What People Think
—
Advances in Public Opinion Measurement Using Ordinal Variables

PhD Dissertation Defense
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6 April 2021

American University
Washington, DC

Outline

- Surveys assess public opinion
- Survey experiments test reactions to treatments
- Only as good as the measurement techniques we use
- Ordinal variables
  - Ordered categorical variables with unevenly spaced distances
  - Important EV in political science is ordinal (education)
- Current common practice makes unwarranted assumptions
- Fill the gap: Ordered probit approach with latent continuous structure
- Chapter II: Blocking in Survey Experiments
- Chapter III: Missing Data Solutions in Surveys
- Chapter IV: Morality, Self-Interest, and Frame Strength

Ordinal Variables and Proposed Ordered Probit Approach

Ordinal Variables

- Categorical variables: Nominal, interval, ordinal
- Nominal (e.g. race)
  - Not intrinsically ordered
  - Often made binary
- Interval (e.g. income)
  - Ordered, evenly spaced categories
  - Often made numerical
- Ordinal
  - Ordered, unevenly spaced categories
  - Often made binary or numerical
- Problems
  - Binary conversion assumes arbitrary ordering
  - Numerical conversion assumes evenly spaced categories
  - Both can lead to inversions of effects and Type I/II errors

Ordered Probit Approach

- Probit/logit models widely spread
- Most suggest quantifying non-quantitative variables according to their empirical distributions
- Assumes presence of continuous underlying variable
- Uses ordinal information provided and respects uneven distances
- Literature focuses on ordinal variables as outcome variables
- I estimate continuous distribution to then use for further analysis

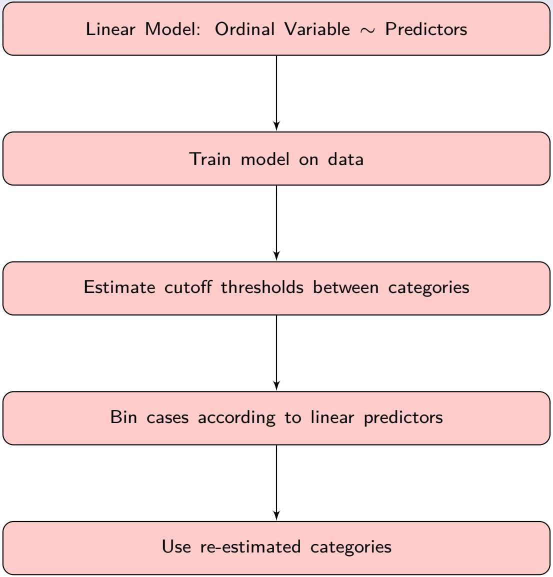

Figure 2.3: Ordered Probit Workflow

Chapter II: Blocking in Survey Experiments with a New Method to Measure Ordinal Variables

Train Linear Model on Data

- Apply ordered probit approach to 2016 ANES
- $\text{Education}_i \sim \beta_0 + \beta_1 \text{Gender}_i + \beta_2 \text{Race}_i + \beta_3 \text{Age}_i + \beta_4 \text{Income}_i + \beta_5 \text{Occupation}_i + \beta_6 \text{Party ID}_i + \epsilon_i$

Thresholds		Coefficients
Up to 1st	1st-4th	-7.869
⋮		
HS grad	Some college	-0.711
Some college	Associate	0.384
Associate	Bachelor's	1.045
Bachelor's	Master's	2.478
Master's	Professional	4.099
Professional	Doctorate	4.838

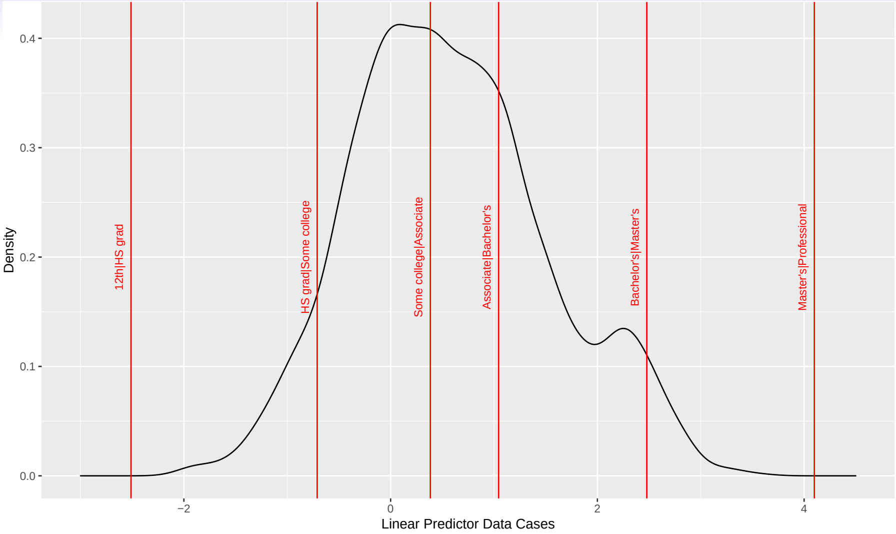

Figure 2.4: Distribution of Education Linear Predictor Data Cases. Vertical Lines Are Threshold Cutpoints. No Cases Fall Lower than '12th|HS grad' or Higher than 'Master's|Professional'

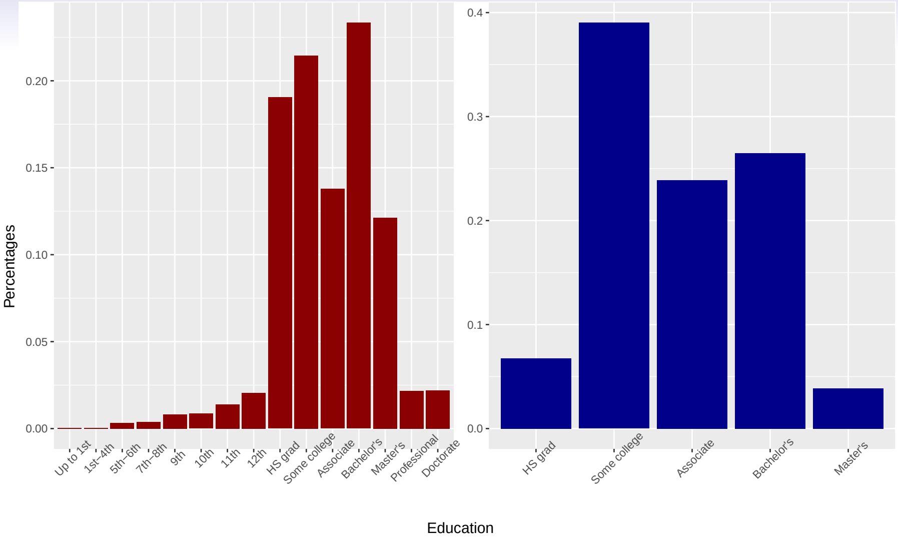

Figure 2.5: Distribution of Education Categories. Original ANES Categories on the Left, Ordered Probit Estimated Categories on the Right. Categories Below ‘High School Graduate‘ and ‘Above Master's‘ Are Gone. OP Categories Can Now Be Used For Blocking

Tests and Results

- Block 2016 ANES on education into 3 treatment groups twice: Once for OP categories, once for ANES categories
- ANOVA + GLM regressions
  - One regression per treatment group: Variable $\sim$ Education Set
  - No significant differences between sets for numerical variables
  - Significantly different intercepts for factor variables
- Block into 2 treatment groups twice
- Placebo OLS regression
  - $$\text{Feel Trump}_i \sim \beta_0 + \beta_1 \text{Group}_i + \beta_2 \text{Democrat}_i + \beta_3 \text{Republican}_i + \beta_4 \text{Income}_i + \beta_5 \text{Male}_i + \beta_6 \text{White}_i + \beta_7 \text{Black}_i + \beta_8 \text{Hispanic}_i + \epsilon_i$$
  - OP `Group` distribution closer to expected zero than ANES
- Re-estimation of categories potentially meaningful

Chapter III: Quality Comparison of Major Missing Data Solutions with a Proposed New Method for Ordinal Variables

Missing Data Solutions

- State of the art: multiple imputation
- Multiple hot deck imputation more precise for discrete data
  - Preserves integrity of discrete data
  - Does not change size of standard errors
  - Estimates affinity scores for each missing value to measure similarity
- But:
  - Does not account for ordinal variables
  - Algorithm for affinity score based on evenly spaced sequential numbers
- Apply ordered probit approach to multiple hot deck imputation

hd.ord: Multiple Hot Deck Imputation with Ordinal Variables

- Apply `polr` to estimate cutoff thresholds
- Calculate mid-cutpoints for each newly estimated category
- Scale mid-cutpoints
- Use scaled mid-cutpoints to measure distances for affinity scores
- Illustrative example:

Thresholds	Coefficients
Less Than High School | Some High School	2.418
Some High School | High School Graduate	3.495
Education Categories	**Mid-Cutpoints**
Some High School	2.956

Tests and Results

- Ampute complete CCES and ANES data
- Impute with `mice`, `amelia`, `hot.deck`, `hd.ord`; also use `na.omit`
- MAR and MNAR for 5 variables with NA, increased number of ordinal variables, increased missingness
- Test for accuracy and speed for binary, ordinal, interval variables
- `hd.ord` worse than `mice` and `amelia` in many cases, but on par in others (binary variables in data MNAR)
- Gain in speed somewhat negligible

Chapter IV: Morality, Self-Interest, and Frame Strength

Framing

- Presenting an issue to affect the way people see it
- Reorganizes existing information already present and directs attention to particular considerations
- Frames can have substantial influence on people's opinions
- Uncover which types of frames have more influence than others
- Test influence of morality and self-interest in political framing

