INTL 601 Research Methods I - Exercise #1

Voter Mobilization Field Experiment

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1. Data Overview

The dataset contains 5,000 observations from a simulated voter mobilization field experiment based on Gerber and Green (2000). The key variables are:

Variable	Type	Description
`Y`	Binary	Outcome: 1 = voted, 0 = did not vote
`Z`	Binary	Random assignment: 1 = assigned to canvassing, 0 = not assigned
`T`	Binary	Treatment received: 1 = actually contacted, 0 = not contacted
`age`	Integer	Voter age
`educ`	Integer	Years of education
`pastvote`	Binary	Past turnout (1 = voted before, 0 = did not)
`party_id`	Continuous	Partisan strength (higher = stronger partisan)
`competitive`	Binary	District competitiveness (1 = competitive)

Descriptive statistics:

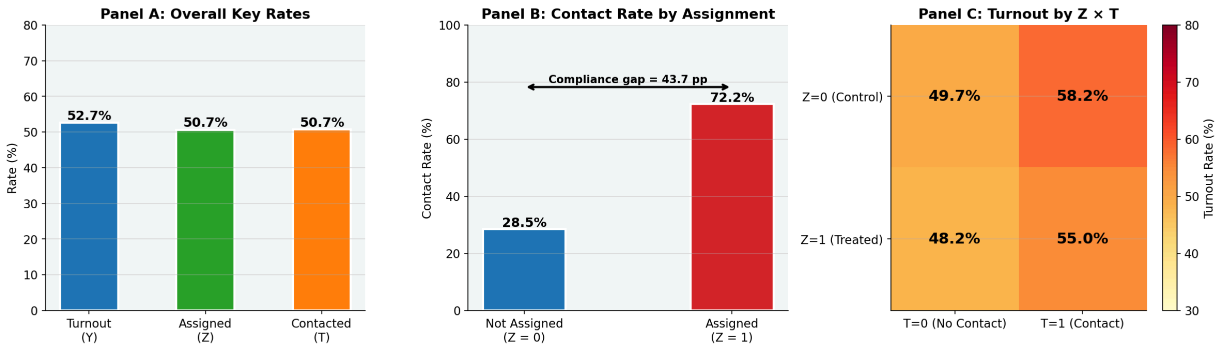
	mean	std	min	max
Y	0.527	0.499	0	1
Z	0.507	0.5	0	1
T	0.507	0.5	0	1
age	45.226	11.912	18	87
educ	13.96	2.037	8	20
pastvote	0.591	0.492	0	1
party_id	0.005	1.001	-3.714	3.099
competitive	0.507	0.5	0	1

Key rates:

Metric	Value
Turnout rate (Y = 1)	52.7%
Assignment rate (Z = 1)	50.7%
Contact rate (T = 1)	50.7%
Contact rate given Z = 1	72.2%
Contact rate given Z = 0	28.5%
Compliance gap	43.7 percentage points

Among those assigned to canvassing (Z = 1), 72.2% were actually contacted, compared to 28.5% among those not assigned (Z = 0), a compliance gap of 43.7 pp. Compliance is imperfect in both directions: some assigned voters were never contacted (never-takers) and some non-assigned voters were contacted through other channels (always-takers). This is a case of **two-sided noncompliance**.

Figure 1 — Descriptive Statistics



2. OLS Univariate Analysis and Difference of Means

Difference-of-means test:

Group	N	Mean Turnout
Not contacted (T = 0)	2,466	49.31%
Contacted (T = 1)	2,534	55.92%
Difference	-	6.61 pp

