Global Families Project

Global Families Project Team

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1 Project Summary

Gender inequality perpetuates harmful norms that justify violence against women and children and is associated with higher rates of family violence.

Worldwide, parental physical abuse is a common form of family violence that children are exposed to at alarming rates. Parental engagement in physical abuse is linked to negative child outcomes including depression, anxiety, and aggression that may persist into adulthood. Globally, these continuing mental health and aggression problems may have high financial costs, with effects both on social service systems and developing economies.

Despite the substantial scholarship on parent- and family-level predictors of parent-to-child physical violence, important questions remain about societal-level predictors of parental physical abuse and its associations with young children's development in developing and transitional countries.

A further gap in prior literature is the lack of studies that have examined potential moderators such as child age and household economic status in the associations between gender inequality and parental violence against children.

Using data from over 520,000 families in 57 low- and middle-income countries (LMICs), the current project seeks to address these research gaps by examining the associations of country-level gender inequality and violent social contexts with caregivers' use of physically abusive behavior and child social-emotional development. We will employ multilevel models using data on parental physical violence against children, family socio-economic characteristics, and children's social-emotional development from the UNICEF Multiple Indicator Cluster Surveys (MICS) and data on country-level gender inequality and violent social contexts from the United Nations Development Programme on Human Development and the World Health Organization Global Health Observatory.

The specific aims are to 1) examine the associations of gender inequality with parental child physical abuse in LMICs, and the moderating roles of child age and household economic status in these associations, 2) examine the associations of violent social norms and crimes with parental physical abuse in LMICs, and 3) examine the associations of parental physical abuse with child social-emotional development in the context of gender inequality and violent norms and crimes in LMICs, and whether country-level normativeness of physical abuse moderates these associations.

The proposed studies will advance the understanding of macro-level social and economic indicators that perpetuate caregivers' physical violence against children in international contexts.

Study findings will inform cross-cultural programs and policies that reduce gender disparities and prevent parental physical abuse to promote child social-emotional development across the globe.

In addition, these studies will provide rigorous research engagement opportunities to undergraduate students and graduate students and strengthen the research environment at the University of Michigan-Flint.

2 Research Team

Julie Ma, Principal Investigator

Associate Professor of Social Work and Chair, Department of Social Work, School of Education and Human Services, The University of Michigan-Flint

Professor Ma's research interests center around the effects of parental physical violence and cultural norms that endorse such violence on the well-being of children, both at local and global levels. Her ongoing research projects primarily focus on examining the link between parental physical abuse and the social-emotional development of young children. She specifically focuses on exploring these associations within the context of gender inequality and violent norms and crimes in low- and middle-income countries.

Andy Grogan-Kaylor, Co-Investigator

Sandra K. Danziger Collegiate Professor, Professor of Social Work, University of Michigan School of Social Work

Professor Grogan-Kaylor's research focuses on basic and intervention research on children and families with the aim of reducing violence against children and improving family and child wellbeing. Grogan-Kaylor's current research projects examine parenting behaviors such as physical punishment and parental expressions of emotional warmth and support, and their effects on children's aggression, antisocial behavior, anxiety, and depression.

Shawna Lee, Co-Investigator

Professor of Social Work, University of Michigan School of Social Work

Professor Lee is a professor at the University of Michigan School of Social Work. She is the director of the Parenting in Context Research Lab and the director of the Program Evaluation Group at the School. Lee has published on topics related to child maltreatment, fathers' parenting, father-child relationships, parenting stress and family functioning, and parental discipline. Her recent research focuses on parenting and stress during the COVID-19 pandemic.

Dana Charles McCoy, Consultant

Marie and Max Kargman Associate Professor in Human Development and Urban Education Advancement, the Harvard Graduate School of Education

Professor McCoy's work focuses on understanding the ways that poverty and violence in children's home, school, and neighborhood environments affect the development of their cognitive

and socioemotional skills in early childhood. She is also interested in the development, refinement, and evaluation of early intervention programs designed to promote positive development and resilience in young children, particularly in terms of their self-regulation and executive function.

Elizabeth Heger Boyle, Consultant

Professor of Sociology & Law, University of Minnesota

Professor Boyle studies women's and children's right to health, with a focus on the negative impacts of violence. She is committed to making comparative health microdata more accessible to researchers around the world; to that end, she is Principal Investigator of IPUMS Global Health, a set of online tools with free harmonized health and well-being data from the DHS Program, UNICEF, and Performance Monitoring for Action. Professor Boyle's recent research focuses on orphans' experience with violent discipline in sub-Saharan Africa and the relationship between women and children's health and armed conflict.

Meghana Kodali, Research Assistant

Meghana Kodali's research focus is on exploring gender inequality affecting women and children that leads to family violence. As a research assistant, she examined the effectiveness of telehealth services for adolescents. She also investigated trends in Medicare reimbursements for patients with cervical cancer within the first year of diagnosis and presented a poster on this work at the American Association for Cancer Research (AACR). Currently, she is interested in further examining potential moderators driving gender inequality and parental abuse against children.

Marilyn Kubek, Research Assistant

Marilyn Kubek has over 10 years of experience in the healthcare field, both during her undergraduate studies and in her professional positions. As a current Graduate Student Research Assistant (GSRA) on this project, she is excited to participate in the advanced research environment offered through the UM-Flint Department of Social Work, expanding her knowledge of data analytics and grant-funded projects.

