Das Experiment

Warum sollten wir *randomisieren*?

Das Fundamentale Problem der *kausalen* Inferenz:

- Auf individueller Ebene können keine kausalen Effekte beobachtet werden
- Es gibt keine individuellen Alternativszenarien (außer in "Zurück in die Zukunft")

> Dies bedeutet wir müssen uns durchschnittliche Effekte auf Gruppenebene anschauen!

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Dies bedeutet wir müssen uns durchschnittliche Effekte auf Gruppenebene anschauen!

Wenn wir durchschnittliche Effekte zwischen Gruppen von Personen betrachten wollen, dann funktioniert dies nur, wenn die Gruppen die gleichen Eigenschaften haben.

Warum sollten wir *randomisieren*?

Mit einer ausreichend großen Stichprobe erhalten Sie durch Randomisierung Gruppen, die in ihren (pre-Treatment) Charakteristika gleich sind.

Übertragen auf ihr DAG bedeutet die Randomisierung: Confounder beeinflussen ihr Treatment nicht!

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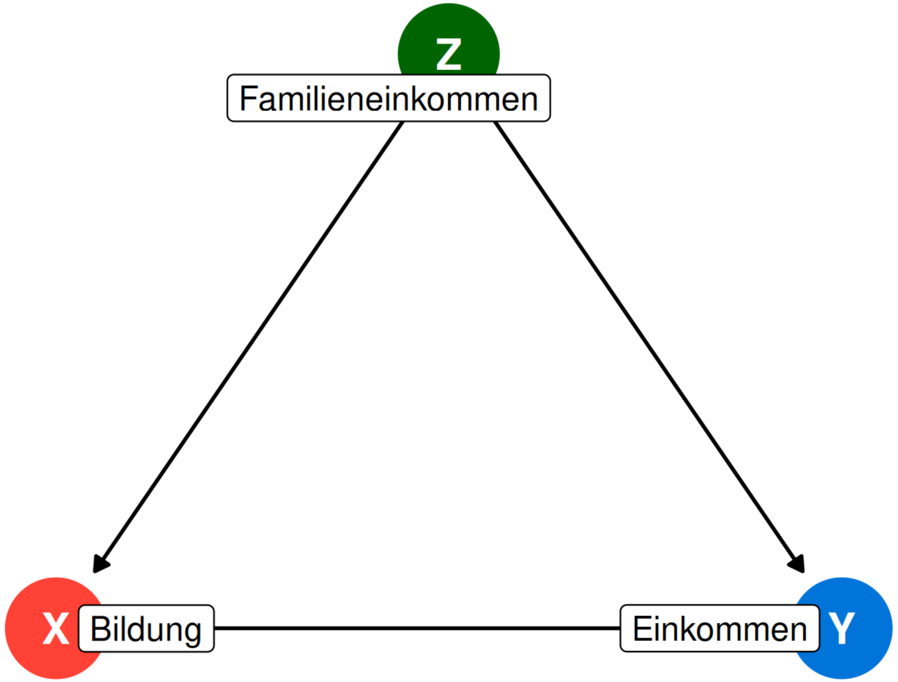
Übertragen auf ihr DAG bedeutet die Randomisierung: Confounder beeinflussen ihr Treatment nicht!



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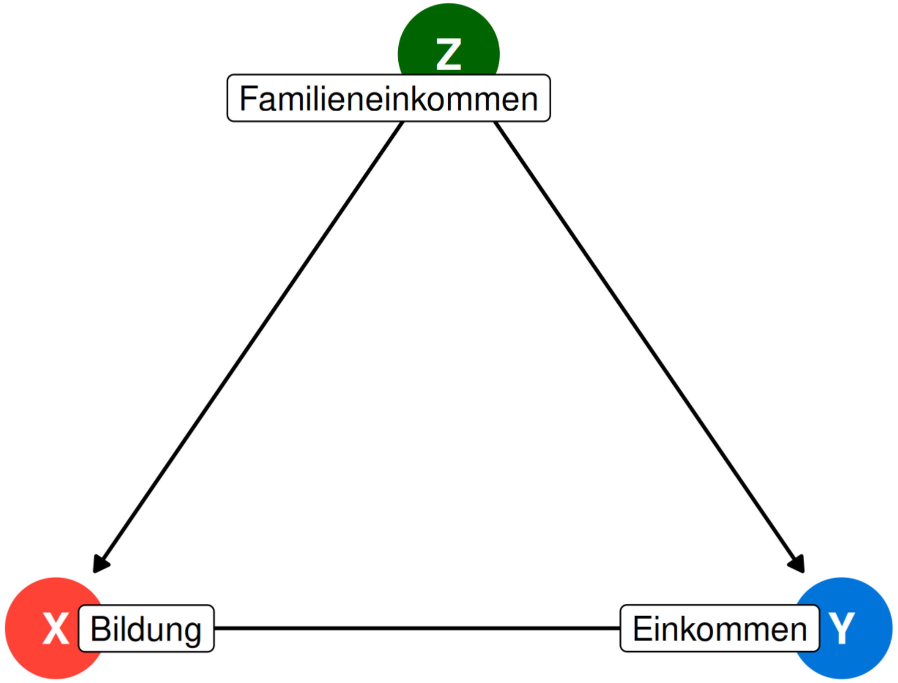
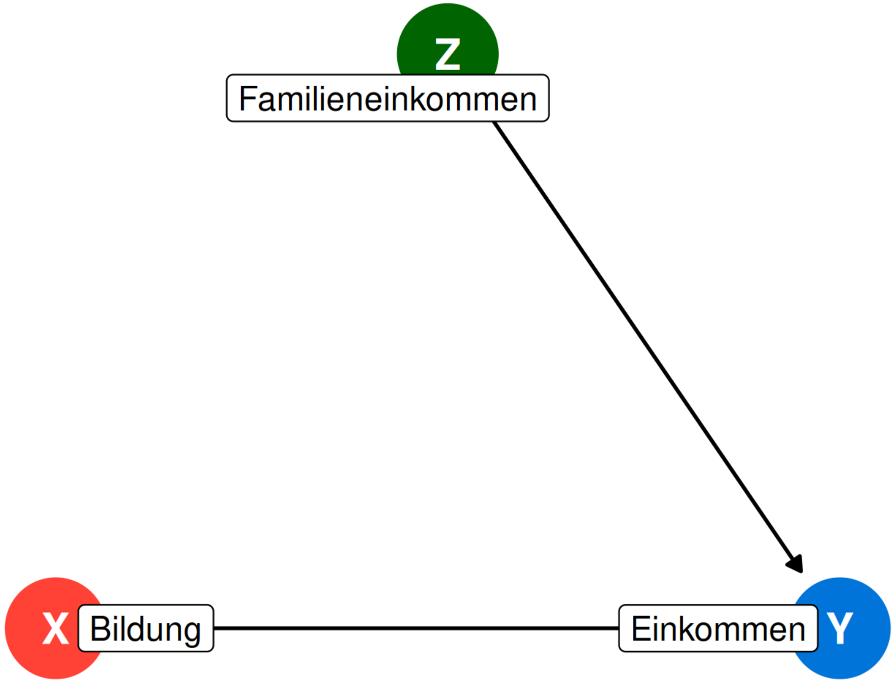
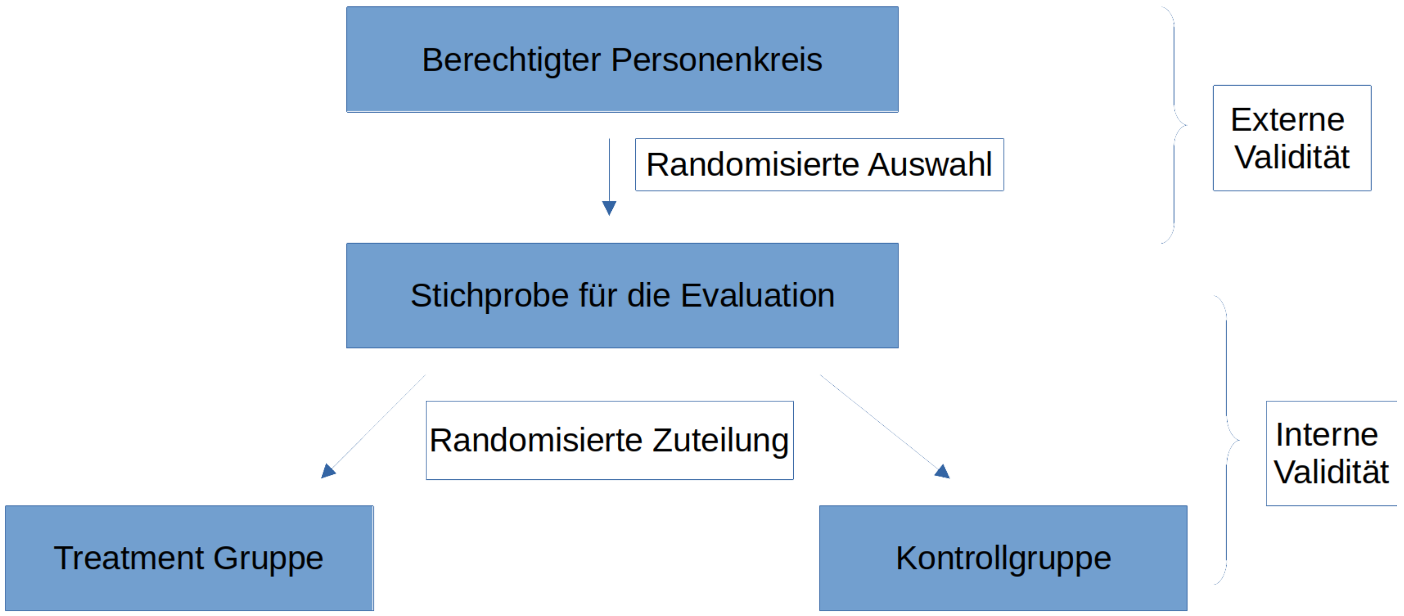




Wie wird randomisiert?



Validität

Interne Validität: Misst ihre Methodik das was sie tatsächlich herausfinden wollen? D.h. können Sie die Änderung von Y *kausal* auf die Änderung von X zurückführen?

Externe Validität: Lassen sich die Ergebnisse auch auf andere Datensätze übertragen/generalisieren?

Validität

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Uns interessiert insbesondere die *interne Validität* unserer Ergebnisse!

Probleme für die interne Validität

- **Omitted Variables Bias**: Selbstselektion, Attrition (Schwund)
- **Trends in den Daten**: Reifung, Globale Trends, Saisonalität, Wiederholung, Regression zur Mitte
- **Kalibrierung der Studie**: Messfehler, Zeitrahmen
- **Kontamination**: Hawthorne, John Henry, Spillovers

Ommitted Variable Bias

Selbstselektion

- Problem: Personen können selbst entscheiden ob (oder wann) Sie an einem Programm teilnehmen oder nicht
- Lösung: Randomisierung in Treatment und Kontrollgruppe und über die Zeit

Attrition (Schwund)

- Problem: Personen die das Experiment verlassen sind unterschiedlich zu denen die bleiben
- *Überprüfung*: Wie ähnlich sind die Personen die bleiben zu denen die gehen auf Basis beobachtbarer Charakteristika?

Trends in den Daten

Reifung

- Problem: Personen ändern sich alleine durch zunehmendes Alter zwischen zwei Messungen
- Lösung: Kontrollgruppe verwenden um den Trend heraus rechnen zu können

Globale Trends

- Problem: Globale Ereignisse können die Änderung in den Daten erklären
- Lösung: Kontrollgruppe verwenden um den Trend heraus rechnen zu können

Saisonalität

- Problem: Änderungen in den Daten basieren auf saisonalen Schwankungen
- Lösung: Beobachtungen aus der gleichen Periode miteinander vergleichen

Trends in den Daten

Wiederholung

- Problem: Personen lernen natürlicherweise, wenn Sie immer den gleichen Fragen/Aufgaben ausgesetzt sind
- Lösung: Tests verändern, Kontrollgruppen verwenden

Regression zur Mitte

- Problem: Extreme Beobachtungen werden mit der Zeit weniger Extrem (Glück, Pech ...)
- Lösung: Keine Ausreiser selektieren, Randomisierung

Kalibrierung der Studie

Falsche Messung

- Problem: Der Output wird nicht richtig gemessen
- Lösung: Output muss richtig gemessen werden

Zeitrahmen

- Problem: Studie ist zu kurz (oder zu lange) angelegt
- Lösung: Richtigen Zeitrahmen anlegen

Kontamination

Hawthorne Effekt

- Problem: Personen verhalten sich unterscheidlich wenn diese beobachtet werden
- Lösung: Versteckte Kontrollgruppen verwenden?

John Henry Effekt

- Problem: Kontrollgruppe arbeitet sehr hart um zu zeigen das sie so gut wie die Treatment Gruppe sind
- Lösung: Kontroll und Treatmentgruppe separat halten

Spillover Effekt

- Problem: Kontrollgruppe lernt über die Zeit von der Treatment Gruppe
- Lösung: Räumlich getrennte Kontrollgruppen verwenden

Randomisiertes Experiment

Randomisierung löst viele Probleme der internen Validität!

Wie lassen sich die Ergebnisse eines Experiments interpretieren?

Randomisiertes Experiment

Randomisierung löst viele Probleme der internen Validität!

Wie lassen sich die Ergebnisse eines Experiments interpretieren?

