The effect of messages on vaccinations

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July 30, 2021

## The file expanding the aggregated data  
wrkdat <- read\_csv(file.path(DATA\_DIR, "dat\_indiv.csv"))  
## This next makes an error in case the original data changed. Mostly to make us pay attention.  
stopifnot(nrow(wrkdat) == 158103)  
  
## The latest file from Kevin  
wrkdat2 <- read\_csv(file.path(DATA\_DIR, "final\_data\_one\_line\_per\_individual.csv"))  
nrow(wrkdat2)

[1] 158103

stopifnot(nrow(wrkdat2) == 158103)  
stopifnot(all(!is.na(wrkdat2$date\_sent)))  
## This next fails  
  
wrkdat\_design\_tab <- with(wrkdat, table(date\_sent, assigned\_message, exclude = c()))  
wrkdat2\_design\_tab <- with(wrkdat2, table(date\_sent, assigned\_message, exclude = c()))  
stopifnot(all.equal(wrkdat\_design\_tab, wrkdat2\_design\_tab, exclude = c()))  
  
wrkdat\_outcomes\_tab <- with(wrkdat, table(date\_sent, is\_vax\_after\_send))  
wrkdat2\_outcomes\_tab <- with(wrkdat2, table(date\_sent, is\_vax\_after\_send))  
stopifnot(all.equal(wrkdat\_design\_tab, wrkdat2\_design\_tab, exclude = c()))  
  
## Add ZCTA data to wrkdat2:  
  
zctadat <- read\_csv(file.path(DEMO\_DATA\_DIR, "combined\_demo\_data\_by\_zcta.csv"))

Warning: Missing column names filled in: 'X1' [1]

## The first column, auto-named to X1 is noise  
zctadat$X1 <- NULL  
  
zctadat <- zctadat %>% mutate(  
 pct\_any\_blk = any\_black\_population / total\_population,  
 pct\_hisp = hispanic\_population / total\_population,  
 pct\_dem = dem\_vote / total\_vote,  
 pct\_gop = gop\_vote / total\_vote,  
 pct\_vote = total\_vote / total\_population  
)  
  
## Any mismatch in ZCTA ids?  
## using https://stackoverflow.com/questions/19797954/function-to-find-symmetric-difference-opposite-of-intersection-in-r  
sym\_diff2 <- function(a, b) unique(c(setdiff(a, b), setdiff(b, a)))  
sym\_diff2(unique(wrkdat2$zcta), unique(zctadat$zcta))

[1] "00000"

## So some people with no ZCTA. We will address this in the supplementary analyses later  
wrkdat3 <- left\_join(wrkdat2, zctadat, by = "zcta")  
stopifnot(nrow(wrkdat3) == nrow(wrkdat2))  
## We will use wrkdat3 for the rest of the time

# Design

This study randomly assigned 8 sms message types plus 1 control arm (no msg) (9 arms total) to roughly 160,000 (exactly 158,103) Rhode Islanders and recorded whether or not these people were vaccinated during the study period.

The randomization occurred each week and then, within arm, people were randomly assigned to a day on which they could be sent a text message. This nested randomization can be represented as complete randomization to one of 9 arms within each active day of the study. The table below, created by with(wrkdat3, table(date\_sent, assigned\_message, exclude = c())), shows a pattern of assignment by day consistent with this idea — roughly equal numbers assigned per message condition per day within each iteration.

The experiment also involve adaptive randomization, and the Thompson sampling algorithm assigned more people to arm 6 in the final week, for example. A block-randomized experiment can often have variation in probabilities assigned to treatment, and the analysis of such an experiment thus is no different whether there are changes in assignment probabilities between blocks or not.

# Data Setup

We drop observations assigned to be sent a message on June 15, 2021 because those messages were not sent and because people were assigned to that date at random.

wrkdat3 <- wrkdat3 %>%  
 filter(date\_sent < "2021-06-15") %>%  
 droplevels()  
stopifnot(nrow(wrkdat3) == 142428)

## Some recoding to make things nicer for coin etc..  
## Also coin wants factor variables for the CMH tests (since those are test of independence of contingency tables)  
wrkdat3$messageF <- factor(wrkdat3$assigned\_message)  
wrkdat3$vaccinated <- as.numeric(wrkdat3$is\_vax\_after\_send)  
wrkdat3$vaccinatedF <- factor(wrkdat3$vaccinated)  
  
wrkdat3$vac\_in\_week <- as.numeric(wrkdat3$is\_within\_one\_week\_after\_send)  
wrkdat3$vac\_in\_weekF <- factor(wrkdat3$vac\_in\_week)  
  
## Checking that vaccinated in week is a subset of vaccinated  
with(wrkdat3, table(vac\_in\_weekF, vaccinatedF, exclude = c()))

vaccinatedF  
vac\_in\_weekF 0 1  
 0 139684 1453  
 1 0 1291

wrkdat3$date\_sentF <- factor(wrkdat3$date\_sent)  
## A new variable that records the "any message" versus "no message" contrast  
wrkdat3$not\_control <- as.numeric(wrkdat3$messageF != "message\_0")  
with(wrkdat3, table(messageF, not\_control, exclude = c()))

not\_control  
messageF 0 1  
 message\_0 11327 0  
 message\_1 0 10491  
 message\_2 0 12440  
 message\_3 0 11962  
 message\_4 0 10110  
 message\_5 0 15243  
 message\_6 0 47058  
 message\_7 0 12363  
 message\_8 0 11434

wrkdat3$not\_controlF <- factor(wrkdat3$not\_control)  
  
## This next does not involve all possible dates, only those existing in the data:  
unique(wrkdat3$date\_sent)

[1] "2021-06-03" "2021-06-08" "2021-05-26" "2021-06-11" "2021-06-10" "2021-06-02" "2021-05-28" "2021-06-14" "2021-06-04"  
[10] "2021-05-27" "2021-06-09" "2021-06-07" "2021-05-25"

## Any missing dates will be assigned NA and the code will stop if any NA are detected  
wrkdat3 <- wrkdat3 %>% mutate(iteration = case\_when(  
 date\_sent <= "2021-05-28" ~ 1,  
 date\_sent >= "2021-06-02" & date\_sent <= "2021-06-08" ~ 2,  
 date\_sent > "2021-06-08" ~ 3  
))  
stopifnot(any(!is.na(wrkdat3$iteration)))  
## Inspect by hand  
with(wrkdat3, table(date\_sent, iteration, exclude = c()))

iteration  
date\_sent 1 2 3  
 2021-05-25 10003 0 0  
 2021-05-26 9999 0 0  
 2021-05-27 9999 0 0  
 2021-05-28 9999 0 0  
 2021-06-02 0 7941 0  
 2021-06-03 0 7941 0  
 2021-06-04 0 7948 0  
 2021-06-07 0 7942 0  
 2021-06-08 0 7937 0  
 2021-06-09 0 0 15682  
 2021-06-10 0 0 15679  
 2021-06-11 0 0 15679  
 2021-06-14 0 0 15679

Notice that assignment is consistent with complete randomization in iteration 1 (equal numbers assigned to each message that week). It diverges from uniform assignment in iteration 2 and 3 because we are using the -Thompson adaptive algorithm for assignment. Notice that within iteration, roughly equal numbers are allocated to each day within message type. This was also done at random, making this a study that can be treated as if it were block-randomized by day.

with(wrkdat3, table(iteration, assigned\_message, exclude = c()))

assigned\_message  
iteration message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
 1 4445 4445 4445 4445 4444 4444 4444 4444 4444  
 2 3494 3069 5647 5053 2414 8502 1990 5591 3949  
 3 3388 2977 2348 2464 3252 2297 40624 2328 3041

with(wrkdat3, table(date\_sentF, assigned\_message, exclude = c()))

assigned\_message  
date\_sentF message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
 2021-05-25 1112 1112 1112 1112 1111 1111 1111 1111 1111  
 2021-05-26 1111 1111 1111 1111 1111 1111 1111 1111 1111  
 2021-05-27 1111 1111 1111 1111 1111 1111 1111 1111 1111  
 2021-05-28 1111 1111 1111 1111 1111 1111 1111 1111 1111  
 2021-06-02 699 616 1131 1010 485 1698 398 1117 787  
 2021-06-03 697 611 1131 1010 481 1700 399 1122 790  
 2021-06-04 699 616 1132 1011 485 1701 397 1118 789  
 2021-06-07 698 612 1124 1011 482 1704 398 1121 792  
 2021-06-08 701 614 1129 1011 481 1699 398 1113 791  
 2021-06-09 847 745 587 616 813 575 10156 582 761  
 2021-06-10 847 744 587 616 813 574 10156 582 760  
 2021-06-11 847 744 587 616 813 574 10156 582 760  
 2021-06-14 847 744 587 616 813 574 10156 582 760

## Message types  
## 0. Control  
## 1. Ownership (baseline prompt)  
## 2. Safety  
## 3. Pros of vaccination (implicit choice): no hospitals  
## 4. Epistemic humility + pros of vaccination (implicit choice): no hospitals  
## 5. Access  
## 6. Family concern  
## 7. Social proof  
## 8. Social proof + family concern

with(wrkdat3, table(iteration, exclude = FALSE))

iteration  
 1 2 3   
40000 39709 62719

with(wrkdat3, table(date\_sent, exclude = FALSE))

date\_sent  
2021-05-25 2021-05-26 2021-05-27 2021-05-28 2021-06-02 2021-06-03 2021-06-04 2021-06-07 2021-06-08 2021-06-09 2021-06-10 2021-06-11   
 10003 9999 9999 9999 7941 7941 7948 7942 7937 15682 15679 15679   
2021-06-14   
 15679

## Weight Creation

A block-randomized study is a collection of mini-experiments. Overall tests and estimates involve some kind of combination of those block-level quantities, using weights to give larger and more informative blocks more weight and/or to target specific kinds of treatment effects. We pre-specified that we would use block-size weights because we know that these produce unbiased estimators. Right now, the difference\_in\_means command will use those estimators by default, but only for a comparison of two arms. To make things easier later on, we therefore create weights here to be used in our standard linear regression command (lm\_robust) that we use for general estimation in randomized studies (because, in part, it uses randomization justified standard errors by default, and thus allows less typing than lm).

