Experimental Methods: Lecture 6

Social Media and Experimental Design

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Road Map

- Digital Trace
- Behavioral Outcomes
- Embedded experiments
- Treatment Delivery
- Twitter data collection

Digital Trace and Machine Learning with Post-Stratification to Measure Public Opinion [Cerina and Duch, 2020]

Digital Vote Overview

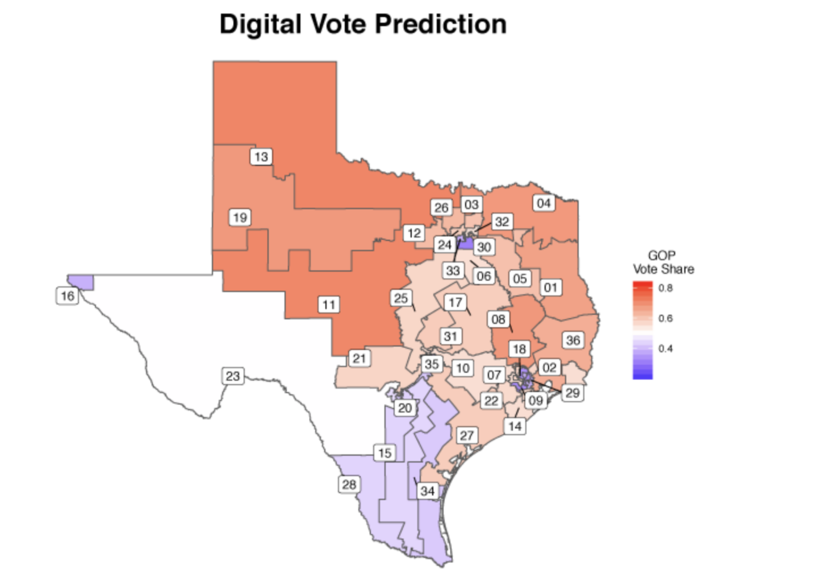
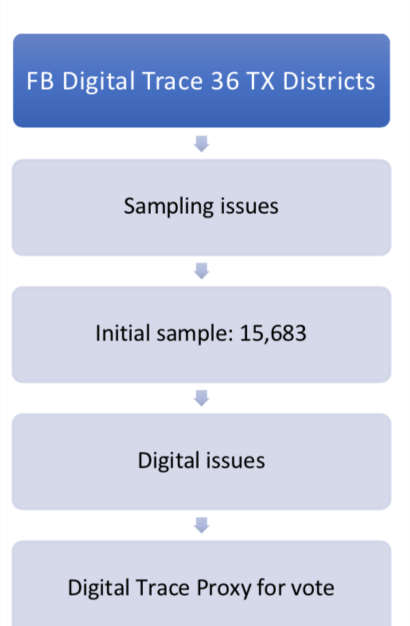
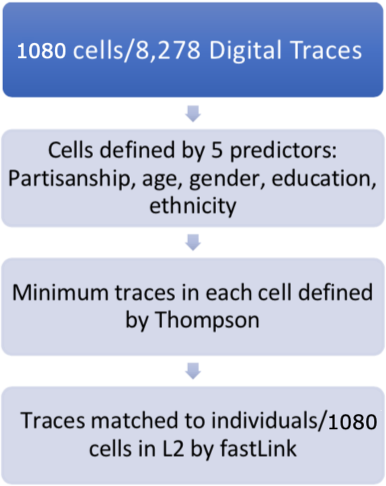


Figure 1: Digital Vote predicted GOP Percent Vote Share.

