MRP example: self-reported abortion in Uganda

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Contents

1 Overview

This document goes through a worked example of multilevel regression and post-stratification to get estimates of self-reported abortion incidence in Uganda. The data used are the 2018 PMA survey and the 2014 Census. Both datasets were obtained through IPUMS.

2 Load in data and tidy up

Load in the packages:

```
library(tidyverse)
library(here)
library(brms)
library(tidybayes)
```

2.1 PMA

Load in the PMA data and make an age category variable:

```
d <- read_csv(here("data/pma.csv"))

d <- d %>% filter(age>14, age<50)

age_groups <- seq(15, 45, by = 5)
d$age_group <- as.numeric(as.character(cut(d$age,
                                           breaks= c(age_groups, Inf),
                                           labels = age_groups,
                                           right = FALSE)))

d <- d %>% mutate(age_group = factor(age_group)) %>%
  mutate(age_group = fct_relevel(age_group, "35", after = 0))
```

Create a new `region_2` variable with slightly bigger regions (that match the census data):

```
d <- d %>% mutate(region_2 = case_when(region == "north"|region== "karamoja"|region == "west nile" ~ "n
                                       region == "eastern" ~ "eastern",
                                       region == "central 1"|region == "central 2"|region == "east centr
                                       region == "western"|region == "south west" ~ "western"))
```

2.2 Census

Load in the data, select the columns we want and make an age category variable:

```
dc <- haven::read_dta(here("data/uganda_census.dta"))

dc <- dc %>%
  select(regnug, perwt, age, marst, edattain) %>%
  mutate(regnug = as_factor(regnug),
         marst = as_factor(marst),
         edattain = as_factor(edattain))

dc <- dc %>% filter(age>14, age<50)


dc$age_group <- as.numeric(as.character(cut(dc$age,
                                           breaks= c(age_groups, Inf),
                                           labels = age_groups,
                                           right = FALSE)))

dc <- dc %>% mutate(age_group = factor(age_group)) %>%
  mutate(age_group = fct_relevel(age_group, "35", after = 0))
```

2.3 Recode education and marital status

The PMA and census have different education and marital status categories. Let's recode so they are the same:

```
# EDUCATION

#table(d$educattgen)
#table(dc$edattain)


d <- d %>% mutate(educ = case_when(educattgen=="never attended"~"less than primary",
                                   educattgen=="primary/middle school" ~"primary",
                                   educattgen=="secondary/post-primary"|educattgen=="tertiary/post-secon
                                   TRUE ~ "NA")) %>%
  filter(educ != "NA", marstat!="no response or missing")

dc <- dc %>% mutate(educ = case_when(edattain=="less than primary completed"~"less than primary",
                                     edattain=="primary completed"~ "primary",
                                     edattain=="secondary completed"|edattain=="university completed" ~
                                     TRUE ~ "NA")) %>%
  filter(educ !="NA")

## MARITAL STATUS

#table(d$marstat)
#table(dc$marst)

d <- d %>% mutate(marital = case_when(marstat == "never married" ~ "single/never married",
                                      marstat == "currently living with partner"| marstat == "currently
                                      marstat== "divorced or separated" ~ "divorced/separated",
                                      marstat== "widow or widower"~ "widowed",
                                      TRUE ~ "NA"))

dc <- dc %>% mutate(marital = case_when(marst == "single/never married" ~ "single/never married",
                                        marst == "married/in union" ~ "married/in union",
                                        marst== "separated/divorced/spouse absent" ~ "divorced/separate
                                        marst== "widowed"~ "widowed",
                                      TRUE ~ "NA")) %>%
  filter(marital != "NA")
```

