Pre-Analysis Plan for 'The Effects of Media Messages on Social Attitudes in Uganda'

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1 Pre-Analysis Plan

This document summarizes key features of Phase I of the Media and Social Norms in Uganda Randomized Trial and describes the authors' pre-analysis plan (PAP). This document predates endline data collection, and our plan is therefore blind to outcomes. Any contingency not accounted for in this PAP will be dealt with according to the Standard Operating Procedures for Don Green's lab at Columbia as of December 22, 2015.

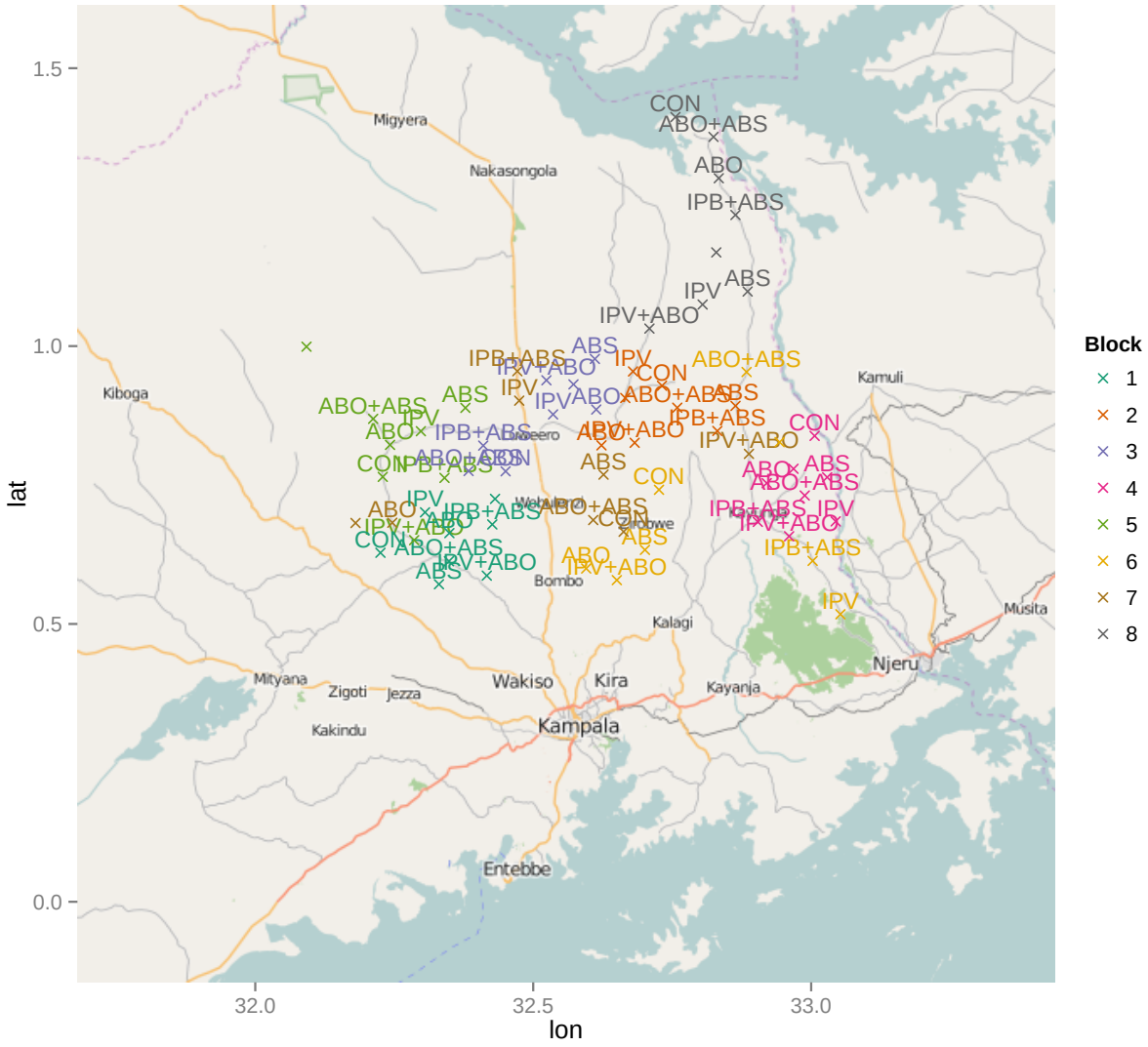
2 Motivation

The objective of this study is to estimate the impact of short video vignettes on the attitudes of viewers and those in their local community. Specifically, the project evaluates the impact of dramatized messages on attitudes towards three issues: stigma against women who have had abortions, domestic violence against women, and teacher absenteeism. Three short videos for each issue were produced and screened in rural Uganda, where these three issues are prominent social concerns. The videos themselves, which were produced by Peripheral Vision International in the local Lugandan language using Ugandan actors, may be found in the digital materials that supplement this PAP.

3 Intervention Description

Screenwriters for each video were instructed to emphasize prescriptive social norms: authoritative statements from leaders, professionals, or sympathetic characters about proper behavior. In the case of abortion, the prescriptive norm in question is that we are obliged to help those who suffer from complications resulting from an abortion regardless of our personal views about abortion. For domestic violence, the norm is that village leaders disapprove of wife-beating, it is against Ugandan law, and is never acceptable regardless of its purpose. For absenteeism, parents are urged to monitor this problem and take action with other parents to address it if it arises. The overarching hypothesis is that viewers will become sensitized to these norms and diffuse them throughout the community.

The video vignettes were inserted in commercial breaks during films that were presented free of charge during a four-week film festival in 56 Ugandan villages that took place during November-December of 2015. The attached map shows the location of the villages in this study. Villages were blocked by geographic location and census characteristics (described below) and randomly assigned to one of seven treatment arms: placebo (no vignettes), vignettes on abortion only, vignettes on domestic violence only, vignettes on teacher absenteeism only, vignettes on abortion and domestic violence, vignettes on abortion and absenteeism, and vignettes on domestic violence and absenteeism Each messaging treatment was administered during each of four successive weekends, when a feature-length film unrelated to the three topics was aired. The film festival and randomly assigned video messages were administered as planned in all 56 sites. The videos can be viewed at this address: http://tiny.cc/uganda_media.



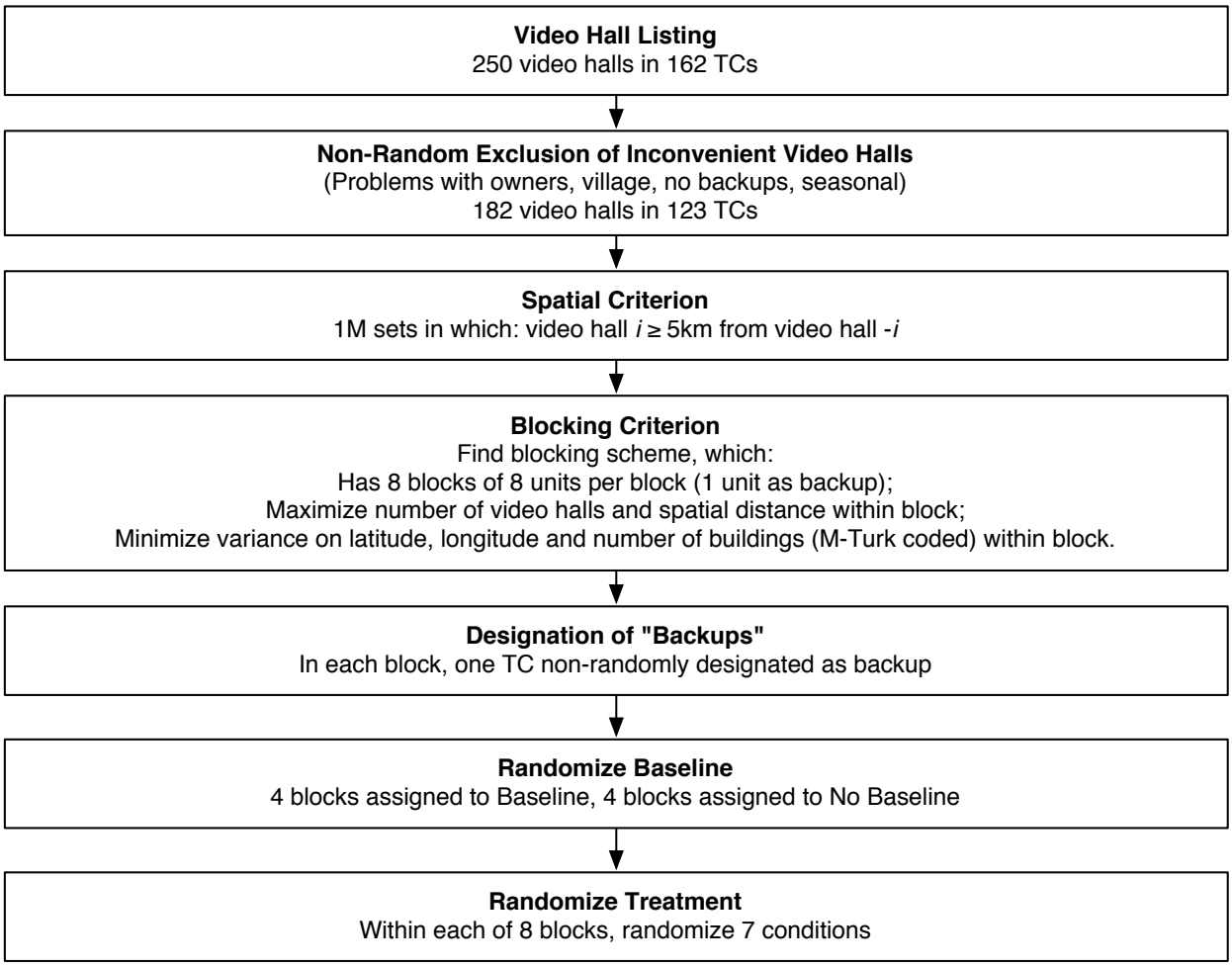
4 Design and Randomization

4.1 Site selection and blocking

As the intervention requires the presence of a video hall in all study sites, we conducted an initial census of all Ugandan trading centers (TC) with video halls in the districts of Luwero and Kayunga, which led to the identification of 250 video halls in 162 candidate trading centers. During this census, potentially problematic sites (i.e. video halls that operated seasonally, or did not have backup generators) were identified and non-randomly excluded, narrowing down the candidate trading centers to 123.

The target experimental population was 56 sites (trading centers), organized into 8 blocks of 7 trading centers, within which the seven treatment units would be assigned. We firstly selected blocks of 8, so as to have one site in each block that could be dropped from the study prior to randomization. We thus selected our 56

sites by firstly selecting 64 sites in order to address concerns about spatial spillovers and statistical power. In a first step, a random walk algorithm permuted 1 million unique ways of selecting sites such that each site would be at least 5km distant from every other site. Among these sets, we then selected the set that maximized the total distance between units as well as the number of video-halls within trading centers in the set, while minimizing the within-block variance on latitude, longitude, and the approximate population size of each trading center (coded by workers on Amazon Mechanical Turk using satellite imagery).