Two-sample t-test: t = 4.689, $p < 0.001$

OLS regression: reg Y T

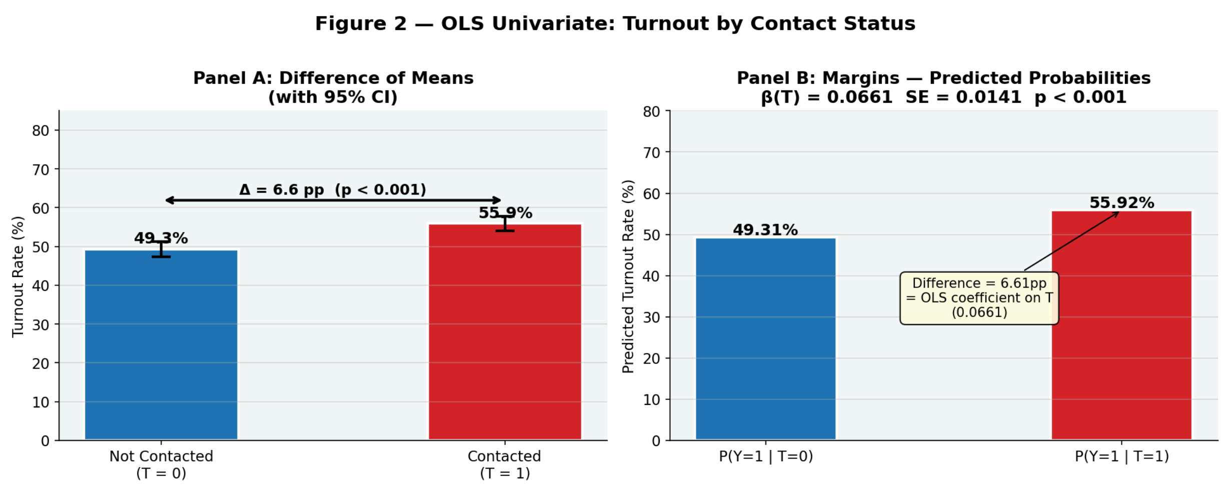
Variable	Coef	Std Err	t	p-value	95% CI
Intercept	0.4931***	0.0100	49.142	< 0.001	[0.4734, 0.5128]
T	0.0661***	0.0141	4.689	< 0.001	[0.0385, 0.0937]

*N = 5000 | R^2 = 0.0044 | *p<0.05 **p<0.01 ***p<0.001*

Margins: predicted probabilities at T = 0 and T = 1:

	Value
P(Y = 1 | T = 0)	0.4931 (49.31%)
P(Y = 1 | T = 1)	0.5592 (55.92%)
Difference	0.0661 (6.61 pp)

In a linear probability model (LPM), the coefficient on a binary treatment equals the difference in predicted means between the two groups. The difference in predicted probabilities (6.61 pp) is exactly equal to the OLS coefficient on T (0.0661). The `margins at(T=(0 1))` command in Stata recovers the same quantity as computing predicted values at T = 0 and T = 1 from the regression.



3. OLS with Control Variables

Regression: reg Y T age educ pastvote party_id competitive

Variable	Coef	Std Err	t	p-value	95% CI
Intercept	-0.1011	0.0534	-1.893	0.058	[-0.2059, 0.0036]
T	0.0575***	0.0132	4.348	< 0.001	[0.0316, 0.0834]
age	0.0044***	0.0006	8.006	< 0.001	[0.0033, 0.0055]
educ	0.0134***	0.0032	4.159	< 0.001	[0.0071, 0.0198]
pastvote	0.3270***	0.0134	24.444	< 0.001	[0.3008, 0.3532]
party_id	0.0530***	0.0066	8.070	< 0.001	[0.0401, 0.0659]
competitive	0.0337*	0.0132	2.552	0.011	[0.0078, 0.0595]

*N = 5000 | $R^2 = 0.1345$ | *p<0.05 **p<0.01 ***p<0.001*

The coefficient on T changes from 0.0661 to 0.0575 when controls are added, a change of -0.0086 (13.0%). This small change is expected: because T derives from random assignment Z, T is approximately uncorrelated with pre-treatment covariates. Adding controls in a randomized experiment primarily increases precision rather than correcting omitted-variable bias.

In a linear probability model, the marginal effect of T equals the regression coefficient: **0.0575**.

