Appendix: Refugees to the Rescue? Motivating Pro-Refugee Public Engagement during the COVID-19 Pandemic

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Appendix

A Consort diagrams

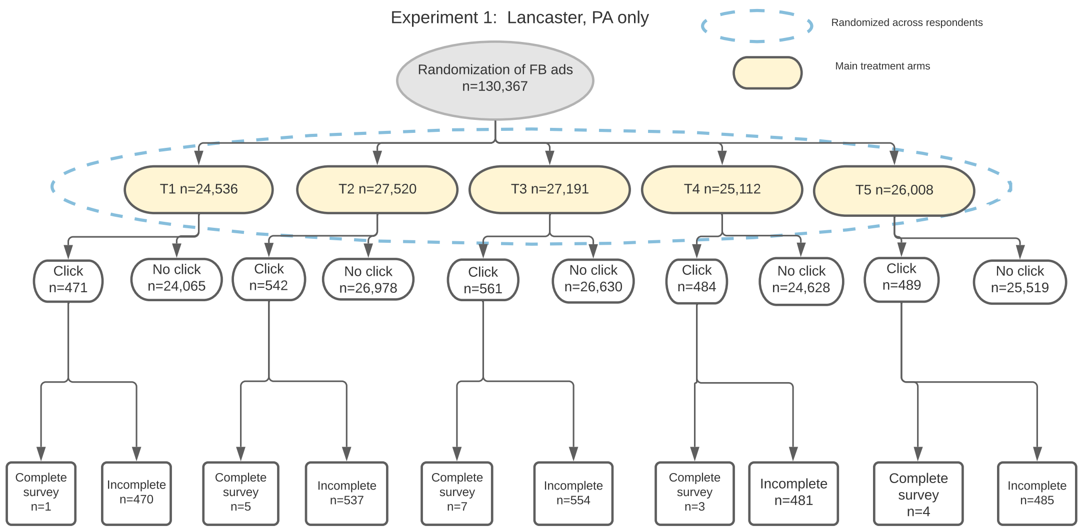

Figure A.1: Updated consort diagram for experimental design for Experiment 1 (Mustafa ads), with actualized sample sizes.

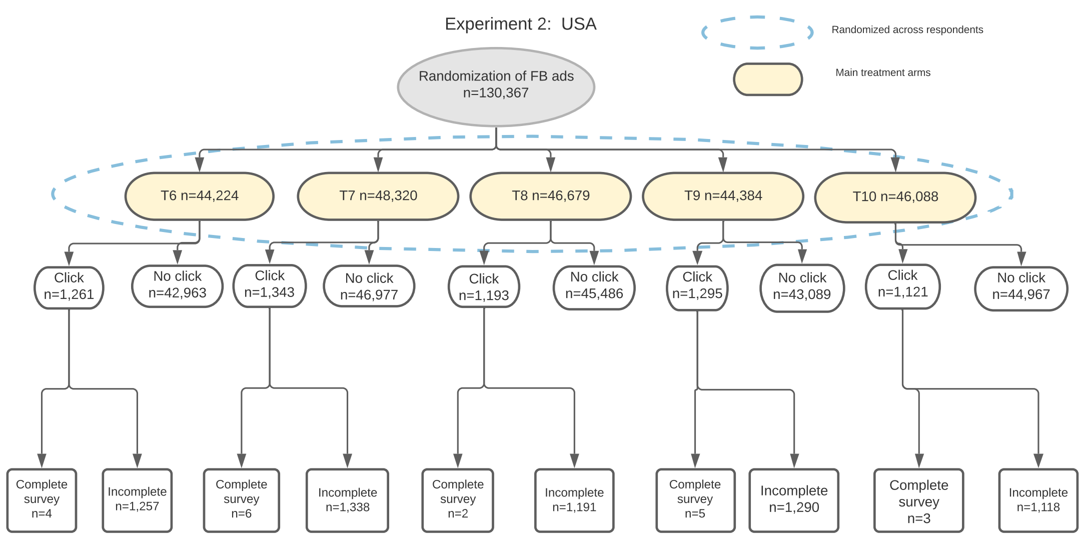

Figure A.2: Updated consort diagram for experimental design for Experiment 2 (Kelli ads), with actualized sample sizes.

B Simulations of experimental design

As our study involved manipulating and testing neighborhood effects, we explicitly planned to show ads to target populations of a given size (all available Facebook profiles in the Pennsylvania state area for Experiment 1 and a sample of 450,000 Facebook users in the U.S. for Experiment 2), theoretically feasible through the Facebook ad platform. As such, our simulations were designed to evaluate statistics of interest such as power (we use a power threshold of 0.9) and bias, *given a sample size* of sampling 450,000 profiles in each experiment (with $n = 450,000$ as a conservative lower bound on Experiment 2). We are interested in estimating the difference in ad-click rates across every pairwise treatment arm, thus our main statistic tests are t-tests of differences in means.

For Experiment 1, we made several effect size assumptions (see Table B.1). As of this writing, there is limited work on the effects of priming individuals with news about COVID-19, rarer still on the effects on interest in supporting refugees. However, a conservative estimate of effect size from related literature on disaster areas and willingness to donate suggests that a treatment effect size of 0.1 is reasonable (see Zagefka et al. 2013 among others). From there, we again, conservatively assumed that location effects are increasingly smaller the further away from Lancaster the respondent is (Lancaster= 0.08, Pennsylvania= 0.075, U.S.= 0.05, compared against a baseline of no location).

In our simulations for Experiment 2 (see Table B.2) we carried forth the conservative estimate of the "COVID prime effect" as 0.1, and made assumptions about the effect sizes for presenting respondents with Refugee or Immigrant ads (versus no information, "Neither"); again we took a very conservative route of assuming the refugee and immigrant effects are smaller than the COVID-19 one, and that the former is larger (0.075) compared to the latter (0.025).

We constructed a multi-arm `DeclareDesign` (see Blair et al. 2019) for each experiment with the above assumptions. This involved specifying a data generating process of potential outcomes under each treatment arm from an underlying population, delineating all pairwise comparisons of expected potential outcomes as our inquiry of interest, randomly assigning 450,000 profiles to the five treatment arms (for 90,000 respondents in each arm), and finally estimating the pairwise differences in means corresponding to each estimand. We ran five hundred simulations for each of the experiments, as well as the pair of follow-up click-to-survey settings, for a total of two thousand simulated experiments. In the ad-click experiments, which are randomized across 450,000 respondents each, we wish to learn whether there is differential support for refugees on Facebook under different treatment arms as proxied by clicking on ads. We specify a data generating process under which potential outcomes are defined according to the treatments received ("Model"), indicate an interest in all pairwise comparisons between treatment arms as our estimands ("Inquiry"), specify a data strategy ("Data strategy") of equal probability assignment to each treatment arm, and present an answer strategy that involves taking the pairwise differences in means corresponding to specific estimands. We are interested in pairwise comparisons across treatments. Throughout the simulations, we make key assumptions on treatment effects, errors, and the existence of interactions.

Our simulation results suggested that the ad-click outcome was well powered with no biases for estimators on our estimands of interest. Throughout, power is larger than 0.95; estimands are predominantly average treatment effects and average treatment on the treated, estimated with estimators of differences in sample means (Tables B.3 and B.10). The assumed sample sizes in the simulations were based off of what was deemed feasibly accessible via Facebook's ad platform, however our roll-out of the experiments resulted in technical issues on the Facebook platform side (see Section **??** Results for details), ultimately resulting in a smaller actualized sample size than assumed in our simulations. As such, we conducted the same exact series of simulation experiments described above with the realized sample sizes to assess power in that setting. Results are presented in Tables B.4-B.11. We find that with the exception of slightly lower power for a single estimand (power for ATE difference in outcome under arm 3 and arm 2 in Table B.4 at 0.79), all estimands were well-powered. While not explicitly framed as testable hypotheses in this study, we also conducted simulations reflective of our capture of survey responses for each experiment conditional on clicking on the ads. These can also be found in Online Appendix Section B.

We use alpha levels of 0.05 as a criterion for statistical inference. Controlling for false discovery rate (FDR) offers a way to increase power while maintaining some principled bound on error; we propose using Benjamini and Hochberg (1995)'s approach, which prespecifies an α such that we achieve the following testing threshold:

$$T_{BH} = \max\left\{P_{(i)} :\, P_{(i)} \leq \alpha \frac{i}{m},\, 0 \leq i \leq m\right\}$$

where the ith p-value of the multiple hypothesis tests is $P_{(i)}$, with m total tests. Benjamini and Hochberg proved that using this procedure guarantees that the FDR is controlled such that it is equal to $E\left(\frac{FD}{D}\right) \leq \alpha)$ (with FD as False Discovery and D as Discovery). Since Facebook ad data only provides sample population level aggregate statistics of gender, we are unable to conduct traditional covariate-based balance tests.

B.1 Experiment 1: Covid and neighborhood effects

The Facebook ad campaign in experiment 1 is composed of five arms that vary information on covid-19 and the location of Mustafa's community efforts. Table B.1 presents the assumptions we make in our simulations for Experiment 1 design for ad clicking.

Using `DeclareDesign` (Blair et al. 2019), we form a diagnosis of all the designs. For Experiment 1, our diagnosis can be found in Table B.3, which presents results on the

Assumption	Size
Covid prime effect (versus no covid prime)	0.1
US effect (versus no location)	0.05
Pennsylvania effect (versus no location)	0.075
Lancaster effect (versus no location)	0.08
No interaction effect on average between covid prime and location primes	
Errors drawn from standard normal, with individual standard deviation	0.2

Table B.1: Experiment 1 treatment effects on ad click assumptions

	Assumption	Size
Effect on R_i		
	T1: Covid prime, location U.S.	0.5
	T2: Covid prime, location Pennsylvania	0.6
	T3: Covid prime, location Lancaster	0.7
	T4: Covid prime, no location information	0.4
	T5: No covid prime, location U.S.	0.2
	No interaction effect on average between covid prime and location primes	
	Error drawn from standard normal	
Effect on Y_i		
	T2: Covid prime, location Pennsylvania	0.6
	T3: Covid prime, location Lancaster	0.7
	T4: Covid prime, no location information	0.4
	T5: No covid prime, location U.S.	0.2
	No interaction effect on average between covid prime and location primes	
	Errors drawn from standard normal	
Correlation ρ	ρ	$\{0.0, 0.2, 0.8\}$

Table B.2: Experiment 1 assumptions for survey outcomes

following diagnosands: bias, root mean squared error (RMSE), power, coverage, mean estimate, standard deviation (SD) estimate, mean standard error (SE), type s-rate and mean estimand. The design has over 90% power and coverage over 95%. Similar diagnoses are conducted for the remaining three classes of experiments.

For the survey outcomes upon clicking through Experiment 1, we consider a data generating process that includes a response variable R_i, outcome Y_i, which is correlated with response variable through parameter ρ. Y_i^{obs} is the measured version of Y_i, which is only observed when $R_i = 1$. In our setting, when a respondent is willing to click on the ad and answer the survey $R_i = 1$. Our simulations are conducted with assumptions detailed in Table B.2, accounting for variation in ρ values we consider in our simulated experiments.

Again, we form a diagnosis of the above design in Experiment 1 in Tables B.5-B.7, in much the same way as the ad-click set up.

We want to learn whether there is differential support for refugees on Facebook, as proxied by clicking on ads. We have a classical randomized experiment and ask whether respondents differentially click on an ad based on its content. We are also interested in respondent attitudes and behaviors, conditional on having clicked on an ad, towards refugees. Respondents are randomly assigned to receive ads with refugees with information on the above five arms. Assignment to each of the five arms is with equal probabilities, and other than mention of COVID-19 and location, ads are otherwise identical. We define our primary outcome of interest as the difference in click rates between experimental conditions.

Model We specify a population of size N where a unit i has a potential outcome, $Y_i(Z = 0)$, when it remains untreated and M $(m = 1, 2, ..., M)$ potential outcomes defined according to the treatment that it receives. The effect of each treatment on the outcome of unit i is equal to the difference in the potential outcome under treatment condition m and the control condition: $Y_i(Z = m) - Y_i(Z = 0)$. We simulate a draw of $450,000$ respondents (our sample size via Facebook's ad platform) in this exercise.

Inquiry We are interested in all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$.

Data strategy We randomly assign $N/5 = 90,000$ units to each of the treatment arms.

Answer strategy Take every pairwise difference in means corresponding to the specific estimand.

Table B.1 presents the assumptions we make in our simulations for Experiment 1 design for ad clicking.

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S_Rate	Mean Estimand
ate_Y_2_1	(Z_2 - Z_1)	0.00	0.00	1.00	0.94	0.03	0.00	0.00	0.00	0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	(Z_3 - Z_1)	0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	(Z_3 - Z_2)	-0.00	0.00	1.00	0.96	0.00	0.00	0.00	0.00	0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	(Z_4 - Z_1)	0.00	0.00	1.00	0.95	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	(Z_4 - Z_2)	-0.00	0.00	1.00	0.95	-0.08	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	(Z_4 - Z_3)	0.00	0.00	1.00	0.96	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	(Z_5 - Z_1)	0.00	0.00	1.00	0.96	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	(Z_5 - Z_2)	-0.00	0.00	1.00	0.96	-0.13	0.00	0.00	0.00	-0.12
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	(Z_5 - Z_3)	-0.00	0.00	1.00	0.96	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	(Z_5 - Z_4)	-0.00	0.00	1.00	0.95	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors of all estimates are shown in the rows below. Results are from 500 simulated experiments. The first two columns describe the estimand and estimator of interest, where the name of the treatment arms follow “ate_y”, as well as “Z_”.

Table B.3: Experiment 1 design diagnosands.

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean_Estimate	SD_Estimate	Mean_SE	Type_S_Rate	Mean_Estimand
ate_Y_2_1	DIM (Z_2 - Z_1)	0.00	0.00	1.00	0.94	0.03	0.00	0.00	0.00	0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	DIM (Z_3 - Z_1)	-0.00	0.00	1.00	0.93	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	DIM (Z_3 - Z_2)	-0.00	0.00	0.79	0.95	0.00	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	DIM (Z_4 - Z_1)	0.00	0.00	1.00	0.95	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	DIM (Z_4 - Z_2)	-0.00	0.00	1.00	0.94	-0.08	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	DIM (Z_4 - Z_3)	0.00	0.00	1.00	0.94	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	DIM (Z_5 - Z_1)	-0.00	0.00	1.00	0.95	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	DIM (Z_5 - Z_2)	-0.00	0.00	1.00	0.95	-0.13	0.00	0.00	0.00	-0.12
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	DIM (Z_5 - Z_3)	-0.00	0.00	1.00	0.94	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	DIM (Z_5 - Z_4)	-0.00	0.00	1.00	0.95	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Table B.4: Post experiment 1 checks for power on actualized N sizes.

Our secondary outcome of interest is the average refugee thermometer rating conditional on clicking an ad.

Since obtaining the refugee thermometer rating requires respondents to follow through with clicking the ad and answering the survey, we consider this a possible missing data problem, specifically one of attrition which may be affected by the potential outcome. Since this type of problem can affect both power and introduce bias, we consider how much attrition might be too much – or how high the correlation between the propensity to be missing and the refugee thermometer rating outcome has to be before the study cannot estimate the estimands of interest.

Again, we are interested in pairwise comparisons across treatments.

Model We specify a model with a population N that has three variables affected by treatment: response variable R_i, outcome (here refugee thermometer rating in the survey) Y_i, which is correlated with response variable through parameter ρ. Y_i^{obs} is the measured version of Y_i, which is only observed when $R_i = 1$. For our setting, when a respondent is willing to click on the ad and answer the survey $R_i = 1$.

Inquiry Here we're interested in knowing the average of all respondents' differences in treatment arm potential outcomes, all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$. But we're also interested in the average treatment effect on reporting $E[R_i(m) - R_i(m')]$ as well as the pairwise comparison between treatment arms among those who report: $E[Y_i(m) - Y_i(m')|R_i = 1]$.

Data strategy Respondents are randomly assigned so that $N/5 = 90,000$ units are in each of the treatment arms.

Answer strategy R_i and Y_i^{obs}, take every pairwise difference in means corresponding to the specific estimand.

Assumptions are detailed in Table B.2, including for variation in ρ values we consider in our simulated experiments.

Again, we form a diagnosis of the above design in Experiment 1 in Tables B.5-B.7, which present results from 500 simulations each on the following diagnosands (used in all diagnoses): bias (expected difference between estimate and estimand), root mean squared error (RMSE), power (probability of rejecting null hypothesis of no effect), coverage (probability that estimand falls within confidence interval), mean estimate, standard deviation (SD) estimate, mean standard error (SE), type S-rate (probability estimate has incorrect sign, if statistically significant) and mean estimand.

The effect on reporting (R) can always be estimated with high power and no bias, even as ρ grows to 0.8. However any design strategy that conditions on Y_{obs} suffers from bias, even for the estimands that are conditional on reporting, such that a small amount of correlation (0.2) between missingness and outcomes can affect inferences. When the correlation is small (ρ is 0.2 rather than 0.8) the amount of bias remains smaller however, in the magnitude of -0.01 to 0.03. As ρ increases to 0.8 however, the magnitude in range grows to $(-0.04, 0.08)$. While the mean estimates differ from the mean estimands, the direction of the effect is captured consistently. The large sample size allows for power to remain quite high throughout.

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	-0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	0.00	0.00	1.00	0.96	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	0.00	0.00	1.00	0.99	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	-0.00	0.00	1.00	0.98	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	-0.00	0.00	1.00	0.98	-0.11	0.00	0.00	0.00	-0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	-0.00	0.00	1.00	0.98	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	-0.00	0.00	1.00	0.98	-0.06	0.00	0.00	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	-0.00	0.01	1.00	0.97	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	0.00	0.01	1.00	0.98	0.20	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	-0.00	0.01	1.00	0.98	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	0.00	0.01	1.00	0.95	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.98	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	-0.00	0.01	1.00	0.97	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	-0.40	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	-0.00	0.01	1.00	0.98	-0.50	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	-0.00	0.01	1.00	0.97	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	-0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	0.00	0.01	1.00	0.96	0.20	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	-0.00	0.01	1.00	0.98	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	-0.00	0.01	1.00	0.96	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	-0.00	0.01	1.00	0.97	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	-0.00	0.01	1.00	0.96	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	-0.40	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	-0.00	0.01	1.00	0.95	-0.50	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	-0.00	0.01	1.00	0.96	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.5: Experiment 1 $\rho = 0.0$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	-0.00	0.00	1.00	0.98	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	0.00	0.00	1.00	0.97	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	0.00	0.00	1.00	0.97	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	0.00	0.00	1.00	0.97	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	0.00	0.00	1.00	0.96	-0.11	0.00	0.00	0.00	-0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	0.00	0.00	1.00	0.97	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	0.00	0.00	1.00	0.96	-0.06	0.00	0.00	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	-0.00	0.01	1.00	0.97	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	0.00	0.01	1.00	0.96	0.20	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	-0.00	0.01	1.00	0.98	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	0.00	0.01	1.00	0.97	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.97	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	-0.00	0.01	1.00	0.95	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	0.00	0.01	1.00	0.96	-0.40	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	-0.00	0.01	1.00	0.94	-0.50	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	-0.00	0.01	1.00	0.97	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	-0.01	0.01	1.00	0.93	0.09	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	-0.01	0.01	1.00	0.79	0.19	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.00	0.01	1.00	0.93	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.01	0.01	1.00	0.94	-0.09	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.01	0.01	1.00	0.75	-0.19	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.01	0.02	1.00	0.56	-0.28	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	0.02	0.02	1.00	0.50	-0.28	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	0.02	0.02	1.00	0.24	-0.38	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	0.03	0.03	1.00	0.14	-0.47	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	0.01	0.01	1.00	0.76	-0.19	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.6: Experiment 1 $\rho = 0.2$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	-0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	-0.00	0.00	1.00	0.97	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	-0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	-0.00	0.00	1.00	0.97	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	0.00	0.00	1.00	0.97	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	-0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	0.00	0.00	1.00	0.96	-0.11	0.00	0.00	0.00	-0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	0.00	0.00	1.00	0.97	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	-0.00	0.00	1.00	0.97	-0.06	0.00	0.00	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	0.00	0.01	1.00	0.97	0.20	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	-0.00	0.01	1.00	0.97	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	0.00	0.01	1.00	0.98	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	-0.00	0.01	1.00	0.97	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.97	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	-0.00	0.01	1.00	0.96	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	-0.40	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	-0.00	0.01	1.00	0.97	-0.50	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	-0.00	0.01	1.00	0.95	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	-0.02	0.02	1.00	0.30	0.08	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	-0.04	0.04	1.00	0.00	0.16	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.02	0.02	1.00	0.31	0.08	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.02	0.02	1.00	0.22	-0.08	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.04	0.04	1.00	0.00	-0.16	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.06	0.06	1.00	0.00	-0.24	0.01	0.01	0.00	-0.29
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	0.07	0.07	1.00	0.00	-0.23	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	0.08	0.09	1.00	0.00	-0.31	0.01	0.01	0.00	-0.39
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	0.10	0.10	1.00	0.00	-0.39	0.01	0.01	0.00	-0.49
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	0.04	0.04	1.00	0.00	-0.15	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.7: Experiment 1 $\rho = 0.8$

B.2 Experiment 2: Covid and refugee effects

Our second Facebook ad campaign experiment is composed of five arms that vary information on COVID-19 and whether Dr. Kelli is a refugee, immigrant or no mention of either. Again, we wish to learn whether there is differential support for refugee ads on Facebook. Respondents are randomly assigned to receive ads with refugees with information on the above five arms. Assignment to each of the five arms is with equal probabilities, and other then mention of COVID and type of individual (refugee, immigrant, neither), ads otherwise identical. We define our first outcome of interest as the difference in click rates between experimental conditions.