Schritt 1: Untersuchen Sie ob die demographischen Faktoren und andere Charakteristika zwischen Treatment und Kontrollgruppe ähnlich sind (gebalanced)

Schritt 2: Untersuchen Sie die durchschnittlichen Differenzen im Ergebnis zwischen Treatment und Kontrollgruppe

Experiment - Wochenbettdepressionen

Wir wollen uns einem Experiment zuwenden, dessen zeitliche Abfolge Sie hier sehen:

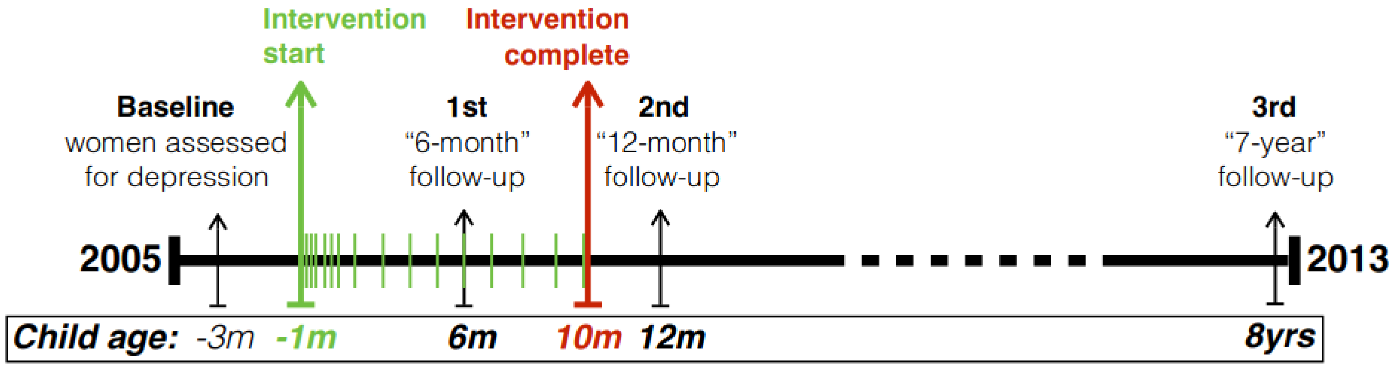

FIGURE 1. TIMELINE OF INTERVENTION AND FOLLOW-UPS

Quelle: Baranov, Victoria, Sonia Bhalotra, Pietro Biroli, and Joanna Maselko. 2020. "Maternal Depression, Women's Empowerment, and Parental Investment: Evidence from a Randomized Controlled Trial." American Economic Review, 110 (3): 824-59.

Experiment - Wochenbettdepressionen

Was sind Wochenbettdepressionen?

Postpartale Stimmungskrisen (von lat. partus Geburt, Entbindung) beschreiben psychische Zustände oder Störungen, die in einem **zeitlichen Zusammenhang mit dem Wochenbett** auftreten (lat. post = nach; partus = Entbindung, Trennung).[1] Die Bandbreite der im Wochenbett auftretenden affektiven Zustände reicht von einer leichten Traurigkeit über Depressionen bis hin zu schweren psychotischen Erkrankungen.

Quelle: Wikipedia

Experiment - Wochenbettdepressionen

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Quelle: Wikipedia

Die Folgen einer Wochenbettdepression können langfristige Effekte auf die ganze Familie haben. Neben den negativen Folgen für die Gesundheit der Frau und des Kindes, verursachen Depressionen auch hohe wirtschaftliche Kosten.

Experiment - Wochenbettdepressionen

```
thp <- read_csv("../case-study/data/THP_clean.csv")

thp %>%
  select(treat, depressed_1y, age_baseline, kids_no, first_child, employed_mo_baseline, MIL, mate
  glimpse()
```

```
Rows: 1,203
Columns: 10
$ treat                <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1…
$ depressed_1y         <dbl> 1, 0, NA, 0, NA, 1, 1, 0, 0, 0, NA, 0, 0, 0, 0, 0…
$ age_baseline         <dbl> 28, 37, NA, 29, NA, 23, 30, 22, 30, 25, NA, 27, 2…
$ kids_no              <dbl> 3, 6, NA, 2, NA, 1, 3, 0, 4, 1, NA, 2, 2, 1, 2, 3…
$ first_child          <dbl> 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1…
$ employed_mo_baseline <dbl> 0, 0, NA, 0, NA, 0, 0, 0, 0, 0, NA, 0, 0, 0, 0, 0…
$ MIL                  <dbl> 1, 0, NA, 0, NA, 1, 0, 0, 0, 1, NA, 0, 1, 1, 0, 0…
$ maternalgma          <dbl> 0, 0, NA, 0, NA, 0, 0, 0, 0, 0, NA, 1, 0, 0, 0, 0…
$ edu_fa_baseline      <dbl> 10, 8, NA, 10, NA, 10, 0, 7, 8, 10, NA, 10, 10, 8…
$ employed_fa_baseline <dbl> 1, 0, NA, 1, NA, 1, 1, 1, NA, 1, NA, 1, 0, 1, 1, …
```

Schritt 1: Unterschiede untersuchen

count: false

```r
thp
```

```
# A tibble: 1,203 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>           <d
 1    NA          NA     1 <NA>        <NA>
 2   226           1     1 No          No
 3   222           6     1 Yes         No
 4     3           1     1 No          No
 5   217           3     1 No          No
 6   354           1     1 Yes         No
 7    NA          NA     1 <NA>        <NA>
 8    NA          NA     1 <NA>        <NA>
 9   225           4     1 No          No
10     2           4     1 Yes         No
# ℹ 1,193 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```r
thp %>%
  filter(THP_sample==1)
```

```
# A tibble: 903 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>            <d
 1    NA          NA     1 <NA>        <NA>
 2   226           1     1 No          No
 3     3           1     1 No          No
 4   354           1     1 Yes         No
 5    NA          NA     1 <NA>        <NA>
 6    NA          NA     1 <NA>        <NA>
 7   225           4     1 No          No
 8     2           4     1 Yes         No
 9   729           1     1 No          No
10    NA          NA     1 <NA>        <NA>
# ℹ 893 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```r
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
```

```
# A tibble: 903 × 10
   treat depressed_1y age_baseline kids_no first_child em
   <dbl>        <dbl>        <dbl>   <dbl>       <dbl>
 1     1            1           28       3           0
 2     1            0           37       6           0
 3     1            0           29       2           0
 4     1            1           23       1           0
 5     1            1           30       3           0
 6     1            0           22       0           1
 7     1            0           30       4           0
 8     1            0           25       1           0
 9     1            0           27       2           0
10     1            0           26       2           0
# i 893 more rows
# i 4 more variables: MIL <dbl>, maternalgma <dbl>, edu_f
#   employed_fa_baseline <dbl>
```

```r
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
```

```
# A tibble: 8,127 × 3
   treat variable             value
   <dbl> <chr>                <dbl>
 1     1 depressed_1y             1
 2     1 age_baseline            28
 3     1 kids_no                  3
 4     1 first_child              0
 5     1 employed_mo_baseline     0
 6     1 MIL                      1
 7     1 maternalgma              0
 8     1 edu_fa_baseline         10
 9     1 employed_fa_baseline     1
10     1 depressed_1y             0
# ℹ 8,117 more rows
```

```r
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable)
```

```
# A tibble: 9 × 2
  variable                                 data
  <chr>                      <list<tibble[,2]>>
1 MIL                                 [903 × 2]
2 age_baseline                        [903 × 2]
3 depressed_1y                        [903 × 2]
4 edu_fa_baseline                     [903 × 2]
5 employed_fa_baseline                [903 × 2]
6 employed_mo_baseline                [903 × 2]
7 first_child                         [903 × 2]
8 kids_no                             [903 × 2]
9 maternalgma                         [903 × 2]
```

```
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
```

```
# A tibble: 9 × 3
  variable                               data t.test
  <chr>                    <list<tibble[,2]>> <list>
1 MIL                               [903 × 2] <tibble [1 × 10
2 age_baseline                      [903 × 2] <tibble [1 × 10
3 depressed_1y                      [903 × 2] <tibble [1 × 10
4 edu_fa_baseline                   [903 × 2] <tibble [1 × 10
5 employed_fa_baseline              [903 × 2] <tibble [1 × 10
6 employed_mo_baseline              [903 × 2] <tibble [1 × 10
7 first_child                       [903 × 2] <tibble [1 × 10
8 kids_no                           [903 × 2] <tibble [1 × 10
9 maternalgma                       [903 × 2] <tibble [1 × 10
```

```r
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test)
```

```
# A tibble: 9 × 12
  variable             data estimate estimate1 estimate2 stati
  <chr>          <list<ti>    <dbl>     <dbl>     <dbl>     <
1 MIL            [903 × 2] -0.0642     0.402     0.467     -1
2 age_basel…     [903 × 2]  0.505     27        26.5        1
3 depressed…     [903 × 2]  0.316      0.589     0.273      9
4 edu_fa_ba…     [903 × 2]  0.134      7.09      6.95       0
5 employed_…     [903 × 2]  0.0124     0.913     0.901      0
6 employed_…     [903 × 2]  0.0125     0.0341    0.0216     1
7 first_chi…     [903 × 2] -0.00586    0.186     0.192     -0
8 kids_no        [903 × 2]  0.172      2.33      2.16       1
9 maternalg…     [903 × 2] -0.0299     0.05      0.0799    -1
# i 4 more variables: conf.low <dbl>, conf.high <dbl>, me
#   alternative <chr>
```

```r
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test) %>%
  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
```

```
# A tibble: 9 × 16
  variable             data estimate estimate1 estimate2 stati
  <chr>           <list<ti>    <dbl>     <dbl>     <dbl>     <
1 MIL           [903 × 2] -0.0642     0.402     0.467     -1
2 age_basel…    [903 × 2]  0.505     27        26.5        1
3 depressed…    [903 × 2]  0.316      0.589     0.273      9
4 edu_fa_ba…    [903 × 2]  0.134      7.09      6.95       0
5 employed_…    [903 × 2]  0.0124     0.913     0.901      0
6 employed_…    [903 × 2]  0.0125     0.0341    0.0216     1
7 first_chi…    [903 × 2] -0.00586    0.186     0.192     -0
8 kids_no       [903 × 2]  0.172      2.33      2.16       1
9 maternalg…    [903 × 2] -0.0299     0.05      0.0799    -1
# ℹ 8 more variables: conf.low <dbl>, conf.high <dbl>, me
#   alternative <chr>, Mean_Treatment <dbl>, Mean_Kontrol
#   Differenz <dbl>, Signifikanz <dbl>
```

```
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test) %>%
  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontro
```

```r
thp %>%
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  select( treat, depressed_1y, age_ba
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  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test) %>%
  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontro

rownames(total) <- c("Alter der Mutte
```

```r
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
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    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontro

rownames(total) <- c("Alter der Mutte

total
```

```
# A tibble: 9 × 4
  Mean_Treatment Mean_Kontrolle Differenz Signifikanz
           <dbl>          <dbl>     <dbl>       <dbl>
1           0.47           0.4       0.06        0.05
2          26.5           27        -0.51        0.14
3           0.27           0.59     -0.32        0
4           6.95           7.09     -0.13        0.61
5           0.9            0.91     -0.01        0.53
6           0.02           0.03     -0.01        0.26
7           0.19           0.19      0.01        0.82
8           2.16           2.33     -0.17        0.15
9           0.08           0.05      0.03        0.07
```

```r
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
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  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontro

rownames(total) <- c("Alter der Mutte

total %>%
  kbl(col.names = c("Treatment", "Kor
      caption = "Balancing Tabelle fü
```

Balancing Tabelle für die Grundcharakteristika

Treatment	Kontrolle	Differenz	p-Wert
0.47	0.40	0.06	0.05
26.49	27.00	-0.51	0.14
0.27	0.59	-0.32	0.00
6.95	7.09	-0.13	0.61
0.90	0.91	-0.01	0.53
0.02	0.03	-0.01	0.26
0.19	0.19	0.01	0.82
2.16	2.33	-0.17	0.15
0.08	0.05	0.03	0.07

```
thp %>%
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  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test) %>%
  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontrc

rownames(total) <- c("Alter der Mutte

total %>%
  kbl(col.names = c("Treatment", "Kor
      caption = "Balancing Tabelle fü
  kable_styling(bootstrap_options = c
```

Balancing Tabelle für die Grundcharakteristika

Treatment	Kontrolle	Differenz	p-Wert
0.47	0.40	0.06	0.05
26.49	27.00	-0.51	0.14
0.27	0.59	-0.32	0.00
6.95	7.09	-0.13	0.61
0.90	0.91	-0.01	0.53
0.02	0.03	-0.01	0.26
0.19	0.19	0.01	0.82
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0.08	0.05	0.03	0.07

```
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  select( treat, depressed_1y, age_ba
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  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test) %>%
  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontro

rownames(total) <- c("Alter der Mutte

total %>%
  kbl(col.names = c("Treatment", "Kon
      caption = "Balancing Tabelle fü
  kable_styling(bootstrap_options = c
  kable_paper(full_width = F)
```

Balancing Tabelle für die Grundcharakteristika

Treatment	Kontrolle	Differenz	p-Wert
0.47	0.40	0.06	0.05
26.49	27.00	-0.51	0.14
0.27	0.59	-0.32	0.00
6.95	7.09	-0.13	0.61
0.90	0.91	-0.01	0.53
0.02	0.03	-0.01	0.26
0.19	0.19	0.01	0.82
2.16	2.33	-0.17	0.15
0.08	0.05	0.03	0.07

```r
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test) %>%
  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontro

rownames(total) <- c("Alter der Mutte

total %>%
  kbl(col.names = c("Treatment", "Kon
      caption = "Balancing Tabelle fü
  kable_styling(bootstrap_options = c
  kable_paper(full_width = F)  %>%
  add_header_above(c(" ", "Stichprobe
```