4.2 The assignment function

The random assignment of interventions to clusters took place within each block. The exact code and data used to perform the population selection and randomization is included in the supporting documents. The assignment function closely resembles that displayed below, which has been slightly modified to allow for randomization inference at both the individual and trading center levels. In all other respects the function works in an identical manner.

```
assign_treatment <- function(
  data,
  block_vector_name = "block",
  condition_names = c(
    "placebo",
    "IPV",
    "abortion",
```

```
    "absenteeism",
    "IPV_abortion",
    "IPV_absenteeism",
    "abortion_absenteeism"),
  cluster_vector_name = "tc"
){
  clust_block <- data[,c(cluster_vector_name,block_vector_name)]

  unique_clust_block <- unique(clust_block)

  clust_block$id <- paste0(
    clust_block[,cluster_vector_name],
    clust_block[,block_vector_name])

  unique_clust_block$id <- paste0(
    unique_clust_block[,cluster_vector_name],
    unique_clust_block[,block_vector_name])

  block_vector <- unique_clust_block[,block_vector_name]
  cluster_vector <- unique_clust_block[,cluster_vector_name]

  block_lengths <- table(block_vector)
  unique_blocks <- unique(block_vector)

  if(any(block_lengths != length(condition_names)))
    stop("There must be as many condition names as units within each block.")

  # Create assignment vector
  assignment_vector <- rep(NA, length(block_vector))

  # Permute treatment within blocks
  for(block_j in unique_blocks){
    assignment_vector[block_vector == block_j] <- sample(condition_names)
  }

  unique_clust_block$treatment <- assignment_vector

  return_data <- merge(x = clust_block,
                       y = unique_clust_block,
                       by = "id",all.x = T)

  return(return_data$treatment)

}

dummy_treatment <- function(treatment_vector){
  sapply(X = c("IPV","abortion","absenteeism","placebo"),
         FUN = grepl,
         x = treatment_vector
  ) * 1
}
```

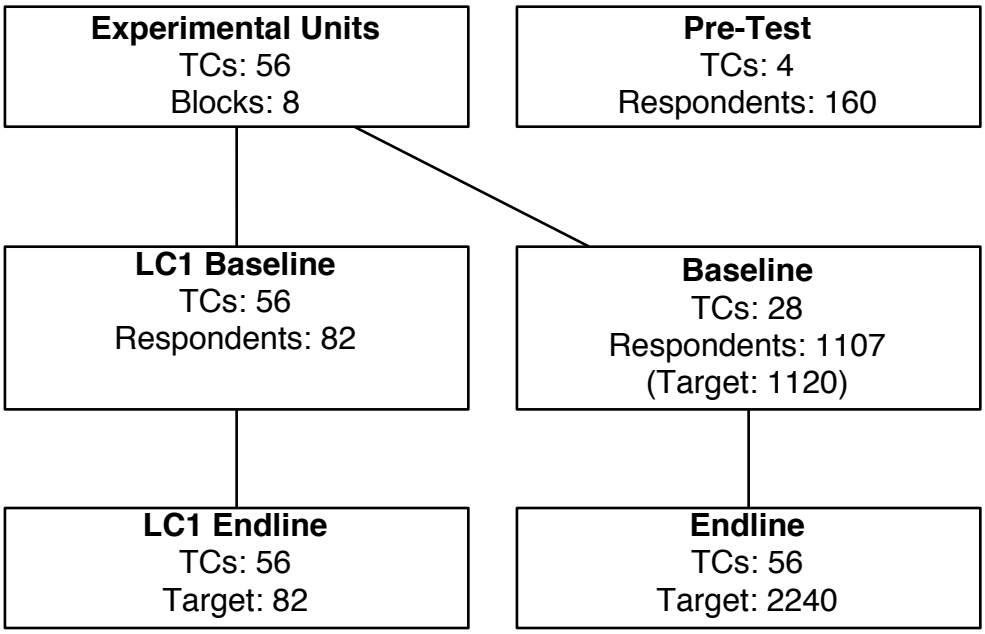
4.2.1 Solomon four-group design

Randomized trials commonly administer two rounds of surveys, a baseline survey administered prior to the intervention and an endline survey administered some time after the intervention. Baseline surveys are not required for unbiased inference, thanks to random assignment, but they may improve the precision with which treatment effects are estimated. Since the 1940s, however, researchers have expressed concern that the presence of survey takers at baseline and the content of the baseline survey itself may sensitize subjects to the treatment they will later receive or to the questions posed in the endline survey. To address these concerns, the so-called Solomon four-group design randomly assigns only some of the subjects to receive a baseline survey. In our study, precisely half of the villages received a baseline survey. Thus, we have villager survey covariates for half of the villages. (We have baseline and endline surveys with local leaders - LC1 chairpersons - for all villages.) In some villages where baseline surveys were conducted, some respondents were randomly selected for interviews at both baseline and endline; for these respondents, we will have individual-level baseline covariates.

4.3 Sampling and subjects

For the baseline survey, our goal was to interview 40 respondents in each of 28 trading centers. This yields a target of 1120 interviews of which 1107 were conducted. For the endline survey, we plan to conduct 2240 interviews (40 respondents in each of 56 trading centers).

Within each trading center, respondents are sampled from a circular area around the video hall that was used to screen the treatment messages. Enumerators receive a map for each trading center that shows a circle around this video hall with a radius of between 200 and 800 meters. The radius was chosen based on the population density of the given trading center as judged from satellite images. Enumerators work with village leaders (LC1 chairpersons) or other knowledgeable members of the community to produce a list of all households that reside within the circle indicated on the map. From this list, 40 households are randomly selected. 20 of these are randomly chosen as households within which a female respondent will be interviewed. A male respondent will be interviewed in each of the other 20 households. Upon entering a household, enumerators list all adult household members (aged 18-65) of the relevant gender and randomly select one of them as the respondent. If no respondent of the relevant gender resides in the selected household, another household is randomly chosen from the list of households within the circle around the video hall. Apart from the household surveys, we also conduct interviews with the 82 LC1 chairpersons of all villages that form part of the 58 trading centers in our sample during both the baseline and the endline surveys (Trading centers are often made up of more than one village). Finally, we implemented a small pre-test of our intervention in four trading centers that do not form part of our main sample and surveyed 40 respondents in each of these.



5 Covariates

5.1 Variable selection

We employ two sets of covariates: those that are predictive of cluster level outcomes, and those that predict outcomes at the individual level. We use a mix of baseline and endline covariates, where the endline covariates are plausibly pre-treatment (though measured following our intervention).

We selected covariates via lasso regression applied to the baseline data. Firstly, we dummied all of our categorical covariates, and included these alongside all continuous covariates. Secondly, we used a cross-validation algorithm in order to select the regularization parameter for our lasso models: this involved choosing the value for the regularization parameter that minimized the 10-fold cross-validation error averaged over 10 runs, across every outcome and covariate. Having obtained this tuning parameter value, we performed variable selection via the lasso, on all outcomes using all covariates in the baseline data. We selected the covariates that were non-zero and strongly correlated most often with our outcomes. Both the cluster and individual level covariates were chosen using this cross-validated lasso method on pre-treatment data.

5.2 Code used to clean and impute covariates

This is the code that will be run on the endline (`el`), baseline (`bl`) and LC1 (`lc1`) data in order to prepare covariates. Some of the labels on the variables may change slightly (i.e. `lantern_q17_17` becomes `lantern_q16_17`).

```
# Baseline covariates ------------------------------------------------------

# Firstly generate baseline means for TCs where they exist
bl_agg <- bl[,c("tc",
                "ABO_attitude_index",
                "ABO_norm_index",
                "ABS_attitude_index",
                "ABS_norm_index",
```

```
                "IPV_attitude_index",
                "IPV_norm_index"
                )]
bl_agg <- aggregate(. ~ tc, data = bl_agg, FUN = mean)

# Expand to full TC list
bl_agg <- merge(data.frame(tc = unique(el$tc)),bl_agg,by = "tc",all.x = T)
names(bl_agg)[-1] <- paste0(names(bl_agg)[-1],"_bl")

# For every unobserved baseline level, impute the baseline mean
bl_agg <- cbind.data.frame(
  tc = bl_agg$tc,
  apply(
    X = bl_agg[,-1],
    MARGIN = 2,
    FUN = function(x){
      x[is.na(x)] <- mean(x,na.rm = T)
      return(x)
    }))

# Merge back into endline
el <- merge(x = el, y = bl_agg, by = "tc")

# Endline covariates ------------------------------------------------------

# Create numeric version of all variables
el <- mutate(
  .data = el,
  mud_floor = as.numeric(floor_q16_6 %in% c("Mud","Rammed earth")),
  electric_light = as.numeric(light_q16_7 %in% c("Electricity","Solar Light")),
  no_educ = as.numeric(educ_q2_21 == "None"),
  block = block,
  female = as.numeric(sex_q2_1 == "Female"),
  lantern = as.numeric(lantern_q17_17 == "Yes"),
  brick_walls = as.numeric(walls_q16_5 == "Burnt bricks"),
  motorcycle = as.numeric(motorcycle_q17_15 == "Yes"),
  sofa = as.numeric(sofa_q17_8 == "Yes"),
  tv = as.numeric(tv_q17_2 == "Yes"),
  radio = as.numeric(radio_q17_1 == "Yes"),
  chair = as.numeric(chair_q17_7 == "Yes"),
  gov_responsible = as.numeric(government_q9_1b == "Statement 1"),
  moth_fath = as.numeric(moth_fath_16 == "Yes"),
  big_city = as.numeric(big_city_q2_14 == "Yes"),
  rooms = rooms_q16_2,
  age = age_q2_3,
  bed = as.numeric(el$bed_q17_10 == "Yes")
)

el$watch_tv <- el$ppl_known <- el$mobile_use <- el$walk3 <-
  el$new_ideas <- el$literacy <- el$latitude <- el$elevation <-
  el$longitude <- el$asset_index <- el$compliance <- NA

el <- within(el,{
```

```
  walk3[walk3_q2_20%in%"Never"] <- 0
  walk3[walk3_q2_20%in%"Less than once a month"] <- 1
  walk3[walk3_q2_20%in%"A few times a month"] <- 2
  walk3[walk3_q2_20%in%"A few times a week"] <- 3
  walk3[walk3_q2_20%in%"Every day"] <- 4

  mobile_use[mobile_q4_2 == "Never"] <- 0
  mobile_use[mobile_q4_2 == "Less than once a month"] <- 1
  mobile_use[mobile_q4_2 == "A few times a month"] <- 2
  mobile_use[mobile_q4_2 == "A few times a week"] <- 3
  mobile_use[mobile_q4_2 == "Every day"] <- 4

  ppl_known[ppl_known_q2_13 == "Not many people at all"] <- 0
  ppl_known[ppl_known_q2_13 == "Some people"] <- 1
  ppl_known[ppl_known_q2_13 == "Almost everyone"] <- 2
  ppl_known[ppl_known_q2_13 == "Everyone"] <- 3

  watch_tv[watchTV_q4_1 == "Never watch TV"] <- 0
  watch_tv[watchTV_q4_1 == "Less than one hour a day"] <- 1
  watch_tv[watchTV_q4_1 == "1-2 hours a day"] <- 2
  watch_tv[watchTV_q4_1 == "2-3 hours a day"] <- 3
  watch_tv[watchTV_q4_1 == "3-4 hours a day"] <- 4
  watch_tv[watchTV_q4_1 == "More than 4 hours a day"] <- 5

  literacy[read_q2_22 == "None"] <- 0
  literacy[read_q2_22 %in% c("Write only","Read only")] <- 1
  literacy[read_q2_22 == "Write and read"] <- 2

  latitude[gps_latitude != 999] <- gps_latitude[gps_latitude != 999]
  longitude[gps_longitude != 999] <- gps_longitude[gps_longitude != 999]
  elevation[gps_altitude != 999] <- gps_altitude[gps_altitude != 999]

  new_ideas[new_ideas_q6_2a == "Not at all important"] <- 0
  new_ideas[new_ideas_q6_2a == "Not very important"] <- 1
  new_ideas[new_ideas_q6_2a == "Somewhat important"] <- 2
  new_ideas[new_ideas_q6_2a == "Very important"] <- 3

  asset_index <- tv + radio + chair + sofa + rooms + bed + (1-mud_floor) +
    radio + tv + motorcycle

  compliance[compliance_q17_1 == "0 did not know about screenings"] <-
    0 # Residual
  compliance[compliance_q17_1 == "0 but knew about screenings"] <-
    1 # Indirect
  compliance[compliance_q17_1 %in% c("All 4","3","2","1")] <-
    2 # Direct

})

# LC1 Data ----------------------------------------------------------------

lc1$num_brick <- lc1$brick_q3_8_num
lc1$num_brick[is.na(lc1$num_brick)] <-
```

```
  (lc1$hhs_q2_2 * lc1$brick_q3_8_perc/100)[is.na(lc1$num_brick)]

lc1_agg <- ddply(
  .data = lc1,.variables = .(tc),.fun = summarize,
  lc1_HH_est = mean(hhs_q2_2,na.rm = T),
  has_fam_plan = mean(lc1$fam_plan_q5_1 == "Yes",na.rm = T),
  viol_once_week = mean(report_viol_q7_3 == "Once a week",na.rm = T),
  brick_dwellings = mean(num_brick,na.rm = T),
  viol_w_month_bl = mean(vaw_q7_5_bl,na.rm = T), # <- Baseliine outcome measure
  viol_w_month_el = mean(vaw_q7_5,na.rm = T),    # <- Endline outcome measure
  viol_w_month = viol_w_month_el - viol_w_month_bl # <- Pre-post change
      )

el <- merge(el,lc1_agg,by = "tc",all.x = T,all.y = F)

# Covariate imputation ----------------------------------------------------

# Names of baseline outcomes used as covariates
tc_baseline_outcomes <- c(
  "IPV_attitude_index_bl",
  "IPV_norm_index_bl",
  "ABO_attitude_index_bl",
  "ABO_norm_index_bl",
  "ABS_attitude_index_bl",
  "ABS_norm_index_bl"
)

# Covariates used in analyses run at trading center (cluster) level
tc_covariates <- c(
  "mud_floor","electric_light",
  "asset_index","walk3",
  "no_educ","latitude")

# Covariates used in analyses run at individual level
el_covariates <- c(
  "female","lantern","motorcycle","chair",
  "rooms","electric_light","mobile_use","gov_responsible",
  "block","brick_dwellings","ppl_known","watch_tv","literacy",
  "moth_fath","brick_walls","asset_index","radio","viol_once_week",
  "big_city","mud_floor","longitude","latitude","elevation",
  "has_fam_plan","lc1_HH_est","new_ideas","age","bed","sofa","tv")

# Subgroup identifiers
subgroups <- c(
  "compliance","female"
)

# Full list of covariates
covariates <- unique(c(tc_baseline_outcomes,
                       tc_covariates,
                       el_covariates))

# Grab covariates to impute
```

```
covariate_imp <- el[,c(covariates,subgroups)]

# Perform imputation
covariate_imp <- complete(mice(covariate_imp))

# Remove originals from endline data
el <- el[,-which(names(el) %in% c(covariates,subgroups))]

# Put in the new imputed covariates
el <- data.frame(el,covariate_imp)
```