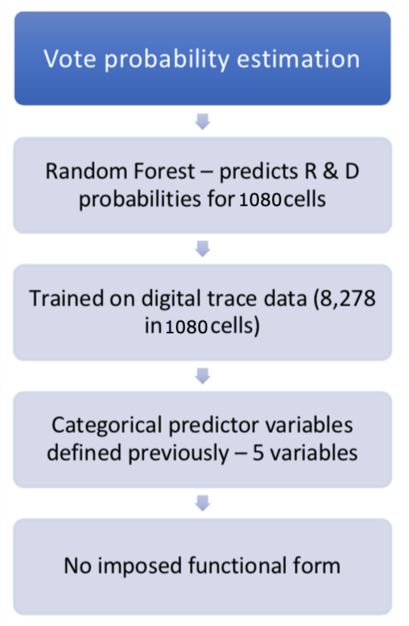
Digital Vote Overview



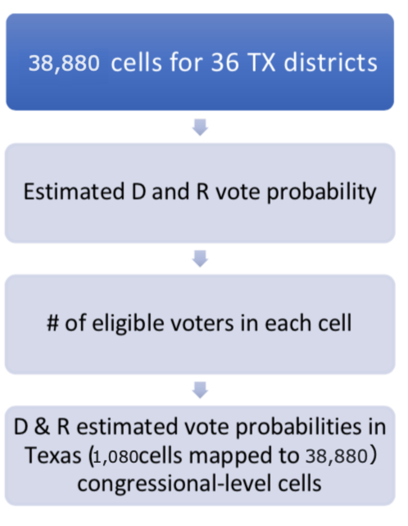
Digital Vote Overview



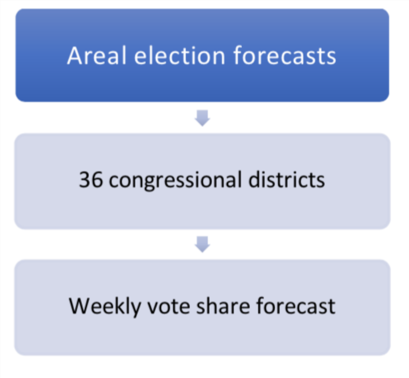
Digital Vote Overview



Digital Vote Overview



Digital Vote Overview



Sampling

Sampling

- Tune sample-size to capture differences in prevalence of voting-groups;
- theoretical sampling distribution:

$$\boldsymbol{n} \sim \text{Multinomial}(p_{1,r=1}, \ldots, p_{G,r=1}, p_{1,r=0}, \ldots, p_{G,r=0}, N); \quad (1)$$

- *worst-case-scenario* sampling for a multinomial distribution following the recommendations of Thompson[Thompson, 1987];
- digital sample is non-probability, but we use theoretical probability distribution as benchmark to guide our power calculation

Sampling

- find N such that we have probability of at least 0.9 that all estimates of the multinational parameters are within 0.025 of the population proportions;
- ensures sample will contain representatives from groups which are 2.5% of voting population or higher;
- N = 1610 per week[Thompson, 1987]

Facebook Sampling

Sampling

- monitor 7 *weeks-to-election-day*;
- assume each multinomial parameter is time-independent;
- sample N for every week within our monitoring frame, for a total of $N = 11270$;
- effective weekly sample size must be further inflated to account for sample loss by poor matching with the voter registry;
- parameter independence is likely true only for swing-voters who are affected by the election-cycle - too harsh for other categories.

Matching

Matching

- get rich voter profiles by matching our social media sample to the state-wide Texas L2 voter registration file;
- individual-level data for over 13 million registered Texas residents, ranging from voting history to socio-economic and demographic characteristics;
- use `R` package `fastLink`[Enamorado et al., 2018] to match our virtual sample to the voter registration list, based on names, *sex* and *city of residency*.

Matching

Threshold	0.75	0.85	0.9	0.95	0.99
Match Count	8739	8394	8384	8283	7322
Match Rate (%)	54.59	52.89	52.84	52.24	46.31
FDR (%)	2.03	1.18	1.16	1.08	0.81

Table 1: `fastLink` output summary table.

- From $15,683$ digital traces in the sample, we successfully match $8,278$;
- success rate of 52.8%;
- these come from $4,475$ distinct registered users;
- `fastlink` reveals $1,417$ borderline cases.