Balancing Tabelle für die Grundcharakteristika

Stichprobe Baseline (N = 903)			
Treatment	Kontrolle	Differenz	p-Wert
0.47	0.40	0.06	0.05
26.49	27.00	-0.51	0.14
0.27	0.59	-0.32	0.00
6.95	7.09	-0.13	0.61
0.90	0.91	-0.01	0.53
0.02	0.03	-0.01	0.26
0.19	0.19	0.01	0.82
2.16	2.33	-0.17	0.15
0.08	0.05	0.03	0.07

```
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test) %>%
  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontro

rownames(total) <- c("Alter der Mutte

total %>%
  kbl(col.names = c("Treatment", "Kon
      caption = "Balancing Tabelle fü
  kable_styling(bootstrap_options = c
  kable_paper(full_width = F)  %>%
  add_header_above(c(" ", "Stichprobe
  footnote(general = "Diese Tabelle t
```

Balancing Tabelle für die Grundcharakteristika

	Stichprobe Baseline (N = 903)			
	Treatment	Kontrolle	Differenz	p-Wert
	0.47	0.40	0.06	0.05
	26.49	27.00	-0.51	0.14
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	0.90	0.91	-0.01	0.53
	0.02	0.03	-0.01	0.26
	0.19	0.19	0.01	0.82
	2.16	2.33	-0.17	0.15
	0.08	0.05	0.03	0.07

Note:

Diese Tabelle testet, wie ausbalanciert die Beobachtungen in der Baseline Stichprobe sind. In den ersten beiden Spalten wird der Mittelwert für die Treatment bzw. Kontrollgruppe für die Baseline Stichprobe gezeigt. Spalte (3) zeigen die Differenz zwischen den Mittelwerten der Treatment und Kontrollgruppe für die jeweilige Stichprobe und die Spalte (4) zeigt die p-Werte und damit ob die einzelnen Mittelwerte statistisch signifikant unterschiedlich voneinander sind.

```
thp %>%
  filter(THP_sample==1) %>%
  select( treat, depressed_1y, age_ba
  pivot_longer(cols = -treat, names_t
  group_nest(variable) %>%
  mutate(t.test = map(data, ~tidy(t.t
  unnest(t.test) %>%
  mutate( Mean_Treatment = round(esti
          Mean_Kontrolle = round(esti
    Differenz = -round(estimate, 2),
          Signifikanz = round(p.value
  select( Mean_Treatment, Mean_Kontro

rownames(total) <- c("Alter der Mutte

total %>%
  kbl(col.names = c("Treatment", "Kon
      caption = "Balancing Tabelle fü
  kable_styling(bootstrap_options = c
  kable_paper(full_width = F)  %>%
  add_header_above(c(" ", "Stichprobe
  footnote(general = "Diese Tabelle t
```

Balancing Tabelle für die Grundcharakteristika

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	6.95	7.09	-0.13	0.61
	0.90	0.91	-0.01	0.53
	0.02	0.03	-0.01	0.26
	0.19	0.19	0.01	0.82
	2.16	2.33	-0.17	0.15
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Note:

Diese Tabelle testet, wie ausbalanciert die Beobachtungen in der Baseline Stichprobe sind. In den ersten beiden Spalten wird der Mittelwert für die Treatment bzw. Kontrollgruppe für die Baseline Stichprobe gezeigt. Spalte (3) zeigen die Differenz zwischen den Mittelwerten der Treatment und Kontrollgruppe für die jeweilige Stichprobe und die Spalte (4) zeigt die p-Werte und damit ob die einzelnen Mittelwerte statistisch signifikant unterschiedlich voneinander sind.

SCHRITT 1: UNTERSCHIEDE UNTERSUCHEN

Balancing Tabelle für die Grundcharakteristika

	Stichprobe Baseline (N = 903)		
Treatment	Kontrolle	Differenz	p-Wert
0.47	0.40	0.06	0.05
26.49	27.00	-0.51	0.14
0.27	0.59	-0.32	0.00
6.95	7.09	-0.13	0.61
0.90	0.91	-0.01	0.53
0.02	0.03	-0.01	0.26
0.19	0.19	0.01	0.82
2.16	2.33	-0.17	0.15
0.08	0.05	0.03	0.07

Note:

Diese Tabelle testet, wie ausbalanciert die Beobachtungen in der Baseline Stichprobe sind. In den ersten beiden Spalten wird der Mittelwert für die Treatment bzw. Kontrollgruppe für die Baseline Stichprobe gezeigt. Spalte (3) zeigen die Differenz zwischen den Mittelwerten der Treatment und Kontrollgruppe für die jeweilige Stichprobe und die Spalte

Schritt 1: Unterschiede untersuchen

Wann nutzt uns eine solche Balancing Tabelle?

Wir sollten eine solche Tabelle immer dann erstellen, wenn wir uns nicht ganz sicher sein können, ob unsere Randomisierung erfolgreich war, d.h. insbesondere bei der Untersuchung von Feldexperimenten.

- Wenn wir die Randomisierung nicht selbst durchgeführt haben, insbesondere in Feldexperimenten
- Bei *Attrition*, d.h. Schwund bei den Teilnehmern des Experiments

Schritt 1: Unterschiede untersuchen

Was lernen wir aus der Balancing Tabelle?

Aus dieser Balancing Tabelle lernen wir mehrere Dinge:

- In den meisten Grundcharakteristika unterscheiden sich Treatment und Kontrollgruppe **nicht** voneinander.
- Einige Variablen sind jedoch signifikant unterschiedlich zwischen Treatment und Kontrollgruppe, insbesondere ob die Oma väterlicherseits oder mütterlicherseits mit im Haushalt lebt.
- Wir verlieren einige Teilnehmer über die Zeit (903 -> 704 -> 585 Beobachtungen), d.h. wir haben nach 7 Jahren nur noch 64,8% der Mütter, die ursprünglich am Experiment teilgenommen haben, in der Stichprobe.

Schritt 2: Durchschnittliche Differenzen

count: false

```r
thp
```

```
# A tibble: 1,203 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>          <d
 1    NA          NA     1 <NA>        <NA>
 2   226           1     1 No          No
 3   222           6     1 Yes         No
 4     3           1     1 No          No
 5   217           3     1 No          No
 6   354           1     1 Yes         No
 7    NA          NA     1 <NA>        <NA>
 8    NA          NA     1 <NA>        <NA>
 9   225           4     1 No          No
10     2           4     1 Yes         No
# ℹ 1,193 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```r
thp %>%
  select(treat, depressed_6m, depress
```

```
# A tibble: 1,203 × 4
   treat depressed_6m depressed_1y depressed
   <dbl>        <dbl>        <dbl>     <dbl>
 1     1            0            1        NA
 2     1            0            0         0
 3     1           NA           NA         0
 4     1            0            0         0
 5     1           NA           NA         0
 6     1            1            1         0
 7     1            1            1        NA
 8     1            0            0        NA
 9     1            0            0         0
10     1            0            0         0
# ℹ 1,193 more rows
```

```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1)
```

```
# A tibble: 1,203 × 5
   treat depressed_6m depressed_1y depressed Baseline
   <dbl>        <dbl>        <dbl>     <dbl>    <dbl>
 1     1            0            1        NA        1
 2     1            0            0         0        1
 3     1           NA           NA         0        1
 4     1            0            0         0        1
 5     1           NA           NA         0        1
 6     1            1            1         0        1
 7     1            1            1        NA        1
 8     1            0            0        NA        1
 9     1            0            0         0        1
10     1            0            0         0        1
# ℹ 1,193 more rows
```

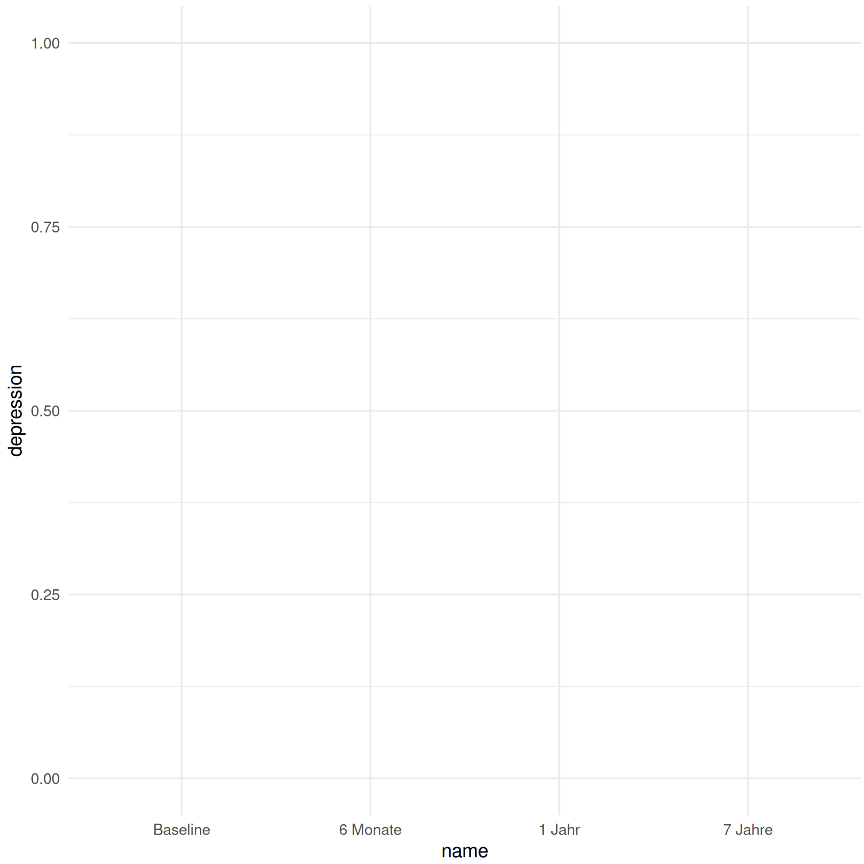
```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
```

```
# A tibble: 4,812 × 3
   treat name         depression
   <dbl> <chr>             <dbl>
 1     1 depressed_6m          0
 2     1 depressed_1y          1
 3     1 depressed            NA
 4     1 Baseline              1
 5     1 depressed_6m          0
 6     1 depressed_1y          0
 7     1 depressed             0
 8     1 Baseline              1
 9     1 depressed_6m         NA
10     1 depressed_1y         NA
# i 4,802 more rows
```

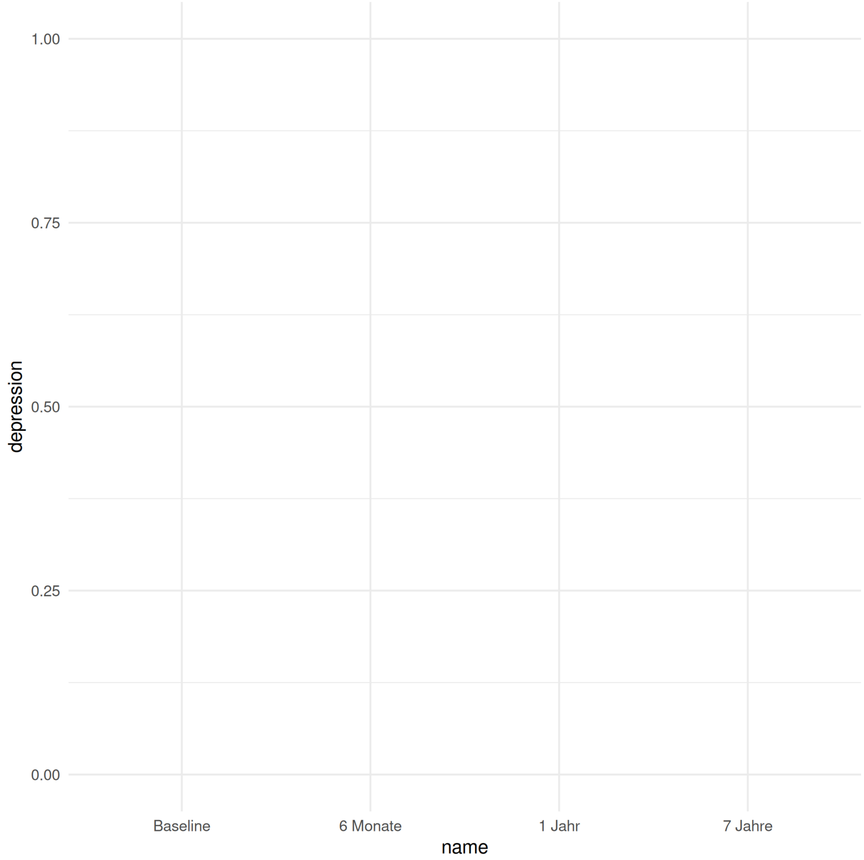
```r
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                           "6 Monate"
                           "1 Jahr" =
                           "7 Jahre"
         treat_factor = as.factor(ife
```

```
# A tibble: 4,812 × 4
   treat name     depression treat_factor
   <dbl> <fct>         <dbl> <fct>
 1     1 6 Monate          0 Treatment
 2     1 1 Jahr            1 Treatment
 3     1 7 Jahre          NA Treatment
 4     1 Baseline          1 Treatment
 5     1 6 Monate          0 Treatment
 6     1 1 Jahr            0 Treatment
 7     1 7 Jahre           0 Treatment
 8     1 Baseline          1 Treatment
 9     1 6 Monate         NA Treatment
10     1 1 Jahr           NA Treatment
# ℹ 4,802 more rows
```