Experiment Design

- Online, Lucid, 2,165 respondents
- Morality: foundation of Care/Harm
- Self-interest: personal autonomy, health/safety, wealth, status
- Issues: healthcare, environment
- 5 frames (2 supporting, 2 opposing, 1 control)
- Hypotheses
  - **H1**. Moral frames move people more than self-interest frames
  - **H2**. Moral frames move people with higher morality scores more than people with lower morality scores
  - **H3**. Self-interest frames move people with higher self-interest scores more than people with lower self-interest scores
- Respondents blocked on education for ANES and OP set (chapter II method)
- Missing data inserted and imputed (chapter III method)

Results

- **H1**: Reject null for opposing frames, fail to reject for supporting frames
- **H2**: Reject null for high morality opposing, fail to reject for supporting
- **H3**: Fail to reject null
- Methods application:
  - No substantive differences between blocked sets of categories
  - `hd.ord` performs worse than `amelia`, `mice` for missing data

Conclusion

Conclusion

- Attempt to use unique information provided in one of most important predictors of political behavior to measure what people think as well as possible
- Focus on keeping integrity of the discrete data intact
- Evidence points against endorsing my ordered probit approach
  - Blocking shows mixed results
  - `hd.ord` does not improve on current multiple imputation methods in many cases
  - No substantive differences in framing results
- Take away
  - On par results for blocking
  - Method might work for certain specific cases of missing data (MNAR, binary variables)
  - Morality (Care/Harm) plays role in frame influence regarding things we oppose

Thank you!

Chapter II

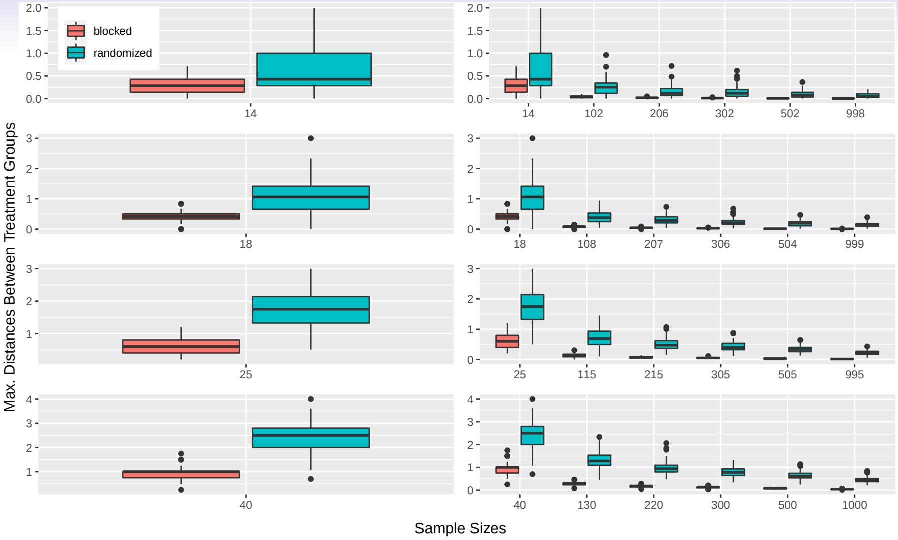

Figure 2.1: Distances Between Treatment Group Means in Randomized and Blocked Data. Increasing Sample Size for 2 (Top Row), 3 (Second Row), 5 (Third Row), and 10 Treatment Groups (Bottom Row). Leftmost Pair on the Right Panel Is the Same as the Pair on the Left Panel

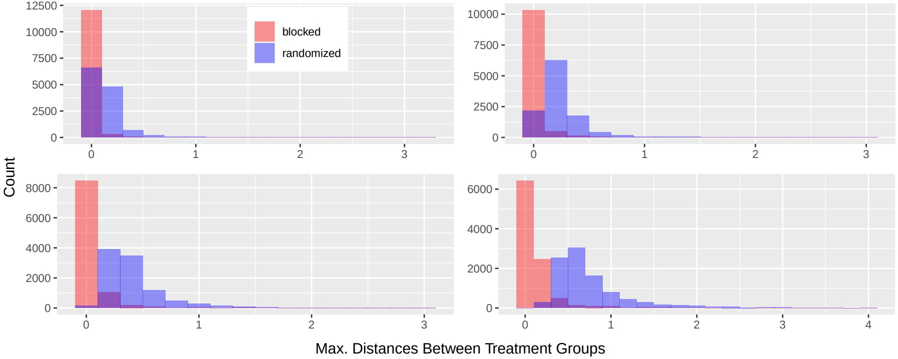

Figure 2.2: Distribution of Treatment Group Differences in Randomized and Blocked Data for 2 (Top Left), 3 (Top Right), 5 (Bottom Left), and 10 Treatment Groups (Bottom Right). Overlapping Area Shown in Dark Purple

- $\boldsymbol{X}$: $n \times k$ matrix of explanatory variables
- $\boldsymbol{Y}$: observed on ordered categories $\boldsymbol{Y}_i \in [1, \ldots, k]$, for $i = 1, \ldots n$
- Assumption: $\boldsymbol{Y}$ produced by unobserved latent continuous variable $\boldsymbol{Y^{cont}}$ on $\Re$ from $-\infty$ to ∞
- 'Response mechanism' for r^{th} category: $Y = r \Longleftrightarrow \xi_{r-1} < Y^{cont} < \xi_r$
- Thresholds on R:
  $Y_i^{cont}: \ \xi_0 \underset{a=1}{\longleftrightarrow} \xi_1 \underset{a=2}{\longleftrightarrow} \xi_2 \underset{a=3}{\longleftrightarrow} \xi_3 \ldots \xi_{A-1} \underset{a=A}{\longleftrightarrow} \xi_A$
- $\boldsymbol{Y^{cont}}$ determined by linear model of explanatory variables, $Y^{cont} = X\beta + \mu$
- Thresholds on $\Re$ partition variable into regions corresponding to ordinal categories
- Linear model $\boldsymbol{Y^{cont}}$ bins observations between thresholds according to predictors

Table 2.1: Ordered Probit Threshold Estimates

Thresholds		Coefficients	Standard Errors	t-values
Up to 1st	1st-4th	-7.869	1.024	-7.681
1st-4th	5th-6th	-7.146	0.717	-9.965
5th-6th	7th-8th	-5.379	0.326	-16.515
7th-8th	9th	-4.671	0.253	-18.472
9th	10th	-3.920	0.206	-19.070
10th	11th	-3.468	0.188	-18.489
11th	12th	-2.984	0.174	-17.100
12th	HS grad	-2.511	0.166	-15.116
HS grad	Some college	-0.711	0.154	-4.607
Some college	Associate	0.384	0.154	2.500
Associate	Bachelor's	1.045	0.154	6.766
Bachelor's	Master's	2.478	0.160	15.538
Master's	Professional	4.099	0.177	23.144
Professional	Doctorate	4.838	0.197	24.589

Table 2.2: Summary of ANOVA Regression of Variable on ANES/OP Indicator. Differentiated by Treatment Group

	Df	Sum.Sq	Mean.Sq	F-value	p-value
Age					
T1	1	0.107	0.107	0.000	0.985
T1 Residuals	2,098	641,917.600	305.966		
T2	1	414.519	414.519	1.340	0.247
T2 Residuals	2,098	648,946.600	309.317		
T3	1	427.954	427.954	1.401	0.237
T3 Residuals	2,098	641,038.400	305.547		
Feel Trump					
T1	1	1,164.808	1,164.808	0.979	0.323
T1 Residuals	2,098	2,496,492.000	1,189.939		
T2	1	7,054.667	7,054.667	5.699	0.017
T2 Residuals	2,098	2,597,204.000	1,237.943		
T3	1	2,486.298	2,486.298	2.023	0.155
T3 Residuals	2,098	2,577,984.000	1,228.782		

Table 2.3: Summary of GLM Regression of Variable on ANES/OP Indicator. Differentiated by Treatment Group (reduced)

	Estimate	Std.Error	z-value	p-value
Race				
T1 Intercept	-1.061	0.071	-15.024	0.000
T1	-0.035	0.100	-0.351	0.726
T2 Intercept	-1.153	0.072	-15.952	0.000
T2	0.041	0.102	0.407	0.684
T3 Intercept	-1.206	0.073	-16.452	0.000
T3	-0.005	0.104	-0.052	0.959
Income				
T1 Intercept	1.334	0.076	17.557	0.000
T1	-0.006	0.107	-0.054	0.957
T2 Intercept	1.227	0.074	16.649	0.000
T2	0.038	0.105	0.367	0.714
T3 Intercept	1.398	0.077	18.058	0.000
T3	-0.036	0.109	-0.327	0.744
Party ID				
T1 Intercept	0.530	0.064	8.297	0.000
T1	0.125	0.091	1.367	0.172
T2 Intercept	0.655	0.065	10.065	0.000
T2	-0.125	0.091	-1.367	0.172
T3 Intercept	0.609	0.065	9.421	0.000
T3	-0.000	0.091	-0.000	1.000

