Data Analysis of Take Ten Program for Academic Year 2014/2015 and

Recommendations for Future Years of the Program

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The current report describes the results of the Take Ten program for the 2014 – 2015 academic year. The report focuses on the data and their analysis. Specifically, this report explores the structure, psychometrics, descriptive and inferential statistics, and limitations of the data. Two appendices are attached: Appendix A contains several tables and figures that provide visual clarity to the results presented in the report. Appendix B includes the *R* (R Core Team, 2015) code that was used in the data analysis.

My report will follow this general outline: first, I will introduce the data generally, their structure and design; second, I will report on psychometrics (e.g., reliability) and descriptive statistics of each of the measures across the program; third, I will provide inferential statistics using longitudinal data analysis. These analyses will help us understand the effectiveness of the Take Ten program.

1 The Structure of the Take Ten Data

The structure and design of the Take Ten program (hereafter "Program") and its data collection is one of the strengths. The Program claims to help elementary, middle and high school students identify and resolve conflicts in order to reduce bullying, aggression, and violence. In order to evaluate this claim, the Program uses a "between-subjects" experimental design in which several schools receive the "treatment" (i.e., the Take Ten Program), and other schools receive a "control" (e.g., no intervention). With such a design we are able to compare the two groups of schools/students ("treatment" vs. "control") to identify any differences in bullying, aggressive behavior, or conflict resolution strategies. Further, the Program is a yearlong intervention that allows for change over time within and across groups (“treatment”, “control”). With such a design, we are able to confidently claim that the Program is effective. Further, we are able to see the change over time from the beginning of the year to the end. Data were collected at three time points for the experimental group and two time points for the control group throughout the academic year. Time 1 occurred in the Fall of 2014 (experimental and control), Time 2 occurred the Winter of 2014/2015 (experimental only), and Time 3 occurred in the Spring of 2015 (experimental and control). By collecting data at three time points, the longitudinal data analysis plan allows us to model different types of trajectories of change, compared to a 2-time point data collection (e.g., quadratic vs. linear change; latent growth curve modeling). Since control group data were only collected at two time points, the between-groups comparisons will only use two time points—the first and the last. Further analyses within the experimental groups can utilized all three time points.

Participants. As mentioned previously, there are two groups of schools: an experimental group and a control group. However, the data can be further broken down by age or grade. Depending on a student’s grade in school, they received one of two packets to fill out. Form A packets were given to younger students (elementary schools; grades 3 and 4) and Form B packets were given to older students (middle and high schools; grades 5 – 12). With the two Forms and the two groups, we have four sets of data for students: Form A experimental, Form A Control, Form B experimental, and Form B control. Lastly, teachers from all groups filled out teacher questionnaires[1]. Table

[1] Teachers filled out slightly different surveys than students, focused mostly on school and classroom climate. The teacher’s data are not included in these preliminary analyses.

1 provides basic demographic information of students in all datasets (e.g., age, gender, grade, ethnicity).

Measures

The 2014-2015 Program assessments for both Forms A and B included measures of school climate, others that were specific to Take Ten curriculum, the Illinois Bullying Scale, and a child's version of Social Desirability. Tables 2 and 3 illustrate psychometrics of all measures at each time point for each group and condition.

School Climate: "About Your School"

Students answered seven questions about school climate on a 4-point Likert scale (Strongly Disagree to Strongly Agree). Sample item: "Students treat each other with respect." and "School feels like prison. [reversed]" Items were summed to create a composite score.

Take Ten Curriculum.

"How Do You Feel?" Students answered three questions about how they felt about reacting to bullying behavior on a 4-point scale: *No*; *Maybe*; *Probably*; *Yes*. Sample item: "It's OK to do whatever it takes to protect myself." Items were summed to create a composite score.

"How Do You Act?" These questions tap into how students act to reduce bullying and aggression in schools. Students respond to six questions on a 4-point Likert scale (Strongly Disagree to Strongly Agree). Sample item: "I encourage my classmates to be respectful to others." Items were summed to create a composite score; higher scores indicated more constructive action toward reducing bullying.

“*What Can You Do?”* Students answered four questions about their self-efficacy when it comes to certain conflict resolution strategies. Students used a 4-point Likert scale (Strongly Disagree to Strongly Agree). Sample item: “I can stop my friends from fighting.” Sum-scores of the four items indicate the self-efficacy of using conflict resolution strategies.

“*What Do You Think?”* Seven items were used to assess student’s thoughts on the salience and effects of violence and conflict in daily life. Students used a 4-point Likert scale (Strongly Disagree to Strongly Agree). Sample item: “My actions determine what happens in a conflict.” Like other scales, a sum score was created, with higher scores indicating more constructive thoughts about the salience and effects of violence and conflict in daily life.

“Illinois Bullying Scale” and Witnessing Violence.

Illinois Bullying Scale. The Illinois Bullying Scale was used to assess three separate bullying behaviors: Bullying (6 items, e.g., “I teased other students.”), Victimization (2 items, e.g., “I got hit and pushed by other students.”), and Fighting (3 items, e.g., “I got in a physical fight.”). Directions: “For each of the following questions, choose how many times you did this activity or how many times these things happened to you in the LAST 2 WEEKS.” Items were rated on a 5-point Likert scale (Never, 1 or 2 times, 3 or 4 times, 5 or 6 times, 7 or more times). For each sub-scale, a summed composite was created to indicate the frequency of bullying, victimization, and fighting behaviors.

Witnessing Violence “In Your School?” Students answered five questions about the frequency of witnessing violence: “In the last 2 weeks, how often have people in your school…”. Behaviors were rated on a 4-point Likert scale (Never, Once, A Few Times, Often). Sample behavior: “Fight and Hit?” Summed composite scored indicated the extent of violence witnessed in the past two weeks.

Social Desirability.

Since many of the previous questions and measures suggested socially desirable answers, we included a child’s version of a Social Desirability scale. Students responded to nine statements were “True for me” or “False for me”. Sample items: “Have you ever broken a rule?” and “Do you sometimes feel anger when you don’t get your way?” Three statements’ responses were reverse-scored then the responses were summed to create a social desirability score; the higher the score, the more socially desirable.

Results

Preliminary Analyses

In order to make the claim that the Program is effective, I performed several analyses to validate several of the measures and explored their descriptive statistics. By so doing, we can be more confident in the results of the primary analyses. Tables 2 and 3 illustrate the preliminary analyses for Forms A and B of the Program assessment, respectively.

{Table 2 contains correlations and descriptive stats (and alphas) for Form A exp and control across time points}

{Table 3 contains correlations and descriptive stats (and alphas) for Form B exp and control across time points}

Since Forms A and B were practically identical, I combined the Form A and Form B data for all Primary Analyses.

Primary Analyses

To best estimate the longitudinal differences of the schools that received the Program and those who did not, I used multi-level modeling (MLM). MLM provides several advantages over other possible methods for longitudinal data analysis. These advantages were explained in previous Program Reports.

To what extent does the Take Ten Program Have an Effect on Bullying and Other Outcomes (Controlling for Social Desirability)?

Due the design of the Take Ten Program, we can perform statistical tests that indicate the extent to which the Program effectively decreases bullying behaviors and increases conflict resolution. Further with the longitudinal nature of the data, we are able to perform tests that explore change over time. In other words, we are able to see if students changed from the beginning of the year to the end of the year. So in all, we can see how students' behavior changed and if these changes were due to the fact they were in the Program or not.

Multi-level models were used to compare control schools with experimental schools. As mentioned previously, the control schools participated in data collection at the first and the third time points, and so only these time points were used from the experimental group. With two time points, we are able to explore the linear (straight line) change over time for our outcomes of interest. For this report most of the measures were "outcomes of interest" or dependent variables (the four Take Ten Curriculum variables, the three sub-scales of the Illinois Bullying Scale, and witnessing violence in school). The independent variable was the group a student was in, either control or experimental. Eight models were analyzed within each Form of the assessment—one for each outcome.

For all models, Social Desirability was used as a control variable. A control variable is a variable that is used in combination with independent variables to help identify the unique effect of the independent variable has on the dependent variable. For example, when we include Social Desirability in our statistical models, we are essentially partitioning the students into “Social Desirability” categories and then those students with the same Social Desirability score are compared. Furthering the example, say there are several students in both the control and experimental groups who scored highly on the Social Desirability scale. These high socially desirability students, alone, will be compared across groups. The same thing will happen for other groups of social desirability, and then the average difference between control and experimental groups from all the categories of social desirability will be calculated.

The reason why I am explaining statistical control in such depth is to prepare you for the fact that when we use Social Desirability as a control variable, we find no significant effect of group. In other words, there are no differences between groups in any of the outcomes for any of the Forms by the end of the academic year. In fact, regardless of if we use Social Desirability as a control or not, we find no significant differences at the end of the intervention. This is rather unfortunate since we want to make the claim that the Program is better than no bullying intervention (control group). Therefore, I cannot be confident in making this conclusion. I can, however, explore reasons why these non-significant differences occur and unearth trends within the Program data set. I explore this in my next sub-section and I further discuss possible reasons for the lack of difference between groups in the Discussion section.

To what extent does Take Ten Program Knowledge affect bullying and other behaviors?

To explore the Program's effectiveness, I looked only at the experimental schools, ignoring control schools since they did not receive the Program. Again, I used multi-level modeling (MLM) to analyze the effectiveness of the Program across time. I am defining Program effectiveness based on decreases in bullying behavior (bullying, fighting, victimization, and witnessing violence). With these indicators in mind, I will be testing four models, one for each indicator with gender, age, and social desirability as control variables. A new variable was created called "Take Ten Knowledge", which is a composite score of the four measures specific to the Take Ten Program, where the higher the score, the greater the Take Ten knowledge. Figures 1 through 4 show visual trends of the Program's effectiveness. The colored lines in the Figures are specific to Take Ten Knowledge scores (TT). The dashed line shows the predicted change in the outcome over time based on all the control and independent variables.

Bullying.

There are no significant changes across time in bullying behavior, meaning, on average, bullying behavior does not increase or decrease. However, we find in our control variables that at time 3 (Spring) older students are bullying less than younger students, males are bullying more than females, and students with higher social desirability scores indicate lower amounts of fighting. More importantly, we find that higher Take Ten knowledge has lower bullying in the Spring, suggesting that as student learn and retain Take Ten Knowledge, they have less bullying behavior than those who do not learn or retain Take Ten Knowledge.

Fighting.

Again, for Fighting, there are somewhat similar findings: no change over time, older students fight less, students with higher social desirability fight less, and males fight more in the Spring. And, again, more importantly, higher Take Ten knowledge in the Spring shows lower fighting behaviors.

Victimization.

Like Bullying and Fighting, there is not change in victimization over time. We find that older students are victimized less, students with higher social desirability scores are victimized less, and males are victimized more in the Spring. Unfortunately, Take Ten knowledge does not explain any of the differences in victimization in the Spring, suggesting that Take Ten knowledge does not increase or decrease the chance of being a victim of violence.

Witnessing Violence in School.

For witnessing violence in school, there is a decrease of witnessed violence across time. Further, students with higher social desirability indicate less witnessed violence in the Spring. Interestingly, students with higher Take Ten Knowledge seem to witness more violence than students with lower Take Ten Knowledge. Perhaps this is not as bad as it sounds. Students who have learned and retained Take Ten Knowledge are potentially more aware of violence in their school. In all, students with higher Take Ten Knowledge bully less, fight less, and are more aware of violence than students with lower Take Ten Knowledge.

Discussion

The purpose of this Report was to present Program data in an interpretable manner so that interested readers can see the effects of the Take Ten program have on South Bend school communities. Unfortunately, comparisons between experimental schools and control schools show little effect of the Program. However, when digging deeper into the data, we find that increases in Take Ten Knowledge decrease bullying and fighting and increase violence awareness.

There are several reasons why we did not find a “raw” difference between the experimental and control groups. First, floor and ceiling effects; several of the students selected the minimum (floor) or maximum (ceiling) on all items of a scale at one or multiple time points. By doing this, we are able to fully capture change. For example, if a student indicated they “Strongly Agreed” on all the items in the “What Can You Do?” measure, they would get a high score of 16. We want students in the Program to improve their conflict resolution strategies, but when they indicate the maximum values, there is no room for them to improve. I would recommend some slight modifications to the measures and the addition of more reverse-scored items. In addition, I am aware that there are innovative methods to adjust for ceiling/floor effects in longitudinal research (Wang & Zhang, 2011). I will look into those for more advanced analyses.

A second, related problem is social desirability; although we included a child’s version of a social desirability scale, we found that this measure was a major predictor in explaining the differences between control and experimental groups. Further, since there were no significant interaction between social desirability and what group a student was in, we cannot say that one group was responding more socially desirable. With this being said, I would recommend creating reverse-scored items and “attention items” that we can use to “clean” the data set. If students “straight-line” responses, we can see that they were potentially not paying attention (e.g., marking “Strongly Agree” for every item including reverse-scored or “attention” items). There are several cutting-edge methods, when combined with strong assessments that can detect respondent “fatigue” or “laziness” (Cheng and colleagues).

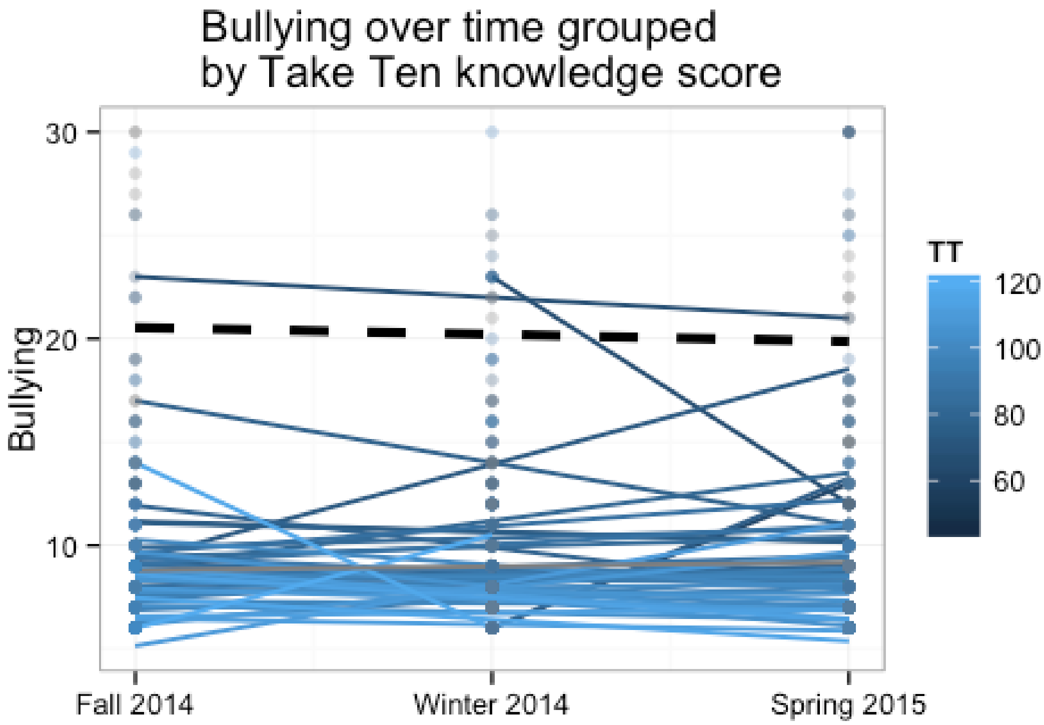
A third, and overarching problem is that fact that all measures are self-reported. Self-report measures (vs. other-report) have a long history of being potentially biased on individuals’ psychological and social data. However, when it comes to a school setting, self-report assessments are one of the more effective methods to assess students’ thoughts and behavior. The teachers or instructors do not have enough time to answer questions about specific [bullying] behavior for each one of their students; therefore, I would not recommend collecting specific student data from teachers. I would, however, recommend finding ways in which we can obtain more “objective” bullying or misbehavior measures. For example, the schools may keep the records of number of fights and who was involved. This type of measure could be included on a school- or student-level and predicted by the Program.