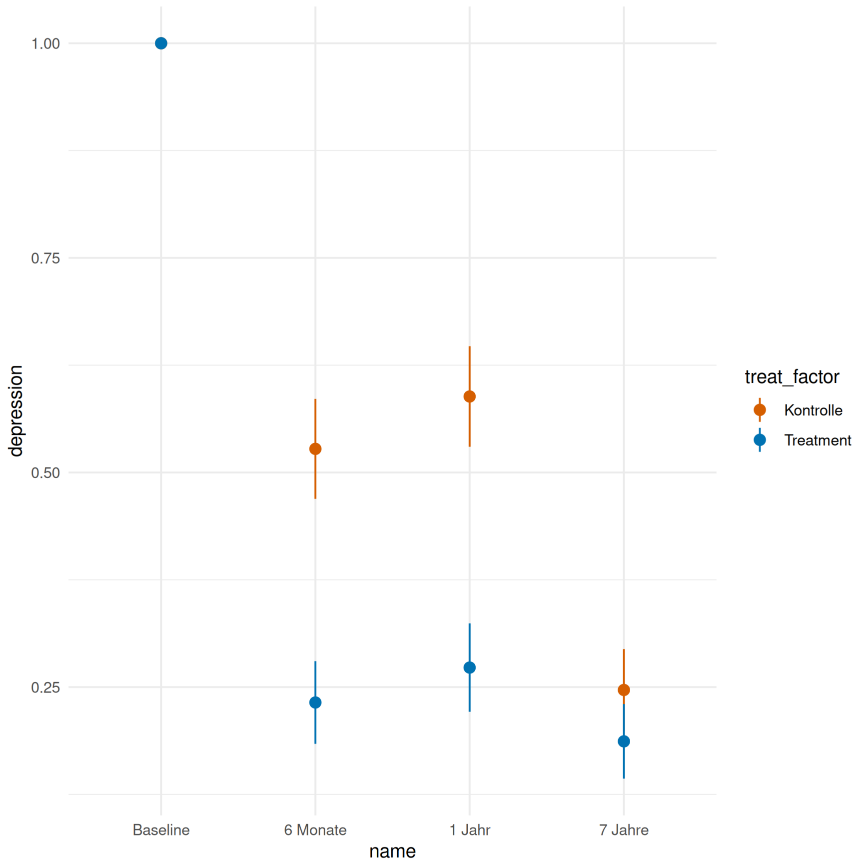
```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                           "6 Monate"
                           "1 Jahr" =
                           "7 Jahre"
         treat_factor = as.factor(ife
  ggplot(aes(x = name, y = depressior
             color = treat_factor))
```



```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                           "6 Monate"
                           "1 Jahr" =
                           "7 Jahre"
         treat_factor = as.factor(ife
  ggplot(aes(x = name, y = depression
             color = treat_factor)) +
  scale_color_manual(values = c("#D55
```



```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                          "6 Monate"
                          "1 Jahr" =
                          "7 Jahre"
         treat_factor = as.factor(ife
  ggplot(aes(x = name, y = depression
             color = treat_factor)) +
  scale_color_manual(values = c("#D55
  stat_summary(geom = "pointrange",
               fun.data = "mean_se",
               fun.args = list(mult=2
```



```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                           "6 Monate"
                           "1 Jahr" =
                           "7 Jahre"
         treat_factor = as.factor(ife
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             color = treat_factor)) +
  scale_color_manual(values = c("#D55
  stat_summary(geom = "pointrange",
               fun.data = "mean_se",
               fun.args = list(mult=2
  ylim(0,1)
```
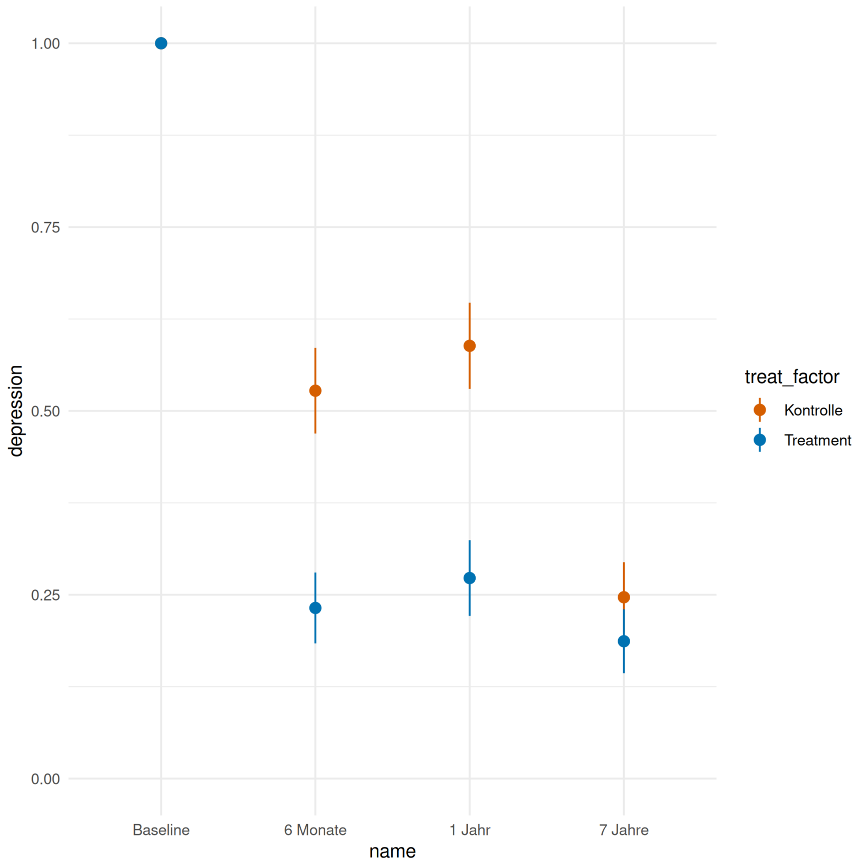
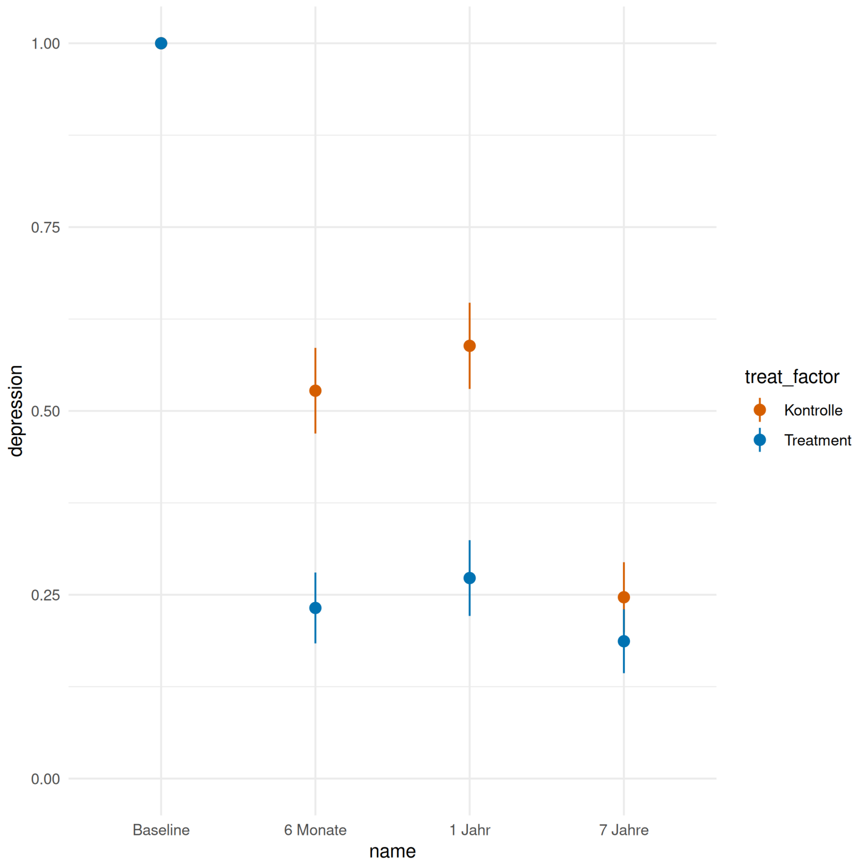
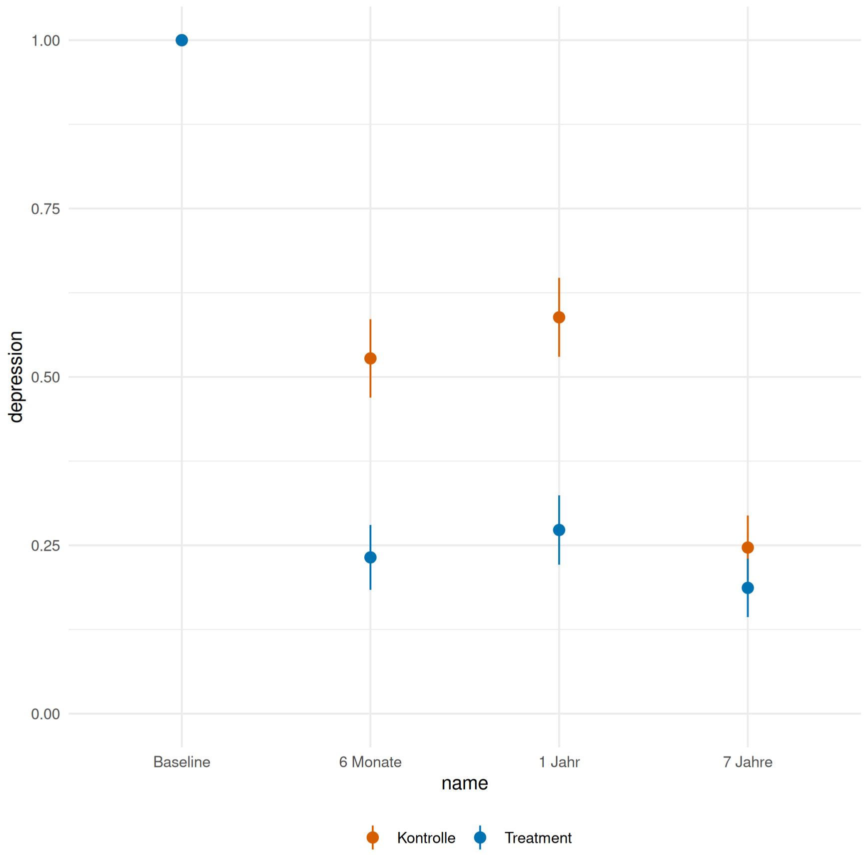



```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                           "6 Monate"
                           "1 Jahr" =
                           "7 Jahre"
         treat_factor = as.factor(ife
  ggplot(aes(x = name, y = depression
             color = treat_factor)) +
  scale_color_manual(values = c("#D55
  stat_summary(geom = "pointrange",
               fun.data = "mean_se",
               fun.args = list(mult=2
  ylim(0,1) +
  theme_minimal()
```



```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                           "6 Monate"
                           "1 Jahr" =
                           "7 Jahre"
         treat_factor = as.factor(ife
  ggplot(aes(x = name, y = depression
             color = treat_factor)) +
  scale_color_manual(values = c("#D55
  stat_summary(geom = "pointrange",
               fun.data = "mean_se",
               fun.args = list(mult=2
  ylim(0,1) +
  theme_minimal() +
  theme(legend.title = element_blank(
        legend.position = "bottom")
```



```
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                            "6 Monate"
                            "1 Jahr" =
                            "7 Jahre"
         treat_factor = as.factor(ife
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             color = treat_factor)) +
  scale_color_manual(values = c("#D55
  stat_summary(geom = "pointrange",
               fun.data = "mean_se",
               fun.args = list(mult=2
  ylim(0,1) +
  theme_minimal() +
  theme(legend.title = element_blank(
        legend.position = "bottom") +
  labs(x = NULL,
       y = "Anteil an Depressionen",
       title = "Treatment Effekte auf
       caption = "Gezeigt wird der Mi
```

