Contact in the Classroom: A Field Experiment on Virtual Intergroup Contact in Elementary Schools

Pre-Analysis Plan

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Contents

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1 Hierarchical Clustering of Outcome Variables

I use an unsupervised hierarchical machine learning algorithm to identify latent clusters in the t0 data. Below is the code used to create these clusters, using a sample of n = 688 student t0 surveys. These clusters form the key outcomes, as well as an item on generalized empathy (which did not theoretically align with the rest of the outcomes included here), and a re-coded version of the cross-ethnic tolerance questions to reflect ethnic outgroups (coded in relation to the respondent's self-reported ethnicity).
The following are the attitudinal outcomes of interest from the student survey instrument. All variables are made binary for the purpose of creating the indices, where "wouldn't care" or "not sure" are coded as 0's.

1.1 Estimation Code

```
outcome_vars <- c("knowledge_foreign_t0",
                  "penpal_interest_t0", "meet_foreign_t0" ,
                  "play_wht_t0" ,  "play_hisp_t0" ,
                  "play_blk_t0" ,  "common_foreign_t0",
                  "norm_friends_t0" ,  "norm_parents_t0" )

 # Ensure package recognizes the variables as "qualitative" (ie, categorical)
df <- df %>% mutate_at(vars(one_of(outcome_vars)), funs(as.factor(.)))

# Apply clustering algorithm
tree <- hclustvar(X.quali = clust[outcome_vars])

plot.hclustvar(tree, type = "tree")
plot.hclustvar(tree, type = "index")

# The dendrogram and scree plot suggest that 4 clusters are suitable

# Factor Analysis

create_factor <- function(data, dv_names, verbose = TRUE) {

  # Keep variables of interest and ensure that they're numeric
  sub <- data[, dv_names] %>% mutate_all(funs(as.numeric(as.character(.))))

  # Impute missing values with median
  impute <- sub
  impute <- sapply(impute, function(x) ifelse(is.na(x), median(x, na.rm = T), x))

  # Principal component, scaled to have mean 0/sd 1
  f <- princomp(impute, cor = TRUE)
  if (verbose) print(loadings(f))
  dv <- f$scores[, 1]
  dv <- as.numeric(scale(dv))
```

```
  # Make sure the variable points the correct way

  # if (cor(dv, data$meet_foreign_binary, use = "complete") > 0) dv <- -1 * dv

  # If a row in the original data has more than 50% NAs, then replace the score
  # with NA
  bool <- apply(sub, 1, function(x) sum(is.na(x)) / ncol(sub) > 0.5)
  dv[bool] <- NA
  dv

}

## Creating the clusters

dv_cross_ethnic <- c("play_wht_t0", "play_hisp_t0", "play_blk_t0")

dv_cross_country <- c("knowledge_foreign_t0", "common_foreign_t0")

dv_curiosity <- c("penpal_interest_t0", "meet_foreign_t0")

dv_norms <- c("norm_friends_t0", "norm_parents_t0")
```

Below is the code used to generate factor loadings associated with each item using a hierarchical clustering method.

```
> df$dv_cross_ethnic <- create_factor(df, dv_cross_ethnic)

Loadings:
             Comp.1 Comp.2 Comp.3
play_wht_t0 -0.561 0.808 0.179
play_hisp_t0 -0.591 -0.240 -0.770
play_blk_t0 -0.580 -0.538 0.612

             Comp.1 Comp.2 Comp.3
SS loadings   1.000 1.000 1.000
Proportion Var 0.333 0.333 0.333
Cumulative Var 0.333 0.667 1.000
> df$dv_cross_ethnic <- create_factor(df, dv_cross_ethnic)

Loadings:
             Comp.1 Comp.2 Comp.3
play_wht_t0 -0.561 0.808 0.179
play_hisp_t0 -0.591 -0.240 -0.770
play_blk_t0 -0.580 -0.538 0.612

             Comp.1 Comp.2 Comp.3
```

```
SS loadings   1.000 1.000 1.000
Proportion Var 0.333 0.333 0.333
Cumulative Var 0.333 0.667 1.000
>
> df$dv_cross_country <- create_factor(df, dv_cross_country)

Loadings:
                  Comp.1 Comp.2
knowledge_foreign_t0 -0.707 0.707
common_foreign_t0 -0.707 -0.707

             Comp.1 Comp.2
SS loadings     1.0   1.0
Proportion Var  0.5   0.5
Cumulative Var  0.5   1.0
>
> df$dv_curiosity <- create_factor(df, dv_curiosity)

Loadings:
                Comp.1 Comp.2
penpal_interest_t0 0.707 -0.707
meet_foreign_t0  0.707 0.707

             Comp.1 Comp.2
SS loadings     1.0   1.0
Proportion Var  0.5   0.5
Cumulative Var  0.5   1.0
>
> df$dv_norms <- create_factor(df, dv_norms)

Loadings:
              Comp.1 Comp.2
norm_friends_t0 -0.707 0.707
norm_parents_t0 -0.707 -0.707

             Comp.1 Comp.2
SS loadings     1.0   1.0
Proportion Var  0.5   0.5
Cumulative Var  0.5   1.0
```

