

# Online Supporting Information

## All in the Family: Partisan Disagreement and Electoral Mobilization in Intimate Networks - a Spillover Experiment

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## Direct and Indirect Treatment Effects

The effect of treatment on an individual can be defined as the difference between two potential outcomes: the outcome if an individual were treated and the outcome (at the same point in time) if the individual were not treated (Gerber and Green 2012; Imbens and Rubin 2015; Rubin 1974, 1978). By randomly assigning individuals to treatment and control groups we ensure that the potential outcomes of these groups of subjects are, in expectation, identical before applying the treatments. Under the three core-assumptions of independence, excludability and non-interference (SUTVA) (Imbens and Rubin 2015; Rubin 1986, 1980), the difference in the average outcomes of those subjects assigned to the treatment and those assigned to the control group will provide an unbiased estimator of the true Intent-to-Treat (ITT) effect (Gerber and Green 2012).<sup>1</sup>

Let us say that in every two-voter household  $h$  one of two subjects, subject  $i_1$  ( $i_1 \in \{1, \dots, N_1\}$ ), was randomly sampled to be included in the experimental assignment, and randomly assigned to one of two treatment groups, or to the control group. The second subject in the household, subject  $i_2$  ( $i_2 \in \{1, \dots, N_2\}$ ), was randomly sampled to be excluded from experimental assignment. Let  $Z$  be the treatment indicator, indicating whether  $i_1$  in household  $h$  was assigned to receive a low partisan intensity ( $Z = 1$ ) or a high partisan intensity phone call ( $Z = 2$ ) encouraging subjects to vote in the upcoming election, or to receive no call, i.e. the control group ( $Z = 0$ ).

Our binary outcomes of interest,  $Y_{i_1}$  and  $Y_{i_2}$  are voter turnout. The potential outcomes for  $i_1$  are defined as follows:

If  $Z = 0$ , then  $Y_{i_1}(0) = 0$  or  $Y_{i_1}(0) = 1$

If  $Z = 1$ , then  $Y_{i_1}(1) = 0$  or  $Y_{i_1}(1) = 1$

If  $Z = 2$ , then  $Y_{i_1}(2) = 0$  or  $Y_{i_1}(2) = 1$

Following the discussions in Gerber and Green (2012, chapter 2), and Imbens and Rubin (2015, chapter 1) the respective direct unit-level causal effects  $\tau_{i_1}$  can then be defined as the

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<sup>1</sup>We estimate the ITT effect rather than the Average Treatment Effect (ATE) because not all subjects who were assigned to treatment in our experiment actually received the treatment.

difference between two potential outcomes:

$$\tau_{(10),i_1} = Y_{i_1}(1) - Y_{i_1}(0) \quad (1)$$

$$\tau_{(20),i_1} = Y_{i_1}(2) - Y_{i_1}(0) \quad (2)$$

$$\tau_{(21),i_1} = Y_{i_1}(2) - Y_{i_1}(1) \quad (3)$$

The direct ITT can be defined as the sum of each of the unit-level treatment assignment effects  $\tau_{(10),i_1}$ ,  $\tau_{(20),i_1}$ , and  $\tau_{(21),i_1}$  divided by  $N_1$  (the total number of assigned subjects), and is equal to the difference in the average potential outcomes under the various treatment assignment conditions (Gerber and Green 2012). E.g. the ITT effect of assignment to the low partisan intensity treatment is:

$$\frac{1}{N_1} \sum_{i_1=1}^{N_1} (Y_{i_1}(1) - Y_{i_1}(0)) = \frac{1}{N_1} \sum_{i_1=1}^{N_1} Y_{i_1}(1) - \frac{1}{N_1} \sum_{i_1=1}^{N_1} Y_{i_1}(0) \quad (4)$$

Given random assignment to treatment and control conditions, excludability, and non-interference, the difference-in-proportions estimator is, in expectation, an unbiased estimator of the ITT. If we define  $m_1$  as a subsample of  $N_1$  consisting of subjects  $i_1$  who were assigned to the low intensity partisan phone call and  $m_2$  as a subsample of  $N_1$  consisting of subjects  $i_1$  who were assigned to the high intensity partisan phone call, then the direct ITT estimator of the low partisan intensity treatment can be defined as:

$$\widehat{ITT}_{(10),i_1} = \frac{1}{m_1} \sum_{i_1=1}^{m_1} Y_{i_1}(1) - \frac{1}{N_1 - (m_1 + m_2)} \sum_{i_1=(m_1+m_2+1)}^{N_1} Y_{i_1}(0) \quad (5)$$

Likewise for the high intensity partisan treatment, the direct ITT estimator can be identified as:

$$\widehat{ITT}_{(20),i_1} = \frac{1}{m_2} \sum_{i_1=(m_1+1)}^{m_2} Y_{i_1}(2) - \frac{1}{N_1 - (m_1 + m_2)} \sum_{i_1=(m_1+m_2+1)}^{N_1} Y_{i_1}(0) \quad (6)$$

And finally, the direct ITT estimator of the high versus the low intensity partisan treatment is:

$$\widehat{ITT}_{(21),i_1} = \frac{1}{m_2} \sum_{i_1=(m_1+1)}^{m_2} Y_{i_1}(2) - \frac{1}{m_1} \sum_{i_1=1}^{m_1} Y_{i_1}(1) \quad (7)$$