6 Outcomes

6.1 Outcome measures

Our outcomes are drawn primarily from villager endline surveys. (In one instance, outcomes come from reports from LC1 endline surveys.) The questionnaire is presented in a supplementary appendix. A large number of individual survey questions concerning abortion, domestic violence, and teacher absenteeism comprise our outcome measures, but to keep the analysis manageable and to improve the reliability of our outcome measures, additive indexes will be created for two aspects of each issue domain: personal views and perceived social norms. For example, in the abortion domain, respondents are asked a series of questions about their personal views about abortion and their willingness to help those who suffer adverse health consequences; these respondents also answer several questions concerning their perception of what others in the community think about abortion and about helping those who suffer medical complications. Although these two categories of additive indexes do not fully encompass all of the survey questions we asked (e.g., a question that asked about knowledge of Ugandan law regarding abortion), they allow us to assess whether personal views and perceived social norms have shifted in the wake of the treatments. The details of index construction are given below, including procedures for imputing item-level missing data, that is, instances in which the respondent fails to provide answers to one or more items that comprise an index.

For completeness, we also analyze each of the individual survey items within each of the three domains. We recognize that this creates a multiple comparisons problem, which we address by the following procedure. Estimated t-ratios for the analyses will be sorted in descending order (for all one-tailed hypotheses). A null distribution of t-ratios will be simulated by repeating the random assignment 10,000 times and for each simulation generating a vector of estimated t-ratios. To obtain the p-value for the largest estimated t-ratio, we will ask, What proportion of the simulations generated a largest p-value at least as large as what we obtained empirically? The same procedure will be applied to the second largest p-value, and so forth (Anderson 2008).

6.2 Item-level missingness

Non-response to outcome questions will be dealt with through imputation methods. Specifically, we will use multivariate imputation via chained equations (MICE) as implemented in the `mice` package for `R`. Imputations will be performed within issue areas: missing responses to IPV outcomes will be imputed using observed responses to all other IPV outcomes, and so forth. See below for the code.

6.3 Code used to clean and impute outcomes

```
# Outcome variables ------------------------------------------------------
```

```r
# Binary outcomes
el <- mutate(
  .data = el,
  disobey_cat =
    ifelse(
      is.na(as.character(disobeys_yes)),
      as.character(disobeys_no),
      as.character(disobeys_yes)
    ),
  gossip = (gossip_q8_1b == "No") * 1,
  unfaith = (unfaithful_q8_1c == "No") * 1,
  neglects = (neglects_q8_1d == "No") * 1,
  housework = (no_housework_q8_1e == "No") * 1,
  no_sex = (no_sex_q8_1f == "No") * 1,
  comm_gossips = (gossip_comm_q8_3 == "No") * 1,
  comm_disobeys = (disobeys_comm_q8_2 == "No") * 1,
  comm_neglects = (neglects_comm_q8_4 == "No") * 1,
  comm_unfaithful = (unfaith_comm_q8_4 == "No") * 1,
  fam_together = (famtogether_q8_6 == "Disagree") * 1,
  fam_together_women = (famtogether_women_q8_7 == "No") * 1,
  fam_together_men = (famtogether_men_q8_8 == "No") * 1,
  law_easier = (law_easier_q8_11 == "Agree") * 1,
  moth_health = (mother_health_q12_5a == "Approve") * 1,
  handicap = (handicap_q12_5b == "Approve") * 1,
  rape = (rape_q12_5e == "Approve") * 1,
  no_children = (no_children_q12_5d == "Approve") * 1,
  abortion_law_cat =  ifelse(
      is.na(as.character(doct_law_q12_8a)),
      as.character(doct_law_q12_8b),
      as.character(doct_law_q12_8a)
    ),
  fire_teach = (fire_teach_q10_1 == "Action 1") * 1,
  pta = (pta_q10_2 == "Action 1") * 1,
  bring_up = (bring_up_q10_3 == "Action 1") * 1,
  assemble = (assemble_q10_4 == "Action 1") * 1,
  take_serious = (take_serious_q10_5 == "Statement 1") * 1,
  repeat_absence = (repeat_absence_q10_7 == "Statement 1") * 1,
  village_action = (village_action_q10_8 == "Statement 1") * 1,
  change_abs = (change_abs_q10_9 == "Statement 1") * 1,
  involved = (involved_q12_1 == "Statement 1") * 1,
  involved_comm = (involved_comm_q12_2 == "Statement 1") * 1,
  involved_doct = (involved_doct_q12_3 == "No") * 1,
  involved_lc1 = (involved_lc1_q12_4 == "No") * 1,
  violence_law_cat =
    ifelse(
      is.na(as.character(viol_law_yesq8_10)),
      as.character(viol_law_noq8_10),
      as.character(viol_law_yesq8_10)
    )
)

el$violence_law <- el$people_reaction <- el$school_abs <-
  el$turn_back <- el$abortion_freq <- el$disobey <- el$abortion_law <-  NA
```

```r
el <- within(el,{
  violence_law[grepl("definitely not",violence_law_cat,T)] <- 0
  violence_law[grepl("probably not",violence_law_cat,T)] <- 1
  violence_law[grepl("probably breaking",violence_law_cat,T)] <- 2
  violence_law[grepl("definitely breaking",violence_law_cat,T)] <- 3

  people_reaction[grepl("discipline",react_q8_9)] <- 0
  people_reaction[grepl("depends",react_q8_9)] <- 1
  people_reaction[grepl("outraged",react_q8_9)] <- 2

  turn_back[grepl("Most people",turn_backs_q12_6,T)] <- 0
  turn_back[grepl("Almost",turn_backs_q12_6,T)] <- 1
  turn_back[grepl("Only",turn_backs_q12_6,T)] <- 2
  turn_back[grepl("No one",turn_backs_q12_6,T)] <- 3

  abortion_freq[grepl("never",abort_comm_q12_7,T)] <- 0
  abortion_freq[grepl("rarely",abort_comm_q12_7,T)] <- 1
  abortion_freq[grepl("every now",abort_comm_q12_7,T)] <- 2
  abortion_freq[grepl("happen all",abort_comm_q12_7,T)] <- 3

  school_abs[grepl("never",school_abs_q10_10,T)] <- 0
  school_abs[grepl("every",school_abs_q10_10,T)] <- 1
  school_abs[grepl("always",school_abs_q10_10,T)] <- 2

  disobey[grepl("More force",el$disobey_cat,T)] <- 0
  disobey[grepl("Slapped",el$disobey_cat,T)] <- 1
  disobey[grepl("Yes",el$disobey_cat,T)] <- 2
  disobey[grepl("No",el$disobey_cat,T)] <- 3

  abortion_law[grepl("definitely breaking",abortion_law_cat,T)] <- 0
  abortion_law[grepl("probably breaking",abortion_law_cat,T)] <- 1
  abortion_law[grepl("probably not",abortion_law_cat,T)] <- 2
  abortion_law[grepl("definitely not",abortion_law_cat,T)] <- 3

})

responsibility <- el[,c("responsibility_q10_6_1",
                        "responsibility_q10_6_2",
                        "responsibility_q10_6_3",
                        "responsibility_q10_6_4",
                        "responsibility_q10_6_5")]

# The higher ranked parents are, the higher the resp scores out of 5
el$responsibility <- apply(
  X = responsibility,
  MARGIN = 1,
  FUN = function(resp_row) {
    5 - which(grepl("parents",resp_row,T))
  }
)

# Create lists that will be used in analysis formulae and elsewhere
```

```r
# Attitude outcomes for IPV
IPV_att_outs <- c(
  "disobey",
  "gossip",
  "unfaith",
  "neglects",
  "housework",
  "no_sex",
  "fam_together",
  "law_easier"
)

# Norm outcomes for IPV
IPV_norm_outs <- c(
  "comm_disobeys",
  "comm_gossips",
  "comm_neglects",
  "comm_unfaithful",
  "fam_together_women",
  "fam_together_men",
  "people_reaction"
)

# Attitude outcomes for ABS
ABS_att_outs <- c(
  "fire_teach",
  "pta",
  "bring_up",
  "assemble",
  "take_serious",
  "responsibility",
  "repeat_absence"
)

# Norm outcomes for ABS
ABS_norm_outs <- c(
  "village_action",
  "change_abs"
)

# Attitude outcomes for ABO
ABO_att_outs <- c(
  "involved",
  "moth_health",
  "handicap",
  "no_children",
  "rape"
)

# Norm outcomes for ABO
ABO_norm_outs <- c(
  "involved_comm",
  "involved_doct",
```

```
  "involved_lc1",
  "turn_back"
)

# Knowledge and perception outcomes
knowl_perc_outs <- c(
  "school_abs",
  "violence_law",
  "abortion_law",
  "abortion_freq"
)

# Long list of non-index outcomes
non_index_outs <- c(
  IPV_att_outs,IPV_norm_outs,
  ABO_att_outs,ABO_norm_outs,
  ABS_att_outs,ABS_norm_outs
)

# Approval indices
approval_indices <- c(
  "violence_disapproval","violence_disapproval_comm",
  "abortion_approval",
  "absenteeism_disapproval"
)

# Omnibus indices
omnibus_indices <- c(
  "IPV_attitude_index",
  "IPV_norm_index",
  "ABO_attitude_index",
  "ABO_norm_index",
  "ABS_attitude_index",
  "ABS_norm_index"
)

# Outcomes for trading center (cluster) level analyses
tc_outcomes <- c(
  omnibus_indices
)

# Outcomes for individual level analyses
el_outcomes <- c(
  non_index_outs,
  approval_indices,
  omnibus_indices
)

# Imputation of missing outcome items ----------------------------------

library(mice)

# Impute missing values for IPV attitudes
```

```
IPV_imp_att <- el[,IPV_att_outs]

if(any(is.na(IPV_imp_att))) {
  IPV_imp_att <- complete(mice(IPV_imp_att))
}

# Impute missing values for IPV norms

IPV_imp_norm <- el[,IPV_norm_outs]

if(any(is.na(IPV_imp_norm))) {
  IPV_imp_norm <- complete(mice(IPV_imp_norm))
}

# Impute missing abortion attitude values

ABO_imp_att <- el[,ABO_att_outs]

if(any(is.na(ABO_imp_att))) {
  ABO_imp_att <- complete(mice(ABO_imp_att))
}

# Impute missing abortion norm data
ABO_imp_norm <- el[,ABO_norm_outs]

if(any(is.na(ABO_imp_norm))) {
  ABO_imp_norm <- complete(mice(ABO_imp_norm))
}

# Impute missing absenteeism attitude values

ABS_imp_att <- el[,ABS_att_outs]

if(any(is.na(ABS_imp_att))) {
  ABS_imp_att <- complete(mice(ABS_imp_att))
}

# Impute missing absenteeism norms values

ABS_imp_norm <- el[,ABS_norm_outs]

if(any(is.na(ABS_imp_norm))) {
  ABS_imp_norm <- complete(mice(ABS_imp_norm))
}

# Impute missing knowledge and perception values

knowl_perc_imp <- el[,knowl_perc_outs]

if(any(is.na(knowl_perc_outs))) {
  knowl_perc_imp <- complete(mice(knowl_perc_imp))
}
```

```r
# Overwrite original outcome data
el <- el[,-which(names(el) %in% non_index_outs)]

# Reinsert the imputed data back into main data.frame
el <- data.frame(
  el,
  IPV_imp_att,IPV_imp_norm,
  ABO_imp_att,ABO_imp_norm,
  ABS_imp_att,ABS_imp_norm,
  knowl_perc_imp
  )

# Generate outcome indices ------------------------------------------------

# Create approval indices
el <- mutate(
  el,
  violence_disapproval =
    (disobey + gossip + unfaith + neglects + housework + no_sex) / 6,
  violence_disapproval_comm =
    (comm_disobeys + comm_gossips + comm_neglects + comm_unfaithful) / 4,
  abortion_approval =
    (moth_health + handicap + no_children + rape) / 4,
  absenteeism_disapproval =
    (fire_teach + pta + bring_up + assemble) / 4
    )

# Create omnibus indices
el <- mutate(
  el,
  IPV_attitude_index =
    (disobey + gossip + unfaith + neglects + housework +
    no_sex + fam_together + law_easier) / (3+1+1+1+1+1+1+1),
  IPV_norm_index =
    (comm_disobeys + comm_gossips + comm_neglects + comm_unfaithful +
    fam_together_women + fam_together_men + people_reaction) / (1+1+1+1+1+1+2),
  ABO_attitude_index =
    (involved + moth_health + handicap + no_children +
    rape ) / (1+1+1+1+1),
  ABO_norm_index =
    (involved_comm + involved_doct + involved_lc1 +
    turn_back ) / (1+1+1+3),
  ABS_attitude_index =
    (fire_teach + pta + bring_up + assemble + take_serious +
    responsibility + repeat_absence ) / (1+1+1+1+1+4+1),
  ABS_norm_index =
    (village_action + change_abs) / (1+1))
```

