`drlate`: Doubly Robust and Covariate-Balancing Estimation of LATE in Stata

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Overview

This talk:

1. **Empirical goal:** When and why do we need LATE?
2. **Econometric framework:** Doubly robust estimation with covariate-balancing propensity scores
3. **The `drlate` package:** Estimators, inference, and testing
4. **Empirical example:** Abadie (2003)

Companion papers:

- Słoczyński, Uysal, & Wooldridge (2022): *Doubly Robust Estimation of Local Average Treatment Effects Using Inverse Probability Weighted Regression Adjustment*
- Słoczyński, Uysal, & Wooldridge (2025): *Covariate Balancing and the Equivalence of Weighting and Doubly Robust Estimators*

Empirical Goal: Why LATE?

The Causal Inference Problem with Instruments

Setting: We observe (Y_i, D_i, Z_i, X_i) for $i = 1, \ldots, n$

Variables:

- Y_i outcome (continuous, binary, count)
- D_i treatment (binary, endogenous)
- Z_i binary instrument
- X_i covariates (controls)

Classic examples (Y, D, Z):

- earnings, military service, draft lottery
- wages, college attendance, distance to college
- household saving, 401(k) participation, 401(k) eligibility

The problem: D_i is endogenous — OLS is biased.

Potential Outcomes Framework

Potential treatment (what D_i *would be* under each instrument value):

$$D_i(1) \in \{0,1\}: \text{ treatment status if } Z_i = 1, \qquad D_i(0) \in \{0,1\}: \text{ treatment status if } Z_i = 0$$

Observed treatment: $D_i = Z_i D_i(1) + (1 - Z_i) D_i(0)$.

Potential outcome (what Y_i *would be* under each treatment value):

$$Y_i(1): \text{ outcome with treatment}, \qquad Y_i(0): \text{ outcome without treatment}$$

Observed outcome: $Y_i = D_i Y_i(1) + (1 - D_i) Y_i(0)$.

Example (Abadie, 2003)

Z_i: eligible for a 401(k) retirement plan.
$D_i(1), D_i(0)$: participation in a 401(k) plan depending on eligibility.
$Y_i(1), Y_i(0)$: household wealth with and without 401(k) participation.

For each unit we only ever observe *one* potential outcome and *one* potential treatment — the fundamental problem of causal inference.

Complier Subpopulations and the LATE

With a binary treatment and binary instrument, every unit belongs to one of four groups:

Type	$D_i(0)$	$D_i(1)$	**Respond to Z?**
Always-takers	1	1	No
Never-takers	0	0	No
Compliers	**0**	**1**	**Yes**
Defiers	1	0	Yes (oppositely)

Causal effects of interest:

- $\tau^{LATE} = E[Y_i(1) - Y_i(0) \mid D_i(1) > D_i(0)]$ — effect for all compliers
- $\tau^{LATT} = E[Y_i(1) - Y_i(0) \mid D_i(1) > D_i(0),\ D_i = 1]$ — effect for *treated* compliers

The Classical Solution: Linear IV

Traditional econometric framework:

$$Y_i = \alpha + \tau D_i + X_i'\beta + u_i, \qquad \text{cov}(D_i, u_i) \neq 0$$

with instrument Z_i: $\text{cov}(Z_i, D_i) \neq 0$, $\text{cov}(Z_i, u_i) = 0$.
Case 1 — Z_i valid without conditioning on X_i:

$$\tau = \frac{\text{cov}(Y_i, Z_i)}{\text{cov}(D_i, Z_i)} = \tau^{LATE} \quad \Longrightarrow \quad \hat{\tau}_{2SLS} = \widehat{\tau^{LATE}}$$

2SLS and LATE coincide — the textbook case (Imbens & Angrist, 1994).
Case 2 — Z_i valid only after conditioning on X_i (typical in applied work):

- $\hat{\tau}_{2SLS} \neq \widehat{\tau^{LATE}}$ in general $\Rightarrow$ no clear causal interpretation
- $\hat{\tau}_{2SLS}$ is a weighted average of X-specific LATEs (Angrist & Imbens, 1995) with undesirable weights (Słoczyński, forthcoming)

Implication

Once covariates are needed for identification, 2SLS no longer reliably recovers the LATE under heterogeneous effects. We need an estimator that **targets τ^{LATE} directly**.

Econometric Framework

Identifying Assumptions

Let $Y_i(d, z)$ denote the potential outcome under $(D_i{=}d, Z_i{=}z)$ and $D_i(z)$ the potential treatment under $Z_i{=}z$.

