Male-Female fertility differences at the regional level

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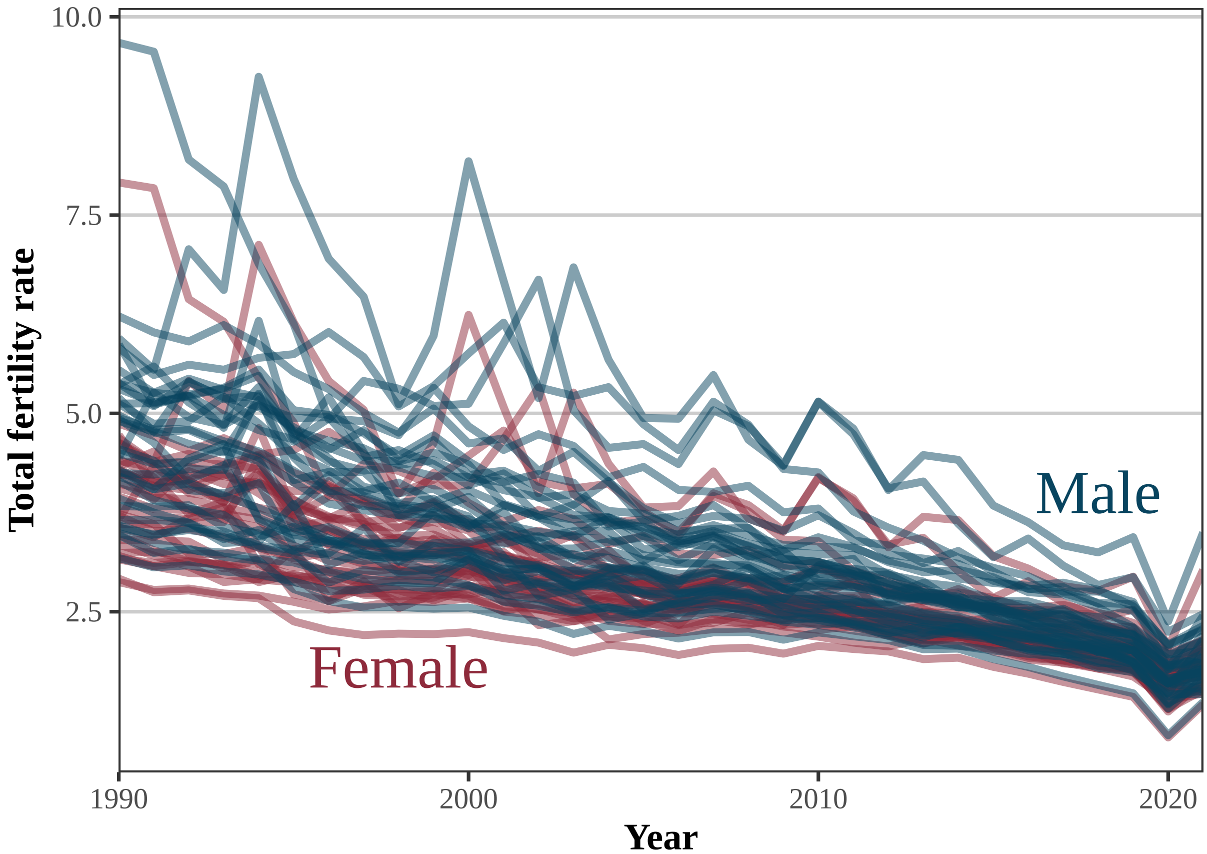
Sub-national level

Now, we are looking at the variation at the sub-national level.