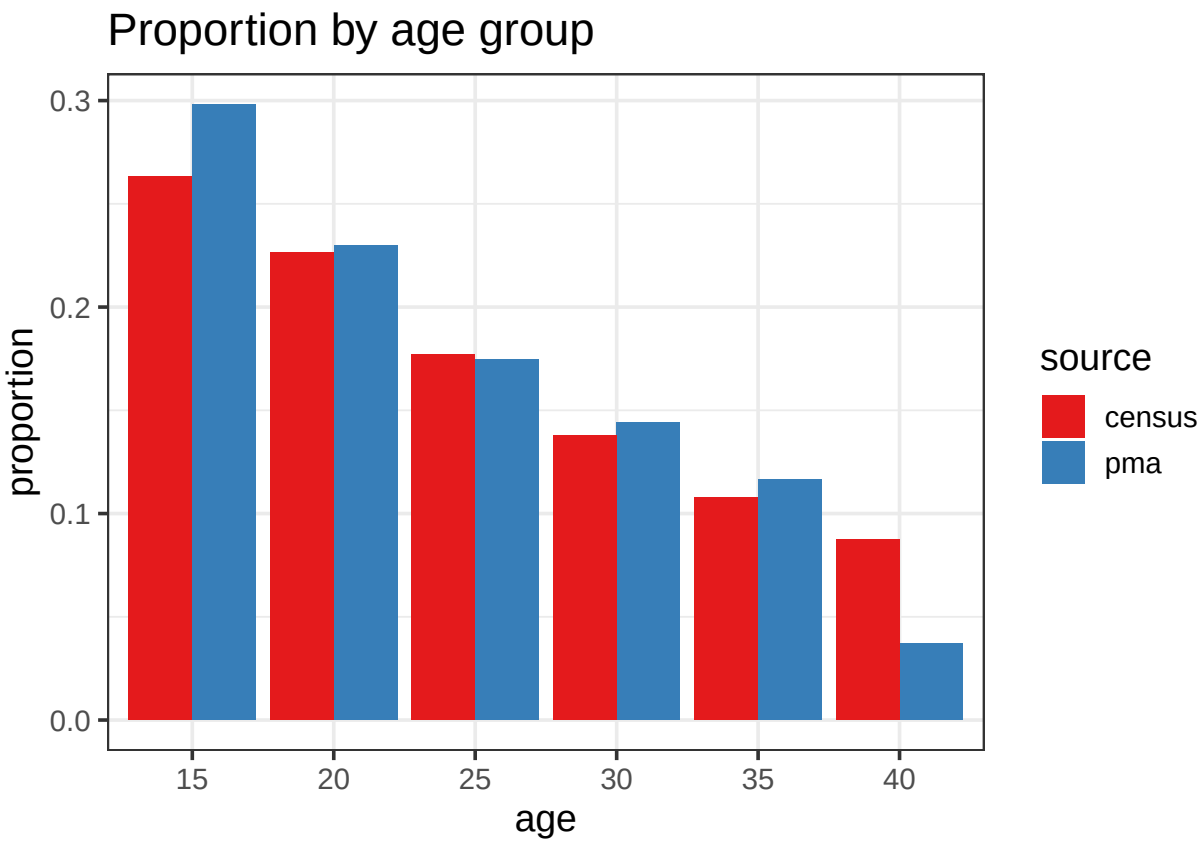
3 Plot data

Lets calculate the census population by key subgroups:

```
census_counts <- dc %>%
  group_by(regnug, marital, educ, age_group) %>%
  summarize(n = sum(perwt)) %>%
  filter(age_group!="45") %>%
  rename(region_2 = regnug)
```

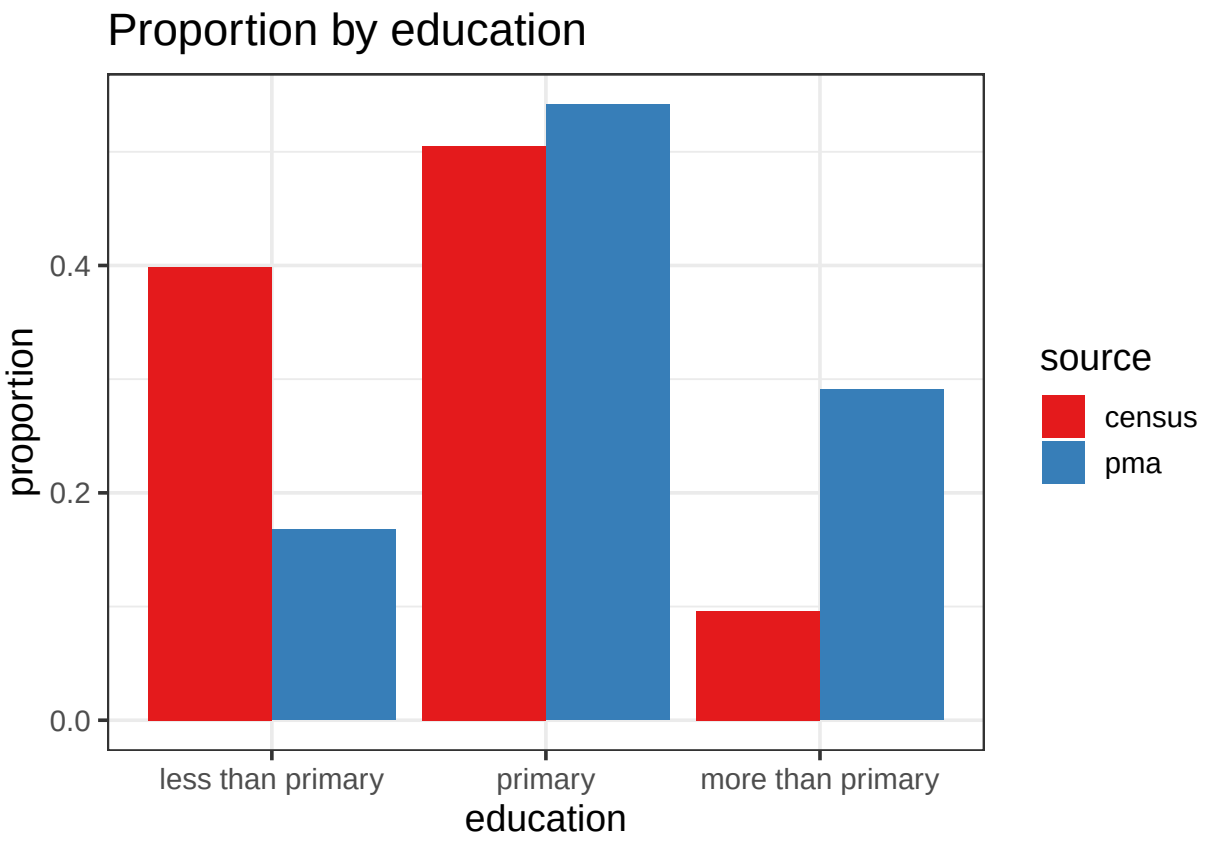
We can get an idea of differences in population distributions by plotting the PMA and census proportions by different variables:

```r
d %>%
  group_by(age_group) %>%
  tally() %>%
  mutate(pma = n/sum(n)) %>%
  left_join(census_counts %>%
              group_by(age_group) %>%
              summarize(n = sum(n)) %>%
              mutate(census = n/sum(n)) %>%
              select(-n)) %>%
  mutate(age_group = as.character(age_group)) %>%
  arrange(age_group) %>%
  pivot_longer(pma:census) %>%
  ggplot(aes(age_group, value, fill = name)) + geom_bar(stat = "identity", position = 'dodge')+
  theme_bw(base_size = 14) +
  labs( x = "age", y = "proportion", title = "Proportion by age group")+
  scale_fill_brewer(palette = "Set1", name = "source")
```