Here we add weights to the data set since each block (date\_sent involved different assignments to treatment (actually it was each iteration but the sms were then divided at random into days for sending and we are then treating each moment of administering the treatment as a block).

I’m doing this slow to convince myself, and perhaps, others that (1) there are different ways to weight blocks and (2) that what we are seeing from the canned R commands with weights makes sense. During the weight creation we will be doing some analyses of the effects of the study, they are mainly to help us ensure that we creating the weights correctly. A cleaner analysis is below, under “Pre-specified analyses”.

## The two arm version:  
## Creating the weights following the examples in the randomizr vignettes  
block\_m\_each\_bin <- with(wrkdat3, table(date\_sentF, not\_control, exclude = c()))  
declared\_randomization\_twoarm <- declare\_ra(blocks = wrkdat3$date\_sentF, block\_m = block\_m\_each\_bin[, "1"])  
wrkdat3$IPW\_weight\_bin <- 1 / obtain\_condition\_probabilities(declaration = declared\_randomization\_twoarm, assignment = wrkdat3$not\_control)  
## unique(wrkdat3$IPW\_weight\_bin)  
## Now doing this by hand, following Gerber and Green Chap 3 (creating regression weights to reflect block-size weighting)  
wrkdat3 <- wrkdat3 %>%  
 group\_by(date\_sentF) %>%  
 mutate(  
 nb = n(),  
 p\_not\_control = mean(not\_control),  
 nbwt\_bin = ifelse(not\_control == 1, 1 / p\_not\_control, 1 / (1 - p\_not\_control)),  
 ) %>%  
 ungroup()  
  
stopifnot(all.equal(wrkdat3$IPW\_weight\_bin, wrkdat3$nbwt\_bin))  
  
lm\_bin0 <- difference\_in\_means(vaccinated ~ not\_control, blocks = date\_sentF, data = wrkdat3)  
lm\_bin1 <- lm\_robust(vaccinated ~ not\_control, data = wrkdat3, weights = nbwt\_bin)  
lm\_bin2 <- lm\_robust(vaccinated ~ not\_control, data = wrkdat3, weights = IPW\_weight\_bin)  
lm\_bin1

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.02061 0.001312 15.711 1.406e-55 0.018038 0.023180 142426  
not\_control -0.00147 0.001366 -1.077 2.817e-01 -0.004147 0.001207 142426

stopifnot(all.equal(lm\_bin0$coef, lm\_bin1$coef["not\_control"]))  
stopifnot(all.equal(lm\_bin0$coef, lm\_bin2$coef["not\_control"]))  
  
## Now for the precision weighted version  
## lm\_bin3 <- lm\_robust(vaccinated~not\_control,fixed\_effects=~date\_sentF,data=wrkdat3)  
## lm\_bin3

We cannot use difference\_of\_means for a multi-armed treatment, but we follow the same general approach:

### Multiple arm version  
block\_m\_each <- with(wrkdat3, table(date\_sentF, messageF, exclude = c()))  
block\_prob\_each <- block\_m\_each / rowSums(block\_m\_each)  
declared\_randomization\_multarm <- declare\_ra(blocks = wrkdat3$date\_sentF, block\_m\_each = block\_m\_each, conditions = sort(unique(wrkdat3$messageF)))  
wrkdat3$IPW\_weight\_multarm <- 1 / obtain\_condition\_probabilities(declaration = declared\_randomization\_multarm, assignment = wrkdat3$messageF)  
## unique(wrkdat3$IPW\_weight\_multarm)  
  
stopifnot(all.equal(sort(unique(1 / wrkdat3$IPW\_weight\_multarm)), sort(unique(block\_prob\_each))))  
  
lm\_multarm\_ipw <- lm\_robust(vaccinated ~ messageF, data = wrkdat3, weights = IPW\_weight\_multarm)  
## lm1\_mult\_fe <- lm\_robust(vaccinated~messageF,data=wrkdat3,fixed\_effects=~date\_sentF)  
lm\_multarm\_ipw

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.02060861 0.001312 15.71145 1.406e-55 0.018038 0.0231795 142419  
messageFmessage\_1 -0.00208199 0.001842 -1.13002 2.585e-01 -0.005693 0.0015291 142419  
messageFmessage\_2 -0.00002266 0.001898 -0.01194 9.905e-01 -0.003742 0.0036968 142419  
messageFmessage\_3 0.00232052 0.002012 1.15339 2.488e-01 -0.001623 0.0062638 142419  
messageFmessage\_4 -0.00222375 0.001863 -1.19395 2.325e-01 -0.005874 0.0014267 142419  
messageFmessage\_5 0.00015034 0.001886 0.07972 9.365e-01 -0.003546 0.0038467 142419  
messageFmessage\_6 -0.00260175 0.001719 -1.51333 1.302e-01 -0.005971 0.0007679 142419  
messageFmessage\_7 -0.00316289 0.001824 -1.73444 8.284e-02 -0.006737 0.0004113 142419  
messageFmessage\_8 -0.00012584 0.001844 -0.06826 9.456e-01 -0.003739 0.0034876 142419

## lm1\_mult\_fe  
  
## Creating the weights by hand to verify understanding:  
wrkdat3 <- wrkdat3 %>%  
 group\_by(date\_sentF) %>%  
 mutate(  
 p\_m\_0 = mean(messageF == "message\_0"),  
 p\_m\_1 = mean(messageF == "message\_1"),  
 p\_m\_2 = mean(messageF == "message\_2"),  
 p\_m\_3 = mean(messageF == "message\_3"),  
 p\_m\_4 = mean(messageF == "message\_4"),  
 p\_m\_5 = mean(messageF == "message\_5"),  
 p\_m\_6 = mean(messageF == "message\_6"),  
 p\_m\_7 = mean(messageF == "message\_7"),  
 p\_m\_8 = mean(messageF == "message\_8"),  
 nbwt\_mult = as.numeric(messageF == "message\_0") / p\_m\_0 +  
 as.numeric(messageF == "message\_1") / p\_m\_1 +  
 as.numeric(messageF == "message\_2") / p\_m\_2 +  
 as.numeric(messageF == "message\_3") / p\_m\_3 +  
 as.numeric(messageF == "message\_4") / p\_m\_4 +  
 as.numeric(messageF == "message\_5") / p\_m\_5 +  
 as.numeric(messageF == "message\_6") / p\_m\_6 +  
 as.numeric(messageF == "message\_7") / p\_m\_7 +  
 as.numeric(messageF == "message\_8") / p\_m\_8  
 ) %>%  
 ungroup()  
## Verify that the IPW weights using randomizr are the same as those we created by hand  
stopifnot(all.equal(sort(unique(wrkdat3$IPW\_weight\_multarm)), sort(unique(wrkdat3$nbwt\_mult))))

Now estimate effects by first aggregating to the block level and then weighting (this is just to check that we can get the same numbers as when we use lm\_robust etc..):

wrkdat3\_b <- wrkdat3 %>%  
 group\_by(date\_sentF) %>%  
 summarize(  
 nb = n(),  
 effect\_1 = mean(vaccinated[messageF == "message\_1"]) - mean(vaccinated[messageF == "message\_0"]),  
 effect\_2 = mean(vaccinated[messageF == "message\_2"]) - mean(vaccinated[messageF == "message\_0"]),  
 effect\_3 = mean(vaccinated[messageF == "message\_3"]) - mean(vaccinated[messageF == "message\_0"]),  
 effect\_4 = mean(vaccinated[messageF == "message\_4"]) - mean(vaccinated[messageF == "message\_0"]),  
 effect\_5 = mean(vaccinated[messageF == "message\_5"]) - mean(vaccinated[messageF == "message\_0"]),  
 effect\_6 = mean(vaccinated[messageF == "message\_6"]) - mean(vaccinated[messageF == "message\_0"]),  
 effect\_7 = mean(vaccinated[messageF == "message\_7"]) - mean(vaccinated[messageF == "message\_0"]),  
 effect\_8 = mean(vaccinated[messageF == "message\_8"]) - mean(vaccinated[messageF == "message\_0"]),  
 effect\_any\_msg = mean(vaccinated[messageF != "message\_0"]) - mean(vaccinated[messageF == "message\_0"])  
 )  
## The ATE over all is just the weighted average of the block ATEs  
simp\_est <- wrkdat3\_b %>% summarize(across(  
 .cols = contains("effect"),  
 .fns = function(x) {  
 weighted.mean(x, w = nb)  
 }  
))  
## Test the block-based algorithm itself  
stopifnot(all.equal(with(wrkdat3\_b, weighted.mean(x = effect\_1, w = nb)), simp\_est$effect\_1))  
stopifnot(all.equal(with(wrkdat3\_b, weighted.mean(x = effect\_6, w = nb)), simp\_est$effect\_6))  
  
## Verifying that we get the same answer with explicit weighting (building up from the block-level estimates)  
## versus regression weights  
## The "any message" effect differs slightly but everything else is identical  
rbind(by\_hand = simp\_est, by\_lm = lm\_multarm\_ipw$coef[-1])

# A tibble: 2 x 9  
 effect\_1 effect\_2 effect\_3 effect\_4 effect\_5 effect\_6 effect\_7 effect\_8 effect\_any\_msg  
\* <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>  
1 -0.00208 -0.0000227 0.00232 -0.00222 0.000150 -0.00260 -0.00316 -0.000126 -0.00147  
2 -0.00208 -0.0000227 0.00232 -0.00222 0.000150 -0.00260 -0.00316 -0.000126 -0.00208

Ok. So, I’m satisfied with the regression weights as doing their job, and we can move on to basic descriptives and the pre-registered analyses using tools like lm\_robust. Weighting the different blocks is implicit (and optimal from a statistical testing perspective) in cmh\_test.

