IPV Perpetration according to race and employment status

An intersectional analysis using FFCWS data

First, we load the data and the necessary packages:

# packages ----------------------------------------------------------------  
packages <- c("tidyverse", "here", "marginaleffects", "survey", "srvyr", "modelsummary")  
groundhog\_day <- "2024-01-11"  
  
# (install and) load package versions available on the specified day to try  
# to ensure reproducibility  
  
library(groundhog)  
  
groundhog::meta.groundhog(groundhog\_day)  
  
groundhog::groundhog.library(pkg = packages, date = groundhog\_day)  
  
  
dat <- readRDS(file = here::here("01\_data-processing", "data\_private", "data\_final\_imputed\_cases.RDS"))  
  
dat\_weights <- dat |>   
 dplyr::filter(f\_national\_sample == 1) |>   
 srvyr::as\_survey\_rep(  
 repweights = dplyr::contains("f1natwt\_rep"),  
 weights = f1natwt,  
 combined\_weights = TRUE,  
 # why: https://stats.stackexchange.com/questions/409463/duplicating-stata-survey-design-using-svrepdesign-from-survey-package-in-r  
 type = "JKn",  
 scales = 1,  
 rscales = 1,  
 mse = TRUE  
 )

# Regression Models

## Race -> IPV

Without considering employment, is race associated with different IPV rates?

We perform a linear regression, adjusting for all control variables.

mod\_race\_ipv <- survey::svyglm(  
 formula = ipv\_prop ~ f\_race +   
 f\_age + f\_education + f\_alcohol + f\_drugs +  
 f\_children + f\_poverty + f\_incarceration +  
 f\_home + f\_depression,  
 design = dat\_weights,  
 family = "gaussian"  
)  
  
summary(mod\_race\_ipv)

Call:  
survey::svyglm(formula = ipv\_prop ~ f\_race + f\_age + f\_education +   
 f\_alcohol + f\_drugs + f\_children + f\_poverty + f\_incarceration +   
 f\_home + f\_depression, design = dat\_weights, family = "gaussian")  
  
Survey design:  
Called via srvyr  
  
Coefficients:  
 Estimate Std. Error t value Pr(>|t|)  
(Intercept) 1.206e-01 5.619e-02 2.146 0.0443  
f\_raceBlack 7.357e-03 1.578e-02 0.466 0.6462  
f\_age -9.617e-05 1.604e-03 -0.060 0.9528  
f\_educationHS and above -2.435e-02 1.999e-02 -1.218 0.2373  
f\_alcohol<1 / month -1.011e-02 1.635e-02 -0.618 0.5433  
f\_alcohol>1 / month 2.965e-02 1.777e-02 1.669 0.1108  
f\_drugs<1 / month 6.969e-03 2.758e-02 0.253 0.8031  
f\_drugs>1 / month -6.988e-03 2.366e-02 -0.295 0.7708  
f\_children -1.256e-03 9.305e-03 -0.135 0.8940  
f\_poverty -2.781e-03 2.530e-03 -1.099 0.2847  
f\_incarcerationExperienced incarceration 5.805e-02 2.282e-02 2.544 0.0193  
f\_homeRented 1.332e-03 1.315e-02 0.101 0.9203  
f\_depression -7.807e-04 9.387e-03 -0.083 0.9345  
   
(Intercept) \*  
f\_raceBlack   
f\_age   
f\_educationHS and above   
f\_alcohol<1 / month   
f\_alcohol>1 / month   
f\_drugs<1 / month   
f\_drugs>1 / month   
f\_children   
f\_poverty   
f\_incarcerationExperienced incarceration \*  
f\_homeRented   
f\_depression   
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
  
(Dispersion parameter for gaussian family taken to be 25.41959)  
  
Number of Fisher Scoring iterations: 2

marginaleffects::avg\_predictions(mod\_race\_ipv, variables = "f\_race")

f\_race Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 White 0.117 0.00992 11.7 <0.001 103.4 0.0971 0.136  
 Black 0.124 0.01126 11.0 <0.001 91.1 0.1018 0.146  
  
Columns: f\_race, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_comparisons(mod\_race\_ipv, variables = "f\_race")

Term Contrast Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 f\_race Black - White 0.00736 0.0158 0.466 0.641 0.6 -0.0236 0.0383  
  
Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

And now without covariates:

mod\_race\_ipv\_nocov <- survey::svyglm(  
 formula = ipv\_prop ~ f\_race,  
 design = dat\_weights,  
 family = "gaussian"  
)  
  
summary(mod\_race\_ipv\_nocov)

