Moving the Needle on Public Opinion: An Experiment on the Persuasive Effects of Moral Frames

W241 Experiments and Causality

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Abstract

Through this experiment we tested the treatment effect of various presentations of the moral foundations ("the frame") on a person's feelings towards a particular topic.

1 Introduction

We make hundreds of decisions each day. We may spend minutes, even hours, considering information to arrive at a decision. But sometimes it's just seconds. A gut response. That response, the baseline opinion anchoring the choices we make, is different for everyone and can be extremely difficult to change.

In the early 2000s, psychologists Jonathan Haidt, Craigh Joseph and Jesse Graham proposed a framework to explain why our opinions are different, but also similar. Their "moral foundations theory" built upon an earlier proposal stating that morality stems from matters of harm, rights and justice. Haidt and his colleagues, however, describe five doctrines or foundations that ultimately influence human decision and behavior: **harm/care**, **fairness/reciprocity**, **ingroup/loyalty**, **authority/respect** and **purity/sanctity**. *Haidt and Graham (2007)*

Moral foundations theory has often been applied to studies of political science, the differences between cultures and intuitive ethics. They offer a concrete understanding of the morals that unite and divide us all. In his book, The Righteous Mind (2012), Haidt explored how the five foundations are used by both conservatives and liberals to support moral questions in the political realm. Those leaning more to the political left are guided predominantly by harm/care and fairness/reciprocity, while those leaning right rely on all five foundations. It follows then that conservatives weigh the first two foundations less when making decisions or judgments; harm/care and fairness/reciprocity comprise one-fifth of the equation, respectively, instead of one-half.

Perhaps in a perfect world, every voter would decide on issues and candidates based on thorough research of policy and practice, but we know this is not the case. In the 2016 United States presidential election we experienced both sides trying to manipulate voter opinion by playing to emotions and the moral foundations that ground them. The Republican party paid millions of dollars to Cambridge Analytica, who leveraged large scale analytics and Facebook ads to target voters' emotions because "content works well if it makes you very emotional." *Price (2017); Ghosh and Scott (2018)* Democrats, on the other hand, battled to make their candidate seem more "likeable", which is arguably not the most critical characteristic of a successful leader, and certainly not the only one. *Newton-Small (2016)* Haidt would likely agree that these are examples of political organizations attempting to trigger certain moral foundations to â get your vote, your money, or your time." But is this possible?

2 Hypothesis & Motivation

Can tapping into one or more moral foundations modify how an individual feels about a topic, particularly those which are politically-relevant? Assume that an opinion can be represented as a point on a line, capable of moving to the left or the right (or up or down, if we want to avoid confusion with the colloquial political spectrum). With this assumption we can test the following hypothesis: **framing a politically divisive topic with a targeted moral foundation can move a subject's opinion away from its original point on the line, in either direction.**

Online marketing campaigns and social media has increased the specificity with which political campaigns–or anyone–can target individuals with persuasion (or manipulation?) tactics. A study in 2014 by Martin Day, Susan Fiske, Emily Downing and Thomas Trail examined the effects of Haidt's moral foundations on the opinions of liberals and conservatives, for what the researchers described as "pro-attitudinal and counter-attitudinal" positions on issues. *Day et al. (2014)*

Day et al executed two experiments to test the effects of moral foundation-based "frames". A frame can take several forms–stories, pictures, newspaper articles, to name a few. In Day's studies, the participants were shown a number of morally framed stances. For example, a "morally framed conservative stance" on immigration which targets the fairness foundation reads, "It is only fair to preserve the rights of long-term citizens ahead of recent immigrants." *Day et al. (2014)*

Both studies supported the hypothesis that an individual's political attitude is bolstered by relevant moral foundation-based frames, however only one study supported that the same frames may persuade a subject to shift his or her opinion away from one side of the political spectrum.

Another study that played a key role in defining this experiment was a paper by Lene Aaroe, Michael Bang Petersen and Kevin Arceneaux on 'Why and How Individual Differences in Disgust Sensitivity Underlie Opposition to Immigration'. *AARØE, PETERSEN, and ARCENEAUX (2017)* The subjects are tested on their support for immigration after their disgust response is triggered. This study finds some causal factors that influence political attitudes outside of one's conscious awareness and confirms that leveraging framing as a treatment lever does produce an observable effect on subjects.

To build on the conclusions of Day et al's work, we designed a study to measure the effect of moral foundation-based frame on opinions on Universal Basic Income (UBI). UBI is a topic for which political conservatives and liberals are generally accepted to have opposing views. To maximize resources available, we decided to only test two of the moral foundations: purity/sanctity and fairness/reciprocity.

3 Experimental Design

3.1 Participants

Given the numerous arms of our proposed study (described in detail in Experiment Design: Procedure), we required 150 participants at an absolute minimum. We determined an online platform was the best available route to gather a sufficient random sample of this size given time, budget and geographic constraints. We recruited a total sample size of 505 adults living in the United States using Prolific, an online platform that connects researchers with participants around the world.