Similarly, the potential outcomes for  $i_2$  are:

$$\text{If } Z = 0, \text{ then } Y_{i_2}(0) = 0 \text{ or } Y_{i_2}(0) = 1$$

$$\text{If } Z = 1, \text{ then } Y_{i_2}(1) = 0 \text{ or } Y_{i_2}(1) = 1$$

$$\text{If } Z = 2, \text{ then } Y_{i_2}(2) = 0 \text{ or } Y_{i_2}(2) = 1$$

And the respective indirect unit-level causal effects  $\tau_{i_2}$  can then be defined as the difference between two potential outcomes:

$$\tau_{(10),i_2} = Y_{i_2}(1) - Y_{i_2}(0) \quad (8)$$

$$\tau_{(20),i_2} = Y_{i_2}(2) - Y_{i_2}(0) \quad (9)$$

$$\tau_{(21),i_2} = Y_{i_2}(2) - Y_{i_2}(1) \quad (10)$$

If we define  $m_3$  as a subsample of  $N_2$  consisting of household members  $i_2$  of subjects  $i_1$  who were assigned to the low intensity partisan phone call and  $m_4$  as a subsample of  $N_2$  consisting of household members  $i_2$  of subjects  $i_1$  who were assigned to the high intensity partisan phone call, then the indirect ITT estimator of assignment to the low partisan intensity treatment can be defined as:

$$\widehat{ITT}_{(10),i_2} = \frac{1}{m_3} \sum_{i_2=1}^{m_3} Y_{i_2}(1) - \frac{1}{N_2 - (m_3 + m_4)} \sum_{i_2=(m_3+m_4+1)}^{N_2} Y_{i_2}(0) \quad (11)$$

Likewise for the high intensity partisan treatment, the indirect ITT estimator can be identified as:

$$\widehat{ITT}_{(20),i_2} = \frac{1}{m_4} \sum_{i_2=(m_3+1)}^{m_4} Y_{i_2}(2) - \frac{1}{N_2 - (m_3 + m_4)} \sum_{i_2=(m_3+m_4+1)}^{N_2} Y_{i_2}(0) \quad (12)$$

And finally, the indirect ITT estimator of the high versus the low intensity partisan treatment is:

$$\widehat{ITT}_{(21),i_2} = \frac{1}{m_4} \sum_{i_2=(m_3+1)}^{m_4} Y_{i_2}(2) - \frac{1}{m_3} \sum_{i_2=1}^{m_3} Y_{i_2}(1) \quad (13)$$

In Table A3 (Model III) in the Supporting Information we report the results from a logistic regression model of turnout  $Y_{i_2}$  on assignment to either of the two treatments ( $Z=1$  or  $Z=2$ ), household partisan composition dummies, the interaction between treatment assignment and household partisan composition dummies, a n-by-k matrix of pretreatment covariates ( $X$ ) and the interaction between  $X$  and  $Z$ :

$$\begin{aligned} \text{Logit } Y_{i_2} = & \gamma_0 + \gamma_1 Z + \gamma_2 (\text{Labour})_{i_1} + \gamma_3 (\text{Unattached})_{i_1} + \gamma_4 (\text{Homogeneous})_h + \\ & \gamma_5 (\text{Unattached})_h + \gamma_6 Z (\text{Homogeneous})_h + \gamma_7 Z (\text{Unattached})_h + \\ & \Gamma X + \Gamma X Z + \epsilon_{i_2} \end{aligned} \quad (14)$$

In Table A5 (Model V) in the Supporting Information we report the estimation results from a logistic regression model of turnout  $Y_{i_2}$  on assignment to either of the two treatments  $Z$  ( $Z=1$  or  $Z=2$ ), the partisanship of the experimental subject, the partisanship of her household member and the two- and three-way interactions between the treatment and the party preferences of both household members. The model also includes a n-by-k matrix of

pretreatment covariates ( $X$ ) and the interaction between  $X$  and  $Z$ .

$$\begin{aligned}
\text{Logit } Y_{i_2} = & \gamma_0 + \gamma_1 Z + \gamma_2(\text{Labour})_{i_1} + \gamma_3(\text{Unattached})_{i_1} + \gamma_4(\text{Labour})_{i_2} + \gamma_5(\text{Unattached})_{i_2} + \\
& \gamma_6(\text{Labour})_{i_1}(\text{Labour})_{i_2} + \gamma_7(\text{Labour})_{i_1}(\text{Unattached})_{i_2} + \gamma_8(\text{Unattached})_{i_1}(\text{Labour})_{i_2} + \\
& \gamma_9(\text{Unattached})_{i_1}(\text{Unattached})_{i_2} + \gamma_{10}Z(\text{Labour})_{i_1} + \gamma_{11}Z(\text{Unattached})_{i_1} + \\
& \gamma_{12}Z(\text{Labour})_{i_2} + \gamma_{13}Z(\text{Unattached})_{i_2} + \gamma_{14}Z(\text{Labour})_{i_1}(\text{Labour})_{i_2} + \\
& \gamma_{15}Z(\text{Labour})_{i_1}(\text{Unattached})_{i_2} + \gamma_{16}Z(\text{Unattached})_{i_1}(\text{Labour})_{i_2} + \\
& \gamma_{17}Z(\text{Unattached})_{i_1}(\text{Unattached})_{i_2} + \Gamma X + \Gamma XZ + \epsilon_{i_2}
\end{aligned}
\tag{15}$$

## CACE Estimators Treatment versus Control Group

Table A2 in the Supporting Information reports the Complier Average Causal Effects (CACE), the average treatment effects for the subgroup of ‘compliers’ (Gerber and Green 2012, chapter 5). Compliers are defined as subjects  $i_1$  and  $i_2$  who live in households  $h$  that would be successfully contacted if the assigned member was assigned to receive either the high or the low partisan intensity phone call. We distinguish between  $Z$ , the treatment assignment indicator, and  $D$ , a contact indicator reporting whether  $i_1$  in household  $h$  was successfully contacted with a low partisan intensity ( $D = 1$ , short D(1)) or a high partisan intensity phone call ( $D = 2$ , short D(2)), or was not contacted ( $D = 0$ , short D(0)). Assuming one-sided non-compliance, the  $ITT_D$  effect of treatment assignment ( $Z$ ) on receiving the treatment ( $D$ ) equals the proportion of successfully contacted households (idem). For both of our treatment groups  $ITT_d = .45$  (Table 1 in the manuscript).