1.2 Cluster Descriptions

With the clustering analysis above as a guideline, I keep the 4 clusters identified in the dendrogram intact. Below are the descriptions of each item included in the seven indices, all coded in a pro-tolerant direction. In the paper, I will analyze the indices as dependent variables as well as specific items, for ease of substantively interpreting marginal effect sizes. I also analyze the three items on wanting to play with children of different backgrounds (which make up the in-group bias cluster) in relation to the respondent's self-reported skin tone, by redefining these variables in terms of outgroups (Black, White, and Hispanic).

Index #1: Cross-ethnic Attitudes

- Want to play with Black children (based on a photo)
- Want to play with White children (based on a photo)
- Want to play with Hispanic children (based on a photo)

Index #2: Cross-country Perceptions and Knowledge

- Having a lot in common with kids from other countries
- Knowing a lot about life in other countries

Index #3: Cross-country Curiosity

- Want to send messages back and forth to a kid in another country
- Would want to meet with a kid who just moved into town from another country

Index #4: Social Norms

- Parents would be happy if respondent played with a kid from another country
- Friends would be happy if respondent played with a kid from another country

2 Estimation

2.1 ATE Estimation

Using the same ATE estimation code described in the original PAP, I add the following covariates: 1) block fixed effect (each block has a treatment and control unit), 2) teaching fellowship (the channel through which the classroom enrolled in the study), and 3) school location type (rural, urban, or suburban).

I will also run a supplementary, descriptive analysis to capture dosage effects. I do this by subsetting the sample to treated classrooms, and including the number of exchanges completed as independent variables (I construct this both as a continuous variable, and then as an ordinal variable binned as follows: one exchange, two exchanges, three or more exchanges).

2.2 Treatment Effect Heterogeneity by Subject Attributes

To the original PAP, I add a fourth subgroup analysis: heterogenous effects depending on classroom ethnic homogeneity. I define a class as ethnically homogenous if 90% or more of the students are co-ethnics.

2.3 Sample

The main analyses will exclude classrooms who exclusively conducted exchanges over mobile, or exclusively conducted exchanges offline (i.e. sending pre-recorded videos to the partner classroom). The nature of these exchanges is significantly different from the standard real-time format.

The two main analyses will: 1) pool classrooms across four teaching fellowships, then 2) remove data from the one teaching fellowship where classrooms needed to have completed exchanges in the past in order to qualify. Although the ATE estimation accounts for baseline differences between classrooms, the experience of students in the study who have completed several exchanges previously is substantively quite different from the rest of the sample.

2.4 Non-Compliance

Non-compliance occurs in three cases: 1) if teachers administer the baseline surveys after having already conducted an exchange, 2) if treated classrooms do not complete any exchanges during the academic year, or 3) if control classrooms conduct an exchange during the academic year. I make the no-defiers assumption. I will adjust the point estimates above to account for non-compliance by dividing the point estimates by the proportion of treated compliers in the treatment group minus the proportion of treated compliers in the contacted control group.