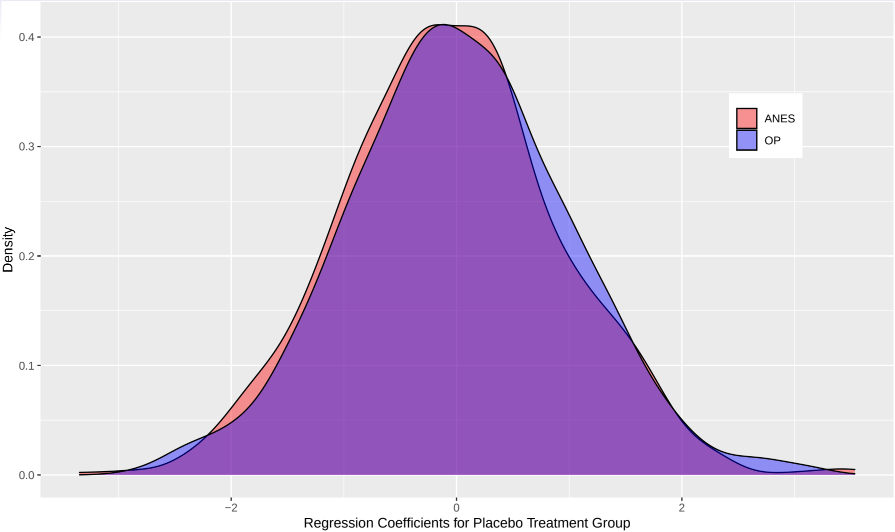

Figure 2.6: Distribution of Placebo Treatment Coefficients by Education Set. Overlapping Area Shown in Dark Purple

Chapter III

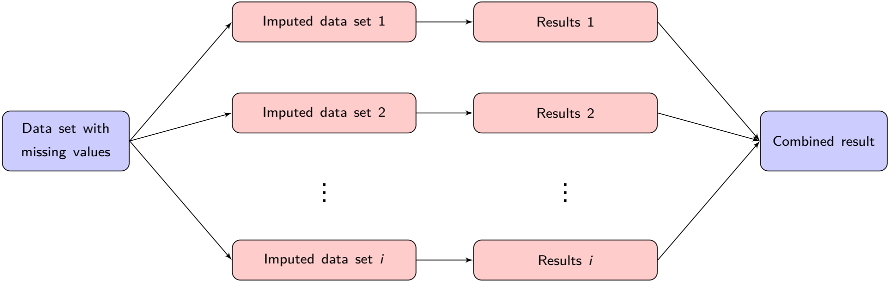

Figure 3.1: Multiple Imputation Workflow

- $\boldsymbol{X}$: $n \times v$ matrix with data on n respondents for v variables
- $\boldsymbol{X}$ formed of missing, $\boldsymbol{X}^{\boldsymbol{miss}}$, and observed data, $\boldsymbol{X}^{\boldsymbol{obs}}$
- Vector of unknown parameters $\boldsymbol{\theta}$
- $\boldsymbol{X}$: Random sample from z-variate multivariate distribution, $\boldsymbol{Z}(\boldsymbol{X}|\boldsymbol{\theta})$
- Question: How to estimate multivariate distribution of $\boldsymbol{\theta}$
- Chained equations model: Estimate posterior distribution of $\boldsymbol{\theta}$ by sampling from conditional distributions:

$$Z(X_1|X_{-1}, \theta_1)$$
$$\vdots$$
$$Z(X_z|X_{-z}, \theta_z)$$

- Iteration n of chained equations is Gibbs sampler
- Chain starts from random draw from observed marginal distributions
- $\boldsymbol{X}_{\boldsymbol{i}}^{\boldsymbol{(n)}} = (\boldsymbol{X}_{\boldsymbol{i}}^{\boldsymbol{obs}}, \boldsymbol{X}_{\boldsymbol{i}}^{*\boldsymbol{(n)}})$ is the ith imputed variable at iteration n

- $\boldsymbol{X^{obs}}$ and $\boldsymbol{X^{miss}}$) are MVN, $\boldsymbol{X} \sim \boldsymbol{N_v}(\mu, \sum)$
- Vector of unknown parameters $\boldsymbol{\theta}$ with $\boldsymbol{\theta} = (\mu, \sum)$
- Missingness matrix $\boldsymbol{R}$; likelihood of observed data prob($\boldsymbol{X^{obs}}, \boldsymbol{R}|\boldsymbol{\theta}$)
- MAR assumption: prob($\boldsymbol{R} = 0|\boldsymbol{X^{obs}}, \boldsymbol{\theta}$)
- Likelihood under MAR assumption:
$$\text{prob}(X^{obs}|\theta) = \int \text{prob}(X|\theta) x X^{miss}$$
- Posterior:
$$\text{prob}(\theta|X^{obs}) \propto \text{prob}(X^{obs}|\theta) = \int \text{prob}(X|\theta) x X^{miss}$$
- Take draws from posterior by combining EM and bootstrapping:
  - Bootstrap data to simulate estimation uncertainty for each draw
  - Run EM algorithm to find mode of the posterior bootstrapped data
  - Impute by drawing from $\boldsymbol{X^{miss}}$ conditional on $\boldsymbol{X^{obs}}$ and draws of $\boldsymbol{\theta}$

- Affinity scores $\boldsymbol{\alpha_{co}}$ (each 0-1)
- measure similarity between recipient c and potential donor o
- Vector (p, v) with p the DV and v a vector of discrete EVs of length k
- If recipient c has q_c missing values in v_c, then potential donor vector v_o has between 0 and $k - q_c$ exact matches with c
- w_{co}: Number of variables where c and o have non-identical values
- Thus $k - q_c - w_{co}$: Number of variables where they have identical values
- Scaled by highest number of possible matches $(k - q_c)$ shows affinity score:

$$\alpha_{co} = \frac{k - q_c - w_{co}}{k - q_c}$$

- Close potential donors for hth variable treated differently from distant ones
- 'Close': $v_{o[h]}$ and $v_{c[h]}$ in same concentric standard deviation from $\overline{h}$
- Values outside of range penalized while values within range count as matches

Table 3.1: Illustrative Data

Respondent	Age	Party ID	Education	Income	Gender
A	25	Republican	High School Graduate	$30-40,000	Male
B	40	NA	Some High School	$20-30,000	Female
C	30	Democrat	Bachelor's Degree	$50-60,000	Female

Table 3.2: Illustrative Data ‘polr‘ Results

Thresholds		Coefficients
Less Than High School	Some High School	2.418
Some High School	High School Graduate	3.495
High School Graduate	Some College	4.214
Some College	Bachelor’s Degree	5.727
Bachelor’s Degree	Master’s Degree	7.412

Table 3.3: Illustrative Data Value Replacements

Original Education Categories	Mid-Cutpoints
Less Than High School	1.879
Some High School	2.956
High School Graduate	3.854
Some College	4.970
Bachelor's Degree	6.569
Master's Degree	8.254

Table 3.4: Accuracy of Multiple Imputation Methods. ANES and CCES Data, MAR, 5 Variables with NA (reduced)

Method	Variable	ANES	CCES
true	Male	0.4890	0.4830
hd.ord	Male	–0.0013	–0.0011
hot.deck	Male	–0.0013	–0.0014
amelia	Male	+0.0002	–0.0001
mice	Male	+0.0001	–0.0001
na.omit	Male	–0.0392	–0.0414
true	Interest	2.9340	3.3290
hd.ord	Interest	–0.0130	–0.0125
hot.deck	Interest	–0.0191	–0.0196
amelia	Interest	+0.0003	+0.0003
mice	Interest	+0.0003	+0.0000
na.omit	Interest	–0.0705	–0.0724
true	Age	50.0410	52.8230
hd.ord	Age	–0.3888	–0.2616
hot.deck	Age	–0.4597	–0.3895
amelia	Age	+0.0007	–0.0033
mice	Age	+0.0017	–0.0073
na.omit	Age	–1.1875	–1.2361

Table 3.5: Accuracy of Multiple Imputation Methods. ANES and CCES Data, MNAR, 5 Variables with NA (reduced)

Method	Variable	ANES	CCES
true	Male	0.4890	0.4830
hd.ord	Male	–0.0136	–0.0116
hot.deck	Male	–0.0133	–0.0124
amelia	Male	–0.0132	–0.0121
mice	Male	–0.0132	–0.0120
na.omit	Male	–0.0214	–0.0219
true	Interest	2.9340	3.3290
hd.ord	Interest	–0.0288	–0.0246
hot.deck	Interest	–0.0335	–0.0296
amelia	Interest	–0.0167	–0.0146
mice	Interest	–0.0167	–0.0146
na.omit	Interest	–0.0379	–0.0372
true	Age	50.0410	52.8230
hd.ord	Age	–0.6319	–0.4596
hot.deck	Age	–0.7415	–0.5929
amelia	Age	–0.2450	–0.2266
mice	Age	–0.2369	–0.2160
na.omit	Age	–0.6427	–0.6392

Table 3.6: Accuracy of Multiple Imputation Methods. ANES and CCES Data, 2 Ordinal Variables (Education, Interest), MAR, 4 Variables with NA (reduced)

Method	Variable	ANES	CCES
true	Democrat	0.3420	0.3770
hd.ord	Democrat	−0.0008	+0.0002
hot.deck	Democrat	−0.0018	−0.0005
amelia	Democrat	+0.0002	+0.0001
mice	Democrat	+0.0001	+0.0002
ha.omit	Democrat	−0.0333	−0.0294
true	Income	16.6140	6.4810
hd.ord	Income	−0.0830	−0.0246
hot.deck	Income	−0.1523	−0.0516
amelia	Income	+0.0010	−0.0006
mice	Income	−0.0008	+0.0002
ha.omit	Income	−0.5771	−0.2564

Table 3.7: Accuracy of Multiple Imputation Methods. ANES and CCES Data, 2 Ordinal Variables (Education, Interest), MNAR, 4 Variables with NA (reduced)