The indirect CACE estimators of the two treatments compared to the control group for individuals  $i_1$  can subsequently be defined as:

$$\widehat{CACE}_{(10),i_1} = \frac{\widehat{ITT}_{(10),i_1}}{\widehat{ITT}_{D(1)}}
\tag{16}$$

and

$$\widehat{CACE}_{(20),i_1} = \frac{\widehat{ITT}_{(20),i_1}}{\widehat{ITT}_{D(2)}} \quad (17)$$

Similarly, the indirect CACE estimators for the two treatments compared to the control group for individuals  $i_2$  can be defined as:

$$\widehat{CACE}_{(10),i_2} = \frac{\widehat{ITT}_{(10),i_2}}{\widehat{ITT}_{D(1)}} \quad (18)$$

and

$$\widehat{CACE}_{(20),i_2} = \frac{\widehat{ITT}_{(20),i_2}}{\widehat{ITT}_{D(2)}} \quad (19)$$

If  $Y_{i_2}$  was turnout for the unassigned household member, then the spillover CACE model we estimate can be formally written as:

$$Y_{i_2} = \beta_0 + \beta_1 D(1) + \beta_2 D(2) + \mu_{i_2}, \quad (20)$$

in which

$$D(1) = \gamma_0 + \gamma_1 Z(1) + \epsilon_{1,i_2} \quad (21)$$

and

$$D(2) = \delta_0 + \delta_1 Z(2) + \epsilon_{2,i_2} \quad (22)$$

## CACE Spillover Estimator Treatment versus Treatment

Since (1) one subject per two-voter household, subject  $i_1$ , was randomly sampled to be assigned to one of the three experimental groups, (2) the assigned subjects  $i_1$  did not know in advance whether they were about to receive a high or the low partisan intensity call, and (3) compliance for unassigned household members  $i_2$  is defined as living with a household member  $i_1$  in household  $h$  who would answer the phone when called, it follows that the share of compliers among unassigned subjects in the high and the low partisan intensity call groups corresponds to the share of compliers among assigned household members. In expectation, the share of compliers in both treatment groups should be identical (Gerber, Green, Kaplan and Kern 2010, 302-305). Following Gerber et al. (2010) the latter "perfect blindness" assumption can be formalized as:

$$(D|Z = 2) = (D|Z = 1) \tag{23}$$

where  $Z$  indicates if subject  $i_1$  in household  $h$  was assigned to treatment 2 (high partisan intensity message) or treatment 1 (low partisan intensity message), and  $D$  indicates whether subject  $i_1$  in household  $h$  complied with  $Z=2$  or  $Z=1$ .

If the perfect blindness assumption holds, then the indirect treatment effect  $\tau_{(21),i_2}$  for the subgroup of unassigned compliers, defined as subjects  $i_2$  living in household  $h$  with household member  $i_1$  who would answer the phone if called with the high or the low intensity partisan phone call, can be identified as:

$$\tau_{(21),i_2} = E[Y_{i_2}(D = 2, Z = 2) - Y_{i_2}(D = 1, Z = 1)] \tag{24}$$

In Table 2 (Model V) of the manuscript we report the results from a logistic regression model of turnout  $Y_{i_2}$  on compliance with the high partisan intensity treatment  $D(2, 1) = 2$  as opposed to compliance with the low partisan intensity treatment  $D(2, 1) = 1$ , house-



hold partisan composition dummies, the interaction between  $D(2,1)$  and household partisan composition dummies, a  $n$ -by- $k$  matrix of pretreatment covariates ( $X$ ) and the interaction between  $X$  and  $D(2,1)$ :

$$\begin{aligned}
 \text{Logit } Y_{i_2} = & \beta_0 + \beta_1 D(2,1) + \beta_2 (\text{Labour})_{i_1} + \beta_3 (\text{Unattached})_{i_1} + \beta_4 (\text{Homogeneous})_h + \\
 & \beta_5 (\text{Unattached})_h + \beta_6 D(2,1) (\text{Homogeneous})_h + \beta_7 D(2,1) (\text{Unattached})_h + \\
 & BX + BXD(2,1) + \mu_{i_2}
 \end{aligned}
 \tag{25}$$

## Randomization Inference

In Table 1 in the manuscript, and Table A2 in the Supporting Information we report randomization-inference based p-values and confidence intervals.

### Estimating P-Values

Following Gerber and Green (2012) and Aronow and Samii (2012) we first calculate the differences-in-proportions between subjects assigned to treatment and subjects assigned to control. We then simulate a large number of hypothetical randomization outcomes under the assumption of the sharp null hypothesis that the Intent-to-Treat Effect (ITT) equals 0 for all subjects. If the ITT equaled 0 for all subjects, we could randomly reassign subjects to experimental groups and estimate the ITT resulting from every reassignment. If we reassign subjects 10,000 times, we get the sampling distribution of ITTs under the assumption of no treatment effect for any subject. We then compare the differences-in-proportions estimate from our experimental data to the sampling distribution of all differences-in-proportions estimates over all hypothetical randomization outcomes.

