STAT 511 Group Project

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Author Contributions

Chengyuan: Simulation study, . . . **Daniel**: Exploratory data analysis, report writing, . . . **Junjie** Model and methods description, . . .

1 Problem Description and Modeling Objective In the paper "Estimating treatment effect heterogeneity in randomized program evaluation,"[1] the authors are concerned with "treatment effect heterogeneity" which they define as "the degree to which different treatments have differential causal effects on each unit." The authors' objective is to estimate treatment effect heterogeneity in order to (1) select the most effective treatment among a large number of available treatments, (2) design optimal treatments for sub-groups of units, (3) test the existence of treatment effect heterogeneity, and (4) generalize causal effect estimates from a sample to a target population.

2 Data Description and Availability of Dataset The `R` package `FindIt` includes the data from two well-known randomized evaluation studies in the social sciences that the authors' apply their model to.[2] Including the dataset `GerberGreen`, which is data from the 1998 New Haven Get-Out-the-Vote filed experiment where many different mobilization techniques were randomly administered to voters in the 1998 election. As well as the dataset `LaLonde`, which is data from the national supported work (NSW) program that was a job training program intended to increase earnings of workers conducted from 1975 to 1978 over 15 sites in the United States.

2.1 Gerber and Green (1998) New Haven Get-Out-the-Vote The `GerberGreen` dataset includes one binary outcome variable, four treatment variables, and four pre-treatment control covariates. Specifically, `voted98` is the binary outcome variable of whether a registered voter voted or not in the 1998 election. The appendix includes a preview of `GerberGreen` at Table A1 as well as additional details on the covariates.

Of the 14,774 registered voters collected in `GerberGreen`, 5,879 (39.8%), voted in the 1998 election. Figure 1 provides the proportion that voted in the 1998 election by the levels of each of the four treatment types. Whereas, Figure 2 provides the proportion that voted in the 1998 election by the levels of each of the four pre-treatment controls.

Further, Table A2 provides a breakdown of the proportion of registered voters that voted in 1998 by each of the combinations of the four treatment variables present in `GerberGreen`. Finally, Table A3 provides a breakdown of the proportion of registered voters that voted in 1998 by each of the combinations of the pre-treatment control covariates.

These figures demonstrate the heterogeneity in voting outcome by both treatment type and control condition and motivate the need for a model that can detect causal effects in such an environment.