## Basic Descriptions and Visualization

Here is a rough plot to show the proportions vaccinated by message by date plus binomial 95% confidence intervals for those proportions. These are not effects, just proportions. Each panel shows a gray vertical line at the proportion vaccinated in the control condition.

mtypeF  
mtype Control Ownership Safety Preventing bad outcomes Epistemic humility+no bad outcomes Access  
 Access 0 0 0 0 0 13  
 Control 13 0 0 0 0 0  
 Epistemic humility+no bad outcomes 0 0 0 0 13 0  
 Family concern 0 0 0 0 0 0  
 Ownership 0 13 0 0 0 0  
 Preventing bad outcomes 0 0 0 13 0 0  
 Safety 0 0 13 0 0 0  
 Social proof 0 0 0 0 0 0  
 Social proof+family concern 0 0 0 0 0 0  
 mtypeF  
mtype Family concern Social proof Social proof+family concern  
 Access 0 0 0  
 Control 0 0 0  
 Epistemic humility+no bad outcomes 0 0 0  
 Family concern 13 0 0  
 Ownership 0 0 0  
 Preventing bad outcomes 0 0 0  
 Safety 0 0 0  
 Social proof 0 13 0  
 Social proof+family concern 0 0 13

messageF  
mtype message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
 Access 0 0 0 0 0 13 0 0 0  
 Control 13 0 0 0 0 0 0 0 0  
 Epistemic humility+no bad outcomes 0 0 0 0 13 0 0 0 0  
 Family concern 0 0 0 0 0 0 13 0 0  
 Ownership 0 13 0 0 0 0 0 0 0  
 Preventing bad outcomes 0 0 0 13 0 0 0 0 0  
 Safety 0 0 13 0 0 0 0 0 0  
 Social proof 0 0 0 0 0 0 0 13 0  
 Social proof+family concern 0 0 0 0 0 0 0 0 13

messageF  
mtypeF message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
 Control 13 0 0 0 0 0 0 0 0  
 Ownership 0 13 0 0 0 0 0 0 0  
 Safety 0 0 13 0 0 0 0 0 0  
 Preventing bad outcomes 0 0 0 13 0 0 0 0 0  
 Epistemic humility+no bad outcomes 0 0 0 0 13 0 0 0 0  
 Access 0 0 0 0 0 13 0 0 0  
 Family concern 0 0 0 0 0 0 13 0 0  
 Social proof 0 0 0 0 0 0 0 13 0  
 Social proof+family concern 0 0 0 0 0 0 0 0 13

Proportion vaccinated by date and message arm (these are the point values in the above plot):

prop\_vac\_arr <- matrix(plotdat1$prop\_vac,  
 nrow = 13, byrow = TRUE,  
 dimnames = list(sort(unique(as.character(plotdat1$date\_sent))), sort(unique(plotdat1$messageF)))  
)  
  
zapsmall(prop\_vac\_arr, digits = 2)

message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
2021-05-25 0.045 0.032 0.046 0.045 0.029 0.055 0.031 0.027 0.037  
2021-05-26 0.037 0.047 0.039 0.032 0.032 0.026 0.028 0.027 0.032  
2021-05-27 0.027 0.023 0.038 0.030 0.029 0.030 0.033 0.030 0.032  
2021-05-28 0.034 0.029 0.025 0.025 0.029 0.045 0.031 0.021 0.041  
2021-06-02 0.020 0.021 0.026 0.027 0.025 0.016 0.020 0.020 0.025  
2021-06-03 0.014 0.020 0.022 0.021 0.027 0.017 0.025 0.020 0.027  
2021-06-04 0.017 0.013 0.017 0.018 0.023 0.016 0.015 0.023 0.020  
2021-06-07 0.013 0.008 0.008 0.014 0.012 0.011 0.008 0.015 0.020  
2021-06-08 0.027 0.021 0.013 0.015 0.017 0.019 0.018 0.018 0.016  
2021-06-09 0.014 0.011 0.017 0.016 0.012 0.028 0.013 0.022 0.018  
2021-06-10 0.011 0.011 0.009 0.021 0.011 0.014 0.012 0.014 0.011  
2021-06-11 0.014 0.013 0.014 0.019 0.012 0.005 0.009 0.003 0.007  
2021-06-14 0.011 0.008 0.010 0.019 0.004 0.002 0.008 0.003 0.005

Can we see any patterns in the extent to which any given message, sent any given day, elicited more vaccinations than control? Not really, each message was, in absolute terms, sometimes better than and sometimes worse than control. No message stands out for always being worse or better than control (and notice this little table weighs all days equally).

prop\_diffs <- apply(prop\_vac\_arr, 2, function(x) {  
 x - prop\_vac\_arr[, 1]  
})  
  
prop\_diffs

message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
2021-05-25 0 -0.0125899 0.0008993 0.0000000 -0.0161611 0.0099415 -0.01436097 -0.017961 -0.00806034  
2021-05-26 0 0.0099010 0.0018002 -0.0045005 -0.0054005 -0.0108011 -0.00900090 -0.009901 -0.00540054  
2021-05-27 0 -0.0045005 0.0108011 0.0027003 0.0018002 0.0027003 0.00630063 0.002700 0.00540054  
2021-05-28 0 -0.0054005 -0.0090009 -0.0090009 -0.0054005 0.0108011 -0.00360036 -0.013501 0.00630063  
2021-06-02 0 0.0010753 0.0056124 0.0067041 0.0047137 -0.0041276 0.00007189 -0.000333 0.00538435  
2021-06-03 0 0.0052927 0.0077571 0.0064449 0.0126798 0.0027116 0.01071545 0.006152 0.01223508  
2021-06-04 0 -0.0041804 -0.0003829 0.0006368 0.0055130 -0.0007065 -0.00205403 0.006088 0.00311145  
2021-06-07 0 -0.0047240 -0.0048869 0.0009537 -0.0004459 -0.0017437 -0.00535629 0.002271 0.00730804  
2021-06-08 0 -0.0059315 -0.0138180 -0.0122673 -0.0104721 -0.0076809 -0.00951620 -0.009135 -0.01066924  
2021-06-09 0 -0.0034294 0.0028681 0.0020661 -0.0018675 0.0136584 -0.00067809 0.008169 0.00422920  
2021-06-10 0 0.0001270 -0.0021079 0.0104782 0.0004444 0.0033115 0.00128840 0.003120 -0.00009942  
2021-06-11 0 -0.0007268 -0.0005390 0.0053129 -0.0018675 -0.0089412 -0.00491204 -0.010731 -0.00758870  
2021-06-14 0 -0.0025612 -0.0004043 0.0088548 -0.0069357 -0.0088836 -0.00304401 -0.007189 -0.00536258

signs\_prop\_diffs <- sign(prop\_diffs)  
  
signs\_prop\_diffs

message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
2021-05-25 0 -1 1 0 -1 1 -1 -1 -1  
2021-05-26 0 1 1 -1 -1 -1 -1 -1 -1  
2021-05-27 0 -1 1 1 1 1 1 1 1  
2021-05-28 0 -1 -1 -1 -1 1 -1 -1 1  
2021-06-02 0 1 1 1 1 -1 1 -1 1  
2021-06-03 0 1 1 1 1 1 1 1 1  
2021-06-04 0 -1 -1 1 1 -1 -1 1 1  
2021-06-07 0 -1 -1 1 -1 -1 -1 1 1  
2021-06-08 0 -1 -1 -1 -1 -1 -1 -1 -1  
2021-06-09 0 -1 1 1 -1 1 -1 1 1  
2021-06-10 0 1 -1 1 1 1 1 1 -1  
2021-06-11 0 -1 -1 1 -1 -1 -1 -1 -1  
2021-06-14 0 -1 -1 1 -1 -1 -1 -1 -1

## Number of times greater than control  
gt\_control <- apply(signs\_prop\_diffs, 2, function(x) {  
 sum(x > 0)  
})  
lt\_control <- apply(signs\_prop\_diffs, 2, function(x) {  
 sum(x < 0)  
})  
  
rbind(gt\_control, lt\_control)

message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
gt\_control 0 4 6 9 5 6 4 6 7  
lt\_control 0 9 7 3 8 7 9 7 6

What about patterns in the extent to which one message was higher ranked in a given day? Not really, the average rank out of 9 messages is about 4,5 or 6 for each message across the days. The number of times that a message is lowest or highest ranked is not huge (out of 13 days): like less than 3 days out of 13 does one message appear worst or best.

prop\_rank <- t(apply(prop\_vac\_arr, 1, function(x) {  
 rank(x)  
}))  
  
prop\_rank

message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
2021-05-25 6.5 4.0 8.0 6.5 2.0 9 3 1 5.0  
2021-05-26 7.0 9.0 8.0 6.0 4.5 1 3 2 4.5  
2021-05-27 2.0 1.0 9.0 5.0 3.0 5 8 5 7.0  
2021-05-28 7.0 4.5 2.5 2.5 4.5 9 6 1 8.0  
2021-06-02 3.0 5.0 8.0 9.0 6.0 1 4 2 7.0  
2021-06-03 1.0 3.0 6.0 5.0 9.0 2 7 4 8.0  
2021-06-04 5.0 1.0 4.0 6.0 8.0 3 2 9 7.0  
2021-06-07 6.0 3.0 2.0 7.0 5.0 4 1 8 9.0  
2021-06-08 9.0 8.0 1.0 2.0 4.0 7 5 6 3.0  
2021-06-09 4.0 1.0 6.0 5.0 2.0 9 3 8 7.0  
2021-06-10 3.0 4.0 1.0 9.0 5.0 8 6 7 2.0  
2021-06-11 8.0 6.0 7.0 9.0 5.0 2 4 1 3.0  
2021-06-14 8.0 6.0 7.0 9.0 3.0 1 5 2 4.0

apply(prop\_rank, 2, mean)

message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8   
 5.346 4.269 5.346 6.231 4.692 4.692 4.385 4.308 5.731

apply(prop\_rank, 2, function(x) {  
 sum(x == min(x))  
})

message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8   
 1 3 2 1 2 3 1 3 1

apply(prop\_rank, 2, function(x) {  
 sum(x == max(x))  
})

message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8   
 1 1 1 4 1 3 1 1 1

As a reminder about the sample sizes in each message and day:

with(wrkdat3, table(date\_sent, messageF, exclude = c()))

messageF  
date\_sent message\_0 message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8  
 2021-05-25 1112 1112 1112 1112 1111 1111 1111 1111 1111  
 2021-05-26 1111 1111 1111 1111 1111 1111 1111 1111 1111  
 2021-05-27 1111 1111 1111 1111 1111 1111 1111 1111 1111  
 2021-05-28 1111 1111 1111 1111 1111 1111 1111 1111 1111  
 2021-06-02 699 616 1131 1010 485 1698 398 1117 787  
 2021-06-03 697 611 1131 1010 481 1700 399 1122 790  
 2021-06-04 699 616 1132 1011 485 1701 397 1118 789  
 2021-06-07 698 612 1124 1011 482 1704 398 1121 792  
 2021-06-08 701 614 1129 1011 481 1699 398 1113 791  
 2021-06-09 847 745 587 616 813 575 10156 582 761  
 2021-06-10 847 744 587 616 813 574 10156 582 760  
 2021-06-11 847 744 587 616 813 574 10156 582 760  
 2021-06-14 847 744 587 616 813 574 10156 582 760