Prolific also facilitated blocking to obtain an equal distribution of participants who identified as being either politically conservative or politically liberal. This was performed by selecting one of the prescreened characteristics for subjects who indicating their ideological identification within the US Political Spectrum.

Of the 505 subjects who participated in the study, all but three from the conservative block and one from the liberal block completed all required tasks. Those who did not complete all tasks were automatically replaced by Prolific. Those participants received $0.70 as compensation for participating in the study, and Prolific received $0.30.

Our study specifically targeted subjects who identified as either politically liberal or conservative. There is less available research on the moral groundings of political moderates, thus we did not target this group for our experiment.

The subject pool comprised of XX (x%) .. Figure 1 shows further detail on the political identifications of the participants. XX (x%) identified as female, XX (x%) identified as male.

Collection of participants took place over several days. We had limited funds available with which to execute the experiment, so we agreed to gather 100 conservative and 100 liberal participants in the first wave, conduct initial covariate balance checks, and proceed with additional participants as deemed necessary.

Overall, we had X waves. Table 1 provides additional information on each wave. Overall, we gathered an effective sample size for analysis of X participants: xx. stats.

We have a high level of confidence in the randomization of our effective participant population due to the use of Prolific to gather subjects. Qualtrics was leveraged to randomly assign subjects to control or one of the 4 other treatment conditions so there would be an even distribution across all 5 survey arms. We noted that the temporal nature of the waves may affect responses, so this was noted as a covariate to be included during our analysis.

3.2 Procedure

We developed two treatment options for both moral foundations included in our experiment, executed via a written story with accompanying photographs (for further detail, see Materials section).

All subjects assigned to treatment would read a "base" story designed to trigger either the purity/sanctity or fairness/reciprocity foundations. Some subjects within the treatment group were selected, via random assignment, to read an extension to the base story which offered a positive resolution to moral conflict from the base. The intended effect of the extension was to specifically trigger the participant's "pro-attitudinal..

We implemented a timer on the treatment pages of the survey requiring participants to stay on the page for at least 15-20 seconds, depending on the length of the frame. This was done to prevent subjects from clicking through the pages without adequate time to read and digest the frame.

Figure X offers a detailed description of the four treatment arms and control arm for the experiment. Participants were randomly assigned to one of the five arms using five-way random sampling without replacement executed within the Qualtrics survey platform.

After navigating through treatment or control, the subjects were asked to share their degree of support for the concept of UBI on an eleven point likert scale from zero to ten.

All participants answered the following demographic questions before concluding the survey: age, gender, urbanicity and political orientation. The political orientation demographic was requested to confirm successful blocking executed via Prolific. Subjects who self-identified as moderates in the survey were dropped from the analysis.

Participants in the pilot study and select waves were also asked about their reactions to the frames to assess whether they triggered the intended moral foundation. The pilot was executed with a small group of X participants to test the strength of the stories with regards to hitting on the intended moral foundations and find whether the study was receiving a balanced mix of participants while examining different covariates.

See *Figure 4* for detailed flowchart of study design.

3.3 Materials

Please refer to the Appendix of this report to view the moral foundations-frames employed in our experiment.

3.4 Modifications

Our first wave of participants comprised of 100 conservatives and 100 liberals split evenly amongst the 5 arms of the experiment (roughly 20 participants per arm, per block). We conducted a preliminary analysis to evaluate balance among possible covariates (e.g. gender, age), effect size and directionality. We noted that there was an imbalance of gender in the conservative block and proceeded to recruit additional female conservatives. This wave was consequently excluded from analysis due to lack of randomized collection (i.e. participants were targeted rather than randomly recruited).

We noted the greatest movement amongst the conservatives being treated with the purity frame. In general, the liberal block had high support of the concept of UBI, which decreased the likelihood that we would observe a measured change in attitude, particularly given our limited sample size. The conservatives generally had lower support of UBI (without treatment) and thus had more room for change in response to treatment.

In a world with limitless funds, we would have been able to collect enough participants to supply sufficient power to each arm of the study, however this was not the case. Thus, we dedicated our remaining resources to the treatment arm showing promise of a statistically significant effect.

4 Analysis of Results

4.1 Comparison of Potential Outcomes

[TBD]