Control variables ranked by absolute t-statistic:

Variable	Coefficient	Std Err	t-statistic	p-value
pastvote	0.3270	0.0134	**24.44**	< 0.001
party_id	0.0530	0.0066	**8.07**	< 0.001
age	0.0044	0.0006	**8.01**	< 0.001
educ	0.0134	0.0032	**4.16**	< 0.001
competitive	0.0337	0.0132	**2.55**	0.011

`pastvote` has the largest absolute t-statistic (|t| = 24.44), indicating the strongest marginal association with turnout after controlling for all other variables.

Figure 3 — OLS with Control Variables

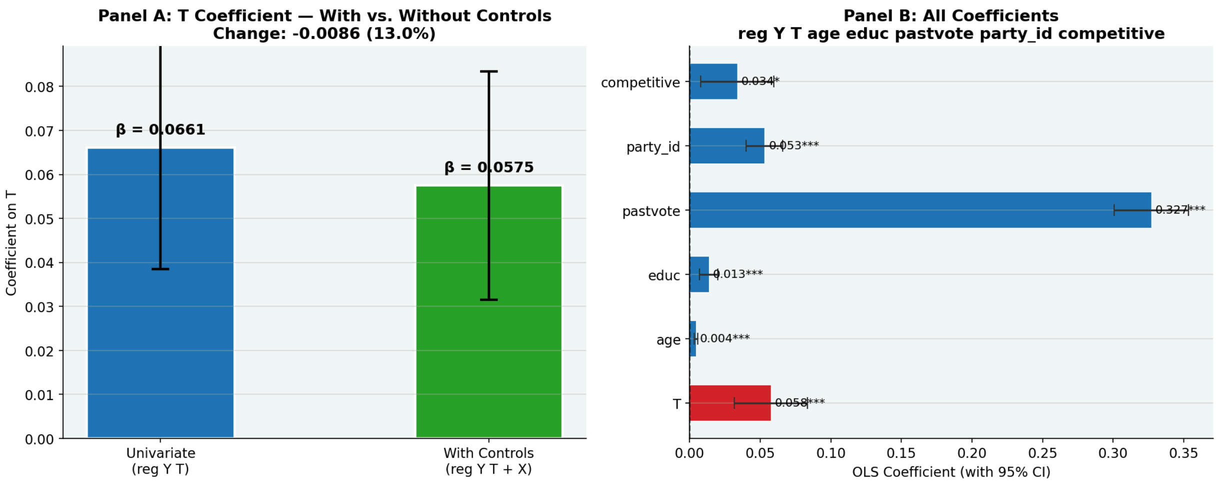
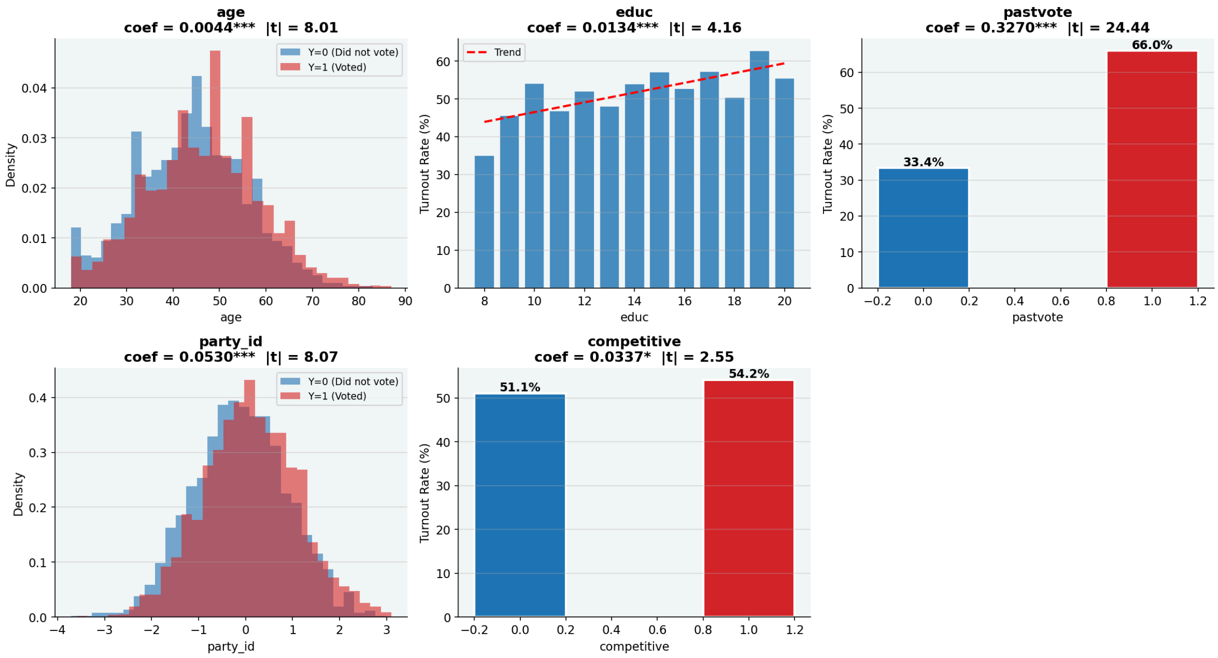