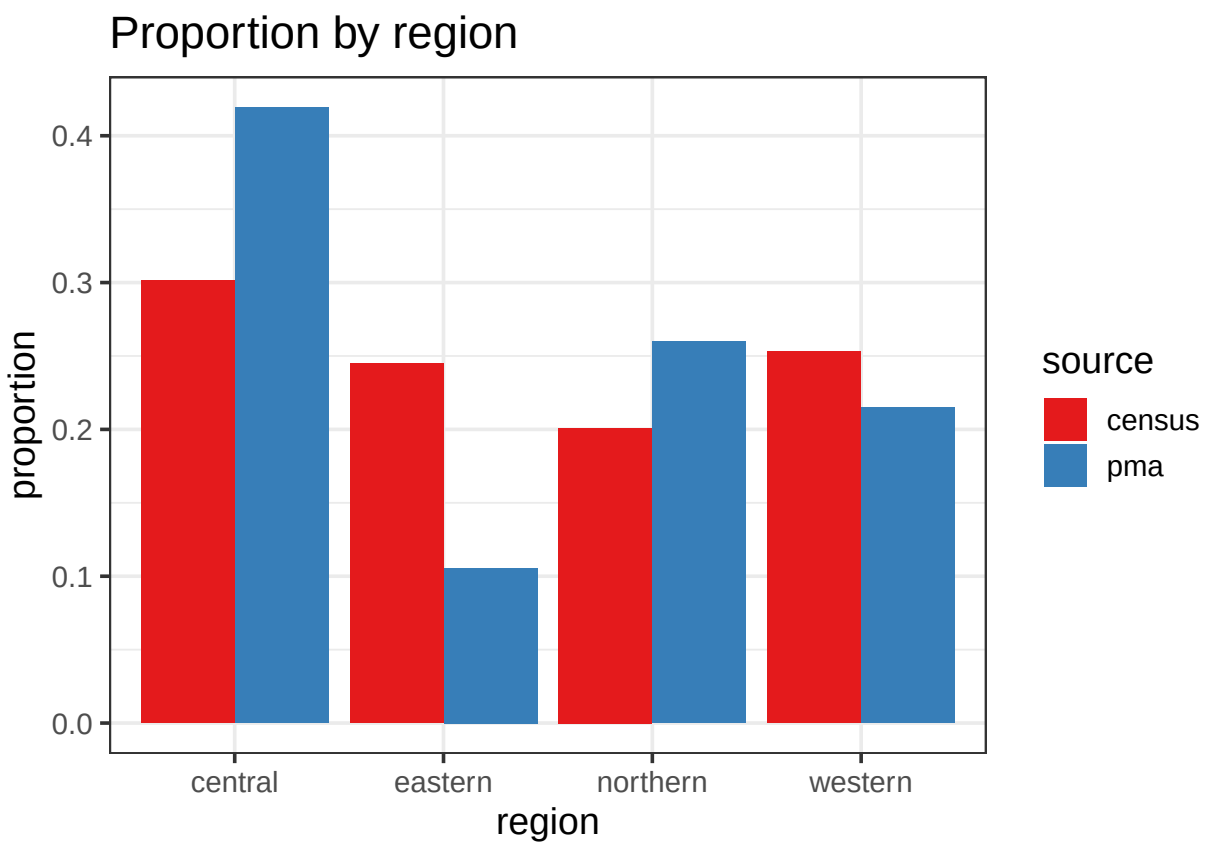



```r
d %>%
  group_by(educ) %>%
  tally() %>%
  mutate(pma = n/sum(n)) %>%
  left_join(census_counts %>%
              group_by(educ) %>%
              summarize(n = sum(n)) %>%
              mutate(census = n/sum(n)) %>%
              select(-n)) %>%
```