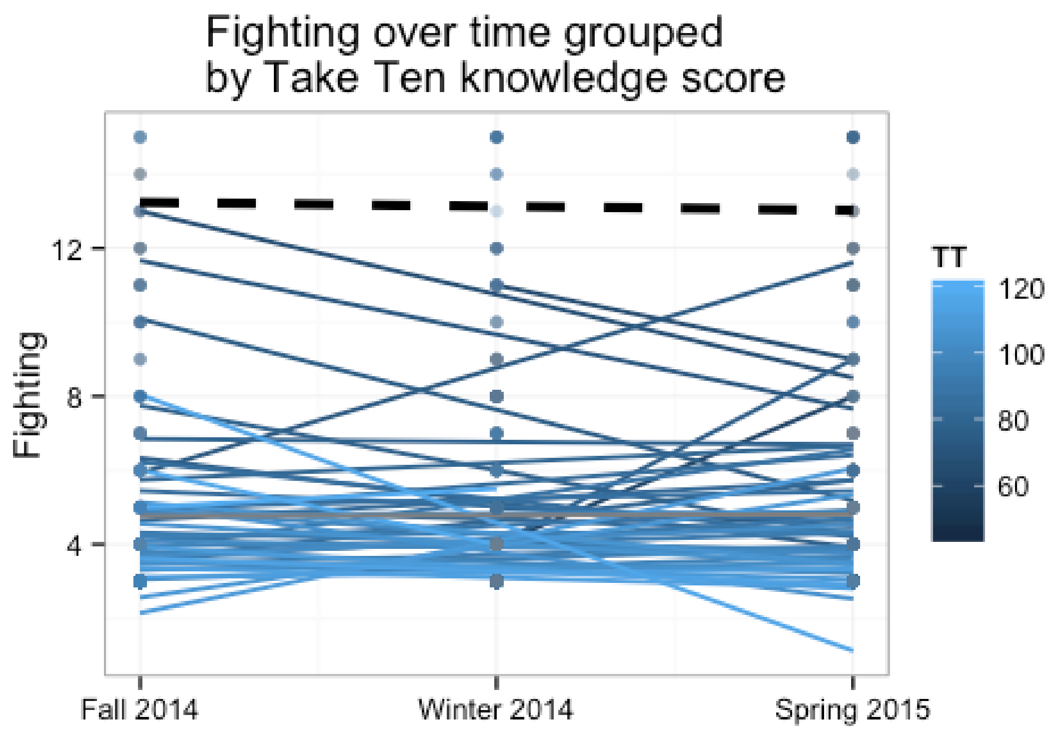
Lastly, a major issue with most longitudinal data is missing data. This project is no exception. When great amounts of missing data are present, they are known to have an effect on statistical analyses. Missing data can occur for several reasons, for example, when a student responses to a survey packet at time 1, but not time 2; therefore, this student’s time 2 data is considered “missing”. Missingness has different levels of severity from “best” to “worst”: Missing Completely at Random (MCAR), Missing at Random (MAR), Missing Not at Random (MNAR). MCAR assumes there is no measured or unmeasured mechanism that is causing the missingness. MCAR has been found to be the least bias on statistical analyses. MAR assumes a related, but non-important variable is causing the missingness (e.g., age). MNAR assumes an important variable is causing the missingness, such as the dependent variable. For example, we may find that “bullies” are less likely to answer questions than “non-bullies”. Missing data is a field of study in and of itself—a field of study I know very little. For the sake of this report, I am assuming MAR, which may be causing some bias in the estimates, but not enough bias to diminish the findings.

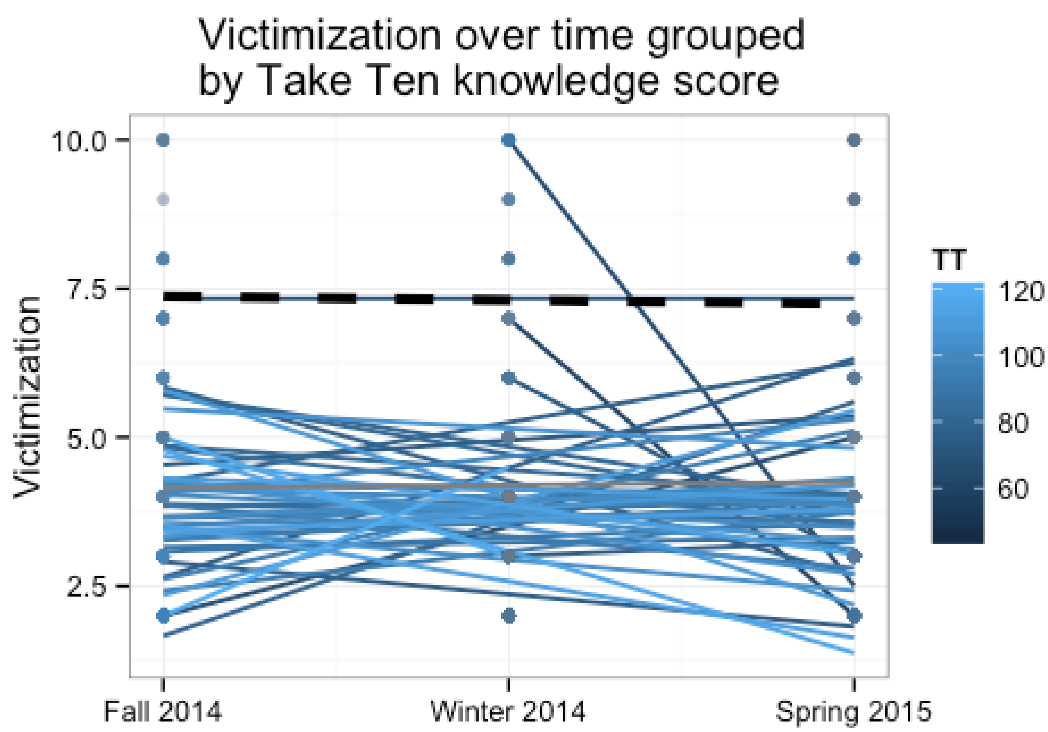
The Take Ten Program claims to reduce violence, bullying, and aggressive through the use of constructive conflict resolution strategies. Data suggest that such a claim can be supported.

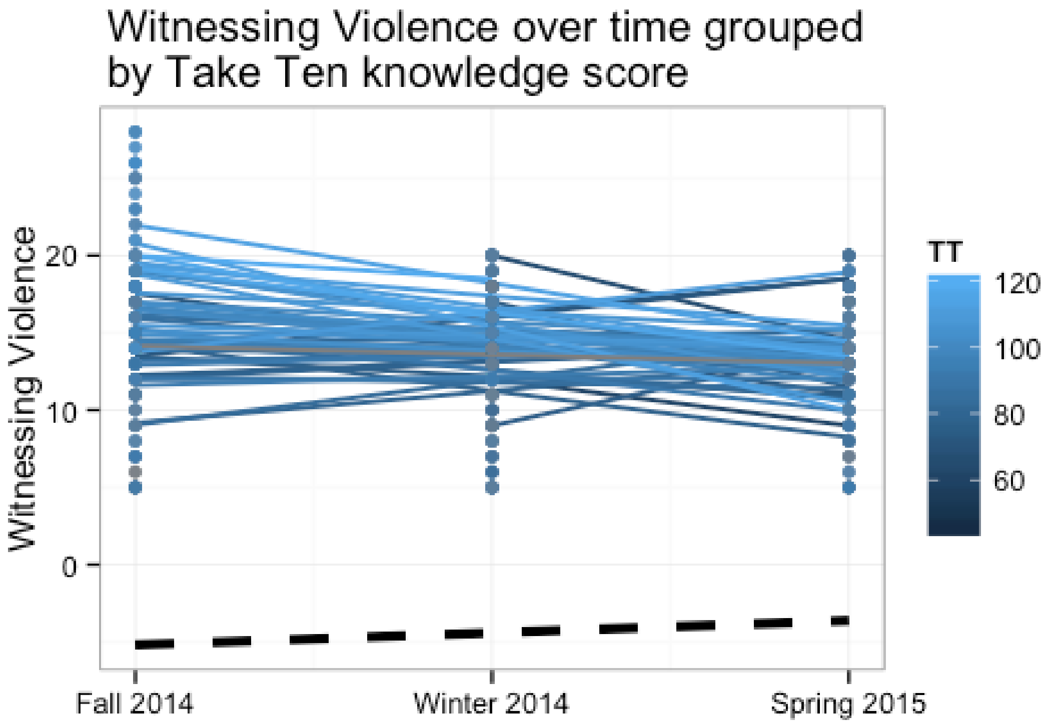
Appendix A

Figures 1 – 4 illustrate how Take Ten Knowledge affects Bullying, Fighting, Victimization, and Witnessing Violence, respectively.




Fighting over time grouped
by Take Ten knowledge score
Fighting
12
8
4
Fall 2014
Winter 2014
Spring 2015
TT
120
100
80
60


Victimization over time grouped
by Take Ten knowledge score
Victimization
10.0
7.5
5.0
2.5
Fall 2014
Winter 2014
Spring 2015
TT
120
100
80
60


Witnessing Violence over time grouped by Take Ten knowledge score
Witnessing Violence
0
10
20
Fall 2014
Winter 2014
Spring 2015
TT
120
100
80
60

