LARF in Casual inference
Theoretical Analysis and Empirical Application

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Summary and Take-Away

- Theoretical analysis and mathematic deduction of **LARF** based on Abadie (2003).
- Three replication of research papers pulished on top journals using **LARF** package.
- Comparasion among **LARF**, 2SLS and other IV estimation methods and potential explanation of the differences of different estimates.

Motivation

Question: How to get appropriate IV estimation of treatment causal effects when both the endogenous treatment and its instrument are binary (dummy or 0/1 variable)?

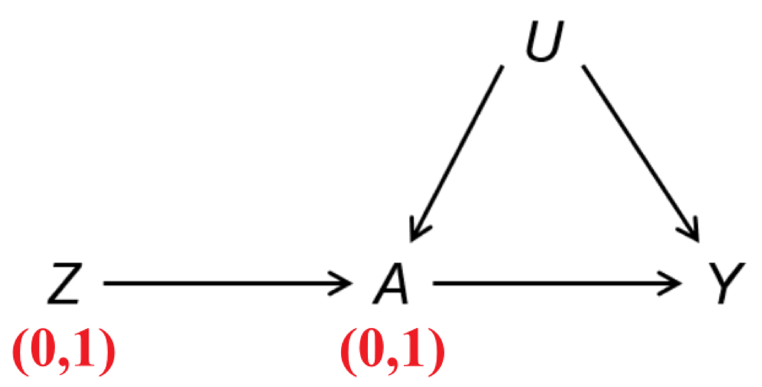

Figure 1: IV Graph

Motivation

- 2SLS and IV: With no covariates, $\widehat{LATE}$ can be calculated via 2SLS; With covariates, it will not be same except for the constant treatment effect assumption.
- To identify LATE in this case, Abadie(2003) developed a **LARF** method with the assumption of Conditional Independence, First Stage and Monotonicity.

Comparasion

LARF fills an important gap in IV estimations. When both the endogenous treatment and its instrument are binary, **LARF** can provide more appropriate estimations of treatment effects for both continuous and binary outcomes.

- `ivprobit` (**STATA**): not suitable for binary treatment variable.
- `systemfit` (**R**); `ivregress` and `ivregress2` (**STATA**): not suitable for binary dependent variable.
- bivariate probit model (`biprobit` in **STATA**, `binom2.rho` in **R**): not suitable for continuous dependent variable. (*A unrealistic assumption: the joint distribution for the outcome and the treatment is correctly known.*)

References

Abadie, A. (2003). Semiparametric instrumental variable estimation of treatment response models. Journal of econometrics, 113(2), 231-263.

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Banerjee, A., Duflo, E., Glennerster, R., & Kinnan, C. (2015). The miracle of microfinance? Evidence from a randomized evaluation. American economic journal: Applied economics, 7(1), 22-53.

Duflo, E., Dupas, P., & Kremer, M. (2015). Education, HIV, and early fertility: Experimental evidence from Kenya. American Economic Review, 105(9), 2757-2797.

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Banerjee et al. (2015): A typical RCT

Experiment Design

- In 2005, 52 of 104 poor neighborhoods in Hyderabad, India were randomly selected for opening of an Micro Finance Institution branch.
- **Total sample**: 6,864 households, 90% maintained contact.

Simplified Empirical Strategy

- **Treatment**: `spandana_1` (Has outstanding loan from Spandana at endline 1, Binary)
- **Instrument Variable**: `treatment` (whether be selected as treatment area, Binary)
- **Outcomes**: the household expenditure and its structure.

	total expenditure per capita	durables	nondurable	temptation
2SLS	267.8	868.6**	308.6	−189.9**
	(164.2)	(342.9)	(668.8)	(89.4)
LARF (LS)	275.7*	907.6**	323.1	−190.1**
	(166.2)	(370.1)	(691.5)	(93.2)
LARF (MLE)	378.9**	907.6**	532.8	−128.3
	(172.2)	(412.8)	(694.5)	(95.9)

Duflo et al. (2015): RCT with binary Y

Experiment Design

- A seven-year randomized evaluation to find the effect of **education subsidies** and **HIV curriculum** on adolescent girls' dropout, pregnancy, marriage and sexually transmitted infection in Kenya.
- **Education Subsidies**: providing two free school uniforms over the last three years of primary school.
- **HIV curriculum**: three teachers in each primary school received government-provided training to help them deliver Kenya's national HIV/AIDS curriculum.