4.2 Data

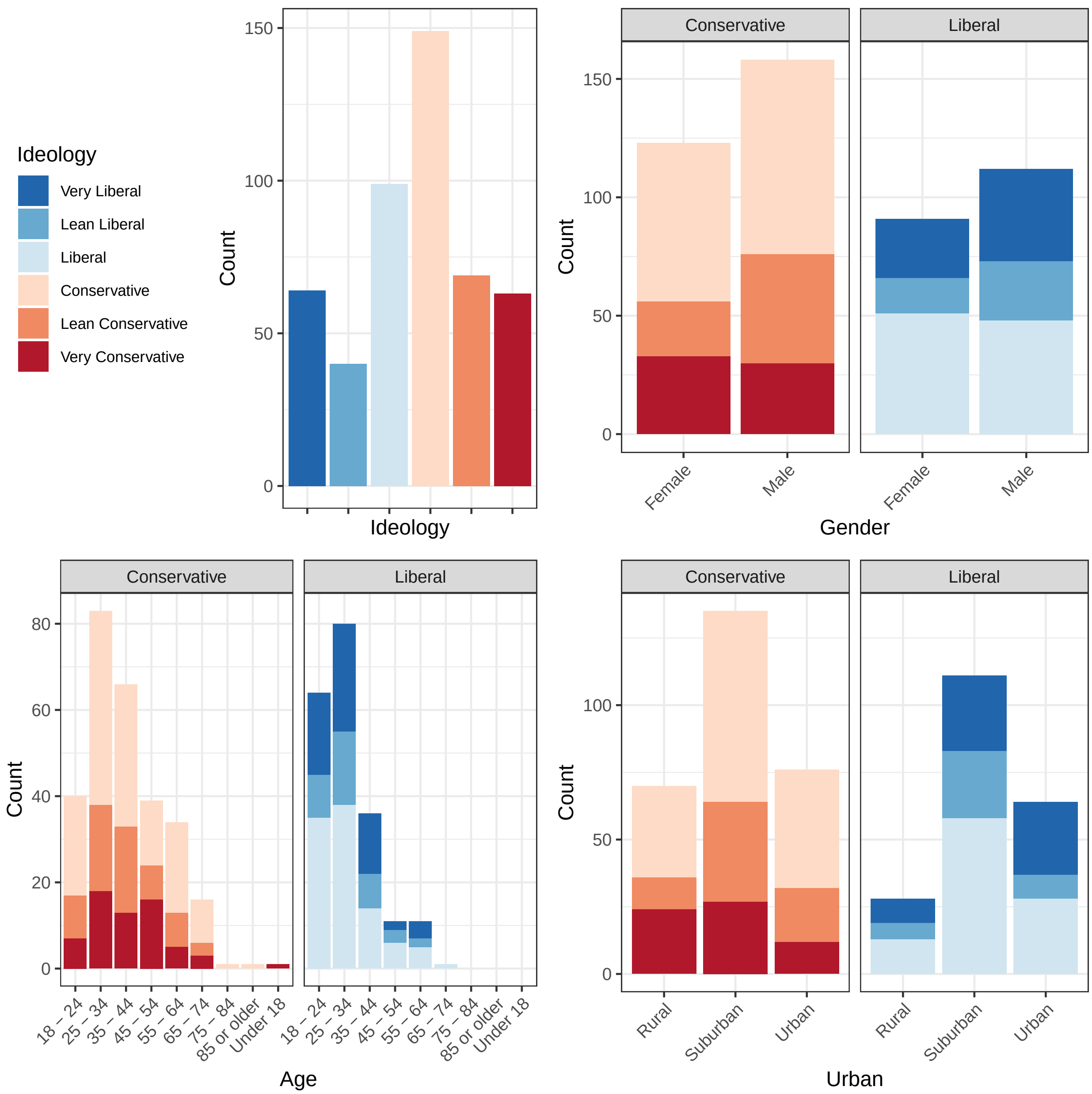

Figure 1: Demographics

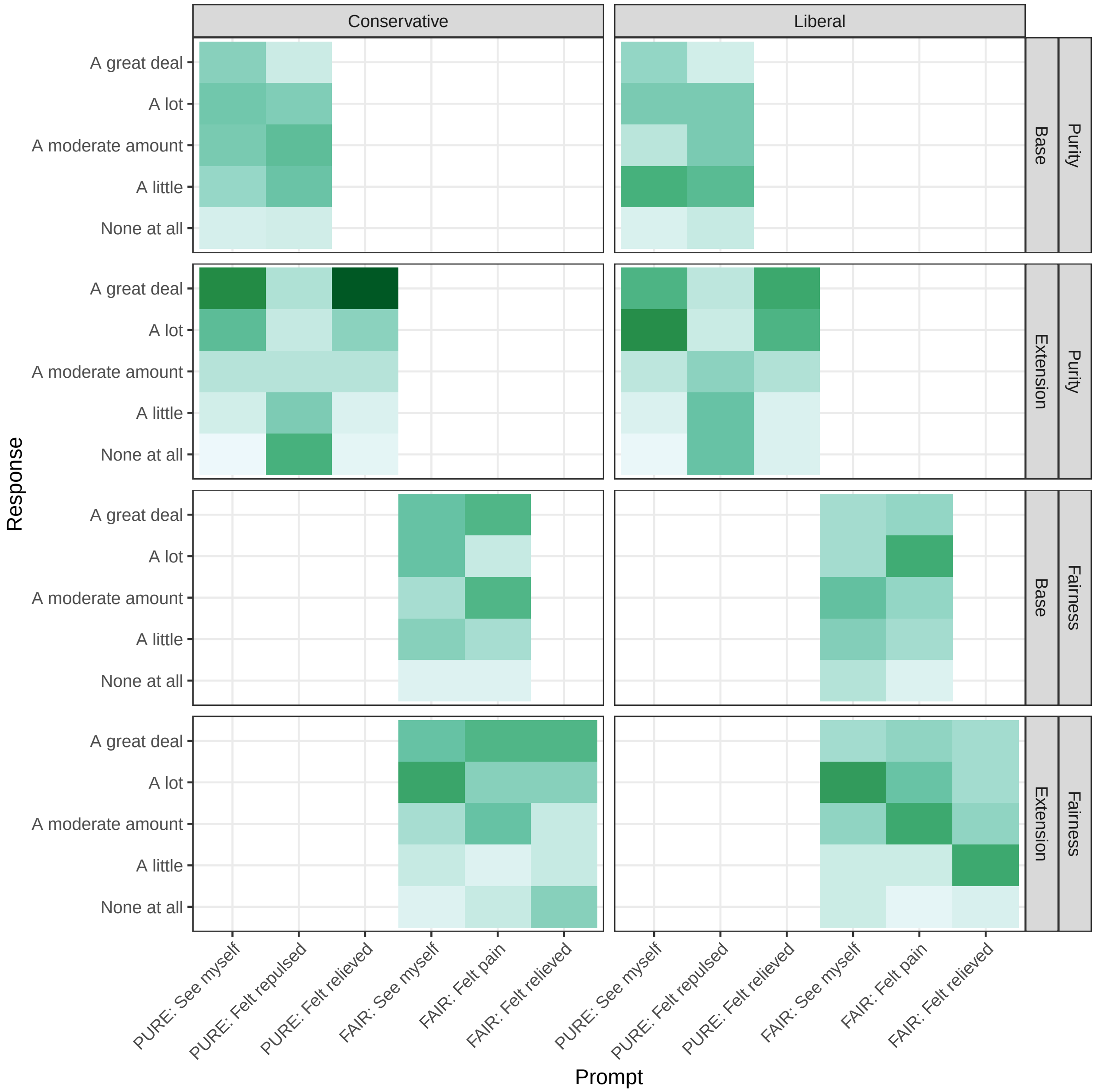

Figure 2: Reactions

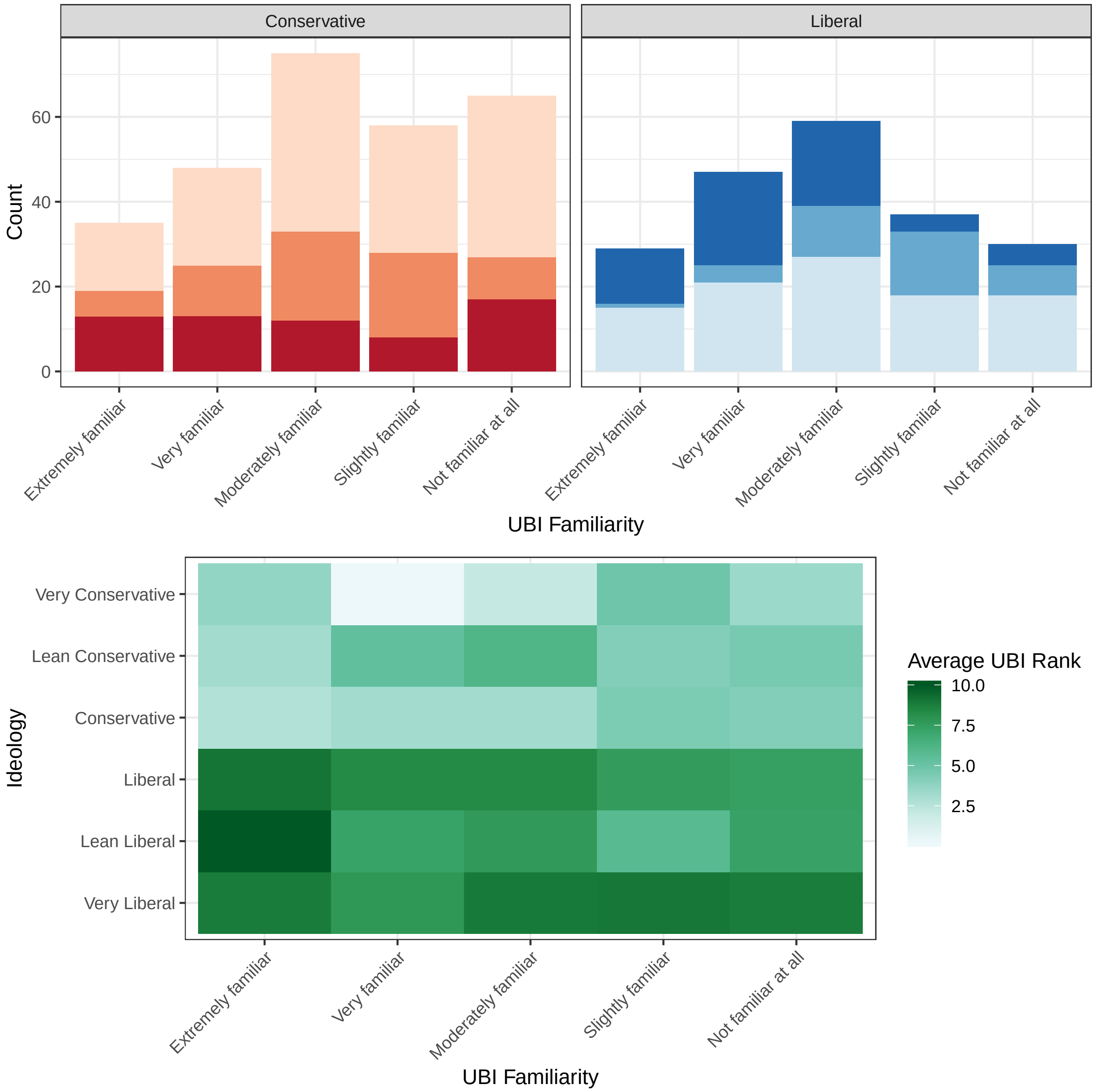

Figure 3: Outcomes

4.3 Models

Preliminary results with partial data informed our focus on Con + Pure (see Table 4)

Given that we collected in waves, wanted to ensure the wave/day blocking did not introduce an effect on our results (see Table 5)

Our design was not factorial (see **??***), which should preobably be deleted*

We still collected more data for all arms to confirm that of design, Con + Pure was most impactful (see Table 1)

Table 1: By Arm

	Four Study Arms			
	UBI Ranking			
	Lib + Fair	Lib + Pure	Con + Fair	Con + Pure
	(1)	(2)	(3)	(4)
Base Only Treatment	−0.241	−0.146	0.119	0.354
	(0.488)	(0.451)	(0.919)	(0.518)
	p = 0.621	p = 0.746	p = 0.897	p = 0.495
Base + Extension Treatment	−0.799	0.000	1.341	1.072^{**}
	(0.493)	(0.479)	(1.022)	(0.533)
	p = 0.105	p = 1.000	p = 0.190	p = 0.045