A figure with proportion vaccinated at all, and another with proportion vaccinated within a week.

plotdat1$line\_thick <- ifelse(plotdat1$messageF == "message\_0", 2, 1)  
plotdat1$control\_msg <- plotdat1$messageF == "message\_0"  
  
g\_prop\_vac <- ggplot(plotdat1, aes(x = date\_sent, y = prop\_vac, group = mtypeF, color = mtypeF, size = control\_msg)) +  
 geom\_point() +  
 geom\_line() +  
 guides(color = guide\_legend(title = "Message")) +  
 scale\_colour\_brewer(type = "div") +  
 ylab("Vaccinated by June 22") +  
 xlab("Date Assigned Message") +  
 scale\_size\_manual(values = c(0.5, 1.2), guide = "none") +  
 scale\_linetype\_manual(values = c("solid", "dashed"), guide = "none") +  
 theme\_classic(base\_family = "Open Sans") +  
 theme(  
 text = element\_text(size = 16),  
 axis.text.x = element\_text(angle = 0, hjust = 1),  
 legend.position = c(.6, 0.8)  
 )  
  
# g\_prop\_vac  
  
g\_prop\_vac\_smooth <- ggplot(plotdat1, aes(x = date\_sent, y = prop\_vac, group = mtypeF, color = mtypeF, size = control\_msg)) +  
 geom\_point() +  
 geom\_smooth(se = FALSE, method = "loess", span = 2 / 3, method.args = list(degree = 1, family = "symmetric")) +  
 guides(color = guide\_legend(title = "Message")) +  
 scale\_colour\_brewer(type = "div") +  
 ylab("Vaccinated by June 22") +  
 xlab("Date Assigned Message") +  
 scale\_size\_manual(values = c(0.5, 1.2), guide = "none") +  
 scale\_linetype\_manual(values = c("solid", "dashed"), guide = "none") +  
 theme\_classic(base\_family = "Open Sans") +  
 theme(  
 text = element\_text(size = 16),  
 axis.text.x = element\_text(angle = 0, hjust = 1),  
 legend.position = c(.6, 0.8)  
 )  
  
# g\_prop\_vac\_smooth  
  
## Trying to break lines in between iterations. Not working well.  
## blah <- tidyr::complete(plotdat1, date\_sent = seq(min(date\_sent), max(date\_sent), by = "day"))  
  
g\_prop\_vac\_in\_week <- ggplot(plotdat1, aes(x = date\_sent, y = prop\_vac\_in\_week, group = mtypeF, color = mtypeF, size = control\_msg)) +  
 geom\_point() +  
 geom\_path() +  
 # facet\_wrap(~iteration,scales="free")+  
 guides(color = guide\_legend(title = "Message")) +  
 scale\_colour\_brewer(type = "div") +  
 ylab("Vaccinated within a Week of Message Assignment") +  
 xlab("Date Assigned Message") +  
 scale\_size\_manual(values = c(0.5, 1.2), guide = "none") +  
 scale\_linetype\_manual(values = c("solid", "dashed"), guide = "none") +  
 theme\_classic(base\_family = "Open Sans") +  
 theme(  
 text = element\_text(size = 16),  
 axis.text.x = element\_text(angle = 0, hjust = 1)  
 )  
  
# g\_prop\_vac\_in\_week  
  
g\_prop\_vac\_smooth\_in\_week <- ggplot(plotdat1, aes(x = date\_sent, y = prop\_vac\_in\_week, group = mtypeF, color = mtypeF, size = control\_msg)) +  
 geom\_point() +  
 geom\_smooth(se = FALSE, method = "loess", span = 2 / 3, method.args = list(degree = 1, family = "symmetric")) +  
 guides(color = guide\_legend(title = "Message")) +  
 ylab("Vaccinated within a Week of Message Assignment") +  
 xlab("Date Assigned Message") +  
 # geom\_vline(xintercept=as.Date(c("2021-05-31","2021-06-08")))+  
 scale\_size\_manual(values = c(0.5, 1.2), guide = "none") +  
 scale\_colour\_brewer(type = "div") +  
 scale\_linetype\_manual(values = c("solid", "dashed"), guide = "none") +  
 theme\_classic(base\_family = "Open Sans") +  
 theme(  
 text = element\_text(size = 16),  
 axis.text.x = element\_text(angle = 0, hjust = 1)  
 )  
  
# g\_prop\_vac\_smooth\_in\_week  
  
ggsave(file = "prop\_vac.png", path = OUTPUT\_DIR, plot = g\_prop\_vac, type = "cairo-png", dpi = 300)  
ggsave(file = "prop\_vac\_in\_week.png", path = OUTPUT\_DIR, plot = g\_prop\_vac\_in\_week, type = "cairo-png", dpi = 300)  
ggsave(file = "prop\_vac\_smooth.png", path = OUTPUT\_DIR, plot = g\_prop\_vac\_smooth, type = "cairo-png", dpi = 300)  
ggsave(file = "prop\_vac\_smooth\_in\_week.png", path = OUTPUT\_DIR, plot = g\_prop\_vac\_smooth\_in\_week, type = "cairo-png", dpi = 300)

# Pre-specified analyses

These analyses were registered at <https://osf.io/pkhae/>.

## RQ0: Is there any effect of condition assignment?

The following suggests that we have some evidence of differences among the messages:

## This is the asymptotic approx to the randomization inference  
rq0\_asym <- cmh\_test(vaccinatedF ~ messageF | date\_sentF, data = wrkdat3, distribution = asymptotic())  
## This next is the permutation approx to the randomization inference  
set.seed(12345)  
rq0\_perm <- cmh\_test(vaccinatedF ~ messageF | date\_sentF, data = wrkdat3, distribution = approximate(nresample = 10000, paralle = "multicore", ncpus = 4))  
  
rq0\_asym

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by  
 messageF (message\_0, message\_1, message\_2, message\_3, message\_4, message\_5, message\_6, message\_7, message\_8)   
 stratified by date\_sentF  
chi-squared = 13, df = 8, p-value = 0.1

rq0\_perm

Approximative Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by  
 messageF (message\_0, message\_1, message\_2, message\_3, message\_4, message\_5, message\_6, message\_7, message\_8)   
 stratified by date\_sentF  
chi-squared = 13, p-value = 0.1

pvalue(rq0\_asym)

[1] 0.1153

thetab <- with(wrkdat3, table(messageF, vaccinatedF, date\_sentF))  
  
rq0a <- mantelhaen.test(thetab)  
rq0a

Cochran-Mantel-Haenszel test  
  
data: thetab  
Cochran-Mantel-Haenszel M^2 = 13, df = 8, p-value = 0.1

## RQ1: Is there an effect of receiving a message as opposed to not receiving a message?

The below shows little evidence of effect of “any message” versus “control”.

rq1\_asym <- cmh\_test(vaccinatedF ~ not\_controlF | date\_sentF, data = wrkdat3, distribution = asymptotic())  
rq1\_perm <- cmh\_test(vaccinatedF ~ not\_controlF | date\_sentF, data = wrkdat3, distribution = approximate(nresample = 10000, paralle = "multicore", ncpus = 4))  
  
rq1\_asym

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 1.2, df = 1, p-value = 0.3

rq1\_perm

Approximative Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 1.2, p-value = 0.3

pvalue(rq1\_asym)

[1] 0.2663

We can show the estimated difference in proportion here:

rq1\_est <- difference\_in\_means(vaccinated ~ not\_controlF, blocks = date\_sentF, data = wrkdat3)  
rq1\_est

Design: Blocked   
 Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
not\_controlF -0.00147 0.001363 -1.079 0.2806 -0.004141 0.001201 142402

rq1\_week\_est <- difference\_in\_means(vaccinated ~ not\_controlF, blocks = iteration, data = wrkdat3)  
rq1\_week\_est

Design: Blocked   
 Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
not\_controlF -0.001473 0.001363 -1.081 0.2797 -0.004145 0.001198 142422

lm\_bin0 <- difference\_in\_means(vaccinated ~ not\_control, blocks = date\_sentF, data = wrkdat3)  
lm\_bin1 <- lm\_robust(vaccinated ~ not\_control, data = wrkdat3, weights = nbwt\_bin)  
lm\_bin2 <- lm\_robust(vaccinated ~ not\_control, data = wrkdat3, weights = IPW\_weight\_bin)  
lm\_bin1

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.02061 0.001312 15.711 1.406e-55 0.018038 0.023180 142426  
not\_control -0.00147 0.001366 -1.077 2.817e-01 -0.004147 0.001207 142426

stopifnot(all.equal(lm\_bin0$coef, lm\_bin1$coef["not\_control"]))  
stopifnot(all.equal(lm\_bin0$coef, lm\_bin2$coef["not\_control"]))  
stopifnot(all.equal(lm\_bin0$coef[[1]], rq1\_est$coef[["not\_controlF"]]))  
  
## Proportion vaccinated by end in the "not control" combination condition  
sum(coef(lm\_bin1))

[1] 0.01914

## RQ2: Does any given message differ from control (focal tests)?

Overall, we have approx 2% of the control group getting vaccinated (weighted average across the days), and very small differences from that rate for each message — all less than 1/3 pct point different in magnitude from the control group.

rq2\_est <- lm\_robust(vaccinated ~ messageF, weights = IPW\_weight\_multarm, data = wrkdat3)  
rq2\_est