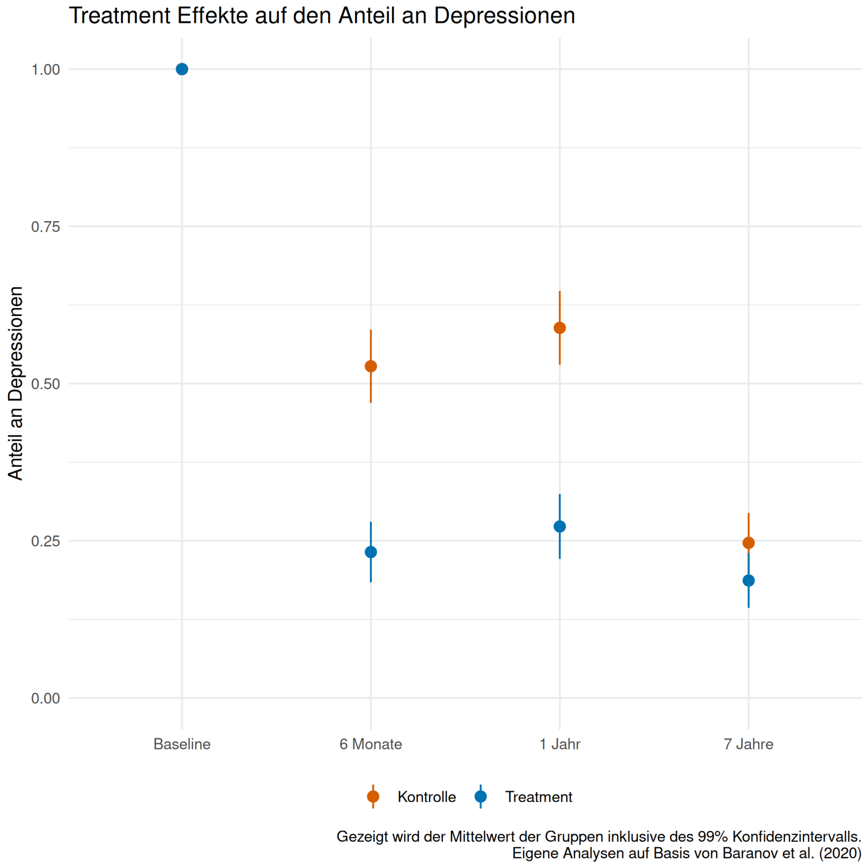

```r
thp %>%
  select(treat, depressed_6m, depress
  mutate(Baseline = 1) %>%
  pivot_longer( cols = -treat, names_
  mutate(name = fct_relevel(name, "Ba
         name = fct_recode(name,
                           "6 Monate"
                           "1 Jahr" =
                           "7 Jahre"
         treat_factor = as.factor(ife
  ggplot(aes(x = name, y = depression
             color = treat_factor)) +
  scale_color_manual(values = c("#D55
  stat_summary(geom = "pointrange",
               fun.data = "mean_se",
               fun.args = list(mult=2
  ylim(0,1) +
  theme_minimal() +
  theme(legend.title = element_blank(
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       y = "Anteil an Depressionen",
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```
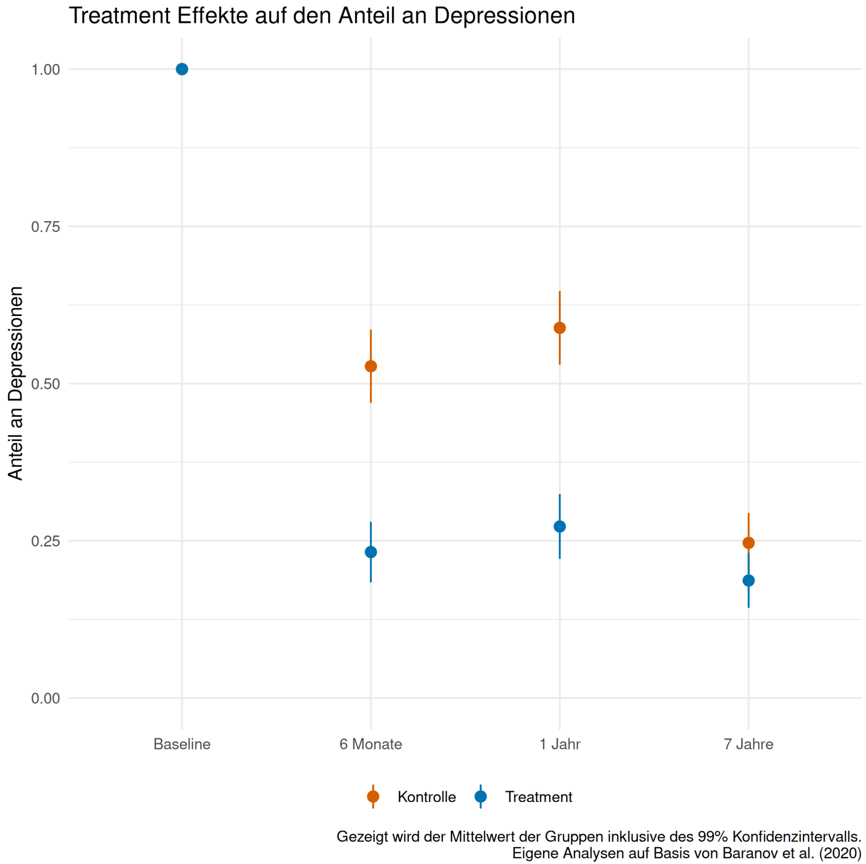
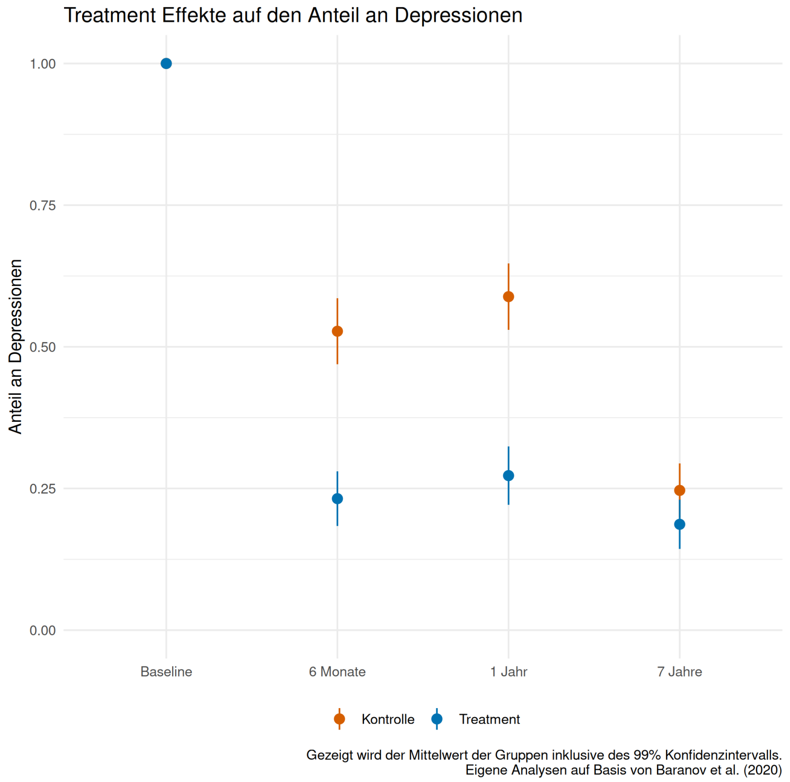
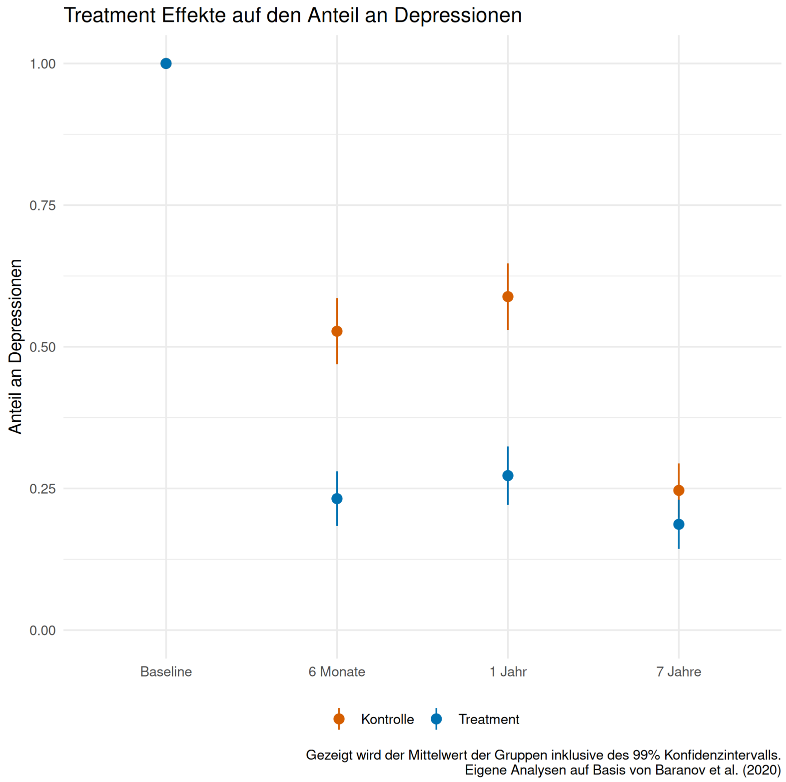



Schritt 2: Durchschnittliche Differenzen



- Die Treatmentgruppe hat einen sehr raschen Rückgang bei den Depressionen
  - Bereits nach 6 Monaten auf rund 25%
  - Stagniert auf rund 25% auch nach einem Jahr
  - Geht zurück auf unter 20% nach sieben Jahren
- Die Kontrollgruppe verzeichnet auch einen starken Rückgang der Depressionen
  - Nach 6 Monaten auf etwas mehr als 50%
  - Stagniert bei etwas über 50% auch nach einem Jahr
  - Geht zurück auf rund 25% nach sieben Jahren

Schritt 2: Durchschnittliche Differenzen



- Die Treatmentgruppe hat einen sehr raschen Rückgang bei den Depressionen
  - Bereits nach 6 Monaten auf rund 25%
  - Stagniert auf rund 25% auch nach einem Jahr
  - Geht zurück auf unter 20% nach sieben Jahren
- Die Kontrollgruppe verzeichnet auch einen starken Rückgang der Depressionen
  - Nach 6 Monaten auf etwas mehr als 50%
  - Stagniert bei etwas über 50% auch nach einem Jahr
  - Geht zurück auf rund 25% nach sieben Jahren

Ein naiver Vergleich nur innerhalb der Treatmentgruppe vorher/nachher würde den Effekt des Treatments stark überschätzen!

Regressionsanalysen

Schritt 2: Durchschnittliche Differenzen

count: false

```r
thp
```

```
# A tibble: 1,203 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>           <d
 1    NA          NA     1 <NA>        <NA>
 2   226           1     1 No          No
 3   222           6     1 Yes         No
 4     3           1     1 No          No
 5   217           3     1 No          No
 6   354           1     1 Yes         No
 7    NA          NA     1 <NA>        <NA>
 8    NA          NA     1 <NA>        <NA>
 9   225           4     1 No          No
10     2           4     1 Yes         No
# ℹ 1,193 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
```

```
# A tibble: 585 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>            <d
 1   226           1     1 No          No
 2     3           1     1 No          No
 3   354           1     1 Yes         No
 4   225           4     1 No          No
 5     2           4     1 Yes         No
 6   729           1     1 No          No
 7   228           4     1 No          No
 8   180           4     1 No          No
 9   178           1     1 No          No
10   224           7     1 Yes         No
# ℹ 575 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat)
```

```
# A tibble: 585 × 394
# Groups:   treat [2]
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>            <d
 1   226           1     1 No          No
 2     3           1     1 No          No
 3   354           1     1 Yes         No
 4   225           4     1 No          No
 5     2           4     1 Yes         No
 6   729           1     1 No          No
 7   228           4     1 No          No
 8   180           4     1 No          No
 9   178           1     1 No          No
10   224           7     1 Yes         No
# ℹ 575 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp
```

```
# A tibble: 1,203 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>          <d
 1    NA          NA     1 <NA>        <NA>
 2   226           1     1 No          No
 3   222           6     1 Yes         No
 4     3           1     1 No          No
 5   217           3     1 No          No
 6   354           1     1 Yes         No
 7    NA          NA     1 <NA>        <NA>
 8    NA          NA     1 <NA>        <NA>
 9   225           4     1 No          No
10     2           4     1 Yes         No
# ℹ 1,193 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
```

```
# A tibble: 585 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>          <d
 1   226           1     1 No          No
 2     3           1     1 No          No
 3   354           1     1 Yes         No
 4   225           4     1 No          No
 5     2           4     1 Yes         No
 6   729           1     1 No          No
 7   228           4     1 No          No
 8   180           4     1 No          No
 9   178           1     1 No          No
10   224           7     1 Yes         No
# i 575 more rows
# i 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(c

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat)
```

```
# A tibble: 585 × 394
# Groups:   treat [2]
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>          <d
 1   226           1     1 No          No
 2     3           1     1 No          No
 3   354           1     1 Yes         No
 4   225           4     1 No          No
 5     2           4     1 Yes         No
 6   729           1     1 No          No
 7   228           4     1 No          No
 8   180           4     1 No          No
 9   178           1     1 No          No
10   224           7     1 Yes         No
# ℹ 575 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp
```

```
# A tibble: 1,203 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>          <d
 1    NA          NA     1 <NA>        <NA>
 2   226           1     1 No          No
 3   222           6     1 Yes         No
 4     3           1     1 No          No
 5   217           3     1 No          No
 6   354           1     1 Yes         No
 7    NA          NA     1 <NA>        <NA>
 8    NA          NA     1 <NA>        <NA>
 9   225           4     1 No          No
10     2           4     1 Yes         No
# ℹ 1,193 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
```

```
# A tibble: 585 × 394
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>          <d
 1   226           1     1 No          No
 2     3           1     1 No          No
 3   354           1     1 Yes         No
 4   225           4     1 No          No
 5     2           4     1 Yes         No
 6   729           1     1 No          No
 7   228           4     1 No          No
 8   180           4     1 No          No
 9   178           1     1 No          No
10   224           7     1 Yes         No
# ℹ 575 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat)
```

```
# A tibble: 585 × 394
# Groups:   treat [2]
   newid interviewer    uc grandmother employed_mo income
   <dbl>       <dbl> <dbl> <chr>       <chr>            <d
 1   226           1     1 No          No
 2     3           1     1 No          No
 3   354           1     1 Yes         No
 4   225           4     1 No          No
 5     2           4     1 Yes         No
 6   729           1     1 No          No
 7   228           4     1 No          No
 8   180           4     1 No          No
 9   178           1     1 No          No
10   224           7     1 Yes         No
# ℹ 575 more rows
# ℹ 386 more variables: edu_mo <dbl>, edu_fa <dbl>, ideal
#   no_kids_over5_dead <dbl>, no_kids_1_5_dead <dbl>, no_
#   mo_185 <chr>, mo_358 <chr>, mo_360 <chr>, c_wt <dbl>,
#   ch_27 <chr>, ch_28 <chr>, ch_29 <chr>, ch_30 <chr>, c
#   ch_32 <chr>, ch_33 <chr>, ch_34 <chr>, ch_35 <chr>, c
#   mo_ht <dbl>, mo_bmi <dbl>, hamd_baseline <dbl>, bdq_b
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1
```

```
# A tibble: 2 × 2
  treat dep6m_avg
  <dbl>     <dbl>
1     0     0.522
2     1     0.201
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2)
```

```
# A tibble: 4 × 3
  treat dep6m_avg depressed_1y
  <dbl>     <dbl>        <dbl>
1     0     0.522       NA
2     1     0.201       NA
3     0    NA            0.583
4     1    NA            0.249
```

```
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2) %>%
  bind_rows(dep3)
```