7 Hypotheses

7.1 Intention to Treat (ITT) Effects and Complier Average Causal Effects (CACE)

Our initial analysis focuses on what might be termed intent-to-treat effects, i.e., the effect of village-level assignment regardless of whether the respondent attended the film festival. The ITT summarizes the effect of all forms of treatment influence: direct exposure, exposure via friends or family who attended the festival, and discussions within the community. This analysis addresses the policy question of whether providing public service announcements on topics such as these has effects on villagers' survey responses weeks after the intervention.

The most pessimistic null hypothesis concerning these ITT effects may be characterized as the global sharp null: in the SUR model described above, the 6 free parameters in the core model are zero for all subjects. This null hypothesis may be tested by way of a likelihood ratio test of the joint significance of all six parameter estimates, using the randomization inference functions detailed below. Failing to reject this null hypothesis suggests that the apparent community-level effects of the suite of media messages are not greater than would be expected by chance.

This analysis can be used to zero in on three important subgroups. The first group may be called Compliers – those who would attend a film festival regardless of the video messages embedded in its commercial breaks. Under the exclusion restriction, which stipulates that nothing about treatment assignment influences potential outcomes apart from exposure to the messages, we can obtain unbiased estimates of the CACE by restricting the SUR and individual item analyses to those subjects who in the endline survey report having attended at least one of the films.

A second subgroup comprises Indirect Compliers: those who did not attend the film(s) themselves but report that family or friends attended.

The residual group are those who, according to their endline survey reports, neither attended nor have direct family or friendship ties to those who attended. We hypothesize that treatment effects become steadily weaker as we move from Compliers to Indirect Compliers to Others.

7.2 Baseline effects

We refer to the effect of receiving a baseline survey in one's village as a baseline survey effect (BSE). We do not expect strong BSEs, but our one-tailed hypothesis is as follows:

The baseline survey will itself heighten sensitivity to social norms, which will amplify the effect of the media treatments. Thus, we will test for positive interactions between the baseline survey indicator (at the village level and, where applicable, at the respondent level) and the media treatment indicator.

7.3 Crossover effects

When designing the study, we expected each of the three messages to affect only views and perceived norms in that issue domain. In other words, we expect messages about domestic violence to affect views and perceived norms regarding domestic violence but not regarding abortion or absenteeism. Thus, our core model is one in which views or norms regarding a given topic are represented as a function of village-level exposure to messages on that topic and that topic only. This core model is a nested subset of a more general model that allows for crossover effects from messaging in one domain to views or norms in a different domain. In the seemingly unrelated regression (SUR) model described below, each issue domain has two dependent variables (additive indexes summarizing views or norms), and there are three issue domains. Thus, the core model below has 6 free treatment parameters. The crossover model frees an additional 12 parameters, representing treatment effects from messages in other issue areas. We will test the null hypothesis that these 12 parameters

are jointly zero, accepting the core model if we fail to reject the null at the 0.05 level using a likelihood ratio test. Should we reject the null model, then the item-level analysis below will include crossover effects by regressing each item not only on the issue-specific treatment but also on indicators for the other two treatments.

7.4 Outcome-specific hypotheses

7.4.1 disobey

In your opinion, does a man have good reason to hit his wife if she disobeys him?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	disobeys_q8_1a	disobey

Hypothesis: More respondents will state that the man does not have a good reason to hit his wife or should use less force against her. (One-tailed).

7.4.2 gossip

In your opinion, does a man have good reason to hit his wife if she spends time gossipping with the neighbors?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	gossip_q8_1b	gossip

Hypothesis: More respondents will state that the man does not have a good reason to hit his wife. (One-tailed).

7.4.3 unfaith

In your opinion, does a man have good reason to hit his wife if he finds out that she has been unfaithful?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	unfaithful_q8_1c	unfaith

Hypothesis: More respondents will state that the man does not have a good reason to hit his wife. (One-tailed).

7.4.4 neglects

In your opinion, does a man have good reason to hit his wife if she neglects taking care of the children?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	neglects_q8_1d	neglects

Hypothesis: More respondents will state that the man does not have a good reason to hit his wife. (One-tailed).

7.4.5 housework

In your opinion, does a man have good reason to hit his wife if she does not complete her household work?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	no_housework_q8_1e	housework

Hypothesis: More respondents will state that the man does not have a good reason to hit his wife. (One-tailed).

7.4.6 no_sex

In your opinion, does a man have good reason to hit his wife if she refuses to have sexual relations with him?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	no_sex_q8_1f	no_sex

Hypothesis: More respondents will state that the man does not have a good reason to hit his wife. (One-tailed).

7.4.7 violence_disapproval

Index of 0-7 counting up number of 'yes' answers to 8.1a-8.1g

Type	Reference Point	Variable Name	Recoded Name
Index	Respondent attitude	n/a	violence_disapproval

Hypothesis: The average number of items of which respondents think that the man does not have good reason to hit his wife will increase. (One-tailed).

7.4.8 comm_disobeys

In some of the villages we have visited, people think that a man has good reason to hit his wife if she disobeys him, while people in other communities do not think this is a good reason to hit one's wife. In your community, do people think a man has a good reason to hit his wife if she disobeys him?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	disobeys_comm_q8_2	comm_disobeys

Hypothesis: More respondents will state that in his / her community, people do not think the man has good reason to hit his wife (One-tailed).

7.4.9 comm_gossips

Again, let's talk about the opinion of other people in your community. In your community, do most people think a man has a good reason to hit his wife if she spends time gossiping with neighbors?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	gossip_comm_q8_3	comm_gossips

Hypothesis: More respondents will state that in his / her community, people do not think the man has good reason to hit his wife (One-tailed).

7.4.10 comm_neglects

Still thinking about the opinion of the people who live nearby, do people in your community think that a man has good reason to hit his wife if she neglects taking care of the children?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	neglects_comm_q8_4	comm_neglects

Hypothesis: More respondents will state that in his / her community, people do not think the man has good reason to hit his wife (One-tailed).

7.4.11 comm_unfaithful

And, again thinking of attitudes held by those who live nearby, do people in your community think that a man has good reason to hit his wife if she has been unfaithful?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	unfaith_comm_q8_4	comm_unfaithful

Hypothesis: More respondents will state that in his / her community, people do not think the man has good reason to hit his wife (One-tailed).

7.4.12 fam_together

Please tell me if you agree or disagree with the following statement: A wife should tolerate getting a slap from her husband in order to keep the family together.

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	famtogether_q8_6	fam_together

Hypothesis: More respondents will disagree that a wife should tolerate getting a slap. (One-tailed).

7.4.13 fam_together_women

Do women in your community think women should tolerate getting a slap from their husband from their husband to keep the family together?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	famtogether_women_q8_7	fam_together_women

Hypothesis: More respondents will state that women do not think that a wife should tolerate a slap. (One-tailed).

7.4.14 fam_together_men

Do men in your community think women should tolerate getting a slap from their husband to keep the family together?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	famtogether_men_q8_8	fam_together_men

Hypothesis: More respondents will state that men do not think that a wife should tolerate a slap. (One-tailed).

7.4.15 people_reaction

If people in your community were to find out that a man was slapping his wife or girlfriend, how would most of them react? They would think that it is his right to discipline his wife or girlfriend, regardless of what she has done They would say that it depends on what she has done They would be outraged, regardless of what she has done

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	react_q8_9	people_reaction

Hypothesis: More respondents will state that people in the community would be outraged. (One-tailed).

7.4.16 violence_law

Is a man breaking Ugandan law if he slaps his wife? - Yes, definitely - Yes, probably - No, probably - No, definitely

Type	Reference Point	Variable Name	Recoded Name
Individual question	Knowledge	violence_law_q8_10	violence_law

Hypothesis: More respondents will state that the man is definitely breaking the law. (One-tailed).