Appendix B

```
##########################################
###### Title: Take Ten 2014-2015 analyses
###### Author: Ryan Woodbury
###### Start Date: Oct. 2015
##########################################

########## NOTES
      # Read in all data DONE
      # split data sets (A and B, with control groups) for EFA and CFA
      # run reliabilites
            # Experimental A DONE
            # Control A DONE
            # Experimental B DONE
            # Control B DONE
            # Teacher
      # Calculate composites for each time point
            # Experimental A DONE
            # Control A DONE
            # Experimental B DONE
            # Control B DONE
            # Teacher
      # Create composites datasets
            # Experimental A DONE
            # Control A DONE
            # Experimental B DONE
            # Control B DONE
            # Teacher
      # Combine Form A and Form B composite datasets
            # Measurement invariance by Forms/age
            # Measurement invariance by gender
      # LDA
            # Multi-level modeling
            # Latent growth curve modeling
            # explore quadratic growth
      # Research questions
            # How are the schools (individually) doing?--intra-school
change
            # Does the Take Ten program work? Intervention vs. Control
groups.
            # Does it matter where the intervention takes place?
                  # During or After school?
            # Does gender matter? (boys vs. girls)
            # Does age/class/form matter?



##############
##### Libraries Used

library(psych)
library(lavaan)
library(lme4)
library(ggplot2)
#library(ltm)
```

```
#library(gdata)
library(car)
library(moments)
library(Hmisc)
library(QuantPsyc)
library(RAMpath)
library(foreign)
library(memisc)

setwd('/Volumes/Maxtor/Users/rywood89/Documents/Take Ten/2014-2015
materials/DATA')


#### Read in raw data from SPSS files
TTAraw <- as.data.set(spss.system.file('Form A All.sav'))
head(TTAraw)
names(TTAraw)

TTA.cont.raw <- as.data.set(spss.system.file('Coquillard Control All
Form A.sav'))
head(TTA.cont.raw)

TTBraw <- as.data.set(spss.system.file('Form B All.sav'))
head(TTBraw)

TTB.cont.raw <- as.data.set(spss.system.file('Marshall Control All Form
B.sav'))
head(TTB.cont.raw)
names(TTB.cont.raw)

TTteacherRaw <- as.data.set(spss.system.file('Teacher Evals.sav'))
head(TTteacherRaw)
names(TTteacherRaw)
dim(TTteacherRaw)


#######################################################################
#############################################################
################## FORM A ##################
############# Experimental Group  #############
#######################################################################
#############################################################

###################
#### Composites, reliabilities, and Exploratory factor analyses (at
time 1), and Confirmatory factor analysis (at time 2) of measures
## We are assuming measurement invariance across time, age, gender,
etc.
###################

#### About School
#### School connectedness

## Time 1 (FALL)

about.school1.dat <- data.frame(TTAraw[,c(10:16)], stringsAsFactors =
F)
```

```
about.school1.dat <- sapply(about.school1.dat, as.numeric)
about.school1.5r <- 5 - about.school1.dat[,5]
about.school1.dat <- data.frame(about.school1.dat[,c(1:4)],
about.school1.5r, about.school1.dat[,c(6:7)])

abt.sch.fa <- fa(cor(about.school1.dat, use = 'pairwise'), nfactors =
1)
print(abt.sch.fa)
fa.parallel(about.school1.dat) # 1 factor will work!

about.school1 <- apply(about.school1.dat, 1, sum, na.rm = F)
alpha(about.school1.dat, check.keys = T) # .77
#omega(about.school1.dat, nfactors = 2)


## Time 2 (Winter)

about.school2.dat <- data.frame(TTAraw[,c(71:77)], stringsAsFactors =
F)
about.school2.dat <- sapply(about.school2.dat, as.numeric)
about.school2.5r <- 5 - about.school2.dat[,5]
about.school2.dat <- data.frame(about.school2.dat[,c(1:4)],
about.school2.5r, about.school2.dat[,c(6:7)])

about.school2 <- apply(about.school2.dat, 1, sum, na.rm = F)
alpha(about.school2.dat, check.keys = T) # .81

abt.sch.mod <- '
abtsch =~ aboutschool1mid + aboutschool2mid + aboutschool3mid +
aboutschool4mid + aboutschool5mid + aboutschool6mid + aboutschool7mid
'
abt.sch.fit <- cfa(abt.sch.mod, data = about.school2.dat, missing =
'fiml', test = 'yuan', se = 'robust')
summary(abt.sch.fit, fit = T)

## Time 3 (Spring)

about.school3.dat <- data.frame(TTAraw[,c(131:137)], stringsAsFactors =
F)
about.school3.dat <- sapply(about.school3.dat, as.numeric)
about.school3.5r <- 5 - about.school3.dat[,5]
about.school3.dat <- data.frame(about.school3.dat[,c(1:4)],
about.school3.5r, about.school3.dat[,c(6:7)])

about.school3 <- apply(about.school3.dat, 1, sum, na.rm = F)
alpha(about.school3.dat, check.keys = T) # .81


#### Feel

## Time 1

feel1.dat <- data.frame(TTAraw[,c(17:19)], stringsAsFactors = F)
feel1.dat <- sapply(feel1.dat, as.numeric)
feel1.r <- 5 - feel1.dat[,c(1,3)]
feel1.dat <- data.frame(feel1.r[,1], feel1.dat[,2], feel1.r[,2])
```

```
feel1 <- apply(feel1.dat, 1, sum, na.rm = F)
alpha(feel1.dat, check.keys = T) # .60

feel.fa <- fa(cor(feel1.dat, use='pairwise'), nfactors = 1)
print(feel.fa)
fa.parallel(feel1.dat) # NOT good fit, but there are only three items.

## Time 2

feel2.dat <- data.frame(TTAraw[,c(78:80)], stringsAsFactors = F)
feel2.dat <- sapply(feel2.dat, as.numeric)
feel2.r <- 5 - feel2.dat[,c(1,3)]
feel2.dat <- data.frame(feel2.r[,1], feel2.dat[,2], feel2.r[,2])

feel2 <- apply(feel2.dat, 1, sum, na.rm = F)
alpha(feel2.dat, check.keys = T) # .53
# Low reliability because there are only three items.

feel.mod <- '
feel =~ feel1mid + feel2mid + feel3mid
'
feel.fit <- cfa(feel.mod, data = feel2.dat, missing = 'fiml', se =
'robust', test = 'yuan')
summary(feel.fit , fit = T)
# problems. negative variance on item 1. Still only three items.


## Time 3

feel3.dat <- data.frame(TTAraw[,c(138:140)], stringsAsFactors = F)
feel3.dat <- sapply(feel3.dat, as.numeric)
feel3.r <- 5 - feel3.dat[,c(1,3)]
feel3.dat <- data.frame(feel3.r[,1], feel3.dat[,2], feel3.r[,2])

feel3 <- apply(feel3.dat, 1, sum, na.rm = F)
alpha(feel3.dat, check.keys = T) # .59


#### Act

## Time 1

act1.dat <- data.frame(TTAraw[,c(20:25)], stringsAsFactors = F)
act1.dat <- sapply(act1.dat, as.numeric)
act1 <- apply(act1.dat, 1, sum, na.rm = F)
alpha(act1.dat, check.keys = T) # .75

act1.fa <- fa(cor(act1.dat, use='pairwise'), nfactors = 1)
print(act1.fa)
fa.parallel(act1.dat) # one factor can work


## Time 2

act2.dat <- data.frame(TTAraw[,c(81:86)], stringsAsFactors = F)
act2.dat <- sapply(act2.dat, as.numeric)
act2 <- apply(act2.dat, 1, sum, na.rm = F)
```

```
alpha(act2.dat, check.keys = T) # .78

## Time 3

act3.dat <- data.frame(TTAraw[,c(141:146)], stringsAsFactors = F)
act3.dat <- sapply(act3.dat, as.numeric)
act3 <- apply(act3.dat, 1, sum, na.rm = F)
alpha(act3.dat, check.keys = T) # .81


#### In School

## Time 1

inSchool1.dat <- data.frame(TTAraw[,c(26:30)], stringsAsFactors = F)
inSchool1.dat <- sapply(inSchool1.dat, as.numeric)
inSchool1 <- apply(inSchool1.dat, 1, sum, na.rm = F)
alpha(inSchool1.dat, check.keys = T) # .84

inSchool1.fa <- fa(cor(inSchool1.dat, use='pairwise'), nfactors = 1)
print(inSchool1.fa)
fa.parallel(inSchool1.dat) # one factor can work


## Time 2

inSchool2.dat <- data.frame(TTAraw[,c(87:91)], stringsAsFactors = F)
inSchool2.dat <- sapply(inSchool2.dat, as.numeric)
inSchool2 <- apply(inSchool2.dat, 1, sum, na.rm = F)
alpha(inSchool2.dat, check.keys = T) # .84

## Time 3

inSchool3.dat <- data.frame(TTAraw[,c(147:151)], stringsAsFactors = F)
inSchool3.dat <- sapply(inSchool3.dat, as.numeric)
inSchool3 <- apply(inSchool3.dat, 1, sum, na.rm = F)
alpha(inSchool3.dat, check.keys = T) # .83


#### Can you Do?

## Time 1

canDo1.dat <- data.frame(TTAraw[,c(31:34)], stringsAsFactors = F)
canDo1.dat <- sapply(canDo1.dat, as.numeric)
canDo1 <- apply(canDo1.dat, 1, sum, na.rm = F)
alpha(canDo1.dat, check.keys = T) # .57

canDo1.fa <- fa(cor(canDo1.dat, use='pairwise'), nfactors = 1)
print(canDo1.fa)
fa.parallel(canDo1.dat) # yes

## Time 2

canDo2.dat <- data.frame(TTAraw[,c(92:95)], stringsAsFactors = F)
canDo2.dat <- sapply(canDo2.dat, as.numeric)
canDo2 <- apply(canDo2.dat, 1, sum, na.rm = F)
```

```
alpha(canDo2.dat, check.keys = T) # .59

## Time 3

canDo3.dat <- data.frame(TTAraw[,c(152:155)], stringsAsFactors = F)
canDo3.dat <- sapply(canDo3.dat, as.numeric)
canDo3 <- apply(canDo3.dat, 1, sum, na.rm = F)
alpha(canDo3.dat, check.keys = T) # .57


#### You think

## Time 1

youThink1.dat <- data.frame(TTAraw[,c(35:41)], stringsAsFactors = F)
youThink1.dat <- sapply(youThink1.dat, as.numeric)
youThink1.6r <- 5 - youThink1.dat[,6]
youThink1.dat <- data.frame(youThink1.dat[,c(1:5)], youThink1.6r,
youThink1.dat[,7])

youThink1 <- apply(youThink1.dat, 1, sum, na.rm = F)
alpha(youThink1.dat) # .37 Item 6 should be reverse-scored, -Violence
only hurts someone physically- However, analysis suggests it should be
the same direction as other items.

youThink1.fa <- fa(cor(youThink1.dat, use='pairwise'), nfactors = 1)
print(youThink1.fa)
fa.parallel(youThink1.dat) # yes


## Time 2

youThink2.dat <- data.frame(TTAraw[,c(96:102)], stringsAsFactors = F)
youThink2.dat <- sapply(youThink2.dat, as.numeric)
youThink2.6r <- 5 - youThink2.dat[,6]
youThink2.dat <- data.frame(youThink2.dat[,c(1:5)], youThink2.6r,
youThink2.dat[,7])

youThink2 <- apply(youThink2.dat, 1, sum, na.rm = F)
alpha(youThink2.dat, check.keys = F) # .45

## Time 3

youThink3.dat <- data.frame(TTAraw[,c(156:162)], stringsAsFactors = F)
youThink3.dat <- sapply(youThink3.dat, as.numeric)
youThink3.6r <- 5 - youThink3.dat[,6]
youThink3.dat <- data.frame(youThink3.dat[,c(1:5)], youThink3.6r,
youThink3.dat[,7])

youThink3 <- apply(youThink3.dat, 1, sum, na.rm = F)
alpha(youThink3.dat, check.keys = F) # .52


#### Illinois Bully and Victimization scale
### Your Experience
### sub-scales (no reverse-scoring)
```

```
## Time 1

# Bully
bully1.dat <- data.frame(TTAraw[,c(44,48:52)], stringsAsFactors = F)
bully1.dat <- sapply(bully1.dat, as.numeric)
bully1 <- apply(bully1.dat, 1, sum, na.rm = F)
alpha(bully1.dat, check.keys = T) # .83

# Victim
victim1.dat <- data.frame(TTAraw[,c(42:43)], stringsAsFactors = F)
victim1.dat <- sapply(victim1.dat, as.numeric)
victim1 <- apply(victim1.dat, 1, sum, na.rm = F)
alpha(victim1.dat, check.keys = T) # .60 or r = .44

# Fighting
fight1.dat <- data.frame(TTAraw[,c(45:47)], stringsAsFactors = F)
fight1.dat <- sapply(fight1.dat, as.numeric)
fight1 <- apply(fight1.dat, 1, sum, na.rm = F)
alpha(fight1.dat, check.keys = T) # .79


## Time 2

# Bully
bully2.dat <- data.frame(TTAraw[,c(105,109:113)], stringsAsFactors = F)
bully2.dat <- sapply(bully2.dat, as.numeric)
bully2 <- apply(bully2.dat, 1, sum, na.rm = F)
alpha(bully2.dat, check.keys = T) # .81

# Victim
victim2.dat <- data.frame(TTAraw[,c(103:104)], stringsAsFactors = F)
victim2.dat <- sapply(victim2.dat, as.numeric)
victim2 <- apply(victim2.dat, 1, sum, na.rm = F)
alpha(victim2.dat, check.keys = T) # .69 or r = .53

# Fighting
fight2.dat <- data.frame(TTAraw[,c(106:108)], stringsAsFactors = F)
fight2.dat <- sapply(fight2.dat, as.numeric)
fight2 <- apply(fight2.dat, 1, sum, na.rm = F)
alpha(fight2.dat, check.keys = T) # .78

## Time 3

# Bully
bully3.dat <- data.frame(TTAraw[,c(165,169:173)], stringsAsFactors = F)
bully3.dat <- sapply(bully3.dat, as.numeric)
bully3 <- apply(bully3.dat, 1, sum, na.rm = F)
alpha(bully3.dat, check.keys = T) # .85

# Victim
victim3.dat <- data.frame(TTAraw[,c(163:164)], stringsAsFactors = F)
victim3.dat <- sapply(victim3.dat, as.numeric)
victim3 <- apply(victim3.dat, 1, sum, na.rm = F)
alpha(victim3.dat, check.keys = T) # .73 or r = .58

# Fighting
fight3.dat <- data.frame(TTAraw[,c(166:168)], stringsAsFactors = F)
```

```
fight3.dat <- sapply(fight3.dat, as.numeric)
fight3 <- apply(fight3.dat, 1, sum, na.rm = F)
alpha(fight3.dat, check.keys = T) # .80


#### social desirability (more questions)

## Time 1

socD1.dat <- data.frame(TTAraw[,c(53:61)], stringsAsFactors = F)
socD1.dat <- sapply(socD1.dat, as.numeric)
socD1.r <- 3 - socD1.dat[,c(3,8)]
socD1.dat <- data.frame(socD1.dat[,c(1:2)], socD1.r[,1],
socD1.dat[,c(4:7)], socD1.r[,2], socD1.dat[,9])

socD1 <- apply(socD1.dat, 1, sum, na.rm = F)
alpha(socD1.dat, check.keys = T) # .80

## Time 2

socD2.dat <- data.frame(TTAraw[,c(114:122)], stringsAsFactors = F)
socD2.dat <- sapply(socD2.dat, as.numeric)
socD2.r <- 3 - socD2.dat[,c(3,8)]
socD2.dat <- data.frame(socD2.dat[,c(1:2)], socD2.r[,1],
socD2.dat[,c(4:7)], socD2.r[,2], socD2.dat[,9])

socD2 <- apply(socD2.dat, 1, sum, na.rm = F)
alpha(socD2.dat, check.keys = T) # .80

## Time 3

socD3.dat <- data.frame(TTAraw[,c(174:182)], stringsAsFactors = F)
socD3.dat <- sapply(socD3.dat, as.numeric)
socD3.r <- 3 - socD3.dat[,c(3,8)]
socD3.dat <- data.frame(socD3.dat[,c(1:2)], socD3.r[,1],
socD3.dat[,c(4:7)], socD3.r[,2], socD3.dat[,9])

socD3 <- apply(socD3.dat, 1, sum, na.rm = F)
alpha(socD3.dat, check.keys = T) # .81




############################################
#### Creating a large data set with all the composites and variables of
interest.
#### Explore descriptive stats of composite scores
############################################

#### Recoding a few things

# Gender 1 = female; 2 = male; NA = NA
TTAraw$gender <- ifelse(TTAraw$gender == 'Male', 1,
ifelse(TTAraw$gender == 'Female', 0, NA))
TTAraw$gendermid <- ifelse(TTAraw$gendermid == 'Male', 1,
ifelse(TTAraw$gendermid == 'Female', 0, NA))
```

```
TTAraw$genderpost <- ifelse(TTAraw$genderpost == 'Male', 1,
ifelse(TTAraw$genderpost == 'Female', 0, NA))