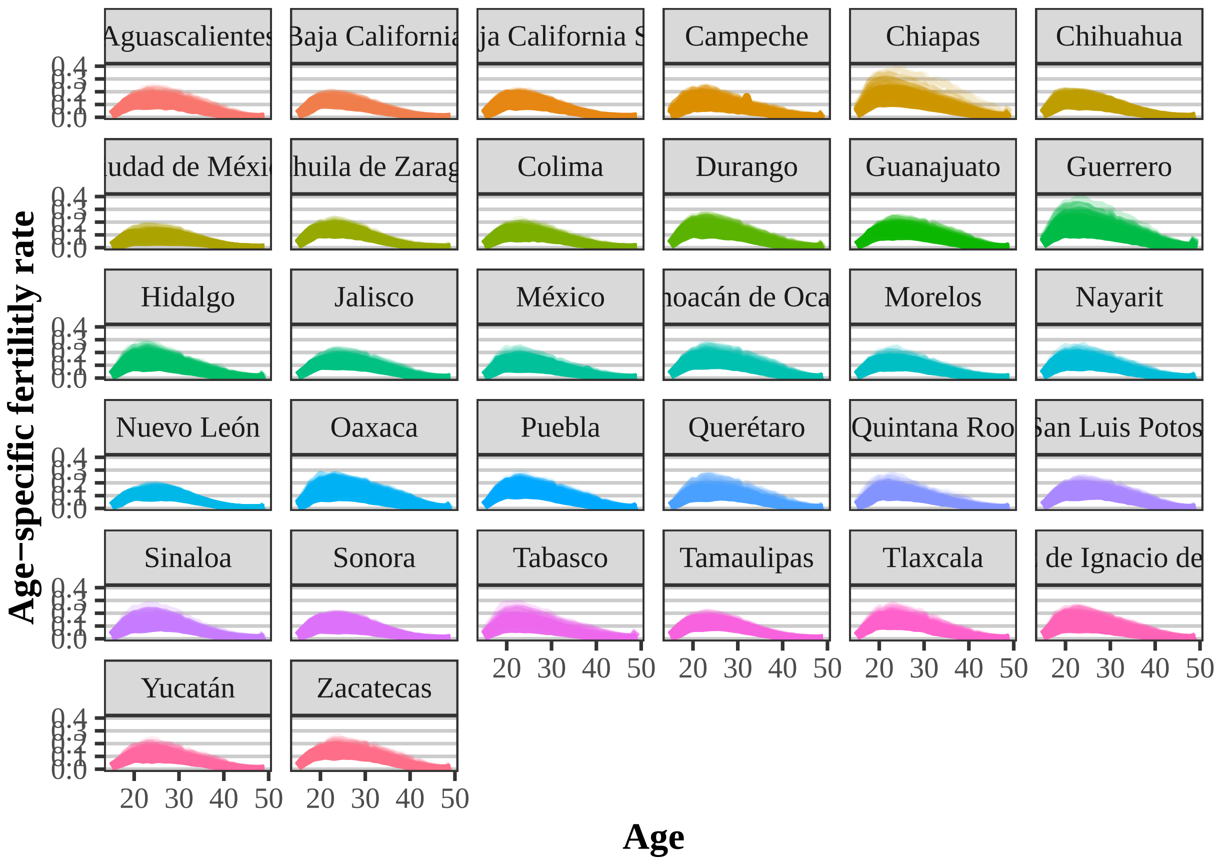
```
# Load the national level data
load("Data/tfr_regional_mexico.Rda")

# What is the trend in the national tfr s
ggplot(tfr_reg, aes(year)) +
  geom_line(aes(y = tfr_f, colour = "female", group = entity), linewidth = 1.4, alpha = 0.5) +
  geom_line(aes(y = tfr_m, colour = "male", group = entity), linewidth = 1.4, alpha = 0.5) +
  annotate(geom = "text",
           x = 2018, y = 4,
           label = "Male",
           colour = MPIDRblue, size = 8, family = "serif") +
  annotate(geom = "text",
           x = 1998, y = 1.8,
           label = "Female",
           colour = MPIDRred, size = 8, family = "serif") +
  scale_colour_manual(values = c(MPIDRred, MPIDRblue)) +
  scale_x_continuous(expand = c(0, 0)) +
  ylab("Total fertility rate") +
  xlab("Year") +
  guides(colour = "none")
```