Table B.8 presents the assumptions we make in our simulations for Experiment 2 design for ad clicking.

Assumption	**Size**
Covid prime effect (versus no covid prime)	0.1
Refugee effect (versus neither)	0.075
Immigrant effect (versus neither)	0.025
Effect of mentioning neither (for type of respondent)	0.00
No interaction effect on average between covid prime and profile type primes	
Errors drawn from standard normal, with individual standard deviation	0.2

Table B.8: Experiment 2 ad click assumptions

Our design is similarly declared as in Experiment 1 (see 'Model, Inquiry, Data Strategy, Answer Strategy'), including $N = 450000$ and $N/5$ units in each of the treatment arms. The resulting diagnosis of the ad click rate can be found in Table B.10. For the outcomes measured in the survey, measured conditional on clicking an ad, we utilize a similar design as Experiment 1. Assumptions are detailed in Table B.9, including for variation in ρ values we consider in our simulated experiments.

	Assumption	Size
Effect on R_i		
	T1: Covid prime, refugee	0.375
	T2: No covid prime, refugee	0.275
	T3: Covid prime, no type	0.3
	T4: No covid prime, no type	0.22
	T5: Covid prime, immigrant	0.325
	No interaction effect on average between covid prime and type of profiles	
	Errors drawn from standard normal	
Effect on Y_i		
	T1: Covid prime, refugee	0.175
	T2: No covid prime, refugee	0.075
	T3: Covid prime, no type	0.1
	T4: No covid prime, no type	0.02
	T5: Covid prime, immigrant	0.125
	No interaction effect on average between covid prime and type of profiles	
	Errors drawn from standard normal	
Correlation ρ	ρ	$\{0.0, 0.2, 0.8\}$

Table B.9: Experiment 2 assumptions for survey outcomes

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S_Rate	Mean Estimand
ate_Y_2_1	(Z_2 - Z_1)	0.00	0.00	1.00	0.94	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	(Z_3 - Z_1)	0.00	0.00	1.00	0.96	-0.07	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	(Z_3 - Z_2)	-0.00	0.00	1.00	0.96	0.02	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	(Z_4 - Z_1)	0.00	0.00	1.00	0.95	-0.17	0.00	0.00	0.00	-0.17
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	(Z_4 - Z_2)	-0.00	0.00	1.00	0.95	-0.08	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	(Z_4 - Z_3)	0.00	0.00	1.00	0.96	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	(Z_5 - Z_1)	0.00	0.00	1.00	0.96	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	(Z_5 - Z_2)	-0.00	0.00	1.00	0.96	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	(Z_5 - Z_3)	-0.00	0.00	1.00	0.96	0.02	0.00	0.00	0.00	0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	(Z_5 - Z_4)	-0.00	0.00	1.00	0.95	0.12	0.00	0.00	0.00	0.12
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors of all estimates are shown in the rows below. Results are from 500 simulated experiments. The first two columns describe the estimand and estimator of interest, where the name of the treatment arms follow "ate_y", as well as "Z_".

Table B.10: Experiment 2 design diagnosands.

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean_Estimate	SD_Estimate	Mean_SE	Type_S_Rate	Mean_Estimand
ate_Y_2_1	DIM (Z_2 - Z_1)	0.00	0.00	1.00	0.94	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	DIM (Z_3 - Z_1)	0.00	0.00	1.00	0.94	-0.07	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	DIM (Z_3 - Z_2)	-0.00	0.00	1.00	0.96	0.02	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	DIM (Z_4 - Z_1)	0.00	0.00	1.00	0.94	-0.17	0.00	0.00	0.00	-0.17
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	DIM (Z_4 - Z_2)	-0.00	0.00	1.00	0.95	-0.08	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	DIM (Z_4 - Z_3)	-0.00	0.00	1.00	0.95	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	DIM (Z_5 - Z_1)	0.00	0.00	1.00	0.95	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	DIM (Z_5 - Z_2)	-0.00	0.00	1.00	0.95	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	DIM (Z_5 - Z_3)	0.00	0.00	1.00	0.93	0.03	0.00	0.00	0.00	0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	DIM (Z_5 - Z_4)	0.00	0.00	1.00	0.95	0.13	0.00	0.00	0.00	0.12
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Table B.11: Post experiment 2 checks for power on actualized N sizes.

We form a diagnosis of the above design in Experiment 2 in Tables **??**-B.14, which present results on all previously used diagnosands. Simulation code follows.

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	0.00	0.00	1.00	0.96	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	0.00	0.00	0.85	0.97	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	0.00	0.00	1.00	0.96	-0.04	0.00	0.00	0.00	-0.04
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	-0.00	0.00	1.00	0.96	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	-0.00	0.00	1.00	0.95	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	0.00	0.00	1.00	0.97	-0.01	0.00	0.00	0.00	-0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	0.00	0.00	1.00	0.96	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	-0.00	0.00	0.83	0.97	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	0.00	0.01	1.00	0.95	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	0.00	0.01	1.00	0.97	-0.07	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	0.00	0.01	0.96	0.96	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	0.00	0.01	1.00	0.97	-0.15	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	0.00	0.01	1.00	0.95	-0.05	0.01	0.01	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	0.00	0.01	1.00	0.95	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	0.00	0.01	1.00	0.95	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	-0.00	0.01	0.96	0.96	0.02	0.01	0.01	0.00	0.03
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	-0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	0.00	0.01	1.00	0.95	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	-0.00	0.01	1.00	0.96	-0.07	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.00	0.01	0.80	0.97	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.00	0.01	1.00	0.97	-0.15	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.00	0.01	1.00	0.94	-0.05	0.01	0.01	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.00	0.01	1.00	0.96	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	-0.00	0.01	1.00	0.97	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	0.00	0.01	0.82	0.96	0.03	0.01	0.01	0.00	0.03
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	-0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.12: Experiment 2 $\rho = 0.0$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	0.00	0.00	1.00	0.97	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	-0.00	0.00	0.82	0.96	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	0.00	0.00	1.00	0.96	-0.04	0.00	0.00	0.00	-0.04
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	-0.00	0.00	1.00	0.97	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.95	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	-0.00	0.00	1.00	0.96	-0.01	0.00	0.00	0.00	-0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	-0.00	0.00	1.00	0.98	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	-0.00	0.00	0.83	0.97	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	-0.00	0.00	1.00	0.97	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	-0.00	0.01	1.00	0.95	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	-0.00	0.01	1.00	0.97	-0.08	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	-0.00	0.01	0.96	0.94	0.03	0.01	0.01	0.00	0.03
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	-0.00	0.01	1.00	0.95	-0.16	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	-0.00	0.01	1.00	0.96	-0.06	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.96	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	-0.00	0.01	1.00	0.95	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	0.00	0.01	1.00	0.95	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	0.00	0.01	0.96	0.96	0.03	0.01	0.01	0.00	0.02
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	0.00	0.01	1.00	0.96	0.11	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	0.01	0.01	1.00	0.89	-0.09	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	0.00	0.01	1.00	0.93	-0.07	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.00	0.01	0.77	0.96	0.02	0.01	0.01	0.00	0.03
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.01	0.01	1.00	0.84	-0.15	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.00	0.01	1.00	0.96	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.00	0.01	1.00	0.93	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	0.00	0.01	1.00	0.95	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	-0.00	0.01	1.00	0.95	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	-0.00	0.01	0.79	0.96	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	-0.01	0.01	1.00	0.91	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.13: Experiment 2 $\rho = 0.2$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	-0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	-0.00	0.00	1.00	0.98	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	-0.00	0.00	0.83	0.96	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	-0.00	0.00	1.00	0.97	-0.04	0.00	0.00	0.00	-0.04
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	-0.00	0.00	1.00	0.96	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.95	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	0.00	0.00	1.00	0.98	-0.01	0.00	0.00	0.00	-0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	0.00	0.00	1.00	0.96	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	0.00	0.00	0.84	0.95	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	0.00	0.00	1.00	0.97	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	0.00	0.01	1.00	0.97	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	-0.00	0.01	1.00	0.96	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	-0.00	0.01	0.96	0.98	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	-0.00	0.01	1.00	0.96	-0.16	0.01	0.01	0.00	-0.16
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	-0.00	0.01	1.00	0.96	-0.06	0.01	0.01	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.97	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	0.00	0.01	1.00	0.97	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	0.00	0.01	0.96	0.98	0.03	0.01	0.01	0.00	0.03
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	0.00	0.01	1.00	0.96	0.11	0.01	0.01	0.00	0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	0.02	0.02	1.00	0.23	-0.08	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	0.02	0.02	1.00	0.48	-0.06	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.01	0.01	0.60	0.89	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.03	0.04	1.00	0.01	-0.12	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.01	0.01	1.00	0.73	-0.04	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.02	0.02	1.00	0.41	-0.06	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	0.01	0.01	1.00	0.72	-0.04	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	-0.01	0.01	1.00	0.71	0.04	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	-0.01	0.01	0.64	0.90	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	-0.02	0.02	1.00	0.19	0.08	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.14: Experiment 2 $\rho = 0.8$

B.3 Simulation code

Design for "Refugee narratives and public opinion during the COVID-19 pandemic"

this ver: Thursday April 30, 2020

We're going to use *DeclareDesign*.

```
knitr::opts_chunk$set(echo = TRUE)
install.packages(c("DeclareDesign", "fabricatr", "randomizr", "estimatr", "DesignLibrary"))
library(DeclareDesign)
library(fabricatr)
library(randomizr)
library(estimatr)
library(DesignLibrary)
library(tidyverse)
library(kableExtra)
library(xtable)
```

For hypotheses please refer to main text.

Experiment 1: 5 arms

- T1 = covid - US
- T2 = covid - PA
- T3 = covid - Lancaster
- T4 = covid - No location
- T5 = no covid - US

We want to learn whether there is differential support for refugee ads on Facebook. Respondents are randomly assigned to receive ads with refugees with information on the above five arms. Assignment to each of the five arms is with equal probabilities, and other then mention of covid and location, ads otherwise identical. We define our outcome of interest as the difference in click rates between experimental conditions.

In settings of multiple treatment arms, we could do a number of pairwise comparisons: across treatments and each treatment against control.

Design Declaration A

- Model:

We specify a population of size N where a unit i has a potential outcome, $Y_i(Z = 0)$, when it remains untreated and M $(m = 1, 2, \cdots, M)$ potential outcomes defined according to the treatment that it receives. The effect of each treatment on the outcome of unit i is equal to the difference in the potential outcome under treatment condition m and the control condition: $Y_i(Z = m) - Y_i(Z = 0)$.

- Inquiry:

We are interested in all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$.

- Data strategy:

We randomly assign k/N units to each of the treatment arms.

- Answer strategy:

Take every pairwise difference in means corresponding to the specific estimand.

```
set.seed(123)
N <- 450000 #450K
covid_effect<-0.1
us_effect<-0.05
pa_effect<-0.075
lancaster_effect<-0.08
outcome_means <- c(covid_effect+us_effect #covid-us
                   ,covid_effect+pa_effect #covid-pa
                   ,covid_effect+lancaster_effect #covid-lancaster
                   ,covid_effect #covid-nolocation
                   ,us_effect #nocovid-us
                   )
sd_i <- 0.2
outcome_sds <- c(0, 0, 0, 0, 0)

# Population
population <- declare_population(N = N, u_1 = rnorm(N, 0, outcome_sds[1L]),
    u_2 = rnorm(N, 0, outcome_sds[2L]), u_3 = rnorm(N, 0, outcome_sds[3L]),
    u_4 = rnorm(N, 0, outcome_sds[4L]), u_5 = rnorm(N, 0, outcome_sds[5L]),
    u = rnorm(N) * sd_i)
# Potential outcomes
potential_outcomes <- declare_potential_outcomes(formula = Y ~ (outcome_means[1] +
    u_1) * (Z == "1") + (outcome_means[2] + u_2) * (Z == "2") +
    (outcome_means[3] + u_3) * (Z == "3") + (outcome_means[4] +
    u_4) * (Z == "4") + + (outcome_means[5] +
    u_5) * (Z == "5") + u ,  conditions = c("1", "2", "3", "4", "5"),
    assignment_variables = Z)
# Estimands
estimand <- declare_estimands(ate_Y_2_1 = mean(Y_Z_2 - Y_Z_1), ate_Y_3_1 = mean(Y_Z_3 -
    Y_Z_1), ate_Y_4_1 = mean(Y_Z_4 - Y_Z_1), ate_Y_5_1 = mean(Y_Z_5 - Y_Z_1),
    ate_Y_3_2 = mean(Y_Z_3 - Y_Z_2), ate_Y_4_2 = mean(Y_Z_4 - Y_Z_2),
    ate_Y_5_2 = mean(Y_Z_5 - Y_Z_2), ate_Y_4_3 = mean(Y_Z_4 -
    Y_Z_3), ate_Y_5_3 = mean(Y_Z_5 - Y_Z_3), ate_Y_5_4 = mean(Y_Z_5 - Y_Z_4))
# Assignment
assignment <- declare_assignment(num_arms = 5, conditions = c("1", "2", "3",
"4","5"), assignment_variable = Z)
reveal_Y <- declare_reveal(assignment_variables = Z)
# Estimator
estimator <- declare_estimator(handler = function(data) {
    estimates <- rbind.data.frame(
      ate_Y_2_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_Y_3_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_Y_4_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_Y_5_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_Y_3_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_Y_4_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_Y_5_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_Y_4_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_Y_5_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_Y_5_4 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "4", condition2 = "5")
      )
```

```r
    names(estimates)[names(estimates) == "N"] <- "N_DIM"
    estimates$estimator_label <- c("DIM (Z_2 - Z_1)", "DIM (Z_3 - Z_1)",
    "DIM (Z_4 - Z_1)", "DIM (Z_5 - Z_1)","DIM (Z_3 - Z_2)", "DIM (Z_4 - Z_2)", "DIM (Z_5 - Z_2)",
    "DIM (Z_4 - Z_3)", "DIM (Z_5 - Z_3)", "DIM (Z_5 - Z_4)")
    estimates$estimand_label <- rownames(estimates)
    estimates$estimate <- estimates$coefficients
    estimates$term <- NULL
    return(estimates)
})
multi_arm_design <- population + potential_outcomes + assignment +
    reveal_Y + estimand + estimator

# Diagnose Experiment 1 ad click rate:
t<-Sys.time()
diagnosis <- diagnose_design(multi_arm_design,diagnosands=)
Sys.time()-t
saveRDS(diagnosis,file="diagnosis-1.rds")

dat1<-diagnosis$diagnosands_df[,c("estimand_label","estimator_label","bias","rmse","power","coverage","
dat2<-diagnosis$diagnosands_df[,c("estimand_label","estimator_label","se(bias)","se(rmse)","se(power)",
dat2$estimand_label<-NA
dat2$estimator_label<-NA
tmp_n<-nrow(dat1)+nrow(dat2)
dat<-data.frame(Estimand=rep(NA,tmp_n),Estimator=rep(NA,tmp_n)
                ,Bias=rep(NA,tmp_n),RMSE=rep(NA,tmp_n)
                ,Power=rep(NA,tmp_n),Coverage=rep(NA,tmp_n)
                ,Mean_Estimate=rep(NA,tmp_n),SD_Estimate=rep(NA,tmp_n)
                ,Mean_SE=rep(NA,tmp_n) ,Type_S_Rate=rep(NA,tmp_n)
                ,Mean_Estimand=rep(NA,tmp_n),N_Sims=rep(NA,tmp_n))

j1<-j2<-1
for(i in 1:tmp_n){
  if(i%%2==0){
  dat[i,]<-dat2[j2,]
  j2<-j2+1
  }else{
  dat[i,]<-dat1[j1,]
  j1<-j1+1
  }
}
print(xtable(dat[,1:(ncol(dat)-1)],digits=2), include.rownames=FALSE)
```

Outcome of refugee thermometer, after clicking on ad:

Some respondents will not have thermometer ratings because of not clicking on the ads to be routed to the surveys; we can consider this as a type of attrition/missing data. This can affect both power and bias.

As such, we set up a design that accounts for attrition.

Design Declaration B

- Model:

We specify a model with a population N that has three variables affected by treatment: response variable R_i, outcome (here refugee thermometer rating in the survey) Y_i, which is correlated with response variable through parameter ρ. Y_i^{obs} is the measured version of Y_i, which is only observed when $R_i = 1$. For our setting, when a respondent is willing to click on the ad and answer the survey $R_i = 1$.

- Inquiry:

Here we're interested in knowing the average of all respondents' differences in treatment arm potential outcomes, all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$. But we're also interested in the average treatment effect on reporting $E[R_i(m) - R_i(m')]$ as well as the pairwise comparison between treatment arms among those who report: $E[Y_i(m) - Y_i(m')|R_i = 1]$.

- Data strategy:

We randomly assign $N/k = 90,000$ units to each of the treatment arms.

- Answer strategy:

R_i and Y_i^{obs}, take every pairwise difference in means corresponding to the specific estimand.