Kaylee Fisher, Research Assistant

Kaylee Fisher is an undergraduate student majoring in psychology and minoring in Human Resources Management at UM-Flint. Her research interests encompass brain functions, human behavior, cognition, child development, and related topics such as how social norms and the environment influence these processes. She is a member of the UM-Flint Undergraduate Research Opportunity Program (UROP) and is currently applying to doctoral programs in clinical psychology.

3 Simulated Multi-Country Data

This website makes use of simulated data. Data come from 30 hypothetical countries. Data contain measures of a few key aspects of parenting[1] or caregiving that have proven salient in the empirical literature on parenting to date. The outcome is `aggression` against other children.

> **Download The Data**
>
> - R format
> - Stata Format
> - SPSS

```
load("./simulate-data/MICSsimulated.RData")
```

3.1 Variables and Variable Labels

```
labelled::look_for(MICSsimulated)
```

```
pos variable   label                    col_type values
1   id         id                       int
2   country    country                  int
3   GII        Gender Inequality Index  int
4   HDI        Human Development Index  int
5   cd1        spank                    int
6   cd2        beat                     int
7   cd3        shout                    int
8   cd4        explain                  int
9   aggression aggression               int
```

[1] We use the term parenting throughout this site, but are aware that such parenting may come from biological parents, or from other caregivers.

3.2 A Sample Of The Data

A sample of the data is given below.

```
head(MICSsimulated)
```

```
  id country GII HDI cd1 cd2 cd3 cd4 aggression
1  1       1  20  24   0   0   1   1          1
2  2       1  20  24   0   0   1   1          1
3  3       1  20  24   0   0   1   1          1
4  4       1  20  24   0   0   0   0          1
5  5       1  20  24   1   0   1   1          0
6  6       1  20  24   0   0   1   1          1
```

4 A Quick Introduction to R

4.1 Why Use R?

R has a reputation for being difficult to learn, and a lot of that reputation is deserved. However, it is possible to teach R in an accessible way, and **a little bit of R can take you a long way**.

R is open source, and therefore free, statistical software that is particularly good at obtaining, analyzing and visualizing data.

R Commands are stored in a *script* or *code* file that usually ends in .R, e.g. `myscript.R`. The command file is distinct from your actual data, stored in an .RData file, e.g. `mydata.RData`.

A great deal of data analysis and visualization involves the same core set of steps.

Given the fact that we often want to apply the same core set of tasks to new questions and new data, there are ways to overcome the steep learning curve and learn a replicable set of commands that can be applied to problem after problem. **The same 5 to 10 lines of R code can often be tweaked over and over again for multiple projects.**

have a question → get data → process and clean data →

visualize data → analyze data → make conclusions

4.2 Get R

R is available at https://www.r-project.org/. R is a lot easier to run if you run it from RStudio, http://www.rstudio.com.

4.3 Get Data

Data may already be in R format, or may come from other types of data files like SPSS, Stata, or Excel. Especially in beginning R programming, getting the data into R can be the most complicated part of your program.

4.3.1 Data in R Format

```
load("./simulate-data/MICSsimulated.RData") # data in R format
```

4.3.2 Data in Other Formats

If data are in other formats, slightly different code may be required.

```
library(haven) # library for importing data
mydata <- read_sav("the/path/to/mySPSSfile.sav") # SPSS
mydata <- read_dta("the/path/to/myStatafile.dta") # Stata

library(readxl) # library for importing Excel files
mydata <- read_excel("the/path/to/mySpreadsheet.xls")

save(mydata, file = "mydata.RData") # save in R format
```

4.4 Process and Clean Data

4.4.1 The $ Sign

The `$` sign is a kind of "connector". `mydata$x` means: "The variable `x` in the dataset called `mydata`".

4.4.2 Recoding Data

Data sometimes need to be recoded. For example, outliers may need to be changed to missing, or a value that is supposed to indicated missing data (e.g. `-9`) may need to be changed to missing.

Recoding uses the following construction:

`data$variable[condition] <- new value`

For example, change an outlier value: When `cd1` is `2` change it to missing (`NA`).

```
MICSsimulated$cd1[MICSsimulated$cd1 == 2] <- NA # outlier (2) to NA
```

Change variable cd1 to missing (`NA`) when it is `-9`.

```r
MICSsimulated$cd1[MICSsimulated$cd1 == -9] <- NA # missing (-9) to NA
```

4.4.3 Numeric and Factor Variables

R makes a strong distinction between *continuous numeric* variables that measure scales like mental health or neighborhood safety, and *categorical factor variables* that measure non-ordered categories like religious identity or gender identity.

Many statistical and graphical procedures are designed to recognize and work with different variable types. You often *don't* need to use all of the options. e.g. `mydata$w <- factor(mydata$z)` will often work just fine. **Changing variables from factor to numeric, and vice versa can sometimes be the simple solution that solves a lot of problems when you are trying to graph your variables.**

```r
MICSsimulated$aggression <-
  factor(MICSsimulated$aggression, # original numeric variable
         levels = c(0, 1),
         labels = c("no aggression", "aggression"),
         ordered = TRUE) # whether order matters

# MICSsimulated$z <- as.numeric(MICSsimulated$w) # factor to numeric
```

4.5 Visualize Data

4.5.1 Histogram

```r
hist(MICSsimulated$GII, # what I'm graphing
        main = "Gender Inequality Index", # title
        xlab = "GII", # label for x axis
        col = "blue") # color
```