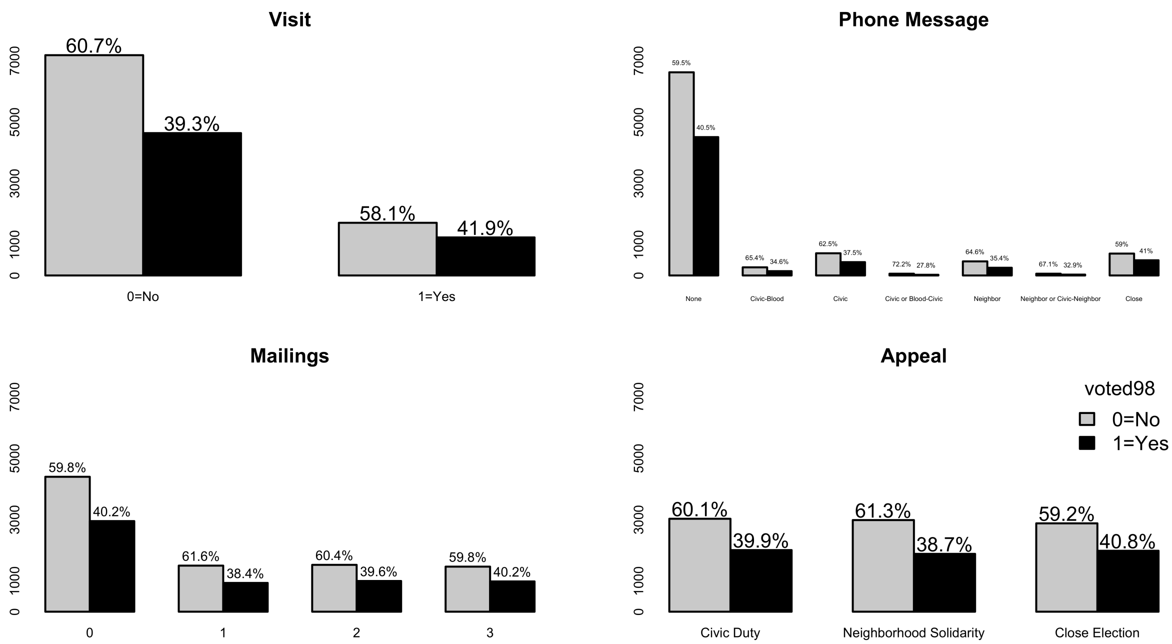

Figure 1: Voting Outcome by Treatment Type

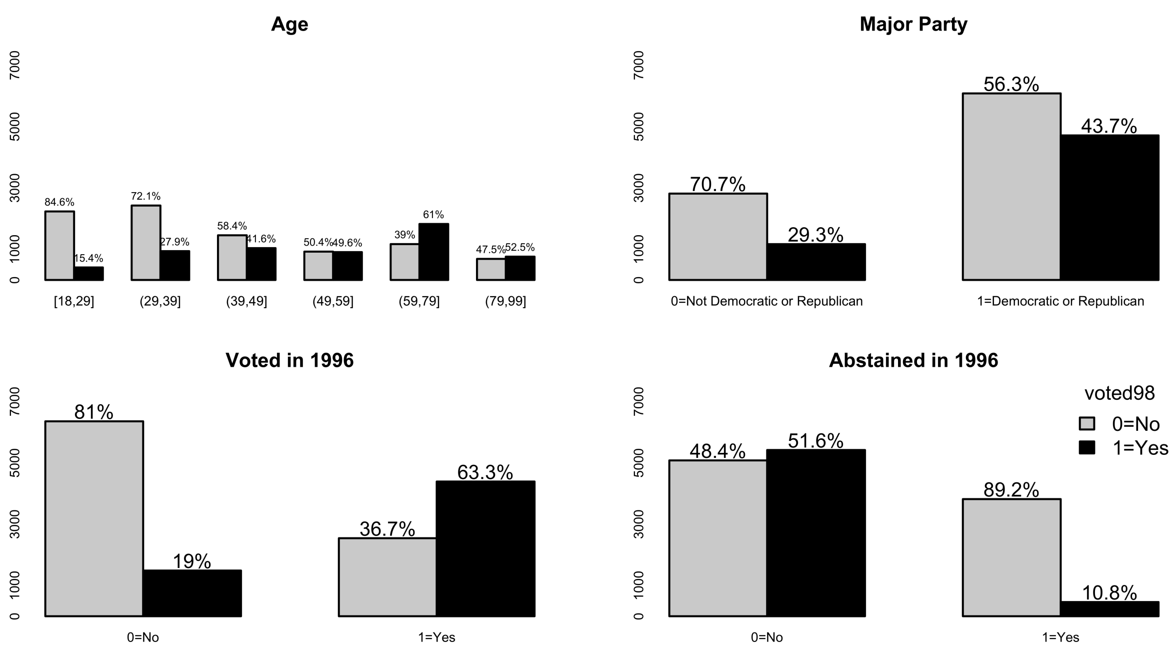

Figure 2: Voting Outcome by Pre-Treatment Control

2.2 LaLonde (1996) National Supported Work Study The `LaLonde` dataset one binary outcome variable, one binary treatment variable, and ten pre-treatment control covariates. Specifically, `outcome` is a binary outcome variable of whether earnings in 1978 are larger than in 1975. The appendix includes a preview of `LaLonde` at Table A4 as well as additional details on the covariates.