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.02060861 0.001312 15.71145 1.406e-55 0.018038 0.0231795 142419  
messageFmessage\_1 -0.00208199 0.001842 -1.13002 2.585e-01 -0.005693 0.0015291 142419  
messageFmessage\_2 -0.00002266 0.001898 -0.01194 9.905e-01 -0.003742 0.0036968 142419  
messageFmessage\_3 0.00232052 0.002012 1.15339 2.488e-01 -0.001623 0.0062638 142419  
messageFmessage\_4 -0.00222375 0.001863 -1.19395 2.325e-01 -0.005874 0.0014267 142419  
messageFmessage\_5 0.00015034 0.001886 0.07972 9.365e-01 -0.003546 0.0038467 142419  
messageFmessage\_6 -0.00260175 0.001719 -1.51333 1.302e-01 -0.005971 0.0007679 142419  
messageFmessage\_7 -0.00316289 0.001824 -1.73444 8.284e-02 -0.006737 0.0004113 142419  
messageFmessage\_8 -0.00012584 0.001844 -0.06826 9.456e-01 -0.003739 0.0034876 142419

## In percentage point differences from messsage\_0 (except for Intercept which is proportion vaccinated (on average, weighted by day) in message\_0)  
zapsmall(rq2\_est$coef \* 100)

(Intercept) messageFmessage\_1 messageFmessage\_2 messageFmessage\_3 messageFmessage\_4 messageFmessage\_5 messageFmessage\_6   
 2.0609 -0.2082 -0.0023 0.2321 -0.2224 0.0150 -0.2602   
messageFmessage\_7 messageFmessage\_8   
 -0.3163 -0.0126

## Adding the fixed effects estimates (biased, but more precise/statistically powerful)  
rq2\_fe\_est <- lm\_robust(vaccinated ~ messageF, fixed\_effects = ~date\_sentF, data = wrkdat3)  
rq2\_fe\_est

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_1 -0.0022322 0.002007 -1.1125 0.26595 -0.006165 0.0017006 142407  
messageFmessage\_2 -0.0002051 0.001966 -0.1044 0.91688 -0.004058 0.0036474 142407  
messageFmessage\_3 0.0005308 0.002000 0.2654 0.79071 -0.003390 0.0044514 142407  
messageFmessage\_4 -0.0029133 0.002013 -1.4469 0.14792 -0.006860 0.0010330 142407  
messageFmessage\_5 -0.0006247 0.001874 -0.3334 0.73881 -0.004297 0.0030474 142407  
messageFmessage\_6 -0.0027722 0.001567 -1.7690 0.07689 -0.005844 0.0002992 142407  
messageFmessage\_7 -0.0034071 0.001902 -1.7915 0.07321 -0.007135 0.0003204 142407  
messageFmessage\_8 0.0004312 0.002011 0.2144 0.83020 -0.003510 0.0043723 142407

The unadjusted tests tests of independence of each message versus control using permutation approximations to the randomization inference and the Cochrane-Mantel-Haenszel test for 2x2xK experiments show no differences between any message and control at .

test\_msgs <- function(msg1, msg2) {  
 ## msg1 and msg2 are strings indicating message assignment in messageF  
 effect\_test <- cmh\_test(vaccinatedF ~ messageF | date\_sentF,  
 data = wrkdat3,  
 subset = wrkdat3$messageF %in% c(msg1, msg2),  
 distribution = approximate(nresample = 10000, parallel = "multicore", ncpu = 6)  
 )  
 return(pvalue(effect\_test)[1])  
}  
  
message\_test\_ps <- sapply(levels(wrkdat3$messageF)[-1], function(msg) {  
 test\_msgs("message\_0", msg)  
})  
  
message\_test\_ps

message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8   
 0.2768 1.0000 0.6912 0.1779 0.9314 0.0948 0.0543 0.8947

We specified that we would report adjusted p-values, although it is hardly necessary since we are not reporting any discoveries.

The FDR adjustments (direct and q-values):

cbind(message\_test\_ps, fdr\_adjusted = p.adjust(message\_test\_ps, method = "fdr"))

message\_test\_ps fdr\_adjusted  
message\_1 0.2768 0.5536  
message\_2 1.0000 1.0000  
message\_3 0.6912 1.0000  
message\_4 0.1779 0.4744  
message\_5 0.9314 1.0000  
message\_6 0.0948 0.3792  
message\_7 0.0543 0.3792  
message\_8 0.8947 1.0000

Here are the q-values (same as the “adjusted p-values” above) (not clearly worth diving into since we have no effects but including a link to an explanation here <https://www.bioconductor.org/packages/devel/bioc/vignettes/qvalue/inst/doc/qvalue.pdf>)

library(qvalue)  
rq2\_qvals <- qvalue(message\_test\_ps, lambda = seq(0.05, 0.65, 0.05))  
rq2\_qvals$qvalues

message\_1 message\_2 message\_3 message\_4 message\_5 message\_6 message\_7 message\_8   
 0.5536 1.0000 1.0000 0.4744 1.0000 0.3792 0.3792 1.0000

A figure showing the results from rq2 estimation with 95% confidence intervals.

rq2plot\_dat <- tidy(rq2\_est)  
  
rq2plot\_dat$term <- c("Control", paste("M", 1:8, " v Ctrl", sep = ""))  
  
rq2plot\_dat$mtype <- c("Control", "Ownership", "Safety", "Preventing bad outcomes", "Epistemic humility+no bad outcomes", "Access", "Family concern", "Social proof", "Social proof+family concern")  
  
rq2plot\_dat <- rq2plot\_dat %>%  
 filter(term != "Control") %>%  
 arrange(estimate)  
rq2plot\_dat$termF <- factor(rq2plot\_dat$term, levels = rq2plot\_dat$term)  
  
rq2xlim <- range(c(rq2plot\_dat$conf.low, rq2plot\_dat$conf.high))  
  
rq2plot <- ggplot(rq2plot\_dat, aes(x = estimate, y = termF)) +  
 geom\_vline(aes(xintercept = 0), color = "grey") +  
 geom\_point() +  
 geom\_errorbarh(mapping = aes(xmin = conf.low, xmax = conf.high), height = .2) +  
 xlab("Difference in Vaccination Proportion vs No Message (95% CI)") +  
 geom\_text(aes(label = mtype), check\_overlap = TRUE, nudge\_y = .2, family = "Open Sans", size = 4.5) +  
 ylab("") +  
 theme\_classic(base\_family = "Open Sans") +  
 xlim(rq2xlim) +  
 theme(  
 text = element\_text(size = 13),  
 axis.line.y = element\_blank(),  
 axis.text.y = element\_blank(),  
 axis.ticks.y = element\_blank(),  
 axis.text.x = element\_text(angle = 0, hjust = 1)  
 )  
  
# print(rq2plot)

ggsave(file = "rq2plot.pdf", path = OUTPUT\_DIR, plot = rq2plot, device = cairo\_pdf)  
ggsave(file = "rq2plot.png", path = OUTPUT\_DIR, plot = rq2plot, type = "cairo-png", dpi = 300)

include\_graphics(here(OUTPUT\_DIR, "rq2plot.pdf"))

![](data:application/pdf;base64,)

## RQ3: Does epistemic humility help?

Message 4 vs. 3 (CMH test, difference of proportions estimator). Only very small differences between those two arms.

rq3\_est <- difference\_in\_means(vaccinated ~ messageF, blocks = date\_sent, data = wrkdat3, subset = wrkdat3$messageF %in% c("message\_3", "message\_4"))  
rq3\_est

Design: Blocked   
 Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_4 -0.003194 0.002074 -1.54 0.1235 -0.00726 0.0008707 22046

rq3\_test <- test\_msgs("message\_3", "message\_4")  
rq3\_test

[1] 0.1063

## RQ5: How do social proof and appeals to the family interact?

We will test the overall hypothesis of no difference between 6 (family concern), 7 (social proof), and 8 (family concern + social proof). If we reject this, we test 6 versus 8 and 7 versus 8.

rq5\_overall <- cmh\_test(vaccinatedF ~ messageF | date\_sentF, data = wrkdat3, subset = wrkdat3$messageF %in% c("message\_6", "message\_7", "message\_8"))  
rq5\_overall\_perm <- cmh\_test(vaccinatedF ~ messageF | date\_sentF, data = wrkdat3, subset = wrkdat3$messageF %in% c("message\_6", "message\_7", "message\_8"), distribution = approximate(nresample = 10000, parallel = "multicore", ncpus = 6))  
rq5\_overall

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by  
 messageF (message\_6, message\_7, message\_8)   
 stratified by date\_sentF  
chi-squared = 5.1, df = 2, p-value = 0.08

rq5\_overall\_perm

Approximative Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by  
 messageF (message\_6, message\_7, message\_8)   
 stratified by date\_sentF  
chi-squared = 5.1, p-value = 0.08

So, since we have a marginal rejection, we do the other tests. The differences are still quite small.

test\_msgs("message\_6", "message\_7")

[1] 0.568

test\_msgs("message\_6", "message\_8")

[1] 0.1666

test\_msgs("message\_7", "message\_8")

[1] 0.0257

rq\_5a\_est <- difference\_in\_means(vaccinated ~ messageF, blocks = date\_sent, data = wrkdat3, subset = wrkdat3$messageF %in% c("message\_6", "message\_7"))  
rq\_5b\_est <- difference\_in\_means(vaccinated ~ messageF, blocks = date\_sent, data = wrkdat3, subset = wrkdat3$messageF %in% c("message\_6", "message\_8"))  
rq\_5c\_est <- difference\_in\_means(vaccinated ~ messageF, blocks = date\_sent, data = wrkdat3, subset = wrkdat3$messageF %in% c("message\_7", "message\_8"))  
  
rq\_5a\_est

Design: Blocked   
 Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_7 -0.0002589 0.001726 -0.15 0.8807 -0.003642 0.003124 59395

rq\_5b\_est

Design: Blocked   
 Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_8 0.0009202 0.001569 0.5863 0.5577 -0.002156 0.003996 58466

rq\_5c\_est

Design: Blocked   
 Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_8 0.004312 0.001919 2.247 0.02463 0.0005511 0.008073 23771

## RQ6: Did adaptive randomization increase vaccinations over fixed randomization?

We also will report the effect of using adaptive randomization versus fixed randomization on total vaccinations –- since we withheld 25% of each of the three weeks experimental pools for fixed randomization and adapted the other 100 – 25%. Our aim in this study was to (1) learn about which messages worked best but also (2) increase vaccination. The fixed randomization maximized statistical power to detect effects whereas the adaptive randomization increased the numbers of people exposed to more effective messages.