Method	Variable	ANES	CCES
true	Democrat	0.3420	0.3770
hd.ord	Democrat	–0.0142	–0.0133
hot.deck	Democrat	–0.0155	–0.0131
amelia	Democrat	–0.0136	–0.0131
mice	Democrat	–0.0127	–0.0130
na.omit	Democrat	–0.0211	–0.0185
true	Income	16.6140	6.4810
hd.ord	Income	–0.2481	–0.1034
hot.deck	Income	–0.3174	–0.1303
amelia	Income	–0.1555	–0.0741
mice	Income	–0.1568	–0.0730
na.omit	Income	–0.3114	–0.1513

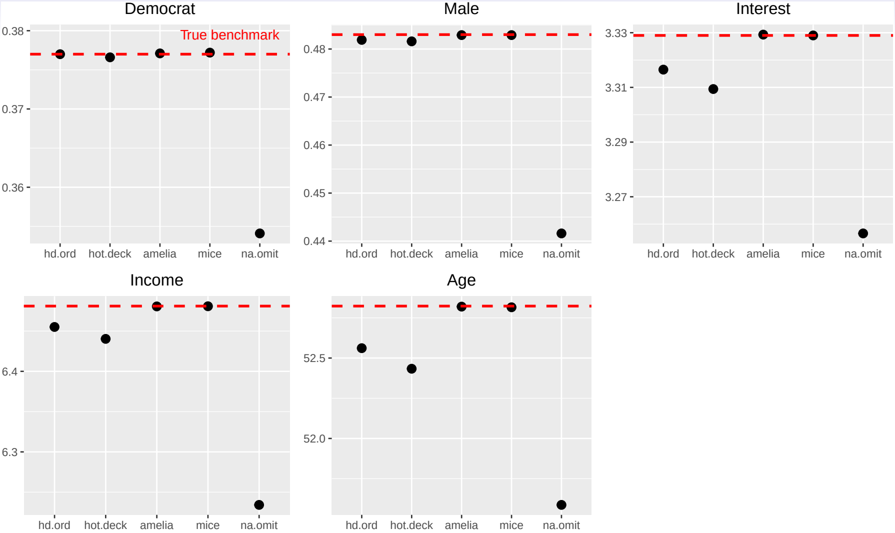

Figure 3.6: Accuracy of Multiple Imputation Methods for 20 Percent Missingness. CCES Data, MAR, Five Variables with NA. Y-Axis Shows Percentages/Means

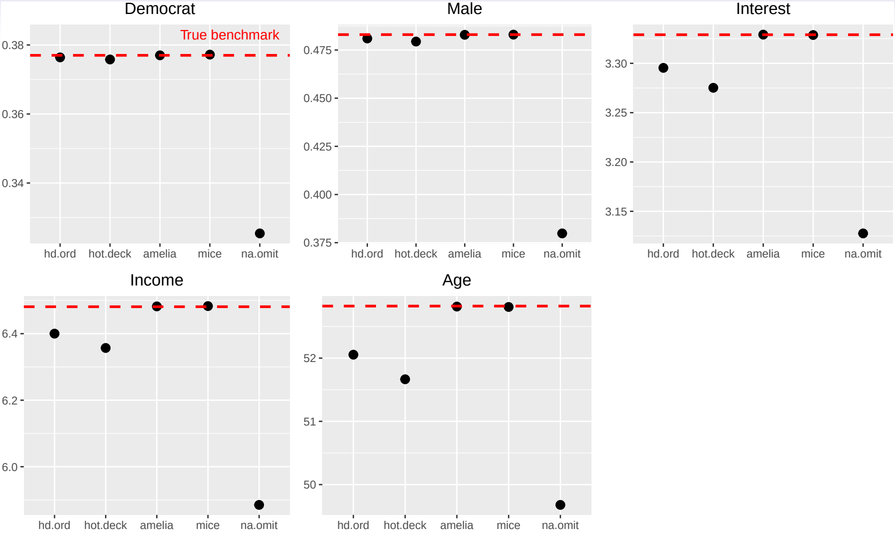

Figure 3.7: Accuracy of Multiple Imputation Methods for 50 Percent Missingness. CCES Data, MAR, Five Variables with NA. Y-Axis Shows Percentages/Means

Table 3.8: Runtimes of Multiple Imputation Methods (in Minutes). ANES and CCES Data, MAR, 5 Variables with NA

	ANES	CCES
hd.ord	2.632	2.778
hot.deck	2.628	2.786
amelia	9.052	10.611
mice	50.445	57.205

Table 3.9: Runtimes of Multiple Imputation Methods (in Minutes) by Percentage of Missingness. CCES Data

Method	20% NA	50% NA
hd.ord	2.780	12.920
hot.deck	2.790	13.030
amelia	10.610	28.770
mice	57.210	158.840

Table 3.10: ‘lm‘ and ‘polr‘ Differences in 1992 ANES Data as Used by Bartels (1999)

	Dependent variable:		
	Campaign Interest	Education	Education
	OLS	*OLS*	*ordered logistic*
Education	0.023 (0.004)		
Age	0.002 (0.001)	−0.032 (0.004)	−0.021 (0.003)
Income	0.071 (0.037)	4.092 (0.245)	3.133 (0.204)
Black	−0.028 (0.028)	−0.865 (0.198)	−0.673 (0.150)
Female	−0.055 (0.018)	−0.058 (0.133)	−0.054 (0.102)
Partisan strength	0.214 (0.027)	0.290 (0.198)	0.196 (0.152)
Days before election	−0.001 (0.0005)	0.014 (0.004)	0.012 (0.003)
Constant	0.391 (0.038)	−0.388 (0.273)	
Observations	1,359	1,359	1,359
R^2	0.114	0.248	
Adjusted R^2	0.109	0.245	
Residual Std. Error	0.331 (df = 1351)	2.401 (df = 1352)	
F Statistic	24.750 (df = 7; 1351)	74.507 (df = 6; 1352)	

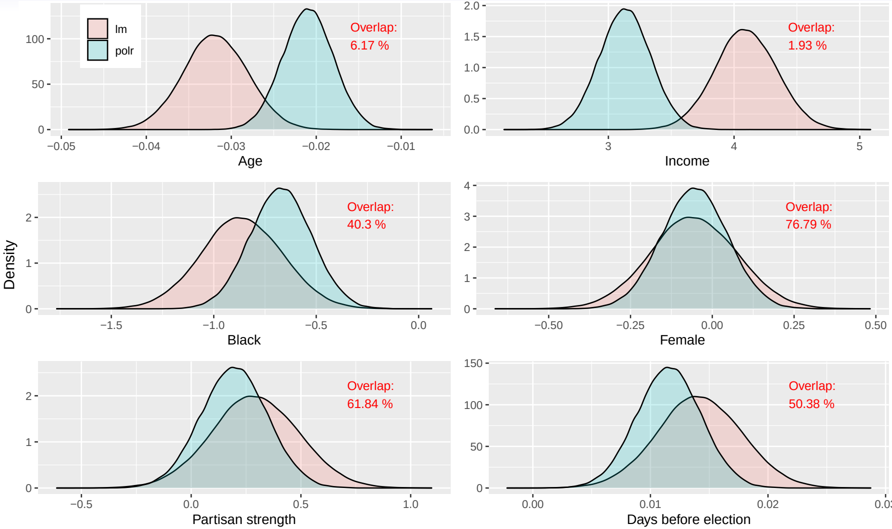

Figure 3.8: Distributions of 'lm' and 'polr' Coefficients in 1992 ANES Data as Used by Bartels (1999)

Chapter IV

Table 4.1: Foundations of Moral Intuitions

Positive		Negative	
Care	Cherishing, protecting others	*Harm*	Hurting others
Fairness	Rendering justice by shared rules	*Cheating*	Flouting justice/shared rules
Loyalty	Standing with your group	*Betrayal*	Opposing your group
Authority	Submitting to tradition/authority	*Subversion*	Resisting tradition/authority
Sanctity	Repulsion at disgust	*Degradation*	Enjoyment of disgust
Liberty	Acting without constraint	*Oppression*	Dominate/Constrain others

Positive and negative foundations are conceptual opposites.

Table 4.2: Ordinal Logistic Regression Results (reduced)

	Dependent variable:	
	Healthcare	
	ANES	OP
Moral opposing	0.001 (−0.373, 0.376)	−0.773 (−1.121, −0.425)
Moral supporting	0.481 (0.124, 0.838)	−0.352 (−0.696, −0.007)
Self-interest opposing	−0.053 (−0.385, 0.279)	−0.578 (−0.928, −0.228)
Self-interest supporting	0.132 (−0.227, 0.490)	−0.212 (−0.548, 0.124)
	Environment	
	ANES	OP
Moral opposing	−0.662 (−1.035, −0.288)	−0.390 (−0.730, −0.051)
Moral supporting	−0.128 (−0.503, 0.247)	−0.222 (−0.571, 0.127)
Self-interest opposing	−0.207 (−0.575, 0.161)	−0.270 (−0.614, 0.073)
Self-interest supporting	0.292 (−0.056, 0.640)	−0.054 (−0.397, 0.289)
Observations	1,062	1,103