Constant	8.213^{***}	8.213^{***}	3.270^{***}	3.270^{***}
	(0.288)	(0.288)	(0.370)	(0.370)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Observations	111	139	125	245
R^2	0.023	0.001	0.017	0.018
Adjusted R^2	0.005	−0.014	0.001	0.010
Residual Std. Error	2.108 (df = 108)	2.299 (df = 136)	3.539 (df = 122)	3.347 (df = 242)
F Statistic	1.299 (df = 2; 108)	0.061 (df = 2; 136)	1.082 (df = 2; 122)	2.200 (df = 2; 242)
Note:				*p<0.1; **p<0.05; ***p<0.01
				HC Robust Standard Errors

4.3.1 *We tested hypotheses about covariates that might affect outcomes with our arm of interest: Con + Pure (see Table 2)*

Table 2: Conservative + Purity Treatment Arm Interaction Specifications

	Con + Pure Arm Only			
	UBI Ranking			
	No Covariates	Gender	UBI Familiarity	Reaction
	(1)	(2)	(3)	(4)
Base Only Treatment	0.354	0.476	0.371	0.824
	(0.518)	(0.518)	(0.519)	(0.712)
	p = 0.495	p = 0.358	p = 0.475	p = 0.248
Base + Extension Treatment	1.072^{**}	1.207^{**}	1.074^{**}	−0.993