It looks like slightly more people were vaccinated in the non-adaptive arm of the study.

with(wrkdat3, table(date\_sent, is\_chosen\_from\_uniform, exclude = c()))

is\_chosen\_from\_uniform  
date\_sent FALSE TRUE  
 2021-05-25 0 10003  
 2021-05-26 0 9999  
 2021-05-27 0 9999  
 2021-05-28 0 9999  
 2021-06-02 5947 1994  
 2021-06-03 5969 1972  
 2021-06-04 5919 2029  
 2021-06-07 5933 2009  
 2021-06-08 5988 1949  
 2021-06-09 10437 5245  
 2021-06-10 10503 5176  
 2021-06-11 10501 5178  
 2021-06-14 10499 5180

rq6\_est <- difference\_in\_means(vaccinated ~ is\_chosen\_from\_uniform, blocks = date\_sentF, data = wrkdat3, subset = wrkdat3$date\_sent >= "2021-06-02")  
rq6\_est

Design: Blocked   
 Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
is\_chosen\_from\_uniform 0.0009958 0.0008211 1.213 0.2252 -0.0006135 0.002605 102410

rq6\_cmh\_perm <- cmh\_test(vaccinatedF ~ factor(is\_chosen\_from\_uniform) | date\_sentF, data = wrkdat3, subset = wrkdat3$date\_sent >= "2021-06-02", distribution = approximate(nresample = 10000, parallel = "multicore", ncpus = 6))  
rq6\_cmh\_perm

Approximative Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by  
 factor(is\_chosen\_from\_uniform) (FALSE, TRUE)   
 stratified by date\_sentF  
chi-squared = 1.5, p-value = 0.2

# Exploratory Analyses Not Pre-registered

## Effects on vaccination within a week

The experiment ran during a time of national campaigns in favor of vaccination. The control group in our experiment would have been exposed to this, and thus, might have gotten vaccinated for reasons other than a nudge from a text message.

No strong evidence that people were likely to be vaccinated within a week in “any message” versus control or versus any given message.

rq7\_test <- cmh\_test(vac\_in\_weekF ~ not\_controlF | date\_sentF, data = wrkdat3)  
rq7\_test

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vac\_in\_weekF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 0.00041, df = 1, p-value = 1

rq7a\_test <- cmh\_test(vac\_in\_weekF ~ messageF | date\_sentF, data = wrkdat3)  
rq7a\_test

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vac\_in\_weekF by  
 messageF (message\_0, message\_1, message\_2, message\_3, message\_4, message\_5, message\_6, message\_7, message\_8)   
 stratified by date\_sentF  
chi-squared = 8.7, df = 8, p-value = 0.4

rq7a\_est <- lm\_robust(vac\_in\_week ~ messageF, weights = IPW\_weight\_multarm, data = wrkdat3)  
rq7a\_est

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.009127748 0.0009266 9.851260 6.884e-23 0.0073117 0.010944 142419  
messageFmessage\_1 0.000124368 0.0013438 0.092548 9.263e-01 -0.0025095 0.002758 142419  
messageFmessage\_2 0.000262444 0.0013718 0.191314 8.483e-01 -0.0024263 0.002951 142419  
messageFmessage\_3 0.002280338 0.0014842 1.536381 1.244e-01 -0.0006287 0.005189 142419  
messageFmessage\_4 -0.001289688 0.0012946 -0.996239 3.191e-01 -0.0038270 0.001248 142419  
messageFmessage\_5 -0.000005737 0.0013428 -0.004273 9.966e-01 -0.0026376 0.002626 142419  
messageFmessage\_6 -0.000254321 0.0011945 -0.212902 8.314e-01 -0.0025956 0.002087 142419  
messageFmessage\_7 -0.000963766 0.0013199 -0.730162 4.653e-01 -0.0035508 0.001623 142419  
messageFmessage\_8 0.000933308 0.0013295 0.702014 4.827e-01 -0.0016724 0.003539 142419

rq7plot\_dat <- tidy(rq7a\_est)  
  
rq7plot\_dat$term <- c("Control", paste("M", 1:8, " v Ctrl", sep = ""))  
  
rq7plot\_dat$mtype <- c("Control", "Ownership", "Safety", "Preventing bad outcomes", "Epistemic humility+no bad outcomes", "Access", "Family concern", "Social proof", "Social proof+family concern")  
  
rq7plot\_dat <- rq7plot\_dat %>% filter(term != "Control")  
rq7plot\_dat$termF <- factor(rq7plot\_dat$term, levels = rq2plot\_dat$term)  
with(rq7plot\_dat, table(term, termF, exclude = c()))

termF  
term M7 v Ctrl M6 v Ctrl M4 v Ctrl M1 v Ctrl M8 v Ctrl M2 v Ctrl M5 v Ctrl M3 v Ctrl  
 M1 v Ctrl 0 0 0 1 0 0 0 0  
 M2 v Ctrl 0 0 0 0 0 1 0 0  
 M3 v Ctrl 0 0 0 0 0 0 0 1  
 M4 v Ctrl 0 0 1 0 0 0 0 0  
 M5 v Ctrl 0 0 0 0 0 0 1 0  
 M6 v Ctrl 0 1 0 0 0 0 0 0  
 M7 v Ctrl 1 0 0 0 0 0 0 0  
 M8 v Ctrl 0 0 0 0 1 0 0 0

rq7plot <- ggplot(rq7plot\_dat, aes(x = estimate, y = termF)) +  
 geom\_vline(aes(xintercept = 0), color = "grey") +  
 geom\_point() +  
 geom\_errorbarh(mapping = aes(xmin = conf.low, xmax = conf.high), height = .2) +  
 xlab("Difference in Vaccination Proportion vs No Message within a Week (95% CI)") +  
 geom\_text(aes(label = mtype), check\_overlap = TRUE, nudge\_y = .2, family = "Open Sans", size = 4.5) +  
 ylab("") +  
 theme\_classic(base\_family = "Open Sans") +  
 xlim(rq2xlim) +  
 theme(  
 text = element\_text(size = 13),  
 axis.line.y = element\_blank(),  
 axis.text.y = element\_blank(),  
 axis.ticks.y = element\_blank(),  
 axis.text.x = element\_text(angle = 0, hjust = 1)  
 )  
  
# print(rq7plot)

ggsave(file = "rq7plot.pdf", path = OUTPUT\_DIR, plot = rq7plot, device = cairo\_pdf)  
ggsave(file = "rq7plot.png", path = OUTPUT\_DIR, plot = rq7plot, type = "cairo-png", dpi = 300)

rq2\_rq7\_plot <- ggarrange(rq2plot, rq7plot, nrow = 1)

Warning in grid.Call(C\_stringMetric, as.graphicsAnnot(x$label)): font family 'Open Sans' not found in PostScript font database  
  
Warning in grid.Call(C\_stringMetric, as.graphicsAnnot(x$label)): font family 'Open Sans' not found in PostScript font database  
  
Warning in grid.Call(C\_stringMetric, as.graphicsAnnot(x$label)): font family 'Open Sans' not found in PostScript font database  
  
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Warning in grid.Call(C\_stringMetric, as.graphicsAnnot(x$label)): font family 'Open Sans' not found in PostScript font database  
  
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Warning in grid.Call(C\_stringMetric, as.graphicsAnnot(x$label)): font family 'Open Sans' not found in PostScript font database  
  
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Warning in grid.Call(C\_stringMetric, as.graphicsAnnot(x$label)): font family 'Open Sans' not found in PostScript font database  
  
Warning in grid.Call(C\_stringMetric, as.graphicsAnnot(x$label)): font family 'Open Sans' not found in PostScript font database  
  
Warning in grid.Call(C\_stringMetric, as.graphicsAnnot(x$label)): font family 'Open Sans' not found in PostScript font database

# print(rq2\_rq7\_plot)  
  
ggsave(file = "rq2\_rq7\_plot.pdf", path = OUTPUT\_DIR, plot = rq2\_rq7\_plot, device = cairo\_pdf, width = 12, height = 6)  
ggsave(file = "rq2\_rq7\_plot.png", path = OUTPUT\_DIR, plot = rq2\_rq7\_plot, type = "cairo-png", dpi = 300, width = 12, height = 6)

## Each iteration separately

We looked at both overall vaccination and vaccination within a week (only available for those assigned in the first week). The following table shows that we have no strong arguments against the claim that our messages were the same as control in regards either outcome. (Not adjusting p-values here because this is exploratory work and because we have so few small p-values).

test\_msgs2 <- function(msg1, msg2, the\_iteration, thefmla = vaccinatedF ~ messageF | date\_sentF) {  
 ## msg1 and msg2 are strings indicating message assignment in messageF  
 effect\_test <- cmh\_test(thefmla,  
 data = wrkdat3,  
 subset = wrkdat3$messageF %in% c(msg1, msg2) & wrkdat3$iteration == the\_iteration,  
 distribution = asymptotic() # approximate(nresample = 10000, parallel = "multicore", ncpu = 6)  
 )  
 return(pvalue(effect\_test)[1])  
}  
  
msg\_by\_iteration <- as\_tibble(expand.grid(iteration = 1:3, messageF = levels(wrkdat3$messageF)[-1], stringsAsFactors = FALSE))  
  
test\_msgs2(msg1 = "message\_0", msg2 = msg\_by\_iteration$messageF[1], the\_iteration = 3)

[1] 0.5406

set.seed(12345)  
msg\_by\_iteration <- msg\_by\_iteration %>%  
 rowwise() %>%  
 mutate(p\_vs\_ctrl = test\_msgs2("message\_0", messageF, iteration)) %>%  
 arrange(iteration, messageF)  
  
msg\_by\_iteration <- msg\_by\_iteration %>%  
 rowwise() %>%  
 mutate(p\_vac\_week\_vs\_ctrl = test\_msgs2("message\_0", messageF, iteration, thefmla = vac\_in\_weekF ~ messageF | date\_sentF))  
  
msg\_by\_iteration <- msg\_by\_iteration %>% mutate(p\_vac\_week\_vs\_ctrl = ifelse(p\_vac\_week\_vs\_ctrl == p\_vs\_ctrl, NA, p\_vac\_week\_vs\_ctrl))  
print(msg\_by\_iteration, n = 100)