# ethinicity (alphabetical order)
#TTAraw$ethnicity <- factor(TTAraw$ethnicity)
#TTAraw$ethnicitymid <- factor(TTAraw$ethnicitymid)
#TTAraw$ethinicitypost <- factor(TTAraw$ethnicitypost)

# age (making numeric)
TTAraw$age <- sapply(TTAraw$age, as.numeric)
TTAraw$agemid <- sapply(TTAraw$agemid, as.numeric)
TTAraw$agepost <- sapply(TTAraw$agepost, as.numeric)

# grade (making numeric)
TTAraw$grade <- sapply(TTAraw$grade, as.numeric)
TTAraw$grademid <- sapply(TTAraw$grademid, as.numeric)
TTAraw$gradepost <- sapply(TTAraw$gradepost, as.numeric)


TTA.comp <- cbind(about.school1, feel1, act1, inSchool1, canDo1,
youThink1, bully1, victim1, fight1, socD1, TTAraw[,c(1,2,4:7)],
about.school2, feel2, act2, inSchool2, canDo2, youThink2, bully2,
victim2, fight2, socD2, TTAraw[,c(63,65:68)], about.school3, feel3,
act3, inSchool3, canDo3, youThink3, bully3, victim3, fight3, socD3,
TTAraw[,c(123,125:128)])
TTA.comp <- as.data.frame(TTA.comp, stringsAsFactors = F)
head(TTA.comp)
names(TTA.comp)
write.csv(TTA.comp, 'TTA.comp.csv')
#TTA.comp <- read.csv('TTA.comp.csv', stringsAsFactors = F)
#TTA.comp <- TTA.comp[,-1]

TTA.wide <- cbind(about.school1, about.school2, about.school3, feel1,
feel2, feel3, act1, act2, act3, inSchool1, inSchool2, inSchool3,
canDo1, canDo2, canDo3, youThink1, youThink2, youThink3, bully1,
bully2, bully3, victim1, victim2, victim3, fight1, fight2, fight3,
socD1, socD2, socD3, TTAraw$name, TTAraw[,c(2,63,123)],
TTAraw[,c(4,65,125)], TTAraw[,c(5,66,126)], TTAraw[,c(6,67,127)],
TTAraw[,c(7,68,128)])
TTA.wide <- as.data.frame(TTA.wide, stringsAsFactors = F)
head(TTA.wide)
names(TTA.wide)
write.csv(TTA.wide, 'TTA.wide.csv')
# TTA.wide <- read.csv('TTA.wide.csv', stringsAsFactors = F)
# TTA.wide <- TTA.wide[,-1]


TTA.explore <- TTA.comp[,-c(11:12,14,27,29,42,44)]
num_var=ncol(TTA.explore)

skew2 <- rep(NA, num_var)
kurt2 <- rep(NA, num_var)
mean2 <- rep(NA, num_var)
sd2 <- rep(NA, num_var)
min2 <- rep(NA, num_var)
max2 <- rep(NA, num_var)
sample2 <- rep(NA, num_var)
```

```
for(i in 1:num_var) {
      skew2[i] <- skewness(TTA.explore[,i], na.rm = T)
      kurt2[i] <- kurtosis(TTA.explore[,i], na.rm = T)
      mean2[i] <- mean(TTA.explore[,i], na.rm = T)
      sd2[i] <- sd(TTA.explore[,i], na.rm = T)
      min2[i] <- min(TTA.explore[,i], na.rm = T)
      max2[i] <- max(TTA.explore[,i], na.rm = T)
      sample2[i] <-
length(TTA.explore[,i][which(complete.cases(TTA.explore[,i] == TRUE))])
}

dtableTTA <- cbind(mean2, sd2, min2, max2, skew2, kurt2, sample2)
dtableTTA <- round(dtableTTA, digits = 2)
dtableTTA <- as.data.frame(dtableTTA)
rownames(dtableTTA) <- colnames(TTA.explore)
dtableTTA


corstarsl <- function(x){
require(Hmisc)
x <- as.matrix(x)
R <- rcorr(x)$r
p <- rcorr(x)$P
## define notions for significance levels; spacing is important.
mystars <- ifelse(p < .001, "***", ifelse(p < .01, "** ", ifelse(p <
.05, "* ", " ")))
## trunctuate the matrix that holds the correlations to two decimal
R <- format(round(cbind(rep(-1.11, ncol(x)), R), 2))[,-1]
## build a new matrix that includes the correlations with their
apropriate stars
Rnew <- matrix(paste(R, mystars, sep=""), ncol=ncol(x))
diag(Rnew) <- paste(diag(R), " ", sep="")
rownames(Rnew) <- colnames(x)
colnames(Rnew) <- paste(colnames(x), " ", sep="")
## remove upper triangle
Rnew <- as.matrix(Rnew)
Rnew[upper.tri(Rnew, diag = TRUE)] <- " "
Rnew <- as.data.frame(Rnew)
## remove last column and return the matrix (which is now a data frame)
Rnew <- cbind(Rnew[1:length(Rnew)-1])
return(Rnew)
}

TTA.corr <- corstarsl(TTA.explore)
write.csv(cbind(TTA.corr, dtableTTA), 'TTA.exp.corrsANDdesc.csv')





#######################################################################
#############################################################
################## FORM A ##################
############### Control Group  ################
############## No Mid-point! ##################
```

```
########################################################################
#############################################################

###################
#### Composites, reliabilities, and Exploratory factor analyses (at
time 1), and Confirmatory factor analysis (at time 2) of measures
## We are assuming measurement invariance across time, age, gender,
etc.
###################

#### About School
#### School connectedness

## Time 1 (FALL)

about.schoolC1.dat <- data.frame(TTA.cont.raw[,c(9:15)],
stringsAsFactors = F)
about.schoolC1.dat <- sapply(about.schoolC1.dat, as.numeric)
about.schoolC1.5r <- 5 - about.schoolC1.dat[,5]
about.schoolC1.dat <- data.frame(about.schoolC1.dat[,c(1:4)],
about.schoolC1.5r, about.schoolC1.dat[,c(6:7)])

abt.schC.fa <- fa(cor(about.schoolC1.dat, use = 'pairwise'), nfactors =
1)
print(abt.schC.fa)
fa.parallel(about.schoolC1.dat) # 1 factor will work!

about.schoolC1 <- apply(about.schoolC1.dat, 1, sum, na.rm = F)
alpha(about.schoolC1.dat, check.keys = T) # .69


## Time 2 (Winter)
      # DNE

## Time 3 (Spring)

about.schoolC3.dat <- data.frame(TTA.cont.raw[,c(67:73)],
stringsAsFactors = F)
about.schoolC3.dat <- sapply(about.schoolC3.dat, as.numeric)
about.schoolC3.5r <- 5 - about.schoolC3.dat[,5]
about.schoolC3.dat <- data.frame(about.schoolC3.dat[,c(1:4)],
about.schoolC3.5r, about.schoolC3.dat[,c(6:7)])

about.schoolC3 <- apply(about.schoolC3.dat, 1, sum, na.rm = F)
alpha(about.schoolC3.dat, check.keys = T) # .75


#### Feel

## Time 1

feelC1.dat <- data.frame(TTA.cont.raw[,c(16:18)], stringsAsFactors = F)
feelC1.dat <- sapply(feelC1.dat, as.numeric)
feelC1.r <- 5 - feelC1.dat[,c(1,3)]
feelC1.dat <- data.frame(feelC1.r[,1], feelC1.dat[,2], feelC1.r[,2])

feelC1 <- apply(feelC1.dat, 1, sum, na.rm = F)
```

```
alpha(feelC1.dat, check.keys = T) # .47

feelC.fa <- fa(cor(feelC1.dat, use='pairwise'), nfactors = 1)
print(feelC.fa)
fa.parallel(feelC1.dat) # NOT good fit, but there are only three items.

## Time 2
      # DNE


## Time 3

feelC3.dat <- data.frame(TTA.cont.raw[,c(74:76)], stringsAsFactors = F)
feelC3.dat <- sapply(feelC3.dat, as.numeric)
feelC3.r <- 5 - feelC3.dat[,c(1,3)]
feelC3.dat <- data.frame(feelC3.r[,1], feelC3.dat[,2], feelC3.r[,2])

feelC3 <- apply(feelC3.dat, 1, sum, na.rm = F)
alpha(feelC3.dat, check.keys = T) # .59


#### Act

## Time 1

actC1.dat <- data.frame(TTA.cont.raw[,c(19:24)], stringsAsFactors = F)
actC1.dat <- sapply(actC1.dat, as.numeric)
actC1 <- apply(actC1.dat, 1, sum, na.rm = F)
alpha(actC1.dat, check.keys = T) # .71

## Time 2
      # DNE

## Time 3

actC3.dat <- data.frame(TTA.cont.raw[,c(77:82)], stringsAsFactors = F)
actC3.dat <- sapply(actC3.dat, as.numeric)
actC3 <- apply(actC3.dat, 1, sum, na.rm = F)
alpha(actC3.dat, check.keys = T) # .76


#### In School

## Time 1

inSchoolC1.dat <- data.frame(TTA.cont.raw[,c(25:29)], stringsAsFactors
= F)
inSchoolC1.dat <- sapply(inSchoolC1.dat, as.numeric)
inSchoolC1 <- apply(inSchoolC1.dat, 1, sum, na.rm = F)
alpha(inSchoolC1.dat, check.keys = T) # .78

## Time 2
      # DNE

## Time 3
```

```
inSchoolC3.dat <- data.frame(TTA.cont.raw[,c(83:87)], stringsAsFactors
= F)
inSchoolC3.dat <- sapply(inSchoolC3.dat, as.numeric)
inSchoolC3 <- apply(inSchoolC3.dat, 1, sum, na.rm = F)
alpha(inSchoolC3.dat, check.keys = T) # .78


#### Can you Do?

## Time 1

canDoC1.dat <- data.frame(TTA.cont.raw[,c(30:33)], stringsAsFactors =
F)
canDoC1.dat <- sapply(canDoC1.dat, as.numeric)
canDoC1 <- apply(canDoC1.dat, 1, sum, na.rm = F)
alpha(canDoC1.dat, check.keys = T) # .57

## Time 2
      # DNE

## Time 3

canDoC3.dat <- data.frame(TTA.cont.raw[,c(88:91)], stringsAsFactors =
F)
canDoC3.dat <- sapply(canDoC3.dat, as.numeric)
canDoC3 <- apply(canDoC3.dat, 1, sum, na.rm = F)
alpha(canDoC3.dat, check.keys = T) # .46


#### You think

## Time 1

youThinkC1.dat <- data.frame(TTA.cont.raw[,c(34:40)], stringsAsFactors
= F)
youThinkC1.dat <- sapply(youThinkC1.dat, as.numeric)
youThinkC1.6r <- 5 - youThinkC1.dat[,6]
youThinkC1.dat <- data.frame(youThinkC1.dat[,c(1:5)], youThinkC1.6r,
youThinkC1.dat[,7])

youThinkC1 <- apply(youThinkC1.dat, 1, sum, na.rm = F)
alpha(youThinkC1.dat) # .44

## Time 2
      # DNE

## Time 3

youThinkC3.dat <- data.frame(TTA.cont.raw[,c(92:98)], stringsAsFactors
= F)
youThinkC3.dat <- sapply(youThinkC3.dat, as.numeric)
youThinkC3.6r <- 5 - youThinkC3.dat[,6]
youThinkC3.dat <- data.frame(youThinkC3.dat[,c(1:5)], youThinkC3.6r,
youThinkC3.dat[,7])

youThinkC3 <- apply(youThinkC3.dat, 1, sum, na.rm = F)
alpha(youThinkC3.dat, check.keys = F) # .43
```

```
#### Illinois Bully and Victimization scale
### Your Experience
### sub-scales (no reverse-scoring)

## Time 1

# Bully
bullyC1.dat <- data.frame(TTA.cont.raw[,c(43,47:51)], stringsAsFactors
= F)
bullyC1.dat <- sapply(bullyC1.dat, as.numeric)
bullyC1 <- apply(bullyC1.dat, 1, sum, na.rm = F)
alpha(bullyC1.dat, check.keys = T) # .79

# Victim
victimC1.dat <- data.frame(TTA.cont.raw[,c(41:42)], stringsAsFactors =
F)
victimC1.dat <- sapply(victimC1.dat, as.numeric)
victimC1 <- apply(victimC1.dat, 1, sum, na.rm = F)
alpha(victimC1.dat, check.keys = T) # .77 or r = .63

# Fighting
fightC1.dat <- data.frame(TTA.cont.raw[,c(44:46)], stringsAsFactors =
F)
fightC1.dat <- sapply(fightC1.dat, as.numeric)
fightC1 <- apply(fightC1.dat, 1, sum, na.rm = F)
alpha(fightC1.dat, check.keys = T) # .80


## Time 2

# Bully
# Victim
# Fighting
      # DNE

## Time 3

# Bully
bullyC3.dat <- data.frame(TTA.cont.raw[,c(101,105:109)],
stringsAsFactors = F)
bullyC3.dat <- sapply(bullyC3.dat, as.numeric)
bullyC3 <- apply(bullyC3.dat, 1, sum, na.rm = F)
alpha(bullyC3.dat, check.keys = T) # .81

# Victim
victimC3.dat <- data.frame(TTA.cont.raw[,c(99:100)], stringsAsFactors =
F)
victimC3.dat <- sapply(victimC3.dat, as.numeric)
victimC3 <- apply(victimC3.dat, 1, sum, na.rm = F)
alpha(victimC3.dat, check.keys = T) # .74 or r = .61

# Fighting
fightC3.dat <- data.frame(TTA.cont.raw[,c(102:104)], stringsAsFactors =
F)
fightC3.dat <- sapply(fightC3.dat, as.numeric)
```

```
fightC3 <- apply(fightC3.dat, 1, sum, na.rm = F)
alpha(fightC3.dat, check.keys = T) # .73


#### social desirability (more questions)

## Time 1

socDC1.dat <- data.frame(TTA.cont.raw[,c(52:60)], stringsAsFactors = F)
socDC1.dat <- sapply(socDC1.dat, as.numeric)
socDC1.r <- 3 - socDC1.dat[,c(3,8)]
socDC1.dat <- data.frame(socDC1.dat[,c(1:2)], socDC1.r[,1],
socDC1.dat[,c(4:7)], socDC1.r[,2], socDC1.dat[,9])

socDC1 <- apply(socDC1.dat, 1, sum, na.rm = F)
alpha(socDC1.dat, check.keys = T) # .73

## Time 2

      # DNE

## Time 3

socDC3.dat <- data.frame(TTA.cont.raw[,c(110:118)], stringsAsFactors =
F)
socDC3.dat <- sapply(socDC3.dat, as.numeric)
socDC3.r <- 3 - socDC3.dat[,c(3,8)]
socDC3.dat <- data.frame(socDC3.dat[,c(1:2)], socDC3.r[,1],
socDC3.dat[,c(4:7)], socDC3.r[,2], socDC3.dat[,9])

socDC3 <- apply(socDC3.dat, 1, sum, na.rm = F)
alpha(socDC3.dat, check.keys = T) # .77




############################################
#### Creating a large data set with all the composites and variables of
interest.
#### Explore descriptive stats of composite scores
############################################

#### Recoding a few things

# Gender 1 = female; 2 = male; NA = NA
TTA.cont.raw$gender <- ifelse(TTA.cont.raw$gender == 'Male', 1,
ifelse(TTA.cont.raw$gender == 'Female', 0, NA))
#TTA.cont.raw$gendermid <- ifelse(TTA.cont.raw$gendermid == 'Male', 1,
ifelse(TTA.cont.raw$gendermid == 'Female', 0, NA))
TTA.cont.raw$genderpost <- ifelse(TTA.cont.raw$genderpost == 'Male', 1,
ifelse(TTA.cont.raw$genderpost == 'Female', 0, NA))

# ethinicity (alphabetical order)
#TTA.cont.raw$ethnicity <- factor(TTA.cont.raw$ethnicity)
#TTA.cont.raw$ethnicitymid <- factor(TTA.cont.raw$ethnicitymid)
#TTA.cont.raw$ethinicitypost <- factor(TTA.cont.raw$ethnicitypost)
```

```
# age (making numeric)
TTA.cont.raw$age <- sapply(TTA.cont.raw$age, as.numeric)
#TTA.cont.raw$agemid <- sapply(TTA.cont.raw$agemid, as.numeric)
TTA.cont.raw$agepost <- sapply(TTA.cont.raw$agepost, as.numeric)

# grade (making numeric)
TTA.cont.raw$grade <- sapply(TTA.cont.raw$grade, as.numeric)
#TTA.cont.raw$grademid <- sapply(TTA.cont.raw$grademid, as.numeric)
TTA.cont.raw$gradepost <- sapply(TTA.cont.raw$gradepost, as.numeric)


TTA.control <- cbind(about.schoolC1, feelC1, actC1, inSchoolC1,
canDoC1, youThinkC1, bullyC1, victimC1, fightC1, socDC1,
TTA.cont.raw[,c(1:6)], about.schoolC3, feelC3, actC3, inSchoolC3,
canDoC3, youThinkC3, bullyC3, victimC3, fightC3, socDC3,
TTA.cont.raw[,c(61:64)])
TTA.control <- as.data.frame(TTA.control, stringsAsFactors = F)
head(TTA.control)
names(TTA.control)
write.csv(TTA.control, 'TTA.control.csv')
# TTA.control <- read.csv('TTA.control.csv', stringsAsFactors = F)
# TTA.control <- TTA.control[,-1]

TTA.Cwide <- cbind(about.schoolC1, about.schoolC3, feelC1, feelC3,
actC1, actC3, inSchoolC1, inSchoolC3, canDoC1, canDoC3, youThinkC1,
youThinkC3, bullyC1, bullyC3, victimC1, victimC3, fightC1, fightC3,
socDC1, socDC3, TTA.cont.raw$name, TTA.cont.raw$site,
TTA.cont.raw[,c(3,61)], TTA.cont.raw[,c(4,62)], TTA.cont.raw[,c(5,63)],
TTA.cont.raw[,c(6,64)])
TTA.Cwide <- as.data.frame(TTA.Cwide, stringsAsFactors = F)
head(TTA.Cwide)
names(TTA.Cwide)
write.csv(TTA.Cwide, 'TTA.Cwide.csv')
# TTA.Cwide <-read.csv('TTA.Cwide.csv', stringsAsFactors = F)
# TTA.Cwide <- TTA.Cwide[,-1]


TTA.Cexplore <- TTA.control[,-c(11:12,14,28)]
num_var=ncol(TTA.Cexplore)

skew2 <- rep(NA, num_var)
kurt2 <- rep(NA, num_var)
mean2 <- rep(NA, num_var)
sd2 <- rep(NA, num_var)
min2 <- rep(NA, num_var)
max2 <- rep(NA, num_var)
sample2 <- rep(NA, num_var)

for(i in 1:num_var) {
      skew2[i] <- skewness(TTA.Cexplore[,i], na.rm = T)
      kurt2[i] <- kurtosis(TTA.Cexplore[,i], na.rm = T)