Of the 722 workers in `LaLonde`, 408 (56.5%), had larger earnings in 1978 compared to 1975. Figure 3 provides the proportion that had larger earnings in the control and treatment groups. Whereas, Figure 4 provides the proportion that had larger earnings by the levels of each of the pre-treatment controls.

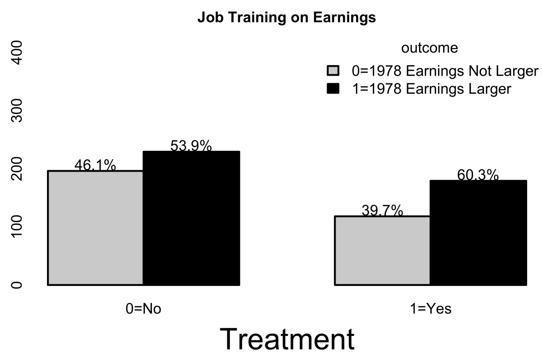

Figure 3: Earnings Outcome by Treatment

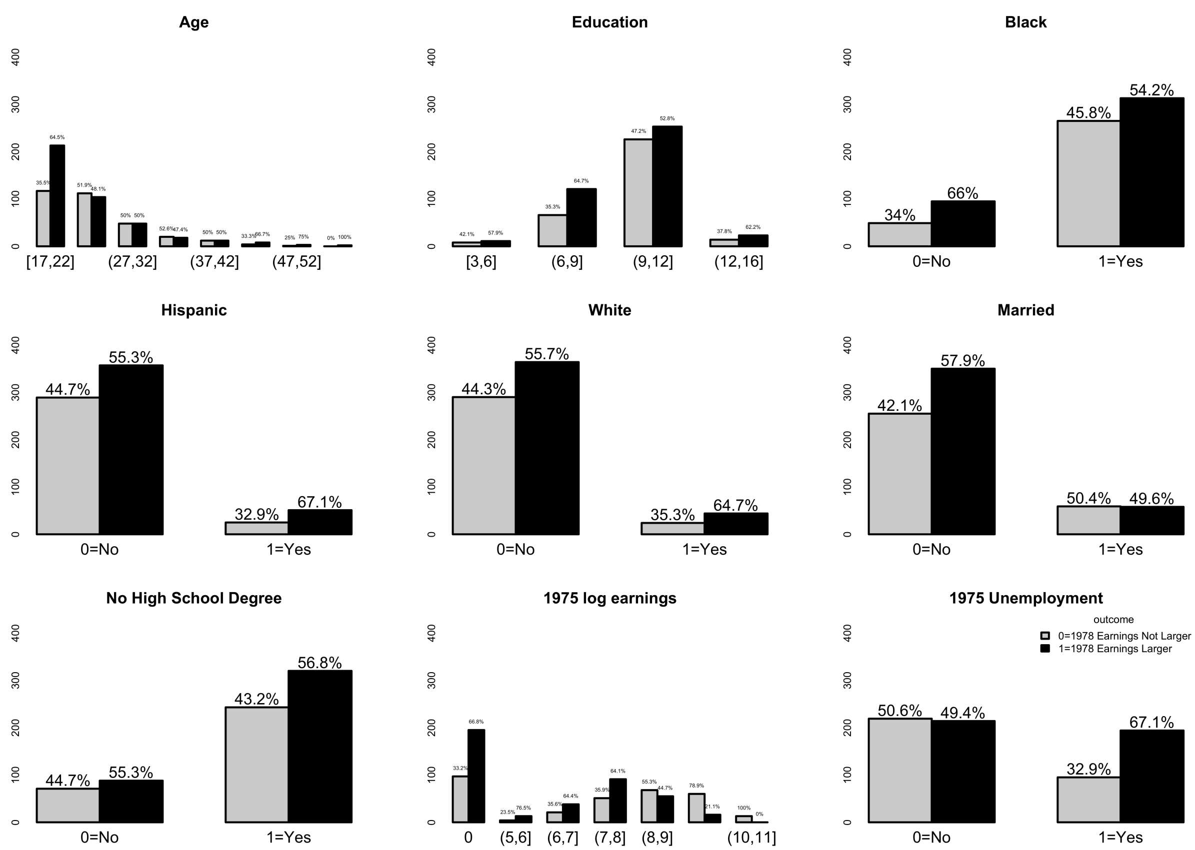

Figure 4: Earnings Outcome by Pre-Treatment Control

3 Model and Methods Description

3.1 Framework In order to overcome the methodological challenges of (1) extracting useful information from sparse randomized evaluation study data, (2) identifying sub-groups for whom a treatment is beneficial, and (3) generalizing the results of an experiment to a target population, the authors' formulate the estimation of heterogeneous treatment effects as a variable selection problem. Specifically, the paper develops a Squared Loss Support Vector Machine (L2-SVM) with separate LASSO constraints over the pre-treatment and causal heterogeneity parameters, such that the causal heterogeneity variables of interest are separated from the rest of the variables.

The proposed model is grounded within the potential outcomes framework for causal inference. In this framework, the causal effect of treatment t for unit i is defined as $Y_i(t) - Y_i(0)$, where Y_i is the potential outcome for unit i under treatment or control. Thus, by leveraging the fact that the L2-SVM is an optimal classifier, the proposed model can estimate heterogeneous treatment effects by predicting the potential outcomes $Y_i(t)$ directly from the fitted model and estimate the conditional treatment effect as the difference between the predicted outcome under treatment status t and under the control condition.