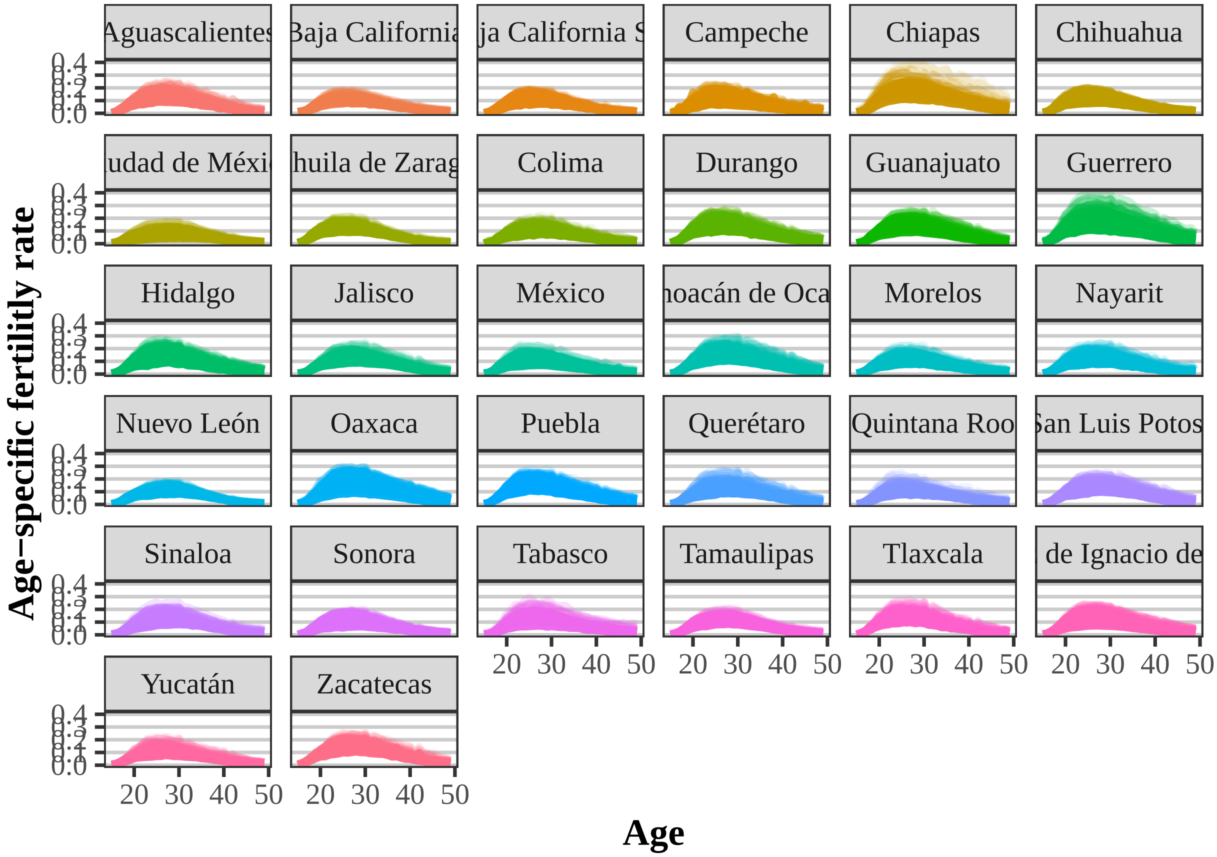



```r
# Load the national level data
load("Data/asfr_regional_mexico.Rda")

# What is the trend in the national TFR for women
ggplot(asfr_reg, aes(x = age, alpha = year)) +
  geom_line(aes(y = asfr_f, colour = entity_name, group = interaction(year, entity)),
            linewidth = 1.4) +
  ylab("Age-specific fertility rate") +
  xlab("Age") +
  facet_wrap(~ entity_name) +
  guides(alpha = "none", colour = "none")
```