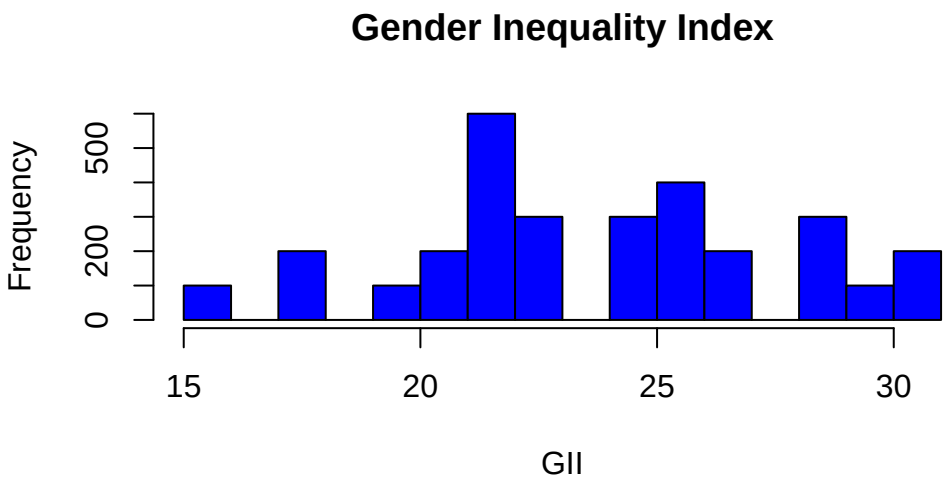


Figure 4.1: Histogram of Gender Inequality Index

> **Tip**
>
> You often *don't* need to use all of the options. e.g. `hist(mydata$x)` will work just fine.

4.5.2 Barplot

```
barplot(table(MICSsimulated$aggression), # what I'm graphing
        main = "Child Displays Aggression", # title
        xlab = "Aggression", # label for x axis
        col = "gold") # color
```

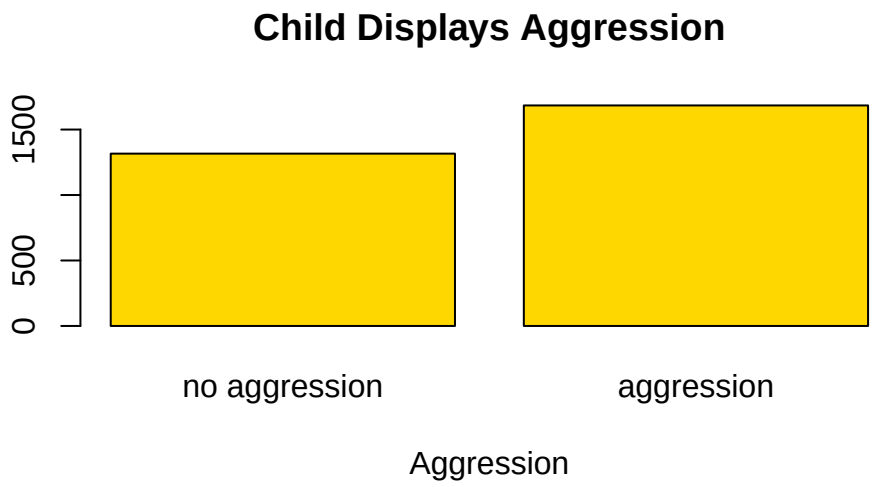


Figure 4.2: Barplot of Aggression

> **Tip**
>
> You often *don't* need to use all of the options. e.g. `barplot(table(mydata$z))` will work just fine.

4.6 Analyze Data: Descriptive Statistics

```
summary(mydata$x) # for continuous or factor variables

table(mydata$z) # especially suitable for factor variables
```

```
summary(MICSsimulated$GII)
```

```
 Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 15.0    22.0    24.0    24.2    27.0    31.0
```

```
table(MICSsimulated$aggression)
```

```
no aggression    aggression
         1316          1684
```

5 A Quick Introduction To `ggplot2`

5.1 Why Use `ggplot`?[1]

A great deal of data analysis and visualization involves the same core set of steps: get some data, clean it up a little, run some descriptive statistics, run some bivariate statistics, create a graph or a visualization. **ggplot2** can be an important part of a replicable, automated, documented workflow for complex projects.

have a question → get data → process and clean data →

visualize data → analyze data → make conclusions

Given the fact that we often want to apply the same core set of tasks to new questions and new data, there are ways to overcome the steep learning curve and learn a replicable set of commands that can be applied to problem after problem.

> The same 5 to 10 lines of ggplot2 code can often be tweaked over and over again for multiple projects.

5.2 The Essential Idea Of `ggplot` Is Simple

There are 3 essential elements to any `ggplot` call:

1. A reference to the data you are using.
2. An *aesthetic* that tells `ggplot` which variables are being mapped to the *x axis*, *y axis*, (and often other attributes of the graph, such as the *color*, * color fill*, or even the* shape*,* size*,* transparency*, or* line type*). Intuitively, the aesthetic can be thought of as **what you are graphing**.
3. A *geom* or *geometry* that tells ggplot about the basic structure of the graph. Intuitively, the geom can be thought of as **how you are graphing it**.

You can also add other options, such as a *graph title*, *axis labels* and *overall theme* for the graph.

