0, Z) - U_D > 0,$$

(2)

where $Z$ is a (non-degenerate) vector of observed random variables (instruments) influencing the decision equation but not the potential outcome equations, $\mu_0$ is an unknown function of $X_0$ and $Z$, and $U_D$ is a random variable that captures $X_U$ and all remaining unobserved random variables influencing choice. By definition, $U_D \perp \vartheta$, which also defines the distinction between $X_U$ and $\vartheta$ in (1). Equations (1) and (2) represent the nonparametric models that conform to the Imbens and Angrist’s (1994) independence and monotonicity assumptions needed to interpret instrumental variable estimates in a model of heterogeneous returns (Vytlacil 2002). As in Heckman and Vytlacil (1999), we can rewrite (2) as

$$D = 1 \text{ if } P(X_0 = x_0, Z = z) > V,$$

(3)

where $V = F_{U_D}[U_D | X_0 = x_0, Z = z], P(x_0, z) = F_{U_D}[x_0, z] \mu_b(x_0, z)$ and $F$ represents a cumulative distribution function. Therefore, for any arbitrary distribution of $U_D$ conditional on $X_0$ and $Z$, by definition, $V \sim \text{Unif}[0, 1]$ conditional on $X_0$ and $Z$. Under regular IV assumptions, Marginal Treatment Effects can be identified by

$$\frac{\partial E_{\vartheta}(Y | X_0 = x_0, Z = z)}{\partial \vartheta} = E_{\vartheta}((Y_1 - Y_0) | X_0, V = v) = MTE(x_0, v),$$

(4)

where $Y = D^*Y_1 + (1 - D)^*Y_0$ is the observed outcomes and $v = P(x_0, z)$.

MTE is perhaps the most nuanced estimable effect. It identifies an effect for an individual who is at the margin of choice such that one’s levels of $X_0$ and $Z$ are just balanced by one’s
level of $V$ (which includes $X_0$), i.e. $P(x_0, z) = v$. Basu (2014) extends the LIV methods to identify PeT effects, which, for persons who choose treatment, follow

$$E_{x_i|x_0, P(z), D} (Y_1 - Y_0 \mid x_0, P(z), D = 1) = E(Y_1 - Y_0 \mid x_0, v, V < P(z))$$

$$= P(z)^{-1} \int_0^{P(z)} MTE(x_0, v) \, dv. \quad (5)$$

Similarly, conditional effect for a person who did not choose treatment is obtained by integrating $MTEs$ over values of $V$ greater than $P(z)$.

Conceptually, a PeT effect is also a weighted version of MTEs. This is because an MTE is the treatment effect of a hypothetical individual who is at the margin of choice because their propensity to choose treatment based on $X_0$ and $Z$ is balanced by the propensity to select the alternative based on $V$. As the value of $V$ is changed from this point, this person would either choose the treatment or the alternative. The PeT effect for a real individual is then the average of MTEs, with same $X_0$ and $Z$ levels as those for this real individual, over those values of $V$ that corresponds to the real individual’s own treatment choice. That is, for any given individual, the first step is to identify the specific margins of $V$ where that individual may belong given its individual values of $X_0$, $P(Z)$ and $D$. Then the average the MTEs over those margins, but not all as in CATE, is calculated to obtain a PeT effect. Further details can be found in Basu (2014).

### 3. A numerical algorithm to compute PeT effects

In order to estimate PeT effects of a binary exposure on an outcome, the analyst is advised to follow the following steps:

1. **Check strength and validity of the instrumental variable(s) using standard methods.** Run the first stage by regressing the indicator for exposure ($D$) against observed factors ($X$) and the instrument ($Z$) using a probit / logit or other model appropriate for a binary outcome. Propensity score $\hat{p}(x, z)$ is predicted for every individual in the dataset.

2. **Ensure that $\hat{p}(x, z)$ has mass at any value (rounded to 0.01) for both levels of exposure.** Observations corresponding to particular values of $\hat{p}(x, z)$ that do not meet this criteria are dropped.

3. **Denote** $minp = \min\{\hat{p}(x, z)\}$ and $maxp = \max\{\hat{p}(x, z)\}$
4. Determine the appropriate specification for \( g(Y) = \alpha_0 + \alpha_1 \cdot X + \alpha_2 \cdot \hat{p} \cdot X + K(\alpha; \hat{p}) \), where the link function \( g() \) and polynomial function of \( \hat{p}(x,z) \), \( K() \), are determined by the analyst using various goodness of fit tests.