1. **Independence:** $(Y_i(d, z), D_i(z)) \perp Z_i \mid X_i$ for all $d, z \in \{0, 1\}$
2. **Exclusion restriction:** $Y_i(d, 1) = Y_i(d, 0)$ a.s. for $d \in \{0, 1\}$
3. **Monotonicity:** $D_i(1) \geq D_i(0)$ a.s.
4. **Relevance:** $P(D_i(1) > D_i(0) \mid X_i) > 0$ a.s.
5. **Overlap (LATE):** $0 < P(Z_i{=}1 \mid X_i) < 1$ a.s.

Under Assumptions 1–5, the **instrument propensity score** $p(X_i) = P(Z_i{=}1 \mid X_i)$ plays the same role as the propensity score under unconfoundedness.

Targeting the LATE Directly

Key identification result (Frölich, 2007; Tan, 2006)

Under Assumptions 1–5, the LATE is identified as a ratio of reduced forms:

$$\tau^{LATE} = \frac{E\big[E(Y_i \mid Z_i{=}1, X_i) - E(Y_i \mid Z_i{=}0, X_i)\big]}{E\big[E(D_i \mid Z_i{=}1, X_i) - E(D_i \mid Z_i{=}0, X_i)\big]}$$

This ratio can be estimated by your favorite estimator of the average treatment effect of Z_i, applied twice — once for the outcome, once for the treatment.

Several such estimators exist: inverse probability weighting (IPW), regression adjustment (RA), augmented IPW (AIPW), and IPW regression adjustment (IPWRA). All are implemented in `drlate`.

Estimating the Instrument Propensity Score

The IPS $p(X_i) = P(Z_i{=}1 \mid X_i)$ is unknown and modeled as $p(X_i'\gamma)$. Three estimation approaches:

Logit MLE: maximizes the likelihood of Z_i given X_i. Does not guarantee covariate balance in finite samples.

IPT (Graham, Pinto, & Egel, 2012): two $\hat{\gamma}$'s from balancing conditions,

$$\frac{1}{n}\sum_i \frac{Z_i X_i}{p(X_i'\hat{\gamma}_1)} = \bar{X}, \qquad \frac{1}{n}\sum_i \frac{(1-Z_i)X_i}{1-p(X_i'\hat{\gamma}_0)} = \bar{X}$$

Reweighted covariate means **exactly equal** the full-sample means in each group. ← recommended

CBPS (Imai & Ratkovic, 2014): a single $\hat{\gamma}$ balancing the two groups against each other.

Why prefer IPT?

IPT yields exact covariate balance and, as shown in Słoczyński, Uysal, & Wooldridge (2025), makes the choice among IPW, AIPW, and IPWRA irrelevant — all give numerically identical LATE estimates.

Estimators of LATE with Covariates

Let $\hat{p}(X_i)$ = estimated IPS, $\hat{\lambda}_i = Z_i/\hat{p}(X_i) - (1-Z_i)/(1-\hat{p}(X_i))$; $\hat{\mu}_Y^z$, $\hat{\mu}_D^z$ = outcome/treatment models in the $Z{=}z$ group (linear, logit, or Poisson).

Method	LATE estimator	Outcome/treatment model
IPW	$\hat{\tau}_{IPW}^{LATE} = \dfrac{n^{-1}\sum_i \hat{\lambda}_i Y_i}{n^{-1}\sum_i \hat{\lambda}_i D_i}$	none
RA	$\hat{\tau}_{RA}^{LATE} = \dfrac{n^{-1}\sum_i [\hat{\mu}_Y^1 - \hat{\mu}_Y^0]}{n^{-1}\sum_i [\hat{\mu}_D^1 - \hat{\mu}_D^0]}$	*unweighted*
AIPW	$\hat{\tau}_{AIPW}^{LATE} = \dfrac{n^{-1}\sum_i [\hat{\lambda}_i (Y_i - \hat{\mu}_Y^{Z_i}) + \hat{\mu}_Y^1 - \hat{\mu}_Y^0]}{n^{-1}\sum_i [\hat{\lambda}_i (D_i - \hat{\mu}_D^{Z_i}) + \hat{\mu}_D^1 - \hat{\mu}_D^0]}$	*unweighted*
IPWRA	$\hat{\tau}_{IPWRA}^{LATE} = \dfrac{n^{-1}\sum_i [\tilde{\mu}_Y^1 - \tilde{\mu}_Y^0]}{n^{-1}\sum_i [\tilde{\mu}_D^1 - \tilde{\mu}_D^0]}$	*IPS-weighted*

Double robustness

AIPW and IPWRA are consistent if *either* the IPS *or* the outcome/treatment models are correctly specified — not necessarily both.

