4. Übungsblatt (Faktorielle Umfrageexperimente)

Daria Tisch

1 Organisation

1.1 Arbeitsverzeichnis festsetzen

1.2 Packages installieren und laden

```
# Packages
pkgs <- c(
  "tidyverse",
  "sjPlot",
  "haven",
  "labelled" ,
  "sandwich",
  "lmtest"
)

## Install uninstalled packages
lapply(pkgs[!(pkgs %in% installed.packages())], install.packages)

## Load all packages to library
lapply(pkgs, library, character.only = TRUE)
```

1.3 Einführung

In dieser Übung replizieren wir die Ergebnisse folgender Studie:

Tisch, Daria, and Tamara Gutfleisch. 'Unequal but Just? Experimental Evidence on Distributive Justice Principles in Parental Inter Vivos Transfers'. Socio-Economic Review 21, no. 3 (2023): 1369–90.

Der Datensatz kann hier heruntergeladen werden.

Schenkungen von Eltern an deren Kinder sind von der moralischen Entscheidung geprägt, welches Kind wie viel erhalten soll. So können Eltern Schenkungen zwischen Kindern nach unterschiedlichen Gerechtigkeitsprinzipien aufteilen. Wenden sie das Gleichheitsprinzip an, schenken sie allen Kindern gleich viel. Wenden sie das Bedürfnisprinzip an, schenken sie den Kindern, die größere Bedürfnisse haben (z. B. Arbeitslosigkeit), mehr. Wenden sie das Austauschprinzip an, schenken sie den Kindern mehr, die im Gegenzug mehr für die Eltern machen (z. B. im Haushalt der Eltern helfen). Wenden sie das Anspruchsprinzip an, schenken sie den Kindern mehr, die bestimmte angeborene Statuscharakteristiken haben (z. B. Erstgeborene). Wir wollen untersuchen, inwiefern diese Prinzipien im Kontext von elterlichen Schenkungen von den Befragten befürwortet werden. Unterstützen die Befragten diese Prinzipien im selben Maße für Töchter und Söhne?

1.4 Daten einlesen

```
# Load the data file
df <- read.csv("../daten/just_transfers.csv")
```

1.5 Variablenlabels einlesen

```
# Load the variable labels
variable_labels <- read.csv("../daten/just_transfers_variable_labels.csv", row.names = 1, st

# View variable labels
#print(variable_labels)


# Loop through the labels and assign them to variables in the dataset
for (var in names(variable_labels)) {
  if (var %in% names(df)) {
    var_label(df[[var]]) <- variable_labels[[var]]
  }
}
```

1.6 Value labels einlesen

```
# Load the value labels
value_labels <- read.csv("../daten/value_labels.csv", stringsAsFactors = FALSE)

# View value labels
head(value_labels)
```

```
   variable                label value
1 firstborn        Son firstborn     1
2 firstborn                Twins     2
3 firstborn  Daughter firstborn     3
4      need       Son unemployed     1
5      need       Equal earnings     2
6      need Daughter unemployed     3
```

2 Fallzahlen

2.1 Wie viele Beobachtungen enthält der Datensatz?

```
nrow(df)
```

```
[1] 4284
```

2.2 Wie viele befragte Personen sind im Datensatz enthalten?

```
length(unique(df$id_resp))
```

```
[1] 714
```

2.3 Wie viele Vignetten hat jede befragte Person bewertet?

```r
length(unique(df$id_within))
```

```
[1] 3
```

```r
table(df$id_within)
```

```

   1    2    3 
1428 1428 1428 
```

```r
1428/2
```

```
[1] 714
```

2.4 Wie viele Vignetten gibt es?

```r
table(df$id_vignette)
```

```

  1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17  18  19  20 
134 134 134 162 162 162 180 180 180 168 168 168 146 146 146 174 174 174 154 154 
 21  22  23  24  25  26  27 
154 152 152 152 158 158 158 
```

```r
length(unique(df$id_vignette))
```

```
[1] 27
```

2.5 Wie viele Decks gibt es?

```r
table(df$deck)
```

```
  1   2   3   4   5   6   7   8   9
402 486 540 504 438 522 462 456 474
```

```r
length(unique(df$deck))
```

```
[1] 9
```