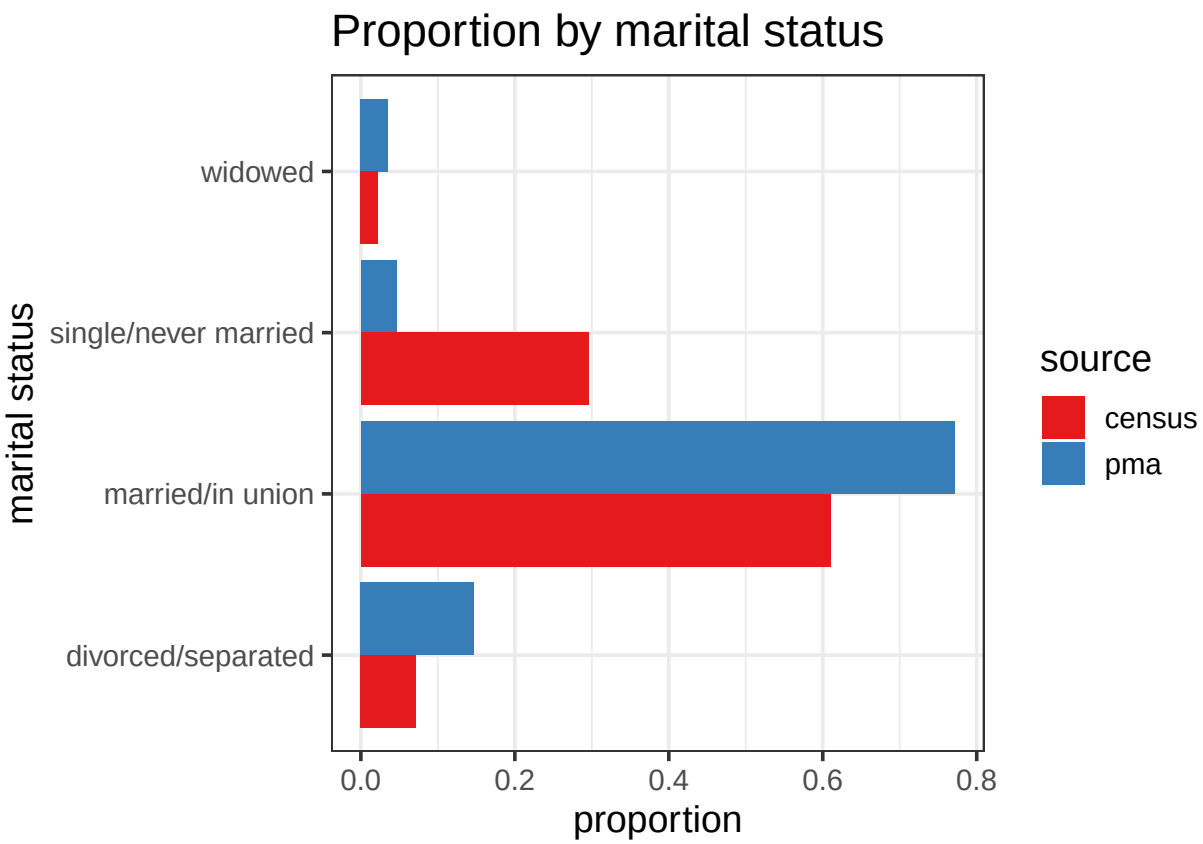
```
  mutate(educ = fct_relevel(educ, "more than primary", after = 2)) %>%
  pivot_longer(pma:census) %>%
  ggplot(aes(educ, value, fill = name)) + geom_bar(stat = "identity", position = 'dodge')+
  theme_bw(base_size = 14) +
  labs( x = "education", y = "proportion", title = "Proportion by education")+
  scale_fill_brewer(palette = "Set1", name = "source")
```




```
d %>%
  group_by(region_2) %>%
  tally() %>%
  mutate(pma = n/sum(n)) %>%
  left_join(census_counts %>%
              group_by(region_2) %>%
              summarize(n = sum(n)) %>%
              mutate(census = n/sum(n)) %>%
              select(-n)) %>%
  pivot_longer(pma:census) %>%
  ggplot(aes(region_2, value, fill = name)) + geom_bar(stat = "identity", position = 'dodge')+
  theme_bw(base_size = 14) +
  labs( x = "region", y = "proportion", title = "Proportion by region")+
  scale_fill_brewer(palette = "Set1", name = "source")
```




```
d %>%
  group_by(marital) %>%
  tally() %>%
  mutate(pma = n/sum(n)) %>%
  left_join(census_counts %>%
              group_by(marital) %>%
              summarize(n = sum(n)) %>%
              mutate(census = n/sum(n)) %>%
              select(-n)) %>%
  pivot_longer(pma:census) %>%
  ggplot(aes(marital, value, fill = name)) + geom_bar(stat = "identity", position = 'dodge')+
  theme_bw(base_size = 14) +
  labs( x = "marital status", y = "proportion", title = "Proportion by marital status")+
  scale_fill_brewer(palette = "Set1", name = "source")+coord_flip()
```



4 Multilevel regression

Let's run a logistic regression of whether or not an individual reported ever having an abortion with covariates education, age group, and region modelled hierarchically

4.1 Run the model

```
mod <- brm(abortion ~ (1|region_2)+educ+ marital +age_group, data = d, family = "bernoulli", silent = T
summary(mod)
```

```
##  Family: bernoulli
##   Links: mu = logit
## Formula: abortion ~ (1 | region_2) + educ + marital + age_group
##    Data: d (Number of observations: 2774)
## Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup samples = 4000
##
## Group-Level Effects:
## ~region_2 (Number of levels: 4)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.75      0.43     0.26     1.92 1.01      939     1271
##
## Population-Level Effects:
```

```
##                             Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## Intercept                      -2.35      0.49    -3.29    -1.30 1.00      959
## educmorethanprimary             0.79      0.24     0.32     1.26 1.00     2642
## educprimary                     0.71      0.22     0.30     1.15 1.00     2480
## maritalmarriedDinunion         -0.47      0.15    -0.76    -0.17 1.00     3449
## maritalsingleDnevermarried     -1.17      0.38    -1.93    -0.44 1.00     3798
## maritalwidowed                 -0.90      0.43    -1.80    -0.11 1.00     4056
## age_group15                     0.01      0.24    -0.43     0.49 1.00     1670
## age_group20                     0.12      0.24    -0.33     0.60 1.00     1514
## age_group25                     0.35      0.24    -0.11     0.84 1.00     1706
## age_group30                     0.10      0.26    -0.41     0.60 1.00     1801
## age_group40                     0.04      0.39    -0.72     0.80 1.00     2591
##                             Tail_ESS
## Intercept                       1168
## educmorethanprimary             2599
## educprimary                     2331
## maritalmarriedDinunion          2426
## maritalsingleDnevermarried      2749
## maritalwidowed                  2509
## age_group15                     2004
## age_group20                     1524
## age_group25                     1995
## age_group30                     2085
## age_group40                     2475
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
# optional: cf to lme4
#summary(lme4::glmer(abortion ~ (1|region_2)+marital+educ+ age_group, data = d, family = "binomial"))
```