	(0.533)	(0.537)	(0.534)	(1.402)
	p = 0.045	p = 0.025	p = 0.045	p = 0.479
Male		1.009^{**}		
		(0.426)		
		p = 0.018		
Familiar w/ UBI			−0.330	
			(0.520)	
			p = 0.526	
Repulsed				−0.739
				(0.729)
				p = 0.311
Relieved				1.747
				(1.454)
				p = 0.230
Repulsed then Relieved				2.163^{**}
				(1.065)
				p = 0.043
Constant	3.270^{***}	2.623^{***}	3.518^{***}	3.270^{***}
	(0.370)	(0.445)	(0.552)	(0.370)
	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Observations	245	245	245	245
R^2	0.018	0.040	0.020	0.052
Adjusted R^2	0.010	0.028	0.007	0.032
Residual Std. Error	3.347 (df = 242)	3.316 (df = 241)	3.351 (df = 241)	3.309 (df = 239)
F Statistic	2.200 (df = 2; 242)	3.330^{**} (df = 3; 241)	1.603 (df = 3; 241)	2.624^{**} (df = 5; 239)

Note: *p<0.1; **p<0.05; ***p<0.01
HC Robust Standard Errors

5 Conclusion

Our experiment leveraging the concept of Universal Basic Income demonstrates that political attitudes can shift (TBC) through exposure to moral foundations.