[1] More information can be found here: https://agrogan1.github.io/R/introduction-to-ggplot2/introduction-to-ggplot2.html

5.3 Get Started

5.3.1 Call Libraries

```
library(ggplot2) # beautiful graphs

library(ggthemes) # nice themes for ggplot2
```

5.3.2 Get Data

```
load("./simulate-data/MICSsimulated.RData") # data in R format
```

5.4 Some Examples[2]

5.4.1 One Continuous Variable

```
# anything that starts with a '#' is a comment

ggplot(MICSsimulated, # the data I am using
       aes(x = GII)) + # the variable I am using
  geom_histogram() # how I am graphing it
```

[2]Changing variables from factor to numeric (e.g. `aes(x = as.numeric(outcome))`), and *vice versa* can sometimes be a simple solution that solves a lot of problems when you are trying to graph your variables.

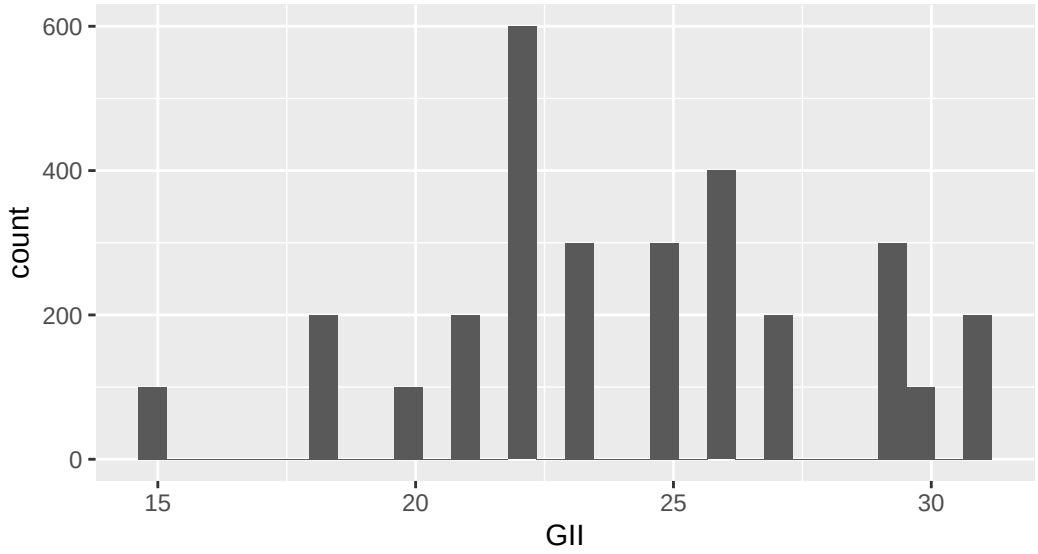


Figure 5.1: Histogram of Gender Inequality Index

We can add color and a theme.

```
# anything that starts with a '#' is a comment

ggplot(MICSsimulated, # the data I am using
       aes(x = GII)) + # the variable I am using
  geom_histogram(fill = "dodgerblue") + # how I am graphing it
  theme_minimal()
```

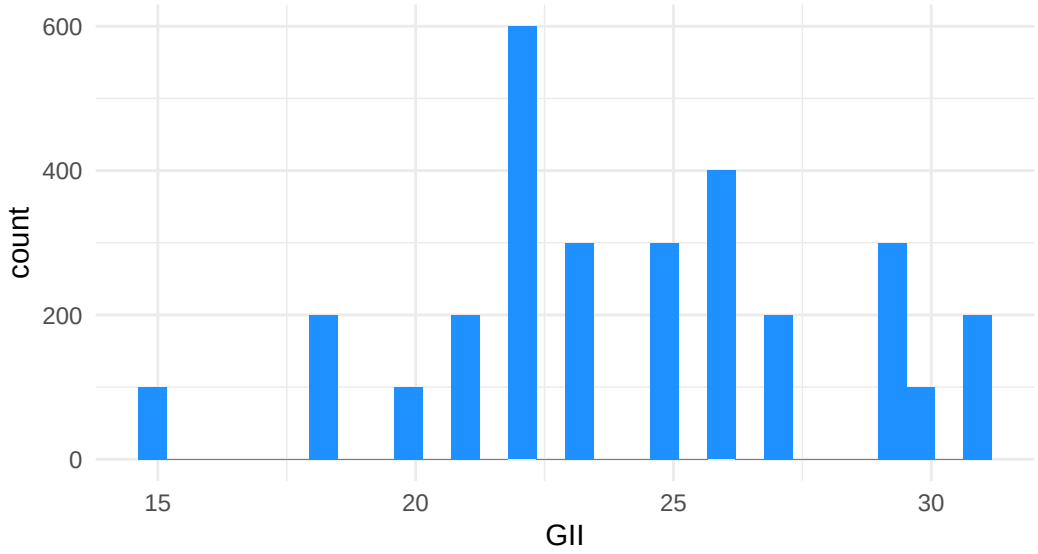


Figure 5.2: Histogram of Gender Inequality Index

5.4.2 One Categorical Variable

Make sure R knows `aggression` is a categorical variable.

```
MICSsimulated$aggression <-
  factor(MICSsimulated$aggression, # original numeric variable
         levels = c(0, 1),
         labels = c("no aggression", "aggression"),
         ordered = TRUE) # whether order matters
```

Now make the graph.

```
ggplot(MICSsimulated, # the data I am using
       aes(x = aggression)) + # the variable I am using
  geom_bar() # how I am graphing it
```