4.2 Get estimated proportions of abortion incidence

Now we need to get the estimated proportions of abortion incidence by each subpopulation of interest. (i.e. by region, marital status, education and age group). First, initiate a tibble with all possible combinations:

```
regions <- unique(d$region_2)
marital_groups <- unique(d$marital)
educ_groups  <- unique(d$educ)

pred_df <- tibble(region_2 = NA, marital = NA, educ = NA, age_group = NA) %>%
  tidyr::complete(region_2 = regions,
                  marital = marital_groups,
                  educ = educ_groups,
                  age_group = age_groups) %>%
  mutate_all(.funs = funs(as_factor(.))) %>%
  drop_na() %>%
  mutate(age_group = fct_relevel(age_group, "35", after = 0)) %>%
  filter(age_group != "45")
```

We can use the `fitted_draws` function to obtain posterior samples of the estimated proportion of women reporting an abortion by each group:

```
pred_probs_draws <- mod %>%
  fitted_draws(pred_df  %>%
                   select(region_2:age_group) %>%
                   mutate(age_group = factor(age_group, levels = age_groups[-length(age_groups)])))
```

5 Post-stratify the predicted proportions

For the post-stratfication, we need a data frame that tells us how many women in the census are in each subgroup of interest. Let's join the census counts to the `pred_probs_draws` table above, replacing any NAs with 0's:

```
pred_probs_draws <- pred_probs_draws %>%
  left_join(census_counts) %>%
  replace_na(replace = list(n = 0))
```

For each group and draw, we can calculate the estimated number of women reporting an abortion:

```
pred_probs_draws <- pred_probs_draws %>%
  mutate(n_abo = n*.value)
```

We can now use this as a basis of getting estimates by any group of interest. For example, the national estimate and lower/upper bounds is

```
pred_probs_draws %>%
  group_by(.draw) %>%
  summarize(prop_abo = sum(n_abo)/sum(n)) %>%
  ungroup() %>%
  summarize(prop_abo_group = median(prop_abo),
            lower = quantile(prop_abo, 0.1),
            upper = quantile(prop_abo, 0.9))
```

```
## # A tibble: 1 x 3
##   prop_abo_group  lower upper
##            <dbl>  <dbl> <dbl>
## 1         0.0899 0.0801 0.101
```

By age group:

```
prop_by_age <- pred_probs_draws %>%
  group_by(.draw, age_group) %>%
  summarize(prop_abo = sum(n_abo)/sum(n)) %>%
  group_by(age_group) %>%
  summarize(prop_abo_group = median(prop_abo),
            lower = quantile(prop_abo, 0.1),
            upper = quantile(prop_abo, 0.9))

prop_by_age
```

```
## # A tibble: 6 x 4
```

```
##   age_group prop_abo_group  lower  upper
##   <fct>              <dbl>  <dbl>  <dbl>
## 1 15                0.0631 0.0478 0.0847
## 2 20                0.0954 0.0802 0.113
## 3 25                0.123  0.105  0.143
## 4 30                0.0936 0.0769 0.112
## 5 35                0.0842 0.0655 0.104
## 6 40                0.0830 0.0559 0.120
```

By marital status:

```
prop_by_marital <- pred_probs_draws %>%
  group_by(.draw, marital) %>%
  summarize(prop_abo = sum(n_abo)/sum(n)) %>%
  group_by(marital) %>%
  summarize(prop_abo_group = median(prop_abo),
            lower = quantile(prop_abo, 0.1),
            upper = quantile(prop_abo, 0.9))

prop_by_marital
```

```
## # A tibble: 4 x 4
##   marital              prop_abo_group  lower  upper
##   <chr>                         <dbl>  <dbl>  <dbl>
## 1 divorced/separated            0.146  0.125  0.171
## 2 married/in union              0.0998 0.0898 0.110
## 3 single/never married          0.0574 0.0363 0.0859
## 4 widowed                       0.0562 0.0332 0.0894
```

By education:

```
prop_by_educ <- pred_probs_draws %>%
  group_by(.draw, educ) %>%
  summarize(prop_abo = sum(n_abo)/sum(n)) %>%
  group_by(educ) %>%
  summarize(prop_abo_group = median(prop_abo),
            lower = quantile(prop_abo, 0.1),
            upper = quantile(prop_abo, 0.9))

prop_by_educ
```

```
## # A tibble: 3 x 4
##   educ              prop_abo_group  lower  upper
##   <chr>                      <dbl>  <dbl>  <dbl>
## 1 less than primary          0.0574 0.0447 0.0732
## 2 more than primary          0.122  0.104  0.143
## 3 primary                    0.109  0.0959 0.124
```

By region:

```
prop_by_region <- pred_probs_draws %>%
  group_by(.draw, region_2) %>%
  summarize(prop_abo = sum(n_abo)/sum(n)) %>%
  group_by(region_2) %>%
  summarize(prop_abo_group = median(prop_abo),
            lower = quantile(prop_abo, 0.1),
            upper = quantile(prop_abo, 0.9))

prop_by_region
```

```
## # A tibble: 4 x 4
##   region_2 prop_abo_group  lower  upper
##   <fct>             <dbl>  <dbl>  <dbl>
## 1 central          0.118  0.104  0.134
## 2 eastern          0.120  0.0977 0.146
## 3 northern         0.0625 0.0518 0.0744
## 4 western          0.0481 0.0388 0.0599
```

6 Plotting and comparing estimates

We can compare the MRP estimates with raw estimates from the PMA survey and also estimates using normal post-stratification

6.1 Calculating raw estimates and post-stratified estimates

Calculate the raw estimates from the survey:

```
pma_cells <- d %>%
  group_by(region_2, educ, marital, age_group) %>%
  summarize(
            n_sample = n(), n_abo_sample = sum(abortion),
            prop_abo = n_abo_sample/n_sample)
```

We can then combine these with census data to get post-stratified counts:

```
pma_cells <- pma_cells %>%
  left_join(census_counts) %>%
  mutate(n_abo = prop_abo*n) %>%
  replace_na(replace = list(n = 0,n_abo = 0)) %>%
  ungroup()
```