Matching

Conditional on being a registered partisan:

- $\text{P(Dig. Rep.}|\text{Reg. Rep.)} = 0.82$
- $\text{P(Dig. Dem.}|\text{Reg. Dem.)} = 0.82$

Conditional on having attended a partisan primary:

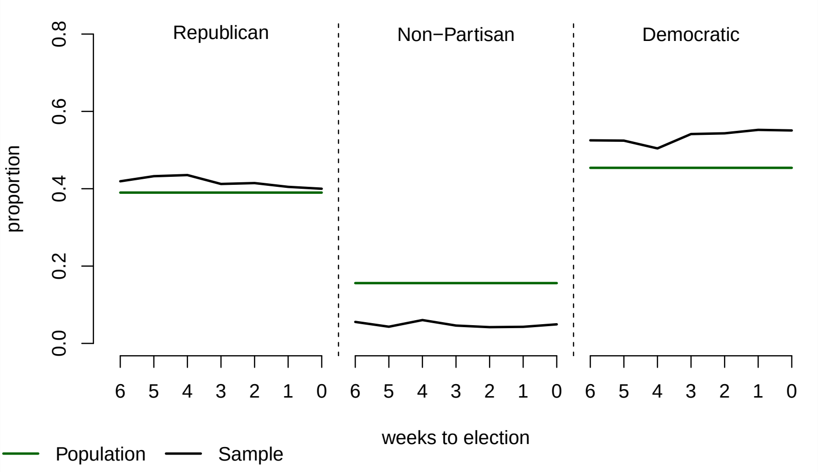
- $\text{P(Dig. Rep.}|\text{Rep. Primary)} = 0.86$
- $\text{P(Dig. Dem.}|\text{Dem. Primary)} = 0.91$

We are comfortable concluding that digital traces represent revealed preferences.

Matching

- final sample size is $8,278$ digital traces;
- slightly below the Thompson number;
- holding probability constant at 0.9, powered to estimate voter categories larger than 2.9% percent of the total population.

Sample v. Population



Vote-Share Estimation

Vote-Share Estimation

Three steps to obtaining area-estimates of vote-share:

- identification of voter characteristics from L2 file to use in vote choice prediction model (voter-categories);
- estimation, at the voter-category level, of vote choice conditional on the probability of vote turnout;
- weighting predictions by cell counts and summing over the area of interest to recover estimates of support.

Vote-Share Estimation

- select just under 50 variables from VR file for turnout prediction at the individual level;
- Missing values in $\boldsymbol{X}$ are imputed with a random-forest multiple-imputation strategy implemented via the packages `ranger`[Wright and Ziegler, 2015] and `missForest`[Stekhoven and Bühlmann, 2011];
- further select subset of variables for vote-choice model Z - we are not powered to include all the variables as we do for turnout;
- define the voter category C_g, for categories $g = 1, ..., G$ as a unique realization of the set of variables which compose $\boldsymbol{Z}$, i.e. $C_g = \{Z_1 = z_1, ..., Z_m = z_m\}$.

Vote-Share Estimation

- Estimate the joint probability of a voter-category supporting the Republican candidate and turning out on election-day;
- decompose the problem similarly to Lauderdale et al.[Lauderdale et al., 2017]:

$$P_g\left(R=1, T=1|C\right) = P_g\left(R=1|T=1, C\right) \times P_g\left(T=1|C\right) \tag{2}$$

.

Vote-Share Estimation

- train a random forest on the expanded (long) turnout dataset $\boldsymbol{X}^{+}$;
- output a prediction probability of turning out for each member of the voting population:

$$\hat{\mathrm{P}}_h\left(T=1|\boldsymbol{x}\right)=\varphi^T\left(\boldsymbol{x}_h\right); \tag{3}$$

- 1) extract turnout probabilities from matched sample $\hat{\mathrm{P}}_s\left(T=1|\boldsymbol{x}\right)$;
- 2) average within voter categories identified by $\boldsymbol{C}$ to obtain category-level estimates of turnout probabilities:

$$\mathrm{P}_g\left(T=1|C\right). \tag{4}$$

Vote-Share Estimation

- calculate global empirical error distribution using the MSPE1 procedure[Lu, 2017];
- Normal distribution does not characterize the empirical distribution perfectly; it is still useful to obtain reasonable prediction intervals:

$$\mathrm{P}_h\left(T = 1|\boldsymbol{x}\right) \sim \mathrm{N}\left(\varphi^T\left(\boldsymbol{x}_h^{\mathsf{I}}\right), (\hat{\sigma}^T_{\text{RMSE1}})^2\right). \tag{5}$$