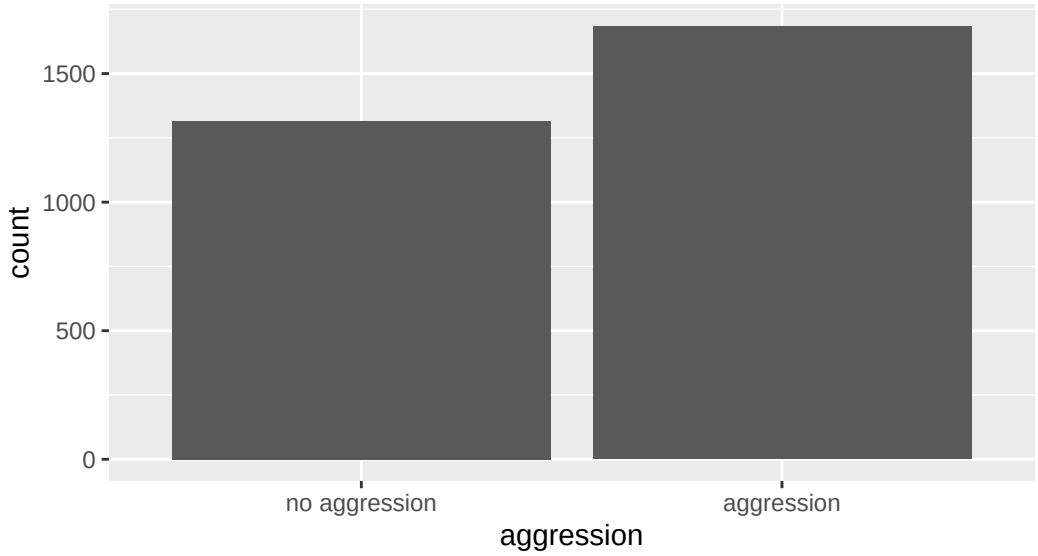


Figure 5.3: Bar Graph of Aggression

We can add color and a theme.[3]

```
ggplot(MICSsimulated, # the data I am using
       aes(x = aggression, # x is aggression
           fill = aggression)) + # fill is also aggression
  geom_bar() + # how I am graphing it
  theme_minimal()
```

[3]Notice how use of `fill` governs both the color fill in the graph below, as well as the legend that is produced in the graph.

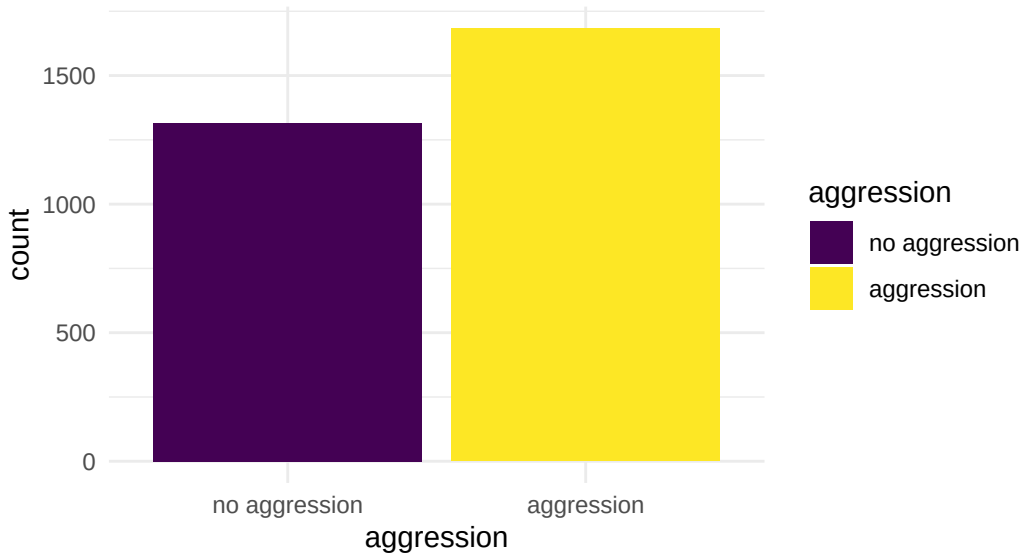


Figure 5.4: Bar Graph of Aggression

5.5 Make a More Complex Graph[4]

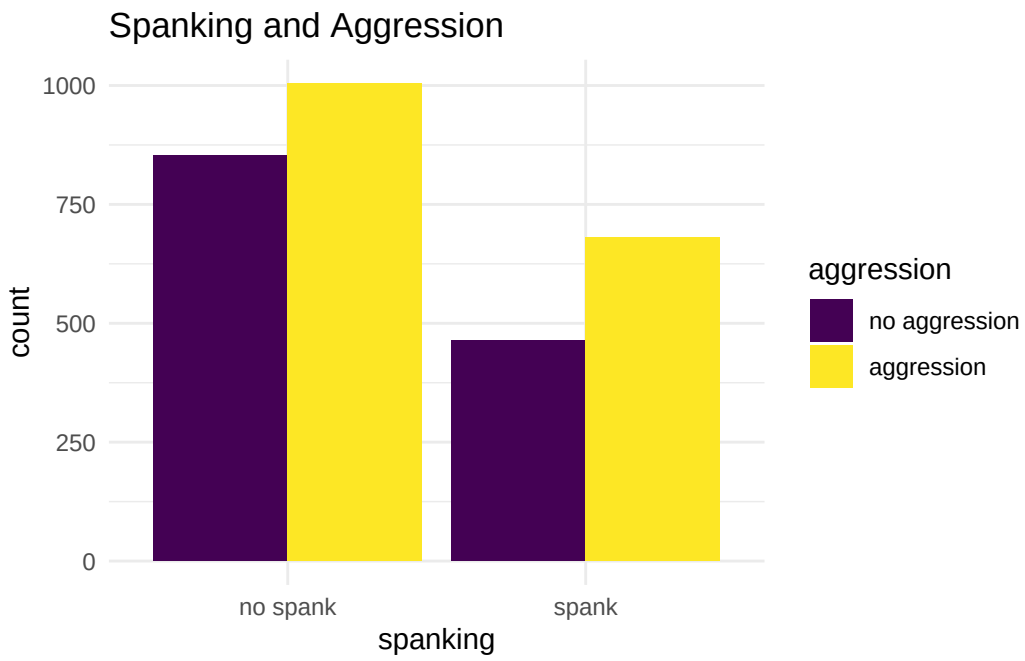
Make sure R knows `cd1` is a categorical variable.

```
MICSsimulated$cd1 <-
  factor(MICSsimulated$cd1, # original numeric variable
         levels = c(0, 1),
         labels = c("no spank", "spank"),
         ordered = TRUE) # whether order matters
```