6.2 Join all estimates together

Calculate raw and postratified estimates by different subpopulations and join them to the MRP estimates. By age group:

```
prop_by_age <- prop_by_age %>%
  mutate(type = "mrp") %>%
  rename(point = prop_abo_group) %>%
  bind_rows(pma_cells %>% group_by(age_group) %>%summarize(poststrat = sum(n_abo)/sum(n)) %>%
  left_join(pma_cells %>% group_by(age_group) %>%summarize(raw = sum(n_abo_sample)/sum(n_sample))) %>%
  pivot_longer(-age_group, names_to = "type", values_to = "point")) %>%
  arrange(age_group)
```

By education:

```
prop_by_educ <- prop_by_educ %>%
  mutate(type = "mrp") %>%
  rename(point = prop_abo_group) %>%
  bind_rows(pma_cells %>% group_by(educ) %>%summarize(poststrat = sum(n_abo)/sum(n)) %>%
  left_join(pma_cells %>% group_by(educ) %>%summarize(raw = sum(n_abo_sample)/sum(n_sample))) %>%
  pivot_longer(-educ, names_to = "type", values_to = "point")) %>%
  arrange(educ)
```

By marital status:

```
prop_by_marital <- prop_by_marital %>%
  mutate(type = "mrp") %>%
  rename(point = prop_abo_group) %>%
  bind_rows(pma_cells %>% group_by(marital) %>%summarize(poststrat = sum(n_abo)/sum(n)) %>%
  left_join(pma_cells %>% group_by(marital) %>%summarize(raw = sum(n_abo_sample)/sum(n_sample))) %>%
  pivot_longer(-marital, names_to = "type", values_to = "point")) %>%
  arrange(marital)
```

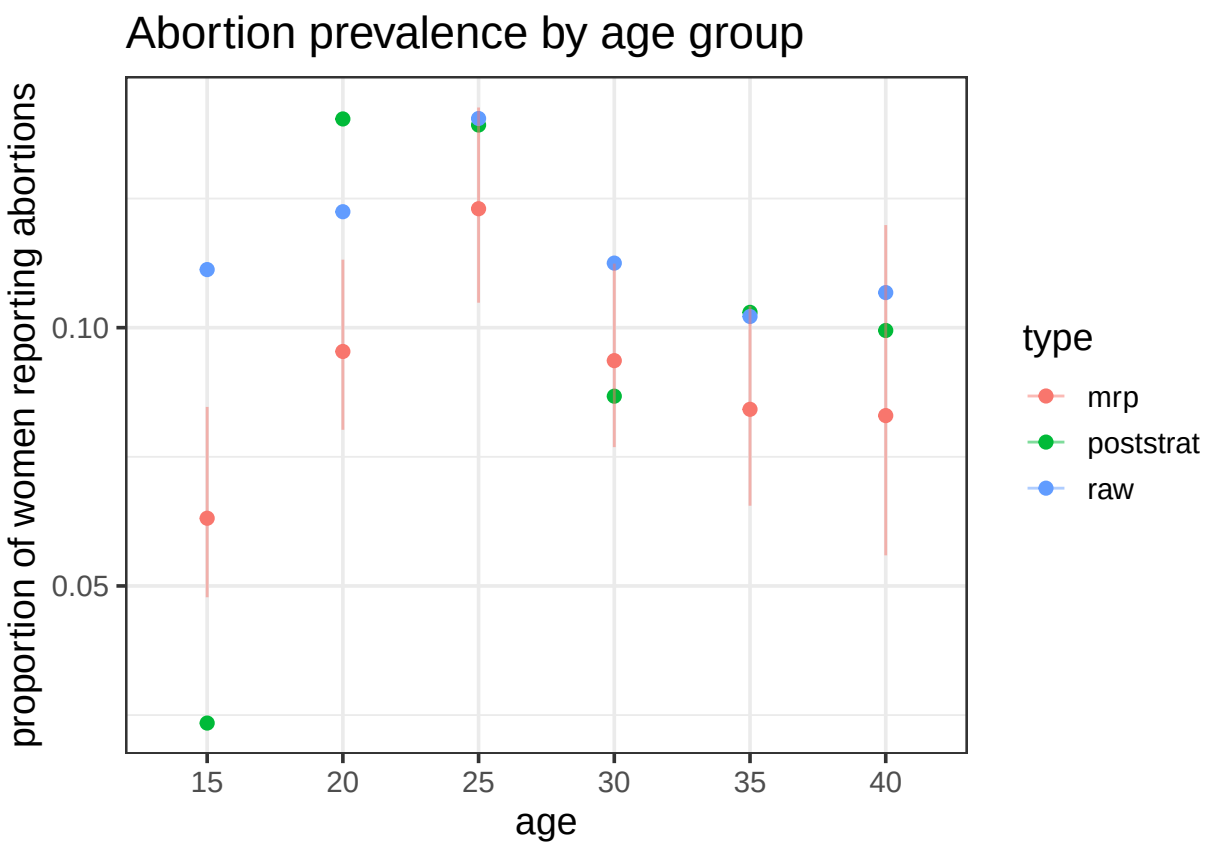
By region:

```
prop_by_region <- prop_by_region %>%
  mutate(type = "mrp") %>%
  rename(point = prop_abo_group) %>%
  bind_rows(pma_cells %>% group_by(region_2) %>%summarize(poststrat = sum(n_abo)/sum(n)) %>%
  left_join(pma_cells %>% group_by(region_2) %>%summarize(raw = sum(n_abo_sample)/sum(n_sample))) %>%
  pivot_longer(-region_2, names_to = "type", values_to = "point")) %>%
  arrange(region_2)
```