      mean2[i] <- mean(TTA.Cexplore[,i], na.rm = T)
      sd2[i] <- sd(TTA.Cexplore[,i], na.rm = T)
      min2[i] <- min(TTA.Cexplore[,i], na.rm = T)
      max2[i] <- max(TTA.Cexplore[,i], na.rm = T)
```

```
      sample2[i] <-
length(TTA.Cexplore[,i][which(complete.cases(TTA.Cexplore[,i] ==
TRUE))])
}

dtableTTA.cont <- cbind(mean2, sd2, min2, max2, skew2, kurt2, sample2)
dtableTTA.cont <- round(dtableTTA.cont, digits = 2)
dtableTTA.cont <- as.data.frame(dtableTTA.cont)
rownames(dtableTTA.cont) <- colnames(TTA.Cexplore)
dtableTTA.cont


TTA.C.corr <- corstarsl(TTA.Cexplore)
write.csv(cbind(TTA.C.corr, dtableTTA.cont),
'TTA.control.corrsANDdesc.csv')






#######################################################################
#############################################################
################## FORM B ##################
############# Experimental Group  #############
#######################################################################
#############################################################

###################
#### Composites, reliabilities, and Exploratory factor analyses (at
time 1), and Confirmatory factor analysis (at time 2) of measures
## We are assuming measurement invariance across time, age, gender,
etc.
###################

#### About School
#### School connectedness

## Time 1 (FALL)

Babout.school1.dat <- data.frame(TTBraw[,c(10:16)], stringsAsFactors =
F)
Babout.school1.dat <- sapply(Babout.school1.dat, as.numeric)
Babout.school1.5r <- 5 - Babout.school1.dat[,5]
Babout.school1.dat <- data.frame(Babout.school1.dat[,c(1:4)],
Babout.school1.5r, Babout.school1.dat[,c(6:7)])

Babt.sch.fa <- fa(cor(Babout.school1.dat, use = 'pairwise'), nfactors =
1)
print(Babt.sch.fa)
fa.parallel(Babout.school1.dat) # 1 factor will work!

Babout.school1 <- apply(Babout.school1.dat, 1, sum, na.rm = F)
alpha(Babout.school1.dat, check.keys = T) # .82


Babt.sch1.cfa <- '
```

```
  bt.sch =~ aboutschool1 + aboutschool2 +aboutschool3 + aboutschool4 +
Babout.school1.5r + aboutschool6 + aboutschool7

'
Babt.sch1.fit <- cfa(Babt.sch1.cfa, data = Babout.school1.dat, missing
= 'fiml', test = 'yuan', se = 'robust')
summary(Babt.sch1.fit, fit = T)
## Good!

## Time 2 (Winter)

Babout.school2.dat <- data.frame(TTBraw[,c(72:78)], stringsAsFactors =
F)
Babout.school2.dat <- sapply(Babout.school2.dat, as.numeric)
Babout.school2.5r <- 5 - Babout.school2.dat[,5]
Babout.school2.dat <- data.frame(Babout.school2.dat[,c(1:4)],
Babout.school2.5r, Babout.school2.dat[,c(6:7)])

Babout.school2 <- apply(Babout.school2.dat, 1, sum, na.rm = F)
alpha(Babout.school2.dat, check.keys = T) # .83

Babt.sch.mod <- '
abtsch =~ aboutschool1mid + aboutschool2mid + aboutschool3mid +
aboutschool4mid + Babout.school2.5r + aboutschool6mid + aboutschool7mid
'
Babt.sch.fit <- cfa(Babt.sch.mod, data = Babout.school2.dat, missing =
'fiml', test = 'yuan', se = 'robust')
summary(Babt.sch.fit, fit = T)

## Time 3 (Spring)

Babout.school3.dat <- data.frame(TTBraw[,c(134:140)], stringsAsFactors
= F)
Babout.school3.dat <- sapply(Babout.school3.dat, as.numeric)
Babout.school3.5r <- 5 - Babout.school3.dat[,5]
Babout.school3.dat <- data.frame(Babout.school3.dat[,c(1:4)],
Babout.school3.5r, Babout.school3.dat[,c(6:7)])

Babout.school3 <- apply(Babout.school3.dat, 1, sum, na.rm = F)
alpha(Babout.school3.dat, check.keys = T) # .76


#### Feel

## Time 1

Bfeel1.dat <- data.frame(TTBraw[,c(17:19)], stringsAsFactors = F)
Bfeel1.dat <- sapply(Bfeel1.dat, as.numeric)
Bfeel1.r <- 5 - Bfeel1.dat[,c(1,3)]
Bfeel1.dat <- data.frame(Bfeel1.r[,1], Bfeel1.dat[,2], Bfeel1.r[,2])

Bfeel1 <- apply(Bfeel1.dat, 1, sum, na.rm = F)
alpha(Bfeel1.dat, check.keys = T) # .59

Bfeel.fa <- fa(cor(Bfeel1.dat, use='pairwise'), nfactors = 1)
print(Bfeel.fa)
fa.parallel(Bfeel1.dat) # NOT good fit, but there are only three items.
```

```
Bfeel1.mod <- '
feel =~ Bfeel1.r...1. + Bfeel1.dat...2. + Bfeel1.r...2.
'
Bfeel1.fit <- cfa(Bfeel1.mod, data = Bfeel1.dat, missing = 'fiml', se =
'robust', test = 'yuan')
summary(Bfeel1.fit, fit = T)
# saturated.

## Time 2

Bfeel2.dat <- data.frame(TTBraw[,c(79:81)], stringsAsFactors = F)
Bfeel2.dat <- sapply(Bfeel2.dat, as.numeric)
Bfeel2.r <- 5 - Bfeel2.dat[,c(1,3)]
Bfeel2.dat <- data.frame(Bfeel2.r[,1], Bfeel2.dat[,2], Bfeel2.r[,2])

Bfeel2 <- apply(Bfeel2.dat, 1, sum, na.rm = F)
alpha(Bfeel2.dat, check.keys = T) # .61

Bfeel.mod <- '
feel =~ feel1mid + feel2mid + feel3mid
'
Bfeel.fit <- cfa(Bfeel.mod, data = Bfeel2.dat, missing = 'fiml', se =
'robust', test = 'yuan')
summary(Bfeel.fit, fit = T)
# problems. negative variance on item 1. Still only three items.


## Time 3

Bfeel3.dat <- data.frame(TTBraw[,c(141:143)], stringsAsFactors = F)
Bfeel3.dat <- sapply(Bfeel3.dat, as.numeric)
Bfeel3.r <- 5 - Bfeel3.dat[,c(1,3)]
Bfeel3.dat <- data.frame(Bfeel3.r[,1], Bfeel3.dat[,2], Bfeel3.r[,2])

Bfeel3 <- apply(Bfeel3.dat, 1, sum, na.rm = F)
alpha(Bfeel3.dat, check.keys = T) # .65


#### Act

## Time 1

Bact1.dat <- data.frame(TTBraw[,c(20:25)], stringsAsFactors = F)
Bact1.dat <- sapply(Bact1.dat, as.numeric)
Bact1 <- apply(Bact1.dat, 1, sum, na.rm = F)
alpha(Bact1.dat, check.keys = T) # .72

Bact1.cfa <-'
Bact =~ act1 + act2 + act3 + act4 + act5 + act6
'
Bact1.fit <- cfa(Bact1.cfa, data = Bact1.dat, missing = 'fiml', test =
'yuan', se = 'robust')
summary(Bact1.fit, fit = T)
# decent fit

## Time 2
```

```
Bact2.dat <- data.frame(TTBraw[,c(82:87)], stringsAsFactors = F)
Bact2.dat <- sapply(Bact2.dat, as.numeric)
Bact2 <- apply(Bact2.dat, 1, sum, na.rm = F)
alpha(Bact2.dat, check.keys = T) # .81

## Time 3

Bact3.dat <- data.frame(TTBraw[,c(144:149)], stringsAsFactors = F)
Bact3.dat <- sapply(Bact3.dat, as.numeric)
Bact3 <- apply(Bact3.dat, 1, sum, na.rm = F)
alpha(Bact3.dat, check.keys = T) # .76


#### In School

## Time 1

BinSchool1.dat <- data.frame(TTBraw[,c(26:32)], stringsAsFactors = F)
BinSchool1.dat <- sapply(BinSchool1.dat, as.numeric)
BinSchool1 <- apply(BinSchool1.dat, 1, sum, na.rm = F)
alpha(BinSchool1.dat, check.keys = T) # .86

BinSch1.cfa <- '
BinSch =~ inschool1 + inschool2 + inschool3 + inschool4 + inschool5 +
inschool6 + inschool7
'
BinSch1.fit <- cfa(BinSch1.cfa, data = BinSchool1.dat, missing =
'fiml', se = 'robust', test = 'yuan')
summary(BinSch1.fit, fit = T)
# decent fit



## Time 2

BinSchool2.dat <- data.frame(TTBraw[,c(88:92)], stringsAsFactors = F)
BinSchool2.dat <- sapply(BinSchool2.dat, as.numeric)
BinSchool2 <- apply(BinSchool2.dat, 1, sum, na.rm = F)
alpha(BinSchool2.dat, check.keys = T) # .86

## Time 3

BinSchool3.dat <- data.frame(TTBraw[,c(150:154)], stringsAsFactors = F)
BinSchool3.dat <- sapply(BinSchool3.dat, as.numeric)
BinSchool3 <- apply(BinSchool3.dat, 1, sum, na.rm = F)
alpha(BinSchool3.dat, check.keys = T) # .82


#### Can you Do?

## Time 1

BcanDo1.dat <- data.frame(TTBraw[,c(33:36)], stringsAsFactors = F)
BcanDo1.dat <- sapply(BcanDo1.dat, as.numeric)
BcanDo1 <- apply(BcanDo1.dat, 1, sum, na.rm = F)
alpha(BcanDo1.dat, check.keys = T) # .39
```

```
BcanDo1.cfa <- '
canDo =~ canyoudo1 + canyoudo2 + canyoudo3 + canyoudo4
'
BcanDo1.fit <- cfa(BcanDo1.cfa, data = BcanDo1.dat, missing = 'fiml',
test = 'yuan', se = 'robust')
summary(BcanDo1.fit, fit = T)
# Not quite, CFI is short of the mark.

## Time 2

BcanDo2.dat <- data.frame(TTBraw[,c(95:98)], stringsAsFactors = F)
BcanDo2.dat <- sapply(BcanDo2.dat, as.numeric)
BcanDo2 <- apply(BcanDo2.dat, 1, sum, na.rm = F)
alpha(BcanDo2.dat, check.keys = T) # .54

## Time 3

BcanDo3.dat <- data.frame(TTBraw[,c(157:160)], stringsAsFactors = F)
BcanDo3.dat <- sapply(BcanDo3.dat, as.numeric)
BcanDo3 <- apply(BcanDo3.dat, 1, sum, na.rm = F)
alpha(BcanDo3.dat, check.keys = T) # .61


#### You think

## Time 1

ByouThink1.dat <- data.frame(TTBraw[,c(37:43)], stringsAsFactors = F)
ByouThink1.dat <- sapply(ByouThink1.dat, as.numeric)
ByouThink1.6r <- 5 - ByouThink1.dat[,6]
ByouThink1.dat <- data.frame(ByouThink1.dat[,c(1:5)], ByouThink1.6r,
ByouThink1.dat[,7])

ByouThink1 <- apply(ByouThink1.dat, 1, sum, na.rm = F)
alpha(ByouThink1.dat) # .44

Bthink1.cfa <- '
youThink =~ youthink1 + youthink2 + youthink3 + youthink4 + youthink5 +
ByouThink1.6r + ByouThink1.dat...7.
'
Bthink1.fit <- cfa(Bthink1.cfa, data = ByouThink1.dat, missing =
'fiml', se = 'robust', test = 'yuan')
summary(Bthink1.fit, fit = T)
## Not good at all!



## Time 2

ByouThink2.dat <- data.frame(TTBraw[,c(99:105)], stringsAsFactors = F)
ByouThink2.dat <- sapply(ByouThink2.dat, as.numeric)
ByouThink2.6r <- 5 - ByouThink2.dat[,6]
ByouThink2.dat <- data.frame(ByouThink2.dat[,c(1:5)], ByouThink2.6r,
ByouThink2.dat[,7])

ByouThink2 <- apply(ByouThink2.dat, 1, sum, na.rm = F)
```

```
alpha(ByouThink2.dat, check.keys = F) # .53

## Time 3

ByouThink3.dat <- data.frame(TTBraw[,c(161:167)], stringsAsFactors = F)
ByouThink3.dat <- sapply(ByouThink3.dat, as.numeric)
ByouThink3.6r <- 5 - ByouThink3.dat[,6]
ByouThink3.dat <- data.frame(ByouThink3.dat[,c(1:5)], ByouThink3.6r,
ByouThink3.dat[,7])

ByouThink3 <- apply(ByouThink3.dat, 1, sum, na.rm = F)
alpha(ByouThink3.dat, check.keys = F) # .53


#### Illinois Bully and Victimization scale
### Your Experience
### sub-scales (no reverse-scoring)

## Time 1

# Bully
Bbully1.dat <- data.frame(TTBraw[,c(46,50:54)], stringsAsFactors = F)
Bbully1.dat <- sapply(Bbully1.dat, as.numeric)
Bbully1 <- apply(Bbully1.dat, 1, sum, na.rm = F)
alpha(Bbully1.dat, check.keys = T) # .80

Bbully1.cfa <- '
Bbully =~ yourexperience3 + yourexperience7 + yourexperience8 +
yourexperience9 + yourexperience10 + yourexperience11
'
Bbully1.fit <- cfa(Bbully1.cfa, data = Bbully1.dat, missing = 'fiml',
se = 'robust', test = 'yuan')
summary(Bbully1.fit, fit = T)


# Victim
Bvictim1.dat <- data.frame(TTBraw[,c(44:45)], stringsAsFactors = F)
Bvictim1.dat <- sapply(Bvictim1.dat, as.numeric)
Bvictim1 <- apply(Bvictim1.dat, 1, sum, na.rm = F)
alpha(Bvictim1.dat, check.keys = T) # .59 or r = .44

# Fighting
Bfight1.dat <- data.frame(TTBraw[,c(47:49)], stringsAsFactors = F)
Bfight1.dat <- sapply(Bfight1.dat, as.numeric)
Bfight1 <- apply(Bfight1.dat, 1, sum, na.rm = F)
alpha(Bfight1.dat, check.keys = T) # .83

Bfight1.cfa <- '
Bbully =~ yourexperience4 + yourexperience5 + yourexperience6
'
Bfight1.fit <- cfa(Bfight1.cfa, data = Bfight1.dat, missing = 'fiml',
se = 'robust', test = 'yuan')
summary(Bfight1.fit, fit = T)



## Time 2
```

```
# Bully
Bbully2.dat <- data.frame(TTBraw[,c(108,112:116)], stringsAsFactors =
F)
Bbully2.dat <- sapply(Bbully2.dat, as.numeric)
Bbully2 <- apply(Bbully2.dat, 1, sum, na.rm = F)
alpha(Bbully2.dat, check.keys = T) # .80

# Victim
Bvictim2.dat <- data.frame(TTBraw[,c(106:107)], stringsAsFactors = F)
Bvictim2.dat <- sapply(Bvictim2.dat, as.numeric)
Bvictim2 <- apply(Bvictim2.dat, 1, sum, na.rm = F)
alpha(Bvictim2.dat, check.keys = T) # .69 or r = .55

# Fighting
Bfight2.dat <- data.frame(TTBraw[,c(109:111)], stringsAsFactors = F)
Bfight2.dat <- sapply(Bfight2.dat, as.numeric)
Bfight2 <- apply(Bfight2.dat, 1, sum, na.rm = F)
alpha(Bfight2.dat, check.keys = T) # .73

## Time 3

# Bully
Bbully3.dat <- data.frame(TTBraw[,c(170,174:178)], stringsAsFactors =
F)
Bbully3.dat <- sapply(Bbully3.dat, as.numeric)
Bbully3 <- apply(Bbully3.dat, 1, sum, na.rm = F)
alpha(Bbully3.dat, check.keys = T) # .85

# Victim
Bvictim3.dat <- data.frame(TTBraw[,c(168:169)], stringsAsFactors = F)
Bvictim3.dat <- sapply(Bvictim3.dat, as.numeric)
Bvictim3 <- apply(Bvictim3.dat, 1, sum, na.rm = F)
alpha(Bvictim3.dat, check.keys = T) # .64 or r = .49

# Fighting
Bfight3.dat <- data.frame(TTBraw[,c(171:173)], stringsAsFactors = F)
Bfight3.dat <- sapply(Bfight3.dat, as.numeric)
Bfight3 <- apply(Bfight3.dat, 1, sum, na.rm = F)
alpha(Bfight3.dat, check.keys = T) # .86


#### social desirability (more questions)

## Time 1

BsocD1.dat <- data.frame(TTBraw[,c(55:63)], stringsAsFactors = F)
BsocD1.dat <- sapply(BsocD1.dat, as.numeric)
BsocD1.r <- 3 - BsocD1.dat[,c(3,8)]
BsocD1.dat <- data.frame(BsocD1.dat[,c(1:2)], BsocD1.r[,1],
BsocD1.dat[,c(4:7)], BsocD1.r[,2], BsocD1.dat[,9])

BsocD1 <- apply(BsocD1.dat, 1, sum, na.rm = F)
alpha(BsocD1.dat, check.keys = T) # .73
plot(BsocD1)
hist(BsocD1)
qplot(BsocD1)
```

```
BsocD1.cfa <- '
BsocD =~ morequestions1 + morequestions2 + BsocD1.r...1. +
morequestions4 + morequestions5 + morequestions6 + morequestions7 +
BsocD1.r...2. + BsocD1.dat...9.
'
BsocD1.fit <- cfa(BsocD1.cfa, data = BsocD1.dat, missing = 'fiml', se =
'robust', test = 'yuan')
summary(BsocD1.fit, fit = T)


## Time 2

BsocD2.dat <- data.frame(TTBraw[,c(117:125)], stringsAsFactors = F)
BsocD2.dat <- sapply(BsocD2.dat, as.numeric)
BsocD2.r <- 3 - BsocD2.dat[,c(3,8)]
BsocD2.dat <- data.frame(BsocD2.dat[,c(1:2)], BsocD2.r[,1],
BsocD2.dat[,c(4:7)], BsocD2.r[,2], BsocD2.dat[,9])

BsocD2 <- apply(BsocD2.dat, 1, sum, na.rm = F)
alpha(BsocD2.dat, check.keys = T) # .68

## Time 3

BsocD3.dat <- data.frame(TTBraw[,c(179:187)], stringsAsFactors = F)
BsocD3.dat <- sapply(BsocD3.dat, as.numeric)
BsocD3.r <- 3 - BsocD3.dat[,c(3,8)]
BsocD3.dat <- data.frame(BsocD3.dat[,c(1:2)], BsocD3.r[,1],
BsocD3.dat[,c(4:7)], BsocD3.r[,2], BsocD3.dat[,9])

BsocD3 <- apply(BsocD3.dat, 1, sum, na.rm = F)
alpha(BsocD3.dat, check.keys = T) # .74




#############################################
#### Creating a large data set with all the composites and variables of
interest.
#### Explore descriptive stats of composite scores
#############################################

#### Recoding a few things

# Gender 1 = female; 2 = male; NA = NA
TTBraw$gender <- ifelse(TTBraw$gender == 'Male', 1,
ifelse(TTBraw$gender == 'Female', 0, NA))
TTBraw$gendermid <- ifelse(TTBraw$gendermid == 'Male', 1,
ifelse(TTBraw$gendermid == 'Female', 0, NA))