Likelihood Estimation

Likelihood Estimation

- train a probability machine as above to estimate the probability of voting Republican, conditional on the individual turning out and the set of their voter characteristics:
$$\hat{\mathrm{P}}_s\left(R = 1 | T = 1, \boldsymbol{z}\right) = \varphi^R\left(\boldsymbol{z}_s | \hat{\mathrm{P}}_s\left(T = 1 | \boldsymbol{x}\right)\right); \qquad (6)$$

- output category-level predictions; for category g such that $s \in g$ if $\boldsymbol{z}_s = C_g$:
$$\hat{\mathrm{P}}_g\left(R = 1 | T = 1, C\right) = \varphi^R\left(C_g\right). \qquad (7)$$

- estimate the global error via MSPE1 and approximate distribution with Normal density:

Area Estimation

Area Estimation

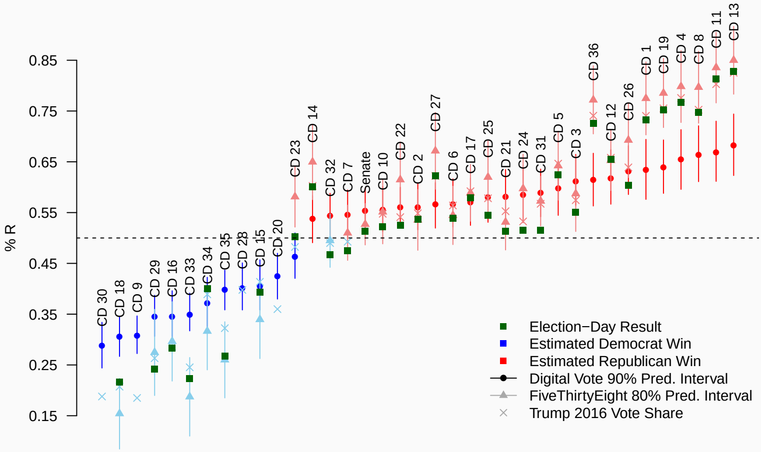
Senate Election (similar for Congress):

- State cell counts: $Q_g = \sum_h 1(\boldsymbol{z}_h = C_g)$;
- Republican support Senate estimate:

$$V^R_{gw} = \frac{\sum_g \mathrm{P}_g \left(R = 1, T = 1 | C, L = 1, W = w\right) \times Q_g}{\sum_g \mathrm{P}_g \left(T = 1 | C, L = 1, W = w\right) \times Q_g}; \tag{9}$$

Results

Results

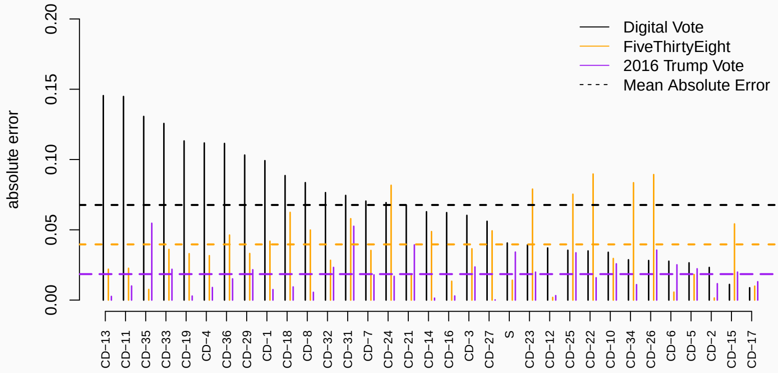


% R
0.85
0.75
0.65
0.55
0.45
0.35
0.25
0.15
CD 30
CD 18
CD 9
CD 29
CD 16
CD 33
CD 34
CD 35
CD 28
CD 15
CD 20
CD 23
CD 14
CD 32
CD 7
Senate
CD 10
CD 22
CD 2
CD 27
CD 6
CD 17
CD 25
CD 21
CD 24
CD 31
CD 5
CD 3
CD 36
CD 12
CD 26
CD 1
CD 19
CD 4
CD 8
CD 11
CD 13
Election−Day Result
Estimated Democrat Win
Estimated Republican Win
Digital Vote 90% Pred. Interval
FiveThirtyEight 80% Pred. Interval
Trump 2016 Vote Share