Experiment 1: 5 arms

- T1 = covid - US
- T2 = covid - PA
- T3 = covid - Lancaster
- T4 = covid - No location
- T5 = no covid - US

```
#Starting parameters
N <- 450000
a_R <- 0
#Likelihood of responding to survey after exposed to treatment arm: let covid effect on going to survey
b1_R <- 0.5 #covid - US
b2_R <- 0.6 #covid - PA
b3_R <- 0.7 #covid - Lancaster
b4_R <- 0.4 #covid - No location (-0.1 from US)
b5_R <- 0.2 #no covid - US
a_Y <- 0
#Effect on thermometer rating after exposed to treatment arm:
b1_Y <- 0.5   #covid - US
b2_Y <- 0.6   #covid - PA
b3_Y <- 0.7   #covid - Lancaster
b4_Y <- 0.4   #covid - No location (-0.1 from US)
b5_Y <- 0.2   #no covid - US
#correl
rho <- c(0.0,0.2,0.8)

#set up
t<-Sys.time()
for(i in 1:3){
  cat("Start Design:",i,"\n")
#Population
population <- declare_population(N = N, u = rnorm(N), v=rnorm(N)
              ,u1_R = rnorm(N),u2_R = rnorm(N),u3_R = rnorm(N),u4_R = rnorm(N),u5_R = rnorm(N)
              ,u1_Y = rnorm(N,mean = rho[i] * u1_R, sd = sqrt(1 - rho[i]^2)),u2_Y = rnorm(N,mean = rho[
              ,u3_Y = rnorm(N,mean = rho[i] * u3_R, sd = sqrt(1 - rho[i]^2)),u4_Y = rnorm(N,mean = rho[
              ,u5_Y = rnorm(N,mean = rho[i] * u5_R, sd = sqrt(1 - rho[i]^2))
              ) #one error eqn Y; one error eqn R;  errors for each condition in R; errors for each con
#Potential outcomes
  #R
```

```r
potential_outcomes_R <- declare_potential_outcomes(
  R ~ (a_R + b1_R + u1_R)* (Z == "1") + (a_R + b2_R + u2_R)* (Z == "2")
  + (a_R + b3_R + u3_R)* (Z == "3") + (a_R + b4_R + u4_R)* (Z == "4")
  + (a_R + b5_R + u5_R)* (Z == "5") > v, conditions = c("1", "2", "3", "4", "5"), assignment_variables =
  #Y
potential_outcomes_Y <- declare_potential_outcomes(
  Y ~ (a_Y + b1_Y + u1_Y)* (Z == "1") + (a_Y + b2_Y + u2_Y)* (Z == "2")
  + (a_Y + b3_Y + u3_Y)* (Z == "3") + (a_Y + b4_Y + u4_Y)* (Z == "4")
  + (a_Y + b5_Y + u5_Y)* (Z == "5") + u, conditions = c("1", "2", "3", "4", "5"), assignment_variables =
#Estimands: 3 types -- ATE on R, ATE on Y, ATE on Y|R
estimand <- declare_estimands(
  #ATE on R
  ate_R_2_1 = mean(R_Z_2 - R_Z_1), ate_R_3_1 = mean(R_Z_3 - R_Z_1), ate_R_4_1 = mean(R_Z_4 - R_Z_1), at
  ate_R_3_2 = mean(R_Z_3 - R_Z_2), ate_R_4_2 = mean(R_Z_4 - R_Z_2), ate_R_5_2 = mean(R_Z_5 - R_Z_2),
  ate_R_4_3 = mean(R_Z_4 - R_Z_3), ate_R_5_3 = mean(R_Z_5 - R_Z_3), ate_R_5_4 = mean(R_Z_5 - R_Z_4)
  #ATE on Y
  ,ate_Y_2_1 = mean(Y_Z_2 - Y_Z_1), ate_Y_3_1 = mean(Y_Z_3 - Y_Z_1), ate_Y_4_1 = mean(Y_Z_4 - Y_Z_1), a
  ate_Y_3_2 = mean(Y_Z_3 - Y_Z_2), ate_Y_4_2 = mean(Y_Z_4 - Y_Z_2), ate_Y_5_2 = mean(Y_Z_5 - Y_Z_2),
  ate_Y_4_3 = mean(Y_Z_4 - Y_Z_3), ate_Y_5_3 = mean(Y_Z_5 - Y_Z_3), ate_Y_5_4 = mean(Y_Z_5 - Y_Z_4)
  #ATE on Y|R
  ,ate_YR_2_1 = mean((Y_Z_2 - Y_Z_1)[R == 1]), ate_YR_3_1 = mean((Y_Z_3 - Y_Z_1)[R == 1])
  ,ate_YR_4_1 = mean((Y_Z_4 - Y_Z_1)[R == 1]), ate_YR_5_1 = mean((Y_Z_5 - Y_Z_1)[R == 1])
  ,ate_YR_3_2 = mean((Y_Z_3 - Y_Z_2)[R == 1]), ate_YR_4_2 = mean((Y_Z_4 - Y_Z_2)[R == 1])
  ,ate_YR_5_2 = mean((Y_Z_5 - Y_Z_2)[R == 1]), ate_YR_4_3 = mean((Y_Z_4 - Y_Z_3)[R == 1])
  ,ate_YR_5_3 = mean((Y_Z_5 - Y_Z_3)[R == 1]), ate_YR_5_4 = mean((Y_Z_5 - Y_Z_4)[R == 1])
  )
#Assignment
assignment <- declare_assignment(num_arms = 5, conditions = c("1", "2", "3", "4", "5"), assignment_vari
#Reveal/Observed: ??
reveal <- declare_reveal(outcome_variables = c("R", "Y"), assignment_variables = Z)
observed <- declare_step(Y_obs = ifelse(R, Y, NA), handler = fabricate)

#Estimator
estimator <- declare_estimator(handler = function(data) {
    estimates <- rbind.data.frame(
      #ATE on R
      ate_R_2_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_R_3_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_R_4_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_R_5_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_R_3_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_R_4_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_R_5_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_R_4_3 = difference_in_means(formula = R ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_R_5_3 = difference_in_means(formula = R ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_R_5_4 = difference_in_means(formula = R ~ Z, data = data, condition1 = "4", condition2 = "5")
      # ATE on Y conditional on R
      ate_YR_2_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_3_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_4_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_5_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_3_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_4_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
```

```
      ate_YR_5_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_4_3 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "3", condition2 =
      ate_YR_5_3 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "3", condition2 =
      ate_YR_5_4 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "4", condition2 =
      #ATE on Y
      ate_Y_2_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_Y_3_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_Y_4_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_Y_5_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_Y_3_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_Y_4_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_Y_5_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_Y_4_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_Y_5_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_Y_5_4 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "4", condition2 = "5")
      )
    names(estimates)[names(estimates) == "N"] <- "N_DIM"
    estimates$estimator_label <- c(
      #R
      "DIM_R (Z_2 - Z_1)", "DIM_R (Z_3 - Z_1)", "DIM_R (Z_4 - Z_1)", "DIM_R (Z_5 - Z_1)","DIM_R (Z_3 - 2
      , "DIM_R (Z_4 - Z_2)", "DIM_R (Z_5 - Z_2)", "DIM_R (Z_4 - Z_3)", "DIM_R (Z_5 - Z_3)", "DIM_R (Z_5
      #Y|R
      , "DIM_Y_obs (Z_2 - Z_1)", "DIM_Y_obs (Z_3 - Z_1)", "DIM_Y_obs (Z_4 - Z_1)", "DIM_Y_obs (Z_5 - Z_
      , "DIM_Y_obs (Z_4 - Z_2)", "DIM_Y_obs (Z_5 - Z_2)", "DIM_Y_obs (Z_4 - Z_3)", "DIM_Y_obs (Z_5 - Z_
      #Y
      ,"DIM_Y (Z_2 - Z_1)", "DIM_Y (Z_3 - Z_1)", "DIM_Y (Z_4 - Z_1)", "DIM_Y (Z_5 - Z_1)","DIM_Y (Z_3 -
      , "DIM_Y (Z_4 - Z_2)", "DIM_Y (Z_5 - Z_2)", "DIM_Y (Z_4 - Z_3)", "DIM_Y (Z_5 - Z_3)", "DIM_Y (Z_5
      )
    estimates$estimand_label <- rownames(estimates)
    estimates$estimate <- estimates$coefficients
    estimates$term <- NULL
    return(estimates)
})
multi_arm_attrition_design <- population + potential_outcomes_R +
    potential_outcomes_Y + assignment + reveal + observed +
    estimand + estimator
diagnoses <- diagnose_design(multi_arm_attrition_design)
saveRDS(diagnoses,paste("multi_arm_attrition_design-rho",i,".rds",sep=""))
cat("Finished Design:",i," in ", Sys.time()-t,"\n")
}
Sys.time()-t


# Combine and print xtable
rho1<-readRDS("multi_arm_attrition_design-rho1.rds")
rho2<-readRDS("multi_arm_attrition_design-rho2.rds")
rho3<-readRDS("multi_arm_attrition_design-rho3.rds")
dat1<-rho1$diagnosands_df
dat1$design_label<-"rho=0.0"
dat2<-rho2$diagnosands_df
dat2$design_label<-"rho=0.2"
dat3<-rho3$diagnosands_df
dat3$design_label<-"rho=0.8"
```

```r
dat<-rbind(dat1,dat2,dat3)

dat1<-dat[,c("design_label","estimand_label","estimator_label","bias","rmse","power","coverage","mean_e
dat2<-dat[,c("design_label","estimand_label","estimator_label","se(bias)","se(rmse)","se(power)","se(co


dat2$estimand_label<-NA
dat2$estimator_label<-NA

tmp_n<-nrow(dat1)+nrow(dat2)
d<-data.frame(Design=rep(NA,tmp_n),Estimand=rep(NA,tmp_n),Estimator=rep(NA,tmp_n)
                ,Bias=rep(NA,tmp_n),RMSE=rep(NA,tmp_n)
                ,Power=rep(NA,tmp_n),Coverage=rep(NA,tmp_n)
                ,Mean_Estimate=rep(NA,tmp_n),SD_Estimate=rep(NA,tmp_n)
                ,Mean_SE=rep(NA,tmp_n) ,Type_S_Rate=rep(NA,tmp_n)
                ,Mean_Estimand=rep(NA,tmp_n),N_Sims=rep(NA,tmp_n))

j1<-j2<-1
for(i in 1:tmp_n){
  if(i%%2==0){
  d[i,]<-dat2[j2,]
  j2<-j2+1
  }else{
  d[i,]<-dat1[j1,]
  j1<-j1+1
  }
}
print(xtable(d[1:60,2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.0

print(xtable(d[61:120,2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.2

print(xtable(d[121:nrow(d),2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.8
```

Experiment 2: 5 arms

- T1 = covid - Refugee
- T2 = no covid - Refugee
- T3 = covid - Neither
- T4 = no covid - Neither
- T5 = covid - Immigrant

We want to learn whether there is differential support for refugee ads on Facebook. Respondents are randomly assigned to receive ads with refugees with information on the above five arms. Assignment to each of the five arms is with equal probabilities, and other then mention of covid and type of individual, ads otherwise identical. We define our outcome of interest as the difference in click rates between experimental conditions.

We'll focus on pairwise comparisons across treatments (a conservative approach given our main hypotheses will be answered with comparisons of T1-T2, T2-T4, T3-T4, T1-T5, T3-T5).

Design Declaration A

- Model:

We specify a population of size N where a unit i has a potential outcome, $Y_i(Z = 0)$, when it remains untreated and M $(m = 1, 2, \cdots, M)$ potential outcomes defined according to the treatment that it receives.

The effect of each treatment on the outcome of unit i is equal to the difference in the potential outcome under treatment condition m and the control condition: $Y_i(Z = m) - Y_i(Z = 0)$.

- Inquiry:

We are interested in all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$.

- Data strategy:

We randomly assign k/N units to each of the treatment arms.

- Answer strategy:

Take every pairwise difference in means corresponding to the specific estimand.

```
set.seed(123)
N <- 450000 #450K
covid_effect<-0.1 #assume same covid effect as Experiment 1
refugee_effect<-0.075 #assume refugee effect is positive and larger than immigrant
immigrant_effect<-0.025 #assume immigrant effect is positive and smaller than refugee effect
outcome_means <- c(covid_effect+refugee_effect #covid - Refugee
                   ,refugee_effect #no covid - Refugee
                   ,covid_effect#covid - Neither
                   ,0 #no covid - Neither; assume no effect of ad
                   ,covid_effect+immigrant_effect#covid - Immigrant
                   )# also assumes that there are no interaction effects
sd_i <- 0.2
outcome_sds <- c(0, 0, 0, 0, 0)

# Population
population <- declare_population(N = N, u_1 = rnorm(N, 0, outcome_sds[1L]),
    u_2 = rnorm(N, 0, outcome_sds[2L]), u_3 = rnorm(N, 0, outcome_sds[3L]),
    u_4 = rnorm(N, 0, outcome_sds[4L]), u_5 = rnorm(N, 0, outcome_sds[5L]),
    u = rnorm(N) * sd_i)
# Potential outcomes
potential_outcomes <- declare_potential_outcomes(formula = Y ~ (outcome_means[1] +
    u_1) * (Z == "1") + (outcome_means[2] + u_2) * (Z == "2") +
    (outcome_means[3] + u_3) * (Z == "3") + (outcome_means[4] +
    u_4) * (Z == "4") + + (outcome_means[5] +
    u_5) * (Z == "5") + u ,  conditions = c("1", "2", "3", "4", "5"),
    assignment_variables = Z)
# Estimands
estimand <- declare_estimands(ate_Y_2_1 = mean(Y_Z_2 - Y_Z_1), ate_Y_3_1 = mean(Y_Z_3 -
    Y_Z_1), ate_Y_4_1 = mean(Y_Z_4 - Y_Z_1), ate_Y_5_1 = mean(Y_Z_5 - Y_Z_1),
    ate_Y_3_2 = mean(Y_Z_3 - Y_Z_2), ate_Y_4_2 = mean(Y_Z_4 - Y_Z_2),
    ate_Y_5_2 = mean(Y_Z_5 - Y_Z_2), ate_Y_4_3 = mean(Y_Z_4 -
    Y_Z_3), ate_Y_5_3 = mean(Y_Z_5 - Y_Z_3), ate_Y_5_4 = mean(Y_Z_5 - Y_Z_4))
# Assignment
assignment <- declare_assignment(num_arms = 5, conditions = c("1", "2", "3",
"4","5"), assignment_variable = Z)
reveal_Y <- declare_reveal(assignment_variables = Z)
# Estimator
estimator <- declare_estimator(handler = function(data) {
    estimates <- rbind.data.frame(
      ate_Y_2_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_Y_3_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_Y_4_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "4")
```

```
      ate_Y_5_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_Y_3_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_Y_4_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_Y_5_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_Y_4_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_Y_5_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_Y_5_4 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "4", condition2 = "5")
      )
    names(estimates)[names(estimates) == "N"] <- "N_DIM"
    estimates$estimator_label <- c("DIM (Z_2 - Z_1)", "DIM (Z_3 - Z_1)",
    "DIM (Z_4 - Z_1)", "DIM (Z_5 - Z_1)","DIM (Z_3 - Z_2)", "DIM (Z_4 - Z_2)", "DIM (Z_5 - Z_2)",
    "DIM (Z_4 - Z_3)", "DIM (Z_5 - Z_3)", "DIM (Z_5 - Z_4)")
    estimates$estimand_label <- rownames(estimates)
    estimates$estimate <- estimates$coefficients
    estimates$term <- NULL
    return(estimates)
})
multi_arm_design2 <- population + potential_outcomes + assignment +
    reveal_Y + estimand + estimator
# Diagnose Experiment 1 ad click rate:
t<-Sys.time()
diagnosis <- diagnose_design(multi_arm_design2)
Sys.time()-t
saveRDS(diagnosis,file="diagnosis-2.rds")



library(xtable)
dat1<-diagnosis$diagnosands_df[,c("estimand_label","estimator_label","bias","rmse","power","coverage","
dat2<-diagnosis$diagnosands_df[,c("estimand_label","estimator_label","se(bias)","se(rmse)","se(power)",
dat2$estimand_label<-NA
dat2$estimator_label<-NA
tmp_n<-nrow(dat1)+nrow(dat2)
dat<-data.frame(Estimand=rep(NA,tmp_n),Estimator=rep(NA,tmp_n)
                ,Bias=rep(NA,tmp_n),RMSE=rep(NA,tmp_n)
                ,Power=rep(NA,tmp_n),Coverage=rep(NA,tmp_n)
                ,Mean_Estimate=rep(NA,tmp_n),SD_Estimate=rep(NA,tmp_n)
                ,Mean_SE=rep(NA,tmp_n) ,Type_S_Rate=rep(NA,tmp_n)
                ,Mean_Estimand=rep(NA,tmp_n),N_Sims=rep(NA,tmp_n))

j1<-j2<-1
for(i in 1:tmp_n){
  if(i%%2==0){
  dat[i,]<-dat2[j2,]
  j2<-j2+1
  }else{
  dat[i,]<-dat1[j1,]
  j1<-j1+1
  }
}
print(xtable(dat[,1:(ncol(dat)-1)],digits=2), include.rownames=FALSE)
```

Design Declaration B

- Model:

We specify a model with a population N that has three variables affected by treatment: response variable R_i, outcome (here refugee thermometer rating in the survey) Y_i, which is correlated with response variable through parameter ρ. Y_i^{obs} is the measured version of Y_i, which is only observed when $R_i = 1$. For our setting, when a respondent is willing to click on the ad and answer the survey $R_i = 1$.

- Inquiry:

Here we're interested in knowing the average of all respondents' differences in treatment arm potential outcomes, all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$. But we're also interested in the average treatment effect on reporting $E[R_i(m) - R_i(m')]$ as well as the pairwise comparison between treatment arms among those who report: $E[Y_i(m) - Y_i(m')|R_i = 1]$.

- Data strategy:

We randomly assign $N/k = 90,000$ units to each of the treatment arms.

- Answer strategy:

R_i and Y_i^{obs}, take every pairwise difference in means corresponding to the specific estimand.

Experiment 2:

- T1 = covid - Refugee
- T2 = no covid - Refugee
- T3 = covid - Neither
- T4 = no covid - Neither
- T5 = covid - Immigrant

```
#Starting parameters
N <- 450000
a_R <- 0
#Likelihood of responding to survey after exposed to treatment arm: let covid effect on going to survey
b1_R <- 0.1+0.075 + 0.2 #covid - refugee
b2_R <- 0.075 + 0.2  #no covid - refugee
b3_R <- 0.1 + 0.2  #covid - neither
b4_R <- 0.02 + 0.2 #no covid - neither
b5_R <- 0.1+0.025 + 0.2  #covid - immigrant
a_Y <- 0
#Effect on thermometer rating after exposed to treatment arm:
b1_Y <- 0.1+0.075   #covid - refugee
b2_Y <- 0.075   #no covid - refugee
b3_Y <- 0.1   #covid - neither
b4_Y <- 0.02  #no covid - neither
b5_Y <- 0.1+0.025   #covid - immigrant
#correl
rho <- c(0.0,0.2,0.8)

#set up
t<-Sys.time()
for(i in 1:3){
  cat("Start Design:",i,"\n")
#Population
population <- declare_population(N = N, u = rnorm(N), v=rnorm(N)
              ,u1_R = rnorm(N),u2_R = rnorm(N),u3_R = rnorm(N),u4_R = rnorm(N),u5_R = rnorm(N)
              ,u1_Y = rnorm(N,mean = rho[i] * u1_R, sd = sqrt(1 - rho[i]^2)),u2_Y = rnorm(N,mean = rho[
              ,u3_Y = rnorm(N,mean = rho[i] * u3_R, sd = sqrt(1 - rho[i]^2)),u4_Y = rnorm(N,mean = rho[
              ,u5_Y = rnorm(N,mean = rho[i] * u5_R, sd = sqrt(1 - rho[i]^2))
```

```
              ) #one error eqn Y; one error eqn R;  errors for each condition in R; errors for each con
#Potential outcomes
  #R
potential_outcomes_R <- declare_potential_outcomes(
  R ~ (a_R + b1_R + u1_R)* (Z == "1") + (a_R + b2_R + u2_R)* (Z == "2")
  + (a_R + b3_R + u3_R)* (Z == "3") + (a_R + b4_R + u4_R)* (Z == "4")
  + (a_R + b5_R + u5_R)* (Z == "5") > v, conditions = c("1", "2", "3", "4", "5"), assignment_variables =
  #Y
potential_outcomes_Y <- declare_potential_outcomes(
  Y ~ (a_Y + b1_Y + u1_Y)* (Z == "1") + (a_Y + b2_Y + u2_Y)* (Z == "2")
  + (a_Y + b3_Y + u3_Y)* (Z == "3") + (a_Y + b4_Y + u4_Y)* (Z == "4")
  + (a_Y + b5_Y + u5_Y)* (Z == "5") + u, conditions = c("1", "2", "3", "4", "5"), assignment_variables =
#Estimands: 3 types -- ATE on R, ATE on Y, ATE on Y|R
estimand <- declare_estimands(
  #ATE on R
  ate_R_2_1 = mean(R_Z_2 - R_Z_1), ate_R_3_1 = mean(R_Z_3 - R_Z_1), ate_R_4_1 = mean(R_Z_4 - R_Z_1), ate
  ate_R_3_2 = mean(R_Z_3 - R_Z_2), ate_R_4_2 = mean(R_Z_4 - R_Z_2), ate_R_5_2 = mean(R_Z_5 - R_Z_2),
  ate_R_4_3 = mean(R_Z_4 - R_Z_3), ate_R_5_3 = mean(R_Z_5 - R_Z_3), ate_R_5_4 = mean(R_Z_5 - R_Z_4)
  #ATE on Y
  ,ate_Y_2_1 = mean(Y_Z_2 - Y_Z_1), ate_Y_3_1 = mean(Y_Z_3 - Y_Z_1), ate_Y_4_1 = mean(Y_Z_4 - Y_Z_1), a
  ate_Y_3_2 = mean(Y_Z_3 - Y_Z_2), ate_Y_4_2 = mean(Y_Z_4 - Y_Z_2), ate_Y_5_2 = mean(Y_Z_5 - Y_Z_2),
  ate_Y_4_3 = mean(Y_Z_4 - Y_Z_3), ate_Y_5_3 = mean(Y_Z_5 - Y_Z_3), ate_Y_5_4 = mean(Y_Z_5 - Y_Z_4)
  #ATE on Y|R
  ,ate_YR_2_1 = mean((Y_Z_2 - Y_Z_1)[R == 1]), ate_YR_3_1 = mean((Y_Z_3 - Y_Z_1)[R == 1])
  ,ate_YR_4_1 = mean((Y_Z_4 - Y_Z_1)[R == 1]), ate_YR_5_1 = mean((Y_Z_5 - Y_Z_1)[R == 1])
  ,ate_YR_3_2 = mean((Y_Z_3 - Y_Z_2)[R == 1]), ate_YR_4_2 = mean((Y_Z_4 - Y_Z_2)[R == 1])
  ,ate_YR_5_2 = mean((Y_Z_5 - Y_Z_2)[R == 1]), ate_YR_4_3 = mean((Y_Z_4 - Y_Z_3)[R == 1])
  ,ate_YR_5_3 = mean((Y_Z_5 - Y_Z_3)[R == 1]), ate_YR_5_4 = mean((Y_Z_5 - Y_Z_4)[R == 1])
  )
#Assignment
assignment <- declare_assignment(num_arms = 5, conditions = c("1", "2", "3", "4", "5"), assignment_vari
#Reveal/Observed: ??
reveal <- declare_reveal(outcome_variables = c("R", "Y"), assignment_variables = Z)
observed <- declare_step(Y_obs = ifelse(R, Y, NA), handler = fabricate)

#Estimator
estimator <- declare_estimator(handler = function(data) {
    estimates <- rbind.data.frame(
      #ATE on R
      ate_R_2_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_R_3_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_R_4_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_R_5_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_R_3_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_R_4_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_R_5_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_R_4_3 = difference_in_means(formula = R ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_R_5_3 = difference_in_means(formula = R ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_R_5_4 = difference_in_means(formula = R ~ Z, data = data, condition1 = "4", condition2 = "5")
      # ATE on Y conditional on R
      ate_YR_2_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_3_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_4_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
```

```
      ate_YR_5_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_3_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_4_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_5_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_4_3 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "3", condition2 =
      ate_YR_5_3 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "3", condition2 =
      ate_YR_5_4 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "4", condition2 =
      #ATE on Y
      ate_Y_2_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_Y_3_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_Y_4_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_Y_5_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_Y_3_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_Y_4_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_Y_5_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_Y_4_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_Y_5_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_Y_5_4 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "4", condition2 = "5")
      )
    names(estimates)[names(estimates) == "N"] <- "N_DIM"
    estimates$estimator_label <- c(
      #R
      "DIM_R (Z_2 - Z_1)", "DIM_R (Z_3 - Z_1)", "DIM_R (Z_4 - Z_1)", "DIM_R (Z_5 - Z_1)","DIM_R (Z_3 - 
      , "DIM_R (Z_4 - Z_2)", "DIM_R (Z_5 - Z_2)", "DIM_R (Z_4 - Z_3)", "DIM_R (Z_5 - Z_3)", "DIM_R (Z_5
      #Y|R
      , "DIM_Y_obs (Z_2 - Z_1)", "DIM_Y_obs (Z_3 - Z_1)", "DIM_Y_obs (Z_4 - Z_1)", "DIM_Y_obs (Z_5 - Z_
      , "DIM_Y_obs (Z_4 - Z_2)", "DIM_Y_obs (Z_5 - Z_2)", "DIM_Y_obs (Z_4 - Z_3)", "DIM_Y_obs (Z_5 - Z_
      #Y
      ,"DIM_Y (Z_2 - Z_1)", "DIM_Y (Z_3 - Z_1)", "DIM_Y (Z_4 - Z_1)", "DIM_Y (Z_5 - Z_1)","DIM_Y (Z_3 -
      , "DIM_Y (Z_4 - Z_2)", "DIM_Y (Z_5 - Z_2)", "DIM_Y (Z_4 - Z_3)", "DIM_Y (Z_5 - Z_3)", "DIM_Y (Z_5
      )
    estimates$estimand_label <- rownames(estimates)
    estimates$estimate <- estimates$coefficients
    estimates$term <- NULL
    return(estimates)
})
multi_arm_attrition_design <- population + potential_outcomes_R +
    potential_outcomes_Y + assignment + reveal + observed +
    estimand + estimator
diagnoses <- diagnose_design(multi_arm_attrition_design)
saveRDS(diagnoses,paste("multi_arm_attrition_design2-rho",i,".rds",sep=""))
cat("Finished Design:",i," in ", Sys.time()-t,"\n")
}
Sys.time()-t


# Combine and print xtable
rho1<-readRDS("multi_arm_attrition_design2-rho1.rds")
rho2<-readRDS("multi_arm_attrition_design2-rho2.rds")
rho3<-readRDS("multi_arm_attrition_design2-rho3.rds")
dat1<-rho1$diagnosands_df
dat1$design_label<-"rho=0.0"
dat2<-rho2$diagnosands_df
```

```r
dat2$design_label<-"rho=0.2"
dat3<-rho3$diagnosands_df
dat3$design_label<-"rho=0.8"

dat<-rbind(dat1,dat2,dat3)

dat1<-dat[,c("design_label","estimand_label","estimator_label","bias","rmse","power","coverage","mean_e
dat2<-dat[,c("design_label","estimand_label","estimator_label","se(bias)","se(rmse)","se(power)","se(co


dat2$estimand_label<-NA
dat2$estimator_label<-NA

tmp_n<-nrow(dat1)+nrow(dat2)
d<-data.frame(Design=rep(NA,tmp_n),Estimand=rep(NA,tmp_n),Estimator=rep(NA,tmp_n)
                ,Bias=rep(NA,tmp_n),RMSE=rep(NA,tmp_n)
                ,Power=rep(NA,tmp_n),Coverage=rep(NA,tmp_n)
                ,Mean_Estimate=rep(NA,tmp_n),SD_Estimate=rep(NA,tmp_n)
                ,Mean_SE=rep(NA,tmp_n) ,Type_S_Rate=rep(NA,tmp_n)
                ,Mean_Estimand=rep(NA,tmp_n),N_Sims=rep(NA,tmp_n))

j1<-j2<-1
for(i in 1:tmp_n){
  if(i%%2==0){
  d[i,]<-dat2[j2,]
  j2<-j2+1
  }else{
  d[i,]<-dat1[j1,]
  j1<-j1+1
  }
}
print(xtable(d[1:60,2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.0

print(xtable(d[61:120,2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.2

print(xtable(d[121:nrow(d),2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.8
```

C Facebook ads

Ad 1: COVID/United States

Ad Headline: Refugees help America fight coronavirus.

Ad Description: Mustafa volunteers to deliver groceries in the USA. Click to support refugees helping us.

Ad 2: COVID/Pennsylvania

Ad Headline: Refugees help America fight coronavirus.

Ad Description: Mustafa volunteers to deliver groceries in PA. Click to support refugees helping us.

Ad 3: COVID/Lancaster

Ad Headline: Refugees help America fight coronavirus.

Ad Description: Mustafa volunteers to deliver groceries in Lancaster. Click to support refugees helping us.

Ad 4: COVID/No location

Ad Headline: Refugees help America fight coronavirus.

Ad Description: Mustafa volunteers to deliver groceries. Click to support refugees helping us.

Ad 5: No COVID/United States

Ad Headline: Refugees help America.

Ad Description: Mustafa volunteers to deliver groceries in the USA. Click to support refugees helping us.

Ad 6: COVID/Refugee

Ad Headline: Refugee doctors are fighting coronavirus.

Ad Description: Dr. Heval Kelli fights for his coronavirus patients. Click to support refugees helping us.

Ad 7: COVID/Immigrant

Ad Headline: Immigrant doctors are fighting coronavirus.

Ad Description: Dr. Heval Kelli fights for his coronavirus patients. Click to support immigrants helping us.

Ad 8: COVID/Neither

Ad Headline: Doctors are fighting coronavirus.

Ad Description: Dr. Heval Kelli fights for his coronavirus patients. Click to support doctors helping us.

Ad 9: No COVID/Refugee

Ad Headline: Refugee doctors are helping America.

Ad Description: Dr. Heval Kelli fights for his patients. Click to support refugees helping us.

Ad 10: No COVID/Neither

Ad Headline: Doctors are helping America.

Ad Description: Dr. Heval Kelli fights for his patients. Click to support doctors helping us.

D Post Experiment Survey

Arm	N	Women	Education	White	Religion	Party	Refugee Thermometer	Trump Approval	Click	COVID
Pooled	40	0.591	3.714	0.6	Protestant	3.2	85.261	5.353	14	1.214
Kelli ads										
COVID-Immigrant	6	0.333	4.333	0.333	Hindu/Nothing/Catholic	3	93.333	4	3	1.333
COVID-Neither	2	NA							0	
COVID-Refugee	4	0.333	6	0.667	Protestant	2.667	96	6	2	1
No COVID Neither	3	1.000	4	1	Protestant	4	100	6	0	
No COVID Refugee	5	1.000	3	0		1	56		0	
Mustafa ads										
COVID Lancaster	7	0.667	2.8	0.6	Nothing	3.2	94.333	5.5	4	1
COVID No place	3	1.000	4.5	0.5	Protestant	2.5	75.5	6	2	1.5
COVID PA	5	0.500	2.75	0.75	Atheist/Muslim/Other	4	71	6	2	1
COVID US	1	1.000	3	1	Protestant	5	80	3	1	2
No COVID US	4	0.000	3				100		0	

Table D.15: Survey response summaries. Columns ‘Women‘ and ‘White‘ present proportions of women and white respondents within the arm. Education is from 1 to 6, with 1 referring to the least amount of education achieved and 6 the most. Religion presents modal religion category in each arm. Party can take values from 1 (strong Democract) to 7 (strong Republican). The thermometer and approval variables range from 0-100. Covid is a variable that measures whether the respondent feels COVID-19 is a major threat (1), minor threat (2) or not a threat (3). Click refers to whether the respondent clicked on reading more about Refugee Council USA.

E Survey instrument

Refugee Narratives Use

Start of Block: Consent Block

Consent Public Opinion in the USA Thank you for clicking on our Facebook ads. These ads are part of a study about public opinion toward refugees in the United States. In coordination with Refugee Council USA, we are Claire Adida (UC San Diego), Adeline Lo (University of Madison Wisconsin), Lauren Prather (UC San Diego), and Scott Williamson (Stanford University), researchers studying American public opinion. In what follows, we ask you to fill out a brief survey and provide you with an opportunity to connect with Refugee Council USA for information about how to help refugees. If you agree to be in this study, the following will happen to you: you will answer a few questions about yourself and your political attitudes. This survey will take approximately five minutes of your time. Research records will be kept confidential to the extent allowed by law. No identifying information will be collected, such that the researchers will be unable to link your answers to your identity. Participation in research is entirely voluntary. There are no risks associated with this study, but we cannot and do not guarantee that you will receive any benefits from participation. You may refuse to participate or withdraw at any time without penalty or loss of benefits to which you are entitled. If you want additional information or have questions or research-related problems, you may reach Professors Adida at cadida@ucsd.edu, Lo at aylo@wisc.edu, Prather at lprather@ucsd.edu, and Williamson at scottw2@stanford.edu. If you are not satisfied with the response of the research team, have more questions, or want to talk to someone about your rights as a research participant, you should contact the Human Research Protections Program at 858-246-HRPP (858-246-4777).

○ I have read the consent form above and agree to continue with the survey (1)

○ I have read the consent form above and do not agree to continue with the survey (2)

Skip To: End of Survey If Public Opinion in the USA Thank you for clicking on our Facebook ads. These ads are part of a s... = I have read the consent form above and do not agree to continue with the survey

End of Block: Consent Block

Start of Block: Outcome

refugee_therm On a scale from 0 to 100, where 0 equals completely unfavorable and 100 equals completely favorable, how would you describe your feelings toward refugees?

0 10 20 30 40 50 60 70 80 90 100

Feelings toward refugees ()	

End of Block: Outcome

Start of Block: SES

gender What is your gender?

◯ Male (1)

◯ Female (2)

◯ Non-binary (3)

Page Break

yearbirth What is your year of birth?

▼ 2002 (1) ... 1920 (83)

Page Break

edu What is the highest level of education you have achieved?

- ○ Some high school (1)
- ○ Completed high school (2)
- ○ Some college (3)
- ○ Completed college (4)
- ○ Some post-graduate (5)
- ○ Completed post-graduate (6)

Page Break

state In which US state do you currently live?

▼ Alabama (1) ... Wyoming (49)

Page Break

employed Are you currently employed or unemployed?

- Employed, not looking for work (1)
- Employed, looking for work (2)
- Unemployed, not looking for work (3)
- Unemployed, looking for work (4)

Page Break

ethnicity Are you of Hispanic, Latino, or Spanish origins?

○ Yes (1)

○ No (2)

Page Break

race What race do you associate yourself most closely with?

- ○ White (1)
- ○ African American or Black (2)
- ○ American Indiana or Alaska Native (3)
- ○ Asian (4)
- ○ Native Hawaiian or Pacific Islander (5)
- ○ Other (6)

Page Break

Q17 Do you have children living in your household?

○ Yes (1)

○ No (2)

Page Break

party In general, would you describe yourself as a:

- Strong Democrat (1)
- Democrat (2)
- Lean Democrat (3)
- Independent (4)
- Lean Republican (5)
- Republican (6)
- Strong Republican (7)

Page Break

trump Do you approve or disapprove of the way Donald Trump is handling his job as President?

- Strongly approve (1)
- Approve (2)
- Somewhat approve (3)
- Somewhat disapprove (4)
- Disapprove (5)
- Strongly disapprove (6)

Page Break

religion What is your present religion, if any?

- Protestant (1)
- Roman Catholic (2)
- Mormon (3)
- Orthodox, such as Greek or Russian Orthodox (4)
- Jewish (5)
- Muslim (6)
- Buddhist (7)
- Hindu (8)
- Atheist (9)
- Agnostic (10)
- Something else (11) ____
- Nothing in particular (12)

Page Break

news From which of the below sources do you receive most of your news and information? Please select any that you regularly use:

- ☐ Online: Facebook (1)
- ☐ Online: Other social media (e.g., Twitter, Instagram...) (2)
- ☐ Online: news website or app (3)
- ☐ TV (4)
- ☐ Print (newspapers, journals) (5)
- ☐ Radio (6)
- ☐ Other (7) ____

Page Break

Q19 How closely do you follow news and current events?

- Very closely (1)
- Somewhat closely (2)
- A little (3)
- Not at all (4)

Page Break

Q21 Would you say that you have been following the news more closely than normal since the emergence of coronavirus?

- ◯ Yes, a lot more than normal (1)
- ◯ Yes, a little more than normal (2)
- ◯ About the same as normal (3)
- ◯ No, a little less than normal (4)
- ◯ No, a lot less than normal (5)

End of Block: SES

Start of Block: Refugee Website

Mustafa_story Now we would like to remind you of the ad you saw on Facebook that brought you to the survey.

JS

refugee_council Refugee Council USA is a non-profit, non-partisan, non-governmental organization dedicated to promoting efforts that protect and welcome refugees, asylees, asylum-seekers and other forcibly displaced populations, including individuals like Mustafa.

If you are interested in finding out more about this organization, please click on the link below. The website will open in a new window, and what you do on that page will not be accessible to us as the researchers.
Refugee Council USA: https://rcusa.org/covid-19/.

Q15
After you click the link to the contact page, please click the arrow to proceed to the final question.

End of Block: Refugee Website

Start of Block: Covid Treatment

covid Would you say that the Coronavirus (COVID-19) outbreak is a major threat, a minor threat, or not a threat to your personal health?

- ○ A major threat (1)
- ○ A minor threat (2)
- ○ Not a threat (3)

End of Block: Covid Treatment

F Original registered report/PAP

Refugee narratives and public opinion during the COVID-19 pandemic

Abstract

Migrants are often scapegoated during public health crises. Can such crises create opportunities for migrant inclusion instead? Refugee advocates regularly share narratives of refugee contributions to society, and as the COVID-19 pandemic unfolds, many organizations have stepped up their outreach with stories of refugees helping out in the crisis. We have partnered up with one of the country's leading refugee advocate organizations to test whether solidarity narratives improve public attitudes and engagement in support of refugees. We combine a Facebook experimental design with an original survey measuring inclusionary attitudes and behavior toward refugees to evaluate the effectiveness of refugee narratives. We test whether migrant narratives framed in the context of COVID-19, targeted to local communities, or labeled as refugees vs. immigrants enhance public support of refugees. Our results help us understand which refugee narratives shape public support for vulnerable minorities during a public health crisis.

1 Introduction

Public health crises such as the current COVID-19 pandemic can hit refugees particularly hard. Not only are refugees more likely to contract diseases and less likely to receive adequate care (e.g. Kalipeni and Oppong 1998), they are often blamed inaccurately for spreading sickness in their host societies (Khan et al. 2016). This latter problem can heighten prejudice against refugees and other migrants, who already face hostility in many contexts. For instance, the United States has a long history of blaming pandemics on foreigners (Kraut 1995; Shah 2001). As a recent example, politicization of the 2014 Ebola crisis by Republican politicians may have increased hostility to immigrants among their voting base (Adida et al. 2018).

Given the severity of the COVID-19 pandemic and efforts by some American political leaders to blame foreigners for the outbreak (White and King 2020), it is plausible that hostility toward refugees will increase. Yet, this crisis has also seen many refugees and former refugees helping during the pandemic at great personal risk. In this context, countermobilization by pro-refugee organizations emphasizing these acts of solidarity reflects a potentially important check on rising hostility. However, the pandemic also creates challenges for such mobilization by constraining the time, resources, and attention of Americans who feel more favorably toward refugees.

In this study, we have partnered with Refugees International and Refugee Council USA to test strategies for increasing engagement with refugee advocacy in the midst of the COVID-19 pandemic. We randomize the content of Facebook advertisements to test which narratives increase support for refugees. We follow up with a survey that includes both attitudinal and behavioral measures of refugee support, allowing us to more precisely interpret the treatment effect and its mechanisms.

The experimental design allows us to investigate three research questions. First, we test the effects of connecting refugees' actions directly to COVID-19 to see whether it is possible to counter the scapegoat effect by emphasizing the solidarity and contribution of refugees in a time of crisis; second, we test the effects of linking these actions to one's local community, thereby assessing the geographic scope of the effect; and third, building on a recent literature suggesting that the public rewards migrants who display greater vulnerabilities (Bansak et al. 2016), we test the effects of describing these individuals as *refugees* vs. *immigrants*. Our findings will inform efforts to combat migrant scapegoating during a public health crisis by investigating whether pro-refugee organizations can increase public engagement with their mission by emphasizing migrants fighting the pandemic.

2 Research Design and Hypotheses

Our research design and study has been approved by the IRBs at each author's institution; the pre-analysis plan has been uploaded to X on DATE.

The study relies on Facebook's split test feature for advertisements to implement the experiments. This feature allows advertisers to assign several ads to randomly constructed "audiences" of Facebook profiles for the purpose of comparing the relative effectiveness of the ads in achieving some desired outcome. Because the profiles are randomly assigned to view one of the ads but not the others, this relative effectiveness is causally identified. Within the ad, users are directed to click the ad to support refugees. Thus, clicking on ads represents a behavioral measure of refugee support. Once a Facebook user clicks on one of the ads, they will be redirected to a short Qualtrics survey. In the survey, they will be offered the opportunity to sign up for the mailing list of Refugee Council USA, a non-partisan, non-governmental organization whose mission is to promote efforts to protect and welcome forcibly displaced persons. We will also prompt respondents to rate their favorability toward refugees using a feeling thermometer. These latter two outcomes will be used as additional behavioral and attitudinal measures of refugee support. The survey will also include brief demographic questions. A consort diagram of the research design is shown in Figure A.1.

We use these ad experiments to test three hypotheses related to American support for refugees during the COVID-19 pandemic. A rich literature in social sciences has shown that individuals raise barriers to inclusion when they feel threatened – economically, culturally, or physically. In this study, we investigate whether these barriers fall when out-group members take actions of solidarity during times of crisis. Indeed, scholars have shown that out-groups who abide by majority-norms of behavior are rewarded (Choi et al. 2019). And, in times of crisis, the public may seek out heroes, or individuals who contribute to the greater good.