To fit the proposed model the authors' use an estimation algorithm based on a generalized cross-validation (GCV) statistic. Because of the structure of the proposed model, the SVM becomes a least squares problem on a subset of the data, therefore the L2-SVM is fitted through a series of iterated LASSO fits. Accordingly, the authors' employ an efficient coordinate descent algorithm for the LASSO fits.

3.2 Model For modeling, the authors transform the binary outcome to $Y_i^* = 2Y_i - 1 \in \{\pm 1\}$ and then relate the estimated binary outcome $\hat{Y}_i \in \{\pm 1\}$ to the estimated latent variable $\hat{W}_i \in \mathbb{R}$, where

$$\hat{Y}_i = \operatorname{sgn}(\hat{W}_i) \quad \text{and} \quad \hat{W}_i = \hat{\mu} + \hat{\beta}^\top Z_i + \hat{\gamma}^\top V_i,$$

here Z_i is an L_Z dimensional vector of treatment effect heterogeneity variables and V_i is an L_V dimensional vector containing the remaining control covariates. Thus, the causal heterogeneity variables of interest, Z_i, are separated from the rest of the variables.

In order to estimate the parameters (β, γ) the authors adapt a support vector machine (SVM) classifier and place separate LASSO constraints over each set of coefficients. Specifically, the estimates are given by the objective function

$$(\hat{\beta}, \hat{\gamma}) = \underset{(\beta,\gamma)}{\arg\min} \sum_{i=1}^{n} w_i \cdot |1 - Y_i^* \cdot (\mu + \beta^\top Z_i + \gamma^\top V_i)|_+^2 + \lambda_Z \sum_{j=1}^{L_Z} |\beta_j| + \lambda_V \sum_{j=1}^{L_V} |\gamma_j|,$$

where λ_Z and λ_V are pre-determined separate LASSO penalty parameters and w_i is an optional sampling weight for generalizing results from a sample to a target population. Here, the authors formulate the SVM as a penalized squared hinge-loss objective function (L2-SVM) where the hinge-loss is defined as $|x|_+ \equiv \max(x, 0)$.