TTBraw$genderpost <- ifelse(TTBraw$genderpost == 'Male', 1,
ifelse(TTBraw$genderpost == 'Female', 0, NA))

# ethinicity (alphabetical order)
#TTBraw$ethnicity <- factor(TTBraw$ethnicity)
#TTBraw$ethnicitymid <- factor(TTBraw$ethnicitymid)
#TTBraw$ethinicitypost <- factor(TTBraw$ethnicitypost)
```

```
# age (making numeric)
TTBraw$age <- sapply(TTBraw$age, as.numeric)
TTBraw$agemid <- sapply(TTBraw$agemid, as.numeric)
TTBraw$agepost <- sapply(TTBraw$agepost, as.numeric)

# grade (making numeric)
TTBraw$grade <- sapply(TTBraw$grade, as.numeric)
TTBraw$grademid <- sapply(TTBraw$grademid, as.numeric)
TTBraw$gradepost <- sapply(TTBraw$gradepost, as.numeric)


TTB.comp <- cbind(Babout.school1, Bfeel1, Bact1, BinSchool1, BcanDo1,
ByouThink1, Bbully1, Bvictim1, Bfight1, BsocD1, TTBraw[,c(1,2,4:7)],
Babout.school2, Bfeel2, Bact2, BinSchool2, BcanDo2, ByouThink2,
Bbully2, Bvictim2, Bfight2, BsocD2, TTBraw[,c(64,66:69)],
Babout.school3, Bfeel3, Bact3, BinSchool3, BcanDo3, ByouThink3,
Bbully3, Bvictim3, Bfight3, BsocD3, TTBraw[,c(126,128:131)])
TTB.comp <- as.data.frame(TTB.comp, stringsAsFactors = F)
head(TTB.comp)
names(TTB.comp)
write.csv(TTB.comp, 'TTB.comp.csv')
# TTB.comp <- read.csv('TTB.comp.csv', stringsAsFactors = F)
# TTB.comp <- TTB.comp[,-1]

TTB.wide <- cbind(Babout.school1, Babout.school2, Babout.school3,
Bfeel1, Bfeel2, Bfeel3, Bact1, Bact2, Bact3, BinSchool1, BinSchool2,
BinSchool3, BcanDo1, BcanDo2, BcanDo3, ByouThink1, ByouThink2,
ByouThink3, Bbully1, Bbully2, Bbully3, Bvictim1, Bvictim2, Bvictim3,
Bfight1, Bfight2, Bfight3, BsocD1, BsocD2, BsocD3, TTBraw$name,
TTBraw[,c(2,64,126)], TTBraw[,c(4,66,128)], TTBraw[,c(5,67,129)],
TTBraw[,c(6,68,130)], TTBraw[,c(7,69,131)])
TTB.wide <- as.data.frame(TTB.wide, stringsAsFactors = F)
head(TTB.wide)
names(TTB.wide)
write.csv(TTB.wide, 'TTB.wide.csv')
# TTB.wide <- read.csv('TTB.wide.csv', stringsAsFactors = F)
# TTB.wide <- TTB.wide[,-1]


TTB.explore <- TTB.comp[,-c(11,12,14,27,29,42,44)]
num_var=ncol(TTB.explore)

skew2 <- rep(NA, num_var)
kurt2 <- rep(NA, num_var)
mean2 <- rep(NA, num_var)
sd2 <- rep(NA, num_var)
min2 <- rep(NA, num_var)
max2 <- rep(NA, num_var)
sample2 <- rep(NA, num_var)

for(i in 1:num_var) {
      skew2[i] <- skewness(TTB.explore[,i], na.rm = T)
      kurt2[i] <- kurtosis(TTB.explore[,i], na.rm = T)
      mean2[i] <- mean(TTB.explore[,i], na.rm = T)
      sd2[i] <- sd(TTB.explore[,i], na.rm = T)
      min2[i] <- min(TTB.explore[,i], na.rm = T)
      max2[i] <- max(TTB.explore[,i], na.rm = T)
```

```
      sample2[i] <-
length(TTB.explore[,i][which(complete.cases(TTB.explore[,i] == TRUE))])
}

dtableTTB <- cbind(mean2, sd2, min2, max2, skew2, kurt2, sample2)
dtableTTB <- round(dtableTTB, digits = 2)
dtableTTB <- as.data.frame(dtableTTB)
rownames(dtableTTB) <- colnames(TTB.explore)
dtableTTB



TTB.corr <- corstarsl(TTB.explore)
write.csv(cbind(TTB.corr, dtableTTB), 'TTB.exp.corrsANDdesc.csv')






#######################################################################
#############################################################
################### FORM B ##################
############### Control Group  ################
############## No Mid-point! ##################
#######################################################################
#############################################################

###################
#### Composites, reliabilities, and Exploratory factor analyses (at
time 1), and Confirmatory factor analysis (at time 2) of measures
## We are assuming measurement invariance across time, age, gender,
etc.
###################

#### About School
#### School connectedness

## Time 1 (FALL)

Babout.schoolC1.dat <- data.frame(TTB.cont.raw[,c(9:15)],
stringsAsFactors = F)
Babout.schoolC1.dat <- sapply(Babout.schoolC1.dat, as.numeric)
Babout.schoolC1.5r <- 5 - Babout.schoolC1.dat[,5]
Babout.schoolC1.dat <- data.frame(Babout.schoolC1.dat[,c(1:4)],
Babout.schoolC1.5r, Babout.schoolC1.dat[,c(6:7)])

Babt.schC.fa <- fa(cor(Babout.schoolC1.dat, use = 'pairwise'), nfactors
= 1)
print(Babt.schC.fa)
fa.parallel(Babout.schoolC1.dat) # 1 factor will work!

Babout.schoolC1 <- apply(Babout.schoolC1.dat, 1, sum, na.rm = F)
alpha(Babout.schoolC1.dat, check.keys = T) # .76


## Time 2 (Winter)
```

```
      # DNE

## Time 3 (Spring)

Babout.schoolC3.dat <- data.frame(TTB.cont.raw[,c(71:77)],
stringsAsFactors = F)
Babout.schoolC3.dat <- sapply(Babout.schoolC3.dat, as.numeric)
Babout.schoolC3.5r <- 5 - Babout.schoolC3.dat[,5]
Babout.schoolC3.dat <- data.frame(Babout.schoolC3.dat[,c(1:4)],
Babout.schoolC3.5r, Babout.schoolC3.dat[,c(6:7)])

Babout.schoolC3 <- apply(Babout.schoolC3.dat, 1, sum, na.rm = F)
alpha(Babout.schoolC3.dat, check.keys = T) # .76


#### Feel

## Time 1

BfeelC1.dat <- data.frame(TTB.cont.raw[,c(16:18)], stringsAsFactors =
F)
BfeelC1.dat <- sapply(BfeelC1.dat, as.numeric)
BfeelC1.r <- 5 - BfeelC1.dat[,c(1,3)]
BfeelC1.dat <- data.frame(BfeelC1.r[,1], BfeelC1.dat[,2],
BfeelC1.r[,2])

BfeelC1 <- apply(BfeelC1.dat, 1, sum, na.rm = F)
alpha(BfeelC1.dat, check.keys = T) # .55

BfeelC.fa <- fa(cor(BfeelC1.dat, use='pairwise'), nfactors = 1)
print(BfeelC.fa)
fa.parallel(BfeelC1.dat) # NOT good fit, but there are only three
items.

## Time 2
      # DNE

## Time 3

BfeelC3.dat <- data.frame(TTB.cont.raw[,c(78:80)], stringsAsFactors =
F)
BfeelC3.dat <- sapply(BfeelC3.dat, as.numeric)
BfeelC3.r <- 5 - BfeelC3.dat[,c(1,3)]
BfeelC3.dat <- data.frame(BfeelC3.r[,1], BfeelC3.dat[,2],
BfeelC3.r[,2])

BfeelC3 <- apply(BfeelC3.dat, 1, sum, na.rm = F)
alpha(BfeelC3.dat, check.keys = T) # .42


#### Act

## Time 1

BactC1.dat <- data.frame(TTB.cont.raw[,c(19:24)], stringsAsFactors = F)
BactC1.dat <- sapply(BactC1.dat, as.numeric)
BactC1 <- apply(BactC1.dat, 1, sum, na.rm = F)
```

```
alpha(BactC1.dat, check.keys = T) # .69

## Time 2
      # DNE

## Time 3

BactC3.dat <- data.frame(TTB.cont.raw[,c(81:86)], stringsAsFactors = F)
BactC3.dat <- sapply(BactC3.dat, as.numeric)
BactC3 <- apply(BactC3.dat, 1, sum, na.rm = F)
alpha(BactC3.dat, check.keys = T) # .77


#### In School

## Time 1

BinSchoolC1.dat <- data.frame(TTB.cont.raw[,c(25:29)], stringsAsFactors
= F)
BinSchoolC1.dat <- sapply(BinSchoolC1.dat, as.numeric)
BinSchoolC1 <- apply(BinSchoolC1.dat, 1, sum, na.rm = F)
alpha(BinSchoolC1.dat, check.keys = T) # .88

## Time 2
      # DNE

## Time 3

BinSchoolC3.dat <- data.frame(TTB.cont.raw[,c(87:91)], stringsAsFactors
= F)
BinSchoolC3.dat <- sapply(BinSchoolC3.dat, as.numeric)
BinSchoolC3 <- apply(BinSchoolC3.dat, 1, sum, na.rm = F)
alpha(BinSchoolC3.dat, check.keys = T) # .83


#### Can you Do?

## Time 1

BcanDoC1.dat <- data.frame(TTB.cont.raw[,c(32:35)], stringsAsFactors =
F)
BcanDoC1.dat <- sapply(BcanDoC1.dat, as.numeric)
BcanDoC1 <- apply(BcanDoC1.dat, 1, sum, na.rm = F)
alpha(BcanDoC1.dat, check.keys = T) # .50

## Time 2
      # DNE

## Time 3

BcanDoC3.dat <- data.frame(TTB.cont.raw[,c(94:97)], stringsAsFactors =
F)
BcanDoC3.dat <- sapply(BcanDoC3.dat, as.numeric)
BcanDoC3 <- apply(BcanDoC3.dat, 1, sum, na.rm = F)
alpha(BcanDoC3.dat, check.keys = T) # .63
```

```
#### You think

## Time 1

ByouThinkC1.dat <- data.frame(TTB.cont.raw[,c(36:42)], stringsAsFactors
= F)
ByouThinkC1.dat <- sapply(ByouThinkC1.dat, as.numeric)
ByouThinkC1.6r <- 5 - ByouThinkC1.dat[,6]
ByouThinkC1.dat <- data.frame(ByouThinkC1.dat[,c(1:5)], ByouThinkC1.6r,
ByouThinkC1.dat[,7])

ByouThinkC1 <- apply(ByouThinkC1.dat, 1, sum, na.rm = F)
alpha(ByouThinkC1.dat) # .49

## Time 2
      # DNE

## Time 3

ByouThinkC3.dat <- data.frame(TTB.cont.raw[,c(98:104)],
stringsAsFactors = F)
ByouThinkC3.dat <- sapply(ByouThinkC3.dat, as.numeric)
ByouThinkC3.6r <- 5 - ByouThinkC3.dat[,6]
ByouThinkC3.dat <- data.frame(ByouThinkC3.dat[,c(1:5)], ByouThinkC3.6r,
ByouThinkC3.dat[,7])

ByouThinkC3 <- apply(ByouThinkC3.dat, 1, sum, na.rm = F)
alpha(ByouThinkC3.dat, check.keys = F) # .28


#### Illinois Bully and Victimization scale
### Your Experience
### sub-scales (no reverse-scoring)

## Time 1

# Bully
BbullyC1.dat <- data.frame(TTB.cont.raw[,c(45,49:53)], stringsAsFactors
= F)
BbullyC1.dat <- sapply(BbullyC1.dat, as.numeric)
BbullyC1 <- apply(BbullyC1.dat, 1, sum, na.rm = F)
alpha(BbullyC1.dat, check.keys = T) # .76

# Victim
BvictimC1.dat <- data.frame(TTB.cont.raw[,c(43:44)], stringsAsFactors =
F)
BvictimC1.dat <- sapply(BvictimC1.dat, as.numeric)
BvictimC1 <- apply(BvictimC1.dat, 1, sum, na.rm = F)
alpha(BvictimC1.dat, check.keys = T) # .56 or r = .41

# Fighting
BfightC1.dat <- data.frame(TTB.cont.raw[,c(46:48)], stringsAsFactors =
F)
BfightC1.dat <- sapply(BfightC1.dat, as.numeric)
BfightC1 <- apply(BfightC1.dat, 1, sum, na.rm = F)
alpha(BfightC1.dat, check.keys = T) # .59
```

```
## Time 2

# Bully
# Victim
# Fighting
      # DNE

## Time 3

# Bully
BbullyC3.dat <- data.frame(TTB.cont.raw[,c(107,111:115)],
stringsAsFactors = F)
BbullyC3.dat <- sapply(BbullyC3.dat, as.numeric)
BbullyC3 <- apply(BbullyC3.dat, 1, sum, na.rm = F)
alpha(BbullyC3.dat, check.keys = T) # .71

# Victim
BvictimC3.dat <- data.frame(TTB.cont.raw[,c(105:106)], stringsAsFactors
= F)
BvictimC3.dat <- sapply(BvictimC3.dat, as.numeric)
BvictimC3 <- apply(BvictimC3.dat, 1, sum, na.rm = F)
alpha(BvictimC3.dat, check.keys = T) # .67 or r = .53

# Fighting
BfightC3.dat <- data.frame(TTB.cont.raw[,c(108:110)], stringsAsFactors
= F)
BfightC3.dat <- sapply(BfightC3.dat, as.numeric)
BfightC3 <- apply(BfightC3.dat, 1, sum, na.rm = F)
alpha(BfightC3.dat, check.keys = T) # .67


#### social desirability (more questions)

## Time 1

BsocDC1.dat <- data.frame(TTB.cont.raw[,c(54:62)], stringsAsFactors =
F)
BsocDC1.dat <- sapply(BsocDC1.dat, as.numeric)
BsocDC1.r <- 3 - BsocDC1.dat[,c(3,8)]
BsocDC1.dat <- data.frame(BsocDC1.dat[,c(1:2)], BsocDC1.r[,1],
BsocDC1.dat[,c(4:7)], BsocDC1.r[,2], BsocDC1.dat[,9])

BsocDC1 <- apply(BsocDC1.dat, 1, sum, na.rm = F)
alpha(BsocDC1.dat, check.keys = T) # .78

## Time 2

      # DNE

## Time 3

BsocDC3.dat <- data.frame(TTB.cont.raw[,c(116:124)], stringsAsFactors =
F)
BsocDC3.dat <- sapply(BsocDC3.dat, as.numeric)
BsocDC3.r <- 3 - BsocDC3.dat[,c(3,8)]
```

```
BsocDC3.dat <- data.frame(BsocDC3.dat[,c(1:2)], BsocDC3.r[,1],
BsocDC3.dat[,c(4:7)], BsocDC3.r[,2], BsocDC3.dat[,9])

BsocDC3 <- apply(BsocDC3.dat, 1, sum, na.rm = F)
alpha(BsocDC3.dat, check.keys = T) # .75




#############################################
#### Creating a large data set with all the composites and variables of
interest.
#### Explore descriptive stats of composite scores
#############################################

#### Recoding a few things

# Gender 1 = female; 2 = male; NA = NA
TTB.cont.raw$gender <- ifelse(TTB.cont.raw$gender == 'Male', 1,
ifelse(TTB.cont.raw$gender == 'Female', 0, NA))
#TTB.cont.raw$gendermid <- ifelse(TTB.cont.raw$gendermid == 'Male', 1,
ifelse(TTB.cont.raw$gendermid == 'Female', 0, NA))
TTB.cont.raw$genderpost <- ifelse(TTB.cont.raw$genderpost == 'Male', 1,
ifelse(TTB.cont.raw$genderpost == 'Female', 0, NA))

# ethinicity (alphabetical order)
#TTB.cont.raw$ethnicity <- factor(TTB.cont.raw$ethnicity)
#TTB.cont.raw$ethnicitymid <- factor(TTB.cont.raw$ethnicitymid)
#TTB.cont.raw$ethinicitypost <- factor(TTB.cont.raw$ethnicitypost)

# age (making numeric)
TTB.cont.raw$age <- sapply(TTB.cont.raw$age, as.numeric)
#TTB.cont.raw$agemid <- sapply(TTB.cont.raw$agemid, as.numeric)
TTB.cont.raw$agepost <- sapply(TTB.cont.raw$agepost, as.numeric)

# grade (making numeric)
TTB.cont.raw$grade <- sapply(TTB.cont.raw$grade, as.numeric)
#TTB.cont.raw$grademid <- sapply(TTB.cont.raw$grademid, as.numeric)
TTB.cont.raw$gradepost <- sapply(TTB.cont.raw$gradepost, as.numeric)


TTB.control <- cbind(Babout.schoolC1, BfeelC1, BactC1, BinSchoolC1,
BcanDoC1, ByouThinkC1, BbullyC1, BvictimC1, BfightC1, BsocDC1,
TTB.cont.raw[,c(1:6)], Babout.schoolC3, BfeelC3, BactC3, BinSchoolC3,
BcanDoC3, ByouThinkC3, BbullyC3, BvictimC3, BfightC3, BsocDC3,
TTB.cont.raw[,c(64:68)])
TTB.control <- as.data.frame(TTB.control, stringsAsFactors = F)
head(TTB.control)
names(TTB.control)
write.csv(TTB.control, 'TTB.control.csv')
# TTB.control <- read.csv('TTB.control.csv', stringsAsFactors = F)
# TTB.control <- TTB.control[,-1]


TTB.Cwide <- cbind(Babout.schoolC1, Babout.schoolC3, BfeelC1, BfeelC3,
BactC1, BactC3, BinSchoolC1, BinSchoolC3, BcanDoC1, BcanDoC3,
ByouThinkC1, ByouThinkC3, BbullyC1, BbullyC3, BvictimC1, BvictimC3,
```

```
BfightC1, BfightC3, BsocDC1, BsocDC3, TTB.cont.raw$name,
TTB.cont.raw[,c(2,64)], TTB.cont.raw[,c(3,65)], TTB.cont.raw[,c(4,66)],
TTB.cont.raw[,c(5,67)], TTB.cont.raw[,c(6,68)])
TTB.Cwide <- as.data.frame(TTB.Cwide, stringsAsFactors = F)
head(TTB.Cwide)
names(TTB.Cwide)
write.csv(TTB.Cwide, 'TTB.Cwide.csv')
# TTB.Cwide <- read.csv('TTB.Cwide.csv', stringsAsFactors = F)
# TTB.Cwide <- TTB.Cwide[,-1]


TTB.Cexplore <- TTB.control[,-c(11,12,14,27,29)]
num_var=ncol(TTB.Cexplore)

skew2 <- rep(NA, num_var)
kurt2 <- rep(NA, num_var)
mean2 <- rep(NA, num_var)
sd2 <- rep(NA, num_var)
min2 <- rep(NA, num_var)
max2 <- rep(NA, num_var)
sample2 <- rep(NA, num_var)

for(i in 1:num_var) {
      skew2[i] <- skewness(TTB.Cexplore[,i], na.rm = T)
      kurt2[i] <- kurtosis(TTB.Cexplore[,i], na.rm = T)
      mean2[i] <- mean(TTB.Cexplore[,i], na.rm = T)
      sd2[i] <- sd(TTB.Cexplore[,i], na.rm = T)
      min2[i] <- min(TTB.Cexplore[,i], na.rm = T)
      max2[i] <- max(TTB.Cexplore[,i], na.rm = T)
      sample2[i] <-
length(TTB.Cexplore[,i][which(complete.cases(TTB.Cexplore[,i] ==
TRUE))])
}

dtableTTB.cont <- cbind(mean2, sd2, min2, max2, skew2, kurt2, sample2)
dtableTTB.cont <- round(dtableTTB.cont, digits = 2)
dtableTTB.cont <- as.data.frame(dtableTTB.cont)
rownames(dtableTTB.cont) <- colnames(TTB.Cexplore)