## Estimating Confidence Intervals

We need to further impose the constant treatment effect assumption at the ITT level to estimate confidence intervals using randomization-inference (Gerber and Green 2012, 67). Following Gerber and Green (2012, 67-68) we impute unobserved treated potential outcomes by adding the ITT we estimated from our experiment to the observed outcomes in the control group. We then impute unobserved untreated potential outcomes by subtracting our estimated ITT from the observed outcomes in the treatment group. We then use this full schedule of potential outcomes to reassign subjects to treatment and control group 10,000 times. Finally, we list the estimated ITTs from each random reassignment in ascending order: "The 2.5th percentile marks the bottom of the [95% confidence] interval, and the estimate at the 97.5th percentile marks the top" (Gerber and Green 2012, 67). The interpretation of the 95% confidence interval is the following: If we imagine a series of hypothetical random assignments, 9,500 out of 10,000 random assignments will generate intervals that bracket the true (population) ITT.

## References

- Aronow, Peter M. and Cyrus Samii. 2012. “The R Package for Performing Randomization-Based Inference for Experiments. R Package. Version 0.9.” <http://CRAN.R-project.org/package=ri>: Available on CRAN.
- Gerber, Alan S. and Donald P. Green. 2012. *Field Experiments: Design, Analysis and Interpretation*. New York: WW Norton.
- Gerber, Alan S., Donald P. Green, Edward H. Kaplan and Holger L. Kern. 2010. “Baseline, Placebo, and Treatment: Efficient Estimation for Three-Group Experiments.” *Political Analysis* 18(3):297–315.
- Imbens, Guido W. and Donald D. Rubin. 2015. *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*. New York: Cambridge University Press.
- Rubin, Donald. 1986. “Statistics and Causal Inference: Comment: Which Ifs Have Causal Answers.” *Journal of the American Statistical Association* 81(396):961–962.
- Rubin, Donald B. 1974. “Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies.” *Journal of Educational Psychology* 66(5):688–701.
- Rubin, Donald B. 1978. “Bayesian Inference for Causal Effects: The Role of Randomization.” *The Annals of Statistics* 6(1):34–58.
- Rubin, Donald B. 1980. “Randomization Analysis of Experimental Data: The Fisher Randomization Test Comment.” *Journal of the American Statistical Association* 75(371):591–593.

Table A1: Covariate Balance among Unassigned Subjects

	Combined Sample		Heterogeneous Households		Homogeneous Households		Unattached Households					
	Control	Low	High	Control	Low	High	Control	Low	High			
Mean Age	36.9	37.5	36.4	38.6	39.4	40.1	38.8	39.4	37.9	35.5	36.1	35.0
Age Missing	60.7	60.7	61.4	55.0	64.1	47.3	57.5	55.9	63.3	63.4	63.8	61.4
Female	46.3	45.7	44.9	40.0	48.7	40.0	47.0	46.0	46.8	46.3	45.2	44.1
Gender Unknown	10.1	09.3	09.7	13.3	02.6	05.5	09.5	10.0	08.2	10.2	09.3	11.1
Postal	15.8	14.0	15.8	23.3	10.3	20.0	18.2	17.5	20.4	13.6	11.8	12.2
Ward 1	25.9	29.3	25.3	24.2	20.5	21.8	19.1	23.0	22.1	30.6	34.1	28.0
Ward 2	13.7	14.5	13.7	12.5	20.5	20.0	17.7	18.7	17.5	11.1	11.3	10.5
Ward 3	24.7	24.5	26.7	27.5	25.6	30.9	28.2	27.7	27.8	22.0	22.2	25.6
Ward 4	35.7	31.7	34.2	35.8	33.3	27.3	34.9	30.6	32.6	36.3	32.4	36.0
Voted Local 2012	54.7	55.0	56.6	60.0	61.5	67.3	69.8	69.7	70.7	43.8	44.6	45.5
Voted Local 2011	62.1	62.3	61.8	66.7	64.1	67.3	77.3	77.0	76.0	51.3	52.2	51.1
Voted General 2010	77.2	78.5	78.0	81.7	76.9	83.6	88.9	87.4	90.6	68.8	72.5	68.4
Voted Election 1	45.6	44.0	43.7	50.0	48.7	41.8	57.4	55.9	55.9	37.1	35.6	35.2
Voted Election 2	43.1	41.1	43.0	47.5	43.6	50.9	55.9	54.5	55.9	33.9	31.9	33.1
Voted Election 3	50.6	49.6	52.1	61.7	53.8	61.8	63.1	62.1	65.2	41.1	40.9	41.9
Voted Election 4	42.9	43.6	43.2	44.2	51.3	49.1	53.9	55.2	52.0	35.1	35.3	36.4
N	2,793	1,082	1,055	120	39	55	1,093	422	417	1,580	621	583

Note: Figures exclude households with missing turnout data.