5.1 Discussion

[[TBD]]

5.2 Limitations

[[TBD]]

6 Appendix

6.1 Declaration of Conflicting Interests

To the best of their knowledge, the authors have no potential conflicts of interest with respect to the research, distribution of survey, and authorship of this paper.

6.2 Funding

The authors received $500 in financial support from the University of California, Berkeley which was leveraged to pay survey-takers through the Prolific platform and satisfy the statistical power requirements.

In addition, the authors put in $25 out of their own personal income to increase the statistical power of the results and balance the number of subjects between liberals and conservatives.

6.3 Study Flowchart

6.4 Data Dictionary

Variable Name	Variable	Values	Notes
prolific_pid	User ID	10-digit numeric	
panel			
arm			
node			
arm_level			
ideology			
ideology_bin			
age			
gender			
urban			
employment_status			
student_status			
purity_q1_self			
purity_q2_repulsed			
purity_q3_injustice			

Variable Name	Variable	Values	Notes
purity_q4_relieved			
fairness_q1_self			
fairness_q2_pain			
fairness_q3_injustice			
fairness_q4_relieved			
open_text_reaction			
ubi_number	UBI Number	Integer 0-10	
ubi_group			
ubi_familiarity			
ubi_familiarity_bin			

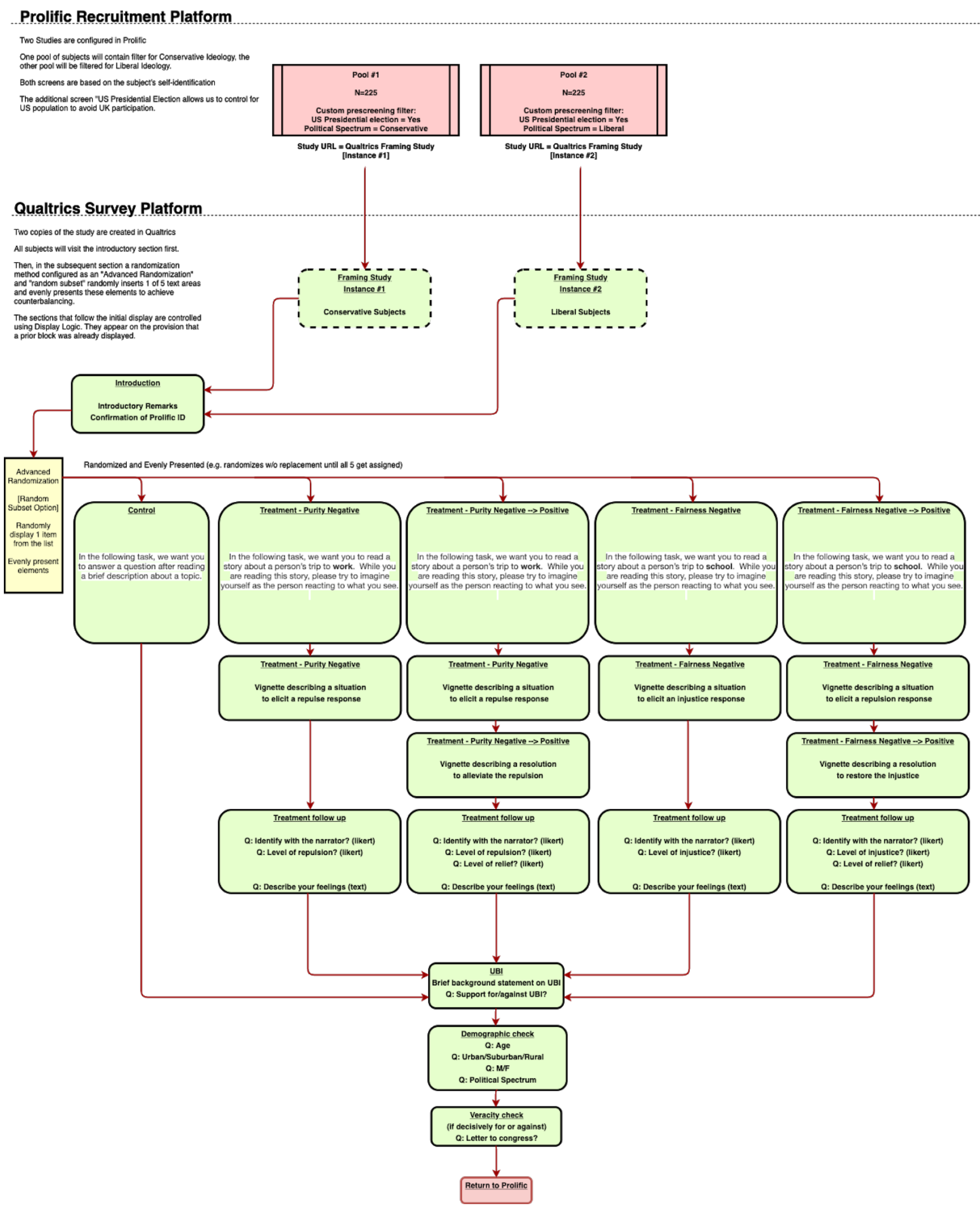

Figure 4: Study Flowchart

6.5 Additional Exploratory Data Analysis

Additional steps taken not included in the body of the report

[[TBD]]