dtableTTB.cont


TTB.C.corr <- corstarsl(TTB.Cexplore)
write.csv(cbind(TTB.C.corr, dtableTTB.cont),
'TTB.control.corrsANDdesc.csv')




############################################
############## Combining Form A ##############
############################################

# Why does the control group not have a midpoint? Every file I see on
Box indicated there should be data? Was it not entered or was it not
merged?
```

```
######### Only combining Time 1 and Time 3 for Experimental (1) and
Control (0) groups

TTA.comp.1n3 <- TTA.comp[,-c(17:31,42)]
TTA.comp.1n3$control <- rep(1, nrow(TTA.comp.1n3))

TTA.CnewNames <- TTA.control
TTA.CnewNames$control <- rep(0, nrow(TTA.CnewNames))

names(TTA.CnewNames) <- names(TTA.comp.1n3)

TTA.all <- rbind(TTA.comp.1n3, TTA.CnewNames)
TTA.all <- as.data.frame(TTA.all, stringsAsFactors = F)
head(TTA.all)
dim(TTA.all) # 470 people X 31 variables
names(TTA.all)


#### Are there differences between the control and exp group at time 3
bullying controlling for time 1 bullying?
bully.modA <- lm(bully3 ~ bully1 + control, TTA.all)
summary(bully.modA) # nope

# no matter the covariates I include, the difference is either not
significant or the control is bullying less than the experiemental
group at time 3.

bully.modA2 <- '
      bully3 ~ bully1 + socD3 + control
'
bully.fitA2 <- sem(bully.modA2, data = TTA.all, missing = 'fiml', test
= 'yuan', mimic = "mplus")
summary(bully.fitA2, fit = T)


efa1.TTAt1 <- fa(cor(TTA.all[,c(2:9)], use = 'pairwise'), nfactors = 1)
print(efa1.TTAt1)

efa2.TTAt1 <- fa(cor(TTA.all[,c(2:9)], use = 'pairwise'), nfactors = 2,
rotate = 'promax')
print(efa2.TTAt1)

fa.parallel(TTA.all[,c(2:9)])

TT.modA1 <- '
      # creating latent variable of Total Take Ten Intervention and
Bully

            # Time 1
                  TT1 =~ feel1 + act1 + inSchool1 + canDo1 + youThink1
                  Bully1 =~ bully1 + fight1
            # Time 3
                  TT3 =~ feel3 + act3 + inSchool3 + canDo3 + youThink3
                  Bully3  =~ bully3 + fight3
      # Regressions
            Bully3 ~ Bully1 + TT3 + control
            TT3 ~ TT1 + control
```

```
'
TT.fitA1 <- sem(TT.modA1, data = TTA.all, missing = 'fiml', se =
'robust', test = 'yuan', mimic = 'mplus')
summary(TT.fitA1, fit = T)

# I have no idea what is going on! It looks like the TT program is not
helping.


######## Use MLM

###### Create long data set

#### re-order data
TTA.allWIDE <-
TTA.all[,c(1,17,2,18,3,19,4,20,5,21,6,22,7,23,8,24,9,25,10,26,13,27,14,
28,15,29,16,30,11,12,31)]
names(TTA.allWIDE)


TTA.allLONG <- reshape(TTA.allWIDE, varying = list(1:2, 3:4, 5:6, 7:8,
9:10, 11:12, 13:14, 15:16, 17:18, 19:20, 21:22, 23:24, 25:26, 27:28),
v.names = c('about.school', 'feel', 'act', 'inSchool', 'canDo',
'youThink', 'bully', 'victim', 'fight', 'socD', 'gender', 'ethnicity',
'age', 'grade'), timevar = 'time', times = c(0:1), direction = 'long')
head(TTA.allLONG)

TTA.allLONG2 <- sort(TTA.allLONG, by = "id")
head(TTA.allLONG2)
TTA.allLONG3 <- TTA.allLONG2
TTA.allLONG3$time <- TTA.allLONG3$time - 1
#TTA.allLONG2$quad <- TTA.allLONG2$time^2
#TTA.allLONG3$quad <- TTA.allLONG3$time^2


library(nlme)

bullyA.MLM <- lme(bully ~  time + control + gender, data = TTA.allLONG3,
random = ~ time | id, na.action = na.omit)
summary(bullyA.MLM)


##### Bully plot
## significantly floor effects for both control and exp groups
bully.plot <- ggplot(data = TTA.allLONG2, aes(x = time, y =
jitter(bully), group = id))
bully.plot +
geom_line() +
scale_x_continuous(breaks = 0:1) +
stat_smooth(aes(group = gender, colour = factor(gender)), method =
'loess')



fightA.MLM <- lme(fight ~  time + control + socD + gender, data =
TTA.allLONG3, random = ~ time | id, na.action = na.omit)
```

```
summary(fightA.MLM)

##### Fight plot
fight.plot <- ggplot(data = TTA.allLONG2, aes(x = time, y =
jitter(fight), group = gender))
fight.plot + geom_line() + scale_x_continuous(breaks = 0:1) +
stat_smooth(aes(group = gender), method = 'loess', na.rm = F)



victimA.MLM <- lme(victim ~  time + control + socD, data = TTA.allLONG3,
random = ~ time | id, na.action = na.omit)
summary(victimA.MLM)

### .

##### Victim plot
victim.plot <- ggplot(data = TTA.allLONG2, aes(x = time, y =
jitter(victim), group = control))
victim.plot + geom_line() + scale_x_continuous(breaks = 0:1) +
stat_smooth(aes(group = control, colour = factor(control)), method =
'loess', na.rm = F)


#### In Bully, Fight, and Victim, we find that in all cases there is a
difference between control and experiemental groups at time 1.
#### Exploring by school, there seems to be some schools that are not
doing so well. The Control school (Coquillard) is doing better than or
as good as 3 of the 5 experimental schools. What is going on?
#### Does it have to do with who is giving the intervention? When the
intervention is being given? Is there an additive effect of how many
time a student as participated in the Take Ten program?

####
inSchoolA.MLM <- lme(inSchool ~  time + control + socD, data =
TTA.allLONG3, random = ~ time | id, na.action = na.omit)
summary(inSchoolA.MLM)

inSchool.plot <- ggplot(data = TTA.allLONG2, aes(x = time, y =
jitter(inSchool), group = id))
inSchool.plot + geom_line() + scale_x_continuous(breaks = 0:1) +
stat_smooth(aes(group = id), method = 'loess', na.rm = F)


####
feelA.MLM <- lme(feel ~  time + control + socD, data = TTA.allLONG3,
random = ~ time | id, na.action = na.omit)
summary(feelA.MLM)


####
actA.MLM <- lme(act ~  time + control + socD, data = TTA.allLONG3,
random = ~ time | id, na.action = na.omit)
summary(actA.MLM)
```

```
#### WRONG WAY!!! Control group is doing better than experimental group
at time 3.
canDoA.MLM <- lme(canDo ~  time + control + socD, data = TTA.allLONG3,
random = ~ time | id, na.action = na.omit)
summary(canDoA.MLM)


#### WRONG WAY!!!  Control group is doing better than experimental group
at time 3. However, -youThink- is increasing over time, which is good.
youThinkA.MLM <- lme(youThink ~  time + control + socD, data =
TTA.allLONG3, random = ~ time | id, na.action = na.omit)
summary(youThinkA.MLM)









#################################
#################################
### Ignore control group.

### Creating a TAKE TEN variable.
TTA.wide$TT1 <- apply(TTA.comp[,c(1:6)], 1, sum, na.rm = F )
TTA.wide$TT2 <- apply(TTA.comp[,c(17:22)], 1, sum, na.rm = F )
TTA.wide$TT3 <- apply(TTA.comp[,c(32:37)], 1, sum, na.rm = F )

### merging schools sites across time so there is less missing data.
## first, rename site, sitemid, and sitepost
names(TTA.wide) <- c(names(TTA.wide[,c(1:30)]), 'name', 'site1',
'site2', 'site3', 'gender1', 'gender2', 'gender3', 'ethnicity1',
'ethnicity2', 'ethnicity3', 'age1', 'age2', 'age3', 'grade1', 'grade2',
'grade3', names(TTA.wide[,c(47:ncol(TTA.wide))]))

## second, merge into one column called TTsite
TTsite <-
ifelse(TTA.wide$site1 == 'McKinley', 'McKinley', ifelse(TTA.wide$site2
== 'McKinley', 'McKinley', ifelse(TTA.wide$site3 == 'McKinley',
'McKinley', ifelse(TTA.wide$site1 == 'Nuner', 'Nuner',
ifelse(TTA.wide$site2 == 'Nuner', 'Nuner', ifelse(TTA.wide$site3 ==
'Nuner', 'Nuner', ifelse(TTA.wide$site1 == 'NDCAC', 'NDCAC',
ifelse(TTA.wide$site2 == 'NDCAC', 'NDCAC', ifelse(TTA.wide$site3 ==
'NDCAC', 'NDCAC', ifelse(TTA.wide$site1 == 'Coquillard', 'Coquillard',
ifelse(TTA.wide$site2 == 'Coquillard', 'Coquillard',
ifelse(TTA.wide$site3 == 'Coquillard', 'Coquillard',
ifelse(TTA.wide$site1 == 'El Campito', 'ElCampito',
ifelse(TTA.wide$site2 == 'El Campito', 'ElCampito',
ifelse(TTA.wide$site3 == 'El Campito', 'ElCampito',
ifelse(TTA.wide$site1 == 'YWCA', 'YWCA', ifelse(TTA.wide$site2 ==
'YWCA', 'YWCA', ifelse(TTA.wide$site3 == 'YWCA', 'YWCA',
ifelse(TTA.wide$site1 == 'BGC', 'BGC', ifelse(TTA.wide$site2 == 'BGC',
'BGC', ifelse(TTA.wide$site3 == 'BGC', 'BGC',
'noSite')))))))))))))))))))))
```

```
#check.site <- cbind(TTsite, TTA.wide[,c(32:34)] )
TTA.wide$TTsite <- TTsite


### creating Dummy codes for schools
site <- dummy(TTA.wide$TTsite)
site <- as.data.frame(site, stringsAsFactors = F)
TTA.wide <- cbind(TTA.wide, site)

site.count <- apply(site, 2, sum)


growth.bully.TTA <- '
      i =~ 1*bully1 +1* bully2 + 1*bully3
      s =~ 0*bully1 + .5*bully2 + 1*bully3

      i ~ Coquillard + ElCampito #+ McKinley + NDCAC + Nuner + YWCA
      s ~ Coquillard + ElCampito #+ McKinley + NDCAC + Nuner + YWCA

'
grow.bully.fitTTA <- growth(growth.bully.TTA, data = TTA.wide, missing
= 'fiml', se = 'robust', test = 'yuan', mimic = 'mplus')
summary(grow.bully.fitTTA, fit = T)
standardizedSolution(grow.bully.fitTTA)


#### Model of School Climate predicting Bullying
## Current model fits data well. Higher (safe) Climate intercept, lower
bullying. Postive changes in School Climate leads to decreases in
bullying across time.
growth.climateBully.TTA <- '
      i =~ 1*bully1 +1* bully2 + 1*bully3
      s =~ 0*bully1 + 1*bully2 + 2*bully3

      climateI =~ 1*about.school1 + 1*about.school2 + 1*about.school3
      climateS =~ 0*about.school1 + 1*about.school2 + 2*about.school3

      i ~ climateI + 0*climateS
      s ~ climateI + climateS

'
grow.climateBully.fitTTA <- growth(growth.climateBully.TTA, data =
TTA.wide, missing = 'fiml', se = 'robust', test = 'yuan', mimic =
'mplus')
summary(grow.climateBully.fitTTA, fit = T)
#inspect(grow.climateBully.fitTTA, 'cov.lv')
standardizedSolution(grow.climateBully.fitTTA)


TTA.LONG <- reshape(TTA.wide, varying = list(1:3, 4:6, 7:9, 10:12,
13:15, 16:18, 19:21, 22:24, 25:27, 28:30, 32:34, 35:37, 38:40, 41:43,
44:46, 47:49), v.names = c('about.school', 'feel', 'act', 'inSchool',
'canDo', 'youThink', 'bully', 'victim', 'fight', 'socD', 'site',
'gender', 'ethnicity', 'age', 'grade', 'TT'), timevar = 'time', times =
c(0:2), direction = 'long')
head(TTA.LONG)
```

```
TTA.LONG2 <- sort(TTA.LONG, by = "id")
head(TTA.LONG2)
TTA.LONG3 <- TTA.LONG2
TTA.LONG3$time <- TTA.LONG3$time - 2

### negative indicators of TAKE TEN effectiveness
bully.expA.MLM <- lme(bully ~  time + age + socD + gender +
about.school, data = TTA.LONG3, random = ~ time | id, na.action =
na.omit)
summary(bully.expA.MLM)
# no time effects
# no age effects
# socD is negative (higher socD = lower bully)!!!!! good
# males bully more at time 3
# higher school climate = lower bullying

fight.expA.MLM <- lme(fight ~  time + age + socD + gender +
about.school, data = TTA.LONG3, random = ~ time | id, na.action =
na.omit)
summary(fight.expA.MLM)
# no time effects
# no age effects
# socD is negative (higher socD = lower fight)!!!! good
# males fight more at time 3
# higher school climate = lower fighting


victim.expA.MLM <- lme(victim ~  time + age + socD + gender +
about.school, data = TTA.LONG3, random = ~ time | id, na.action =
na.omit)
summary(victim.expA.MLM)
# no time effects
# no age effects
# socD is null
# females have higher victimization at time 3
# school climate is null


inSchool.expA.MLM <- lme(inSchool ~  time + age + socD + gender +
about.school, data = TTA.LONG3, random = ~ time | id, na.action =
na.omit)
summary(inSchool.expA.MLM)
# no time effects
# no age effects
# socD is negative (higher socD = lower witnessing)!!!! good
# gender is null (there are differences in bullying awareness between
genders)
# higher school climate = lower witnessed acts of violence


### positive indicators of TAKE TEN effectiveness
act.expA.MLM <- lme(act ~  time + age + socD + gender + about.school,
data = TTA.LONG3, random = ~ time | id, na.action = na.omit)
summary(act.expA.MLM)
# decreases over time
# no age effects
# socD is positive (higher socD = higher act)!!!! fine
```

```
# males act less at time 3
# higher school climate = higher action


canDo.expA.MLM <- lme(canDo ~  time + age + socD + gender +
about.school, data = TTA.LONG3, random = ~ time | id, na.action =
na.omit)
summary(canDo.expA.MLM)
# decreases over time
# no age effects
# socD is positive (higher socD = higher canDo)!!!! fine
# males canDo less at time 3
# higher school climate = higher canDo


youThink.expA.MLM <- lme(youThink ~  time + age + socD + gender +
about.school, data = TTA.LONG3, random = ~ time | id, na.action =
na.omit)
summary(youThink.expA.MLM)
# no time effects
# no age effects
# socD null
# gender is null
# higher school climate = higher youThink


feel.expA.MLM <- lme(feel ~  time + age + socD + gender + about.school,
data = TTA.LONG3, random = ~ time | id, na.action = na.omit)
summary(feel.expA.MLM)
# no time effects
# no age effects
# socD is positive (higher socD = higher feel)!!!! fine
# males feel less at time 3
# higher school climate = higher feel


climate.plot <- ggplot(data = TTA.LONG2, aes(x = time, y =
jitter(socD)))
climate.plot +  scale_x_continuous(breaks = 0:2) + stat_smooth(method =
'loess', na.rm = F)

############################################
############## Combining Form B ##############
############################################

######### Only combining Time 1 and Time 3 for Experimental and Control
groups


############################################
########### Combining All Forms ############
########### (experimental only) ############
############################################
### Creating a TAKE TEN variable.
TTB.wide$TT1 <- apply(TTB.comp[,c(1:6)], 1, sum, na.rm = F )
TTB.wide$TT2 <- apply(TTB.comp[,c(17:22)], 1, sum, na.rm = F )
TTB.wide$TT3 <- apply(TTB.comp[,c(32:37)], 1, sum, na.rm = F )
```

```
TTA.wide$form <- rep(0, nrow(TTA.wide))
TTB.wide$form <- rep(1, nrow(TTB.wide))

names(TTB.wide) <- names(TTA.wide[,c(1:49, 57)])

TTab.wide <- rbind(TTA.wide[,c(1:49, 57)], TTB.wide)
TTab.wide <- as.data.frame(TTab.wide, stringsAsFactors = F)
#TTab.wide[c(355:360),] ## looks good.