3.3 Estimating heterogeneous treatment effects By leveraging the fact that the L2-SVM is an optimal classifier, the proposed model can estimate heterogeneous treatment effects by predicting the potential outcomes $Y_i(t)$ directly from the fitted model and estimate the conditional treatment effect (CTE) as the difference between the predicted outcome under treatment status t and under the control condition: $\hat{\delta}(t; \tilde{X}_i) = \frac{1}{2}(\hat{Y}_i(t) - \hat{Y}_i(0))$. Further, the model can estimate the conditional average treatment effect (CATE), which is defined as $\tau(t; \tilde{x}) = \mathbb{E}(Y_i(t) - Y_i(0) \mid \tilde{X}_i = \tilde{x})$, for a given covariate profile $\tilde{x}$. Specifically, the authors define $\hat{W}_i^*(t)$ as the predicted $\hat{W}_i^*(t)$ values truncated at positive and negative one. Then the CATE is estimated as the difference in truncated values of the predicted outcome variables, $\hat{\tau}(t; \tilde{X}_i) = \frac{1}{2}(\hat{W}_i^*(t) - \hat{W}_i^*(0))$. While not a true difference in probabilities, the authors argue that $\hat{\tau}(t; \tilde{X}_i)$ provides a reasonable approximation of the CATE.

3.4 Estimating algorithm

4 Reproducing Results

5 Results

5.1 Selecting the best get-out-the-vote mobilization strategies To fit their proposed model to the `GerberGreen` data, the authors transform `voted98` to $\{\pm 1\}$, define Z_i as 192 binary indicator variables for the 192 possible treatment combinations, such that $K_Z = 192$, and define V_i as the pre-treatment control covariates including the four main effects of `age`, `majorpty`, `vote96.1`, `vote96.0`; five two-way interaction terms: `age`:`majorpty`, `age`:`vote96.1`, `age`:`vote96.0`, `majorpty`:`vote96.1`, and `vote96.1`:`vote96.0`; and `age`^{2}, such that $K_V = 10$.

The authors find that 15 of the 192 treatment effect combinations are estimated as nonzero. Notably, they find that canvassing in person, i.e., `persngrp` = 1, is the most effective GOTV technique. Specifically, they find that compared to the baseline of no treatment of any type administered, registered voters that received a personal visit were 2.69 percentage points more likely to vote. Further, they find that all mobilization strategies with a phone call and no personal visit either have no effect on voter turnout or are estimated to decrease voter turnout. For example, they find that the mobilization strategy of (`persngrp` = 0, `phnscrpt` = 2−civic appeal, `mailings` = 3, `appeal` = 2− neighborhood solidarity) was estimated to decrease voter turnout by 4.12 percentage points compared to the baseline. Moreover, they find that the most effective treatment combination without canvassing was three mailings with a civic responsibility message and no phone calls, which was estimated to increase voter turnout by 1.17 percentage points. This result is relevant because canvassing is the most expensive mobilization strategy.

Therefore, the authors conclude that in the presence of canvassing, the additional treatments of phone calls or mailings will lessen the canvassing's effectiveness. And if voters are not canvassed, they should be treated with three mailings with a civi duty appeal.

5.2 Identifying workers for whom job training is beneficial In the application of their model to the `LaLonde` dataset, the authors (1) identify groups of workers for whom the training program is beneficial, and (2) generalize the results based on this experiment to a target population, where the target population is a 1978 panel study of income dynamics (PSID) that oversamples low-income individuals.

To fit their proposed model to the `LaLonde` data, the authors transform `outcome` to $\{\pm 1\}$. Then they define the pre-treatment control covariates V as as the 12 main effects of `age`, `age`^{2}, `educ`, `educ`^{2}, `log.re75`, `log.re75`^{2}, `black`, `hisp`, `white`, `marr`, `nodegr`, and `u75`; and 32 two-way interaction terms between the pre-treatment control covariates[1]. Such that $K_V = 44$. The causal heterogeneity variables Z include the binary treatment `treat` and the 44 interaction terms between `treat` and the pre-treatment controls. Thus, $K_Z = 45$.

Overall, the model produces an ATE estimate of 7.61 percentage points for the NSW sample, meaning that workers that received the job training were 7.61 percentage points more likely to have their earnings increase from 1975 to 1978 than those who did not receive the treatment. Crucially, the model is able to identify groups of workers for whom the training program is helpful/harmful. Specifically, the model finds that the CATE for groups of low education, non-Hispanic, high earning workers was as high as 53 percentage points. However, the CATE for groups of high earning Hispanic workers was as low as -21 percentage points.