5. Specify the LIV estimand through the \texttt{-petiv-} command that accomplishes the following:
   a. Run the second stage LIV estimand for outcome \( Y \) using a user specified regression model \( g(Y) = \alpha_0 + \alpha_1 \cdot X + \alpha_2 \cdot \hat{p} \cdot X + K(\alpha; \hat{p}) \).
   b. Draw 1000 deviates \( u \sim \text{Uniform}[\text{minp, maxp}] \)
   c. Perform numerical integration: For each individual \( i \):
      i. Compute \( d\hat{g}(.) / d\hat{p} \) and evaluate it by replacing \( \hat{p}(x,z) \) with each value of \( u \). So there are 1000 values of \( d\hat{g}(.) / d\hat{p} \) for each individual \( i \).
      ii. Compute \( D^* = \Phi^{-1}(\hat{p}(x,z)) + \Phi^{-1}(1-u) \) also generating 1000 values for each individual \( i \), where \( \Phi() \) is the cumulative normal distribution function.
      iii. Compute PeT by averaging \( d\hat{g}(.) / d\hat{p} \) over values of \( u \) for which \( (D^* > 0) \) if \( D=1 \), otherwise, by averaging \( d\hat{g}(.) / d\hat{p} \) over values of \( u \) for which \( (D^* \leq 0) \) if \( D=0 \).

6. Estimated PeT effects provides us with individualized treatment effects. Mean treatment effect parameters can also be computed using these PeT effects. Averaging PeTs over all observations gives an empirical estimate of the average treatment effect (ATE). Averaging PeTs over \( D=1 \) or \( D=0 \) gave us Effect on the treated (TT) and the Effect on the Untreated (TUT) respectively.

**Inference**

Standard errors for individual PeT effects and average treatment effects can be obtained via bootstrap. Specifically, saving the average PeT effects for each individual (i.e. with specific individual ID), where the average is taken if the same individual is sampled more than once within the same bootstrap data replicate, from each bootstrap replicate would lend towards building a distribution of PeT effects for that individual.
4. The *petiv* command

The *petiv* command carries out the LIV estimation and the numerical integration that follows in the calculation of PeT effects, as outlines in the previous section. At the end the command a new variable called “pet\_depvarname” is created in the dataset that stores the individualized effects for each person in the sample.

4.1. Syntax

\texttt{petiv depvar varlist [if exp] [in range], trt(varname) ps(varname) cmd(command\_name) [degree(#) controls(varlist) display options]}

where \texttt{command\_name} is one of

\{ probit | logit | glm | pglm | regress \}

and where \texttt{options} can be any options corresponding to the \texttt{command\_name}.

*petiv* expects the data to be in the conventional form as in any other regression analysis. It requires specification of a dependent variable and at least one covariate that is not the treatment indicator, i.e. it does not fit a constant-only model. The treatment indicator variable is specified using the \texttt{trt()} option. Identification of effects is accomplished via estimated propensity score of treatment receipt as a function of risk factors and instrumental variables. This score should be estimated prior to running the *petiv* command and passed on using the \texttt{ps()} option.

4.2 Options

\textbf{Options for petiv}

degree(#) specifies the degree of polynomial for propensity score variable, specified via ps() option, that will be used in the control function. Default is 1.
The command `contr:ols(varlist)` specifies the list of variables that will be adjusted for in the control function but no interaction with `ps` will be used. The default is an empty list. The variables listed within this option should not be listed under `- varlist -` after `depvar`.

`display` displays the regression results from the estimation of the control function.

### 5. An empirical example using PeT.

Our empirical example follows the analyses presented in Basu (2014). We study the distributional effects of alternative treatment modalities on 7-year health care expenditures among prostate cancer patients. Our data are derived from the 1995 – 2009 SEER-Medicare linked dataset. However, due to proprietary issues, analysis on a simulated version of the original dataset is presented here and this version is available with the `- petiv -` command.

The key variables in our sample are categorized as:

- **Outcomes Variables (Y)**: Total undiscounted 7-year expenditures on health care expressed in 2009 dollars. Expenditures accumulate over all types of medical costs reimbursed by Medicare or a third party payer and patients’ out-of-pocket costs.

- **Treatment (D)**: Comparison is made between the use of surgery in the first six months of diagnosis versus active surveillance that is defined as no use of surgery, hormone therapy or radiation in the first six months of diagnosis along with at least two PSA tests within first year of diagnosis. Treatment indicator takes a value of one for surgery.

- **Independent Risk Factors (X₀)**: These include clinical stage and grade of cancer for patients at diagnosis using standard definitions, demographics, indicator for metropolitan area, Elixhauser comorbidity indices based on hospitalization in year preceding diagnosis, year and state fixed effects, zip-code level area characteristics on racial makeup, density and education levels. We also adjust for HRR-level characteristics.
using logged versions of population size, and per 100,000 patients’ supply of hospital beds, physician, specialists and urologists.

(d) Instrumental Variable (Z): HRR-specific rates of active surveillance in prostate cancer patients in the year prior to the diagnosis of a patient.

Further details of this analysis can be found in Basu (2014). Variables were stored in following macros:

```stata
.global xlist "$xlist1 $xlist2 $xlist3" /* Too long to list */
global control "$clist1 $clist2" /* Too long to list */
global iv "ivrate_activesurv"
global y "payments_7years"
global trt " surgery"
```

5.1 Applying the numerical algorithm to compute PeT effects

1. Our final analytic sample consisted of 13,495 patients, of whom 9,862 (73.3%) received surgery. We ran a logit model for the first stage where the indicator for surgery was regressed on \( X_0 \) and \( Z \). The instrumental variable was found to be strongly predictive of surgery receipt conditional on other factors (F-stat: 10.9, p<0.0001). It was also found that the IV may be particularly suitable in reducing residual confounding in this application since it is able to reduce imbalance in observed factors considerably.