6.6 Additional Regression Tables

Table 4: Preliminary Model - By Arm (Waves 1-2 only)

	Four Study Arms			
	UBI Ranking			
	Lib + Fair	Lib + Pure	Con + Fair	Con + Pure
	(1)	(2)	(3)	(4)
Base Treatment	−0.143	0.531	−0.056	0.608
	(0.773)	(0.595)	(1.075)	(1.157)
	p = 0.854	p = 0.373	p = 0.959	p = 0.600
Extension Treatment	−0.890	0.095	1.167	0.722
	(0.691)	(0.662)	(1.164)	(0.995)
	p = 0.198	p = 0.886	p = 0.317	p = 0.468
Constant	8.048***	8.048***	3.444***	3.444***
	(0.497)	(0.497)	(0.669)	(0.669)
	p = 0.000	p = 0.000	p = 0.00000	p = 0.00000
Observations	61	61	63	64
R^2	0.028	0.015	0.023	0.009
Adjusted R^2	−0.006	−0.019	−0.009	−0.023
Residual Std. Error	2.324 (df = 58)	1.904 (df = 58)	3.581 (df = 60)	3.502 (df = 61)
F Statistic	0.831 (df = 2; 58)	0.436 (df = 2; 58)	0.710 (df = 2; 60)	0.285 (df = 2; 61)

Note: *p<0.1; **p<0.05; ***p<0.01
HC Robust Standard Errors

```r
results_clean_factorial = results_clean_lim %>%
  mutate(liberal = case_when(ideology_bin == "Liberal" ~ 1
                             , TRUE ~ 0)
         , conservative = case_when(ideology_bin == "Conservative" ~ 1
                                    , TRUE ~ 0)
         , fairness = case_when(arm_story == "Fairness" ~ 1
                                , TRUE ~ 0)
         , purity = case_when(arm_story == "Purity" ~ 1
                              , TRUE ~ 0)
         # base_com - if we consider it it's own treatment
         , base_com = case_when(arm_level == "Base" ~ 1
                                , TRUE ~ 0)
         # base_ind - if we consider it indepdent and therefore administered WITH Extension
         , base_ind = case_when(arm_level == "Base" ~ 1
                                , arm_level == "Extension" ~ 1
                                , TRUE ~ 0)
         , extension = case_when(arm_level == "Extension" ~ 1
                                 , TRUE ~ 0)
```

Table 5: By Arm, Recruitment Day Covariates

	Four Study Arms + Control				
			UBI Ranking		
	Control Only	Lib + Fair	Lib + Pure	Con + Fair	Con + Pure
	(1)	(2)	(3)	(4)	(5)
Liberal	5.084***				
	(0.664)				
	p = 0.000				
Base Treatment		−0.212	−0.161	−0.333	0.294
			(0.452)	(1.208)	(0.536)
			p = 0.722	p = 0.783	p = 0.584
Extension Treatment		−0.748	−0.037	0.889	1.054*
			(0.499)	(1.289)	(0.556)
			p = 0.942	p = 0.491	p = 0.058
Wave 2	−0.425			−0.833	−0.646
	(1.318)			(1.420)	(1.265)
	p = 0.748			p = 0.558	p = 0.610
Wave 3	−0.162		0.769	−0.571	−0.347
	(0.946)		(1.242)	(1.084)	(0.606)
	p = 0.864		p = 0.536	p = 0.599	p = 0.567
Wave 4	0.570	−1.027	−2.243	0.278	0.226
	(1.081)		(1.872)	(1.261)	(0.682)
	p = 0.598		p = 0.231	p = 0.826	p = 0.740
Wave 5	−0.370	0.390	−0.091	−1.556	−0.852
	(0.603)		(0.398)	(1.216)	(0.654)
	p = 0.539		p = 0.820	p = 0.201	p = 0.193
Constant	3.314***	8.027	8.309***	3.722***	3.535***
	(0.688)		(0.386)	(0.868)	(0.579)
	p = 0.00001		p = 0.000	p = 0.00002	p = 0.000
Observations	136	111	139	125	245
R^2	0.384	0.035	0.024	0.036	0.029
Adjusted R^2	0.360	−0.002	−0.013	−0.013	0.005
Residual Std. Error	3.071 (df = 130)	2.115 (df = 106)	2.297 (df = 133)	3.564 (df = 118)	3.356 (df = 238
F Statistic	16.188*** (df = 5; 130)	0.953 (df = 4; 106)	0.652 (df = 5; 133)	0.738 (df = 6; 118)	1.192 (df = 6; 23