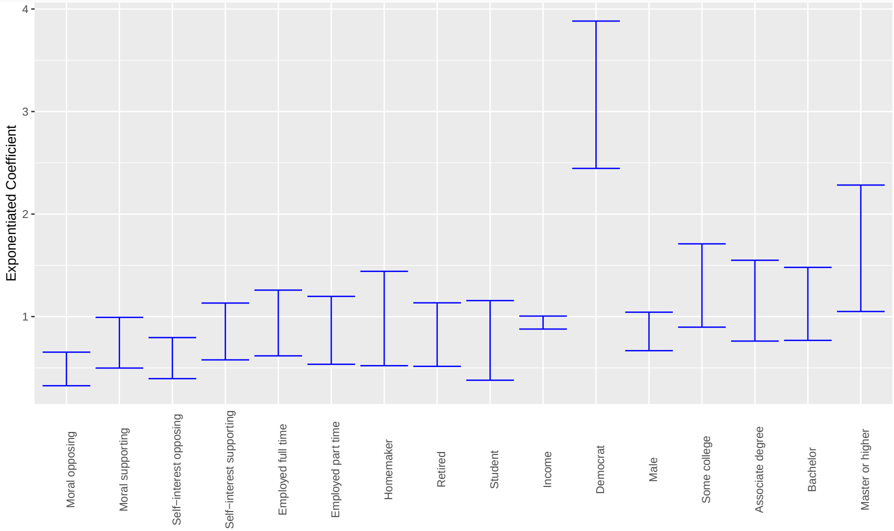

Figure 4.1: Exponentiated Coefficients with Confidence Intervals. OP, Healthcare

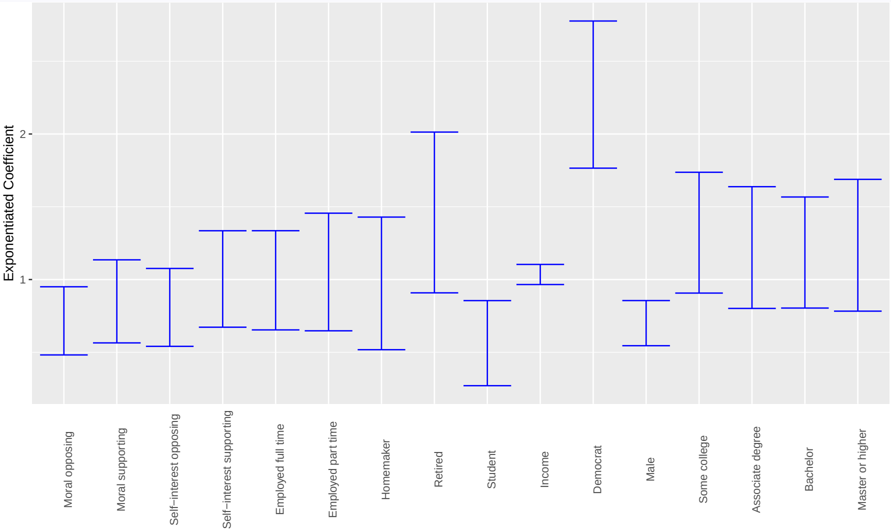

Figure 4.2: Exponentiated Coefficients with Confidence Intervals. OP, Environment

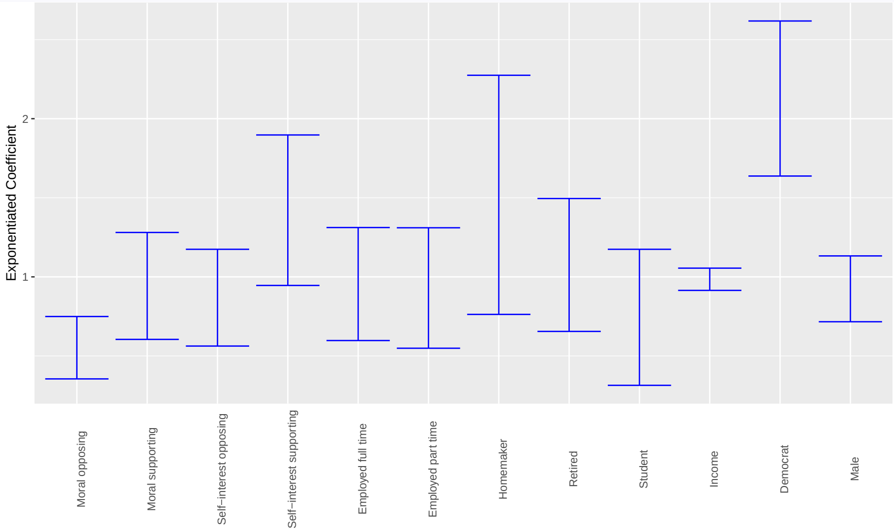

Figure 4.3: Exponentiated Coefficients with Confidence Intervals. ANES, Environment

Table 4.3: Ordinal Logistic Regression Results. High and Low Morality, Healthcare (reduced)

	Dependent variable:	
	Healthcare	
	ANES High	ANES Low
Moral opposing	−0.508 (−1.167, 0.151)	0.205 (−0.513, 0.923)
Moral supporting	0.760 (0.114, 1.406)	0.510 (−0.083, 1.103)
Self-interest opposing	−0.00002 (−0.600, 0.600)	0.013 (−0.552, 0.578)
Self-interest supporting	0.023 (−0.620, 0.667)	0.044 (−0.577, 0.665)
Observations	354	
	OP High	OP Low
Moral opposing	−1.132 (−1.747, −0.517)	−0.467 (−1.084, 0.150)
Moral supporting	−0.452 (−1.069, 0.165)	−0.236 (−0.869, 0.397)
Self-interest opposing	−0.917 (−1.553, −0.282)	−0.463 (−1.102, 0.177)
Self-interest supporting	−0.223 (−0.801, 0.355)	−0.265 (−0.877, 0.348)
Observations	367	

Table 4.4: Ordinal Logistic Regression Results. High and Low Morality, Environment (reduced)

	Dependent variable:	
	Environment	
	ANES High	ANES Low
Moral opposing	−1.059 (−1.706, −0.412)	−0.142 (−0.787, 0.503)
Moral supporting	−0.333 (−1.017, 0.351)	0.409 (−0.264, 1.083)
Self-interest opposing	−0.121 (−0.780, 0.538)	0.110 (−0.582, 0.801)
Self-interest supporting	0.237 (−0.370, 0.844)	0.732 (0.087, 1.377)
Observations	354	
	OP High	OP Low
Moral opposing	−0.987 (−1.613, −0.360)	0.200 (−0.405, 0.805)
Moral supporting	−0.355 (−0.974, 0.263)	0.285 (−0.335, 0.906)
Self-interest opposing	−0.674 (−1.283, −0.065)	0.163 (−0.453, 0.780)
Self-interest supporting	−0.606 (−1.257, 0.045)	0.649 (0.029, 1.270)
Observations	367	

Table 4.5: Ordinal Logistic Regression Results. High and Low Self-Interest, Healthcare (reduced)

	Dependent variable:	
	Healthcare	
	ANES High	ANES Low
Moral opposing	0.024 (−0.634, 0.682)	−0.275 (−0.950, 0.401)
Moral supporting	0.396 (−0.220, 1.013)	0.478 (−0.176, 1.132)
Self-interest opposing	0.203 (−0.419, 0.825)	−0.024 (−0.594, 0.547)
Self-interest supporting	0.261 (−0.374, 0.895)	0.227 (−0.407, 0.862)
Observations	354	
	OP High	OP Low
Moral opposing	−0.877 (−1.526, −0.229)	−0.752 (−1.352, −0.153)
Moral supporting	−0.699 (−1.307, −0.090)	−0.488 (−1.099, 0.123)
Self-interest opposing	−0.666 (−1.296, −0.036)	−0.706 (−1.308, −0.104)
Self-interest supporting	−0.576 (−1.166, 0.015)	−0.014 (−0.613, 0.584)
Observations	367	

Table 4.6: Ordinal Logistic Regression Results. High and Low Self-Interest, Environment (reduced)

	Dependent variable:	
	Environment	
	ANES High	ANES Low
Moral opposing	−0.346 (−1.019, 0.328)	−0.672 (−1.322, −0.022)
Moral supporting	0.435 (−0.248, 1.118)	−0.144 (−0.785, 0.498)
Self-interest opposing	−0.118 (−0.779, 0.543)	−0.127 (−0.794, 0.539)
Self-interest supporting	0.564 (−0.063, 1.192)	0.116 (−0.495, 0.726)
Observations	354	
	OP High	OP Low
Moral opposing	−0.970 (−1.579, −0.362)	−0.484 (−1.074, 0.106)
Moral supporting	−0.999 (−1.620, −0.378)	0.201 (−0.439, 0.840)
Self-interest opposing	−0.600 (−1.239, 0.040)	−0.246 (−0.851, 0.359)
Self-interest supporting	−0.476 (−1.087, 0.134)	−0.008 (−0.608, 0.592)
Observations	367	

Table 4.7: Accuracy of Multiple Imputation Methods. Framing Data, MAR, 5 Variables with NA (reduced)

Method	Variable	ANES	OP
true	Employed	0.5612	0.5684
hot.deck	Employed	+0.0012	+0.0012
hd.ord	Employed	+0.0013	+0.0013
amelia	Employed	+0.0002	+0.0001
mice	Employed	–0.0001	–0.0001
na.omit	Employed	–0.0353	–0.0358
true	Age	46.3475	44.9574
hot.deck	Age	–0.1621	–0.1711
hd.ord	Age	–0.3107	–0.2837
amelia	Age	–0.0009	+0.0040
mice	Age	–0.0073	+0.0000
na.omit	Age	–0.8376	–0.8373

Table 4.8: Accuracy of Multiple Imputation Methods. Framing Data, MNAR, 5 Variables with NA (reduced)

Method	Variable	ANES	OP
true	Employed	0.5612	0.5684
hot.deck	Employed	–0.0027	–0.0028
hd.ord	Employed	–0.0030	–0.0034
amelia	Employed	–0.0031	–0.0030
mice	Employed	–0.0030	–0.0030
na.omit	Employed	–0.0180	–0.0178
true	Age	46.3475	44.9574
hot.deck	Age	–0.4322	–0.4795
hd.ord	Age	–0.6215	–0.5925
amelia	Age	–0.2420	–0.2725
mice	Age	–0.2441	–0.2768
na.omit	Age	–0.5301	–0.5076