2. We computed the predicted propensity score using the standard `predict` command following the `logit` regression:

   ```stata
   . predict ps, p
   ```

   The identified support of the IV-based predicted propensity score, \( ps \), which existed under both treatment arms, ranged from 0.07 to 0.998. 47 observations were lost due to lack of overlap bringing our final analytic sample to 13,448.

3. Appropriate specification for the LIV estimand: Because we are modeling health care expenditures, we started with a generalized linear model with log link and gamma variance specification. We included patient-specific covariates and their interactions with \( ps \). We also
included other supply-level variables as controls (but did not include their interactions with \( ps \) to avoid overfitting). Finally, we varied the degree of polynomial for \( \hat{p}(x,z) \) and tested alternatives using Likelihood ratio tests.

/* Create interactions with \( ps \) */
. global xlisti " "
qui foreach var of global xlist {
    capture drop p_`var'
    gen p_`var' = ps*`var'
    global xlisti "$xlisti p_`var'"
}
/* Test for alternate polynomial specifications */
. glm $y $xlisti $xlist $supply ps, family(gamma) link(log) robust
. est store A
. glm $y $xlisti $xlist $supply ps psc, family(gamma) link(log) robust
. est store B
. lrtest A, force
Likelihood-ratio test                  LR chi2(1)  =      0.14
(Assumption: A nested in B)            Prob > chi2 =    0.7074
. glm $y $xlisti $xlist $supply ps ps2 ps3, family(gamma) link(log) robust
. lrtest B, force
Likelihood-ratio test                  LR chi2(2)  =      0.16
(Assumption: B nested in .)            Prob > chi2 =    0.6904

Based on these results, the first-degree polynomial seemed most appropriate for these data. However, note that unlike linear models, a first-degree polynomial within a non-linear model does not preclude the presence of essential heterogeneity in the additive scale (Heckman et al. 2006; Basu 2011).

4. Finally, we did standard raw-scale residual-based goodness of fit tests with the GLM model with the chosen degree of polynomial for \( \hat{p}(x,z) \) (Basu et al. 2007). No systematic biases were detected from residual-based goodness of fit analyses.

5. Run - petiv -
This creates a variable called `pet_payments_7years` in the dataset. This variable may have missing values for a few observations where all MTEs in the range of the support of `ps` could not be calculated due to numerical overflow. In our case, `pet_payments_7years` was missing for 9 observations. Mean treatment effect parameters can be easily computed.

```
. // ATE
. summ pet_payments_7year

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>pet_payments_7year</td>
<td>13439</td>
<td>-27419.23</td>
<td>43112.39</td>
<td>-549247.7</td>
<td>301288.3</td>
</tr>
</tbody>
</table>

. // TT
. summ pet_payments_7year if $trt==1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>pet_payments_7year</td>
<td>9854</td>
<td>-28662.87</td>
<td>46708.22</td>
<td>-549247.7</td>
<td>169176.8</td>
</tr>
</tbody>
</table>

. //TUT
. summ pet_payments_7year if $trt==0

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>pet_payments_7year</td>
<td>3585</td>
<td>-24000.86</td>
<td>30908.43</td>
<td>-224529.8</td>
<td>301288.3</td>
</tr>
</tbody>
</table>
```

The average treatment effect was estimated to be -$27,419. The effect on the treated and the effect on the untreated were -$28,662 and -$24,001 respectively. The distribution of individual treatment effects is illustrated using a histogram for the `pet_payments_7year` variable in Figure 1. It is estimated that although the mean treatment effect parameters are negative, 22% of the patients is expected to incur positive expenditures from surgery compared to watchful waiting over 7 years.
6. Conclusions

Here we have described a command, petiv, which uses a local instrumental variables (LIV) approach to estimate person-centered treatment (PeT) effects for a variety of specifications for the LIV estimand as outlined in Basu (2014). The petiv command creates a new variable in the dataset that contains the PeT effects for each individual in the dataset. However, the command takes the validity of the instrumental variables(s) and the specification of the LIV estimand as given. Appropriateness of these features of an LIV analyses should be determined prior to running the petiv command. The individual effects can be used to answer a variety of distributional questions and can also be easily aggregated to calculate mean treatment effect parameters.

Practically, we have found that the estimator works best in analyses with larger sample sizes, say over N = 2000, sample sizes that are not uncommon in health economics and health policy applications. One also needs at least one continuous instrumental variable to estimate PeT effects. Finally, standard errors for PeT effects and the mean treatment effects can be obtained via bootstrap methods.

Figure 1: Distribution of pet_payments_7year.
I hope that this methodology and the `petiv` command will be increasingly used in economics and other areas of research to understand distributional effects of interventions.

7. Acknowledgements

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8. References


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