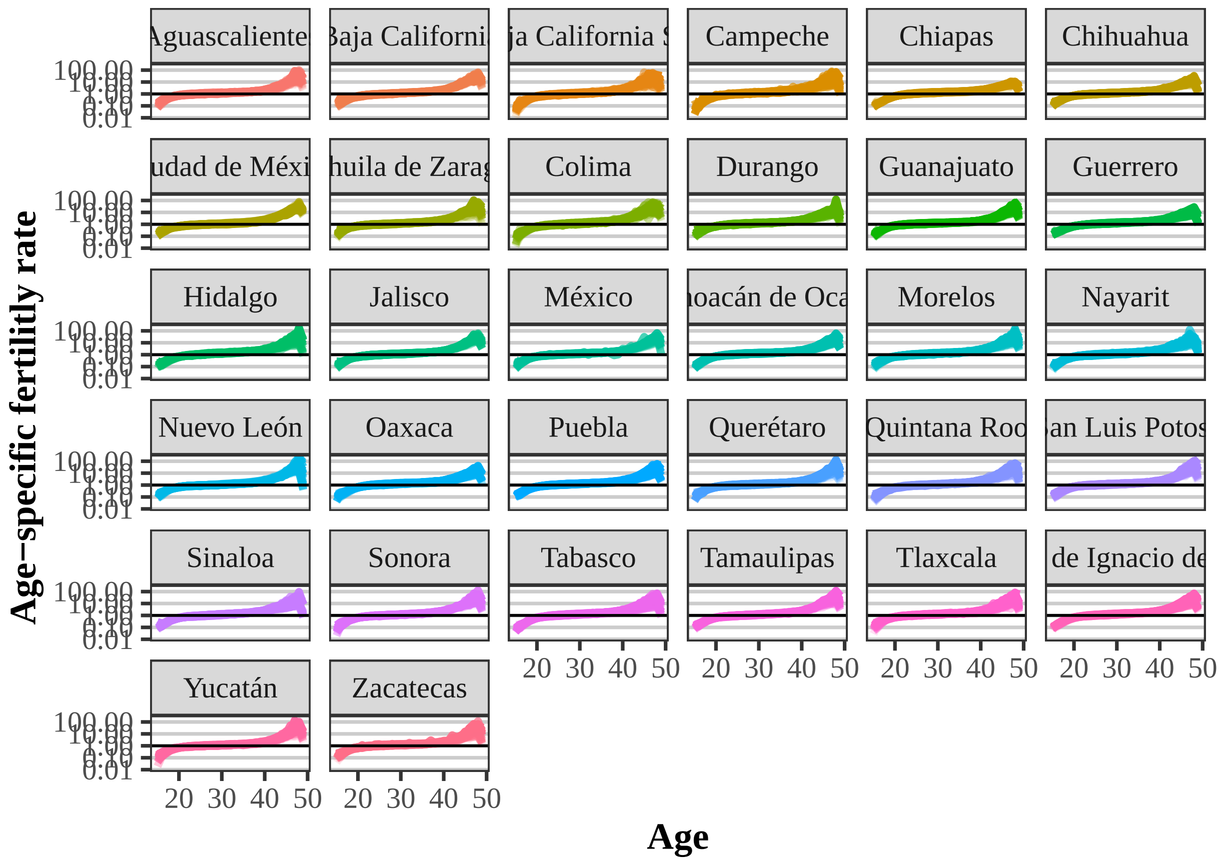



```
# What is the trend in the national TFR for women
ggplot(asfr_reg, aes(x = age, alpha = year)) +
  geom_line(aes(y = asfr_m, colour = entity_name, group = interaction(year, entity)),
            linewidth = 1.4) +
  ylab("Age-specific fertilitly rate") +
  xlab("Age") +
  facet_wrap(~ entity_name) +
  guides(alpha = "none", colour = "none")
```



The graphs are overfull. In order to make the graphics comparable, we estimate the male-to-female asfr ratio

```
# Plot the age-specific fertility rates
asfr_reg %>%
  mutate(asfr_ratio = asfr_m / asfr_f) %>%
  ggplot(aes(x = age, alpha = year)) +
  geom_line(aes(y = asfr_ratio, colour = entity_name, group = interaction(year, entity)),
            linewidth = 1.4) +
  geom_hline(yintercept = 1) +
  ylab("Age-specific fertilitly rate") +
  scale_y_continuous(trans = "log10", labels = scales::label_number_si()) +
  xlab("Age") +
  facet_wrap(~ entity_name) +
  guides(alpha = "none", colour = "none")
```