Appendix for Chapter II

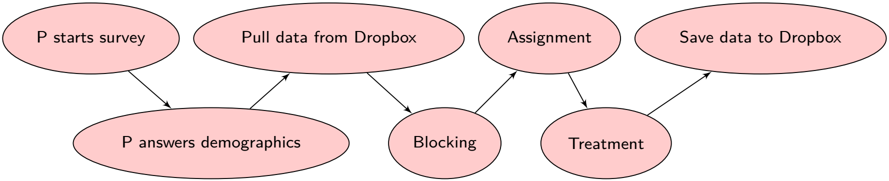

Figure A.1: Online Survey Experiment Workflow

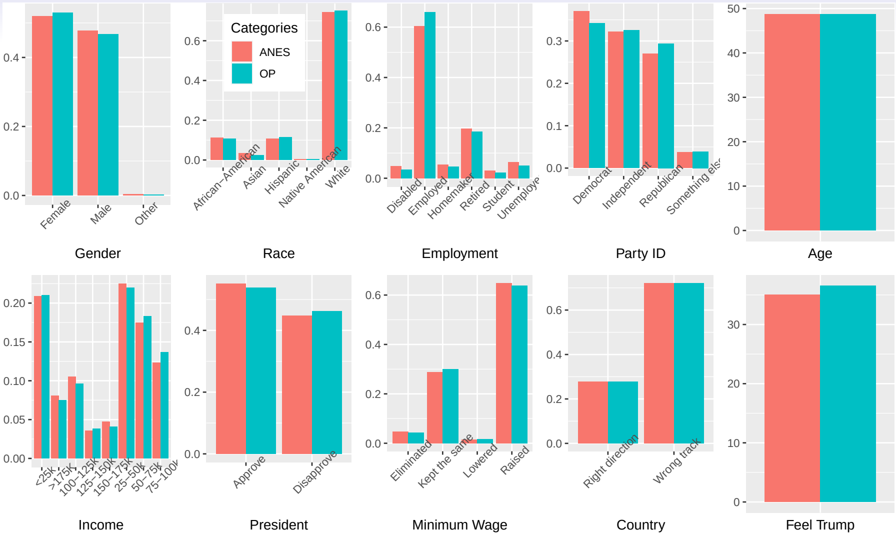

Figure A.2: Variable Proportions/Means After Blocking ANES Data on ANES and OP Education Categories, Treatment Group 1. ‘Age‘ and ‘Feel Trump‘ Show Means, All Others Show Proportions

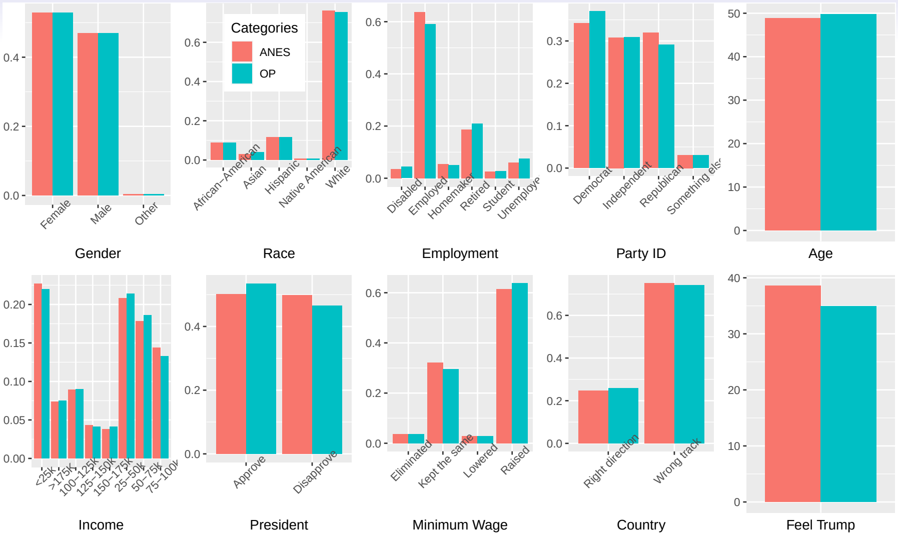

Figure A.3: Variable Proportions/Means After Blocking ANES Data on ANES and OP Education Categories, Treatment Group 2. 'Age' and 'Feel Trump' Show Means, All Others Show Proportions

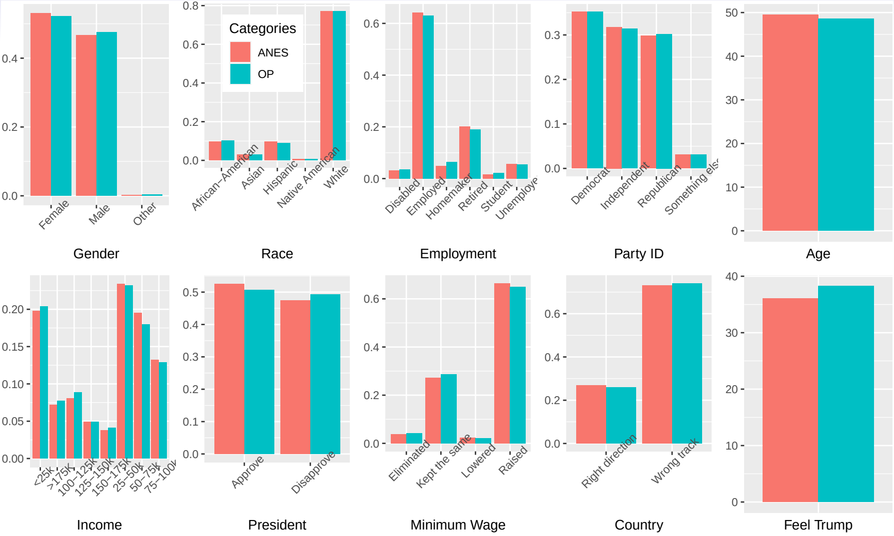

Figure A.4: Variable Proportions/Means After Blocking ANES Data on ANES and OP Education Categories, Treatment Group 3. ‘Age‘ and ‘Feel Trump‘ Show Means, All Others Show Proportions

Appendix for Chapter III

Table B.1: Accuracy of Multiple Imputation Methods. ANES and CCES Data, MAR, 5 Variables with NA, All Observations (reduced)

Method	Variable	ANES	CCES
true	Male	0.4868	0.4521
hd.ord	Male	–0.0004	–0.0001
hot.deck	Male	–0.0008	–0.0002
amelia	Male	+ 0.0001	+ 0.0001
mice	Male	+ 0.0001	+ 0.0001
na.omit	Male	–0.0365	–0.0436
true	Interest	2.8806	3.3301
hd.ord	Interest	–0.0087	–0.0033
hot.deck	Interest	–0.0135	–0.0046
amelia	Interest	+ 0.0001	+ 0.0001
mice	Interest	+ 0.0000	+ 0.0000
na.omit	Interest	–0.0741	–0.0763
true	Age	50.3745	52.8639
hd.ord	Age	–0.2355	–0.0221
hot.deck	Age	–0.3698	–0.0790
amelia	Age	+ 0.0056	–0.0006
mice	Age	+ 0.0053	–0.0132
na.omit	Age	–1.2785	–1.2190
Observations		2395	42205
Iterations		1000	10

Table B.2: Accuracy of Multiple Imputation Methods. ANES and CCES Data, MNAR, 5 Variables with NA, All Observations (reduced)

Method	Variable	ANES	CCES
true	Male	0.4868	0.4521
hd.ord	Male	–0.0138	–0.0129
hot.deck	Male	–0.0136	–0.0131
amelia	Male	–0.0134	–0.0132
mice	Male	–0.0134	–0.0131
na.omit	Male	–0.0196	–0.0244
true	Interest	2.8806	3.3301
hd.ord	Interest	–0.0257	–0.0171
hot.deck	Interest	–0.0299	–0.0179
amelia	Interest	–0.0178	–0.0147
mice	Interest	–0.0179	–0.0148
na.omit	Interest	–0.0407	–0.0418
true	Age	50.3745	52.8639
hd.ord	Age	–0.5240	–0.2331
hot.deck	Age	–0.6609	–0.2764
amelia	Age	–0.2533	–0.2342
mice	Age	–0.2474	–0.2371
na.omit	Age	–0.7188	–0.6476
Observations		2395	42205
Iterations		1000	10

Table B.3: Accuracy of Multiple Imputation Methods. ANES and CCES Data, MAR, 12 Variables with NA (reduced)

Method	Variable	ANES	CCES
true	Male	0.4890	0.4830
hd.ord	Male	–0.0004	–0.0002
hot.deck	Male	–0.0001	–0.0003
amelia	Male	+ 0.0001	–0.0001
mice	Male	+ 0.0000	–0.0002
na.omit	Male	–0.0256	–0.0364
true	Interest	2.9340	3.3290
hd.ord	Interest	–0.0053	–0.0041
hot.deck	Interest	–0.0077	–0.0067
amelia	Interest	+ 0.0001	–0.0001
mice	Interest	+ 0.0000	–0.0001
na.omit	Interest	–0.0620	–0.0515
true	Age	50.0410	52.8230
hd.ord	Age	–0.1391	–0.0883
hot.deck	Age	–0.1835	–0.1435
amelia	Age	+ 0.0056	–0.0015
mice	Age	+ 0.0048	–0.0050
na.omit	Age	–0.8638	–0.5974

Table B.4: Accuracy of Multiple Imputation Methods. ANES and CCES Data, MNAR, 12 Variables with NA (reduced)