Results

- we produce 'hypothetical' estimates for all districts;
- no race-specific effects due to systematic non-response;
- there is evident attenuation bias;
- directionally, our estimates are correct for all but 3 districts (7 and 32 and 23), and correct for the senate;
- on absolute error `FiveThirtyEight` outperforms.

Results



Digital Vote
FiveThirtyEight
2016 Trump Vote
Mean Absolute Error
absolute error
0.00
0.05
0.10
0.15
0.20
CD−13
CD−11
CD−35
CD−33
CD−19
CD−4
CD−36
CD−29
CD−1
CD−18
CD−8
CD−32
CD−31
CD−7
CD−24
CD−21
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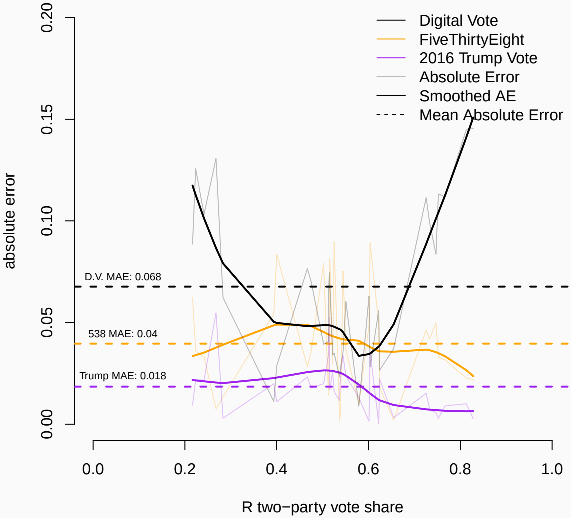
CD−2
CD−15
CD−17

Results



Digital Vote
FiveThirtyEight
2016 Trump Vote
Absolute Error
Smoothed AE
Mean Absolute Error
D.V. MAE: 0.068
538 MAE: 0.04
Trump MAE: 0.018
absolute error
0.00
0.05
0.10
0.15
0.20
0.0
0.2
0.4
0.6
0.8
1.0
R two−party vote share

Sub-Category Predictions

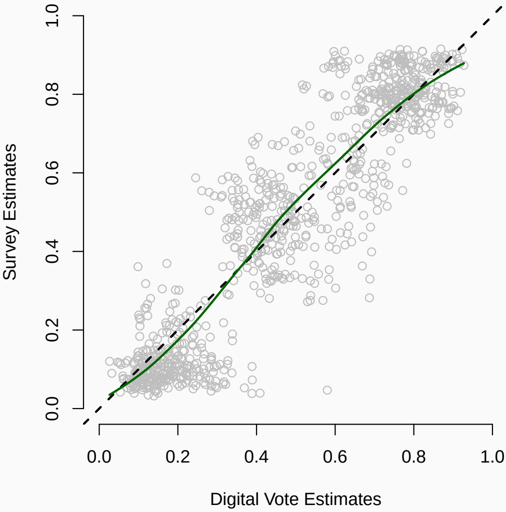


Figure 1: Voter sub-categories comparisons: Surveys v. Digital

Conclusions

Conclusions

- our method is a novel variation on MRP, which exploits Random Forests to gain generalizability (via capturing non-linear relationships) and computing speed;
- our sampling strategy suggests careful sampling on social media with respect to politics can be quite representative of the population of interest;
- digital traces are shown to be highly correlated with partisanship, and hence valid as measures of political support.