```
# A tibble: 6 × 4
  treat dep6m_avg depressed_1y depressed_avg
  <dbl>     <dbl>        <dbl>         <dbl>
1     0     0.522       NA            NA
2     1     0.201       NA            NA
3     0    NA            0.583        NA
4     1    NA            0.249        NA
5     0    NA           NA             0.304
6     1    NA           NA             0.239
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2) %>%
  bind_rows(dep3) %>%
  pivot_longer(cols = -treat, names_t
```

```
# A tibble: 18 × 3
   treat depression     value
   <dbl> <chr>          <dbl>
 1     0 dep6m_avg      0.522
 2     0 depressed_1y  NA
 3     0 depressed_avg NA
 4     1 dep6m_avg      0.201
 5     1 depressed_1y  NA
 6     1 depressed_avg NA
 7     0 dep6m_avg     NA
 8     0 depressed_1y   0.583
 9     0 depressed_avg NA
10     1 dep6m_avg     NA
11     1 depressed_1y   0.249
12     1 depressed_avg NA
13     0 dep6m_avg     NA
14     0 depressed_1y  NA
15     0 depressed_avg  0.304
16     1 dep6m_avg     NA
17     1 depressed_1y  NA
18     1 depressed_avg  0.239
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2) %>%
  bind_rows(dep3) %>%
  pivot_longer(cols = -treat, names_t
  filter( !is.na(value) )
```

```
# A tibble: 6 × 3
  treat depression    value
  <dbl> <chr>         <dbl>
1     0 dep6m_avg     0.522
2     1 dep6m_avg     0.201
3     0 depressed_1y  0.583
4     1 depressed_1y  0.249
5     0 depressed_avg 0.304
6     1 depressed_avg 0.239
```

```
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2) %>%
  bind_rows(dep3) %>%
  pivot_longer(cols = -treat, names_t
  filter( !is.na(value) ) %>%
  pivot_wider( names_from = depressic
```

```
# A tibble: 2 × 4
  treat dep6m_avg depressed_1y depressed_avg
  <dbl>     <dbl>        <dbl>         <dbl>
1     0     0.522        0.583         0.304
2     1     0.201        0.249         0.239
```

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2) %>%
  bind_rows(dep3) %>%
  pivot_longer(cols = -treat, names_t
  filter( !is.na(value) ) %>%
  pivot_wider( names_from = depressic
  kbl(col.names = c("Treatment", "6 M
```

Treatment	6 Monate	1 Jahr	7 Jahre
0	0.522	0.583	0.304
1	0.201	0.249	0.239

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2) %>%
  bind_rows(dep3) %>%
  pivot_longer(cols = -treat, names_t
  filter( !is.na(value) ) %>%
  pivot_wider( names_from = depressic
  kbl(col.names = c("Treatment", "6 M
  kable_styling(bootstrap_options = c
```

Treatment	6 Monate	1 Jahr	7 Jahre
0	0.522	0.583	0.304
1	0.201	0.249	0.239

```
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2) %>%
  bind_rows(dep3) %>%
  pivot_longer(cols = -treat, names_t
  filter( !is.na(value) ) %>%
  pivot_wider( names_from = depressio
  kbl(col.names = c("Treatment", "6 M
  kable_styling(bootstrap_options = c
  kable_paper(full_width = F)
```

Treatment	6 Monate	1 Jahr	7 Jahre
0	0.522	0.583	0.304
1	0.201	0.249	0.239

```r
thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( dep6m_avg = round(mean(d

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_1y = round(mea

thp %>%
  filter(attrit2 == 0 & THP_sample ==
  group_by(treat) %>%
  summarize( depressed_avg = round(me

dep1 %>%
  bind_rows(dep2) %>%
  bind_rows(dep3) %>%
  pivot_longer(cols = -treat, names_t
  filter( !is.na(value) ) %>%
  pivot_wider( names_from = depressic
  kbl(col.names = c("Treatment", "6 M
  kable_styling(bootstrap_options = c
  kable_paper(full_width = F)  %>%
  add_header_above(c(" ", "Anteil an
```

	Anteil an Depressionen		
Treatment	6 Monate	1 Jahr	7 Jahre
0	0.522	0.583	0.304
1	0.201	0.249	0.239

Schritt 2: Durchschnittliche Differenzen

	Anteil an Depressionen		
Treatment	6 Monate	1 Jahr	7 Jahre
0	0.522	0.583	0.304
1	0.201	0.249	0.239

Schritt 2: Durchschnittliche Differenzen

```
reg_dep6m <- lm(depressed_6m ~ treat, data = filter(thp, attrit2 == 0 & THP_sample == 1))
reg_dep6m_long <- lm(depressed_6m ~ treat + age_baseline + age_baseline_sq + employed_mo_baseline

reg_dep1y <- lm(depressed_1y ~ treat, data =  filter(thp, attrit2 == 0 & THP_sample == 1))
reg_dep1y_long <- lm(depressed_1y ~ treat + age_baseline + age_baseline_sq + employed_mo_baseline

reg_dep7y <- lm(depressed ~ treat, data = filter(thp, attrit2 == 0 & THP_sample == 1))
reg_dep7y_long <- lm(depressed ~ treat + age_baseline + age_baseline_sq + employed_mo_baseline +

rows <- tribble(~term,          ~reg_dep6m,  ~reg_dep6m_long, ~reg_dep1y, ~reg_dep1y_long, ~reg_d
                "Kontrollvariablen", "Nein", "Ja", "Nein", "Ja", "Nein", "Ja")

attr(rows, 'position') <- c(3)

modelsummary(list(reg_dep6m, reg_dep6m_long, reg_dep1y, reg_dep1y_long, reg_dep7y, reg_dep7y_long
          type = "html",
          covariate.labels = c("Treatment"),
          keep = "treat",
          add_rows = rows,
          fmt = 2,
          statistic = 'conf.int',
          conf_level = .99,
          gof_omit = 'DF|Deviance|RMSE|AIC|BIC|Log.Lik',
          add.lines = list(c("Kontrollvariablen", "Nein", "Ja", "Nein", "Ja", "Nein", "Ja")),
          title = "Depression bei Müttern, mit und ohne Kontrollvariablen") %>%
          add_header_above(c(" " = 1,"Nach 6 Monaten" = 2, "Nach 1 Jahr" = 2, "Nach 7 Jahren" = 2
```

Schritt 2: Durchschnittliche Differenzen

Depression bei Müttern, mit und ohne Kontrollvariablen

	Nach 6 Monaten		Nach 1 Jahr		Nach 7 Jahren	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Treatment	−0.32	−0.32	−0.33	−0.31	−0.07	−0.05
	[−0.42, −0.22]	[−0.42, −0.22]	[−0.43, −0.23]	[−0.41, −0.21]	[−0.16, 0.03]	[−0.14, 0.05]
Kontrollvariablen	Nein	Ja	Nein	Ja	Nein	Ja
Num.Obs.	584	584	584	584	585	585
R2	0.112	0.221	0.115	0.230	0.005	0.165
R2 Adj.	0.110	0.181	0.113	0.192	0.004	0.123

GEGENÜBERSTELLUNG DER DURCHSCHNITTLICHEN DIFFERENZEN

	Anteil an Depressionen		
Treatment	6 Monate	1 Jahr	7 Jahre
0	0.522	0.583	0.304
1	0.201	0.249	0.239

Depression bei Müttern, mit und ohne Kontrollvariablen

	Nach 6 Monaten		**Nach 1 Jahr**		**Nach 7 Jahren**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Treatment	−0.32	−0.32	−0.33	−0.31	−0.07	−0.05
	[−0.42, −0.22]	[−0.42, −0.22]	[−0.43, −0.23]	[−0.41, −0.21]	[−0.16, 0.03]	[−0.14, 0.05]
Kontrollvariablen	Nein	Ja	Nein	Ja	Nein	Ja
Num.Obs.	584	584	584	584	585	585
R2	0.112	0.221	0.115	0.230	0.005	0.165
R2 Adj.	0.110	0.181	0.113	0.192	0.004	0.123

Schritt 2: Durchschnittliche Differenzen

Sollten wir für irgendwelche Variablen kontrollieren?

Schritt 2: Durchschnittliche Differenzen

Sollten wir für irgendwelche Variablen kontrollieren?

Nein, wir sollten für nichts kontrollieren!

Alle Pfeile in das Treatment wurden im DAG gelöscht, daher gibt es auch theoretisch keine Confounder auf die wir kontrollieren müssten.

Schritt 2: Durchschnittliche Differenzen

count: false

```
reg_financial <- lm(motherfinancial ~
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T)
```

```
# A tibble: 2 × 7
  term              estimate std.error   statistic   p.val
  <chr>                <dbl>     <dbl>       <dbl>     <db
1 (Intercept) 0.00000000741     0.0593 0.000000125 1.00
2 treat       0.341             0.0843 4.04        0.00006
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
```

```
# A tibble: 2 × 7
  term          estimate std.error   statistic   p.val
  <chr>            <dbl>     <dbl>       <dbl>     <db
1 (Intercept) 0.00000000741    0.0593 0.000000125 1.00
2 fin_emp     0.341            0.0843 4.04        0.00006
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
```

```
# A tibble: 4 × 7
  term        estimate std.error    statistic   p.value c
  <chr>          <dbl>     <dbl>        <dbl>     <dbl>
1 (Intercept) 7.41e- 9    0.0593 0.000000125  1.00
2 fin_emp     3.41e- 1    0.0843 4.04         0.0000608
3 (Intercept) 8.03e-10    0.0580 0.0000000138 1.00
4 treat       3.57e- 1    0.0825 4.33         0.0000173
```

```r
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
```

```
# A tibble: 4 × 7
  term        estimate std.error    statistic   p.value c
  <chr>          <dbl>     <dbl>        <dbl>     <dbl>
1 (Intercept) 7.41e- 9    0.0593 0.000000125  1.00
2 fin_emp     3.41e- 1    0.0843 4.04         0.0000608
3 (Intercept) 8.03e-10    0.0580 0.0000000138 1.00
4 money       3.57e- 1    0.0825 4.33         0.0000173
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
```

```
# A tibble: 6 × 7
  term          estimate std.error statistic   p.value con
  <chr>            <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)   7.41e- 9    0.0593  1.25e- 7 1.00        -
2 fin_emp       3.41e- 1    0.0843  4.04e+ 0 0.0000608
3 (Intercept)   8.03e-10    0.0580  1.38e- 8 1.00        -
4 money         3.57e- 1    0.0825  4.33e+ 0 0.0000173
5 (Intercept) -1.35e-11    0.0566 -2.39e-10 1.00        -
6 treat         3.19e- 1    0.0805  3.96e+ 0 0.0000847
```

```r
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
```

```
# A tibble: 6 × 7
  term         estimate std.error statistic   p.value con
  <chr>           <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)  7.41e- 9    0.0593  1.25e- 7 1.00         -
2 fin_emp      3.41e- 1    0.0843  4.04e+ 0 0.0000608
3 (Intercept)  8.03e-10    0.0580  1.38e- 8 1.00         -
4 money        3.57e- 1    0.0825  4.33e+ 0 0.0000173
5 (Intercept) -1.35e-11    0.0566 -2.39e-10 1.00         -
6 time         3.19e- 1    0.0805  3.96e+ 0 0.0000847
```

```r
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
```

```
# A tibble: 8 × 7
  term         estimate std.error statistic   p.value con
  <chr>           <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)  7.41e- 9    0.0593  1.25e- 7 1.00         -0
2 fin_emp      3.41e- 1    0.0843  4.04e+ 0 0.0000608    0
3 (Intercept)  8.03e-10    0.0580  1.38e- 8 1.00         -0
4 money        3.57e- 1    0.0825  4.33e+ 0 0.0000173    0
5 (Intercept) -1.35e-11    0.0566 -2.39e-10 1.00         -0
6 time         3.19e- 1    0.0805  3.96e+ 0 0.0000847    0
7 (Intercept) -1.69e- 9    0.0577 -2.94e- 8 1.00         -0
8 treat        6.31e- 2    0.0820  7.69e- 1 0.442        -0
```

```r
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
```

```
# A tibble: 8 × 7
  term         estimate std.error statistic   p.value con
  <chr>           <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)  7.41e- 9    0.0593  1.25e- 7 1.00          -0
2 fin_emp      3.41e- 1    0.0843  4.04e+ 0 0.0000608  0
3 (Intercept)  8.03e-10    0.0580  1.38e- 8 1.00          -0
4 money        3.57e- 1    0.0825  4.33e+ 0 0.0000173  0
5 (Intercept) -1.35e-11    0.0566 -2.39e-10 1.00          -0
6 time         3.19e- 1    0.0805  3.96e+ 0 0.0000847  0
7 (Intercept) -1.69e- 9    0.0577 -2.94e- 8 1.00          -0
8 style        6.31e- 2    0.0820  7.69e- 1 0.442         -0
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
```

```
# A tibble: 10 × 7
   term         estimate std.error statistic   p.value co
   <chr>           <dbl>     <dbl>     <dbl>     <dbl>
 1 (Intercept)  7.41e- 9    0.0593  1.25e- 7 1.00      -
 2 fin_emp      3.41e- 1    0.0843  4.04e+ 0 0.0000608
 3 (Intercept)  8.03e-10    0.0580  1.38e- 8 1.00      -
 4 money        3.57e- 1    0.0825  4.33e+ 0 0.0000173
 5 (Intercept) -1.35e-11    0.0566 -2.39e-10 1.00      -
 6 time         3.19e- 1    0.0805  3.96e+ 0 0.0000847
 7 (Intercept) -1.69e- 9    0.0577 -2.94e- 8 1.00      -
 8 style        6.31e- 2    0.0820  7.69e- 1 0.442     -
 9 (Intercept) -2.40e- 9    0.0584 -4.11e- 8 1.00      -
10 treat        1.67e- 2    0.0831  2.00e- 1 0.841     -
```