Note: *p<0.1; **p<0.05; ***p<0.
HC Robust Standard Erro

```r
  )

# Arm-specific datasets
results_factorial_lib = results_clean_factorial %>% filter(ideology_bin == 'Liberal')
results_factorial_con = results_clean_factorial %>% filter(ideology_bin == 'Conservative')

results_factorial_fair = results_clean_factorial %>% filter(grepl('Fairness|Control', arm))
results_factorial_pure = results_clean_factorial %>% filter(grepl('Purity|Control', arm))

results_factorial_libfair = results_clean_factorial %>% filter(ideology_bin == 'Liberal' & grepl('Fairne
results_factorial_libpure = results_clean_factorial %>% filter(ideology_bin == 'Liberal' & grepl('Purity
results_factorial_confair = results_clean_factorial %>% filter(ideology_bin == 'Conservative' & grepl('F
results_factorial_conpure = results_clean_factorial %>% filter(ideology_bin == 'Conservative' & grepl('P

cross_tab_factorial = results_clean_factorial %>%
  group_by(liberal, conservative, purity, fairness, base_com, base_ind, extension) %>%
  summarise(n = n())

# REGRESSION
factorial_levels_com = custom_lm_calcs(lm_in = lm(ubi_number ~ conservative * purity * fairness * extens
                                                , data = results_clean_factorial)
                                       , clusters_in = NA)

stargazer(factorial_levels_com$lm
          , se = list(factorial_levels_com$se_robust
          )
          , type = stargazer_type, header = F
          , title            = "All Arms Factorial Specifications"
          , column.labels    = c("Levels Independent")
          , dep.var.caption  = "All Arms"
          , dep.var.labels   = "UBI Ranking"
          , notes            = "HC Robust Standard Errors"
          # , report           = ('v*c*sp')
          , font.size        = "small"
          , column.sep.width = "1pt"
          , label            = "tab:factorialmodel"
          , single.row       = TRUE)
```

```
##
## \begin{table}[!htbp] \centering
##   \caption{All Arms Factorial Specifications}
##   \label{tab:factorialmodel}
## \small
## \begin{tabular}{@{\extracolsep{1pt}}lc}
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{1}{c}{All Arms} \\
## \cline{2-2}
## \\[-1.8ex] & UBI Ranking \\
##  & Levels Independent \\
## \hline \\[-1.8ex]
##  conservative & $-$4.943$^{***}$ (0.469) \\
##   purity & $-$0.146 (0.451) \\
```

```
##   fairness & $-$0.241 (0.488) \\
##   extension & $-$0.558 (0.561) \\
##   conservative:purity & 0.500 (0.687) \\
##   conservative:fairness & 0.361 (1.040) \\
##   purity:fairness &  \\
##   conservative:extension & 1.780$^{**}$ (1.389) \\
##   purity:extension & 0.704 (0.762) \\
##   fairness:extension &  \\
##   conservative:purity:fairness &  \\
##   conservative:purity:extension & $-$1.208 (1.573) \\
##   conservative:fairness:extension &  \\
##   purity:fairness:extension &  \\
##   conservative:purity:fairness:extension &  \\
##   Constant & 8.213$^{***}$ (0.288) \\
##  \hline \\[-1.8ex]
## Observations & 484 \\
## R$^{2}$ & 0.346 \\
## Adjusted R$^{2}$ & 0.333 \\
## Residual Std. Error & 2.977 (df = 474) \\
## F Statistic & 27.852$^{***}$ (df = 9; 474) \\
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{1}{r}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01} \\
##  & \multicolumn{1}{r}{HC Robust Standard Errors} \\
## \end{tabular}
## \end{table}
```

6.7 Covariate Balance Check

Table 6: Preliminary Model - Covarience Check by Arm (Waves 1-2 only)

	Dependent variable:			
	arm == "Purity_Base"	arm == "Purity_Extension"	arm == "Fairness_Base"	arm == "Fa
	(1)	(2)	(3)	
age25 - 34	−0.224	−0.036	0.136	
age35 - 44	−0.220	0.072	−0.037	
age45 - 54	−0.161	−0.258	0.214	
age55 - 64	−0.192	−0.164	0.065	
age65 - 74	0.114	−0.080	0.189	−
age85 or older	−0.412	−0.375	−0.012	−
genderMale	−0.013	−0.024	−0.0004	−
urbanSuburban	−0.043	0.217	−0.190	−
urbanUrban	0.028	0.344	−0.287	−
Constant	0.397	0.055	0.299	
Observations	91	91	91	
R^2	0.062	0.139	0.098	
Adjusted R^2	−0.042	0.043	−0.002	
Residual Std. Error (df = 81)	0.417	0.392	0.401	
F Statistic (df = 9; 81)	0.600	1.450	0.977	

Note:

References

AARØE, LENE, MICHAEL BANG PETERSEN, and KEVIN ARCENEAUX. 2017. "The Behavioral Immune System Shapes Political Intuitions: Why and How Individual Differences in Disgust Sensitivity Underlie Opposition to Immigration." *American Political Science Review* 111 (2): 277–94. https://doi.org/10.1017/S0003055416000770.

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