Figure 4 — Covariate Associations with Turnout (Y)



4. Causal Structure: Z -> T -> Y

First stage: reg T ~ Z + covariates

Variable	Coef	Std Err	t	p-value	95% CI
Intercept	0.1038*	0.0517	2.009	0.045	[0.0025, 0.2051]
Z	0.4369***	0.0126	34.564	< 0.001	[0.4121, 0.4616]
age	0.0031***	0.0005	5.817	< 0.001	[0.0020, 0.0041]
educ	0.0001	0.0031	0.032	0.974	[-0.0060, 0.0062]
pastvote	0.0025	0.0129	0.193	0.847	[-0.0227, 0.0277]
party_id	-0.0068	0.0063	-1.084	0.278	[-0.0192, 0.0055]
competitive	0.0774***	0.0126	6.118	< 0.001	[0.0526, 0.1022]

*N = 5000 | R^2 = 0.2028 | *p<0.05 **p<0.01 ***p<0.001*

The Z coefficient (0.4369, t = 34.564, p < 0.001) shows that random assignment raises the probability of contact by 43.7 pp. The instrument is strong (F-statistic well above 10).

Reduced form (ITT): reg Y ~ Z + covariates

Variable	Coef	Std Err	t	p-value	95% CI
Intercept	-0.0875	0.0539	-1.624	0.104	[-0.1931, 0.0181]
Z	0.0118	0.0132	0.893	0.372	[-0.0141, 0.0376]
age	0.0046***	0.0006	8.341	< 0.001	[0.0035, 0.0057]
educ	0.0134***	0.0032	4.130	< 0.001	[0.0070, 0.0197]
pastvote	0.3271***	0.0134	24.405	< 0.001	[0.3008, 0.3534]
party_id	0.0526***	0.0066	7.996	< 0.001	[0.0397, 0.0655]
competitive	0.0381**	0.0132	2.889	0.004	[0.0122, 0.0639]

*N = 5000 | R^2 = 0.1314 | *p<0.05 **p<0.01 ***p<0.001*

The Z coefficient (0.0118) is the Intention-to-Treat (ITT) effect: the average effect of being assigned to canvassing across all assigned voters, including those never actually contacted. The ITT is not statistically significant (p = 0.372).

2SLS / IV estimate (LATE):

Estimator	Estimate	Std Err	t-stat	p-value
ITT (reduced form)	0.0118	0.0132	0.893	0.372
First stage (Z->T)	0.4369	0.0126	34.564	< 0.001
LATE = ITT / FS	0.0269	-	-	-
2SLS estimate	0.0269	0.0301	0.894	0.371
OLS (T->Y, with controls)	0.0575	0.0132	4.348	< 0.001

LATE = ITT / First Stage = 0.0118 / 0.4369 = 0.0269, which matches the 2SLS estimate (0.0269).