Our first hypothesis draws on recent work demonstrating that there is higher support for refugees when they are seen as contributing to society (Adida et al. 2019). Yet we also know that minorities – especially migrant groups – have historically been scapegoated during public health crises. Indeed, the exclusion of Chinese immigrants to the United States has always been motivated at least in part by disease threat. In the 1990s, Haitian refugees were excluded because they were associated with the threat of HIV/AIDS. And in 2014, when Ebola reached US soil, African immigrants in Dallas were stigmatized. This raises an empirical question. When the public is primed to think about a salient public health crisis, do they invariably turn against migrants? Or do messages of solidarity counteract this well-documented scapegoat effect? We propose that refugees seen to be contributing to crisis-relief efforts will be viewed more favorably than those seen as contributing to society more generally. This leads to our first hypothesis.

> **H1:** Advertisements that mention refugees contributing to the COVID-19 effort explicitly will elicit more clicks to support refugees than advertisements that mention refugees contributing to society more generally, without mention of COVID-19.

Second, there is a large literature debating whether individuals are driven to support policies toward migrants out of their own self-interest or sociotropic concerns. In times of crisis, such as natural disasters, parochial concerns may be particularly salient (Chang 2010). These more parochial interests may lead Americans to place a higher value on the actions of solidarity taken by refugees in their own communities over actions that benefit individuals in other parts of the United States (Kustov 2020). This leads to our second hypothesis.

> **H2:** Advertisements that mention refugees working in the local community targeted by the advertisements will elicit higher clicks to support refugees than advertisements that mention refugees working in more geographically diffuse locations.

Finally, recent work suggests that individuals are more supportive of migrants with severe vulnerabilities (Bansak et al. 2016). Refugee migration is more likely to meet this criterion than is immigration, which is typically understood to be voluntary rather than forced. Additionally, refugee advocates wonder whether labeling a migrant as a refugee or immigrant makes a significant difference in how the public responds. On average, in narratives of doctors helping to fight COVID19, we expect more favorable views about refugee doctors than immigrant doctors.

> **H3:** Advertisements that mention refugee doctors instead of immigrant doctors will elicit higher clicks of support.

We are also interested in how refugee and immigrant profiles compare against simply mentioning doctors (the 'Neither' category in the design Table 1).

> **H3a:** Advertisements that mention refugee doctors or immigrant doctors will elicit different click rates of support compared to advertisements that simply mention doctors.

Our Facebook experimental design will allow us to test hypotheses H1 through H3 in a way that allows for causal inference. Yet the Facebook experimental setup does not allow us to identify what it was about the ad – admittedly a complex treatment – that caught the user's attention, or why it was that the ad had a causal effect. To better interpret our results, we include a Qualtrics survey with measures of attitudinal and behavioral support for refugees, as well as respondent socio-demographic characteristics. Once a user clicks on the ad, she is redirected to this survey. Therefore, while this survey allows us to conduct additional tests to more precisely interpret the identified effects, the sample completing the survey is biased since it inherently results in missing data related to the treatment. As such, we view this portion of the proposed design as an observational study. We try to carefully consider the types of assumptions we can make under an observational study with selection in order to still describe patterns we think may provide evidence in support of our main hypotheses.

First, our Qualtrics survey allows us to explore the mechanisms that underlie our treatment effects. For example, although our ads explicitly say to "click here to support refugees", social science teaches us that anxiety leads to information-seeking (Albertson and Gadarian 2015). Are people seeking more information or expressing their support for refugees when they click on the Facebook ad? To adjudicate between these two mechanisms, our survey measures media consumption and favorability towards refugees. We can rely on a post-treatment average causal mediation effect using twice-matching on the media consumption variable (Blackwell and Strezhnev 2019).

Second, our survey allows us to test the conditions under which individuals increase their engagement with refugee advocates, a question of great interest to organizations like Refugee International. Indeed, our entire experiment offers different levels of engagement, as illustrated by our Consort diagram: a fully-engaged individual will click on the FB ad, consent to taking the survey, complete the survey, and click on the behavioral question to sign up with the Refugee Council USA listserv; a minimally-engaged individual will click on the FB ad and immediately drop off. Our design allows us to identify which respondent-types engage at different levels, and to price out how many fully-engaged individuals an organization attains.

Finally, our survey allows us to collect respondent-level covariates that are otherwise unavailable due to the nature of the Facebook ad platform. While some respondents can drop off from clicking the ad, the remaining provide some if not all pieces of their socioeconomic and attitudinal information. This allows us to consider not only rates of engagement throughout the design, but also which subpopulations are more likely to engage/not-engage. It also means we can assess for controlled direct effects of the ad treatments using respondent-level variables we think might feature in the causal pathway (such as political affiliation, age, etc.; see Acharya et al. 2016).

2.1 Experimental design details

The Facebook experimental design allows only a maximum of five treatment arms per study. We plan to conduct two studies: Study 1 (conditions 1 through 5) will allow us to test H1 and H2. Study 2 (conditions 6 through 10) will allow us to test H1 and H3. The ads themselves and their different versions appear in the Appendix.

Table 1: Facebook experimental design

	Everyday solidarity (refugee Mustafa)				Nurse/Doctor (Dr. Haveli)		
	US	PA	Lancaster	No place	Refugee	Immigrant	Neither
COVID	1	2	3	4	6	7	8
No COVID	5				9		10

The two experiments will use different target audiences on Facebook. For our first experiment about Mustafa, we will specify that any adult Facebook profile within 35 miles of Lancaster, PA can be included in the split test. This provides a potential audience of 450,000 profiles and allows us to test H2 about whether the refugee's actions are taking place within the respondent's local community. For our second experiment about Dr. Kelli, we will specify that any adult Facebook profiles in the United States can be included in the split test. This provides a significantly larger potential audience of 160,000,000 profiles. Of these potential profiles, the actual number who view our ads will be determined by our budget but cannot be precisely defined prior to implementing the experiment. Most Facebook ads receive click rates under 1 percent, and we expect our ads to be similar.

3 Simulations of proposed design

We conduct simulations for Experiments 1 and 2 on ad clicking behavior. For each experiment we then follow with simulations that account for clicking and selecting into answering the survey questions to find whether respondents are differentially favorable towards refugees and differentially willing to click to join the listserv.

Our simulation results for Experiment 1 suggest that the ad-click outcome is well powered with no biases for estimators on our estimands of interest. The effect of answering the survey, or reporting (R), can always be estimated with high power and no bias, even as ρ grows to 0.8. However any design strategy that conditions on the measured version of our survey outcome variables Y_{obs} (such that Y_i is the response variable, whose value is measured as Y_{obs} when $R_i = 1$) suffers from bias, even for the estimands that are conditional on reportion, such that a small amount of correlation (correlation parameter ρ=0.2) between missingness and outcomes can affect inferences. When the correlation is small (ρ is 0.2 rather than 0.8) the amount of bias remains smaller however, in the magnitude of -0.01 to 0.03. As ρ increases to 0.8 however, the magnitude in range grows to $(-0.04, 0.08)$. While the mean estimates differ from the mean estimands, the direction of the effect is captured consistently. The large sample size allows for power to remain quite high throughout. Assumptions made in the simulations of Experiment 1 are found in Tables B.1 and B.2.

For Experiment 2, we use a very similar set up for both the ad-click and survey outcomes as in Experiment 1, only our assumptions on treatment effects differ slightly given that we are testing the refugee and covid primes. These are presented in Tables B.7 and B.8.

Our simulation results for ad-clicking and survey outcomes can be found in the appendix. The classical experiment set up of Experiment 2 ad clicking suggests that our design is well powered with no biases for estimators (difference in means) on our estimands of interest (pair-wise differences of outcomes in expectation under treatment arms). For the survey outcomes, our results suggest that the effect on reporting (R) can always be estimated with high power and no bias, even as ρ grows to 0.8. However any design strategy that conditions on Y_{obs} suffers from bias, even for the estimands that are conditional on reportion, such that a small amount of correlation (0.2) between missingness and outcomes can affect inferences. When the correlation is small (ρ is 0.2 rather than 0.8) the amount of bias remains smaller however, in the magnitude of -0.01 to 0.01, for only three of the ten estimands (among the YR estimands). As the correlation grows to 0.8, this bias increases to ranging from $(-0.02, 0.03)$. Mean estimates are still in the same direction as the mean estimand. Again, the large sample size allows for power to remain quite high throughout. For more on specifics on the simulations, we refer the reader to the appendix, which includes as well as the code to conduct the simulated experiments.

Upon fielding and collecting our experimental data, we plan to use alpha levels of 0.05 as a criteria for statistical inference. We also intend on controlling the false discovery rate with the Benjamini-Hochberg procedure. We note that since Facebook ad data only provides sample population level aggregate statistics of gender, we are unable to conduct traditional covariate-based balance tests.

4 Conclusion: Interpreting effects and nulls

The effect of the COVID-19 pandemic on prejudice and inclusion of the most vulnerable groups among us is not well known. We propose to test the effectiveness of a series of narratives on which refugee advocates rely to boost inclusionary attitudes and behaviors toward migrants in the midst of this crisis. Any evidence consistent with H1–H3 will suggest that it is indeed possible to shape the narrative in an inclusionary manner. Null results, on the other hand, could suggest that a public health crisis the size of COVID-19 limits the potential of these inclusionary narratives to increase engagement with refugee advocacy, and that pro-refugee organizations should look elsewhere for strategies to protect migrants during times of crisis.

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Online Appendix

A Consort diagram

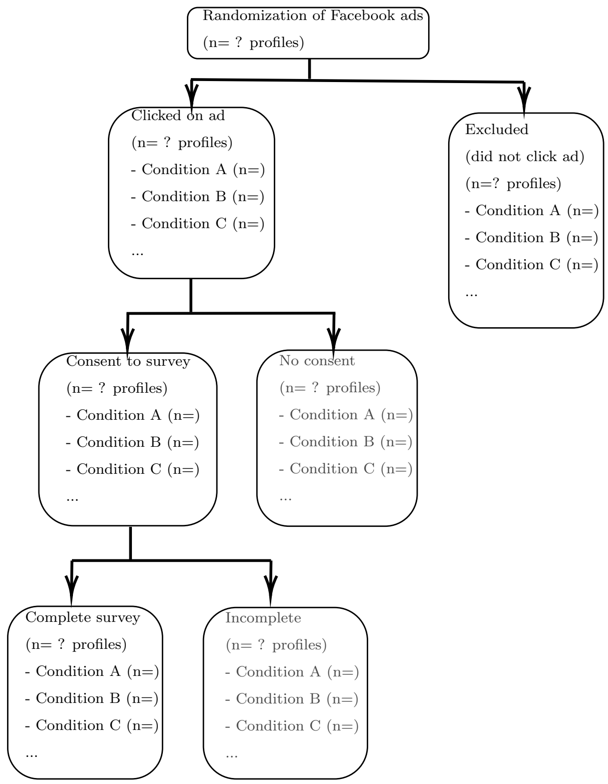

Figure A.1: **Consort diagram of experimental design**. As the exact number of profiles available on Facebook at the point of the intervention is unknown, and attrition rates throughout are unknown in this pre-study, n sizes are denoted with question marks. In the final consort document, we will add the n for each of our 10 experimental conditions.

B Simulation details

We run five hundred simulations for each of the experiments, as well as the pair of follow-up click-to-survey settings, for a total of two thousand simulated experiments. In the ad-click experiments, which are randomized across 450,000 respondents each, we wish to learn whether there is differential support for refugees on Facebook under different treatment arms as proxied by clickong on ads. We specify a data generating process under which potential outcomes are defined according to the treatments received ("Model"), indicate an interest in all pairwise comparisons between treatment arms as our estimands ("Inquiry"), specify a data strategy ("Data strategy") of equal probability assignment to each treatment arm, and present an answer strategy that involves taking the pairwise differences in means corresponding to specific estimands. We are interested in pairwise comparisons across treatments. Throughout the simulations, we make key assumptions on treatment effects, errors, and the existence of interactions.

B.1 Experiment 1: Covid and neighborhood effects

The Facebook ad campaign in experiment 1 is composed of five arms that vary information on covid-19 and the location of Mustafa's community efforts. Table B.1 presents the assumptions we make in our simulations for Experiment 1 design for ad clicking.

Table B.1: Experiment 1 ad click assumptions

Assumption	**Size**
Covid prime effect (versus no covid prime)	0.1
US effect (versus no location)	0.05
Pennsylvania effect (versus no location)	0.075
Lancaster effect (versus no location)	0.08
No interaction effect on average between covid prime and location primes	
Errors drawn from standard normal, with individual standard deviation	0.2

Using `DeclareDesign` (Blair et al. 2019), we form a diagnosis of all the designs. For Experiment 1, our diagnosis can be found in Table B.1 in the Appendix, which presents results on the following diagnosands: bias, root mean squared error (RMSE), power, coverage, mean estimate, standard devation (SD) estimate, mean standard error (SE), type s-rate and mean estimand. The design has over 90% power and coverage over 95%. Similar diagnoses are conducted for the remaining three classes of experiments.

For the survey outcomes upon clicking through Experiment 1, we consider a data generating process that includes a response variable R_i, outcome Y_i, which is correlated with response variable through parameter ρ. Y_i^{obs} is the measured version of Y_i, which is only observed when $R_i = 1$. For our setting, when a respondent is willing to click on the ad and answer the survey $R_i = 1$. Our simulations are conducted with assumptions detailed in Table B.2, including for variation in ρ values we consider in our simulated experiments.

Again, we form a diagnosis of the above design in Experiment 1 in Tables B.4-B.6, in much the same way as the ad-clicking set up.

Table B.2: Experiment 1 assumptions for survey outcomes

	Assumption	**Size**
Effect on R_i		
	T1: Covid prime, location U.S.	0.5
	T2: Covid prime, location Pennsylvania	0.6
	T3: Covid prime, location Lancaster	0.7
	T4: Covid prime, no location information	0.4
	T5: No covid prime, location U.S.	0.2
	No interaction effect on average between covid prime and location primes	
	Error drawn from standard normal	
Effect on Y_i		
	T1: Covid prime, location U.S.	0.5
	T2: Covid prime, location Pennsylvania	0.6
	T3: Covid prime, location Lancaster	0.7
	T4: Covid prime, no location information	0.4
	T5: No covid prime, location U.S.	0.2
	No interaction effect on average between covid prime and location primes	
	Errors drawn from standard normal	
Correlation ρ	ρ	$\{0.0, 0.2, 0.8\}$

We want to learn whether there is differential support for refugees on Facebook, as proxied by clicking on ads. We have a classical randomized experiment and ask whether respondents differentially click on an ad based on its content. We are also interested in respondent attitudes and behaviors, conditional on having clicked on an ad, towards refugees. Respondents are randomly assigned to receive ads with refugees with information on the above five arms. Assignment to each of the five arms is with equal probabilities, and other than mention of covid and location, ads are otherwise identical. We define our primary outcome of interest as the difference in click rates between experimental conditions.

Model We specify a population of size N where a unit i has a potential outcome, $Y_i(Z = 0)$, when it remains untreated and M $(m = 1, 2, ..., M)$ potential outcomes defined according to the treatment that it receives. The effect of each treatment on the outcome of unit i is equal to the difference in the potential outcome under treatment condition m and the control condition: $Y_i(Z = m) - Y_i(Z = 0)$. We simulate a draw of $450,000$ respondents (our sample size via Facebook's ad platform) in this exercise.

Inquiry We are interested in all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$.

Data strategy We randomly assign $N/5 = 90,000$ units to each of the treatment arms.

Answer strategy Take every pairwise difference in means corresponding to the specific estimand.

Table B.1 presents the assumptions we make in our simulations for Experiment 1 design for ad clicking.

Table B.3: Experiment 1 design diagnosands.

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S_Rate	Mean Estimand
ate_Y_2_1	(Z_2 - Z_1)	0.00	0.00	1.00	0.94	0.03	0.00	0.00	0.00	0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	(Z_3 - Z_1)	0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	(Z_3 - Z_2)	-0.00	0.00	1.00	0.96	0.00	0.00	0.00	0.00	0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	(Z_4 - Z_1)	0.00	0.00	1.00	0.95	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	(Z_4 - Z_2)	-0.00	0.00	1.00	0.95	-0.08	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	(Z_4 - Z_3)	0.00	0.00	1.00	0.96	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	(Z_5 - Z_1)	0.00	0.00	1.00	0.96	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	(Z_5 - Z_2)	-0.00	0.00	1.00	0.96	-0.13	0.00	0.00	0.00	-0.12
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	(Z_5 - Z_3)	-0.00	0.00	1.00	0.96	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	(Z_5 - Z_4)	-0.00	0.00	1.00	0.95	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors of all estimates are shown in the rows below. Results are from 500 simulated experiments. The first two columns describe the estimand and estimator of interest, where the name of the treatment arms follow "ate_y", as well as "Z_".

Our secondary outcome of interest is the average refugee thermometer rating conditional on clicking an ad.

Since obtaining the refugee thermometer rating requires respondents to follow through with clicking the ad and answering the survey, we consider this a possible missing data problem, specifically one of attrition which may be affected by the outcome. Since this type of problem can affect both power and inroduce bias, we consider how much attrition might be too much – or how high the correlation between the propensity to be missing and the refugee thermoter rating outcome has to be before the study cannot estimate the estimands of interest.

Again, we are interested in pairwise comparisons across treatments.

Model We specify a model with a population N that has three variables affected by treatment: response variable R_i, outcome (here refugee thermometer rating in the survey) Y_i, which is correlated with response variable through parameter ρ. Y_i^{obs} is the measured version of Y_i, which is only observed when $R_i = 1$. For our setting, when a respondent is willing to click on the ad and answer the survey $R_i = 1$.

Inquiry Here we're interested in knowing the average of all respondents' differences in treatment arm potential outcomes, all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$. But we're also interested in the average treatment effect on reporting $E[R_i(m) - R_i(m')]$ as well as the pairwise comparison between treatment arms among those who report: $E[Y_i(m) - Y_i(m')|R_i = 1]$.

Data strategy Respondents are randomly assigned so that $N/5 = 90,000$ units are in each of the treatment arms.

Answer strategy R_i and Y_i^{obs}, take every pairwise difference in means corresponding to the specific estimand.

Assumptions are detailed in Table B.2, including for variation in ρ values we consider in our simulated experiments.

Again, we form a diagnosis of the above design in Experiment 1 in Tables B.4-B.6, which present results from 500 simulations each on the following diagnosands: bias, root mean squared error (RMSE), power, coverage, mean estimate, standard devation (SD) estimate, mean standard error (SE), type s-rate and mean estimand.

The effect on reporting (R) can always be estimated with high power and no bias, even as ρ grows to 0.8. However any design strategy that conditions on Y_{obs} suffers from bias, even for the estimands that are conditional on reportion, such that a small amount of correlation (0.2) between missingness and outcomes can affect inferences. When the correlation is small (ρ is 0.2 rather than 0.8) the amount of bias remains smaller however, in the magnitude of -0.01 to 0.03. As ρ increases to 0.8 however, the magnitude in range grows to $(-0.04, 0.08)$. While the mean estimates differ from the mean estimands, the direction of the effect is captured consistently. The large sample size allows for power to remain quite high throughout.