6.3 Plot!

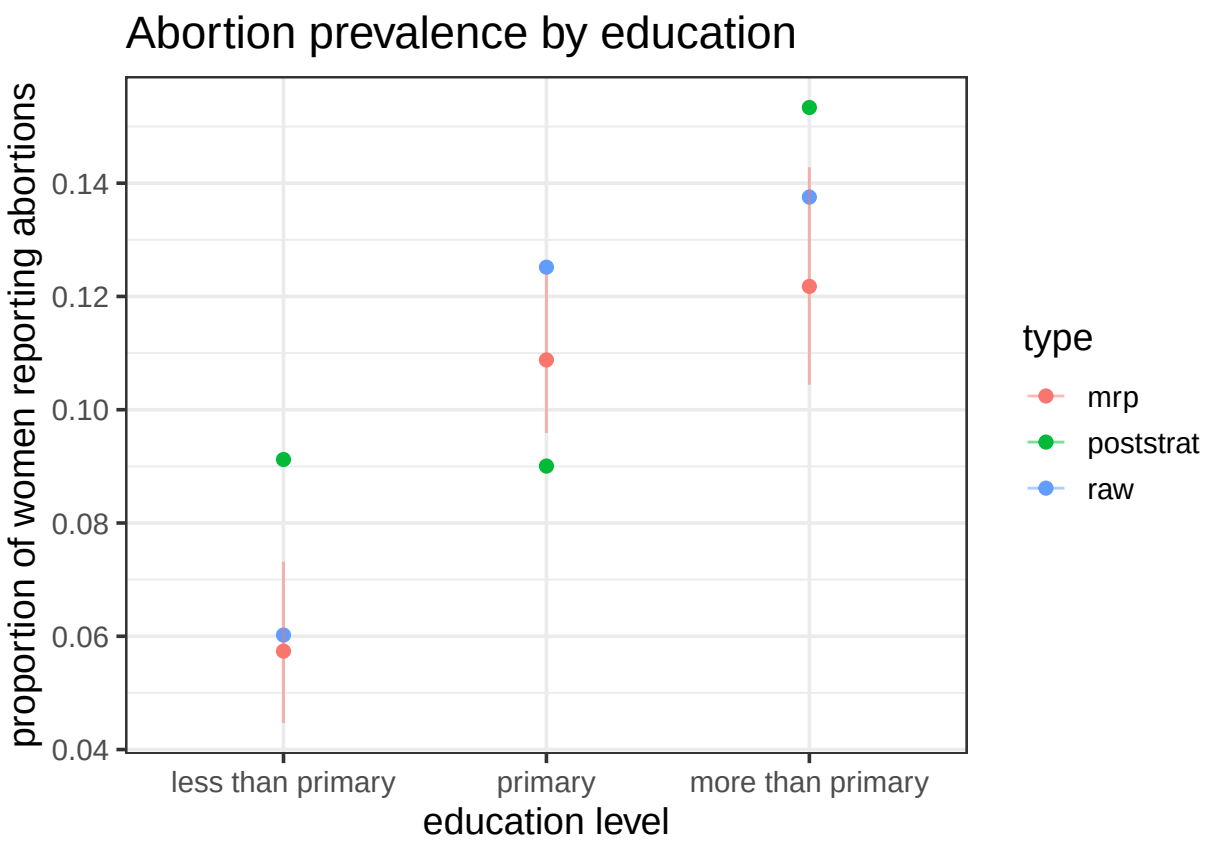
By age group:

```
prop_by_age %>%
  ggplot(aes(age_group, point, color = type)) + geom_point(size = 2) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = NA, alpha = 0.5) +
  theme_bw(base_size = 14) +
  labs(title = "Abortion prevalence by age group", x = "age", y = "proportion of women reporting aborti
```



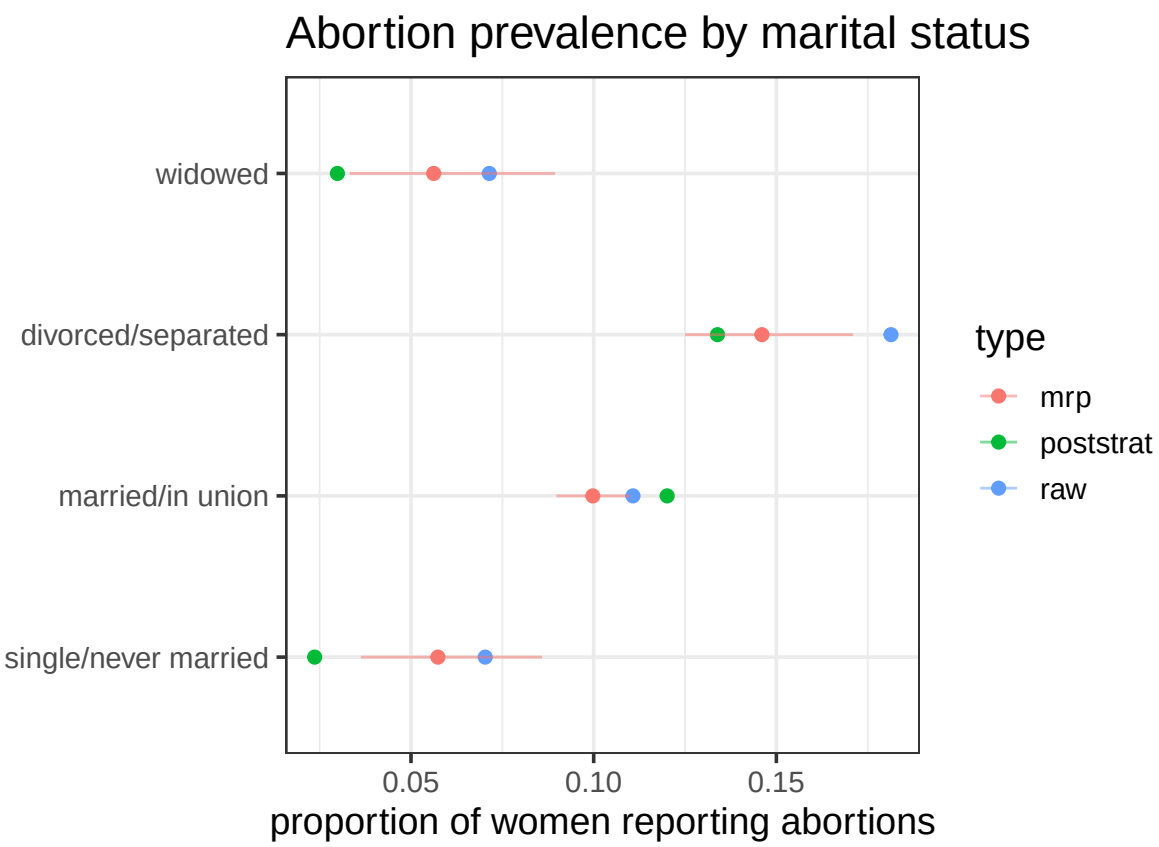
By education:

```
prop_by_educ %>%
  mutate(educ = fct_relevel(educ, "more than primary", after = 2)) %>%
  ggplot(aes(educ, point, color = type)) + geom_point(size = 2) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = NA, alpha = 0.5) +
  theme_bw(base_size = 14) +
  labs(title = "Abortion prevalence by education", x = "education level", y = "proportion of women repo
```