Social Media Treatment + Behavioral Outcomes

Online Political Information [Enrique et al., 2019]

- Outcome: Vote for the incumbent party in Mexico municipal elections
- Treatment: Online malfeasance video campaign
- Design: Saturation

Information Treatment via Social Media

- 61 million person experiment [Bond et al., 2012]
- Twitter India Vaccines: [Alatas et al., 2019]
- Information Architecture Malfeasance: [Duch and Torres, 2021]
- Vaccine Compliance and Incentives: (Duch et al 2021)

[Enrique et al., 2019] Design: Saturation

- Randomly assign municipalities to 20% % 80% saturation
- Block random assignment:
  - 128 Municipalities
  - 42 Blocks – 3 municipalities in each block have similar incumbent governing parties
- Within each block the municipalities are randomly assigned to three treatments:
  - Control: No FB ad
  - Low saturation: FB information ad
  - High saturation: FB information ad
- Within each municipality:
  - 5 equally-populated segments
  - 20% saturation - 1 in 5 assigned FB info
  - 80% saturation - 4 in 5 assigned FB info

[Enrique et al., 2019] Design: Saturation

$$Y_{psm} = \alpha Y_{psm}^{lag} + \beta Facebook\ ads_{sm} + \gamma Spillover_{sm} + \mu_b + \varepsilon_{psm},$$

[]

$$\begin{aligned} Y_{psm} \quad = \quad & \alpha Y_{psm}^{lag} + \beta_1 Facebook\ ads\ in\ Low\ Saturation_{sm} + \beta_2 Facebook\ ads\ in\ High\ Saturation_{sm} \\ & + \gamma_1 Spillover\ in\ Low\ Saturation_{sm} + \gamma_2 Spillover\ in\ High\ Saturation_{sm} + \mu_b + \varepsilon_{psm},\ (2) \end{aligned}$$

[]

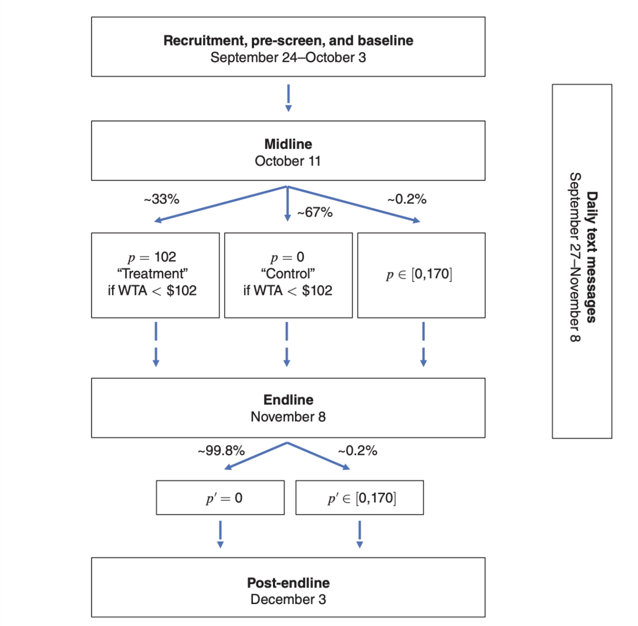
Design: Spillover

- Estimation issues: [Baird et al., 2018]
- Estimation issues: [Aronow et al., 2021]
- Cash Transfer Kenya: [Haushofer and Shapiro, 2016]
- School instruction interventions [Paluck et al., 2016]

Welfare Effects of FB [Allcott et al., 2020]

- Outcome: WTA
- Treatment: FB Deactivation
- Design: Online recruitment and random assignment to T and C

Welfare Effects of FB [Allcott et al., 2020]



Welfare Effects of FB [Allcott et al., 2020]