6 Conclusion

[1] The race indicators are not interacted with each other.

References

[1] Kosuke Imai and Marc Ratkovic. Estimating treatment effect heterogeneity in randomized program evaluation. *The Annals of Applied Statistics*, 7(1), March 2013.

[2] Marc Ratkovic and Kosuke Imai. Findit: R package for finding heterogeneous treatment effects, 2012. Available at Comprehensive R Archive Network (CRAN).

A Appendix

Table A1 provides a preview of the `GerberGreen` dataset. `voted98` is a binary outcome variable of whether a registered voter voted or not in the 1998 election; `persngrp` is a binary treatment variable of whether a personal visit of a registered voter was made; `phnscrpt` is a categorical treatment variable with 7 levels (0 - no phone call, 1 - donate blood, 2 - civic appeal, 3 - civic appeal/donate blood, 4 - neighborhood solidarity, 5 - civic appeal/neighborhood solidarity, 6 - close election), for the phone message scripts read to registered voters; `mailings` is an ordinal treatment variable of the number (0-3) of mailings sent to voters; `appeal` is a categorical treatment variable with 3 levels (1 - civic duty, 2 - neighborhood solidarity, 3 - close election) for the content of the appeal made to registered voters; `age` is an ordinal control for the age of the registered voter; `majorpty` is a binary control for whether the registered voter was registered with either the Democratic or Republican part (1) or not (0); `vote96.1` is a binary control for whether the registered voter voted in the 1996 election; and `vote96.0` is a binary control for whether the registered voter abstained in the 1996 election.

Table A1: Gerber and Green (1998) New Haven Get-Out-the-Vote

	voted98	persngrp	phnscrpt	mailings	appeal	age	majorpty	vote96.1	vote96.0
1	1	0	2	2	1	47	1	1	0
2	0	0	2	2	1	24	1	0	0
3	0	0	4	1	2	64	1	0	1
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
14772	0	0	0	0	2	29	1	1	0
14773	0	0	0	0	1	53	1	1	0
14774	1	0	0	0	1	74	1	1	0

Table A2 below provides a breakdown of the proportion of registered voters that voted in 1998 by each of the combinations of the four treatment variables present in `GerberGreen`. Note, in the original experiment design there were 193 unique treatment combinations randomly administered to registered voters; however, the authors limited their study to single voter households to avoid interference among voters in the same household and thus only 72 treatment combinations are present in the subsetted data.