7.4.17 law_easier

In this country, the law should be changed to make it easier for a woman to leave her husband if he beats her. Do you agree or disagree?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	law_easier_q8_11	law_easier

Hypothesis: More respondents will state that the law should be changed to make it easier for a woman to leave her husband. (One-tailed).

7.4.18 violence_disapproval_comm

Index of community norm perception 0-3 counting up number of 'yes' answers to 8.2 - 8.5.

Type	Reference Point	Variable Name	Recoded Name
Index	Community perception	n/a	violence_disapproval_comm

Hypothesis: The score on the index will be higher on average. (One-tailed).

7.4.19 viol_w_month

[Question 7.4: How many times during last month did you or the police receive reported cases about violence?] Of those cases, how many were of men against women?

Type	Reference Point	Variable Name	Recoded Name
Count	Community incidents	vaw_q7_5	viol_w_month

Hypothesis: Respondents will report higher or lower rates of violence against women. (One-tailed).

7.4.20 IPV_attitude_index

Index summing all of the IPV measures using respondent attitudes as reference point.

Type	Reference Point	Variable Name	Recoded Name
Index	Respondent attitude	n/a	IPV_attitude_index

Hypothesis: Respondents will have higher scores on the index. (One-tailed).

7.4.21 IPV_norm_index

Index summing all of the IPV measures using the community perception as reference point.

Type	Reference Point	Variable Name	Recoded Name
Index	Community perception	n/a	IPV_norm_index

Hypothesis: Respondents will have higher scores on the index. (One-tailed).

7.4.22 involved

Suppose that your 17-year old neighbor has had a deliberate abortion because she[wanted to stay in school / wanted to take a full-time job] (randomized). She has been ostracized from the community and people seem to have turned their backs on her. - She made her choice and has violated god's rule and we should not get involved - Regardless of what this woman did, we should be a friend to her and try to help her.

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	involved_q12_1	involved

Hypothesis: More respondents will say the woman should be helped. (One-tailed).

7.4.23 involved_comm

What do you think most others in your community think about this issue? - She made her choice and has violated god's rule, it is better not to get involved. - Regardless of what this woman did, we should try to help her.

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	involved_comm_q12_2	involved_comm

Hypothesis: More respondents will say that others in the community think she should be helped. (One-tailed).

7.4.24 involved_doct

If the girl who had the deliberate abortion went to the hospital for medication, do you think doctors would look down on her?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	involved_doct_q12_3	involved_doct

Hypothesis: More respondents will say that doctors will NOT look down on her. (One-tailed).

7.4.25 involved_lc1

In this situation, do you think the LC1 chairperson would look down on her or think of her as a bad person?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	involved_lc1_q12_4	involved_lc1

Hypothesis: More respondents will say that the LC1 will NOT look down on her. (One-tailed).

7.4.26 moth_health

If a deliberate abortion could be done completely safely with no risk for the mother's health, do you approve or disapprove of the deliberate abortion under the following circumstances? Where the pregnancy puts the mother's health at risk

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	mother_health_q12_5a	moth_health

Hypothesis: More respondents would approve of abortion under these circumstances. (Two-tailed).

7.4.27 handicap

If a deliberate abortion could be done completely safely with no risk for the mother's health, do you approve or disapprove of the deliberate abortion under the following circumstances? Where it is likely that the child would be born physically handicapped

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	handicap_q12_5b	handicap

Hypothesis: More respondents would approve of abortion under these circumstances. (Two-tailed).

7.4.28 no_children

If a deliberate abortion could be done completely safely with no risk for the mother's health, do you approve or disapprove of the deliberate abortion under the following circumstances? Where a married couple does not want to have any more children

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	no_children_q12_5d	no_children

Hypothesis: More respondents would approve of abortion under these circumstances. (Two-tailed).

7.4.29 rape

If a deliberate abortion could be done completely safely with no risk for the mother's health, do you approve or disapprove of the deliberate abortion under the following circumstances? Where a woman has been raped

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	rape_q12_5e	rape

Hypothesis: More respondents would approve of abortion under these circumstances. (Two-tailed).

7.4.30 turn_back

Imagine that a woman from your community had a deliberate abortion. How many people in your community will turn their backs on her? - No one - Only a few people - Most people - Almost everyone

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	turn_backs_q12_6	turn_back

Hypothesis: On average, respondents will state that fewer people in the community will turn their backs. (One-tailed).

7.4.31 abortion_freq

In other villages within a day's walk from here, how common are deliberate abortions? - They happen all the time - They happen every now and then - They rarely happen - They never happen

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	abort_comm_q12_7	abortion_freq

Hypothesis: On average, respondents will believe deliberate abortions in other villages to be more frequent. (One-tailed).

7.4.32 abortion_law

Is a doctor breaking the law if he or she provides medical care to a woman who has had a secret deliberate abortion?

Type	Reference Point	Variable Name	Recoded Name
Individual question	Knowledge	doct_law_q12_8	abortion_law

Hypothesis: More respondents will state that the doctor is not breaking the law. (One-tailed).

7.4.33 ABO_attitude_index

Index summing all of the abortion measures using the respondent attitudes as reference point.

Type	Reference Point	Variable Name	Recoded Name
Index	Respondent attitude	n/a	ABO_attitude_index

Hypothesis: Respondents will have higher scores on the index. (One-tailed).

7.4.34 ABO_norm_index

Index summing all of the abortion measures using the community perception as reference point.

Type	Reference Point	Variable Name	Recoded Name
Index	Community perception	n/a	ABO_norm_index

Hypothesis: Respondents will have higher scores on the index. (One-tailed).

7.4.35 abortion_approval

Index summing all of the questions about cases in which abortion is approved of.

Type	Reference Point	Variable Name	Recoded Name
Index	Respondent attitude	n/a	abortion_approval

Hypothesis: Respondents will have higher scores on the index. (One-tailed).

7.4.36 fire_teach

In some of the villages we have visited, teachers miss many days or weeks of class when they should be teaching. Imagine that you find out that your child's teacher has been absent for 2 days this week during teaching hours. Suppose there are only two actions that you can take. Please tell us which one you would prefer to take. -ask the headmaster to threaten to fire the teacher -allow your child to leave school to help with the garden on days when the teacher is absent

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	fire_teach_q10_1	fire_teach

Hypothesis: More respondents will chose the option to ask the headmaster to threaten to fire the teacher. (One-tailed).

7.4.37 pta

In some of the villages we have visited, teachers miss many days or weeks of class when they should be teaching. Imagine that you find out that your child's teacher has been absent for 2 days this week during teaching hours. Suppose there are only two actions that you can take. Please tell us which one you would prefer to take. - immediately begin organizing a PTA meeting, even if you know this might start some trouble - wait another few days to see if the problem corrects itself

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	pta_q10_2	pta

Hypothesis: More respondents will chose the option to immediately begin organizing a PTA meeting. (One-tailed).

7.4.38 bring_up

In some of the villages we have visited, teachers miss many days or weeks of class when they should be teaching. Imagine that you find out that your child's teacher has been absent for 2 days this week during teaching hours. Suppose there are only two actions that you can take. Please tell us which one you would prefer to take. - bring it up in the village meeting - pray to god

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	bring_up_q10_3	bring_up

Hypothesis: More respondents will chose the option to bring it up in the village meeting. (One-tailed).

7.4.39 assemble

In some of the villages we have visited, teachers miss many days or weeks of class when they should be teaching. Imagine that you find out that your child's teacher has been absent for 2 days this week during teaching hours. Suppose there are only two actions that you can take. Please tell us which one you would prefer to take. - assemble a group of parents and confront the teacher - send your child to a school in the neighboring village, where the teachers always come to class

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	assemble_q10_4	assemble

Hypothesis: More respondents will chose the option to assemble a group of parents. (One-tailed).

7.4.40 take_serious

Please tell me which of the following statements comes closest to your view: - Teachers who are not showing up for class need to take their jobs more seriously. - Teachers who are not showing up for class likely do not get paid regularly and need to make money in other ways.

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	take_serious_q10_5	take_serious

Hypothesis: More respondents will say that teachers need to take their jobs more seriously. (One-tailed).

7.4.41 responsibility

In your view, who has the biggest responsibility to do something about the problem of teacher absenteeism? Please order the following actors from those who have the biggest to those who have the smallest responsibility: - The headmaster - The ministry of education/the government - The parents - The PTA - The LC1 chairperson

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	responsibility_q10_6	responsibility

Hypothesis: On average, parents will be ranked higher by respondents. (One-tailed).

7.4.42 repeat_absence

Suppose a teacher is repeatedly absent from school. Which of the following statements comes closest to your view? - Parents should call a meeting of the PTA and hold the school accountable for the teacher's absence. - Parents' intervention only leads to conflict and discord. It's better to leave the management of the school to the administrators. cord. It's better to leave the management of the school to the administrators.

Type	Reference Point	Variable Name	Recoded Name
NA	Respondent attitude	repeat_absence_q10_7	repeat_absence

Hypothesis: More respondents will pick to call a PTA meeting. (One-tailed).

7.4.43 village_action

Teachers are often absent during school hours. In some villages, parents wait to get all facts before taking any action, in order to avoid creating unnecessary conflict. In other villages, the parents immediately come together and confront the headmaster. What is your village like? - More like the first villages, where parents wait to get all the facts - More like the second villages, where parents immediately confront the headmaster

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	village_action_q10_8	village_action

Hypothesis: More respondents say their village is like the second village. (One-tailed).

7.4.44 change_abs

Some people think that if parents get together to do something about teacher absenteeism, anything they achieve will quickly disappear and things will go back to how they were. Other people think it should be easy to solve the matter for good by taking action once. Which comes closest to your view? - It is unlikely to change things permanently - Taking action will help resolve the issue of teacher absenteeism.

Type	Reference Point	Variable Name	Recoded Name
Individual question	Respondent attitude	change_abs_q10_9	change_abs

Hypothesis: More respondents will say that taking action will help to resolve the issue. (One-tailed).

7.4.45 school_abs

In some of the villages we have visited, teachers almost always come to school when they are supposed to teach class, while in other villages teachers almost never come to class, even when they are supposed to teach. Thinking of teachers in the schools closest to where you live, which statement best applies: - Teachers almost always come to class - Teachers skip class every now and then - Teachers almost never come to class

Type	Reference Point	Variable Name	Recoded Name
Individual question	Community perception	school_abs_q10_10	school_abs

Hypothesis: More respondents will say in their village, teachers almost always come to class. (One-tailed).

7.4.46 absenteeism_disapproval

Index counting up number of times respondents elected to take action in questions 10.1-10.4

Type	Reference Point	Variable Name	Recoded Name
Index	Respondent attitude	n/a	absenteeism_disapproval

Hypothesis: On average, respondents will chose a higher number of action-taking alternatives (One-tailed).

7.4.47 ABS_attitude_index

Index summing all of the teacher absenteeism measures using respondent attitudes as reference point.

Type	Reference Point	Variable Name	Recoded Name
Index	Respondent attitude	n/a	ABS_attitude_index

Hypothesis: Respondents will have higher scores on the index. (One-tailed).

7.4.48 ABS_norm_index

Index summing all of the teacher absenteeism measures using the community perception as reference point.

Type	Reference Point	Variable Name	Recoded Name
Index	Community perception	n/a	ABS_norm_index

Hypothesis: Respondents will have higher scores on the index. (One-tailed).

8 Analysis

8.1 Intention to Treat (ITT) Effects and Complier Average Causal Effects (CACE)

As noted above, the SUR models fall into three nested variants. The model assuming crossovers allows for 18 free treatment parameters (3 issues x 2 response domains x 3 media treatments): we refer to this as the `saturated` specification. The crossover model will be tested against the core null model, which specifies that media treatments are issue-specific, implying 6 free treatment parameters (3 issues x 2 response domains x 1 media treatment): we refer to this as the `core` specification. The core model will in turn be tested as an alternative to the global null model, which specifies no treatment parameters: we refer to this as the `global_null` model.