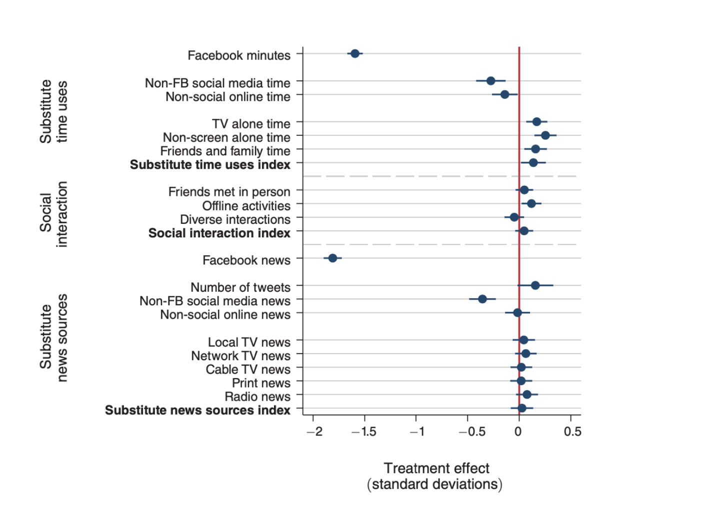
TABLE 1—SAMPLE SIZES

Phase	Sample size
Recruitment and baseline	N = 1,892,191 were shown ads N = 32,201 clicked on ads N = 22,324 completed pre-screen survey N = 20,959 were from United States and born between 1900 and 2000 N = 17,335 had $15 <$ daily Facebook minutes ≤ 600 N = 7,455 consented to participate N = 3,910 finished baseline N = 2,897 had valid baseline and were randomized, of which:
Midline	N = 2,897 began midline N = 2,743 received a price offer, of which: N = 1,661 were in impact evaluation sample
Endline	N = 2,710 began endline N = 2,684 finished endline, of which: N = 1,637 were in impact evaluation sample
Post-endline	N = 2,067 reported Facebook mobile app use, of which: N = 1,219 were in impact evaluation sample

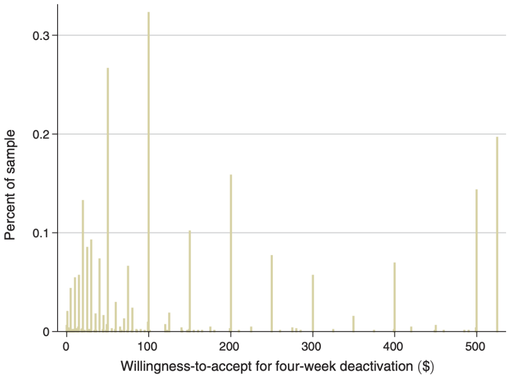
LATE [Allcott et al., 2020]

$$Y_i = \tau D_i + \phi Y_{bi} + \sigma_s + \mu_i \tag{10}$$

Welfare Effects of FB [Allcott et al., 2020]



Welfare Effects of FB [Allcott et al., 2020]



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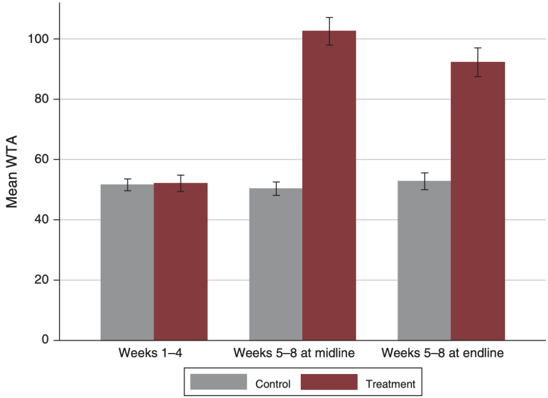