The `drlate` Package

Basic Syntax

```
drlate (ovar [omvarlist] [, omodel]) (tvar [tmvarlist] [, tmodel])
(iv [ivvarlist] [, ivmodel]) [if] [in] [pweight] [, options]
```

omodel/tmodel: `linear`, `logit`, `poisson` **ivmodel:** `logit` (default), `cbps`, `ipt`

Key options: `late/latt`, `method(ipwra|ipw|aipw|ra)`, `vce(robust|cluster` v`)`, `nrm/unnrm`

Continuous outcome:

```
drlate (net_tfa inc i.fsize marr age) ///
(p401    inc i.fsize marr age) ///
(e401    inc i.fsize marr age, ipt)
```

Binary outcome:

```
drlate (pira inc i.fsize marr age, logit) ///
(p401 inc i.fsize marr age) ///
(e401 inc i.fsize marr age, ipt)
```

Estimators Available

Method	Description	LATE	LATT
`ipwra`	IPW Regression Adjustment (default)	✓	✓
`ipw`	Inverse Probability Weighting	✓	✓
`aipw`	Augmented IPW	✓	✓
`ra`	Regression Adjustment (no IPS)	✓	✓
IPS model: `logit` (MLE), `cbps`, `ipt` (CBPS not available for LATT)			

Normalized vs. unnormalized IPW/AIPW:

- **Unnormalized** (`unnrm`): weights $\hat{\lambda}_i$ need not sum to zero; consistent but potentially higher variance
- **Normalized** (`nrm`, default): weights rescaled so treated and control groups each sum to n; more stable in finite samples, Hájek-type estimator
- Under IPT: normalized $\equiv$ unnormalized (automatically satisfied by the balancing conditions)

All estimators use joint GMM

Standard errors account jointly for IPS, outcome, and treatment model estimation — no plug-in formulas that ignore first-stage uncertainty.

What Does Standard Stata Offer?

`lateffects` **(Stata):**

- IPWRA, normalized kappa, and balancing estimators for LATE
- Logit or probit instrument propensity score
- Joint GMM inference (but known SE issue)
- LATE only

Gaps `drlate` **fills:**

- LATT in addition to LATE
- IPT propensity score estimation
- Binary and count outcome models
- Formal tests (coming soon)
- Complier characteristics (coming soon)

Key message

`drlate` extends and corrects `lateffects`, mirroring the relationship between `teffects2` and `teffects` under unconfoundedness.

Coming Soon: Testing and Diagnostics

We are developing four testing/diagnostic procedures for `drlate`.

1. Unconfoundedness test
Requires one-sided noncompliance ($D_i(0)=0$).
Under this condition, LATT $=$ ATT.
Tests $H_0 : \tau^{LATT} = \tau^{ATT}$.
Rejection $\Rightarrow$ instrument endogeneity.
Doubly robust, $\chi^2(1)$.

2. LATE vs. LATT
No additional assumption required.
Tests $H_0 : \tau^{LATE} = \tau^{LATT}$.
Detects treatment effect heterogeneity among compliers.

3. IV vs. DR LATE
Tests $H_0 : \hat{\tau}_{2SLS} = \hat{\tau}^{LATE}$.
Detects heterogeneity in the treatment effect.

4. Complier characteristics
Estimates means of Y and any covariate for:

- All observations
- Treated / Control
- **Compliers**

Doubly robust, joint GMM inference.

Empirical Illustration

Abadie (2003): 401(k) Eligibility and Saving

Research question

- What is the causal effect of 401(k) participation on household saving?

Variables

- Outcome (Y):
  - `net_tfa`: net financial assets
  - `pira`: indicator for participation in an Individual Retirement Account (IRA)
- Treatment (D):
  - $D = 1$ if the individual participates in a 401(k) plan
- Instrument (Z):
  - $Z = 1$ if the individual is eligible for a 401(k) plan
- Covariates (X):
  - income, family size, marital status, age

Why an IV?

- Participation is voluntary.
- Individuals with stronger saving preferences are more likely to participate.
- A simple comparison of participants and non-participants is therefore likely biased.

Identification Assumptions

Conditional independence

$$[Y(0), Y(1), D(0), D(1)] \perp Z \mid X$$

Conditional on observed characteristics, eligibility is assumed to be unrelated to unobserved saving preferences.

Exclusion restriction

$$Y(d, z) = Y(d)$$

Eligibility affects outcomes only through actual 401(k) participation.