Table A2: Direct and Indirect Mobilization Effects, Covariate-adjusted

	Labour	Rival Party	Unattached	Combined
	Intent-to-Treat Effect			
	Direct Effects on Assigned Subjects			
Low Partisan Intensity Call	1.8	2.4	6.0***	3.8**
	[-3.8, 7.3]	[-2.2, 7.2]	[2.8, 9.2]	[1.3, 6.4]
N	996	1,272	1,607	3,875
High Partisan Intensity Call	5.9*	1.1	3.4*	3.3**
	[0.4, 11.4]	[-3.4, 5.9]	[0.3, 6.7]	[0.8, 5.7]
N	997	1,285	1,566	3,848
	Indirect Effects on Unassigned Subjects			
Low Partisan Intensity Call	4.5	4.6	6.6***	5.4***
	[-0.8, 9.7]	[-0.1, 9.4]	[3.3, 9.9]	[2.9, 7.9]
N	996	1272	1607	3875
High Partisan Intensity Call	5.5*	3.2	3.7*	3.9**
	[0.2, 10.8]	[-1.5, 7.8]	[0.4, 7.1]	[1.4, 6.3]
N	997	1,285	1,566	3,848
	Complier Average Causal Effect			
	Direct Effects on Assigned Subjects			
Low Partisan Intensity Contact	3.2	5.5	14.6**	8.5**
	(5.5)	(5.3)	(4.7)	(3.0)
N	996	1272	1607	3875
High Partisan Intensity Contact	12.5*	2.2	8.4	7.3*
	(5.9)	(4.8)	(4.7)	(2.9)
N	997	1,285	1,566	3,848
	Indirect Effects on Unassigned Subjects			
Low Partisan Intensity Contact	8.6	9.8	16.7***	11.9***
	(5.4)	(5.4)	(4.7)	(2.9)
N	996	1272	1607	3875
High Partisan Intensity Contact	11.6*	6.6	9.6*	8.6**
	(5.9)	(4.8)	(4.8)	(2.9)
N	997	1,285	1,566	3,848

Note: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , based on two-tailed tests, standard errors in parentheses, randomization inference-based 95% confidence intervals in brackets. Covariates are turnout in seven previous elections, postal voter, gender, age and electoral ward.

Table A3: Logistic and IV Regression of Turnout of Unassigned Subject on Treatment Assignment of Assigned Subject, Conditional on Household Party Preferences

	I	II	III
	Logistic Regression Results (ITT)		
Telephone Call	.764*	1.103**	1.582*
	(.311)	(.360)	(.643)
Heterogeneous		Reference	
Homogeneous	.375	.270	.277
	(.235)	(.267)	(.279)
Unattached	-.237	.141	.154
	(.248)	(.284)	(.296)
Heterogeneous x Call		Reference	
Homogeneous x Call	-.657*	-.945*	-.917*
	(.327)	(.378)	(.378)
Unattached x Call	-.412	-.592	-.606
	(.328)	(.379)	(.380)
	Instrumental Variable Linear Regression Results (CACE)		
Contact with Canvasser	.320*	.357**	.332*
	(.134)	(.120)	(.168)
Heterogeneous		Reference	
Homogeneous	.069	.051	.052
	(.040)	(.037)	(.037)
Unattached	-.066	.023	.019
	(.038)	(.036)	(.036)
Heterogeneous x Contact		Reference	
Homogeneous x Contact	-.278*	-.312*	-.323*
	(.140)	(.125)	(.128)
Unattached x Contact	-.200	-.223	-.210
	(.139)	(.124)	(.126)
Covariates	No	Yes	Yes
Covariates x Treatment	No	No	Yes
Observations	4,930		

Note: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , based on two-tailed tests, standard errors in parentheses. Covariates are turnout in seven previous elections, postal voter, gender, age and electoral ward. Includes dummies for experimental blocks.

Table A4: Robustness Check: Logistic Regression of Turnout of Unassigned Subject on Treatment Assignment of Assigned Subject, Conditional on Household Party Preferences, 5-Categories Operationalization

	I	II	III
	Logistic Regression Results (ITT)		
Telephone Call	.763*	1.104**	1.548*
	(.312)	(.362)	(.651)
Heterogeneous		Reference	
Homogeneous Rival	.385	.318	.333
	(.258)	(.297)	(.302)
Homogeneous Labour	.361	.207	.212
	(.257)	(.292)	(.296)
Partisan x Unattached	-.218	.158	.169
	(.252)	(.290)	(.294)
Homogeneous Unattached	-.641*	.310	.317
	(.286)	(.330)	(.334)
Heterogeneous x Call		Reference	
Homogeneous Rival x Call	-.693*	-1.067**	-1.033**
	(.341)	(.395)	(.397)
Homogeneous Labour x Call	-.611	-.801*	-.791*
	(.346)	(.400)	(.402)
Partisan x Unattached x Call	-.453	-.630	-.636
	(.339)	(.394)	(.395)
Homogeneous Unattached x Call	-.371	-.521	-.551
	(.353)	(.410)	(.412)
Covariates	No	Yes	Yes
Covariates x Treatment	No	No	Yes
Observations	4,930		

Note: \*\*\* p<0.001, \*\* p<0.01, \* p<0.05, based on two-tailed tests, standard errors in parentheses. Covariates are turnout in seven previous elections, postal voter, gender, age, and electoral ward. Includes dummies for experimental blocks.

Table A5: Logistic Regression of Turnout on Treatment Assignment and Party Preference of Both Subjects, and Interactions between Assignment and Party Preferences

