

EC709 PS2. Treatment Effects

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Due on October 3

Question 1: Effect of 401(k) on Asset Accumulation In this question you are going to estimate the causal effect of 401(k) eligibility and participation on accumulation of assets. The file `sipp1991.dta` contains information of 9,915 households from the Survey of Income and Program Participation (SIPP) for 1991 on the following variables:

Contains data from sipp1991.dta

obs: 9,915

vars: 14

20 Jun 2013 14:08

variable name	storage type	display format	value label	variable label
nifa	float	%9.0g		Net non-401(k) financial assets
net_tfa	float	%9.0g		Net total financial assets
tw	float	%9.0g		Total wealth
age	byte	%9.0g		Age of the head of the household
inc	float	%9.0g		Household income
fsize	byte	%9.0g		Household size
educ	byte	%9.0g		Years of education of the head of the household
db	byte	%9.0g		Defined benefit pension status indicator
marr	byte	%9.0g		Married indicator
twoearn	byte	%9.0g		Two-earner status indicator
e401	byte	%9.0g		401(k) eligibility
p401	byte	%9.0g		401(k) participation
pira	byte	%9.0g		IRA participation indicator
hown	byte	%9.0g		House ownership indicator

Sorted by: e401

1. Verify that

$$E\left[\frac{(1-D)Y}{1-P(X)}\right] = E[E[Y \mid X, D=0]],$$

where $P(X) = P(D=1 \mid X)$ is the propensity score.

2. Estimate the ATE of 401(k) *eligibility* on net total financial assets using the nonparametric regression, propensity score reweighting and double robust estimators with a

low dimensional specification for the controls such as the one seen in class. Do your estimates have a causal interpretation? Define the causal parameter and provide its identification conditions in the context of this application.

[Hint: you can use OLS to estimate conditional expectations and logit to estimate the propensity score.]

3. Estimate the LATE of 401(k) *participation* on net total financial assets with 401(k) eligibility as an instrument using the nonparametric regression, propensity score reweighting and double robust estimators with a low dimensional specification for the controls such as the one seen in class. Do your estimates have a causal interpretation? Define the causal parameter and provide its identification conditions in the context of this application.
4. Estimate the LATE of 401(k) *participation* on net total financial assets with 401(k) eligibility as an instrument using the double robust estimator with a high dimensional specification for the controls such as the one seen in class.

[Hint: you can use Lasso to estimate regression functions of continuous outcomes and logit Lasso to estimate regression functions of binary outcomes. The package `hdm` implements Lasso and logit Lasso regressions in R.]

5. Extra credit: use bootstrap to compute the standard errors of your estimates in parts 2 and 3.

[Hint: the R package `boot` is very useful to implement the bootstrap. It has functionality for parallel computing.]

Question 2: Head Start (Ludwig and Miller, 2007) Ludwig and Miller (2007) estimated the effect of the Head Start program on health and schooling outcomes using a regression discontinuity design.¹ The discontinuity is induced by the program design that targeted just the 300 poorest counties in the country setting a cutoff of 59.1984 in the poverty rate for eligibility into the program. The file `headstart.dta` contains information of 2,810 counties on the following variables:

Contains data from `headstart.dta`

```
obs:      2,810
vars:      13                               29 May 2021 13:52
```

	storage	display	value	
variable name	type	format	label	variable label

¹Ludwig, J., and Miller, D. L. (2007): “Does Head Start improve children’s life chances? Evidence from a regression discontinuity design,” *Quarterly Journal of Economics*, 122, 159–208.

povrate60	float	%9.0g	County Poverty Rate 1960, HS cutoff = 59.1984
mort_age59_re~S	float	%9.0g	Mortality, Ages 5-9, HS related causes, 1973-1983
mort_age25plu..	float	%9.0g	Mortality, Ages 25+, HS related causes, 1973-1983
mort_a~s_postHS	float	%9.0g	Mortality, Ages 25+, Injuries, 1973-1983
census1960_pop	long	%12.0g	Census 1960: county population
census1960_pc~7	float	%9.0g	Census 1960: % attending school, age 14-17
census1960_pc~4	float	%9.0g	Census 1960: % attending school, age 5-34
census1960_pc~s	float	%9.0g	Census 1960: % high-school or more, age 25+
census1960_po~7	long	%12.0g	Census 1960: population, age 14-17
census1960_po~4	long	%12.0g	Census 1960: population, age 5-34
census1960_po~s	long	%12.0g	Census 1960: population, age 25+
census1960_pc~n	float	%9.0g	Census 1990: % urban population
census1960_pc~k	float	%9.0g	Census 1990: % black population

Sorted by:

Read Ludwig and Miller (2007) and reanalyze the data using state of the art methods.

[Hint: Another useful reading is Cattaneo, Titiunik and Vazquez-Bare (2017): “Comparing Inference Approaches for RD Designs: A Reexamination of the Effect of Head Start on Child Mortality,” *Journal of Policy Analysis and Management* 36(3): 643-681.]