Simplified Empirical Strategy

- **Treatment**: Whether dropped out of primary in 2007. (`dropout07v2`: Binary)
- **Instrument**: If school benefit from uniform program (`Utreat`: Binary)
- **Outcome**: marriage, pregnant, child (`evmar07v2`, `evpreg07v2`, `evchild07v2`: also binary)
- **LARF** cannot get estimation if we use the "least square" method (here we only use "Maximum Liklihood" method) (Estimate is "marginal effects at the means" for **LARF**)

	short			long		
	marriage	child	pregnant	marriage	child	pregnant
2SLS	0.65***	0.19	0.42**	0.52***	0.36**	0.45**
	(0.15)	(0.16)	(0.17)	(0.15)	(0.17)	(0.18)
LARF (MLE)	0.61	0.51	0.69	0.43**	0.59*	0.65*
	(0.40)	(0.98)	(1.36)	(0.20)	(0.34)	(0.37)

Duflo et al. (2007): Geographic IV (still in progress)

Fast growing of construction of dams in India. (Trade-off: displacement vs. water-access.)
Treatment: A state with more than a hundred dams by 1999 is a **'high'** construction state. (calculated from `sdistrict1`)
Instrument: A district with less than 90% of river gradient below 1.5% percent is classified as a **'high'** gradient district. ($Slope\% = \frac{Rise}{Run} \times 100\%$, calculated from `damsumstate`)
Outcome: yield of main crops and water-intensive crops (`lyield`, `waterp`)

LARF and 2SLS

- Parameters of linear specification for **LARF**

$$\begin{pmatrix}\alpha_0\\ \beta_0\end{pmatrix} = \left(E\left[\begin{pmatrix}D\\ X\end{pmatrix} \kappa \begin{pmatrix}D\\ X\end{pmatrix}'\right]\right)^{-1} E\left[\begin{pmatrix}D\\ X\end{pmatrix} \kappa \; Y\right]$$

- Probablity limit of 2SLS

$$\begin{pmatrix}\alpha_{2SLS}\\ \beta_{2SLS}\end{pmatrix} = \left(E\left[\begin{pmatrix}Z\\ X\end{pmatrix} \begin{pmatrix}D\\ X\end{pmatrix}'\right]\right)^{-1} E\left[\begin{pmatrix}Z\\ X\end{pmatrix} \; Y\right]$$

Theoretical Analysis

Abadie's Pseudo-Weight

$$\kappa = 1 - \frac{D(1-Z)}{P(Z=0|X)} - \frac{Z(1-D)}{P(Z=1|X)}$$

Theorem 3.1

$$E[g(Y,D,X)|D_1 > D_0] = \frac{1}{P(D_1 > D_0)} E[\kappa * g(Y,D,X)]$$

LS & ML

$$(\alpha_0, \beta_0) = \arg\min_{\alpha,\beta} E[\{Y - (\alpha D + X'\beta)\}^2 | D_1 > D_0]$$

$$(\alpha_0, \beta_0) = \arg\max_{\alpha,\beta} E[lnf(Y,D,X;\alpha_0,\beta_0) | D_1 > D_0]$$

By Theorem 3.1

$$(\alpha_0, \beta_0) = \arg\min_{\alpha,\beta} E[\kappa\{Y - (\alpha D + X'\beta)\}^2]$$

$$(\alpha_0, \beta_0) = \arg\max_{\alpha,\beta} E[\kappa lnf(Y,D,X;\alpha_0,\beta_0)]$$

Two-Step Estimation

- Construct $\hat{\kappa}$ by estimating $P(Z=1|X)$
- Estimate **LARF** using methods above

Potential Explanations

We put forward belowing explanations for the differences between **LARF** and other kinds of estimation methods.

1. In Banerjee's paper, the result of **LARF** shows the significant effect on total expenditure, while 2SLS not. **LARF** with ML shows the effect on temptation consumption is non-significant.
2. In Duflo's paper, the result of **LARF** with ML shows the effect in short-run is non-significant, while it still significant in the long-run.
3. In summary, **LARF** with LS will give coefficient higher than 2SLS, since the existence of negative weight in Abadie's kappa.
4. **LARF** with ML's result seems to be different with 2SLS in significancy and coefficient, that maybe correlated to the data structure and the normal distribution we have assumed.

The analysis above may not be perfect interpretation of our empirical results, we are still exploring the mechanism behind the differences. Thank you for your comprehension!

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