	I	II	III
Telephone Call	.070 (.137)	.038 (.157)	.538 (.580)
Assigned Rival		Reference	
Assigned Lab	-.184 (.302)	-.031 (.347)	-.030 (.353)
Assigned Unattached	-.659** (.196)	-.457* (.225)	-.451* (.228)
Unassigned Rival		Reference	
Unassigned Lab	-.696 (.376)	-.470 (.421)	-.487 (.427)
Unassigned Unattached	-.527** (.180)	-.128 (.210)	-.131 (.214)
Assigned Rival x Unassigned Rival		Reference	
Assigned Lab x Unassigned Lab	.829 (.484)	.572 (.548)	.591 (.556)
Assigned Lab x Unassigned Unattached	.067 (.400)	.188 (.465)	.219 (.474)
Assigned Unattached x Unassigned Lab	.422 (.476)	.536 (.532)	.576 (.538)
Assigned Unattached x Unassigned Unattached	.053 (.275)	.331 (.318)	.346 (.324)
Assigned Rival x Call		Reference	
Assigned Lab x Call	.228 (.482)	.730 (.557)	.685 (.559)
Assigned Unattached x Call	.440 (.277)	.634* (.323)	.615 (.324)
Unassigned Rival x Call		Reference	
Unassigned Lab x Call	1.141* (.473)	1.354* (.541)	1.323* (.544)
Unassigned Unattached x Call	.092 (.271)	.348 (.315)	.308 (.317)
Assigned Rival x Unassigned Rival x Call		Reference	
Assigned Lab x Unassigned Lab x Call	-1.288 (.678)	-1.820* (.780)	-1.770* (.783)
Assigned Lab x Unassigned Unattached x Call	-.083 (.612)	-.632 (.715)	-.624 (.716)
Assigned Unattached x Unassigned Lab x Call	-1.376* (.622)	-1.722* (.709)	-1.720* (.710)
Assigned Unattached x Unassigned Unattached x Call	-.210 (.398)	-.437 (.465)	-.447 (.467)
Covariates	No	Yes	Yes
Covariates x Treatment	No	No	Yes
Observations		4,930	

Note: \*\*\* p<0.001, \*\* p<0.01, \* p<0.05, based on two-tailed tests, standard errors in parentheses. Covariates are turnout in seven previous elections, postal voter, gender, age and electoral ward. Includes dummies for experimental blocks.



Table A6: Robustness Check: Logistic Regression Results: CACE of High vs. Low Partisan Intensity Call on Turnout of Unassigned Subjects, Conditional on Household Party Preferences, 5-Categories Operationalization

	I	II	III	IV	V
Partisan Phone Contact	-.098 (.142)	-.154 (.165)	1.347 (.689)	1.403 (.785)	1.780 (1.370)
Heterogeneous Partisan Homogeneous Rival	Reference Group				
	-.130 (.369)	-.559 (.432)	.776 (.622)	.467 (.686)	.593 (.693)
Homogeneous Labour	-.291 (.392)	-.844 (.466)	.595 (.623)	.018 (.708)	.231 (.720)
Partisan x Unattached	-.567 (.365)	-.636 (.431)	.455 (.609)	.451 (.684)	.649 (.695)
Homogeneous Unattached	-1.230** (.442)	-.829 (.520)	-.360 (.670)	.035 (.755)	.161 (.765)
Heterogeneous x Partisan Contact Homogeneous Rival x Partisan Contact	Reference Group				
			-1.461 (.746)	-1.753* (.850)	-2.065* (.877)
Homogeneous Labour x Partisan Contact			-1.440 (.746)	-1.414 (.850)	-1.653 (.867)
Partisan x Unattached x Partisan Contact			-1.721* (.739)	-1.890* (.847)	-2.232* (.869)
Homogeneous Unattached x Partisan Contact			-1.371 (.773)	-1.381 (.884)	-1.567 (.901)
Covariates	No	Yes	No	Yes	Yes
Covariates x Call	No	No	No	No	Yes
N	965				

Note: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ , based on two-tailed tests, standard errors in parentheses. Covariates are turnout in seven previous elections, postal voter, gender, age, and electoral ward. Includes dummies for experimental blocks.

Table A7: Comparison between Official City Council Elections Results for May 2011 and May 2012, and Complete November 2012 Labour Party Database<sup>a</sup> (Pretreatment) across All Electoral Wards Included in the Experiment

	2011 Elections		2012 Elections	
	Official Results	Labour Database	Official Results	Labour Database
	Party Support Among Voters (%)			
Labour Party	43.5	36.0	45.9	38.7
Rival Party	56.5	31.9	54.1	31.2
Unattached	-	32.1	-	30.1
	Coverage of Database			
N Registered Voters	70,443 <sup>b</sup>	26,827	- <sup>c</sup>	26,827
% in Database		38.1		38.1 <sup>d</sup>
N of Votes	27,626	14,579	22,371	12,921
Turnout (%)	39.2	54.5	- <sup>c</sup>	48.3

Note: Each electoral ward is represented by three city councillors, who serve four year terms. One councillor is elected every year. In the fourth year there are no elections.

<sup>a</sup> The complete database includes registered voters with available landline and mobile phone numbers regardless of household size.

<sup>b</sup> The number of registered voters is estimated using the number of votes and turnout in the 2011 elections.

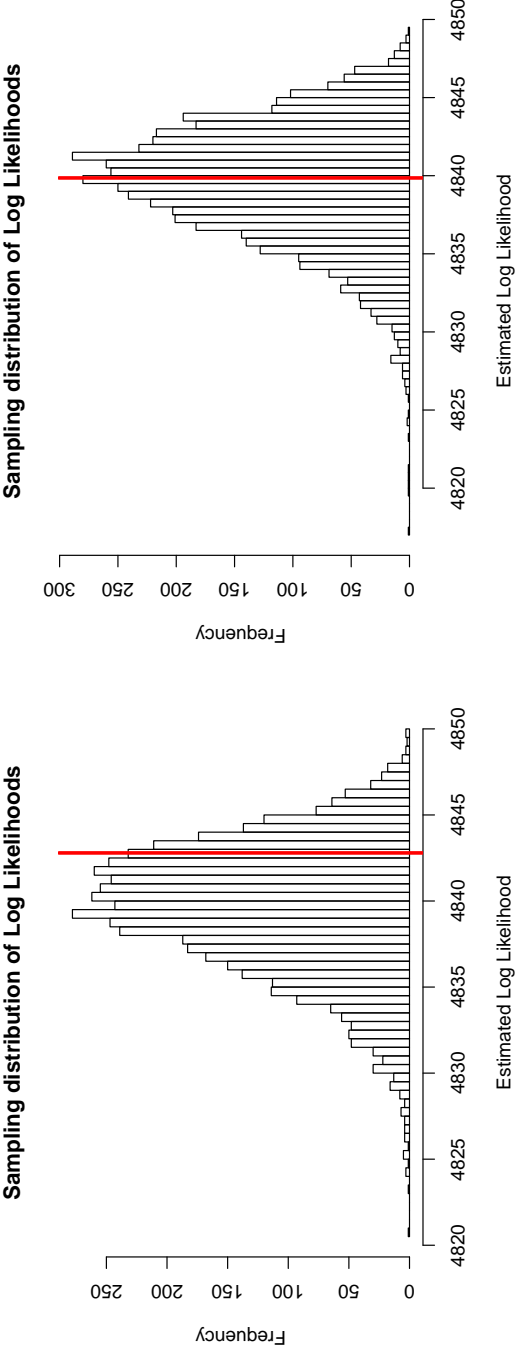
<sup>c</sup> Turnout data for May 2012 City Council elections is not available on the Birmingham City Council website.