Method	Variable	ANES	CCES
true	Male	0.4890	0.4830
hd.ord	Male	–0.0055	–0.0049
hot.deck	Male	–0.0053	–0.0051
amelia	Male	–0.0055	–0.0050
mice	Male	–0.0055	–0.0049
na.omit	Male	–0.0093	–0.0119
true	Interest	2.9340	3.3290
hd.ord	Interest	–0.0113	–0.0090
hot.deck	Interest	–0.0134	–0.0113
amelia	Interest	–0.0068	–0.0061
mice	Interest	–0.0068	–0.0061
na.omit	Interest	–0.0236	–0.0161
true	Age	50.0410	52.8230
hd.ord	Age	–0.2571	–0.1732
hot.deck	Age	–0.3081	–0.2251
amelia	Age	–0.1100	–0.1014
mice	Age	–0.1047	–0.0986
na.omit	Age	–0.3397	–0.1367

Table B.5: Accuracy of Multiple Imputation Methods. ANES and CCES Data, 2 Ordinal Variables (Education, Interest), MAR, 11 Variables with NA (reduced)

Method	Variable	ANES	CCES
true	Democrat	0.3420	0.3770
hd.ord	Democrat	–0.0002	–0.0004
hot.deck	Democrat	–0.0005	–0.0005
amelia	Democrat	+ 0.0000	–0.0001
mice	Democrat	+ 0.0000	+ 0.0000
na.omit	Democrat	–0.0200	–0.0213
true	Income	16.6140	6.4810
hd.ord	Income	–0.0346	–0.0114
hot.deck	Income	–0.0657	–0.0241
amelia	Income	–0.0018	–0.0007
mice	Income	–0.0027	–0.0005
na.omit	Income	–0.6432	–0.2888
true	Religious	0.6460	0.6420
hd.ord	Religious	–0.0001	–0.0002
hot.deck	Religious	–0.0005	–0.0003
amelia	Religious	+ 0.0000	–0.0001
mice	Religious	+ 0.0000	–0.0002
na.omit	Religious	–0.0174	–0.0241

Table B.6: Accuracy of Multiple Imputation Methods. ANES and CCES Data, 2 Ordinal Variables (Education, Interest), MNAR, 11 Variables with NA (reduced)

Method	Variable	ANES	CCES
true	Democrat	0.3420	0.3770
hd.ord	Democrat	–0.0050	–0.0053
hot.deck	Democrat	–0.0053	–0.0053
amelia	Democrat	–0.0047	–0.0049
mice	Democrat	–0.0044	–0.0048
na.omit	Democrat	–0.0097	–0.0097
true	Income	16.6140	6.4810
hd.ord	Income	–0.0841	–0.0349
hot.deck	Income	–0.1142	–0.0473
amelia	Income	–0.0540	–0.0250
mice	Income	–0.0549	–0.0249
na.omit	Income	–0.2112	–0.0982
true	Religious	0.6460	0.6420
hd.ord	Religious	–0.0045	–0.0044
hot.deck	Religious	–0.0047	–0.0042
amelia	Religious	–0.0043	–0.0045
mice	Religious	–0.0043	–0.0045
na.omit	Religious	–0.0055	–0.0077

Table B.7: Runtimes of Multiple Imputation Methods (in Minutes). ANES and CCES Data, MAR, 12 Variables with NA

	ANES	CCES
hd.ord	2.614	2.679
hot.deck	2.640	2.690
amelia	9.038	10.345
mice	104.143	113.390

Appendix for Chapter IV

Research Study

You are being asked to participate in a research study conducted by Jeff Gill and Simon Heuberger. We are researchers in political science at American University. The purpose of this study is to collect opinions on several issues. No prior knowledge is required. All issues will be briefly explained before we ask for your opinion.

Completing the survey will take around 20 minutes and is anonymous. Amazon / Lucid does not share any identifiable information with us. Your identity is never known to us and will not be attached in any way to the final form of this study. Aggregate, non-identifiable data will be presented representing averages or generalizations about the responses as a whole. All the data will be stored in a secure location accessible only to us, the researchers.

Your participation is entirely voluntary. You are free to choose not to participate. You can also withdraw from the survey by closing your browser at any time. Incomplete answers will not be recorded.

If you have any questions, please reach out to us at sh6943a@american.edu. If you feel as though your rights as a research subject have been violated in any way, please contact the American University IRB Coordinator Matt Zembrzuski at irb@american.edu.

If you want to proceed with the survey, please indicate your consent by clicking the checkbox below.

[Checkbox]

To begin, we would like to ask you some questions about your work with Lucid / on Mechanical Turk.

Q1. How long have you been answering surveys with Lucid / How long have you been performing tasks on Mechanical Turk?
Less than a month (1)
1-3 months (2)
3-6 months (3)
Between 6 months and 1 year (4)
More than 1 year (5)

Q2. Why did you start working with Lucid / on Mechanical Turk?
[Open-ended text input]

Q3. What is most important to you when you choose the surveys you answer / the tasks you perform?
Financial compensation (1)
Length of the survey (2)
Topic (3)
Survey description (4)
Something else (5)

Next, we would like to ask you some questions about your social views and how you see yourself. When you are ready, please hit “Continue” below.

When you decide whether something is right or wrong, to what extent are the following considerations relevant to your thinking?

Q4. Whether or not someone suffered emotionally.
Not at all relevant (This consideration has nothing to do with my judgments of right and wrong) (1)
Not very relevant (2)
Slightly relevant (3)
Somewhat relevant (4)
Very relevant (5)
Extremely relevant (This is one of the most important factors when I judge right and wrong) (6)

Q5. Whether or not someone cared for someone weak or vulnerable.
Not at all relevant (1)
Not very relevant (2)
Slightly relevant (3)
Somewhat relevant (4)
Very relevant (5)
Extremely relevant (6)

Q6. Whether or not someone was cruel.
Not at all relevant (1)
Not very relevant (2)
Slightly relevant (3)
Somewhat relevant (4)
Very relevant (5)
Extremely relevant (6)

Please read the following sentences and indicate your agreement or disagreement.

Q7. Compassion for those who are suffering is the most crucial virtue.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Q8. One of the worst things a person could do is hurt a defenseless animal.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Q9. It can never be right to kill a human being.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Please read the following sentences and indicate your agreement or disagreement.

Q10. I have no problem telling “white lies” if it will help me achieve my goals.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Q11. At the end of the day I care mostly for myself, my family, and friends who can help me.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Q12. Even if it meant giving my kids an unfair advantage over others, I’d do it for them.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Please read the following sentences and indicate your agreement or disagreement.

Q13. If the choice was between killing someone or being killed, I'd kill.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Q14. I sometimes lie to others for my own good, and theirs too.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Q15. I mostly help those around me who will help me later.
Strongly disagree (1)
Moderately disagree (2)
Slightly disagree (3)
Slightly agree (4)
Moderately agree (5)
Strongly agree (6)

Next, we would like to ask you some questions about your background. When you are ready, please hit "Continue" below.

Q16. Please select your year of birth.
[Drop-down menu]

Q17. What racial or ethnic group best describes you?
White (1)
Black or African-American (2)
Arab or Middle Eastern (3)
Hispanic or Latino (4)
Asian (5)
American Indian or Alaska Native (6)
Native Hawaiian or other Pacific Islander (7)
Other (8)

Q18. What gender best describes you?
Male (1)
Female (2)
Other (3)

Q19. Please select the correct statement.
The letter K comes before the letter B in the alphabet. (1)
The letter B comes before the letter K in the alphabet. (2)
There are 100 letters in the alphabet. (3)
There are 10 letters in the alphabet. (4)

Q20. What is your current employment status?
Employed part time (1)
Employed full time (2)
Student (3)
Retired (4)
Homemaker (5)
Unemployed (6)

Q21. What is your combined annual household income?
Less than $20,000 (1)
$20,000 to $39,999 (2)
$40,000 to $59,999 (3)
$60,000 to $79,999 (4)
$80,000 to $99,999 (5)
$100,000 to $149,999 (6)
$150,000 or more (7)

Q22. When it comes to politics, would you describe yourself as liberal, conservative, or neither liberal nor conservative?
Liberal (1)
Conservative (2)
Neither (3)

Q23 a). Would you call yourself very liberal or somewhat liberal?
Very liberal (1)
Somewhat liberal (2)

Q23 b).Would you call yourself very conservative or somewhat conservative?
Very conservative (1)
Somewhat conservative (2)

Q23 c). Do you think of yourself as closer to liberals, or conservatives, or neither of these?
Closer to liberals (1)
Closer to conservatives (2)
Neither (3)

Q24. Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or something else?
Democrat (1)
Republican (2)
Independent (3)
Something else (4)

Q25 a). Would you call yourself a strong Republican or a not very strong Republican?
Strong (1)
Not very strong (2)

Q25 b). Would you call yourself a strong Democrat or a not very strong Democrat?
Strong (1)
Not very strong (2)

Q25 c). Do you think of yourself as closer to the Republican Party or to the Democratic Party?
Closer to the Republican Party (1)
Closer to the Democratic Party (2)
Neither (3)

Q26. What is the highest level of school you have completed or the highest degree you have received?

(**Note to researchers**:
A comparison of differing ways to utilize ordinal variables for blocking was part of this study. To make this comparison, each respondent randomly received one of the two sets of education categories below and was blocked on his/her selection. Both sets of categories were blocked separately.)