```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
```

```
# A tibble: 10 × 7
   term         estimate std.error statistic   p.value co
   <chr>           <dbl>     <dbl>     <dbl>     <dbl>
 1 (Intercept)  7.41e- 9    0.0593  1.25e- 7 1.00        -
 2 fin_emp      3.41e- 1    0.0843  4.04e+ 0 0.0000608
 3 (Intercept)  8.03e-10    0.0580  1.38e- 8 1.00        -
 4 money        3.57e- 1    0.0825  4.33e+ 0 0.0000173
 5 (Intercept) -1.35e-11    0.0566 -2.39e-10 1.00        -
 6 time         3.19e- 1    0.0805  3.96e+ 0 0.0000847
 7 (Intercept) -1.69e- 9    0.0577 -2.94e- 8 1.00        -
 8 style        6.31e- 2    0.0820  7.69e- 1 0.442       -
 9 (Intercept) -2.40e- 9    0.0584 -4.11e- 8 1.00        -
10 fertility    1.67e- 2    0.0831  2.00e- 1 0.841       -
```

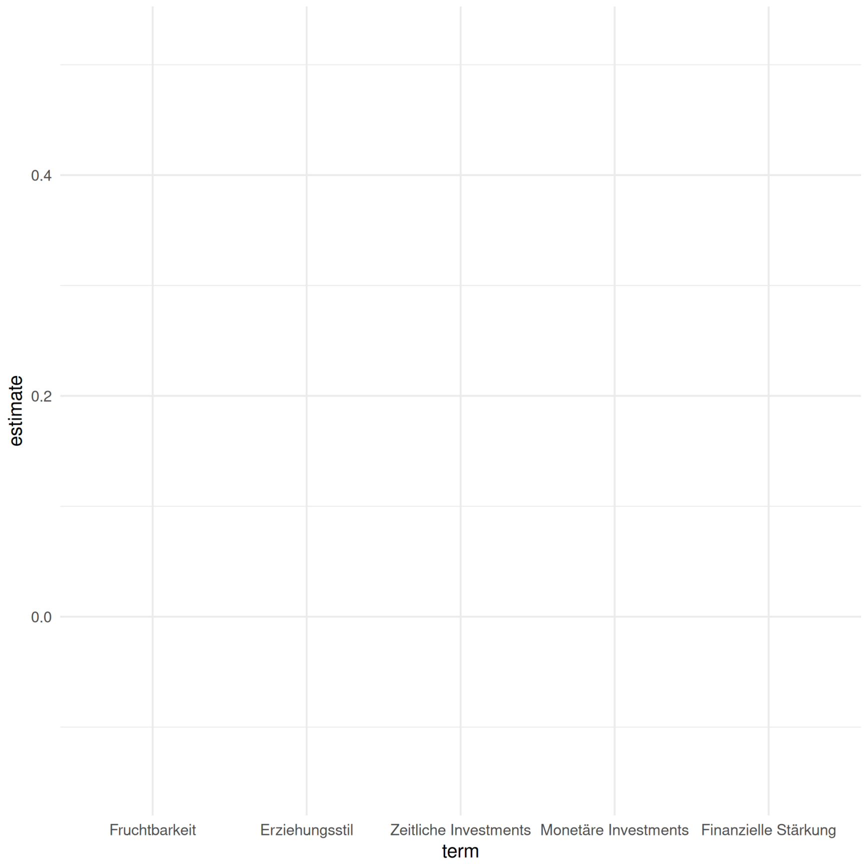
```r
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)")
```

```
# A tibble: 5 × 7
  term      estimate std.error statistic   p.value conf.l
  <chr>        <dbl>     <dbl>     <dbl>     <dbl>    <db
1 fin_emp     0.341     0.0843     4.04  0.0000608   0.17
2 money       0.357     0.0825     4.33  0.0000173   0.19
3 time        0.319     0.0805     3.96  0.0000847   0.16
4 style       0.0631    0.0820     0.769 0.442      -0.09
5 fertility   0.0167    0.0831     0.200 0.841      -0.14
```

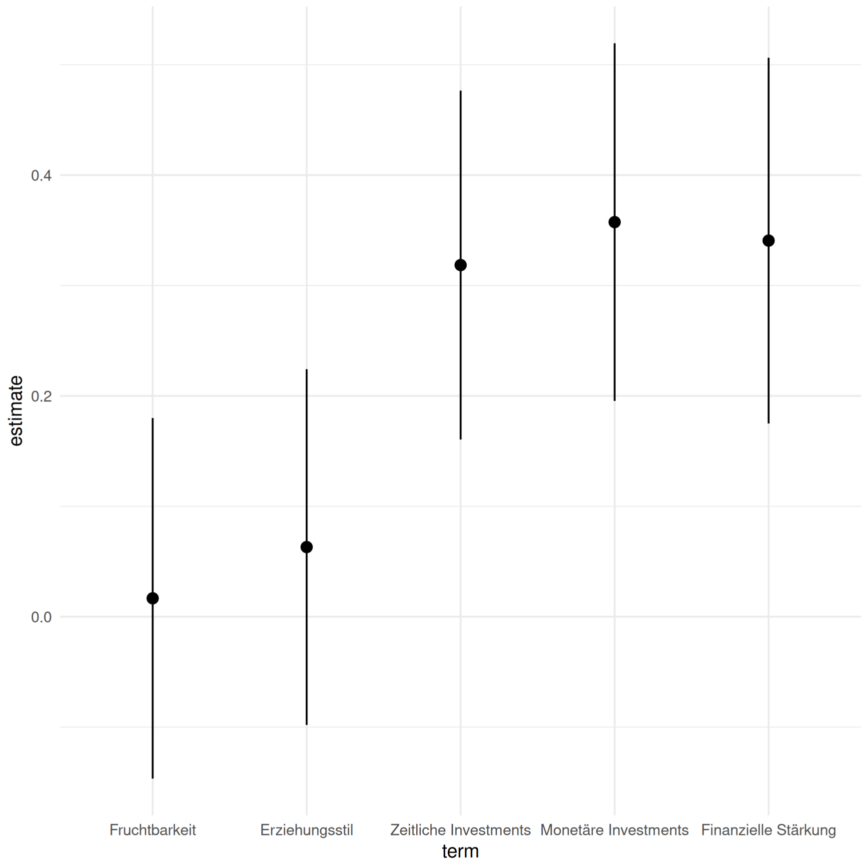
```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)") %>%
    mutate(term = fct_relevel(term, "
           term = fct_recode(term,
                              "Finanziel
                              "Monetäre
                              "Zeitliche
                              "Erziehung
                              "Fruchtbar
```