Now make the graph.

```
ggplot(MICSsimulated, # the data I am using
       aes(x = cd1, # x is spanking
           fill = aggression)) + # fill is aggression
  geom_bar(position = position_dodge()) + # graph with "dodged" bars
  labs(title = "Spanking and Aggression",
       x = "spanking",
       y = "count") +
  theme_minimal()  # theme
```

[4]Notice how use of `fill` governs both the color fill in the graph below, as well as the legend that is produced in the graph.



An interactive tutorial to create this plot can be found here.

6 Quantitative Data Analysis

6.1 Introduction

A great deal of data analysis and visualization involves the same core set of steps.

have a question → get data → process and clean data → analyze data

6.2 Some Tools for Analysis

Below we describe some simple data cleaning with R. We begin, however, by comparing several different tools for analysis including: Excel, Google Sheets, R, and Stata.

Tool	Cost	Ease of Use	Analysis Capabilities	Suitability for Large Data	Keep Track of Complicated Workflows
Excel	Comes installed on many computers	Easy	Limited	Difficult when N > 100	Difficult to Impossible
Google Sheets	Free with a Google account	Easy	Limited	Difficult when N > 100	Difficult to Impossible
R	Free	Challenging	Extensive	Excellent with large datasets	Yes, with script
Stata	Some cost	Learning Curve but Intuitive	Extensive	Excellent with large datasets	Yes, with command file

6.3 Working With R

6.3.1 Our Data

We take a look at our *simulated* data.

```
load("./simulate-data/MICSsimulated.RData") # data in R format

labelled::look_for(MICSsimulated) # look at data
```

```
pos variable   label                     col_type values
1   id         id                        int
2   country    country                   int
3   GII        Gender Inequality Index   int
4   HDI        Human Development Index   int
5   cd1        spank                     int
6   cd2        beat                      int
7   cd3        shout                     int
8   cd4        explain                   int
9   aggression aggression                int
```

6.3.2 Cleaning Data

There are some basic data cleaning steps that are common to many projects.

- Only keep the variables of interest. Section 6.3.2.1
- Add variable labels (if we can). Section 6.3.2.2
- Add value labels (if we can). Section 6.3.2.3
- Recode outliers, values that are errors, or values that should be coded as missing Section 6.3.2.4

Much of R's functionality is accomplished through writing *code*, that is saved in a *script*. Notice how–as our tasks get more and more complicated–the saved script provides documentation for the decisions that we have made with the data.

6.3.2.1 Only keep the variables of interest.

We can easily accomplish this with the `subset` function

```
mynewdata <- subset(MICSsimulated,
                    select = c(id, country, aggression))
```

```
head(mynewdata)
```

```
  id country aggression
1  1       1          1
2  2       1          1
3  3       1          1
4  4       1          1
5  5       1          0
6  6       1          1
```

6.3.2.2 Add variable labels (if we can).

Adding *variable labels* is still somewhat new in R. The `labelled` library allows us to add or change variable labels. However, not every library in R recognizes *variable labels*.

```
library(labelled)

var_label(MICSsimulated$id) <- "id"

var_label(MICSsimulated$country) <- "country"

var_label(MICSsimulated$cd4) <- "explain"
```

6.3.2.3 Add value labels (if we can).

In contrast, *value labels* are straightforward in R, and can be accomplished by creating a *factor variable*. Below we demonstrate how to do this with the happy variable.

```
MICSsimulated$cd4 <- factor(MICSsimulated$cd4,
                            levels = c(0, 1),
                            labels = c("Did not explain",
                                       "Explained"))
```

```
head(MICSsimulated)
```

```
  id country GII HDI cd1 cd2 cd3             cd4 aggression
1  1       1  20  24   0   0   1       Explained          1
2  2       1  20  24   0   0   1       Explained          1
3  3       1  20  24   0   0   1       Explained          1
4  4       1  20  24   0   0   0 Did not explain          1
5  5       1  20  24   1   0   1       Explained          0
6  6       1  20  24   0   0   1       Explained          1
```

6.3.2.4 Recode outliers, values that are errors, or values that should be coded as missing.

We can easily accomplish this using Base R's syntax for recoding: `data$variable[rule] <- newvalue`.

```
MICSsimulated$aggression[MICSsimulated$aggression > 1] <- NA # recode > 1 to NA

MICSsimulated$GII[MICSsimulated$GII > 100] <- NA # recode > 100 to NA
```

```
head(MICSsimulated)
```

```
  id country GII HDI cd1 cd2 cd3             cd4 aggression
1  1       1  20  24   0   0   1       Explained          1
2  2       1  20  24   0   0   1       Explained          1
3  3       1  20  24   0   0   1       Explained          1
4  4       1  20  24   0   0   0 Did not explain          1
5  5       1  20  24   1   0   1       Explained          0
6  6       1  20  24   0   0   1       Explained          1
```

6.3.3 Simple Analysis

Our first step in analysis is to discover what kind of variables we have. We need to make a distinction between *continuous variables* that measure things like mental health or neighborhood safety, or age, and *categorical variables* that measure non-ordered categories like religious identity or gender identity.