#### JUST FOR FUN
# long. mediation
climate.TT.bully.mod <- '

  ## bully
  bully3 ~ cbully*bully1 + bbully*bully2 + ct*TT1 + bt*TT2 +
cc*about.school1 + bc*about.school2
  bully2 ~ a*bully1 + at*TT1 + ac*about.school1

  bully1 ~~ TT1 + about.school1
  bully2 ~~ TT2 + about.school2

  ## TT
  TT3 ~ cTT*TT1 + bTT*TT2 + cb*bully1 + bb*bully2 + ccl*about.school1 +
bcl*about.school2
  TT2 ~ aTT*TT1 + ab*bully1 + acl*about.school1
  TT1 ~~ about.school1
  TT2 ~~ about.school2

  ## school climate
  about.school3 ~ ccli*about.school1 + bcli*about.school2 + ctt*TT1 +
btt*TT2 + cbul*bully1 + bbul*bully2
  about.school2 ~ acli*about.school1 + att*TT1 + abul*bully1
  #about.school1

  ## Indirect paths
  climate.TT.bully := acl*bt
  bully.TT.climate := ab*btt
  bully.climate.TT := abul*bcl
  TT.bully.climate := at*bbul
  TT.climate.bully := att*bc
  climate.bully.TT := ac*bb

'
climate.TT.bully.fit <- sem(climate.TT.bully.mod, data = TTab.wide,
missing = 'fiml', test = 'yuan', se = 'robust', mimic = 'mplus',
fixed.x = F)
summary(climate.TT.bully.fit, fit = T)


### growth model
growth.TT.bully <- '
      i =~ 1*bully1 +1* bully2 + 1*bully3
  s =~ 1*bully1 + 2*bully2 + 3*bully3
```

```
  TTi =~ 1*TT1 + 1*TT2 + 1*TT3
  TTs =~ 1*TT1 + 2*TT2 + 3*TT3

  i ~ TTi + 0*TTs
  s ~ TTi + TTs
'
growth.TT.bully.fit <- growth(growth.TT.bully, data = TTab.wide,
missing = 'fiml', se = 'robust', test = 'yuan', mimic = 'mplus',
control = list(iter.max = 10000))
summary(growth.TT.bully.fit, fit = T)
#inspect(growth.TT.bully.fit, 'cov.lv')
standardizedSolution(growth.TT.bully.fit)


############BIG MODEL
growth.TTall.bully <- '
      i =~ 1*bully1 +1* bully2 + 1*bully3
  s =~ 1*bully1 + 2*bully2 + 3*bully3

  # feel
  feeli =~ 1*feel1 + 1*feel2 + 1*feel3
  feels =~ 1*feel1 + 2*feel2 + 3*feel3
  # act
  acti =~ 1*act1 + 1*act2 + 1*act3
  acts =~ 1*act1 + 2*act2 + 3*act3
  # canDo
  canDoi =~ 1*canDo1 + 1*canDo2 + 1*canDo3
  canDos =~ 1*canDo1 + 2*canDo2 + 3*canDo3
  # youThink
  youThinki =~ 1*youThink1 + 1*youThink2 + 1*youThink3
  youThinks =~ 1*youThink1 + 2*youThink2 + 3*youThink3

i ~ feeli + 0*feels + acti + 0*acts + canDoi + 0*canDos + youThinki +
0*youThinks
s ~ feeli + feels + acti + acts + canDoi + canDos + youThinki +
youThinks

#s ~~ varis*s
#varis > 0

'
growth.TTall.bully.fit <- growth(growth.TTall.bully, data = TTab.wide,
missing = 'fiml', se = 'robust', test = 'yuan', mimic = 'mplus')
summary(growth.TTall.bully.fit, fit = T)
inspect(growth.TTall.bully.fit, 'cov.lv')
eigen(inspect(growth.TTall.bully.fit, 'cov.lv'))$values
#modindices(growth.TTall.bully.fit)
standardizedSolution(growth.TTall.bully.fit)




growth.TT <- '
      #i =~ 1*bully1 +1* bully2 + 1*bully3
  #s =~ 1*bully1 + 2*bully2 + 3*bully3
```

```
  TTi =~ 1*TT1 + 1*TT2 + 1*TT3
  TTs =~ 0*TT1 + 1*TT2 + 2*TT3

#i ~ TTi + 0*TTs
#s ~ TTi + TTs
'
growth.TT.fit <- growth(growth.TT, data = TTab.wide, missing = 'fiml',
se = 'robust', test = 'yuan', mimic = 'mplus')
summary(growth.TT.fit, fit = T)
#inspect(growth.TT.fit, 'cov.lv')
standardizedSolution(growth.TT.fit)


ggplot(data = TTab.LONG2, aes(x = time, y = bully, colour =
factor(TT))) +
  #geom_line(aes(group = id), alpha = .05) +
  #geom_line(aes(group = TT), alpha = .075) +
  stat_smooth(method = lm, se = F) +
  geom_smooth(method = lm, formula = y~poly(x,1), color = 'black', se =
F, size = 1.5, linetype = 2)
  #geom_smooth(method = lm, formula = y~poly(x,2), color = 'red', se =
F) +
  #theme(panel.background = element_rect(fill = 'white'))

### use dplyr use pipe: %>%
# data
# group_by with factor(time) by TT
# summarize

# I want to create a plot that has time on the x-axis, outcome on the
y-axis,
# and different layers of TT relating to the outcome.

TTtimeM2 <- TTab.LONG2 %>% group_by(factor(time), TT) %>%
  summarize(avgBully = mean(bully, na.rm = T),
                       avgTT = mean(TT, na.rm = T),
                       avgFight = mean(fight, na.rm = T),
                       avgVictim = mean(victim, na.rm = T),
                       avgInSchool = mean(inSchool, na.rm = T))
head(TTtimeM2)
plot(TTtimeM2$TT,TTtimeM2$avgBully, type = 'p')

#summarise(group_by(TTab.LONG2, factor(time), mean(TT)))
TT.LONGtime <- group_by(TTab.LONG2, factor(time), TT)
TTtimeM <- summarize(TT.LONGtime, avgTT = mean(TT, na.rm = T), avgBully
= mean(bully, na.rm = T))

ggplot(data = TTtimeM, aes(x = factor(time), y = avgBully)) +
  geom_line(aes(group = id), alpha = .09) +
  theme_classic() +
  #geom_line(aes(group = TT), alpha = .075) +
  #stat_smooth(method = lm, se = F) +
  geom_smooth(method = lm, formula = y~poly(x,1), color = 'black', se =
F, size = 1.5, linetype = 2)
  #geom_smooth(method = lm, formula = y~poly(x,2), color = 'red', size =
1.5, se = F)
```

```
ggplot(data = TTab.LONG2, aes(x = TT, y = fight)) +
  geom_line(aes(group = id), alpha = .09) +
  #geom_line(aes(group = TT), alpha = .075) +
  #stat_smooth(method = lm, se = F) +
  geom_smooth(method = lm, formula = y~poly(x,1), color = 'black', se =
F, size = 1.5, linetype = 2) +
  geom_smooth(method = lm, formula = y~poly(x,2), color = 'red', size =
1.5, se = F)

ggplot(data = TTab.LONG2, aes(x = TT, y = victim)) +
  geom_line(aes(group = id), alpha = .09) +
  #geom_line(aes(group = TT), alpha = .075) +
  #stat_smooth(method = lm, se = F) +
  geom_smooth(method = lm, formula = y~poly(x,1), color = 'black', se =
F, size = 1.5, linetype = 2) +
  geom_smooth(method = lm, formula = y~poly(x,2), color = 'red', size =
1.5, se = F)

ggplot(data = TTab.LONG2, aes(x = TT, y = inSchool)) +
  geom_line(aes(group = id), alpha = .09) +
  #geom_line(aes(group = TT), alpha = .075) +
  #stat_smooth(method = lm, se = F) +
  geom_smooth(method = lm, formula = y~poly(x,1), color = 'black', se =
F, size = 1.5, linetype = 2) +
  geom_smooth(method = lm, formula = y~poly(x,2), color = 'red', size =
1.5, se = F)




## convert to long format
TTab.LONG <- reshape(TTab.wide, varying = list(1:3, 4:6, 7:9, 10:12,
13:15, 16:18, 19:21, 22:24, 25:27, 28:30, 32:34, 35:37, 38:40, 41:43,
44:46, 47:49), v.names = c('about.school', 'feel', 'act', 'inSchool',
'canDo', 'youThink', 'bully', 'victim', 'fight', 'socD', 'site',
'gender', 'ethnicity', 'age', 'grade', 'TT'), timevar = 'time', times =
c(0:2), direction = 'long')
head(TTab.LONG)

TTab.LONG2 <- sort(TTab.LONG, by = "id")
head(TTab.LONG2)
TTab.LONG3 <- TTab.LONG2
TTab.LONG3$time <- TTab.LONG3$time - 2


####### MLMs

### negative indicators of TAKE TEN effectiveness
bully.exp.MLM <- lme(bully ~  time + age + socD + gender + TT, data =
TTab.LONG3, random = ~ time | id, na.action = na.omit)
summary(bully.exp.MLM)
# no time effects
# negative age effects (older = less bullying)
# socD is negative (higher socD = lower bully)!!!!! good
```

```
# males bully more at time 3
# ## NOT INCLUDED:higher school climate = lower bullying
# TT has negative effect (higher TT, lower bullying)
fit.bully <- predict(bully.exp.MLM, TTab.LONG2, na.action = na.pass)
#TTab.LONG2$fit <- fit.bully
fit.bully <- as.data.frame(fit.bully)
fit.bully$TIME <- rep(1:3, 1914/3)

fit.bully.done <- fit.bully %>% group_by(TIME) %>% summarise(avgfit =
mean(fit.bully[1]))

ggplot(TTab.LONG2, aes(time, bully)) +
  geom_smooth(aes(time, bully, group = interaction(TT), col = TT),
method = 'lm', se = F, size = .7, alpha = .25) +
  geom_point(aes(time, bully, group = interaction(TT), col = TT), alpha
= .3) +
  scale_x_continuous(breaks = c(0:2), labels = c('Fall 2014', 'Winter
2014', 'Spring 2015')) +
  theme_bw() +
  theme(axis.title.x = element_blank()) +
  ylab("Bullying") +
  ggtitle(expression('Bullying over time grouped \nby Take Ten knowledge
score')) +
  geom_smooth(data = fit.bully.done, aes(x = TIME-1, y = avgfit), method
= 'lm', se = F, color = 'black', linetype = 2, size = 1.5)



fight.exp.MLM <- lme(fight ~  time + age + socD + gender + TT, data =
TTab.LONG3, random = ~ time | id, na.action = na.omit, control=list(opt
= "optim"))
summary(fight.exp.MLM)
# no time effects
# older = less fighting
# socD is negative (higher socD = lower fight)!!!! good
# males fight more at time 3
# ## NOT INCLUDED:higher school climate = lower fighting
# TT has negative effect (higher TT = lowever fighting)
fit.fight <- predict(fight.exp.MLM, TTab.LONG2, na.action = na.pass)
#TTab.LONG2$fit <- fit.fight
fit.fight <- as.data.frame(fit.fight)
fit.fight$TIME <- rep(1:3, 1914/3)

fit.fight.done <- fit.fight %>% group_by(TIME) %>% summarise(avgfit =
mean(fit.fight[1]))

ggplot(TTab.LONG2, aes(time, fight)) +
  geom_smooth(aes(time, fight, group = interaction(TT), col = TT),
method = 'lm', se = F, size = .7, alpha = .25) +
  geom_point(aes(time, fight, group = interaction(TT), col = TT), alpha
= .3) +
  scale_x_continuous(breaks = c(0:2), labels = c('Fall 2014', 'Winter
2014', 'Spring 2015')) +
  theme_bw() +
  theme(axis.title.x = element_blank()) +
  ylab("Fighting") +
```

```
  ggtitle(expression('Fighting over time grouped \nby Take Ten knowledge
score')) +
  geom_smooth(data = fit.fight.done, aes(x = TIME-1, y = avgfit), method
= 'lm', se = F, color = 'black', linetype = 2, size = 1.5)




victim.exp.MLM <- lme(victim ~  time + age + socD + gender + TT, data =
TTab.LONG3, random = ~ time | id, na.action = na.omit, control=list(opt
= "optim"))
summary(victim.exp.MLM)
# no time effects
# older = less victim at time 3
# socD is negative (higher socD = lower victim)??
# males have higher victimization at time 3
# ## NOT INCLUDED:higher school climate = less victimization
# TT has no effect
fit.victim <- predict(victim.exp.MLM, TTab.LONG2, na.action = na.pass)
#TTab.LONG2$fit <- fit.victim
fit.victim <- as.data.frame(fit.victim)
fit.victim$TIME <- rep(1:3, 1914/3)

fit.victim.done <- fit.victim %>% group_by(TIME) %>% summarise(avgfit =
mean(fit.victim[1]))

ggplot(TTab.LONG2, aes(time, victim)) +
  geom_smooth(aes(time, victim, group = interaction(TT), col = TT),
method = 'lm', se = F, size = .7, alpha = .25) +
  geom_point(aes(time, victim, group = interaction(TT), col = TT), alpha
= .3) +
  scale_x_continuous(breaks = c(0:2), labels = c('Fall 2014', 'Winter
2014', 'Spring 2015')) +
  theme_bw() +
  theme(axis.title.x = element_blank()) +
  ylab("Victimization") +
  ggtitle(expression('Victimization over time grouped \nby Take Ten
knowledge score')) +
  geom_smooth(data = fit.victim.done, aes(x = TIME-1, y = avgfit),
method = 'lm', se = F, color = 'black', linetype = 2, size = 1.5)



inSchool.exp.MLM <- lme(inSchool ~  time + age + socD + gender + TT,
data = TTab.LONG3, random = ~ time | id, na.action = na.omit)
summary(inSchool.exp.MLM)
inSchool.exp.MLM.base <- lme(inSchool ~  time, data = TTab.LONG3, random
= ~ time | id, na.action = na.omit)
summary(inSchool.exp.MLM.base)
# decrease witnessing violence across time
# no age effects
# socD is negative (higher socD = lower witnessing)!!!! good
# gender is null (there are no differences in bullying awareness
between genders)
# ## NOT INCLUDED:higher school climate = lower witnessed acts of
violence at time 3
```

```
# TT has postive effect (higher TT = higher witnessed violence at time
3)

anova(inSchool.exp.MLM,inSchool.exp.MLM.base)
fit.inSchool <- predict(inSchool.exp.MLM, TTab.LONG2, na.action =
na.pass)
#TTab.LONG2$fit <- fit.inSchool
fit.inSchool <- as.data.frame(fit.inSchool)
fit.inSchool$TIME <- rep(1:3, 1914/3)

fit.inSchool.done <- fit.inSchool %>% group_by(TIME) %>%
summarise(avgfit = mean(fit.inSchool[1]))

ggplot(TTab.LONG2, aes(time, inSchool)) +
  geom_smooth(aes(time, inSchool, group = interaction(TT), col = TT),
method = 'lm', se = F, size = .7, alpha = .25) +
  geom_point(aes(time, inSchool, group = interaction(TT), col = TT),
alpha = .3) +
  scale_x_continuous(breaks = c(0:2), labels = c('Fall 2014', 'Winter
2014', 'Spring 2015')) +
  theme_bw() +
  theme(axis.title.x = element_blank()) +
  ylab("Witnessing Violence") +
  ggtitle(expression('Witnessing Violence over time grouped \nby Take
Ten knowledge score')) +
  geom_smooth(data = fit.inSchool.done, aes(x = TIME-1, y = avgfit),
method = 'lm', se = F, color = 'black', linetype = 2, size = 1.5)



### positive indicators of TAKE TEN effectiveness
act.exp.MLM <- lme(act ~  time + age + socD + gender + about.school,
data = TTab.LONG3, random = ~ time | id, na.action = na.omit)
summary(act.exp.MLM)
# decreases over time
# no age effects
# socD is positive (higher socD = higher act)!!!! fine
# males act less at time 3
# higher school climate = higher action at time 3


canDo.exp.MLM <- lme(canDo ~  time + age + socD + gender + about.school,
data = TTab.LONG2, random = ~ time | id, na.action = na.omit)
summary(canDo.exp.MLM)
# decreases over time
# older = higher canDo at time 3
# socD is positive (higher socD = higher canDo)!!!! fine
# males canDo less at time 3
# higher school climate = higher canDo at time 3

canDo.exp.plot <- ggplot(data = TTA.LONG2, aes(x = time, y = canDo,
colour = factor(age)))
canDo.exp.plot + scale_x_continuous(breaks = 0:2) + stat_smooth(method
= lm, se = F)
```

```
youThink.exp.MLM <- lme(youThink ~  time + age + socD + gender +
about.school, data = TTab.LONG3, random = ~ time | id, na.action =
na.omit)
summary(youThink.exp.MLM)
# no time effects
# older = higher youThink at time 3
# socD null
# males have less youThink at time 3 compared to females
# higher school climate = higher youThink


feel.exp.MLM <- lme(feel ~  time + age + socD + gender + about.school,
data = TTab.LONG3, random = ~ time | id, na.action = na.omit)
summary(feel.exp.MLM)
# no time effects
# older = higher feel at time 3
# socD is positive (higher socD = higher feel)!!!! fine
# males feel less at time 3
# higher school climate = higher feel
```