Table A2: Get-Out-the-Vote Treatment Interactions

	Visit	Phone	Mailings	Appeal	Registered	Voted	Proportion
1	Yes	Civic-Blood	1	Civic Duty	13	8	61.5%
2	No	Civic or Blood-Civic	1	Civic Duty	12	6	50.0%
3	Yes	Neighbor	2	Neighborhood Solidarity	46	23	50.0%
4	Yes	Neighbor or Civic-Neighbor	2	Neighborhood Solidarity	4	2	50.0%
5	Yes	Civic	2	Civic Duty	55	26	47.3%
6	Yes	Neighbor or Civic-Neighbor	1	Neighborhood Solidarity	11	5	45.5%
7	Yes	Civic	0	Neighborhood Solidarity	40	18	45.0%
8	Yes	None	1	Close Election	87	39	44.8%
9	Yes	None	0	Civic Duty	506	226	44.7%
10	Yes	None	2	Close Election	112	50	44.6%
11	Yes	None	3	Civic Duty	110	49	44.5%
12	Yes	Neighbor	3	Neighborhood Solidarity	45	20	44.4%
13	Yes	None	0	Close Election	431	190	44.1%
14	Yes	Close	1	Close Election	68	30	44.1%
15	No	Close	2	Close Election	244	107	43.9%
16	Yes	None	3	Close Election	89	39	43.8%
17	Yes	Civic	3	Civic Duty	53	23	43.4%
18	No	None	3	Civic Duty	393	170	43.3%
19	Yes	Civic or Blood-Civic	2	Civic Duty	7	3	42.9%
20	No	None	3	Close Election	397	169	42.6%
21	Yes	Close	2	Close Election	54	23	42.6%
22	No	None	2	Neighborhood Solidarity	421	178	42.3%
23	Yes	None	0	Neighborhood Solidarity	411	174	42.3%
24	Yes	Civic	1	Neighborhood Solidarity	12	5	41.7%
25	Yes	Civic	2	Neighborhood Solidarity	12	5	41.7%
26	No	Close	3	Close Election	250	104	41.6%
27	No	Close	1	Close Election	260	107	41.2%
28	Yes	None	2	Neighborhood Solidarity	105	43	41.0%
29	No	None	0	Close Election	1742	702	40.3%
30	No	None	2	Civic Duty	412	166	40.3%
31	No	None	3	Neighborhood Solidarity	376	151	40.2%
32	No	None	0	Civic Duty	1772	706	39.8%
33	No	Civic	2	Civic Duty	196	78	39.8%
34	No	None	0	Neighborhood Solidarity	1755	693	39.5%
35	Yes	Close	3	Close Election	76	30	39.5%
36	No	None	1	Close Election	386	152	39.4%
37	No	None	1	Civic Duty	438	172	39.3%
38	Yes	None	1	Civic Duty	80	31	38.8%
39	No	Civic	3	Civic Duty	197	76	38.6%
40	No	None	1	Neighborhood Solidarity	400	154	38.5%
41	Yes	Civic-Blood	0	Civic Duty	39	15	38.5%
42	No	Close	0	Close Election	200	76	38.0%
43	No	Civic	1	Civic Duty	187	69	36.9%
44	No	Neighbor or Civic-Neighbor	1	Neighborhood Solidarity	19	7	36.8%
45	Yes	None	2	Civic Duty	110	40	36.4%
46	No	None	2	Close Election	414	150	36.2%
47	Yes	None	1	Neighborhood Solidarity	90	32	35.6%
48	Yes	None	3	Neighborhood Solidarity	93	33	35.5%
49	No	Civic-Blood	2	Civic Duty	48	17	35.4%
50	No	Neighbor	3	Neighborhood Solidarity	207	73	35.3%
51	No	Civic	0	Neighborhood Solidarity	208	71	34.1%
52	No	Civic-Blood	0	Civic Duty	190	64	33.7%
53	No	Neighbor	1	Neighborhood Solidarity	188	63	33.5%
54	Yes	Civic	3	Neighborhood Solidarity	9	3	33.3%
55	No	Civic	3	Neighborhood Solidarity	52	17	32.7%
56	No	Civic-Blood	3	Civic Duty	43	14	32.6%
57	No	Neighbor	2	Neighborhood Solidarity	179	58	32.4%
58	Yes	Close	0	Close Election	56	18	32.1%
59	No	Civic-Blood	1	Civic Duty	50	16	32.0%
60	No	Civic	1	Neighborhood Solidarity	44	14	31.8%
61	Yes	Civic	1	Civic Duty	44	14	31.8%
62	No	Civic	2	Neighborhood Solidarity	48	15	31.2%
63	Yes	Neighbor	1	Neighborhood Solidarity	45	14	31.1%
64	Yes	Civic-Blood	3	Civic Duty	13	4	30.8%
65	No	Neighbor or Civic-Neighbor	2	Neighborhood Solidarity	23	7	30.4%
66	No	Neighbor or Civic-Neighbor	3	Neighborhood Solidarity	21	6	28.6%
67	No	Civic or Blood-Civic	2	Civic Duty	29	8	27.6%
68	Yes	Civic or Blood-Civic	3	Civic Duty	8	2	25.0%
69	Yes	Civic-Blood	2	Civic Duty	9	2	22.2%
70	No	Civic or Blood-Civic	3	Civic Duty	17	3	17.6%
71	Yes	Neighbor or Civic-Neighbor	3	Neighborhood Solidarity	7	1	14.3%
72	Yes	Civic or Blood-Civic	1	Civic Duty	6	0	0.0%

Table A3 below provides a breakdown of the proportion of registered voters that voted in 1998 by each of the combinations of the pre-treatment control covariates.