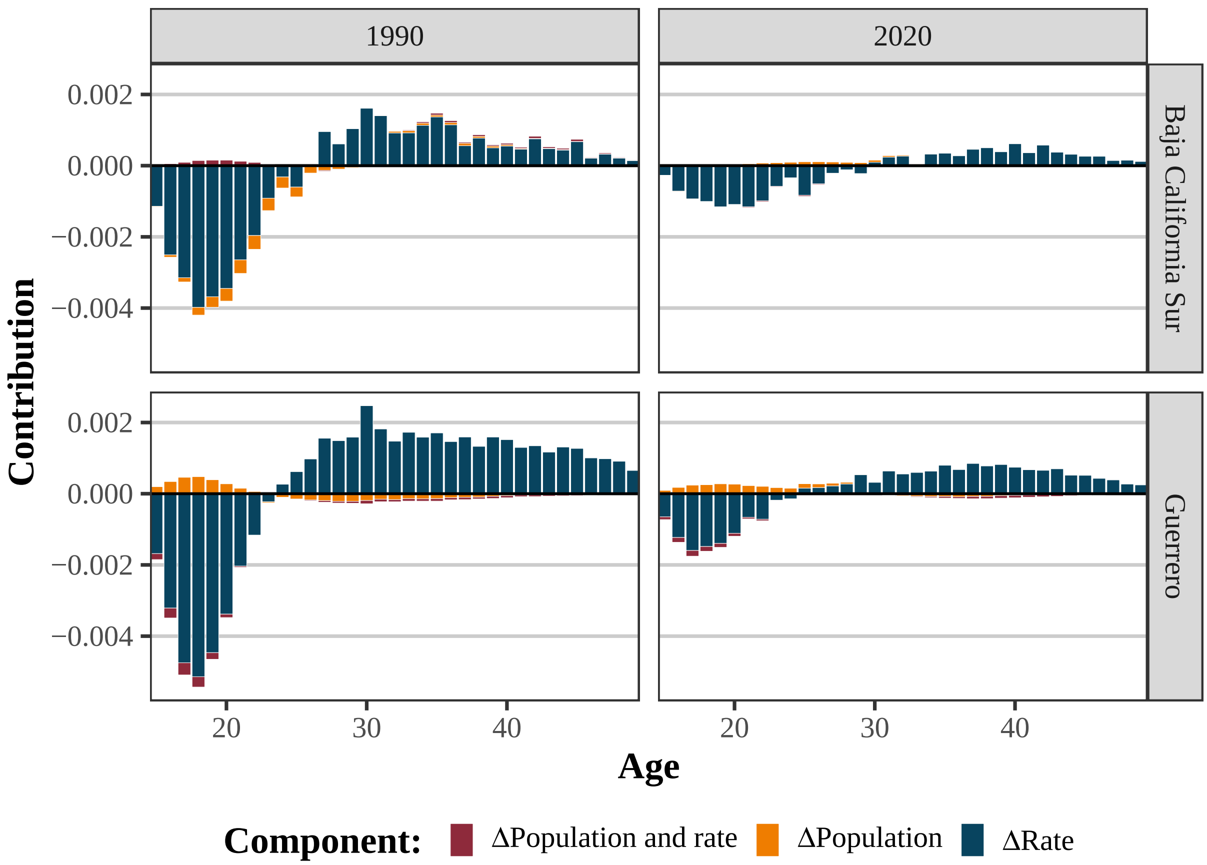
Decomposition of regional differences

```
# Estimate the decomposition
comp_asfr_reg <- asfr_reg %>%
                group_by(year, entity_name, entity) %>%
                mutate(pop_share_f = pop_share(mid_year_pop_f),
                       pop_share_m = pop_share(mid_year_pop_m),
                       delta_pop = difference(pop_share_f, pop_share_m),
                       delta_rate = difference(asfr_f, asfr_m),
                       change_rate = pop_share_f * delta_rate,
                       change_pop  = asfr_f * delta_pop,
                       change_inter = delta_pop * delta_rate)

# Make the decomposition
decomp_reg <- comp_asfr_reg %>%
  select(year, age, change_rate,
         change_pop, change_inter, entity_name) %>%
  pivot_longer(cols = starts_with("change"),
               names_to = "component",
               values_to = "contribution")

# Plot the decomposition
decomp_reg %>%
  filter(year %in% c(1990, 2020) &
         entity_name %in% c("Baja California Sur",
```

```
                                "Guerrero")) %>%
  ggplot(aes(age, contribution, fill = component)) +
  geom_col(colour = "white", linewidth = 0.01) +
  geom_hline(yintercept = 0, colour = "black") +
  facet_grid(entity_name ~ year) +
  scale_fill_manual(values = c(MPIDRred, MPIDRorange, MPIDRblue),
                    labels = c(expression(paste(Delta, "Population and rate")),
                               expression(paste(Delta, "Population")),
                               expression(paste(Delta, "Rate"))),
                    name = "Component: ") +
  scale_x_continuous(expand = c(0, 0)) +
  ylab("Contribution") + xlab("Age") +
  theme(legend.key.width = unit(0.3, "cm"),
        legend.key.height = unit(0.2, "cm"))
```



In order to better understand the size of the contribution, we create tables that display the components with the largest contribution.

```
# Create a table
left_join(decomp_reg, tfr_reg, by = c("year", "entity")) %>%
  mutate(change = tfr_f - tfr_m,
         relative_contribution = contribution / change, 2) %>%
  filter(year == 1990) %>%
  ungroup() %>%
  select(component, entity_name, age, contribution,
         relative_contribution, tfr_f, tfr_m, change) %>%
```

```
arrange(desc(abs(relative_contribution))) %>%
mutate(relative_contribution =  paste(round(100 * relative_contribution, 2), "%")) %>%
slice_head(n = 5) %>%
pander()
```

Table 1: Table continues below

component	entity_name	age	contribution	relative_contribution
change_rate	Baja California Sur	18	-0.003982	1.39 %
change_rate	Baja California Sur	19	-0.003683	1.29 %
change_rate	Quintana Roo	18	-0.00616	1.23 %
change_rate	Baja California Sur	20	-0.003451	1.21 %
change_rate	Quintana Roo	17	-0.0056	1.11 %

tfr_f	tfr_m	change
3.204	3.49	-0.2859
3.204	3.49	-0.2859
4.427	4.93	-0.5026
3.204	3.49	-0.2859
4.427	4.93	-0.5026