# A tibble: 24 x 4  
# Rowwise:   
 iteration messageF p\_vs\_ctrl p\_vac\_week\_vs\_ctrl  
 <int> <chr> <dbl> <dbl>  
 1 1 message\_1 0.414 0.624   
 2 1 message\_2 0.777 0.776   
 3 1 message\_3 0.485 0.554   
 4 1 message\_4 0.0950 0.151   
 5 1 message\_5 0.432 0.999   
 6 1 message\_6 0.174 0.368   
 7 1 message\_7 0.00849 0.185   
 8 1 message\_8 0.911 0.458   
 9 2 message\_1 0.601 0.188   
10 2 message\_2 0.685 0.655   
11 2 message\_3 0.870 0.127   
12 2 message\_4 0.510 0.215   
13 2 message\_5 0.369 0.357   
14 2 message\_6 0.741 0.250   
15 2 message\_7 0.732 0.298   
16 2 message\_8 0.289 0.0548  
17 3 message\_1 0.541 0.731   
18 3 message\_2 0.988 0.893   
19 3 message\_3 0.0394 0.127   
20 3 message\_4 0.321 0.203   
21 3 message\_5 0.944 0.680   
22 3 message\_6 0.318 0.517   
23 3 message\_7 0.567 0.523   
24 3 message\_8 0.405 0.469

Nor is there strong evidence that “any message” was better than control, even when we assess the relationships for each iteration separately:

rq8\_iteration1\_test <- cmh\_test(vaccinatedF ~ not\_controlF | date\_sentF, data = wrkdat3, subset = wrkdat3$iteration == 1)  
rq8\_iteration1\_test

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 1, df = 1, p-value = 0.3

rq8\_iteration2\_test <- cmh\_test(vaccinatedF ~ not\_controlF | date\_sentF, data = wrkdat3, subset = wrkdat3$iteration == 2)  
rq8\_iteration2\_test

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 0.0055, df = 1, p-value = 0.9

rq8\_iteration3\_test <- cmh\_test(vaccinatedF ~ not\_controlF | date\_sentF, data = wrkdat3, subset = wrkdat3$iteration == 3)  
rq8\_iteration3\_test

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vaccinatedF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 0.57, df = 1, p-value = 0.5

## Also looking at vaccinations within a week for the first iteration  
rq9\_iteration1\_test <- cmh\_test(vac\_in\_weekF ~ not\_controlF | date\_sentF, data = wrkdat3, subset = wrkdat3$iteration == 1)  
rq9\_iteration1\_test

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vac\_in\_weekF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 0.36, df = 1, p-value = 0.6

rq9\_iteration2\_test <- cmh\_test(vac\_in\_weekF ~ not\_controlF | date\_sentF, data = wrkdat3, subset = wrkdat3$iteration == 2)  
rq9\_iteration2\_test

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vac\_in\_weekF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 1.9, df = 1, p-value = 0.2

rq9\_iteration3\_test <- cmh\_test(vac\_in\_weekF ~ not\_controlF | date\_sentF, data = wrkdat3, subset = wrkdat3$iteration == 3)  
rq9\_iteration3\_test

Asymptotic Generalized Cochran-Mantel-Haenszel Test  
  
data: vac\_in\_weekF by not\_controlF (0, 1)   
 stratified by date\_sentF  
chi-squared = 0.34, df = 1, p-value = 0.6

# Exploratory Analyses Pre-registered

These analysis all compare effects of messages as they might vary for people who live in different kinds of places (using ZCTA as the place).

## EQ1: Do explicit appeals to the safety of vaccines increase responses in areas with higher proportions of Black or Latinx people? Message 2 vs. control

We cannot detect any simple linear differential effect of pct black or latinx on the message 2 versus control comparison.

wrkdat3\_eq1 <- wrkdat3 %>%  
 filter(messageF %in% c("message\_0", "message\_2") & zcta != "00000") %>%  
 droplevels()  
dim(wrkdat3\_eq1)

[1] 23249 44

table(wrkdat3\_eq1$date\_sent, wrkdat3\_eq1$messageF, exclude = c())

message\_0 message\_2  
 2021-05-25 1089 1087  
 2021-05-26 1095 1099  
 2021-05-27 1087 1087  
 2021-05-28 1092 1088  
 2021-06-02 688 1108  
 2021-06-03 677 1107  
 2021-06-04 675 1109  
 2021-06-07 679 1095  
 2021-06-08 686 1105  
 2021-06-09 830 572  
 2021-06-10 823 576  
 2021-06-11 831 570  
 2021-06-14 819 575

make\_weights <- function(dat) {  
 block\_m\_each <- with(dat, table(date\_sentF, messageF, exclude = c()))  
 block\_prob\_each <- block\_m\_each / rowSums(block\_m\_each)  
 declared\_randomization <- declare\_ra(blocks = dat$date\_sentF, block\_m\_each = block\_m\_each, conditions = sort(unique(dat$messageF)))  
 IPW\_weight <- 1 / obtain\_condition\_probabilities(declaration = declared\_randomization, assignment = dat$messageF)  
 stopifnot(all.equal(sort(unique(1 / IPW\_weight)), sort(unique(block\_prob\_each))))  
 return(IPW\_weight)  
}  
  
wrkdat3\_eq1$IPW\_eq1 <- make\_weights(wrkdat3\_eq1)  
## So, good that I didn't use the multi-arm weights.  
with(wrkdat3\_eq1, cor(IPW\_eq1, IPW\_weight\_multarm))

[1] 0.352

eq1\_blk\_estA <- lm\_robust(vaccinated ~ messageF \* pct\_any\_blk, data = wrkdat3\_eq1, weights = IPW\_eq1)  
## Just including Fixed Effects for curiosity. We will report estA  
eq1\_blk\_estB <- lm\_robust(vaccinated ~ messageF \* pct\_any\_blk, data = wrkdat3\_eq1, fixed\_effects = ~date\_sentF)  
  
eq1\_blk\_estA

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.0188928 0.002016 9.370867 7.829e-21 0.014941 0.022845 23245  
messageFmessage\_2 -0.0002165 0.002783 -0.077775 9.380e-01 -0.005672 0.005239 23245  
pct\_any\_blk 0.0538385 0.018998 2.833943 4.602e-03 0.016602 0.091075 23245  
messageFmessage\_2:pct\_any\_blk -0.0002156 0.026120 -0.008253 9.934e-01 -0.051413 0.050982 23245

eq1\_blk\_estB

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_2 -0.0002700 0.002751 -0.09816 0.921810 -0.005662 0.005122 23233  
pct\_any\_blk 0.0553735 0.018627 2.97276 0.002954 0.018863 0.091884 23233  
messageFmessage\_2:pct\_any\_blk 0.0004877 0.025627 0.01903 0.984818 -0.049744 0.050719 23233

eq1\_lat\_estA <- lm\_robust(vaccinated ~ messageF \* pct\_hisp, data = wrkdat3\_eq1, weights = IPW\_eq1)  
## Just including Fixed Effects for curiosity. We will report estA  
eq1\_lat\_estB <- lm\_robust(vaccinated ~ messageF \* pct\_hisp, data = wrkdat3\_eq1, fixed\_effects = ~date\_sentF)  
  
eq1\_lat\_estA

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.018012 0.001849 9.7392 2.264e-22 0.014387 0.021637 23245  
messageFmessage\_2 0.001080 0.002534 0.4262 6.700e-01 -0.003887 0.006048 23245  
pct\_hisp 0.034689 0.009438 3.6756 2.378e-04 0.016191 0.053187 23245  
messageFmessage\_2:pct\_hisp -0.007924 0.012534 -0.6322 5.272e-01 -0.032492 0.016643 23245

eq1\_lat\_estB

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_2 0.000861 0.002514 0.3424 0.7320161 -0.004067 0.005789 23233  
pct\_hisp 0.033746 0.009169 3.6804 0.0002334 0.015774 0.051717 23233  
messageFmessage\_2:pct\_hisp -0.006495 0.012236 -0.5309 0.5955128 -0.030478 0.017487 23233

## EQ2: Does the implication of choice through emphasis on a conspicuous advantage increase responses in areas with higher proportions of Republican people? Message 3 vs. control

No detectable difference in effects.

wrkdat3\_eq2 <- wrkdat3 %>%  
 filter(messageF %in% c("message\_0", "message\_3") & zcta != "00000") %>%  
 droplevels()  
dim(wrkdat3\_eq2)

[1] 22772 44

table(wrkdat3\_eq2$date\_sent, wrkdat3\_eq2$messageF, exclude = c())

message\_0 message\_3  
 2021-05-25 1089 1080  
 2021-05-26 1095 1096  
 2021-05-27 1087 1091  
 2021-05-28 1092 1084  
 2021-06-02 688 986  
 2021-06-03 677 980  
 2021-06-04 675 989  
 2021-06-07 679 996  
 2021-06-08 686 995  
 2021-06-09 830 603  
 2021-06-10 823 599  
 2021-06-11 831 602  
 2021-06-14 819 600

wrkdat3\_eq2$IPW\_eq2 <- make\_weights(wrkdat3\_eq2)  
  
eq2\_gop\_estA <- lm\_robust(vaccinated ~ messageF \* pct\_gop, data = wrkdat3\_eq2, weights = IPW\_eq2)  
## Just including Fixed Effects for curiosity. We will report estA  
eq2\_gop\_estB <- lm\_robust(vaccinated ~ messageF \* pct\_gop, data = wrkdat3\_eq2, fixed\_effects = ~date\_sentF)  
  
eq2\_gop\_estA

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.033399 0.00480 6.9582 3.541e-12 0.02399 0.042808 22768  
messageFmessage\_3 -0.002249 0.00661 -0.3402 7.337e-01 -0.01520 0.010707 22768  
pct\_gop -0.027623 0.01238 -2.2321 2.562e-02 -0.05188 -0.003366 22768  
messageFmessage\_3:pct\_gop 0.009509 0.01705 0.5576 5.771e-01 -0.02392 0.042935 22768

eq2\_gop\_estB

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_3 -0.001908 0.006526 -0.2924 0.76996 -0.01470 0.0108826 22756  
pct\_gop -0.024921 0.012234 -2.0370 0.04166 -0.04890 -0.0009412 22756  
messageFmessage\_3:pct\_gop 0.008442 0.016846 0.5012 0.61627 -0.02458 0.0414618 22756