Table A3: Get-Out-the-Vote Control Interactions

	Age	Major Party	Voted in '96	Abstained in '96	Registered	Voted	Proportion
1	[18,29]	0	0	0	417	56	13.4%
2	[18,29]	0	0	1	458	17	3.7%
3	[18,29]	0	1	0	267	60	22.5%
4	[18,29]	1	0	0	630	105	16.7%
5	[18,29]	1	0	1	458	30	6.6%
6	[18,29]	1	1	0	411	140	34.1%
7	(29,39]	0	0	0	334	65	19.5%
8	(29,39]	0	0	1	300	15	5.0%
9	(29,39]	0	1	0	335	139	41.5%
10	(29,39]	1	0	0	757	209	27.6%
11	(29,39]	1	0	1	779	68	8.7%
12	(29,39]	1	1	0	861	444	51.6%
13	(39,49]	0	0	0	149	41	27.5%
14	(39,49]	0	0	1	201	17	8.5%
15	(39,49]	0	1	0	276	148	53.6%
16	(39,49]	1	0	0	464	166	35.8%
17	(39,49]	1	0	1	503	78	15.5%
18	(39,49]	1	1	0	901	588	65.3%
19	(49,59]	0	0	0	89	34	38.2%
20	(49,59]	0	0	1	114	10	8.8%
21	(49,59]	0	1	0	200	116	58.0%
22	(49,59]	1	0	0	286	134	46.9%
23	(49,59]	1	0	1	371	56	15.1%
24	(49,59]	1	1	0	772	558	72.3%
25	(59,79]	0	0	0	77	35	45.5%
26	(59,79]	0	0	1	143	26	18.2%
27	(59,79]	0	1	0	359	262	73.0%
28	(59,79]	1	0	0	272	142	52.2%
29	(59,79]	1	0	1	523	111	21.2%
30	(59,79]	1	1	0	1620	1249	77.1%
31	(79,99]	0	0	0	25	8	32.0%
32	(79,99]	0	0	1	92	11	12.0%
33	(79,99]	0	1	0	147	108	73.5%
34	(79,99]	1	0	0	62	32	51.6%
35	(79,99]	1	0	1	337	23	6.8%
36	(79,99]	1	1	0	784	578	73.7%

Table A4 provides a preview of the `LaLonde` dataset. This dataset includes one binary outcome variable, one binary treatment variable, and ten pre-treatment control covariates. Specifically, `outcome` is a binary outcome variable of whether earnings in 1978 are larger than in 1975; `treat` is a binary treatment variable for whether an individual received the job training or not; `age` is an ordinal control for the age in years of workers; `educ` is an ordinal control for the years of education of workers; `black` is a binary control for whether the worker is black or not; `hisp` is a binary control for whether the worker is Hispanic or not; `white` is a binary control for whether the worker is white or not; `marr` is a binary control for whether the worker is married or not; `nodegr` is a binary control for whether the worker has a high school degree or not; `log.re75` is a continuous control for workers pre-treatment log earnings in 1975; `u75` is a binary control for whether the worker was unemployed in 1975 or not.

Table A4: LaLonde (1986) National Supported Work Study

	outcome	treat	age	educ	black	hisp	white	marr	nodegr	log.re75	u75
1	0	0	23	10	1	0	0	0	1	0	1
2	1	0	26	12	0	0	1	0	0	0	1
3	0	0	22	9	1	0	0	0	1	0	1
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
720	0	1	24	10	1	0	0	1	1	8.31	0
721	0	1	33	11	1	0	0	1	1	10.13	0
722	1	1	33	12	1	0	0	1	0	9.3	0