<u>Set A</u>
High school or lower (1)
Some college (2)
Associate degree (3)
Bachelor's degree (4)
Master's degree or higher (5)

<u>Set B</u>
Up to 1st grade (1)
1st-4th grade (2)
5th-6th grade (3)
7th-8th grade (4)
9th grade (5)
10th grade (6)
11th grade (7)
12th grade (8)
High school graduate (9)
Some college (10)
Associate degree (11)
Bachelor's degree (12)
Master's degree (13)
Professional degree (14)
Doctorate (15)

Next, we would like to ask you about your opinion on two political issues. When you are ready, please hit “Continue” below.

(Please note: After you hit Continue, it might take a moment for the next page to load due to processing speeds. If this happens, please do not exit your browser. Your answer will be processed and recorded. This is part of the survey design.)

Please read the following text carefully and answer the questions that follow.

Potential New Healthcare Plan Introduced

Over the past few years, U.S. politicians have repeatedly debated the potential introduction of a new healthcare plan. One option is a healthcare plan that:

- covers everyone in the US
- is paid for with a mix of fees paid by individuals and employers as well as tax dollars
- provides free healthcare for all services and drugs to those over 65 and low income people (unlike Medicare and Medicaid).

[Randomly assign one of the following five treatment frames:]

Control
(Nothing added)

Moral-Opposing
Some people think it is a bad idea to implement this healthcare plan. They argue that elderly people and those with medical conditions will not get the level of care they need. Medical services will get worse and will take longer to access when everyone is covered, which particularly affects these vulnerable groups.

Moral-Supporting
Some people think it is a good idea to implement this healthcare plan. They argue that it helps vulnerable members of society who are suffering. Increased health coverage will provide them with the services and drugs they need to survive. It will protect and support them but does not affect the majority of the population.

Self-Interest-Opposing
Some people think it is a bad idea to implement this healthcare plan. They argue that the majority of people will need to pay more for the same or even worse quality of care. Everyone who is not elderly or has low income will pick up the tab for these groups without receiving any benefits themselves.

Self-Interest-Supporting
Some people think it is a good idea to implement this healthcare plan. They argue that we all want to be healthy and know that we and our families are safe, both financially and medically, if we get ill. We all want to be protected when we get older or in case we ever fall on hard times. We want to look after ourselves and our families and make sure we are protected in times of need.

Q27. How do you feel about this healthcare plan?
Strongly oppose (1)
Somewhat oppose (2)
Neither favor nor oppose (3)
Somewhat favor (4)
Strongly favor (5)

Q28. How would you rate this policy on a scale from 1 to 10, with 1 being the worst and 10 being the best?
[Slider with values from 1:10, including first decimals]

Q29. A moment ago, you were informed about a plan that was recently debated. Which of the following political topics is the plan about?
Immigration (1)
Abortion (2)
Healthcare (3)
Taxes (4)
Gun control (5)
Same-sex marriage (6)
Minimum wage (7)

(Please note: After you hit Continue, it might take a moment for the next page to load due to processing speeds. If this happens, please do not exit your browser. Your answer will be processed and recorded. This is part of the survey design.)

Please read the following text carefully and answer the questions that follow.

Stricter Environmental Regulations Discussed

Over the past few years, politicians have repeatedly debated the potential introduction of new environmental regulations to improve food safety in the US. The restrictions decrease the use of toxic pesticides that:

- might contaminate crops, soil, and ground water
- are particularly harmful to the elderly and those with various medical conditions.

Farmers need to use less toxic substitutes or farm without pesticides. They receive state subsidies to cover parts of their increased costs.

[Randomly assign one of the following five treatment frames:]

<u>Control</u>
(Nothing added)

<u>Moral-Opposing</u>
Some people think it is a bad idea to implement these restrictions. They argue that they increase the burden on farmers and make it harder for them to stay economically viable. Using no or substitute pesticides will lead to a large increase in costs. To cover these costs, they might need to lay off workers, take on debts or even close their business.

<u>Moral-Supporting</u>
Some people think it is a good idea to implement these restrictions. They argue that the elderly and people with medical conditions will suffer from the use of aggressive pesticides. These make them more vulnerable to diseases and even death. Their health deteriorates and they suffer. Increased restrictions give them the vital protection they need to survive and do not affect the majority of people.

<u>Self-Interest-Opposing</u>
Some people think it is a bad idea to implement these restrictions. They argue that the restrictions will increase food production costs and raise food prices. We will all need to pay more to cover the costs of the restrictions and have less money to spend on other things for us and our families.

<u>Self-Interest-Supporting</u>
Some people think it is a good idea to implement these restrictions. They argue that the restrictions protect us and our health. We and our families all benefit from healthier food with fewer chemicals. We will become sick less often, increase our life expectancy, and have more time for our families. This will reduce our healthcare expenditures and give us more time for our families and more money to spend on other things.

Q30. How do you feel about these restrictions?
Strongly oppose (1)
Somewhat oppose (2)
Neither favor nor oppose (3)

Somewhat favor (4)
Strongly favor (5)

Q31. How would you rate this policy on a scale from 1 to 10, with 1 being the worst and 10 being the best?
[Slider with values from 1:10, including first decimals]

Q32. A moment ago, you were informed about a plan that was recently debated. Which of the following political topics is the plan about?
Minimum wage (1)
Same-sex marriage (2)
Taxes (3)
Immigration (4)
Environment (5)
Gun control (6)
Abortion (7)

Finally, do you have any comments for us regarding the design or the questions? If so, please share them here. This section can be left blank, but we are very grateful for any type of feedback you can give us.

Q33. Please enter any comments you have for us.

[Open-ended text input]

You have answered all the questions in this survey. Thank you!

Once you hit “Continue”, you will be redirected.

Table C.1: Ordinal Logistic Regression Results, Republican (reduced)

	Dependent variable:	
	Healthcare	
	ANES	OP
Moral opposing	−0.261 (−1.013, 0.490)	−0.732 (−1.397, −0.067)
Moral supporting	0.131 (−0.586, 0.847)	−0.471 (−1.130, 0.189)
Self-interest opposing	−0.699 (−1.370, −0.028)	−0.949 (−1.603, −0.296)
Self-interest supporting	−0.302 (−1.005, 0.401)	−0.325 (−0.948, 0.298)
	Environment	
	ANES	OP
Moral opposing	−1.009 (−1.711, −0.306)	−0.088 (−0.706, 0.531)
Moral supporting	−0.304 (−1.034, 0.425)	−0.190 (−0.832, 0.452)
Self-interest opposing	−0.343 (−1.026, 0.340)	0.027 (−0.567, 0.622)
Self-interest supporting	0.063 (−0.591, 0.716)	0.258 (−0.360, 0.876)
Observations	318	331

Table C.2: Ordinal Logistic Regression Results, Democrat (reduced)

	Dependent variable:	
	Healthcare	
	ANES	OP
Moral opposing	−0.304 (−0.890, 0.283)	−0.781 (−1.363, −0.199)
Moral supporting	0.415 (−0.167, 0.997)	−0.310 (−0.871, 0.252)
Self-interest opposing	−0.042 (−0.574, 0.490)	−0.136 (−0.712, 0.440)
Self-interest supporting	−0.073 (−0.664, 0.517)	−0.135 (−0.688, 0.419)
	Environment	
	ANES	OP
Moral opposing	−0.676 (−1.317, −0.036)	−0.671 (−1.225, −0.116)
Moral supporting	−0.110 (−0.733, 0.514)	−0.591 (−1.159, −0.022)
Self-interest opposing	−0.145 (−0.763, 0.474)	−0.513 (−1.081, 0.054)
Self-interest supporting	0.497 (−0.085, 1.079)	−0.559 (−1.138, 0.019)
Observations	412	422

Table C.3: Accuracy of Multiple Imputation Methods. Framing Data, MAR, 10 Variables with NA (reduced)

Method	Variable	ANES	OP
true	Employed	0.5612	0.5684
hot.deck	Employed	+ 0.0013	+ 0.0013
hd.ord	Employed	+ 0.0013	+ 0.0014
amelia	Employed	+ 0.0002	+ 0.0001
mice	Employed	+ 0.0000	+ 0.0000
na.omit	Employed	–0.0277	–0.0260
true	Age	46.3475	44.9574
hot.deck	Age	–0.1106	–0.1115
hd.ord	Age	–0.1632	–0.1593
amelia	Age	–0.0019	+ 0.0008
mice	Age	–0.0068	–0.0009
na.omit	Age	–0.0890	–0.0921
true	Conservative	0.3908	0.3744
hot.deck	Conservative	+ 0.0001	+ 0.0004
hd.ord	Conservative	–0.0002	+ 0.0003
amelia	Conservative	+ 0.0000	+ 0.0001
mice	Conservative	–0.0002	+ 0.0002
na.omit	Conservative	–0.0177	–0.0193

Table C.4: Accuracy of Multiple Imputation Methods. Framing Data, MNAR, 10 Variables with NA (reduced)

Method	Variable	ANES	OP
true	Employed	0.5612	0.5684
hot.deck	Employed	–0.0013	–0.0015
hd.ord	Employed	–0.0014	–0.0017
amelia	Employed	–0.0015	–0.0015
mice	Employed	–0.0015	–0.0015
na.omit	Employed	–0.0086	–0.0077
true	Age	46.3475	44.9574
hot.deck	Age	–0.2197	–0.2388
hd.ord	Age	–0.3100	–0.2911
amelia	Age	–0.1196	–0.1307
mice	Age	–0.1207	–0.1341
na.omit	Age	–0.0274	–0.0193
true	Conservative	0.3908	0.3744
hot.deck	Conservative	–0.0043	–0.0038
hd.ord	Conservative	–0.0045	–0.0041
amelia	Conservative	–0.0042	–0.0045
mice	Conservative	–0.0044	–0.0043
na.omit	Conservative	–0.0059	–0.0065