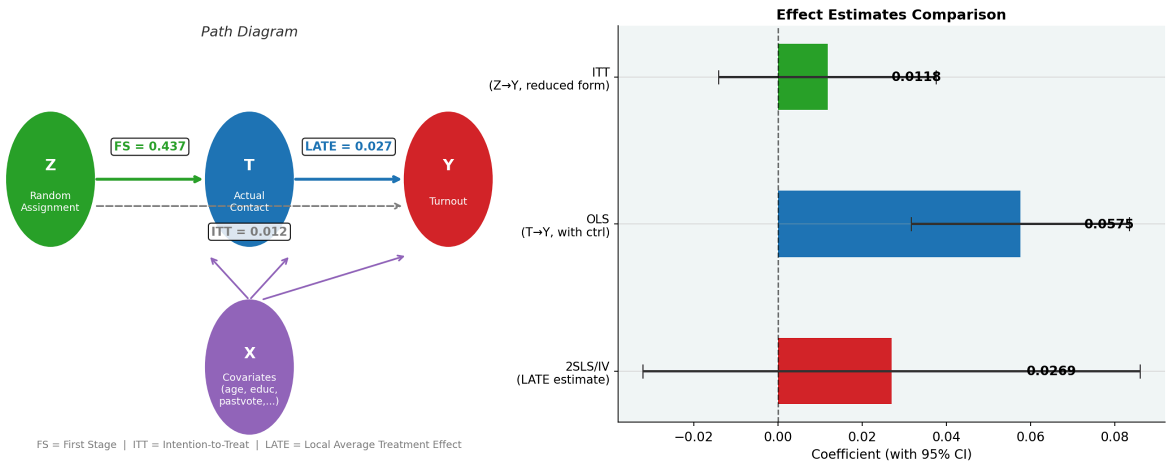
Neither the ITT (0.0118, p = 0.372) nor the LATE (0.0269, p = 0.371) reaches statistical significance at conventional levels. The OLS estimate (0.0575) is statistically significant but reflects selection: contacted voters differ from non-contacted voters in ways that predict turnout independently of canvassing.

The causal structure separates three estimands:

Question	Estimand	Estimate
Effect of being assigned to canvassing	ITT	0.0118
Effect of actual contact for compliers	LATE (2SLS)	0.0269
Association of contact with turnout (with controls)	OLS	0.0575

Z affects Y only through T (exclusion restriction). The ITT (0.0118) captures the path Z -> T -> Y. Dividing by the first stage (0.4369) rescales to the LATE (0.0269), which is the average treatment effect for compliers only.

Figure 5 — Causal Structure: Z → T → Y



5. Targeted Treatment and Confounding Bias

A non-random targeted treatment indicator is generated as:

```
T_target = (runiform() < invlogit(-1 + 1.2*pastvote + 0.5*party_id))
```

Voters with prior voting history and stronger partisan identity are more likely to be targeted. Both characteristics also independently predict higher turnout, creating confounding.

T_target rate: **43.1%**

Contact rate by past vote (tab T_target pastvote, row):

pastvote	0	1
0	73.1898	26.8102
1	45.636	54.364

Voters who previously voted are far more likely to receive the targeted treatment (54.4% vs. 26.8%), creating a direct correlation between T_target and Y through pastvote.