3 Deskriptive Statistik

3.1 Replikation Tabelle 2

Nun wollen wir Tabelle 2 aus dem Artikel replizieren.

```r
# Filter für die Daten anwenden
filtered_data <- df %>%
  filter(id_within == 1, daughter == 1)

# Deskriptive Statistiken berechnen
descriptive_stats <- filtered_data %>%
  summarise(
    Female_Mean = mean(female, na.rm = TRUE),
    Female_SD = sd(female, na.rm = TRUE),
    Female_Min = min(female, na.rm = TRUE),
    Female_Max = max(female, na.rm = TRUE),
    Female_N = sum(!is.na(female)),

    Age_Mean = mean(age, na.rm = TRUE),
    Age_SD = sd(age, na.rm = TRUE),
    Age_Min = min(age, na.rm = TRUE),
    Age_Max = max(age, na.rm = TRUE),
    Age_N = sum(!is.na(age)),

    Child_Mean = mean(child, na.rm = TRUE),
    Child_SD = sd(child, na.rm = TRUE),
```

```r
    Child_Min = min(child, na.rm = TRUE),
    Child_Max = max(child, na.rm = TRUE),
    Child_N = sum(!is.na(child)),

    Mig_Mean = mean(mig, na.rm = TRUE),
    Mig_SD = sd(mig, na.rm = TRUE),
    Mig_Min = min(mig, na.rm = TRUE),
    Mig_Max = max(mig, na.rm = TRUE),
    Mig_N = sum(!is.na(mig)),

    Gifted_Mean = mean(gifted, na.rm = TRUE),
    Gifted_SD = sd(gifted, na.rm = TRUE),
    Gifted_Min = min(gifted, na.rm = TRUE),
    Gifted_Max = max(gifted, na.rm = TRUE),
    Gifted_N = sum(!is.na(gifted)),

    IV_Received_Mean = mean(iv_received, na.rm = TRUE),
    IV_Received_SD = sd(iv_received, na.rm = TRUE),
    IV_Received_Min = min(iv_received, na.rm = TRUE),
    IV_Received_Max = max(iv_received, na.rm = TRUE),
    IV_Received_N = sum(!is.na(iv_received)),

    ABI_Mean = mean(abi, na.rm = TRUE),
    ABI_SD = sd(abi, na.rm = TRUE),
    ABI_Min = min(abi, na.rm = TRUE),
    ABI_Max = max(abi, na.rm = TRUE),
    ABI_N = sum(!is.na(abi))
  )

# Umstrukturierung der Tabelle
descriptive_stats_long <- descriptive_stats %>%
  pivot_longer(
    cols = everything(),
    names_to = c("Variable", ".value"),
    names_pattern = "(.*)_(.*)"
  )

# Tabelle mit sjPlot anzeigen
tab_df(
  descriptive_stats_long,
  title = "Descriptive Statistics of Respondent Characteristics",
  col.header = c("Variable", "Mean", "SD", "Min", "Max", "N")
```

```
)
```

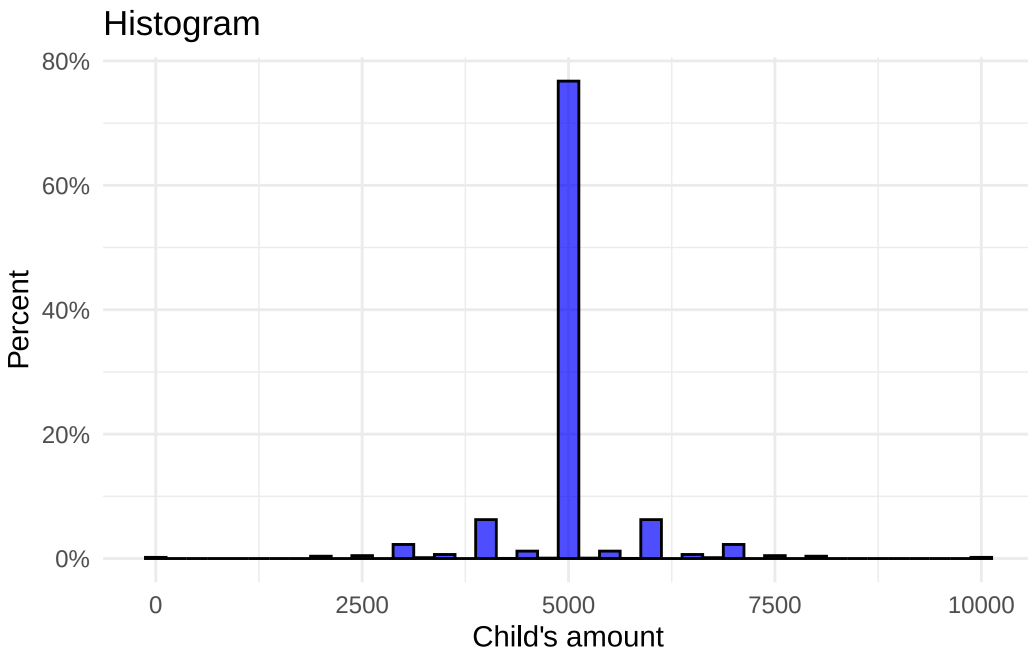
Table 1: Descriptive Statistics of Respondent Characteristics

Variable	Mean	SD	Min	Max	N
Female	0.62	0.49	0	1	702
Age	44.83	15.08	21	73	705
Child	0.50	0.50	0	1	707
Mig	0.12	0.33	0	1	704
Gifted	0.66	0.47	0	1	353
IV_Received	0.87	0.34	0	1	711
ABI	0.86	0.35	0	1	690