- For continuous variables, it is most appropriate to take the *average* or *mean*.
- For categorical variables, it is most appropriate to generate a *frequency table*.

As a mostly command based language, R relies on the idea of `do_something(dataset$variable)`.

```r
summary(MICSsimulated$GII) # descriptive statistics for GII
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   15.0    22.0    24.0    24.2    27.0    31.0
```

```r
table(MICSsimulated$cd4) # frequency table of cd4
```

```
Did not explain       Explained
            674            2326
```

References

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United Nations Development Program. (2023). *Gender Inequality Index (GII)*. https://hdr.undp.org/data-center/thematic-composite-indices/gender-inequality-index#/indicies/GII

A Simulating MICS Data

This appendix details the process of creating the simulated MICS data that is employed in the examples on this website.

MICS data are freely available, but usage of MICS requires completing a user agreement, and registering for a user account, on the MICS website, and thus MICS data should not be shared openly on a public website.

This Appendix is highly technical. It is not necessary to understand this Appendix to benefit from the rest of this website. However, the details of creating this simulated data may be of interest to some users.

A.1 Call Relevant Libraries

We need to call a number of relevant R libraries to simulate the data.

```
library(tibble) # new dataframes

library(ggplot2) # nifty graphs

library(labelled) # labels

library(haven) # write Stata

library(tidyr) # tidy data

library(dplyr) # wrangle data

library(lme4) # multilevel models

library(sjPlot) # nice tables for MLM

library(pander) # nice tables
```

A.2 Setup Some Basic Parameters of the Data

Because simulation is a random process, we set a *random seed* so that the simulation produces the same data set each time it is run.

We are going to simulate data with 30 countries, and 100 individuals per country.

```
set.seed(1234) # random seed

N_countries <- 30 # number of countries

N <- 100 # sample size / country
```

A.3 Simulate Data Based on MICS

This is multilevel data where individuals are nested, or clustered, inside countries. Excellent technical and pedagogical discussions of multilevel models can be found in Raudenbush & Bryk (2002), Singer & Willett (2003), Rabe-Hesketh & Skrondal (2022), Luke (2004), and Kreft & de Leeuw (1998).

A.3.1 Level 2

Simulating the second level of the data is relatively easy. We simply need to provide the number of countries, and then generate random effects for each country. Random effects are discussed in the above references, but essentially represent country level differences in the data.

We also create `GII`, a *Gender Inequality Index* (United Nations Development Program, 2023) variable, and `HDI`, a measure of the *Human Development Index* (United Nations Development Program, 2022), since these are country level, or Level 2 variables.

```
country <- seq(1:N_countries) # sequence 1 to 30

GII <- rbinom(N_countries, 100, .25) # gender inequality index

HDI <- rbinom(N_countries, 100, .25) # Human Development Index

u0 <- rnorm(N_countries, 0, .25) # random intercept

u1 <- rnorm(N_countries, 0, .05) # random slope
```

```
randomeffects <- data.frame(country,
                            GII,
                            HDI,
                            u0,
                            u1) # dataframe of random effects
```

A.3.2 Level 1

Simulating the Level 1 data is more complex.

We `uncount` the data by 100 to create 100 observations for each country. We then create an `id` number.

We create randomly simulated parental discipline variables with proportions similar to those in MICS.

Lastly, we need to create the dependent variable. Because this is a dichotomous outcome, the process is somewhat complex. We need to craete a linear combination `z`, using regression weights derived from MICS. We then calculate predicted probabilities, and lastly generate a dichotomous `aggression` outcome from those probabilities.

```
MICSsimulated <- randomeffects %>%
  uncount(N) %>% # N individuals / country
  mutate(id = row_number()) %>% # unique id
  mutate(cd1 = rbinom(N * N_countries, 1, .38), # spank
         cd2 = rbinom(N * N_countries, 1, .05), # beat
         cd3 = rbinom(N * N_countries, 1, .64), # shout
         cd4 = rbinom(N * N_countries, 1, .78)) %>% # explain
  mutate(z = 0 + # linear combination based on MICS
           .01 * GII +
           .23 * cd1 +
           .52 * cd2 +
           .42 * cd3 +
           -.21 * cd4 +
           u0) %>%
  mutate(p = exp(z) / (1 + exp(z))) %>% # probability
  mutate(aggression = rbinom(N * N_countries, 1, p)) %>% # binomial y
  select(id, country, GII, HDI,
         cd1, cd2, cd3, cd4,
         aggression)
```