<sup>d</sup> The percentage of all registered voters included in the database is estimated using the number of registered voters in the database and the (estimated) total number of registered voters for 2011.

Source: Birmingham City Council. Birmingham Elections 2011 and Election Results - City Council Elections 3 May 2012. Accessed 10 September 2015: <http://www.birmingham.gov.uk/election>

Figure A1: Balance Check: Estimated Log Likelihood Resulting from Multinomial Logistic Regression of Treatment Assignment of Household Member on Pretreatment Covariates Compared to Sampling Distributions of Simulated Log Likelihood Statistics under Sharp Null

a) Left: Assigned Subjects ( $p=.20$ ) b) Right: Household Members ( $p=.50$ )



## Randomization Inference

Following Gerber and Green (2012) and Aronow and Samii (2012) we first calculate the log likelihood from a multinomial logistic regression of treatment assignment on pretreatment covariates. We then simulate a large number of hypothetical randomization outcomes under the assumption that the log likelihood equals zero for all subjects. Under the assumption that the sharp null hypothesis is true and the log likelihood is 0 for all subjects, we can randomly reassign subjects to treatments and estimate the log likelihood resulting from every reassignment. If we reassign subjects 10,000 times, we get the sampling distribution of all log likelihoods under the assumption that the covariates taken together do not predict treatment assignment for any subject. Finally we compare the log likelihood estimate from our experimental data to the distribution of all log likelihood estimates over all hypothetical randomization outcomes.

Figure A2: Attrition Check: Estimated Log Likelihood Resulting from Multinomial Logistic Regression of Treatment Assignment on Missing Outcome Data Compared to Sampling Distributions of Simulated Log Likelihood Statistics under Sharp Null

a) Left: Excluding Household Composition Interactions ( $p=.26$ ) b) Right: Including Household Composition Interactions ( $p=.32$ )

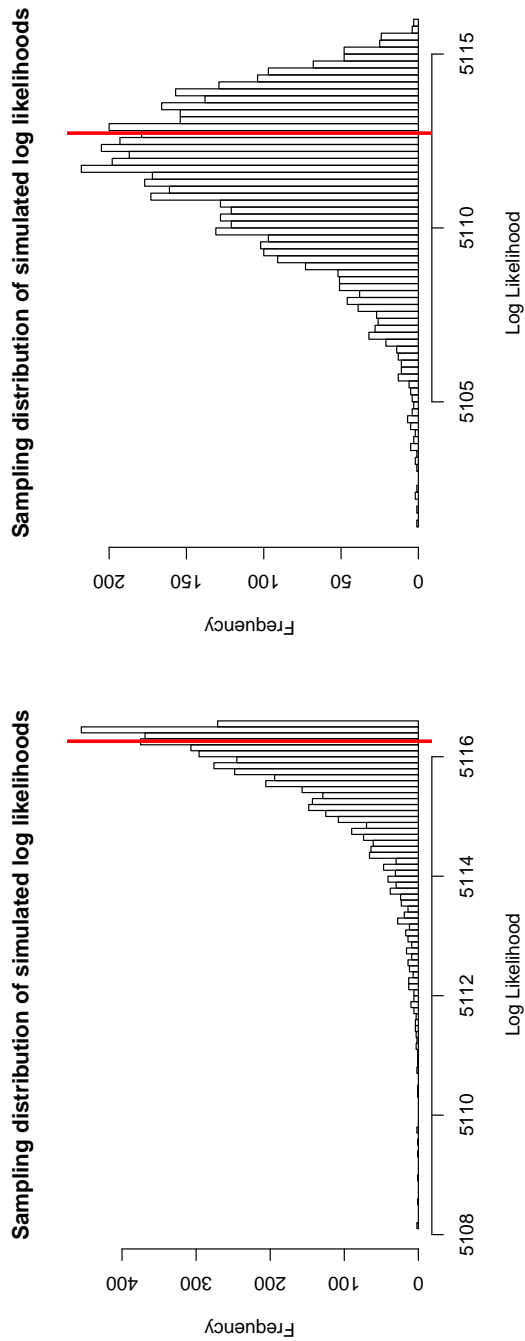


Figure A3: High Partisan Intensity Script

### 2012 PCC Elections Calling Script

When you make a call tick a box in the “Call Attempted” row. Do not leave an answer phone message unless it is the fifth call and we have not made contact yet. Do not call again if a contact has been made (i.e. the larger Question boxes have been filled in), similarly don’t write anything in these boxes unless you make a contact or establish that it is a wrong number.