```
# A tibble: 5 × 7
  term                      estimate std.error statistic   p.v
  <fct>                        <dbl>     <dbl>     <dbl>     <
1 Finanzielle Stärkung        0.341     0.0843     4.04    6.0
2 Monetäre Investments        0.357     0.0825     4.33    1.7
3 Zeitliche Investments       0.319     0.0805     3.96    8.4
4 Erziehungsstil              0.0631    0.0820     0.769   4.4
5 Fruchtbarkeit               0.0167    0.0831     0.200   8.4
```

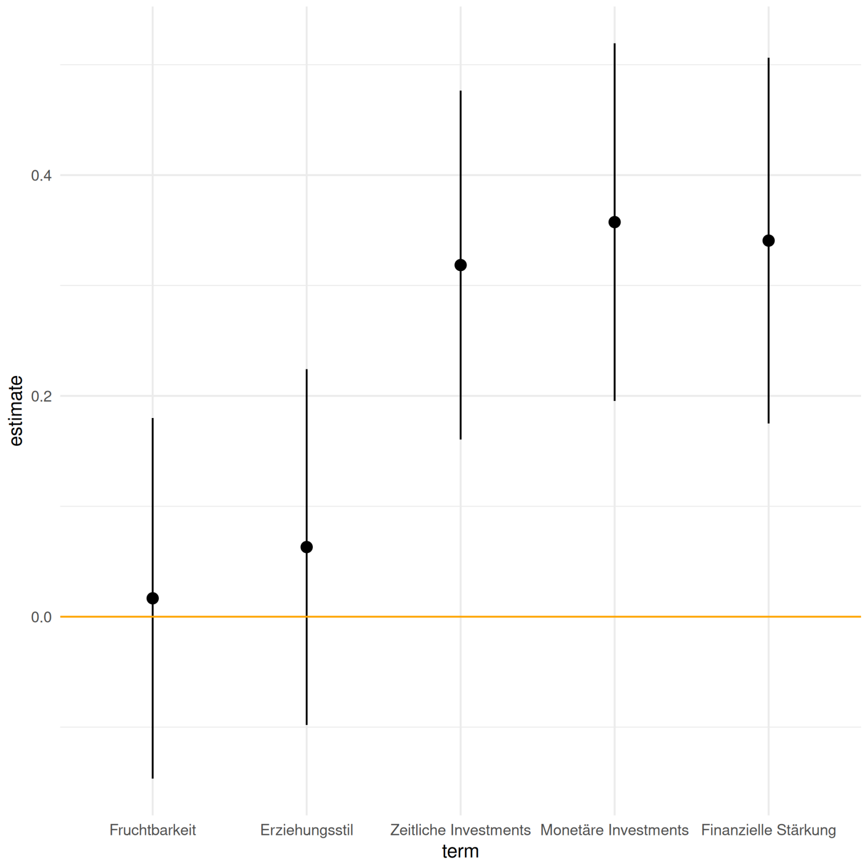
```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)") %>%
    mutate(term = fct_relevel(term, "
           term = fct_recode(term,
                               "Finanziel
                               "Monetäre
                               "Zeitliche
                               "Erziehung
                               "Fruchtbar
  ggplot(aes(x = term, y=estimate, ym
```



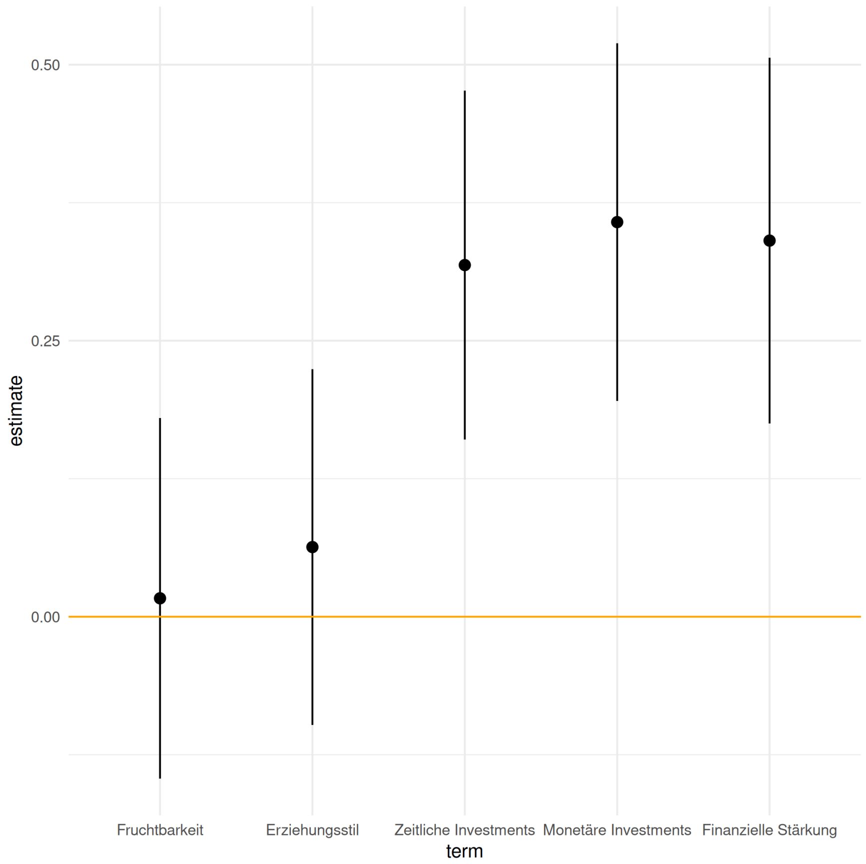
```r
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)") %>%
    mutate(term = fct_relevel(term, "
           term = fct_recode(term,
                             "Finanziel
                             "Monetäre
                             "Zeitliche
                             "Erziehung
                             "Fruchtbar
  ggplot(aes(x = term, y=estimate, ym
  geom_pointrange()
```



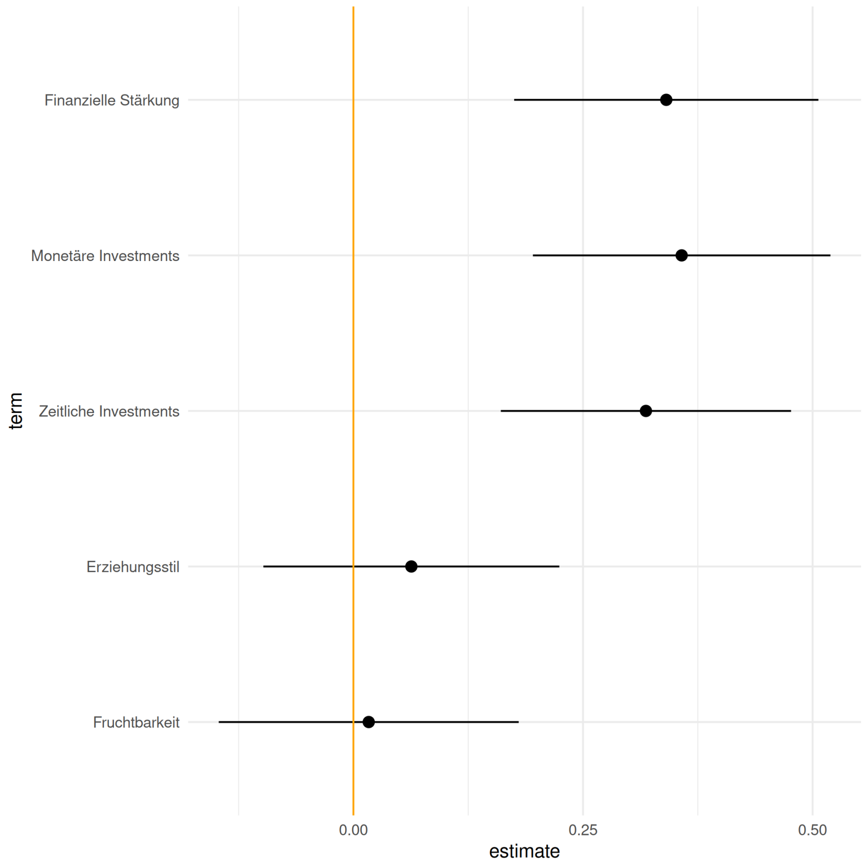
```r
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)") %>%
    mutate(term = fct_relevel(term, "
           term = fct_recode(term,
                              "Finanziel
                              "Monetäre
                              "Zeitliche
                              "Erziehung
                              "Fruchtbar
  ggplot(aes(x = term, y=estimate, ym
  geom_pointrange() +
  geom_hline(yintercept = 0, col = "c
```



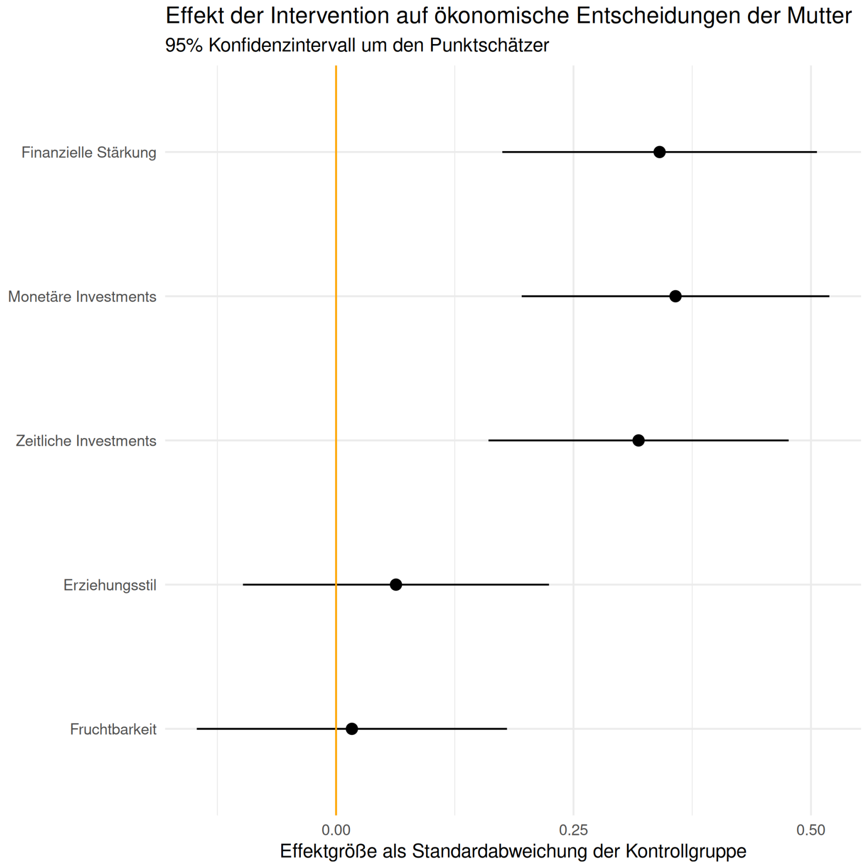
```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)") %>%
    mutate(term = fct_relevel(term, "
           term = fct_recode(term,
                            "Finanziel
                            "Monetäre
                            "Zeitliche
                            "Erziehung
                            "Fruchtbar
  ggplot(aes(x = term, y=estimate, ym
  geom_pointrange() +
  geom_hline(yintercept = 0, col = "c
  scale_y_continuous(breaks = c(-0.25
```



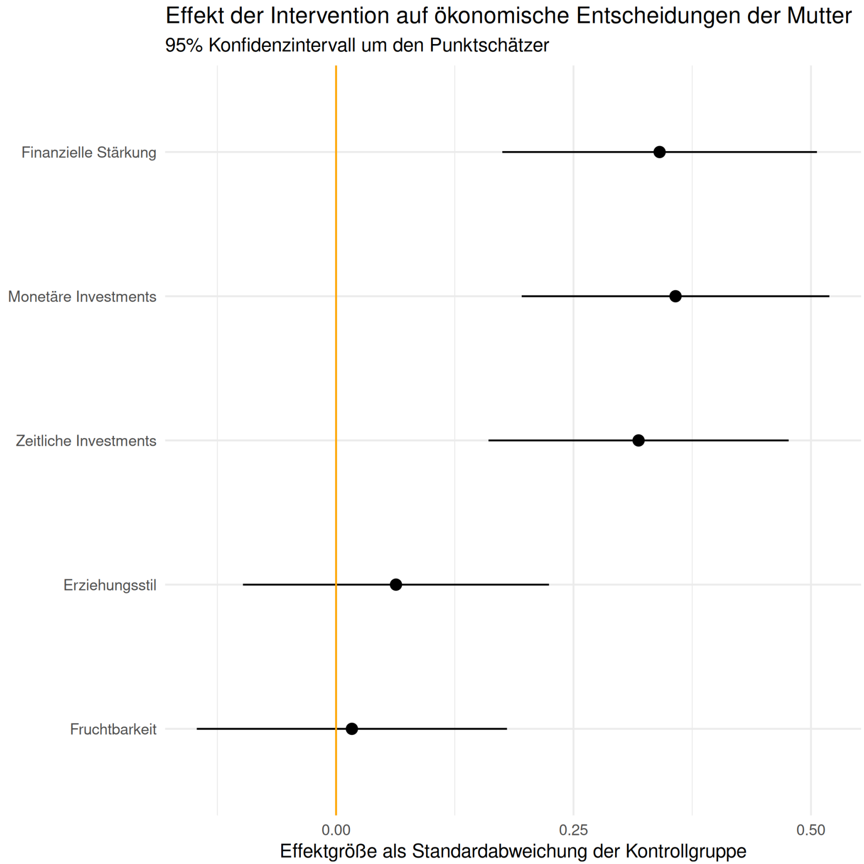
```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)") %>%
    mutate(term = fct_relevel(term, "
           term = fct_recode(term,
                              "Finanziel
                              "Monetäre
                              "Zeitliche
                              "Erziehung
                              "Fruchtbar
  ggplot(aes(x = term, y=estimate, ym
  geom_pointrange() +
  geom_hline(yintercept = 0, col = "c
  scale_y_continuous(breaks = c(-0.25
  coord_flip()
```



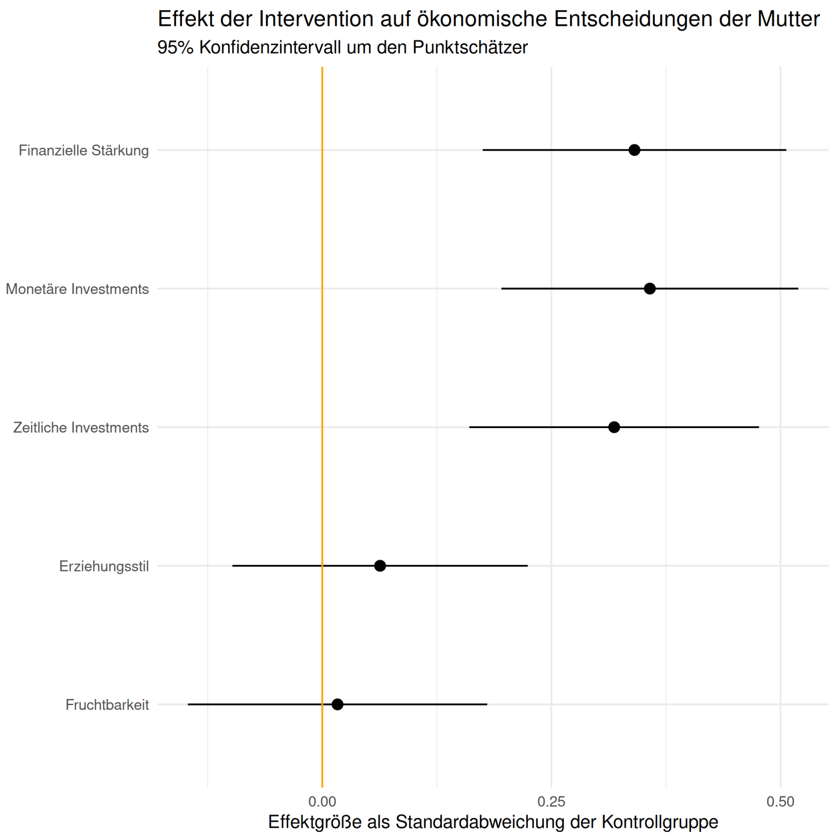
```r
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)") %>%
    mutate(term = fct_relevel(term, "
           term = fct_recode(term,
                           "Finanziel
                           "Monetäre
                           "Zeitliche
                           "Erziehung
                           "Fruchtbar
  ggplot(aes(x = term, y=estimate, ym
  geom_pointrange() +
  geom_hline(yintercept = 0, col = "c
  scale_y_continuous(breaks = c(-0.25
  coord_flip() +
  labs(
    x = NULL, y = "Effektgröße als St
    title = "Effekt der Intervention
    subtitle = "95% Konfidenzinterval
    )
```



```
reg_financial <- lm(motherfinancial ~
reg_money <- lm(parentmoney ~ treat,
reg_time<- lm(parenttime ~ treat, dat
reg_style <- lm(parentstyle ~ treat,
reg_fertility <- lm(fertility_vars ~


tidy(reg_financial, conf.int = T) %>%
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_money, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_time, conf.int =
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_style, conf.int
  mutate(term = ifelse( term == "trea
  bind_rows(tidy(reg_fertility, conf.
  mutate(term = ifelse( term == "trea
  filter( term != "(Intercept)") %>%
    mutate(term = fct_relevel(term, "
           term = fct_recode(term,
                             "Finanziel
                             "Monetäre
                             "Zeitliche
                             "Erziehung
                             "Fruchtbar
  ggplot(aes(x = term, y=estimate, ym
  geom_pointrange() +
  geom_hline(yintercept = 0, col = "c
  scale_y_continuous(breaks = c(-0.25
  coord_flip() +
  labs(
    x = NULL, y = "Effektgröße als St
    title = "Effekt der Intervention
    subtitle = "95% Konfidenzinterval
    ) +
```



Schritt 2: Durchschnittliche Differenzen



Experimente als "Goldstandard"?

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Doch Experimente sind meist sehr schwer durchzuführen und in manchen Situationen gar nicht denkbar!

> Was uns interessiert sind kausale Effekte zu messen und dafür sind Experimente eine wichtige Säule, aber nicht die einzige Möglichkeit!

Experimente und interne Validität

Experimente können sehr viele Probleme bzgl. interner Validität lösen

- Selektion
    - Treatment und Kontrollgruppen sind vergleichbar
    - Keine Selbstselektion
- Trends
    - Keine Saisonalität
    - Keine Regression zur Mitte

Experimente und interne Validität

> **Jedoch:** Experimente können nicht das Problem der *Attrition* beheben!

Wenn Attrition mit dem Treatment korreliert ist haben wir ein Problem

Genauer: Wenn Personen selektiv aufhören an der Studie teilzunehmen, in Abhängigkeit davon ob sie getreatet wurden oder nicht, dann hilft uns auch ein sehr schön designtes Experiment nicht weiter.

Experimente und interne Validität

Für unser Experiment:

- Nach 7 Jahren hatten die Autoren noch eine Befragung der Frauen durchgeführt
- Wenn die Attrition in der Treatment und Kontrollgruppen über diese 7 Jahre hinweg unterschiedlich war und nun z.B. doppelt so viele Frauen aus der Kontrollgruppe in der Stichprobe sind, dann wäre die Attrition mit dem Treatment Status korreliert und unsere Aussagen nicht mehr valide

Experimente und interne Validität

Balancing Tabelle für die Grundcharakteristika

	Stichprobe Baseline (N = 585)			
	Treatment	Kontrolle	Differenz	p-Wert
Stiefoma im Haus	0.48	0.39	0.09	0.04
Alter der Mutter	26.71	27.03	-0.32	0.44
Depressiv (1 Jahr)	0.25	0.58	-0.33	0.00
Bildung des Vaters	6.98	7.20	-0.22	0.48
Vater beschäftigt	0.90	0.90	0.00	0.88
Mutter beschäftigt	0.01	0.02	-0.01	0.38
Erstes Kind	0.18	0.17	0.01	0.65
Anzahl der Kinder	2.08	2.42	-0.34	0.02
Oma im Haus	0.08	0.05	0.03	0.11

Note:

Diese Tabelle testet, wie ausbalanciert die Beobachtungen in der Stichprobe nach 7 Jahren sind. In den ersten beiden

Experimente und interne Validität

Es ist wichtig auf Attrition zu achten:

- Versuchen Sie so viele Charakteristika über ihre Teilnehmer zu bekommen wie möglich
- Untersuchen Sie anhand dieser Charakteristika ob die Attrition zwischen den zwei Gruppen zufällig war
- Versuchen Sie das Committment ihrer Teilnehmer am Experiment so hoch wie möglich zu halten

Ein weiteres Problem des Experiments könnte sein, das die Teilnehmer sich nicht an das halten, was sie vorgeben:

- Manche Teilnehmer der Treatment Gruppe werden das Treatment einfach nicht nehmen
- Manche Teilnehmer der Kontrollgruppe werden eventuell doch an das Treatment kommen