A.3.3 Variable Labels

We add variable labels to the data which will help us to understand the data as we analyze it.

```
var_label(MICSsimulated$id) <- "id"

var_label(MICSsimulated$country) <- "country"

var_label(MICSsimulated$GII) <- "Gender Inequality Index"

var_label(MICSsimulated$HDI) <- "Human Development Index"

var_label(MICSsimulated$cd1) <- "spank"

var_label(MICSsimulated$cd2) <- "beat"

var_label(MICSsimulated$cd3) <- "shout"

var_label(MICSsimulated$cd4) <- "explain"

var_label(MICSsimulated$aggression) <- "aggression"
```

```
pander(labelled::look_for(MICSsimulated)[1:4]) # list out variable labels
```

Table A.1: Variable Labels

pos	variable	label	col_type
1	id	id	int
2	country	country	int
3	GII	Gender Inequality Index	int
4	HDI	Human Development Index	int
5	cd1	spank	int
6	cd2	beat	int
7	cd3	shout	int
8	cd4	explain	int
9	aggression	aggression	int

A.4 Explore The Simulated Data With A Graph

Exploring the simulated data with a graph helps us to ensure that we have simulated plausible data.

```
ggplot(MICSsimulated,
       aes(x = cd1, # x is spanking
           y = aggression, # y is aggression
           color = factor(country))) + # color is country
  geom_smooth(method = "glm", # glm smoother
              method.args = list(family = "binomial"),
              alpha = .1) + # transparency for CI's
  labs(title = "Aggression as a Function of Spanking",
       x = "spank",
       y = "aggression") +
  scale_color_viridis_d(name = "Country") + # nice colors
  theme_minimal()
```

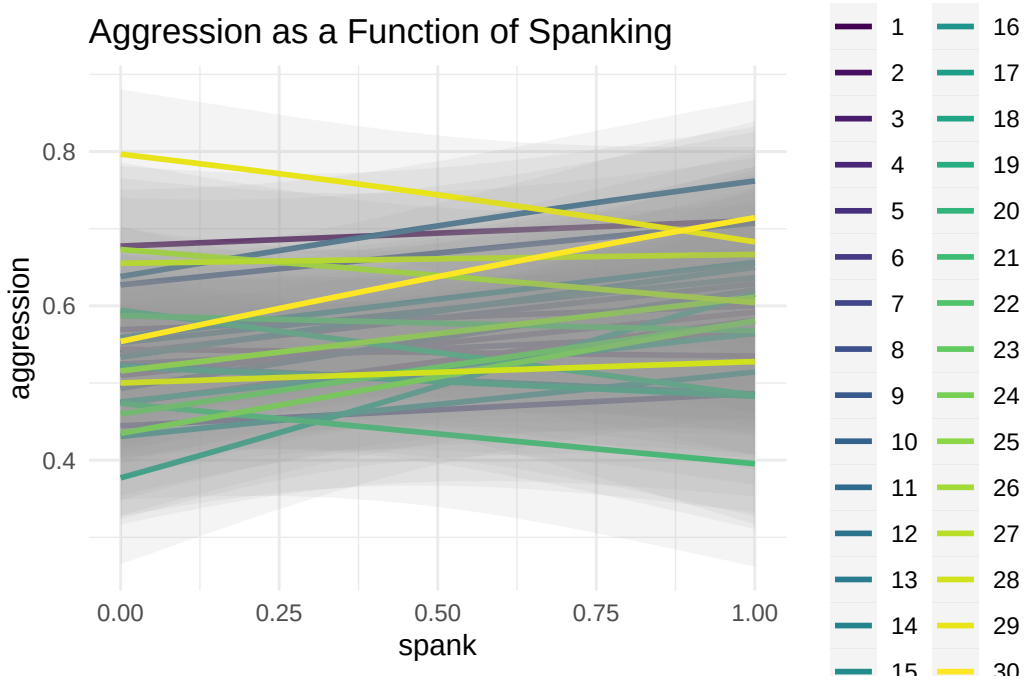

Figure A.1: Graph of Simulated Data

A.5 Explore The Simulated Data With A Logistic Regression

Similarly, exploring the data with a logistic regression confirms that we have created plausible data.

```
fit1 <- glmer(aggression ~ cd1 + cd2 + cd3 + cd4 + GII +
                (1 | country),
              family = "binomial",
              data = MICSsimulated,
              control = glmerControl(optimizer ="bobyqa"))

tab_model(fit1, # nice table
          transform = NULL) # untransformed estimates
```

A.6 Write data to various formats

Lastly, we write the data out to various formats: R, Stata, and SPSS.

```
save(MICSsimulated,
     file = "./simulate-data/MICSsimulated.RData") # R

write_dta(MICSsimulated,
          "./simulate-data/MICSsimulated.dta") # Stata

write_sav(MICSsimulated,
          "./simulate-data/MICSsimulated.sav") # SPSS
```

Table A.2: **?(caption)**

aggression	
Predictors	
Log-Odds	
CI	
p	
(Intercept)	
-0.41	
-1.10 – 0.28	
0.249	
spank	
0.21	
0.06 – 0.37	
0.006	
beat	
0.59	
0.23 – 0.94	
0.001	
shout	
0.45	
0.30 – 0.60	
<0.001	
explain	
-0.37	
-0.55 – -0.19	
<0.001	
Gender Inequality Index	
0.02	
-0.00 – 0.05	
0.102	
Random Effects	
^{2}	
3.29	
$^{00\ \text{country}}$	
0.05	
ICC	
0.01	
N_{country}	
30	
Observations	
3000	
Marginal R^2 / Conditional R^2	
0.031 / 0.044	