Table B.4: Experiment 1 $\rho = 0.0$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	-0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	0.00	0.00	1.00	0.96	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	0.00	0.00	1.00	0.99	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	-0.00	0.00	1.00	0.98	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	-0.00	0.00	1.00	0.98	-0.11	0.00	0.00	0.00	-0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	-0.00	0.00	1.00	0.98	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	-0.00	0.00	1.00	0.98	-0.06	0.00	0.00	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	-0.00	0.01	1.00	0.97	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	0.00	0.01	1.00	0.98	0.20	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	-0.00	0.01	1.00	0.98	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	0.00	0.01	1.00	0.95	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.98	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	-0.00	0.01	1.00	0.97	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	-0.40	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	-0.00	0.01	1.00	0.98	-0.50	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	-0.00	0.01	1.00	0.97	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	-0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	0.00	0.01	1.00	0.96	0.20	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	-0.00	0.01	1.00	0.98	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	-0.00	0.01	1.00	0.96	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	-0.00	0.01	1.00	0.97	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	-0.00	0.01	1.00	0.96	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	-0.40	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	-0.00	0.01	1.00	0.95	-0.50	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	-0.00	0.01	1.00	0.96	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.5: Experiment 1 $\rho = 0.2$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	-0.00	0.00	1.00	0.98	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	0.00	0.00	1.00	0.97	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	0.00	0.00	1.00	0.97	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	0.00	0.00	1.00	0.97	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	0.00	0.00	1.00	0.96	-0.11	0.00	0.00	0.00	-0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	0.00	0.00	1.00	0.97	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	0.00	0.00	1.00	0.96	-0.06	0.00	0.00	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	-0.00	0.01	1.00	0.97	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	0.00	0.01	1.00	0.96	0.20	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	-0.00	0.01	1.00	0.98	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	0.00	0.01	1.00	0.97	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.97	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	-0.00	0.01	1.00	0.95	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	0.00	0.01	1.00	0.96	-0.40	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	-0.00	0.01	1.00	0.94	-0.50	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	-0.00	0.01	1.00	0.97	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	-0.01	0.01	1.00	0.93	0.09	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	-0.01	0.01	1.00	0.79	0.19	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.00	0.01	1.00	0.93	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.01	0.01	1.00	0.94	-0.09	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.01	0.01	1.00	0.75	-0.19	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.01	0.02	1.00	0.56	-0.28	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	0.02	0.02	1.00	0.50	-0.28	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	0.02	0.02	1.00	0.24	-0.38	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	0.03	0.03	1.00	0.14	-0.47	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	0.01	0.01	1.00	0.76	-0.19	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.6: Experiment 1 $\rho = 0.8$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	-0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	-0.00	0.00	1.00	0.97	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	-0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	-0.00	0.00	1.00	0.97	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	0.00	0.00	1.00	0.97	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	-0.00	0.00	1.00	0.97	-0.08	0.00	0.00	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	0.00	0.00	1.00	0.96	-0.11	0.00	0.00	0.00	-0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	0.00	0.00	1.00	0.97	-0.13	0.00	0.00	0.00	-0.13
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	-0.00	0.00	1.00	0.97	-0.06	0.00	0.00	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	0.00	0.01	1.00	0.97	0.20	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	-0.00	0.01	1.00	0.97	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	0.00	0.01	1.00	0.98	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	-0.00	0.01	1.00	0.97	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.97	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	-0.00	0.01	1.00	0.96	-0.30	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	-0.40	0.01	0.01	0.00	-0.40
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	-0.00	0.01	1.00	0.97	-0.50	0.01	0.01	0.00	-0.50
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	-0.00	0.01	1.00	0.95	-0.20	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	-0.02	0.02	1.00	0.30	0.08	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	-0.04	0.04	1.00	0.00	0.16	0.01	0.01	0.00	0.20
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.02	0.02	1.00	0.31	0.08	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.02	0.02	1.00	0.22	-0.08	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.04	0.04	1.00	0.00	-0.16	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.06	0.06	1.00	0.00	-0.24	0.01	0.01	0.00	-0.29
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	0.07	0.07	1.00	0.00	-0.23	0.01	0.01	0.00	-0.30
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	0.08	0.09	1.00	0.00	-0.31	0.01	0.01	0.00	-0.39
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	0.10	0.10	1.00	0.00	-0.39	0.01	0.01	0.00	-0.49
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	0.04	0.04	1.00	0.00	-0.15	0.01	0.01	0.00	-0.20
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

B.2 Experiment 2: Covid and refugee effects

Our second Facebook ad campaign experiment is composed of five arms that vary information on covid-19 and whether Dr. Kelli is a refugee, immigrant or no mention of either. Again, we wish to learn whether there is differential support for refugee ads on Facebook. Respondents are randomly assigned to receive ads with refugees with information on the above five arms. Assignment to each of the five arms is with equal probabilities, and other then mention of covid and type of individual (refugee, immigrant, neither), ads otherwise identical. We define our first outcome of interest as the difference in click rates between experimental conditions.

Table B.7 presents the assumptions we make in our simulations for Experiment 2 design for ad clicking.

Table B.7: Experiment 2 ad click assumptions

Assumption	**Size**
Covid prime effect (versus no covid prime)	0.1
Refugee effect (versus neither)	0.075
Immigrant effect (versus neither)	0.025
Effect of mentioning neither (for type of respondent)	0.00
No interaction effect on average between covid prime and profile type primes	
Errors drawn from standard normal, with individual standard deviation	0.2

Our design is similarly declared as in Experiment 1 (see 'Model, Inquiry, Data Strategy, Answer Strategy'), including $N = 450000$ and $N/5$ units in each of the treatment arms. The resulting diagnosis of the ad click rate can be found in Table B.2. For the outcomes measured in the survey, measured conditional on clicking an ad, we utilize a similar design as Experiment 1. Assumptions are detailed in Table B.8, including for variation in ρ values we consider in our simulated experiments.

Table B.8: Experiment 2 assumptions for survey outcomes

	Assumption	**Size**
Effect on R_i		
	T1: Covid prime, refugee	0.375
	T2: No covid prime, refugee	0.275
	T3: Covid prime, no type	0.3
	T4: No covid prime, no type	0.22
	T5: Covid prime, immigrant	0.325
	No interaction effect on average between covid prime and type of profiles	
	Errors drawn from standard normal	
Effect on Y_i		
	T1: Covid prime, refugee	0.175
	T2: No covid prime, refugee	0.075
	T3: Covid prime, no type	0.1
	T4: No covid prime, no type	0.02
	T5: Covid prime, immigrant	0.125
	No interaction effect on average between covid prime and type of profiles	
	Errors drawn from standard normal	
Correlation ρ	ρ	$\{0.0, 0.2, 0.8\}$

Table B.9: Experiment 2 design diagnosands.

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S_Rate	Mean Estimand
ate_Y_2_1	(Z_2 - Z_1)	0.00	0.00	1.00	0.94	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	(Z_3 - Z_1)	0.00	0.00	1.00	0.96	-0.07	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	(Z_3 - Z_2)	-0.00	0.00	1.00	0.96	0.02	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	(Z_4 - Z_1)	0.00	0.00	1.00	0.95	-0.17	0.00	0.00	0.00	-0.17
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	(Z_4 - Z_2)	-0.00	0.00	1.00	0.95	-0.08	0.00	0.00	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	(Z_4 - Z_3)	0.00	0.00	1.00	0.96	-0.10	0.00	0.00	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	(Z_5 - Z_1)	0.00	0.00	1.00	0.96	-0.05	0.00	0.00	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	(Z_5 - Z_2)	-0.00	0.00	1.00	0.96	0.05	0.00	0.00	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	(Z_5 - Z_3)	-0.00	0.00	1.00	0.96	0.02	0.00	0.00	0.00	0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	(Z_5 - Z_4)	-0.00	0.00	1.00	0.95	0.12	0.00	0.00	0.00	0.12
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors of all estimates are shown in the rows below. Results are from 500 simulated experiments. The first two columns describe the estimand and estimator of interest, where the name of the treatment arms follow "ate_y", as well as "Z_".

We form a diagnosis of the above design in Experiment 2 in Tables **??**-B.12, which present results on all previously used diagnosands. Simulation code follows.

Table B.10: Experiment 2 $\rho = 0.0$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	0.00	0.00	1.00	0.96	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	0.00	0.00	0.85	0.97	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	0.00	0.00	1.00	0.96	-0.04	0.00	0.00	0.00	-0.04
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	-0.00	0.00	1.00	0.96	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	-0.00	0.00	1.00	0.95	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	0.00	0.00	1.00	0.97	-0.01	0.00	0.00	0.00	-0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	0.00	0.00	1.00	0.96	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	-0.00	0.00	0.83	0.97	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	0.00	0.00	1.00	0.96	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	0.00	0.01	1.00	0.95	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	0.00	0.01	1.00	0.97	-0.07	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	0.00	0.01	0.96	0.96	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	0.00	0.01	1.00	0.97	-0.15	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	0.00	0.01	1.00	0.95	-0.05	0.01	0.01	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	0.00	0.01	1.00	0.95	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	0.00	0.01	1.00	0.95	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	-0.00	0.01	0.96	0.96	0.02	0.01	0.01	0.00	0.03
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	-0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	0.00	0.01	1.00	0.95	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	-0.00	0.01	1.00	0.96	-0.07	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.00	0.01	0.80	0.97	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.00	0.01	1.00	0.97	-0.15	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.00	0.01	1.00	0.94	-0.05	0.01	0.01	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.00	0.01	1.00	0.96	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	-0.00	0.01	1.00	0.97	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	0.00	0.01	0.82	0.96	0.03	0.01	0.01	0.00	0.03
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	-0.00	0.01	1.00	0.96	0.10	0.01	0.01	0.00	0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.11: Experiment 2 $\rho = 0.2$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	0.00	0.00	1.00	0.97	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	-0.00	0.00	0.82	0.96	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	0.00	0.00	1.00	0.96	-0.04	0.00	0.00	0.00	-0.04
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	-0.00	0.00	1.00	0.97	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.95	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	-0.00	0.00	1.00	0.96	-0.01	0.00	0.00	0.00	-0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	-0.00	0.00	1.00	0.98	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	-0.00	0.00	0.83	0.97	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	-0.00	0.00	1.00	0.97	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	-0.00	0.01	1.00	0.95	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	-0.00	0.01	1.00	0.97	-0.08	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	-0.00	0.01	0.96	0.94	0.03	0.01	0.01	0.00	0.03
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	-0.00	0.01	1.00	0.95	-0.16	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	-0.00	0.01	1.00	0.96	-0.06	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.96	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	-0.00	0.01	1.00	0.95	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	0.00	0.01	1.00	0.95	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	0.00	0.01	0.96	0.96	0.03	0.01	0.01	0.00	0.02
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	0.00	0.01	1.00	0.96	0.11	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	0.01	0.01	1.00	0.89	-0.09	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	0.00	0.01	1.00	0.93	-0.07	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.00	0.01	0.77	0.96	0.02	0.01	0.01	0.00	0.03
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.01	0.01	1.00	0.84	-0.15	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.00	0.01	1.00	0.96	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.00	0.01	1.00	0.93	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	0.00	0.01	1.00	0.95	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	-0.00	0.01	1.00	0.95	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	-0.00	0.01	0.79	0.96	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	-0.01	0.01	1.00	0.91	0.10	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

Table B.12: Experiment 2 $\rho = 0.8$

Estimand	Estimator	Bias	RMSE	Power	Coverage	Mean Estimate	SD Estimate	Mean SE	Type S Rate	Mean Estimand
ate_R_2_1	R(Z_2 - Z_1)	-0.00	0.00	1.00	0.96	-0.03	0.00	0.00	0.00	-0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_1	R(Z_3 - Z_1)	-0.00	0.00	1.00	0.98	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_3_2	R(Z_3 - Z_2)	-0.00	0.00	0.83	0.96	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_1	R(Z_4 - Z_1)	-0.00	0.00	1.00	0.97	-0.04	0.00	0.00	0.00	-0.04
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_2	R(Z_4 - Z_2)	-0.00	0.00	1.00	0.96	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_4_3	R(Z_4 - Z_3)	0.00	0.00	1.00	0.95	-0.02	0.00	0.00	0.00	-0.02
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_1	R(Z_5 - Z_1)	0.00	0.00	1.00	0.98	-0.01	0.00	0.00	0.00	-0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_2	R(Z_5 - Z_2)	0.00	0.00	1.00	0.96	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_3	R(Z_5 - Z_3)	0.00	0.00	0.84	0.95	0.01	0.00	0.00	0.00	0.01
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_R_5_4	R(Z_5 - Z_4)	0.00	0.00	1.00	0.97	0.03	0.00	0.00	0.00	0.03
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_2_1	Y(Z_2 - Z_1)	0.00	0.01	1.00	0.97	-0.10	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_1	Y(Z_3 - Z_1)	-0.00	0.01	1.00	0.96	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_3_2	Y(Z_3 - Z_2)	-0.00	0.01	0.96	0.98	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_1	Y(Z_4 - Z_1)	-0.00	0.01	1.00	0.96	-0.16	0.01	0.01	0.00	-0.16
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_2	Y(Z_4 - Z_2)	-0.00	0.01	1.00	0.96	-0.06	0.01	0.01	0.00	-0.06
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_4_3	Y(Z_4 - Z_3)	-0.00	0.01	1.00	0.97	-0.08	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_1	Y(Z_5 - Z_1)	0.00	0.01	1.00	0.97	-0.05	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_2	Y(Z_5 - Z_2)	-0.00	0.01	1.00	0.96	0.05	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_3	Y(Z_5 - Z_3)	0.00	0.01	0.96	0.98	0.03	0.01	0.01	0.00	0.03
		0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00
ate_Y_5_4	Y(Z_5 - Z_4)	0.00	0.01	1.00	0.96	0.11	0.01	0.01	0.00	0.11
		0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_2_1	Y_{obs}(Z_2 - Z_1)	0.02	0.02	1.00	0.23	-0.08	0.01	0.01	0.00	-0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_3_1	Y_{obs}(Z_3 - Z_1)	0.02	0.02	1.00	0.48	-0.06	0.01	0.01	0.00	-0.07
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_3_2	Y_{obs}(Z_3 - Z_2)	-0.01	0.01	0.60	0.89	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_4_1	Y_{obs}(Z_4 - Z_1)	0.03	0.04	1.00	0.01	-0.12	0.01	0.01	0.00	-0.15
		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ate_YR_4_2	Y_{obs}(Z_4 - Z_2)	0.01	0.01	1.00	0.73	-0.04	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_4_3	Y_{obs}(Z_4 - Z_3)	0.02	0.02	1.00	0.41	-0.06	0.01	0.01	0.00	-0.08
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_1	Y_{obs}(Z_5 - Z_1)	0.01	0.01	1.00	0.72	-0.04	0.01	0.01	0.00	-0.05
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_2	Y_{obs}(Z_5 - Z_2)	-0.01	0.01	1.00	0.71	0.04	0.01	0.01	0.00	0.05
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
ate_YR_5_3	Y_{obs}(Z_5 - Z_3)	-0.01	0.01	0.64	0.90	0.02	0.01	0.01	0.00	0.02
		0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
ate_YR_5_4	Y_{obs}(Z_5 - Z_4)	-0.02	0.02	1.00	0.19	0.08	0.01	0.01	0.00	0.10
		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors below each estimand-estimator combination.

B.3 Simulation code

Design for "Refugee narratives and public opinion during the COVID-19 pandemic"

this ver: Thursday April 30, 2020

We're going to use *DeclareDesign*.

```
knitr::opts_chunk$set(echo = TRUE)
install.packages(c("DeclareDesign", "fabricatr", "randomizr", "estimatr", "DesignLibrary"))
library(DeclareDesign)
library(fabricatr)
library(randomizr)
library(estimatr)
library(DesignLibrary)
library(tidyverse)
library(kableExtra)
library(xtable)
```

For hypotheses please refer to main text.

Experiment 1: 5 arms

- T1 = covid - US
- T2 = covid - PA
- T3 = covid - Lancaster
- T4 = covid - No location
- T5 = no covid - US

We want to learn whether there is differential support for refugee ads on Facebook. Respondents are randomly assigned to receive ads with refugees with information on the above five arms. Assignment to each of the five arms is with equal probabilities, and other then mention of covid and location, ads otherwise identical. We define our outcome of interest as the difference in click rates between experimental conditions.

In settings of multiple treatment arms, we could do a number of pairwise comparisons: across treatments and each treatment against control.

Design Declaration A

- Model:

We specify a population of size N where a unit i has a potential outcome, $Y_i(Z = 0)$, when it remains untreated and M $(m = 1, 2, \cdots, M)$ potential outcomes defined according to the treatment that it receives. The effect of each treatment on the outcome of unit i is equal to the difference in the potential outcome under treatment condition m and the control condition: $Y_i(Z = m) - Y_i(Z = 0)$.

- Inquiry:

We are interested in all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$.

- Data strategy:

We randomly assign k/N units to each of the treatment arms.

- Answer strategy:

Take every pairwise difference in means corresponding to the specific estimand.

```
set.seed(123)
N <- 450000 #450K
covid_effect<-0.1
us_effect<-0.05
pa_effect<-0.075
lancaster_effect<-0.08
outcome_means <- c(covid_effect+us_effect #covid-us
                   ,covid_effect+pa_effect #covid-pa
                   ,covid_effect+lancaster_effect #covid-lancaster
                   ,covid_effect #covid-nolocation
                   ,us_effect #nocovid-us
                   )
sd_i <- 0.2
outcome_sds <- c(0, 0, 0, 0, 0)

# Population
population <- declare_population(N = N, u_1 = rnorm(N, 0, outcome_sds[1L]),
    u_2 = rnorm(N, 0, outcome_sds[2L]), u_3 = rnorm(N, 0, outcome_sds[3L]),
    u_4 = rnorm(N, 0, outcome_sds[4L]), u_5 = rnorm(N, 0, outcome_sds[5L]),
    u = rnorm(N) * sd_i)
# Potential outcomes
potential_outcomes <- declare_potential_outcomes(formula = Y ~ (outcome_means[1] +
    u_1) * (Z == "1") + (outcome_means[2] + u_2) * (Z == "2") +
    (outcome_means[3] + u_3) * (Z == "3") + (outcome_means[4] +
    u_4) * (Z == "4") + + (outcome_means[5] +
    u_5) * (Z == "5") + u ,  conditions = c("1", "2", "3", "4", "5"),
    assignment_variables = Z)
# Estimands
estimand <- declare_estimands(ate_Y_2_1 = mean(Y_Z_2 - Y_Z_1), ate_Y_3_1 = mean(Y_Z_3 -
    Y_Z_1), ate_Y_4_1 = mean(Y_Z_4 - Y_Z_1), ate_Y_5_1 = mean(Y_Z_5 - Y_Z_1),
    ate_Y_3_2 = mean(Y_Z_3 - Y_Z_2), ate_Y_4_2 = mean(Y_Z_4 - Y_Z_2),
    ate_Y_5_2 = mean(Y_Z_5 - Y_Z_2), ate_Y_4_3 = mean(Y_Z_4 -
    Y_Z_3), ate_Y_5_3 = mean(Y_Z_5 - Y_Z_3), ate_Y_5_4 = mean(Y_Z_5 - Y_Z_4))
# Assignment
assignment <- declare_assignment(num_arms = 5, conditions = c("1", "2", "3",
"4","5"), assignment_variable = Z)
reveal_Y <- declare_reveal(assignment_variables = Z)
# Estimator
estimator <- declare_estimator(handler = function(data) {
    estimates <- rbind.data.frame(
      ate_Y_2_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_Y_3_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_Y_4_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_Y_5_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_Y_3_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_Y_4_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_Y_5_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_Y_4_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_Y_5_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_Y_5_4 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "4", condition2 = "5")
      )
```

```
    names(estimates)[names(estimates) == "N"] <- "N_DIM"
    estimates$estimator_label <- c("DIM (Z_2 - Z_1)", "DIM (Z_3 - Z_1)",
    "DIM (Z_4 - Z_1)", "DIM (Z_5 - Z_1)","DIM (Z_3 - Z_2)", "DIM (Z_4 - Z_2)", "DIM (Z_5 - Z_2)",
    "DIM (Z_4 - Z_3)", "DIM (Z_5 - Z_3)", "DIM (Z_5 - Z_4)")
    estimates$estimand_label <- rownames(estimates)
    estimates$estimate <- estimates$coefficients
    estimates$term <- NULL
    return(estimates)
})
multi_arm_design <- population + potential_outcomes + assignment +
    reveal_Y + estimand + estimator

# Diagnose Experiment 1 ad click rate:
t<-Sys.time()
diagnosis <- diagnose_design(multi_arm_design,diagnosands=)
Sys.time()-t
saveRDS(diagnosis,file="diagnosis-1.rds")

dat1<-diagnosis$diagnosands_df[,c("estimand_label","estimator_label","bias","rmse","power","coverage","
dat2<-diagnosis$diagnosands_df[,c("estimand_label","estimator_label","se(bias)","se(rmse)","se(power)",
dat2$estimand_label<-NA
dat2$estimator_label<-NA
tmp_n<-nrow(dat1)+nrow(dat2)
dat<-data.frame(Estimand=rep(NA,tmp_n),Estimator=rep(NA,tmp_n)
                ,Bias=rep(NA,tmp_n),RMSE=rep(NA,tmp_n)
                ,Power=rep(NA,tmp_n),Coverage=rep(NA,tmp_n)
                ,Mean_Estimate=rep(NA,tmp_n),SD_Estimate=rep(NA,tmp_n)
                ,Mean_SE=rep(NA,tmp_n) ,Type_S_Rate=rep(NA,tmp_n)
                ,Mean_Estimand=rep(NA,tmp_n),N_Sims=rep(NA,tmp_n))

j1<-j2<-1
for(i in 1:tmp_n){
  if(i%%2==0){
  dat[i,]<-dat2[j2,]
  j2<-j2+1
  }else{
  dat[i,]<-dat1[j1,]
  j1<-j1+1
  }
}
print(xtable(dat[,1:(ncol(dat)-1)],digits=2), include.rownames=FALSE)
```

Outcome of refugee thermometer, after clicking on ad:

Some respondents will not have thermometer ratings because of not clicking on the ads to be routed to the surveys; we can consider this as a type of attrition/missing data. This can affect both power and bias.