Monotonicity

$$D(1) \geq D(0)$$

No defiers.

One-sided noncompliance

$$D(0) = 0$$

Individuals who are not eligible cannot participate in a 401(k).

Estimating LATE with `drlate`

```
* Default: IPWRA with logit IPS
drlate (net_tfa inc i.fsize marr age) (p401  inc i.fsize marr age) (e401  inc i.fsize marr age)
```

```
Local average treatment effect                    Number of obs    =     9,275
Estimator          : IPWRA
Outcome model      : linear
Treatment model    : logit
Instrument model   : logit (MLE)
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
LATE						
D on Y	**6308.381**	**2984.615**	**2.11**	**0.035**	**458.6438**	**12158.12**
ATE						
Z on Y	**4288.208**	**2031.14**	**2.11**	**0.035**	**307.2471**	**8269.168**
Z on D	**.6797636**	**.0083238**	**81.67**	**0.000**	**.6634493**	**.6960779**

Estimating LATE with `drlate`

```
* Default: IPWRA with logit IPS
drlate (net_tfa inc i.fsize marr age) (p401  inc i.fsize marr age) (e401  inc i.fsize marr age,
    ipt)
```

```
Local average treatment effect                       Number of obs    =      9,275
Estimator         : IPWRA
Outcome model     : linear
Treatment model   : logit
Instrument model  : logit (IPT)
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
LATE						
D on Y	7085.242	2816.523	2.52	0.012	1564.958	12605.53
ATE						
Z on Y	4817.352	1917.593	2.51	0.012	1058.94	8575.765
Z on D	.6799136	.0083478	81.45	0.000	.6635523	.6962749

Estimating LATE with `drlate`

```
*  LATT with logit outcome model
drlate (pira inc i.fsize marr age, logit) (p401  inc i.fsize marr age) (e401  inc i.fsize marr
     age, ipt), latt
```

```
Local average treatment effect on the treated     Number of obs    =      9,275
Estimator          : IPWRA
Outcome model      : logit
Treatment model    : logit
Instrument model : logit (IPT)
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
LATT						
D on Y	.0472947	.0145422	3.25	0.001	.0187925	.0757969
ATT						
Z on Y	.0333156	.0102646	3.25	0.001	.0131975	.0534338
Z on D	.7044267	.0075662	93.10	0.000	.6895972	.7192562

New Features (Preview)

```
* Complier Characteritics
```

```
. drlate compliers (net_tfa) (p401) (e401 inc fsize marr age25 age25sq, logit), ///
>  sumstats(inc fsize marr age25 age25sq) kappa(kappa1)

Complier characteristics                           Number of obs    =      9,275
IPS: logit (MLE)           Kappa: kappa1
```

Variable	All	Treated	Control	Compliers
inc	39254.6410	49815.1386	35224.2529	42551.2584
	(250.1381)	(529.7561)	(264.2305)	(376.5262)
fsize	2.8851	2.9204	2.8716	2.8905
	(0.0158)	(0.0290)	(0.0189)	(0.0251)
marr	0.6286	0.6956	0.6030	0.6490
	(0.0050)	(0.0091)	(0.0060)	(0.0078)
age25	16.0802	16.5133	15.9149	16.1401
	(0.1069)	(0.1907)	(0.1285)	(0.1725)
age25sq	364.6419	365.8076	364.1971	367.0055
	(4.0445)	(7.1871)	(4.8689)	(6.5259)
Complier share	0.6745			
	(0.0080)			

New Features (Preview)

```
* Hausmann Test for Unconfoundedness
```

```
. drlate (net_tfa inc fsize marr age25 age25sq) (p401 inc fsize marr age25 age25sq, logit) (e401 i
> nc fsize marr age25 age25sq, logit), test(lattatt)
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
DR LATT	10917.78	3709.281	2.94	0.003	3647.72	18187.83
DR ATT	12672.59	3328.85	3.81	0.000	6148.166	19197.02
Diff	-1754.816	2359.999	-0.74	0.457	-6380.329	2870.697

Installation and References

Installation:

```
ssc install drlate
```

Please cite:

- Słoczyński, T., Uysal, S.D., & Wooldridge, J.M. (2022). *Doubly Robust Estimation of Local Average Treatment Effects Using Inverse Probability Weighted Regression Adjustment.* arXiv:2208.01300.
- Słoczyński, T., Uysal, S.D., & Wooldridge, J.M. (2025). *Covariate Balancing and the Equivalence of Weighting and Doubly Robust Estimators of Average Treatment Effects.* arXiv:2310.18563.

Thank you!   Questions?

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