Regression without controls: reg Y T_target

Variable	Coef	Std Err	t	p-value	95% CI
Intercept	0.4822***	0.0093	51.778	< 0.001	[0.4640, 0.5005]
T_target	0.1029***	0.0142	7.253	< 0.001	[0.0751, 0.1307]

*N = 5000 | R^2 = 0.0104 | *p<0.05 **p<0.01 ***p<0.001*

Regression with controls: reg Y T_target age educ pastvote party_id competitive

Variable	Coef	Std Err	t	p-value	95% CI
Intercept	-0.0779	0.0534	-1.457	0.145	[-0.1826, 0.0269]
T_target	-0.0128	0.0142	-0.900	0.368	[-0.0406, 0.0151]
age	0.0046***	0.0006	8.362	< 0.001	[0.0035, 0.0057]
educ	0.0133***	0.0032	4.117	< 0.001	[0.0070, 0.0197]

Variable	Coef	Std Err	t	p-value	95% CI
pastvote	0.3305***	0.0140	23.681	< 0.001	[0.3032, 0.3579]
party_id	0.0540***	0.0068	7.990	< 0.001	[0.0407, 0.0672]
competitive	0.0378**	0.0132	2.871	0.004	[0.0120, 0.0637]

*N = 5000 | R^2 = 0.1314 | *p<0.05 **p<0.01 ***p<0.001*

Coefficient comparison:

Model	Coefficient on Treatment	Notes
T experimental (no controls)	0.0661	Random assignment - unbiased
T_target (no controls)	0.1029	Biased upward by confounding
T_target (with controls)	-0.0128	Effect disappears; sign reverses

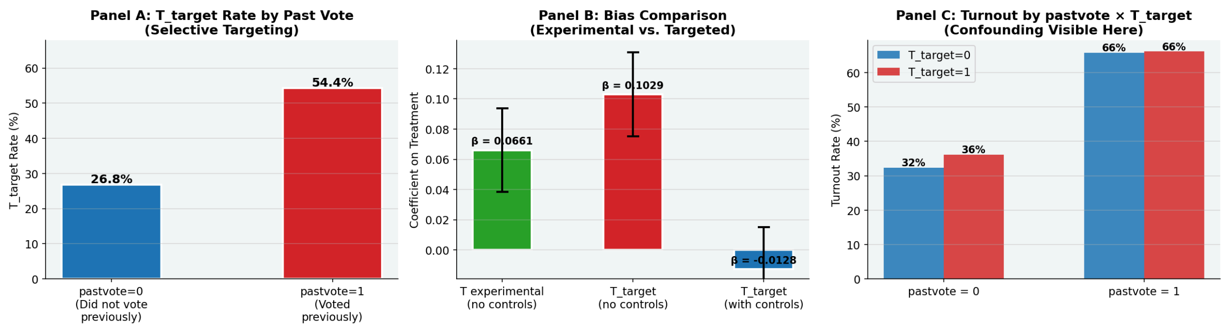
When controls are added, the T_target coefficient drops from 0.1029 to -0.0128: the estimated effect reverses sign and becomes statistically insignificant, indicating the apparent treatment effect was entirely due to confounding by pre-existing characteristics. The experimental T estimate (0.0661) is unbiased because random assignment ensures T is uncorrelated with confounders.

What drives the confounding?

Variable	T_target coefficient	Y coefficient	Confounder?
pastvote	0.2744	0.3270	Yes - strong
party_id	0.1087	0.0530	Moderate
age	0.0007	0.0044	Negligible

pastvote is the primary confounder: it strongly predicts T_target (coefficient of 1.2 in the logit formula by construction) and is the strongest predictor of Y among all covariates (|t| = 24.44 in the outcome regression).

Figure 6 — Targeted Treatment vs. Experimental Treatment



6. Summary

Estimator	Coefficient	Notes
Diff-of-means: E[Y|T=1] - E[Y|T=0]	0.0661	Raw association
OLS: reg Y T	0.0661	Equal to diff-of-means
OLS: reg Y T + controls	0.0575	Controlled association
ITT (Z->Y, reduced form)	0.0118	p = 0.372 (not significant)

Estimator	Coefficient	Notes
LATE (2SLS)	0.0269	p = 0.371 (not significant)
T_target (no controls)	0.1029	Biased by confounding
T_target (with controls)	-0.0128	Effect disappears

Analysis conducted in Python using pandas, statsmodels, scipy, linearmodels, matplotlib, and seaborn.
Dataset: gg_fake.dta - 5,000 simulated observations (teaching dataset).