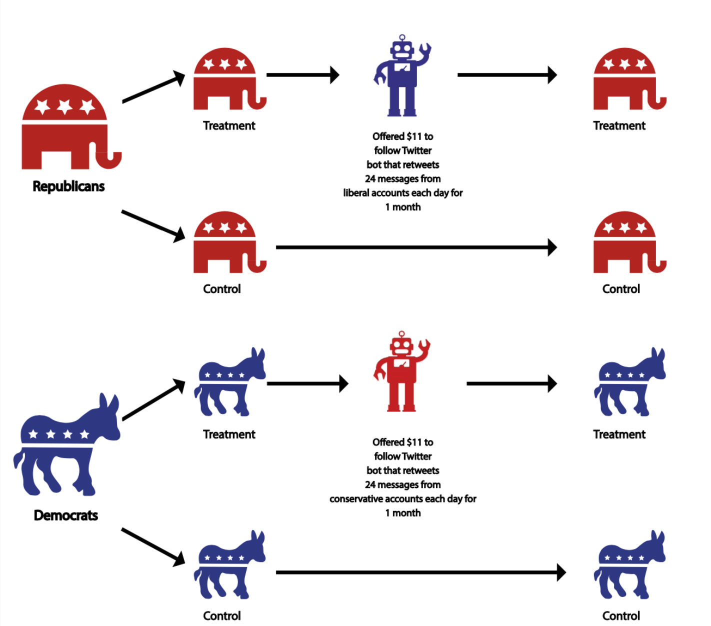
FIGURE 12. AVERAGE VALUATION OF FACEBOOK IN TREATMENT AND CONTROL

Embedded Experiments

Embedded Experiments

- Outcome Unobtrusive
    - Digital Trace
    - Digital Choice
- Outcome Obtrusive
    - Attitudes/Preferences
    - Hypothetical choices
- Treatments
    - Tasks
    - Vignettes/Conjoints
    - Video

Polarization Twitter [Bail et al., 2018]



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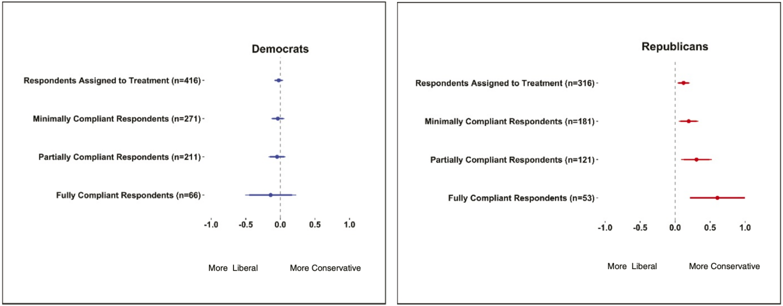


Embedded Experiments: Examples

- [Coppock et al., 2016]; When Treatments are Tweets
- Duch et al 2021 Vaccine Incentives – Video + Digital Choice

Duch et al Vaccine Incentives

```
https://www.dropbox.com/s/ybxiyowhason2qu/
VID-20210601-WA0011.mp4?dl=0
```

Treatment Delivery: WhatsApp

Figure 3: Screen shoots - Negative Standard Temporal treatment

Figure 4: Screen shoots - Positive Severity Temporal treatment

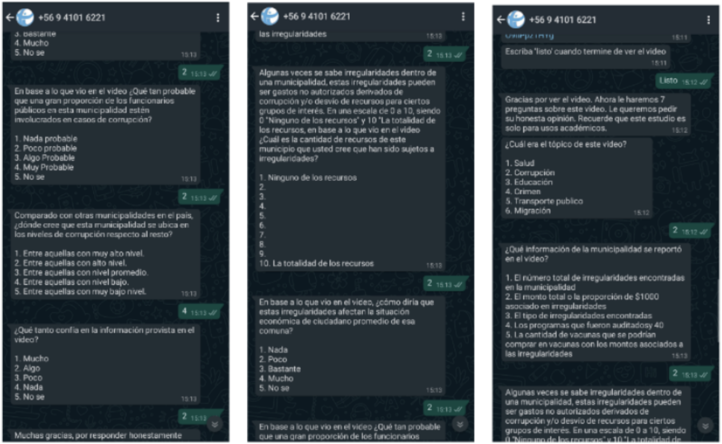
Figure 5: Screen shoots - Positive Resources Temporal treatment

Figure 6: Screen shoots - Positive Standard Spatial treatment

Figure 7: Screen shoots - Positive Resources Foregone treatment

Figure 8: Screen shoots - Negative Program Temporal treatment

Figure 9: Screen shoots - Chatbot survey



Twitter Data Collection

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