We have a message that we would like you to deliver. You can do it in a conversational manner but please do try and hit all the talking points in the message.

Please do make sure to mention that [candidate name] is the Labour party candidate. This is to preserve the integrity of this experiment which will greatly help us in the long run.

**Message:**

“Hello, my name is .... I am phoning from your local Labour Party. I just wanted to remind you to go out and vote for Labour candidate [candidate name] in the Police and Crime Commissioner Election on Thursday. Your local polling station is located at ... during the usual opening hours from 7am to 10pm. Have you heard of the Labour candidate [candidate name]?”

Labour’s [candidate name] is determined to fight the Tory cuts to frontline policing that will hit Birmingham hard if a Conservative is elected. The Conservatives have sacked Police Officers and closed down Police Stations. In contrast, the Labour Party put more Police Officers on the ground and will protect police numbers.

- Are you going to vote for a Police Commissioner?
- Which candidate/party are you going to support in this election?
- If there was a General Election tomorrow, which party would you support?

Thanks a lot for taking the time to talk to me.

**Voice message:** On the 5<sup>th</sup> attempt leave a voice message with the above content but without the ending questions.<sup>i</sup>

Fill in the boxes 1 to 5 according to the criteria laid out on the next page:

Q1	Q2	Q3	Q4	Q5
----	----	----	----	----

<sup>i</sup> Due to the limited number of volunteers there was a maximum of three attempts made at reaching subjects. Two hours before polls closed on Election Day, some volunteers started to leave a small number of personalised messages (addressed to the assigned subject) on mailboxes amounting to 16% of the treatment sample. Due to the fact that these messages were delivered very late on Election Day to phones that had not been answered after two attempts, we judge the probability that they significantly violated the exclusion restriction to be very low.

Figure A4: Low Partisan Intensity Script

### 2012 PCC Elections Calling Script

When you make a call tick a box in the “Call Attempted” row. Do not leave an answer phone message unless it is the fifth call and we have not made contact yet. Do not call again if a contact has been made (i.e. the larger Question boxes have been filled in), similarly don’t write anything in these boxes unless you make a contact or establish that it is a wrong number.

We have a message that we would like you to deliver. You can do it in a conversational manner but please do try and hit all the talking points in the message.

Please do NOT mention that [candidate name] is the Labour party candidate unless the contact brings it up or asks you which party he represents. This is to preserve the integrity of this experiment which will greatly help us in the long run.

**Message:**

“Hello, my name is .... I am phoning to remind you to go out and vote for [candidate name] in the Police and Crime Commissioner Election on Thursday. Your local polling station is located at ... during the usual opening hours from 7am to 10pm. Have you heard of [candidate name]?”

[Candidate name] is a candidate for Police and Crime Commissioner and he is determined to fight the cuts in frontline policing. As [former role] [candidate’s first name] has a strong record in reducing crime and protecting our Police Force. [Candidate name] has been fighting for the victims of crime for over 30 years.

- Are you going to vote for a Police Commissioner?
- Which candidate/party are you going to support in this election?

Thanks a lot for taking the time to talk to me.

**Voice message:** On the 5<sup>th</sup> attempt leave a voice message with the above content but without the ending questions.

Fill in the boxes 1 to 5 according to the criteria laid out on the next page:

Q1	Q2	Q3	Q4	Q5
----	----	----	----	----

Figure A5: Questionnaire

**Filling in Q1-5:**

- Q1** tells us the status of the call so that we can analyse if and how contact was made. Use the following codes to indicate this status:
1. Conversation with the specific individual i.e. you spoke to them and they didn't ask you to "call back later"
  2. Voice message left; do not leave a message unless it is the fifth attempt to contact
  3. Wrong number i.e. number is for a different address/family or the specific individual has moved away
  4. Number not recognised i.e. line is dead or is a fax/modem line
- Q2** tells us whether the message was delivered in full; please use the following codes:
1. Full message delivered
  2. Individual ends the conversation before you can deliver the full message and does not ask you to "call back later"; if you are asked to call back later leave all of the question boxes blank and we will call through the list again later
  3. Individual has already voted i.e. postal voter
- Q3** tells us if the individual is interested in which party [candidate name] represents
1. Individual asks you which party [candidate name] represents
  2. Individual knows and mentions that [candidate name] represents Labour
- Q4** tells us how the person will vote in the PCC election. Please use the following codes:
- |          |                                 |          |   |
|----------|---------------------------------|----------|---|
| <b>L</b> | Labour                          | <b>B</b> | UKIP / [candidate name]   |
| <b>A</b> | Against Labour                  | <b>I</b> | Independent / [candidate names]   |
| <b>D</b> | Don't Know                      | <b>Z</b> | Not voting in PCC elections   |
| <b>X</b> | Won't say                       | <b>J</b> | Will vote for [candidate name] specifically (rather than just the Labour candidate)           |
| <b>T</b> | Conservative / [candidate name] | <b>O</b> | Will vote against [candidate name] personally (rather than just generally Against Labour [A]) |
| <b>S</b> | Lib Dem / [candidate name]      |          |   |
- Q5** IF the individual mentions that [candidate name] is Labour or asks what party he represents, please finish by asking which party they would support if there was a General Election tomorrow and use the following codes:
- |          |              |          |                         |
|----------|--------------|----------|-------------------------|
| <b>L</b> | Labour       | <b>A</b> | Against i.e. not Labour |
| <b>T</b> | Conservative | <b>D</b> | Don't Know              |
| <b>S</b> | Lib Dem      | <b>X</b> | Won't Say               |
| <b>G</b> | Green        | <b>V</b> | BNP                     |
| <b>B</b> | UKIP         | <b>Z</b> | Won't vote              |