As such, we set up a design that accounts for attrition.

Design Declaration B

- Model:

We specify a model with a population N that has three variables affected by treatment: response variable R_i, outcome (here refugee thermometer rating in the survey) Y_i, which is correlated with response variable through parameter ρ. Y_i^{obs} is the measured version of Y_i, which is only observed when $R_i = 1$. For our setting, when a respondent is willing to click on the ad and answer the survey $R_i = 1$.

- Inquiry:

Here we're interested in knowing the average of all respondents' differences in treatment arm potential outcomes, all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$. But we're also interested in the average treatment effect on reporting $E[R_i(m) - R_i(m')]$ as well as the pairwise comparison between treatment arms among those who report: $E[Y_i(m) - Y_i(m')|R_i = 1]$.

- Data strategy:

We randomly assign $N/k = 90,000$ units to each of the treatment arms.

- Answer strategy:

R_i and Y_i^{obs}, take every pairwise difference in means corresponding to the specific estimand.

Experiment 1: 5 arms

- T1 = covid - US
- T2 = covid - PA
- T3 = covid - Lancaster
- T4 = covid - No location
- T5 = no covid - US

```r
#Starting parameters
N <- 450000
a_R <- 0
#Likelihood of responding to survey after exposed to treatment arm: let covid effect on going to survey
b1_R <- 0.5 #covid - US
b2_R <- 0.6 #covid - PA
b3_R <- 0.7 #covid - Lancaster
b4_R <- 0.4 #covid - No location (-0.1 from US)
b5_R <- 0.2 #no covid - US
a_Y <- 0
#Effect on thermometer rating after exposed to treatment arm:
b1_Y <- 0.5   #covid - US
b2_Y <- 0.6   #covid - PA
b3_Y <- 0.7   #covid - Lancaster
b4_Y <- 0.4   #covid - No location (-0.1 from US)
b5_Y <- 0.2   #no covid - US
#correl
rho <- c(0.0,0.2,0.8)

#set up
t<-Sys.time()
for(i in 1:3){
  cat("Start Design:",i,"\n")
#Population
population <- declare_population(N = N, u = rnorm(N), v=rnorm(N)
              ,u1_R = rnorm(N),u2_R = rnorm(N),u3_R = rnorm(N),u4_R = rnorm(N),u5_R = rnorm(N)
              ,u1_Y = rnorm(N,mean = rho[i] * u1_R, sd = sqrt(1 - rho[i]^2)),u2_Y = rnorm(N,mean = rho[
              ,u3_Y = rnorm(N,mean = rho[i] * u3_R, sd = sqrt(1 - rho[i]^2)),u4_Y = rnorm(N,mean = rho[
              ,u5_Y = rnorm(N,mean = rho[i] * u5_R, sd = sqrt(1 - rho[i]^2))
              ) #one error eqn Y; one error eqn R;  errors for each condition in R; errors for each con
#Potential outcomes
  #R
```

```r
potential_outcomes_R <- declare_potential_outcomes(
  R ~ (a_R + b1_R + u1_R)* (Z == "1") + (a_R + b2_R + u2_R)* (Z == "2")
  + (a_R + b3_R + u3_R)* (Z == "3") + (a_R + b4_R + u4_R)* (Z == "4")
  + (a_R + b5_R + u5_R)* (Z == "5") > v, conditions = c("1", "2", "3", "4", "5"), assignment_variables =
  #Y
potential_outcomes_Y <- declare_potential_outcomes(
  Y ~ (a_Y + b1_Y + u1_Y)* (Z == "1") + (a_Y + b2_Y + u2_Y)* (Z == "2")
  + (a_Y + b3_Y + u3_Y)* (Z == "3") + (a_Y + b4_Y + u4_Y)* (Z == "4")
  + (a_Y + b5_Y + u5_Y)* (Z == "5") + u, conditions = c("1", "2", "3", "4", "5"), assignment_variables =
#Estimands: 3 types -- ATE on R, ATE on Y, ATE on Y|R
estimand <- declare_estimands(
  #ATE on R
  ate_R_2_1 = mean(R_Z_2 - R_Z_1), ate_R_3_1 = mean(R_Z_3 - R_Z_1), ate_R_4_1 = mean(R_Z_4 - R_Z_1), ate
  ate_R_3_2 = mean(R_Z_3 - R_Z_2), ate_R_4_2 = mean(R_Z_4 - R_Z_2), ate_R_5_2 = mean(R_Z_5 - R_Z_2),
  ate_R_4_3 = mean(R_Z_4 - R_Z_3), ate_R_5_3 = mean(R_Z_5 - R_Z_3), ate_R_5_4 = mean(R_Z_5 - R_Z_4)
  #ATE on Y
  ,ate_Y_2_1 = mean(Y_Z_2 - Y_Z_1), ate_Y_3_1 = mean(Y_Z_3 - Y_Z_1), ate_Y_4_1 = mean(Y_Z_4 - Y_Z_1), a
  ate_Y_3_2 = mean(Y_Z_3 - Y_Z_2), ate_Y_4_2 = mean(Y_Z_4 - Y_Z_2), ate_Y_5_2 = mean(Y_Z_5 - Y_Z_2),
  ate_Y_4_3 = mean(Y_Z_4 - Y_Z_3), ate_Y_5_3 = mean(Y_Z_5 - Y_Z_3), ate_Y_5_4 = mean(Y_Z_5 - Y_Z_4)
  #ATE on Y|R
  ,ate_YR_2_1 = mean((Y_Z_2 - Y_Z_1)[R == 1]), ate_YR_3_1 = mean((Y_Z_3 - Y_Z_1)[R == 1])
  ,ate_YR_4_1 = mean((Y_Z_4 - Y_Z_1)[R == 1]), ate_YR_5_1 = mean((Y_Z_5 - Y_Z_1)[R == 1])
  ,ate_YR_3_2 = mean((Y_Z_3 - Y_Z_2)[R == 1]), ate_YR_4_2 = mean((Y_Z_4 - Y_Z_2)[R == 1])
  ,ate_YR_5_2 = mean((Y_Z_5 - Y_Z_2)[R == 1]), ate_YR_4_3 = mean((Y_Z_4 - Y_Z_3)[R == 1])
  ,ate_YR_5_3 = mean((Y_Z_5 - Y_Z_3)[R == 1]), ate_YR_5_4 = mean((Y_Z_5 - Y_Z_4)[R == 1])
  )
#Assignment
assignment <- declare_assignment(num_arms = 5, conditions = c("1", "2", "3", "4", "5"), assignment_vari
#Reveal/Observed: ??
reveal <- declare_reveal(outcome_variables = c("R", "Y"), assignment_variables = Z)
observed <- declare_step(Y_obs = ifelse(R, Y, NA), handler = fabricate)

#Estimator
estimator <- declare_estimator(handler = function(data) {
    estimates <- rbind.data.frame(
      #ATE on R
      ate_R_2_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_R_3_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_R_4_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_R_5_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_R_3_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_R_4_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_R_5_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_R_4_3 = difference_in_means(formula = R ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_R_5_3 = difference_in_means(formula = R ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_R_5_4 = difference_in_means(formula = R ~ Z, data = data, condition1 = "4", condition2 = "5")
      # ATE on Y conditional on R
      ate_YR_2_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_3_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_4_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_5_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_3_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_4_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
```

```
      ate_YR_5_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_4_3 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "3", condition2 =
      ate_YR_5_3 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "3", condition2 =
      ate_YR_5_4 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "4", condition2 =
      #ATE on Y
      ate_Y_2_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_Y_3_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_Y_4_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_Y_5_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_Y_3_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_Y_4_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_Y_5_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_Y_4_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_Y_5_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_Y_5_4 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "4", condition2 = "5")
      )
    names(estimates)[names(estimates) == "N"] <- "N_DIM"
    estimates$estimator_label <- c(
      #R
      "DIM_R (Z_2 - Z_1)", "DIM_R (Z_3 - Z_1)", "DIM_R (Z_4 - Z_1)", "DIM_R (Z_5 - Z_1)","DIM_R (Z_3 - Z
      , "DIM_R (Z_4 - Z_2)", "DIM_R (Z_5 - Z_2)", "DIM_R (Z_4 - Z_3)", "DIM_R (Z_5 - Z_3)", "DIM_R (Z_5
      #Y|R
      , "DIM_Y_obs (Z_2 - Z_1)", "DIM_Y_obs (Z_3 - Z_1)", "DIM_Y_obs (Z_4 - Z_1)", "DIM_Y_obs (Z_5 - Z_
      , "DIM_Y_obs (Z_4 - Z_2)", "DIM_Y_obs (Z_5 - Z_2)", "DIM_Y_obs (Z_4 - Z_3)", "DIM_Y_obs (Z_5 - Z_
      #Y
      ,"DIM_Y (Z_2 - Z_1)", "DIM_Y (Z_3 - Z_1)", "DIM_Y (Z_4 - Z_1)", "DIM_Y (Z_5 - Z_1)","DIM_Y (Z_3 -
      , "DIM_Y (Z_4 - Z_2)", "DIM_Y (Z_5 - Z_2)", "DIM_Y (Z_4 - Z_3)", "DIM_Y (Z_5 - Z_3)", "DIM_Y (Z_5
      )
    estimates$estimand_label <- rownames(estimates)
    estimates$estimate <- estimates$coefficients
    estimates$term <- NULL
    return(estimates)
})
multi_arm_attrition_design <- population + potential_outcomes_R +
    potential_outcomes_Y + assignment + reveal + observed +
    estimand + estimator
diagnoses <- diagnose_design(multi_arm_attrition_design)
saveRDS(diagnoses,paste("multi_arm_attrition_design-rho",i,".rds",sep=""))
cat("Finished Design:",i," in ", Sys.time()-t,"\n")
}
Sys.time()-t


# Combine and print xtable
rho1<-readRDS("multi_arm_attrition_design-rho1.rds")
rho2<-readRDS("multi_arm_attrition_design-rho2.rds")
rho3<-readRDS("multi_arm_attrition_design-rho3.rds")
dat1<-rho1$diagnosands_df
dat1$design_label<-"rho=0.0"
dat2<-rho2$diagnosands_df
dat2$design_label<-"rho=0.2"
dat3<-rho3$diagnosands_df
dat3$design_label<-"rho=0.8"
```

```
dat<-rbind(dat1,dat2,dat3)

dat1<-dat[,c("design_label","estimand_label","estimator_label","bias","rmse","power","coverage","mean_e
dat2<-dat[,c("design_label","estimand_label","estimator_label","se(bias)","se(rmse)","se(power)","se(co


dat2$estimand_label<-NA
dat2$estimator_label<-NA

tmp_n<-nrow(dat1)+nrow(dat2)
d<-data.frame(Design=rep(NA,tmp_n),Estimand=rep(NA,tmp_n),Estimator=rep(NA,tmp_n)
                ,Bias=rep(NA,tmp_n),RMSE=rep(NA,tmp_n)
                ,Power=rep(NA,tmp_n),Coverage=rep(NA,tmp_n)
                ,Mean_Estimate=rep(NA,tmp_n),SD_Estimate=rep(NA,tmp_n)
                ,Mean_SE=rep(NA,tmp_n) ,Type_S_Rate=rep(NA,tmp_n)
                ,Mean_Estimand=rep(NA,tmp_n),N_Sims=rep(NA,tmp_n))

j1<-j2<-1
for(i in 1:tmp_n){
  if(i%%2==0){
  d[i,]<-dat2[j2,]
  j2<-j2+1
  }else{
  d[i,]<-dat1[j1,]
  j1<-j1+1
  }
}
print(xtable(d[1:60,2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.0

print(xtable(d[61:120,2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.2

print(xtable(d[121:nrow(d),2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.8
```

Experiment 2: 5 arms

- T1 = covid - Refugee
- T2 = no covid - Refugee
- T3 = covid - Neither
- T4 = no covid - Neither
- T5 = covid - Immigrant

We want to learn whether there is differential support for refugee ads on Facebook. Respondents are randomly assigned to receive ads with refugees with information on the above five arms. Assignment to each of the five arms is with equal probabilities, and other then mention of covid and type of individual, ads otherwise identical. We define our outcome of interest as the difference in click rates between experimental conditions.

We'll focus on pairwise comparisons across treatments (a conservative approach given our main hypotheses will be answered with comparisons of T1-T2, T2-T4, T3-T4, T1-T5, T3-T5).

Design Declaration A

- Model:

We specify a population of size N where a unit i has a potential outcome, $Y_i(Z=0)$, when it remains untreated and M $(m = 1, 2, \cdots, M)$ potential outcomes defined according to the treatment that it receives.

The effect of each treatment on the outcome of unit i is equal to the difference in the potential outcome under treatment condition m and the control condition: $Y_i(Z = m) - Y_i(Z = 0)$.

- Inquiry:

We are interested in all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$.

- Data strategy:

We randomly assign k/N units to each of the treatment arms.

- Answer strategy:

Take every pairwise difference in means corresponding to the specific estimand.

```r
set.seed(123)
N <- 450000 #450K
covid_effect<-0.1 #assume same covid effect as Experiment 1
refugee_effect<-0.075 #assume refugee effect is positive and larger than immigrant
immigrant_effect<-0.025 #assume immigrant effect is positive and smaller than refugee effect
outcome_means <- c(covid_effect+refugee_effect #covid - Refugee
                   ,refugee_effect #no covid - Refugee
                   ,covid_effect#covid - Neither
                   ,0 #no covid - Neither; assume no effect of ad
                   ,covid_effect+immigrant_effect#covid - Immigrant
                   )# also assumes that there are no interaction effects
sd_i <- 0.2
outcome_sds <- c(0, 0, 0, 0, 0)

# Population
population <- declare_population(N = N, u_1 = rnorm(N, 0, outcome_sds[1L]),
    u_2 = rnorm(N, 0, outcome_sds[2L]), u_3 = rnorm(N, 0, outcome_sds[3L]),
    u_4 = rnorm(N, 0, outcome_sds[4L]), u_5 = rnorm(N, 0, outcome_sds[5L]),
    u = rnorm(N) * sd_i)
# Potential outcomes
potential_outcomes <- declare_potential_outcomes(formula = Y ~ (outcome_means[1] +
    u_1) * (Z == "1") + (outcome_means[2] + u_2) * (Z == "2") +
    (outcome_means[3] + u_3) * (Z == "3") + (outcome_means[4] +
    u_4) * (Z == "4") + + (outcome_means[5] +
    u_5) * (Z == "5") + u ,  conditions = c("1", "2", "3", "4", "5"),
    assignment_variables = Z)
# Estimands
estimand <- declare_estimands(ate_Y_2_1 = mean(Y_Z_2 - Y_Z_1), ate_Y_3_1 = mean(Y_Z_3 -
    Y_Z_1), ate_Y_4_1 = mean(Y_Z_4 - Y_Z_1), ate_Y_5_1 = mean(Y_Z_5 - Y_Z_1),
    ate_Y_3_2 = mean(Y_Z_3 - Y_Z_2), ate_Y_4_2 = mean(Y_Z_4 - Y_Z_2),
    ate_Y_5_2 = mean(Y_Z_5 - Y_Z_2), ate_Y_4_3 = mean(Y_Z_4 -
    Y_Z_3), ate_Y_5_3 = mean(Y_Z_5 - Y_Z_3), ate_Y_5_4 = mean(Y_Z_5 - Y_Z_4))
# Assignment
assignment <- declare_assignment(num_arms = 5, conditions = c("1", "2", "3",
"4","5"), assignment_variable = Z)
reveal_Y <- declare_reveal(assignment_variables = Z)
# Estimator
estimator <- declare_estimator(handler = function(data) {
    estimates <- rbind.data.frame(
      ate_Y_2_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_Y_3_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_Y_4_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "4")
```

```
      ate_Y_5_1 = difference_in_means(formula = Y - Z, data = data, condition1 = "1", condition2 = "5")
      ate_Y_3_2 = difference_in_means(formula = Y - Z, data = data, condition1 = "2", condition2 = "3")
      ate_Y_4_2 = difference_in_means(formula = Y - Z, data = data, condition1 = "2", condition2 = "4")
      ate_Y_5_2 = difference_in_means(formula = Y - Z, data = data, condition1 = "2", condition2 = "5")
      ate_Y_4_3 = difference_in_means(formula = Y - Z, data = data, condition1 = "3", condition2 = "4")
      ate_Y_5_3 = difference_in_means(formula = Y - Z, data = data, condition1 = "3", condition2 = "5")
      ate_Y_5_4 = difference_in_means(formula = Y - Z, data = data, condition1 = "4", condition2 = "5")
      )
    names(estimates)[names(estimates) == "N"] <- "N_DIM"
    estimates$estimator_label <- c("DIM (Z_2 - Z_1)", "DIM (Z_3 - Z_1)",
    "DIM (Z_4 - Z_1)", "DIM (Z_5 - Z_1)","DIM (Z_3 - Z_2)", "DIM (Z_4 - Z_2)", "DIM (Z_5 - Z_2)",
    "DIM (Z_4 - Z_3)", "DIM (Z_5 - Z_3)", "DIM (Z_5 - Z_4)")
    estimates$estimand_label <- rownames(estimates)
    estimates$estimate <- estimates$coefficients
    estimates$term <- NULL
    return(estimates)
})
multi_arm_design2 <- population + potential_outcomes + assignment +
    reveal_Y + estimand + estimator
# Diagnose Experiment 1 ad click rate:
t<-Sys.time()
diagnosis <- diagnose_design(multi_arm_design2)
Sys.time()-t
saveRDS(diagnosis,file="diagnosis-2.rds")
```

```
library(xtable)
dat1<-diagnosis$diagnosands_df[,c("estimand_label","estimator_label","bias","rmse","power","coverage","
dat2<-diagnosis$diagnosands_df[,c("estimand_label","estimator_label","se(bias)","se(rmse)","se(power)",
dat2$estimand_label<-NA
dat2$estimator_label<-NA
tmp_n<-nrow(dat1)+nrow(dat2)
dat<-data.frame(Estimand=rep(NA,tmp_n),Estimator=rep(NA,tmp_n)
                ,Bias=rep(NA,tmp_n),RMSE=rep(NA,tmp_n)
                ,Power=rep(NA,tmp_n),Coverage=rep(NA,tmp_n)
                ,Mean_Estimate=rep(NA,tmp_n),SD_Estimate=rep(NA,tmp_n)
                ,Mean_SE=rep(NA,tmp_n) ,Type_S_Rate=rep(NA,tmp_n)
                ,Mean_Estimand=rep(NA,tmp_n),N_Sims=rep(NA,tmp_n))

j1<-j2<-1
for(i in 1:tmp_n){
  if(i%%2==0){
  dat[i,]<-dat2[j2,]
  j2<-j2+1
  }else{
  dat[i,]<-dat1[j1,]
  j1<-j1+1
  }
}
print(xtable(dat[,1:(ncol(dat)-1)],digits=2), include.rownames=FALSE)
```

Design Declaration B

- Model:

We specify a model with a population N that has three variables affected by treatment: response variable R_i, outcome (here refugee thermometer rating in the survey) Y_i, which is correlated with response variable through parameter ρ. Y_i^{obs} is the measured version of Y_i, which is only observed when $R_i = 1$. For our setting, when a respondent is willing to click on the ad and answer the survey $R_i = 1$.

- Inquiry:

Here we're interested in knowing the average of all respondents' differences in treatment arm potential outcomes, all of the pairwise comparisons between arms: $E[Y(m) - Y(m')]$, for all $m \in \{1, \cdots, M\}$. But we're also interested in the average treatment effect on reporting $E[R_i(m) - R_i(m')]$ as well as the pairwise comparison between treatment arms among those who report: $E[Y_i(m) - Y_i(m')|R_i = 1]$.

- Data strategy:

We randomly assign $N/k = 90,000$ units to each of the treatment arms.