In order to address the fact that subjects were cluster assigned by village, the SUR models first aggregate to the cluster level to form mean outcomes. A regression estimator is approximately unbiased because our clusters are similar in size.

```
# Variables used in TC-level regressions
tc_variables <- c("tc","baseline","IPV","abortion","absenteeism","placebo",
                  tc_covariates,tc_outcomes,tc_baseline_outcomes,subgroups,
                  "viol_w_month","block")

# Subset el to tc
tc <- el[,tc_variables]

# Indicator for imputed baseline values
tc$no_baseline <- 1 - tc$baseline
```

```r
# Aggregate via mean
tc <- aggregate(formula = . ~ tc, data = tc, FUN = mean, na.rm = T)
```

We specify the main equations as follows.

```r
# RHS treatment specification assuming no crossover effects
treatment_core <- list(
  IPV_attitude = "IPV",
  IPV_norm = "IPV",
  ABO_attitude = "abortion",
  ABO_norm = "abortion",
  ABS_attitude = "absenteeism",
  ABS_norm = "absenteeism"
)
# RHS treatment specification assuming crossover effects
treatment_saturated <- list(
  IPV_attitude = c("IPV","abortion","absenteeism"),
  IPV_norm     = c("IPV","abortion","absenteeism"),
  ABO_attitude = c("IPV","abortion","absenteeism"),
  ABO_norm     = c("IPV","abortion","absenteeism"),
  ABS_attitude = c("IPV","abortion","absenteeism"),
  ABS_norm     = c("IPV","abortion","absenteeism")
)
# RHS treatment specification assuming null of no effects
treatment_global_null <- list(
  IPV_attitude = NULL,
  IPV_norm     = NULL,
  ABO_attitude = NULL,
  ABO_norm     = NULL,
  ABS_attitude = NULL,
  ABS_norm     = NULL
)

# This function generates a list of equations as a function of whether
# null of no crossovers rejected
make_tc_SUR_equations <- function(
  crossover_null_rejected = FALSE, global_null_model = FALSE
){

  if(crossover_null_rejected){
    treatment <- treatment_saturated
  } else {
    treatment <- treatment_core
  }

  if(global_null_model){
    treatment <- treatment_global_null
  }

  SUR_formula <- list()
  for(i in 1:6){
    SUR_formula[[i]] <-
      reformulate(
```

```
        termlabels = c(tc_covariates,
                       tc_baseline_outcomes[i],
                       treatment[[i]]
                       ),
        response = tc_outcomes[i]
      )
  }
  return(SUR_formula)
}

# List of equations assuming no crossovers (core specification)
SUR_formula_core <- make_tc_SUR_equations(
  crossover_null_rejected = FALSE)

# List of equations assuming crossovers (treatment-saturated specification)
SUR_formula_saturated <- make_tc_SUR_equations(
  crossover_null_rejected = TRUE)

# List of equations assuming no effects (global null specification)
SUR_formula_global_null <- make_tc_SUR_equations(
  global_null_model = TRUE)

SUR_formula_core
```

```
## [[1]]
## IPV_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_attitude_index_bl + IPV
## <environment: 0x7fe6fe80f708>
##
## [[2]]
## IPV_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + IPV_norm_index_bl + IPV
## <environment: 0x7fe6fe80f708>
##
## [[3]]
## ABO_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_attitude_index_bl + abortion
## <environment: 0x7fe6fe80f708>
##
## [[4]]
## ABO_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABO_norm_index_bl + abortion
## <environment: 0x7fe6fe80f708>
##
## [[5]]
## ABS_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_attitude_index_bl + absenteeism
## <environment: 0x7fe6fe80f708>
##
## [[6]]
## ABS_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABS_norm_index_bl + absenteeism
## <environment: 0x7fe6fe80f708>
```

```
SUR_formula_saturated
```

```
## [[1]]
## IPV_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_attitude_index_bl + IPV +
##     abortion + absenteeism
## <environment: 0x7fe6fd77ad20>
##
## [[2]]
## IPV_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + IPV_norm_index_bl + IPV + abortion +
##     absenteeism
## <environment: 0x7fe6fd77ad20>
##
## [[3]]
## ABO_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_attitude_index_bl + IPV +
##     abortion + absenteeism
## <environment: 0x7fe6fd77ad20>
##
## [[4]]
## ABO_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABO_norm_index_bl + IPV + abortion +
##     absenteeism
## <environment: 0x7fe6fd77ad20>
##
## [[5]]
## ABS_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_attitude_index_bl + IPV +
##     abortion + absenteeism
## <environment: 0x7fe6fd77ad20>
##
## [[6]]
## ABS_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABS_norm_index_bl + IPV + abortion +
##     absenteeism
## <environment: 0x7fe6fd77ad20>
```

```
SUR_formula_global_null
```

```
## [[1]]
## IPV_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_attitude_index_bl
## <environment: 0x7fe6fd691040>
##
## [[2]]
## IPV_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + IPV_norm_index_bl
## <environment: 0x7fe6fd691040>
##
## [[3]]
## ABO_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_attitude_index_bl
```

```
## <environment: 0x7fe6fd691040>
##
## [[4]]
## ABO_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABO_norm_index_bl
## <environment: 0x7fe6fd691040>
##
## [[5]]
## ABS_attitude_index ~ mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_attitude_index_bl
## <environment: 0x7fe6fd691040>
##
## [[6]]
## ABS_norm_index ~ mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABS_norm_index_bl
## <environment: 0x7fe6fd691040>
```

We fit the three models using SUR as follows.

```
# Fit the core model
SUR_core <- systemfit(
  formula = SUR_formula_core,
  data = tc,
  method = "SUR")

# Fit the saturated model
SUR_saturated <- systemfit(
  formula = SUR_formula_saturated,
  data = tc,
  method = "SUR")

# Fit the global null model
SUR_global_null <- systemfit(
  formula = SUR_formula_global_null,
  data = tc,
  method = "SUR")
```

We test the core specification against the global null using the following likelihood ratio test. It should be noted that, while we use such parametric tests to get p-values under the null of zero average effect, we use randomization inference with the functions specified below in order to generate p-values under the sharp null of no effect, and consider these the final arbiter for all p-values.

```
library(lmtest)
lrtest(SUR_core,SUR_global_null)
```

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Mon, Jan 18, 2016 - 19:01:34

We test the null of no crossovers by comparing the saturated to the core specification as follows.

```
anova(SUR_saturated,SUR_core)
```

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% Date and time: Mon, Jan 18, 2016 - 19:01:34

Table 1:

Statistic	N	Mean	St. Dev.	Min	Max
#Df	2	72.000	4.243	69	75
LogLik	2	715.469	0.871	714.854	716.085
Df	1	−6.000		−6	−6
Chisq	1	2.462		2.462	2.462
Pr(>Chisq)	1	0.873		0.873	0.873

Table 2:

Statistic	N	Mean	St. Dev.	Min	Max
#Df	2	81.000	8.485	75	87
LogLik	2	722.705	9.363	716.085	729.326
Df	1	−12.000		−12	−12
Chisq	1	26.482		26.482	26.482
Pr(>Chisq)	1	0.009		0.009	0.009

The results of the three SUR specifications will be reported in tables such as the following.

```
create_stargazer_table <- function(SUR_fit){
  fit_list <- lapply(SUR_fit$eq,coeftest)
  stargazer(fit_list)
}

create_stargazer_table(SUR_core)
```

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% Date and time: Mon, Jan 18, 2016 - 19:01:35

```
create_stargazer_table(SUR_saturated)
```

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Mon, Jan 18, 2016 - 19:01:35

```
create_stargazer_table(SUR_global_null)
```

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Mon, Jan 18, 2016 - 19:01:36

For our 47 outcomes, including both indices and item-level outcomes, we employ a hierarchical linear modeling strategy. The model accounts for clustering at the trade-center level through a varying trade center (cluster) level intercept, which is associated with its own set of predictors taken from the covariates used in the SUR specifications. Individual outcomes are associated with the treatment indicator, a block indicator, and other individual covariates.

We firstly merge the predictors for the trading center intercept from the `tc` dataset and merge them into the endline.

Table 3:

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
mud_floor	−0.010	0.147	−0.061	−0.071	−0.069	−0.270**
	(0.098)	(0.094)	(0.050)	(0.056)	(0.075)	(0.117)
electric_light	0.152*	−0.076	−0.020	0.083	−0.038	−0.016
	(0.089)	(0.085)	(0.047)	(0.053)	(0.070)	(0.109)
asset_index	0.022	0.021	−0.008	−0.007	−0.019	−0.012
	(0.020)	(0.019)	(0.010)	(0.012)	(0.015)	(0.024)
walk3	−0.049	−0.027	−0.015	−0.018	0.028	−0.028
	(0.032)	(0.031)	(0.016)	(0.018)	(0.024)	(0.038)
no_educ	0.430***	−0.049	−0.093	0.012	−0.176	0.061
	(0.147)	(0.141)	(0.080)	(0.089)	(0.115)	(0.180)
latitude	−0.138	0.257	−0.265**	−0.001	−0.133	−0.443
	(0.222)	(0.211)	(0.113)	(0.125)	(0.170)	(0.265)
IPV_attitude_index_bl	−0.026					
	(0.131)					
IPV_norm_index_bl		0.072				
		(0.108)				
IPV	−0.014	−0.006				
	(0.012)	(0.012)				
ABO_attitude_index_bl			0.028			
			(0.144)			
ABO_norm_index_bl				0.015		
				(0.171)		
abortion			0.0002	−0.005		
			(0.006)	(0.007)		
ABS_attitude_index_bl					−0.063	
					(0.172)	
ABS_norm_index_bl						0.115
						(0.128)
absenteeism					−0.001	0.004
					(0.009)	(0.014)
Constant	0.609*	0.091	0.596***	0.550***	0.828***	1.062***
	(0.308)	(0.278)	(0.149)	(0.188)	(0.239)	(0.330)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4:

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
mud_floor	0.007	0.183**	−0.048	−0.066	−0.064	−0.278**
	(0.093)	(0.086)	(0.051)	(0.059)	(0.079)	(0.124)
electric_light	0.149*	−0.103	−0.032	0.082	−0.035	−0.013
	(0.085)	(0.078)	(0.047)	(0.054)	(0.072)	(0.112)
asset_index	0.023	0.033*	−0.004	−0.006	−0.018	−0.014
	(0.020)	(0.018)	(0.011)	(0.012)	(0.017)	(0.026)
walk3	−0.047	−0.028	−0.017	−0.019	0.026	−0.026
	(0.030)	(0.028)	(0.016)	(0.019)	(0.026)	(0.040)
no_educ	0.334**	−0.072	−0.115	0.002	−0.189	0.068
	(0.146)	(0.135)	(0.079)	(0.092)	(0.124)	(0.194)
latitude	−0.121	0.236	−0.270**	0.002	−0.115	−0.454
	(0.209)	(0.192)	(0.114)	(0.132)	(0.178)	(0.279)
IPV_attitude_index_bl	−0.048					
	(0.138)					
IPV_norm_index_bl		0.119				
		(0.102)				
ABO_attitude_index_bl			−0.060			
			(0.149)			
ABO_norm_index_bl				0.024		
				(0.175)		
ABS_attitude_index_bl					−0.031	
					(0.191)	
ABS_norm_index_bl						0.119
						(0.134)
IPV	−0.006	0.001	0.004	0.002	0.004	−0.003
	(0.012)	(0.011)	(0.006)	(0.007)	(0.011)	(0.016)
abortion	0.021*	0.003	0.003	−0.003	0.003	−0.001
	(0.012)	(0.011)	(0.006)	(0.007)	(0.010)	(0.016)
absenteeism	0.028**	0.036***	0.013*	0.004	−0.0002	0.0004
	(0.011)	(0.010)	(0.006)	(0.007)	(0.010)	(0.015)
Constant	0.575*	−0.024	0.593***	0.530***	0.779***	1.088***
	(0.301)	(0.254)	(0.152)	(0.196)	(0.277)	(0.360)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5:

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
mud_floor	0.015	0.158*	−0.061	−0.075	−0.068	−0.272**
	(0.096)	(0.090)	(0.049)	(0.055)	(0.074)	(0.116)
electric_light	0.145	−0.078	−0.020	0.088*	−0.038	−0.013
	(0.089)	(0.084)	(0.046)	(0.052)	(0.070)	(0.108)
asset_index	0.028	0.023	−0.008	−0.009	−0.018	−0.013
	(0.019)	(0.018)	(0.010)	(0.011)	(0.015)	(0.023)
walk3	−0.058*	−0.030	−0.015	−0.017	0.028	−0.028
	(0.031)	(0.029)	(0.016)	(0.018)	(0.024)	(0.037)
no_educ	0.422***	−0.053	−0.093	−0.006	−0.176	0.062
	(0.148)	(0.139)	(0.076)	(0.085)	(0.114)	(0.178)
latitude	−0.068	0.283	−0.266**	0.006	−0.134	−0.436
	(0.215)	(0.204)	(0.111)	(0.124)	(0.167)	(0.261)
IPV_attitude_index_bl	0.013					
	(0.129)					
IPV_norm_index_bl		0.083				
		(0.103)				
ABO_attitude_index_bl			0.031			
			(0.141)			
ABO_norm_index_bl				0.027		
				(0.170)		
ABS_attitude_index_bl					−0.062	
					(0.169)	
ABS_norm_index_bl						0.114
						(0.126)
Constant	0.470	0.042	0.595***	0.551***	0.826***	1.066***
	(0.290)	(0.266)	(0.147)	(0.186)	(0.236)	(0.327)

Note: *p<0.1; **p<0.05; ***p<0.01

```
# Grab tc-level covariates
tc_predictors <- tc[,c("tc",tc_covariates)]
names(tc_predictors)[-1] <- paste0(names(tc_predictors)[-1],"_tc")

# Get names for building HLM formulae
tc_level_covariates <- names(tc_predictors)[-1]

# Merge back into endline data
el <- merge(el,tc_predictors,by = "tc")
```

We build the formulae as follows.

```
make_HLM_formula <- function(
  outcome = NULL,
  treatment_indicator = NULL,
  baseline_index = NULL,
  crossover_null_rejected = FALSE
){
  el_covariates_col <- paste(el_covariates,collapse = " + ")
  tc_level_covariates_col <- paste(tc_level_covariates,collapse = " + ")
  if(crossover_null_rejected){
    treatment_indicator <- "IPV + absenteeism + abortion"
  }
  formula_core <- paste0(
    outcome," ~ 1 + (1|tc) + ",treatment_indicator
  )
  HLM_formula <- paste0(
    formula_core," + block + ",
    el_covariates_col," + ",
    tc_level_covariates_col," + ",
    baseline_index
  )
  return(as.formula(HLM_formula))
}

IPV_att_formulae <- lapply(
  X = IPV_att_outs,
  FUN = make_HLM_formula,
  treatment_indicator = "IPV",
  baseline_index = "IPV_attitude_index_bl",
  crossover_null_rejected = FALSE)

IPV_norm_formulae <- lapply(
  X = IPV_norm_outs,
  FUN = make_HLM_formula,
  treatment_indicator = "IPV",
  baseline_index = "IPV_norm_index_bl",
  crossover_null_rejected = FALSE)

ABO_att_formulae <- lapply(
  X = ABO_att_outs,
  FUN = make_HLM_formula,
  treatment_indicator = "abortion",
```

```
  baseline_index = "ABO_attitude_index_bl",
  crossover_null_rejected = FALSE)

ABO_norm_formulae <- lapply(
  X = ABO_norm_outs,
  FUN = make_HLM_formula,
  treatment_indicator = "abortion",
  baseline_index = "ABO_norm_index_bl",
  crossover_null_rejected = FALSE)

ABS_att_formulae <- lapply(
  X = ABS_att_outs,
  FUN = make_HLM_formula,
  treatment_indicator = "absenteeism",
  baseline_index = "ABS_attitude_index_bl",
  crossover_null_rejected = FALSE)

ABS_norm_formulae <- lapply(
  X = ABS_norm_outs,
  FUN = make_HLM_formula,
  treatment_indicator = "absenteeism",
  baseline_index = "ABS_norm_index_bl",
  crossover_null_rejected = FALSE)

knowl_perc_formulae <- mapply(
  outcome = knowl_perc_outs,
  treatment_indicator = c("absenteeism","IPV","abortion","abortion"),
    baseline_index = c("ABS_norm_index_bl","IPV_norm_index_bl",
                       "ABO_norm_index_bl","ABO_norm_index_bl"),
  FUN = make_HLM_formula,
  MoreArgs = list(
    crossover_null_rejected = FALSE)
)

omnibus_index_formulae <- mapply(
  outcome = omnibus_indices,
  treatment_indicator = c("IPV","IPV","abortion",
                          "abortion","absenteeism","absenteeism"),
  baseline_index = c("IPV_attitude_index_bl", "IPV_norm_index_bl",
                     "ABO_attitude_index_bl", "ABO_norm_index_bl",
                     "ABS_attitude_index_bl", "ABS_norm_index_bl" ),
  FUN = make_HLM_formula,
  MoreArgs = list(
    crossover_null_rejected = FALSE))

approval_index_formulae <- mapply(
  outcome = approval_indices,
  treatment_indicator = c("IPV","IPV","abortion","absenteeism"),
  baseline_index = c("IPV_attitude_index_bl", "IPV_norm_index_bl",
                     "ABO_attitude_index_bl", "ABS_attitude_index_bl"),
  FUN = make_HLM_formula,
  MoreArgs = list(
    crossover_null_rejected = FALSE))
```

We fit the HLM models as follows.

```
IPV_att_HLM <- lapply(
  X = IPV_att_formulae,
  FUN = lmer,
  data = el)

IPV_norm_HLM <- lapply(
  X = IPV_norm_formulae,
  FUN = lmer,
  data = el)

ABO_att_HLM <- lapply(
  X = ABO_att_formulae,
  FUN = lmer,
  data = el)

ABO_norm_HLM <- lapply(
  X = ABO_norm_formulae,
  FUN = lmer,
  data = el)

ABS_att_HLM <- lapply(
  X = ABS_att_formulae,
  FUN = lmer,
  data = el)

ABS_norm_HLM <- lapply(
  X = ABS_norm_formulae,
  FUN = lmer,
  data = el)

knowl_perc_HLM <- lapply(
  X = knowl_perc_formulae,
  FUN = lmer,
  data = el)

omnibus_index_HLM <- lapply(
  X = omnibus_index_formulae,
  FUN = lmer,
  data = el
)

approval_index_HLM <- lapply(
  X = approval_index_formulae,
  FUN = lmer,
  data = el
)
```

We report results in tables as follows:

```
stargazer(omnibus_index_HLM,
          omit = c(el_covariates,tc_level_covariates),
          no.space = T,
```

```
          dep.var.labels = c("IPV att.","IPV norm","ABO att.",
                             "ABO norm","ABS att", "ABS norm")
          )
```

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Mon, Jan 18, 2016 - 19:01:52

Table 6:

	Dependent variable:					
	IPV att.	IPV norm	ABO att.	ABO norm	ABS att	ABS norm
	(1)	(2)	(3)	(4)	(5)	(6)
IPV	−0.016	−0.008				
	(0.011)	(0.012)				
abortion			−0.004	−0.005		
			(0.007)	(0.009)		
absenteeism					−0.003	0.0001
					(0.009)	(0.016)
IPV_attitude_index_bl	0.050					
	(0.163)					
IPV_norm_index_bl		0.079				
		(0.140)				
ABO_attitude_index_bl			−0.029			
			(0.164)			
ABO_norm_index_bl				−0.021		
				(0.211)		
ABS_attitude_index_bl					−0.097	
					(0.181)	
ABS_norm_index_bl						0.133
						(0.148)
Constant	4.627***	2.417**	−0.917	1.479*	0.124	0.916
	(1.104)	(1.212)	(0.749)	(0.874)	(0.869)	(1.756)
Observations	2,240	2,240	2,240	2,240	2,240	2,240
Log Likelihood	119.906	−104.112	954.105	626.936	659.877	−932.019
Akaike Inf. Crit.	−161.811	286.223	−1,830.210	−1,175.872	−1,241.755	1,942.038
Bayesian Inf. Crit.	61.044	509.078	−1,607.355	−953.017	−1,018.900	2,164.893
Note:						*p<0.1; **p<0.05; ***p<0.01

8.1.1 Complier Sub-Group Analysis

As stated above, the various groups of compliers (direct, indirect, residual) are only directly comparable if probabilities of compliance do not vary by treatment arm. To test for this possibility, we estimate the an unrestricted multinomial logit model (MNL) in which the compliance status is regressed on treatment indicators and covariates, and a restricted MNL in which the compliance status is regressed on the covariates only.

```
library(nnet)

unrestricted_compliance_formula <- reformulate(
  termlabels = c(el_covariates,"IPV","abortion","absenteeism"),
```

```
  response = "compliance"
)

restricted_compliance_formula <- reformulate(
  termlabels = el_covariates,
  response = "compliance"
)

unrestricted_compliance <- multinom(
  formula = unrestricted_compliance_formula,
  data = el)
```

```
## # weights:  105 (68 variable)
## initial  value 2460.891527
## iter  10 value 1951.650178
## iter  20 value 1935.886254
## iter  30 value 1916.676467
## iter  40 value 1914.188443
## iter  50 value 1912.965489
## iter  60 value 1912.340637
## iter  70 value 1911.324273
## iter  80 value 1910.678081
## final  value 1910.670564
## converged
```

```
restricted_compliance <- multinom(
  formula = restricted_compliance_formula,
  data = el)
```

```
## # weights:  96 (62 variable)
## initial  value 2460.891527
## iter  10 value 1951.789741
## iter  20 value 1937.300280
## iter  30 value 1918.271025
## iter  40 value 1915.391281
## iter  50 value 1914.415005
## iter  60 value 1913.646763
## iter  70 value 1912.518774
## final  value 1912.447742
## converged
```

```
stargazer(
  lrtest(unrestricted_compliance,
         restricted_compliance))
```

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Mon, Jan 18, 2016 - 19:09:33

Failure to reject the null of equal probabilities of compliance across treatment arms enables us to analyze compliance effects in one of two ways, depending on the rate of non-compliance by cluster. Firstly, if there are at least five (direct or indirect) compliers per cluster, we will split the individual-level sample into the compliance subgroups, and then aggregate to the trading center-level in order to fit a SUR model. Secondly, if there are not at least five compliers per cluster, we will run HLM regressions at the individual level.