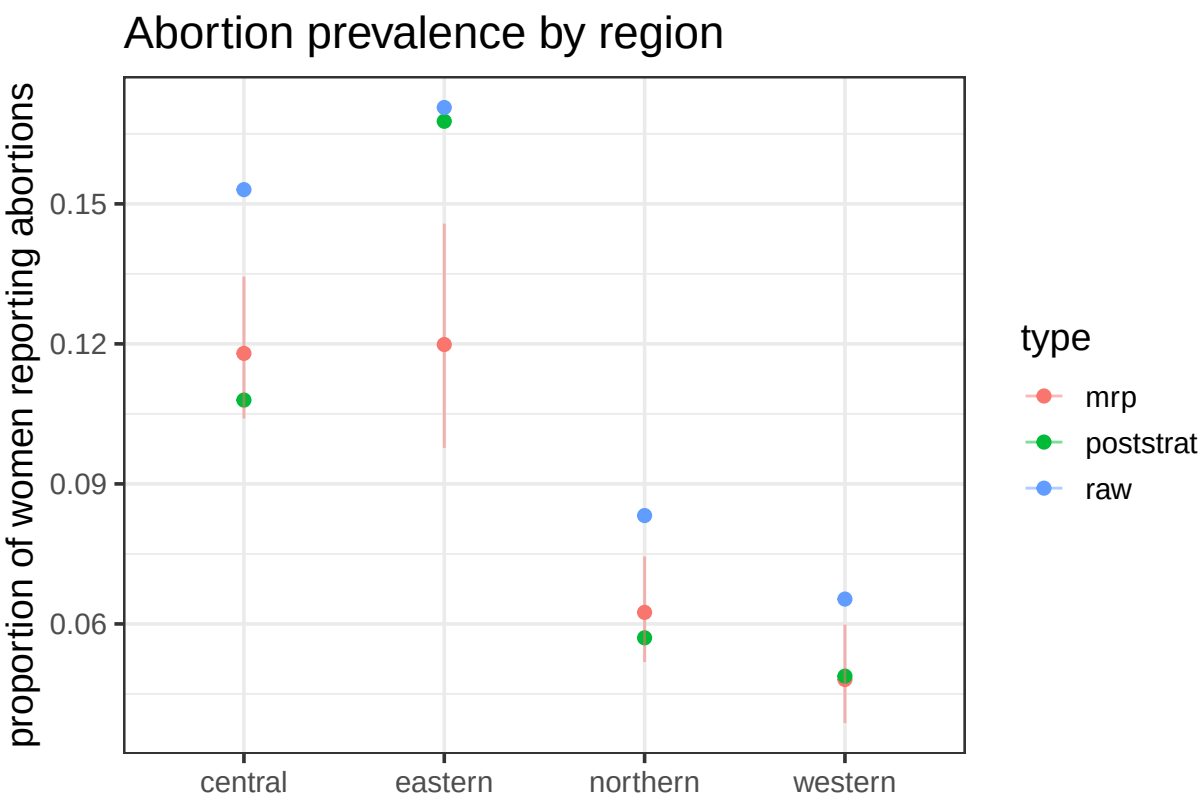
By marital status

```
prop_by_marital %>%
  mutate(marital = factor(marital, c("single/never married", "married/in union", "divorced/separated",
  ggplot(aes(marital, point, color = type)) + geom_point(size = 2) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = NA, alpha = 0.5) +
  theme_bw(base_size = 14) +
  labs(title = "Abortion prevalence by marital status", x = "", y = "proportion of women reporting abor
  coord_flip()
```



By region

```
prop_by_region %>%
  ggplot(aes(region_2, point, color = type)) + geom_point(size = 2) +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = NA, alpha = 0.5) +
  theme_bw(base_size = 14) +
  labs(title = "Abortion prevalence by region", x = "", y = "proportion of women reporting abortions")
```


Abortion prevalence by region
proportion of women reporting abortions
0.15
0.12
0.09
0.06
central
eastern
northern
western
type
mrp
poststrat
raw