## EQ3: Do explicit appeals to ease of access increase responses in areas with higher proportions of Black or Latinx people? Message 5 vs. control

No detectable differences. Magnitude of moderation is large-ish given this phenomenon (on order of 1 or 2 pts, but negative).

wrkdat3\_eq3 <- wrkdat3 %>%  
 filter(messageF %in% c("message\_0", "message\_5") & zcta != "00000") %>%  
 droplevels()  
dim(wrkdat3\_eq3)

[1] 25934 44

table(wrkdat3\_eq3$date\_sent, wrkdat3\_eq3$messageF, exclude = c())

message\_0 message\_5  
 2021-05-25 1089 1084  
 2021-05-26 1095 1086  
 2021-05-27 1087 1088  
 2021-05-28 1092 1091  
 2021-06-02 688 1655  
 2021-06-03 677 1645  
 2021-06-04 675 1653  
 2021-06-07 679 1665  
 2021-06-08 686 1656  
 2021-06-09 830 559  
 2021-06-10 823 566  
 2021-06-11 831 558  
 2021-06-14 819 557

wrkdat3\_eq3$IPW\_eq3 <- make\_weights(wrkdat3\_eq3)  
  
eq3\_blk\_estA <- lm\_robust(vaccinated ~ messageF \* pct\_any\_blk, data = wrkdat3\_eq3, weights = IPW\_eq3)  
## Just including Fixed Effects for curiosity. We will report estA  
eq3\_blk\_estB <- lm\_robust(vaccinated ~ messageF \* pct\_any\_blk, data = wrkdat3\_eq3, fixed\_effects = ~date\_sentF)  
eq3\_blk\_estA

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.018567 0.002043 9.0861 1.098e-19 0.01456 0.022572 25930  
messageFmessage\_5 0.001946 0.002743 0.7095 4.780e-01 -0.00343 0.007322 25930  
pct\_any\_blk 0.051307 0.019179 2.6752 7.473e-03 0.01372 0.088898 25930  
messageFmessage\_5:pct\_any\_blk -0.026276 0.025041 -1.0493 2.940e-01 -0.07536 0.022805 25930

eq3\_blk\_estB

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_5 0.002159 0.002699 0.8001 0.423633 -0.00313 0.007449 25918  
pct\_any\_blk 0.055429 0.018619 2.9771 0.002913 0.01894 0.091922 25918  
messageFmessage\_5:pct\_any\_blk -0.026560 0.024224 -1.0964 0.272898 -0.07404 0.020921 25918

eq3\_lat\_estA <- lm\_robust(vaccinated ~ messageF \* pct\_hisp, data = wrkdat3\_eq3, weights = IPW\_eq3)  
## Just including Fixed Effects for curiosity. We will report estA  
eq3\_lat\_estB <- lm\_robust(vaccinated ~ messageF \* pct\_hisp, data = wrkdat3\_eq3, fixed\_effects = ~date\_sentF)  
eq3\_lat\_estA

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.017433 0.001874 9.3041 1.455e-20 0.013760 0.02111 25930  
messageFmessage\_5 0.001536 0.002512 0.6114 5.410e-01 -0.003388 0.00646 25930  
pct\_hisp 0.034860 0.009734 3.5814 3.424e-04 0.015782 0.05394 25930  
messageFmessage\_5:pct\_hisp -0.011863 0.012585 -0.9426 3.459e-01 -0.036531 0.01280 25930

eq3\_lat\_estB

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_5 0.001597 0.002468 0.6474 0.5173976 -0.003239 0.006434 25918  
pct\_hisp 0.033723 0.009157 3.6828 0.0002311 0.015775 0.051671 25918  
messageFmessage\_5:pct\_hisp -0.011048 0.011843 -0.9328 0.3509152 -0.034261 0.012166 25918

## EQ4: Does epistemic humility increase responses in areas with higher proportions of either Black or Latinx people or Republican people? Message 4 versus 3

No detectable differences in effect.

wrkdat3\_eq4 <- wrkdat3 %>%  
 filter(messageF %in% c("message\_3", "message\_4") & zcta != "00000") %>%  
 droplevels()  
dim(wrkdat3\_eq4)

[1] 21577 44

table(wrkdat3\_eq4$date\_sent, wrkdat3\_eq4$messageF, exclude = c())

message\_3 message\_4  
 2021-05-25 1080 1081  
 2021-05-26 1096 1090  
 2021-05-27 1091 1084  
 2021-05-28 1084 1089  
 2021-06-02 986 475  
 2021-06-03 980 471  
 2021-06-04 989 475  
 2021-06-07 996 471  
 2021-06-08 995 464  
 2021-06-09 603 786  
 2021-06-10 599 799  
 2021-06-11 602 794  
 2021-06-14 600 797

wrkdat3\_eq4$IPW\_eq4 <- make\_weights(wrkdat3\_eq4)  
  
eq4\_gop\_estA <- lm\_robust(vaccinated ~ messageF \* pct\_gop, data = wrkdat3\_eq4, weights = IPW\_eq4)  
## Just including Fixed Effects for curiosity. We will report estA  
eq4\_gop\_estB <- lm\_robust(vaccinated ~ messageF \* pct\_gop, data = wrkdat3\_eq4, fixed\_effects = ~date\_sentF)  
eq4\_gop\_estA

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.031424 0.004622 6.7992 1.079e-11 0.02237 0.040483 21573  
messageFmessage\_4 -0.002244 0.006677 -0.3360 7.369e-01 -0.01533 0.010844 21573  
pct\_gop -0.018053 0.011944 -1.5115 1.307e-01 -0.04146 0.005358 21573  
messageFmessage\_4:pct\_gop -0.003277 0.017226 -0.1902 8.491e-01 -0.03704 0.030487 21573

eq4\_gop\_estB

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_4 -0.002618 0.006497 -0.4030 0.6870 -0.01535 0.010116 21561  
pct\_gop -0.016735 0.011589 -1.4440 0.1488 -0.03945 0.005981 21561  
messageFmessage\_4:pct\_gop -0.002784 0.016703 -0.1667 0.8676 -0.03552 0.029954 21561

eq4\_blk\_estA <- lm\_robust(vaccinated ~ messageF \* pct\_any\_blk, data = wrkdat3\_eq4, weights = IPW\_eq4)  
## Just including Fixed Effects for curiosity. We will report estA  
eq4\_blk\_estB <- lm\_robust(vaccinated ~ messageF \* pct\_any\_blk, data = wrkdat3\_eq4, fixed\_effects = ~date\_sentF)  
eq4\_blk\_estA

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.019125 0.002084 9.17906 4.730e-20 0.015041 0.02321 21573  
messageFmessage\_4 -0.003302 0.002909 -1.13507 2.564e-01 -0.009003 0.00240 21573  
pct\_any\_blk 0.067888 0.020681 3.28267 1.030e-03 0.027352 0.10842 21573  
messageFmessage\_4:pct\_any\_blk -0.001599 0.028836 -0.05547 9.558e-01 -0.058120 0.05492 21573

eq4\_blk\_estB

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_4 -0.0036235 0.002836 -1.277497 0.201440 -0.009183 0.001936 21561  
pct\_any\_blk 0.0613615 0.019686 3.117026 0.001829 0.022776 0.099947 21561  
messageFmessage\_4:pct\_any\_blk -0.0001924 0.027278 -0.007054 0.994371 -0.053659 0.053274 21561

eq4\_lat\_estA <- lm\_robust(vaccinated ~ messageF \* pct\_hisp, data = wrkdat3\_eq4, weights = IPW\_eq4)  
## Just including Fixed Effects for curiosity. We will report estA  
eq4\_lat\_estB <- lm\_robust(vaccinated ~ messageF \* pct\_hisp, data = wrkdat3\_eq4, fixed\_effects = ~date\_sentF)  
eq4\_lat\_estA

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
(Intercept) 0.018922 0.001878 10.0774 7.851e-24 0.015242 0.022603 21573  
messageFmessage\_4 -0.002755 0.002664 -1.0345 3.009e-01 -0.007976 0.002465 21573  
pct\_hisp 0.038470 0.009790 3.9294 8.542e-05 0.019280 0.057660 21573  
messageFmessage\_4:pct\_hisp -0.004235 0.013966 -0.3032 7.617e-01 -0.031610 0.023140 21573

eq4\_lat\_estB

Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper DF  
messageFmessage\_4 -0.002767 0.002619 -1.0565 0.2907542 -0.007901 0.002367 21561  
pct\_hisp 0.036447 0.009411 3.8729 0.0001079 0.018001 0.054893 21561  
messageFmessage\_4:pct\_hisp -0.005410 0.013201 -0.4098 0.6819606 -0.031284 0.020465 21561

## EQ5: Is there a day-of-week effect? Proportions of vaccinations collapsed across all messages by day.

Since the randomization to message occurred **within day** and we have relatively few weeks, it is difficult to disentangle day of week effects from date effects. So, we only present descriptive information here.

summary(wrkdat3$date\_sent)

Min. 1st Qu. Median Mean 3rd Qu. Max.   
"2021-05-25" "2021-05-28" "2021-06-07" "2021-06-04" "2021-06-10" "2021-06-14"

table(weekdays(wrkdat3$date\_sent))

Friday Monday Thursday Tuesday Wednesday   
 33626 23621 33619 17940 33622

wrkdat3$weekday\_sent <- weekdays(wrkdat3$date\_sent)  
  
wrkdat3\_weekday <- wrkdat3 %>%  
 group\_by(weekday\_sent) %>%  
 summarize(  
 prop\_vac = mean(vaccinated),  
 prop\_vac\_in\_week = mean(vac\_in\_week), nweek = n()  
 )  
  
wrkdat3\_weekday

# A tibble: 5 x 4  
 weekday\_sent prop\_vac prop\_vac\_in\_week nweek  
 <chr> <dbl> <dbl> <int>  
1 Friday 0.0181 0.00803 33626  
2 Monday 0.00923 0.00703 23621  
3 Thursday 0.0195 0.00943 33619  
4 Tuesday 0.0294 0.0109 17940  
5 Wednesday 0.0218 0.0102 33622

## EQ6: Is there an iteration effect? Some people were randomly assigned to have 3 weeks to schedule a vaccination and others only 1 week before the study ended. We explore whether there is a difference here.

We addressed this analysis above in our analysis by day of week and iteration.