Table 7:

Statistic	N	Mean	St. Dev.	Min	Max
#Df	2	61.000	4.243	58	64
LogLik	2	−1,911.559	1.257	−1,912.448	−1,910.671
Df	1	−6.000		−6	−6
Chisq	1	3.554		3.554	3.554
Pr(>Chisq)	1	0.737		0.737	0.737

In each case, we will test for the compliance effects through a likelihood-ratio test on a restricted and unrestricted model. The unrestricted model will regress each of the six core indices on treatment, covariates, as well as treatment-by-subgroup and covariate-by-subgroup interactions, while the restricted model will regress each of the six core indices on treatment, covariates and covariate-by-subgroup interactions. In both cases the formula will be constructed as follows.

```
unrestricted_CACE <- lapply(
  X = SUR_formula_core,
  FUN = update.formula,
  new = . ~ I(.) * as.factor(compliance))

restricted_CACE <- list()
for(i in 1:6){
  restricted_CACE[[i]] <- as.formula(
    paste0(
      tc_outcomes[i]," ~ as.factor(compliance) * I(",
      paste(tc_covariates,collapse = " + "),
      " + ",tc_baseline_outcomes[i],
      ") + ",treatment_core[[i]]
    )
  )
}

# If HLM is used
unrestricted_CACE_HLM <-
  lapply(unrestricted_CACE,
         FUN = update.formula,
         new = . ~ 1 + (1|tc) + .)

restricted_CACE_HLM <-
  lapply(restricted_CACE,
         FUN = update.formula,
         new = . ~ 1 + (1|tc) + .)

unrestricted_CACE
```

```
## [[1]]
## IPV_attitude_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_attitude_index_bl + IPV) +
##     as.factor(compliance) + I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_attitude_index_bl + IPV):as.factor(compliance)
## <environment: 0x7fe6fe80f708>
##
```

```
## [[2]]
## IPV_norm_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_norm_index_bl + IPV) + as.factor(compliance) +
##     I(mud_floor + electric_light + asset_index + walk3 + no_educ +
##         latitude + IPV_norm_index_bl + IPV):as.factor(compliance)
## <environment: 0x7fe6fe80f708>
##
## [[3]]
## ABO_attitude_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_attitude_index_bl + abortion) +
##     as.factor(compliance) + I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_attitude_index_bl + abortion):as.factor(compliance)
## <environment: 0x7fe6fe80f708>
##
## [[4]]
## ABO_norm_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_norm_index_bl + abortion) +
##     as.factor(compliance) + I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_norm_index_bl + abortion):as.factor(compliance)
## <environment: 0x7fe6fe80f708>
##
## [[5]]
## ABS_attitude_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_attitude_index_bl + absenteeism) +
##     as.factor(compliance) + I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_attitude_index_bl + absenteeism):as.factor(compliance)
## <environment: 0x7fe6fe80f708>
##
## [[6]]
## ABS_norm_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_norm_index_bl + absenteeism) +
##     as.factor(compliance) + I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_norm_index_bl + absenteeism):as.factor(compliance)
## <environment: 0x7fe6fe80f708>
```

```
restricted_CACE
```

```
## [[1]]
## IPV_attitude_index ~ as.factor(compliance) * I(mud_floor + electric_light +
##     asset_index + walk3 + no_educ + latitude + IPV_attitude_index_bl) +
##     IPV
##
## [[2]]
## IPV_norm_index ~ as.factor(compliance) * I(mud_floor + electric_light +
##     asset_index + walk3 + no_educ + latitude + IPV_norm_index_bl) +
##     IPV
##
## [[3]]
## ABO_attitude_index ~ as.factor(compliance) * I(mud_floor + electric_light +
##     asset_index + walk3 + no_educ + latitude + ABO_attitude_index_bl) +
##     abortion
##
## [[4]]
## ABO_norm_index ~ as.factor(compliance) * I(mud_floor + electric_light +
```

```
##     asset_index + walk3 + no_educ + latitude + ABO_norm_index_bl) +
##     abortion
##
## [[5]]
## ABS_attitude_index ~ as.factor(compliance) * I(mud_floor + electric_light +
##     asset_index + walk3 + no_educ + latitude + ABS_attitude_index_bl) +
##     absenteeism
##
## [[6]]
## ABS_norm_index ~ as.factor(compliance) * I(mud_floor + electric_light +
##     asset_index + walk3 + no_educ + latitude + ABS_norm_index_bl) +
##     absenteeism
```

8.1.2 Gender Sub-Group Analysis

The gender sub-group analysis will follow the same set of procedures as that used for the compliance sub-group analysis.

```
unrestricted_gender <- lapply(
  X = SUR_formula_core,
  FUN = update.formula,
  new = . ~ I(.) * female)

restricted_gender <- list()
for(i in 1:6){
  restricted_gender[[i]] <- as.formula(
    paste0(
      tc_outcomes[i]," ~ female * I(",
      paste(tc_covariates,collapse = " + "),
      " + ",tc_baseline_outcomes[i],
      ") + ",treatment_core[[i]]
    )
  )
}

# If HLM is used
unrestricted_gender_HLM <-
  lapply(unrestricted_CACE,
         FUN = update.formula,
         new = . ~ 1 + (1|tc) + .)

restricted_gender_HLM <-
  lapply(restricted_CACE,
         FUN = update.formula,
         new = . ~ 1 + (1|tc) + .)

unrestricted_gender
```

```
## [[1]]
## IPV_attitude_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_attitude_index_bl + IPV) +
##     female + I(mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + IPV_attitude_index_bl + IPV):female
```

```
## <environment: 0x7fe6fe80f708>
##
## [[2]]
## IPV_norm_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_norm_index_bl + IPV) + female +
##     I(mud_floor + electric_light + asset_index + walk3 + no_educ +
##         latitude + IPV_norm_index_bl + IPV):female
## <environment: 0x7fe6fe80f708>
##
## [[3]]
## ABO_attitude_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_attitude_index_bl + abortion) +
##     female + I(mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABO_attitude_index_bl + abortion):female
## <environment: 0x7fe6fe80f708>
##
## [[4]]
## ABO_norm_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_norm_index_bl + abortion) +
##     female + I(mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABO_norm_index_bl + abortion):female
## <environment: 0x7fe6fe80f708>
##
## [[5]]
## ABS_attitude_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_attitude_index_bl + absenteeism) +
##     female + I(mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABS_attitude_index_bl + absenteeism):female
## <environment: 0x7fe6fe80f708>
##
## [[6]]
## ABS_norm_index ~ I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_norm_index_bl + absenteeism) +
##     female + I(mud_floor + electric_light + asset_index + walk3 +
##     no_educ + latitude + ABS_norm_index_bl + absenteeism):female
## <environment: 0x7fe6fe80f708>
```

```
restricted_gender
```

```
## [[1]]
## IPV_attitude_index ~ female * I(mud_floor + electric_light +
##     asset_index + walk3 + no_educ + latitude + IPV_attitude_index_bl) +
##     IPV
##
## [[2]]
## IPV_norm_index ~ female * I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + IPV_norm_index_bl) + IPV
##
## [[3]]
## ABO_attitude_index ~ female * I(mud_floor + electric_light +
##     asset_index + walk3 + no_educ + latitude + ABO_attitude_index_bl) +
##     abortion
##
## [[4]]
```

```
## ABO_norm_index ~ female * I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABO_norm_index_bl) + abortion
##
## [[5]]
## ABS_attitude_index ~ female * I(mud_floor + electric_light +
##     asset_index + walk3 + no_educ + latitude + ABS_attitude_index_bl) +
##     absenteeism
##
## [[6]]
## ABS_norm_index ~ female * I(mud_floor + electric_light + asset_index +
##     walk3 + no_educ + latitude + ABS_norm_index_bl) + absenteeism
```

8.1.3 LC1 Violence reporting

We test whether our IPV intervention affected the reporting of domestic violence to the LC1 chairperson using the following test.

```
VAW_LC1_formula <- reformulate(
  termlabels = c("IPV",tc_covariates),
  response = "viol_w_month"
)
VAW_LC1 <- lm(VAW_LC1_formula,data = tc)

coeftest(VAW_LC1)
```

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Mon, Jan 18, 2016 - 19:01:55

8.2 Baseline effects

We test for baseline effects by comparing the core model (null) with no baseline index covariates to the core model with baseline indicators added.

```
SUR_formula_core_no_baseline <- mapply(
  formula = SUR_formula_core,
  baseline_index = tc_baseline_outcomes,
  FUN = function(formula,baseline_index){
    update(formula,
           as.formula(paste0(". ~ . - ",baseline_index))
    )
  }
)

SUR_formula_core_baseline <- lapply(
  X = SUR_formula_core_no_baseline,
  FUN = function(SUR_formula){
    update(SUR_formula, . ~ . + baseline)
  }
)

SUR_no_baseline <- systemfit(
  formula = SUR_formula_core_no_baseline,
```

Table 8:

	Dependent variable:
	viol_w_month
IPV	0.516
	(1.015)
mud_floor	5.034
	(8.283)
electric_light	3.701
	(7.488)
asset_index	1.603
	(1.654)
walk3	−3.461
	(2.694)
no_educ	−9.477
	(12.402)
latitude	11.100
	(18.623)
Constant	−20.067
	(23.686)
Observations	56
R^2	0.073
Adjusted R^2	−0.062
Residual Std. Error	3.446 (df = 48)
F Statistic	0.538 (df = 7; 48)
Note:	*p<0.1; **p<0.05; ***p<0.01

```
  data = tc)

SUR_baseline <- systemfit(
  formula = SUR_formula_core_baseline,
  data = tc)

lrtest(SUR_baseline,SUR_no_baseline)
```

```
## Likelihood ratio test
##
## Model 1: SUR_baseline
## Model 2: SUR_no_baseline
##   #Df LogLik Df  Chisq Pr(>Chisq)
## 1  55 715.46
## 2  49 715.18 -6 0.5634      0.997
```

If we reject the null then we include a baseline indicator and baseline-treatment interactions in the main specifications.

8.3 Randomization inference functions

In addition to reporting p-values fit by the models, we will report randomization inference-based p-values for all of our results. The functions below will be used to perform RI. We will also perform RI on all likelihood-ratio tests. Two examples of RI on p-values associated with coefficients are provided.

```
samp_dist_sharp_null <- function(
  formula,
  data,
  extract_function,
  model_type = "HLM",
  sims = 10^5
  ){
  return_vals <- replicate(
    n = sims,
    expr = {
      data$IPV <- data$abortion <- data$absenteeism <- data$placebo <- NULL
      data <- data.frame(data,dummy_treatment(assign_treatment(data)))
      if(model_type == "HLM"){
        model_fit <- lmer(formula = formula,data = data)
      }
      if(model_type == "SUR"){
        model_fit <- systemfit(formula = formula,data = data,method = "SUR")
      }
      extract_function(model_fit)
    })
  return(return_vals)
}

extract_HLM_coef <- function(model_fit){
  coeffs <- fixef(model_fit)
  grab_coef <- names(coeffs) %in% c("IPV","abortion","absenteeism")
  return(coeffs[grab_coef])
```

```
}

extract_SUR_coef <- function(model_fit){
  coeffs <- coef(model_fit)
  grab_coef <- names(coeffs) %in%
    (sapply(X = c("eq1_","eq2_","eq3_","eq4_","eq5_","eq6_"),
            FUN = paste0,c("IPV","abortion","absenteeism")))
  return(coeffs[grab_coef])
}

extract_SSR <- function(model_fit){
  sum((residuals(model_fit))^2)
}

extract_loglik <- function(model_fit){
  logLik(model_fit)[1]
}

# An example of RI using HLM
samp_dist <- samp_dist_sharp_null(
  formula = IPV_att_formulae[[1]],
  data = el,
  extract_function = extract_HLM_coef,
  model_type = "HLM",
  sims = 100)

obs_eff <- fixef(IPV_att_HLM[[1]])["IPV"]

one_tail <- mean(obs_eff <= samp_dist)

# An example of RI using SUR
samp_dist <- samp_dist_sharp_null(
  formula = SUR_formula_core,
  data = tc,
  extract_function = extract_SUR_coef,
  model_type = "SUR",
  sims = 100)

obs_eff <- coef(SUR_core)["eq1_IPV"]

one_tail <- mean(obs_eff <= samp_dist["eq1_IPV",])
```

Finally, we will report all results using the "bare-bones" version of our model, with only treatment and block indicators, and no covariates.

References

Anderson, Michael L. 2008. "Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." *Journal of the American Statistical Association* 484 (484): 1481–95.