- Answer strategy:

R_i and Y_i^{obs}, take every pairwise difference in means corresponding to the specific estimand.

Experiment 2:

- T1 = covid - Refugee
- T2 = no covid - Refugee
- T3 = covid - Neither
- T4 = no covid - Neither
- T5 = covid - Immigrant

```
#Starting parameters
N <- 450000
a_R <- 0
#Likelihood of responding to survey after exposed to treatment arm: let covid effect on going to survey
b1_R <- 0.1+0.075 + 0.2 #covid - refugee
b2_R <- 0.075 + 0.2  #no covid - refugee
b3_R <- 0.1 + 0.2  #covid - neither
b4_R <- 0.02 + 0.2 #no covid - neither
b5_R <- 0.1+0.025 + 0.2  #covid - immigrant
a_Y <- 0
#Effect on thermometer rating after exposed to treatment arm:
b1_Y <- 0.1+0.075   #covid - refugee
b2_Y <- 0.075   #no covid - refugee
b3_Y <- 0.1   #covid - neither
b4_Y <- 0.02  #no covid - neither
b5_Y <- 0.1+0.025   #covid - immigrant
#correl
rho <- c(0.0,0.2,0.8)

#set up
t<-Sys.time()
for(i in 1:3){
  cat("Start Design:",i,"\n")
#Population
population <- declare_population(N = N, u = rnorm(N), v=rnorm(N)
              ,u1_R = rnorm(N),u2_R = rnorm(N),u3_R = rnorm(N),u4_R = rnorm(N),u5_R = rnorm(N)
              ,u1_Y = rnorm(N,mean = rho[i] * u1_R, sd = sqrt(1 - rho[i]^2)),u2_Y = rnorm(N,mean = rho[:
              ,u3_Y = rnorm(N,mean = rho[i] * u3_R, sd = sqrt(1 - rho[i]^2)),u4_Y = rnorm(N,mean = rho[:
              ,u5_Y = rnorm(N,mean = rho[i] * u5_R, sd = sqrt(1 - rho[i]^2))
```

```
            ) #one error eqn Y; one error eqn R;  errors for each condition in R; errors for each con
#Potential outcomes
  #R
potential_outcomes_R <- declare_potential_outcomes(
  R ~ (a_R + b1_R + u1_R)* (Z == "1") + (a_R + b2_R + u2_R)* (Z == "2")
  + (a_R + b3_R + u3_R)* (Z == "3") + (a_R + b4_R + u4_R)* (Z == "4")
  + (a_R + b5_R + u5_R)* (Z == "5") > v, conditions = c("1", "2", "3", "4", "5"), assignment_variables =
  #Y
potential_outcomes_Y <- declare_potential_outcomes(
  Y ~ (a_Y + b1_Y + u1_Y)* (Z == "1") + (a_Y + b2_Y + u2_Y)* (Z == "2")
  + (a_Y + b3_Y + u3_Y)* (Z == "3") + (a_Y + b4_Y + u4_Y)* (Z == "4")
  + (a_Y + b5_Y + u5_Y)* (Z == "5") + u, conditions = c("1", "2", "3", "4", "5"), assignment_variables =
#Estimands: 3 types -- ATE on R, ATE on Y, ATE on Y|R
estimand <- declare_estimands(
  #ATE on R
  ate_R_2_1 = mean(R_Z_2 - R_Z_1), ate_R_3_1 = mean(R_Z_3 - R_Z_1), ate_R_4_1 = mean(R_Z_4 - R_Z_1), ate
  ate_R_3_2 = mean(R_Z_3 - R_Z_2), ate_R_4_2 = mean(R_Z_4 - R_Z_2), ate_R_5_2 = mean(R_Z_5 - R_Z_2),
  ate_R_4_3 = mean(R_Z_4 - R_Z_3), ate_R_5_3 = mean(R_Z_5 - R_Z_3), ate_R_5_4 = mean(R_Z_5 - R_Z_4)
  #ATE on Y
  ,ate_Y_2_1 = mean(Y_Z_2 - Y_Z_1), ate_Y_3_1 = mean(Y_Z_3 - Y_Z_1), ate_Y_4_1 = mean(Y_Z_4 - Y_Z_1), a
  ate_Y_3_2 = mean(Y_Z_3 - Y_Z_2), ate_Y_4_2 = mean(Y_Z_4 - Y_Z_2), ate_Y_5_2 = mean(Y_Z_5 - Y_Z_2),
  ate_Y_4_3 = mean(Y_Z_4 - Y_Z_3), ate_Y_5_3 = mean(Y_Z_5 - Y_Z_3), ate_Y_5_4 = mean(Y_Z_5 - Y_Z_4)
  #ATE on Y|R
  ,ate_YR_2_1 = mean((Y_Z_2 - Y_Z_1)[R == 1]), ate_YR_3_1 = mean((Y_Z_3 - Y_Z_1)[R == 1])
  ,ate_YR_4_1 = mean((Y_Z_4 - Y_Z_1)[R == 1]), ate_YR_5_1 = mean((Y_Z_5 - Y_Z_1)[R == 1])
  ,ate_YR_3_2 = mean((Y_Z_3 - Y_Z_2)[R == 1]), ate_YR_4_2 = mean((Y_Z_4 - Y_Z_2)[R == 1])
  ,ate_YR_5_2 = mean((Y_Z_5 - Y_Z_2)[R == 1]), ate_YR_4_3 = mean((Y_Z_4 - Y_Z_3)[R == 1])
  ,ate_YR_5_3 = mean((Y_Z_5 - Y_Z_3)[R == 1]), ate_YR_5_4 = mean((Y_Z_5 - Y_Z_4)[R == 1])
  )
#Assignment
assignment <- declare_assignment(num_arms = 5, conditions = c("1", "2", "3", "4", "5"), assignment_varia
#Reveal/Observed: ??
reveal <- declare_reveal(outcome_variables = c("R", "Y"), assignment_variables = Z)
observed <- declare_step(Y_obs = ifelse(R, Y, NA), handler = fabricate)

#Estimator
estimator <- declare_estimator(handler = function(data) {
    estimates <- rbind.data.frame(
      #ATE on R
      ate_R_2_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_R_3_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_R_4_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_R_5_1 = difference_in_means(formula = R ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_R_3_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_R_4_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_R_5_2 = difference_in_means(formula = R ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_R_4_3 = difference_in_means(formula = R ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_R_5_3 = difference_in_means(formula = R ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_R_5_4 = difference_in_means(formula = R ~ Z, data = data, condition1 = "4", condition2 = "5")
      # ATE on Y conditional on R
      ate_YR_2_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_3_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_4_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
```

```r
      ate_YR_5_1 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "1", condition2 =
      ate_YR_3_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_4_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_5_2 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "2", condition2 =
      ate_YR_4_3 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "3", condition2 =
      ate_YR_5_3 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "3", condition2 =
      ate_YR_5_4 = difference_in_means(formula = Y_obs ~ Z, data = data, condition1 = "4", condition2 =
      #ATE on Y
      ate_Y_2_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "2")
      ate_Y_3_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "3")
      ate_Y_4_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "4")
      ate_Y_5_1 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "1", condition2 = "5")
      ate_Y_3_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "3")
      ate_Y_4_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "4")
      ate_Y_5_2 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "2", condition2 = "5")
      ate_Y_4_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "4")
      ate_Y_5_3 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "3", condition2 = "5")
      ate_Y_5_4 = difference_in_means(formula = Y ~ Z, data = data, condition1 = "4", condition2 = "5")
      )
    names(estimates)[names(estimates) == "N"] <- "N_DIM"
    estimates$estimator_label <- c(
      #R
      "DIM_R (Z_2 - Z_1)", "DIM_R (Z_3 - Z_1)", "DIM_R (Z_4 - Z_1)", "DIM_R (Z_5 - Z_1)","DIM_R (Z_3 -
      , "DIM_R (Z_4 - Z_2)", "DIM_R (Z_5 - Z_2)", "DIM_R (Z_4 - Z_3)", "DIM_R (Z_5 - Z_3)", "DIM_R (Z_5
      #Y|R
      , "DIM_Y_obs (Z_2 - Z_1)", "DIM_Y_obs (Z_3 - Z_1)", "DIM_Y_obs (Z_4 - Z_1)", "DIM_Y_obs (Z_5 - Z_
      , "DIM_Y_obs (Z_4 - Z_2)", "DIM_Y_obs (Z_5 - Z_2)", "DIM_Y_obs (Z_4 - Z_3)", "DIM_Y_obs (Z_5 - Z_
      #Y
      ,"DIM_Y (Z_2 - Z_1)", "DIM_Y (Z_3 - Z_1)", "DIM_Y (Z_4 - Z_1)", "DIM_Y (Z_5 - Z_1)","DIM_Y (Z_3 -
      , "DIM_Y (Z_4 - Z_2)", "DIM_Y (Z_5 - Z_2)", "DIM_Y (Z_4 - Z_3)", "DIM_Y (Z_5 - Z_3)", "DIM_Y (Z_5
      )
    estimates$estimand_label <- rownames(estimates)
    estimates$estimate <- estimates$coefficients
    estimates$term <- NULL
    return(estimates)
})
multi_arm_attrition_design <- population + potential_outcomes_R +
    potential_outcomes_Y + assignment + reveal + observed +
    estimand + estimator
diagnoses <- diagnose_design(multi_arm_attrition_design)
saveRDS(diagnoses,paste("multi_arm_attrition_design2-rho",i,".rds",sep=""))
cat("Finished Design:",i," in ", Sys.time()-t,"\n")
}
Sys.time()-t


# Combine and print xtable
rho1<-readRDS("multi_arm_attrition_design2-rho1.rds")
rho2<-readRDS("multi_arm_attrition_design2-rho2.rds")
rho3<-readRDS("multi_arm_attrition_design2-rho3.rds")
dat1<-rho1$diagnosands_df
dat1$design_label<-"rho=0.0"
dat2<-rho2$diagnosands_df
```

```
dat2$design_label<-"rho=0.2"
dat3<-rho3$diagnosands_df
dat3$design_label<-"rho=0.8"

dat<-rbind(dat1,dat2,dat3)

dat1<-dat[,c("design_label","estimand_label","estimator_label","bias","rmse","power","coverage","mean_e
dat2<-dat[,c("design_label","estimand_label","estimator_label","se(bias)","se(rmse)","se(power)","se(co


dat2$estimand_label<-NA
dat2$estimator_label<-NA

tmp_n<-nrow(dat1)+nrow(dat2)
d<-data.frame(Design=rep(NA,tmp_n),Estimand=rep(NA,tmp_n),Estimator=rep(NA,tmp_n)
                ,Bias=rep(NA,tmp_n),RMSE=rep(NA,tmp_n)
                ,Power=rep(NA,tmp_n),Coverage=rep(NA,tmp_n)
                ,Mean_Estimate=rep(NA,tmp_n),SD_Estimate=rep(NA,tmp_n)
                ,Mean_SE=rep(NA,tmp_n) ,Type_S_Rate=rep(NA,tmp_n)
                ,Mean_Estimand=rep(NA,tmp_n),N_Sims=rep(NA,tmp_n))

j1<-j2<-1
for(i in 1:tmp_n){
  if(i%%2==0){
  d[i,]<-dat2[j2,]
  j2<-j2+1
  }else{
  d[i,]<-dat1[j1,]
  j1<-j1+1
  }
}
print(xtable(d[1:60,2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.0

print(xtable(d[61:120,2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.2

print(xtable(d[121:nrow(d),2:(ncol(d)-1)],digits=2), include.rownames=FALSE) #rho=0.8
```

B.4 Facebook ads

Ad 1: COVID/United States

Ad Headline: Refugees help America fight coronavirus.

Ad Description: Mustafa volunteers to deliver groceries in the USA. Click to support refugees helping us.

Ad 2: COVID/Pennsylvania

Ad Headline: Refugees help America fight coronavirus.

Ad Description: Mustafa volunteers to deliver groceries in PA. Click to support refugees helping us.

Ad 3: COVID/Lancaster

Ad Headline: Refugees help America fight coronavirus.

Ad Description: Mustafa volunteers to deliver groceries in Lancaster. Click to support refugees helping us.

Ad 4: COVID/No location

Ad Headline: Refugees help America fight coronavirus.

Ad Description: Mustafa volunteers to deliver groceries. Click to support refugees helping us.

Ad 5: No COVID/United States

Ad Headline: Refugees help America.

Ad Description: Mustafa volunteers to deliver groceries in the USA. Click to support refugees helping us.

Ad 6: COVID/Refugee

Ad Headline: Refugee doctors are fighting coronavirus.

Ad Description: Dr. Heval Kelli fights for his coronavirus patients. Click to support refugees helping us.

Ad 7: COVID/Immigrant

Ad Headline: Immigrant doctors are fighting coronavirus.

Ad Description: Dr. Heval Kelli fights for his coronavirus patients. Click to support immigrants helping us.

Ad 8: COVID/Neither

Ad Headline: Doctors are fighting coronavirus.

Ad Description: Dr. Heval Kelli fights for his coronavirus patients. Click to support doctors helping us.

<u>Ad 9: No COVID/Refugee</u>

Ad Headline: Refugee doctors are helping America.

Ad Description: Dr. Heval Kelli fights for his patients. Click to support refugees helping us.

Ad 10: No COVID/Neither

Ad Headline: Doctors are helping America.

Ad Description: Dr. Heval Kelli fights for his patients. Click to support doctors helping us.

B.5 Survey instrument

Refugee Narratives Use

Start of Block: Consent Block

Consent Public Opinion in the USA Thank you for clicking on our Facebook ads. These ads are part of a study about public opinion toward refugees in the United States. In coordination with Refugee Council USA, we are Claire Adida (UC San Diego), Adeline Lo (University of Madison Wisconsin), Lauren Prather (UC San Diego), and Scott Williamson (Stanford University), researchers studying American public opinion. In what follows, we ask you to fill out a brief survey and provide you with an opportunity to connect with Refugee Council USA for information about how to help refugees. If you agree to be in this study, the following will happen to you: you will answer a few questions about yourself and your political attitudes. This survey will take approximately five minutes of your time. Research records will be kept confidential to the extent allowed by law. No identifying information will be collected, such that the researchers will be unable to link your answers to your identity. Participation in research is entirely voluntary. There are no risks associated with this study, but we cannot and do not guarantee that you will receive any benefits from participation. You may refuse to participate or withdraw at any time without penalty or loss of benefits to which you are entitled. If you want additional information or have questions or research-related problems, you may reach Professors Adida at cadida@ucsd.edu, Lo at aylo@wisc.edu, Prather at lprather@ucsd.edu, and Williamson at scottw2@stanford.edu. If you are not satisfied with the response of the research team, have more questions, or want to talk to someone about your rights as a research participant, you should contact the Human Research Protections Program at 858-246-HRPP (858-246-4777).

- I have read the consent form above and agree to continue with the survey (1)
- I have read the consent form above and do not agree to continue with the survey (2)

Skip To: End of Survey If Public Opinion in the USA Thank you for clicking on our Facebook ads. These ads are part of a s... = I have read the consent form above and do not agree to continue with the survey

End of Block: Consent Block

Start of Block: Outcome

refugee_therm On a scale from 0 to 100, where 0 equals completely unfavorable and 100 equals completely favorable, how would you describe your feelings toward refugees?

0 10 20 30 40 50 60 70 80 90 100

Feelings toward refugees ()	

End of Block: Outcome

Start of Block: SES

gender What is your gender?

○ Male (1)

○ Female (2)

○ Non-binary (3)

Page Break

yearbirth What is your year of birth?

▼ 2002 (1) ... 1920 (83)

Page Break

edu What is the highest level of education you have achieved?

- ◯ Some high school (1)
- ◯ Completed high school (2)
- ◯ Some college (3)
- ◯ Completed college (4)
- ◯ Some post-graduate (5)
- ◯ Completed post-graduate (6)

Page Break

state In which US state do you currently live?

▼ Alabama (1) ... Wyoming (49)

Page Break

employed Are you currently employed or unemployed?

- Employed, not looking for work (1)
- Employed, looking for work (2)
- Unemployed, not looking for work (3)
- Unemployed, looking for work (4)

Page Break

ethnicity Are you of Hispanic, Latino, or Spanish origins?

- Yes (1)
- No (2)

Page Break

race What race do you associate yourself most closely with?

- ○ White (1)
- ○ African American or Black (2)
- ○ American Indiana or Alaska Native (3)
- ○ Asian (4)
- ○ Native Hawaiian or Pacific Islander (5)
- ○ Other (6)

Page Break

Q17 Do you have children living in your household?

- ○ Yes (1)
- ○ No (2)

Page Break

party In general, would you describe yourself as a:

- ○ Strong Democrat (1)
- ○ Democrat (2)
- ○ Lean Democrat (3)
- ○ Independent (4)
- ○ Lean Republican (5)
- ○ Republican (6)
- ○ Strong Republican (7)

Page Break

trump Do you approve or disapprove of the way Donald Trump is handling his job as President?

- Strongly approve (1)
- Approve (2)
- Somewhat approve (3)
- Somewhat disapprove (4)
- Disapprove (5)
- Strongly disapprove (6)

Page Break

religion What is your present religion, if any?

- ○ Protestant (1)
- ○ Roman Catholic (2)
- ○ Mormon (3)
- ○ Orthodox, such as Greek or Russian Orthodox (4)
- ○ Jewish (5)
- ○ Muslim (6)
- ○ Buddhist (7)
- ○ Hindu (8)
- ○ Atheist (9)
- ○ Agnostic (10)
- ○ Something else (11) ____
- ○ Nothing in particular (12)

Page Break

news From which of the below sources do you receive most of your news and information? Please select any that you regularly use:

- [ ] Online: Facebook (1)
- [ ] Online: Other social media (e.g., Twitter, Instagram...) (2)
- [ ] Online: news website or app (3)
- [ ] TV (4)
- [ ] Print (newspapers, journals) (5)
- [ ] Radio (6)
- [ ] Other (7) ____

Page Break

Q19 How closely do you follow news and current events?

- Very closely (1)
- Somewhat closely (2)
- A little (3)
- Not at all (4)

Page Break

Q21 Would you say that you have been following the news more closely than normal since the emergence of coronavirus?

- ◯ Yes, a lot more than normal (1)
- ◯ Yes, a little more than normal (2)
- ◯ About the same as normal (3)
- ◯ No, a little less than normal (4)
- ◯ No, a lot less than normal (5)

End of Block: SES

Start of Block: Refugee Website

Mustafa_story Now we would like to remind you of the ad you saw on Facebook that brought you to the survey.

JS

refugee_council Refugee Council USA is a non-profit, non-partisan, non-governmental organization dedicated to promoting efforts that protect and welcome refugees, asylees, asylum-seekers and other forcibly displaced populations, including individuals like Mustafa.

If you are interested in finding out more about this organization, please click on the link below. The website will open in a new window, and what you do on that page will not be accessible to us as the researchers.
Refugee Council USA: https://rcusa.org/covid-19/.

Q15
After you click the link to the contact page, please click the arrow to proceed to the final question.

End of Block: Refugee Website

Start of Block: Covid Treatment

covid Would you say that the Coronavirus (COVID-19) outbreak is a major threat, a minor threat, or not a threat to your personal health?

- ○ A major threat (1)
- ○ A minor threat (2)
- ○ Not a threat (3)

End of Block: Covid Treatment

G Unregistered Bayes factors

To better understand the context of our findings from H1 (pandemic reference effects) and H2 (local effects), we calculate unregistered Bayes factors for each of the parameters of interest. Results are presented in Table G.16 under assumed Gaussian priors centered at zero with a range of variance choices.

Group		Small	Medium	Large
H1	COVID-US vs No COVID-US	0.0652	0.0328	0.0086
H1	COVID-Refugee vs No COVID-Refugee	0.0673	0.0336	0.0087
H1	COVID-Neither vs No COVID-Neither	0.0902	0.0529	0.0125
H2	US vs No Place	0.0582	0.0317	0.0075
H2	PA vs No Place	0.0597	0.0318	0.0080
H2	PA vs US	0.0644	0.0333	0.0086
H2	Lancaster vs PA	0.0759	0.0372	0.0097
H2	Lancaster vs No Place	0.1154	0.0562	0.0142
H2	Lancaster vs US	0.1216	0.0512	0.0162

Table G.16: **H1 and H2 class test Bayes factors**. Calculated with Gaussian priors centered at zero with small (0.02), medium (0.04) and large variances (0.16).