3.2 Replikation Figure 1

```
# Create the histogram
ggplot(df, aes(x = child_vig)) +
  geom_histogram(aes(y = ..count../sum(..count..)*100), binwidth = 250,
                 fill = "blue", color = "black", alpha = 0.7) +
  scale_y_continuous(labels = scales::percent_format(scale = 1)) +
  labs(title = "Histogram",
       x = "Child's amount",
       y = "Percent") +
  theme_minimal()
```

```
Warning: The dot-dot notation (`..count..`) was deprecated in ggplot2 3.4.0.
i Please use `after_stat(count)` instead.
```



4 Regression

4.1 Replikation von Tabelle 3

```
# Ensure reference category is set to 2 for each factor
df$g_firstborn <- relevel(as.factor(df$g_firstborn), ref = "2")
df$g_help <- relevel(as.factor(df$g_help), ref = "2")
df$g_need <- relevel(as.factor(df$g_need), ref = "2")

# Run the regression model
model <- lm(child_vig ~ daughter * g_firstborn +
                      g_help * daughter +
                      g_need * daughter,
            data = df)

# Clustered standard errors
clustered_se <- coeftest(model, vcov = vcovCL, cluster = ~ id_resp)

# Output the results
summary(model)         # Regression summary
```

```
Call:
lm(formula = child_vig ~ daughter * g_firstborn + g_help * daughter +
    g_need * daughter, data = df)

Residuals:
    Min      1Q  Median      3Q     Max
-4989.0  -287.8     0.0   287.8  4989.0

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           4967.074     40.125 123.791  < 2e-16 ***
daughter                65.853     56.745   1.161   0.2459
g_firstborn1            37.237     36.629   1.017   0.3094
g_firstborn3             6.346     36.615   0.173   0.8624
g_help1                320.686     36.613   8.759  < 2e-16 ***
g_help3               -207.280     36.619  -5.660 1.61e-08 ***
g_need1                205.191     36.615   5.604 2.23e-08 ***
g_need3               -313.954     36.599  -8.578  < 2e-16 ***
daughter:g_firstborn1  -43.583     51.792  -0.842   0.4001
daughter:g_firstborn3  -43.583     51.792  -0.842   0.4001
daughter:g_help1      -113.406     51.783  -2.190   0.0286 *
daughter:g_help3      -113.406     51.783  -2.190   0.0286 *
daughter:g_need1       108.763     51.770   2.101   0.0357 *
daughter:g_need3       108.763     51.770   2.101   0.0357 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 691.3 on 4270 degrees of freedom
Multiple R-squared:  0.1624,    Adjusted R-squared:  0.1599
F-statistic:  63.7 on 13 and 4270 DF,  p-value: < 2.2e-16
```

```r
print(clustered_se)    # Results with clustered SE
```

```
t test of coefficients:

                       Estimate Std. Error  t value   Pr(>|t|)
(Intercept)           4967.0737    37.3969 132.8206 < 2.2e-16 ***
daughter                65.8526    74.7937   0.8805   0.37866
g_firstborn1            37.2371    43.2121   0.8617   0.38889
g_firstborn3             6.3457    43.4854   0.1459   0.88399
```

```
g_help1                320.6862    38.9626   8.2306 2.449e-16 ***
g_help3               -207.2799    37.9277  -5.4651 4.889e-08 ***
g_need1                205.1905    38.6142   5.3139 1.128e-07 ***
g_need3               -313.9540    39.6818  -7.9118 3.208e-15 ***
daughter:g_firstborn1  -43.5827    76.4992  -0.5697   0.56890
daughter:g_firstborn3  -43.5827    76.4992  -0.5697   0.56890
daughter:g_help1      -113.4063    58.6378  -1.9340   0.05318 .
daughter:g_help3      -113.4063    58.6378  -1.9340   0.05318 .
daughter:g_need1       108.7634    61.2365   1.7761   0.07578 .
daughter:g_need3       108.7634    61.2365   1.7761   0.07578 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tab_model(model)
```

		Child's amount of inter vivos	
Predictors	Estimates	CI	p
(Intercept)	4967.07	4888.41 – 5045.74	**<0.001**
Focal vignette person daughter	65.85	-45.40 – 177.10	0.246
g firstborn: g firstborn 1	37.24	-34.58 – 109.05	0.309
g firstborn: g firstborn 3	6.35	-65.44 – 78.13	0.862
g help: g help 1	320.69	248.91 – 392.47	**<0.001**
g help: g help 3	-207.28	-279.07 – -135.49	**<0.001**
g need: g need 1	205.19	133.41 – 276.98	**<0.001**
g need: g need 3	-313.95	-385.71 – -242.20	**<0.001**
daughter:g_firstborn1	-43.58	-145.12 – 57.96	0.400
daughter:g_firstborn3	-43.58	-145.12 – 57.96	0.400
daughter:g_help1	-113.41	-214.93 – -11.89	**0.029**
daughter:g_help3	-113.41	-214.93 – -11.89	**0.029**
daughter:g_need1	108.76	7.27 – 210.26	**0.036**
daughter:g_need3	108.76	7.27 – 210.26	**0.036**
Observations	4284		
R^2 / R^2 adjusted	0.162 / 0.160		

5 Render

Wandle dieses Dokument in ein PDF und ein HTML Dokument um.

6 Weiterführende Literatur

- R for Data Science