Call:  
survey::svyglm(formula = ipv\_prop ~ f\_race, design = dat\_weights,   
 family = "gaussian")  
  
Survey design:  
Called via srvyr  
  
Coefficients:  
 Estimate Std. Error t value Pr(>|t|)   
(Intercept) 0.098812 0.006371 15.511 3.7e-16 \*\*\*  
f\_raceBlack 0.028435 0.012688 2.241 0.0323 \*   
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
  
(Dispersion parameter for gaussian family taken to be 27.05409)  
  
Number of Fisher Scoring iterations: 2

marginaleffects::avg\_predictions(mod\_race\_ipv\_nocov, variables = "f\_race")

f\_race Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 White 0.0988 0.00637 15.5 <0.001 177.8 0.0863 0.111  
 Black 0.1272 0.01049 12.1 <0.001 110.2 0.1067 0.148  
  
Columns: f\_race, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_comparisons(mod\_race\_ipv\_nocov, variables = "f\_race")

Term Contrast Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 f\_race Black - White 0.0284 0.0127 2.24 0.025 5.3 0.00357 0.0533  
  
Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

## Race + Employment -> IPV

When using race and employment, are they, respectively, predictive of IPV?

We perform a linear regression, adjusting for all control variables.

mod\_race\_employment\_ipv <- survey::svyglm(  
 formula = ipv\_prop ~ f\_race + f\_employment +  
 f\_age + f\_education + f\_alcohol + f\_drugs +  
 f\_children + f\_poverty + f\_incarceration +  
 f\_home + f\_depression,  
 design = dat\_weights,  
 family = "gaussian"  
)  
  
summary(mod\_race\_employment\_ipv)

Call:  
survey::svyglm(formula = ipv\_prop ~ f\_race + f\_employment + f\_age +   
 f\_education + f\_alcohol + f\_drugs + f\_children + f\_poverty +   
 f\_incarceration + f\_home + f\_depression, design = dat\_weights,   
 family = "gaussian")  
  
Survey design:  
Called via srvyr  
  
Coefficients:  
 Estimate Std. Error t value Pr(>|t|)  
(Intercept) 0.1098422 0.0582557 1.886 0.0747  
f\_raceBlack 0.0088430 0.0166585 0.531 0.6017  
f\_employmentEmployed 0.0139392 0.0189502 0.736 0.4710  
f\_age -0.0001106 0.0016014 -0.069 0.9457  
f\_educationHS and above -0.0257521 0.0207581 -1.241 0.2299  
f\_alcohol<1 / month -0.0099901 0.0163172 -0.612 0.5476  
f\_alcohol>1 / month 0.0294363 0.0177032 1.663 0.1128  
f\_drugs<1 / month 0.0079807 0.0278913 0.286 0.7779  
f\_drugs>1 / month -0.0057122 0.0237763 -0.240 0.8127  
f\_children -0.0016595 0.0093861 -0.177 0.8615  
f\_poverty -0.0029023 0.0024799 -1.170 0.2563  
f\_incarcerationExperienced incarceration 0.0599035 0.0231944 2.583 0.0182  
f\_homeRented 0.0014471 0.0131867 0.110 0.9138  
f\_depression -0.0009669 0.0093963 -0.103 0.9191  
   
(Intercept) .  
f\_raceBlack   
f\_employmentEmployed   
f\_age   
f\_educationHS and above   
f\_alcohol<1 / month   
f\_alcohol>1 / month   
f\_drugs<1 / month   
f\_drugs>1 / month   
f\_children   
f\_poverty   
f\_incarcerationExperienced incarceration \*  
f\_homeRented   
f\_depression   
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
  
(Dispersion parameter for gaussian family taken to be 25.39583)  
  
Number of Fisher Scoring iterations: 2

marginaleffects::avg\_predictions(mod\_race\_employment\_ipv, variables = "f\_race")

f\_race Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 White 0.116 0.00979 11.8 <0.001 104.5 0.0964 0.135  
 Black 0.124 0.01177 10.6 <0.001 84.3 0.1013 0.147  
  
Columns: f\_race, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_predictions(mod\_race\_employment\_ipv, variables = c("f\_race", "f\_employment"))

f\_employment f\_race Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 Employed White 0.118 0.0104 11.34 <0.001 96.6 0.0976 0.138  
 Employed Black 0.127 0.0142 8.96 <0.001 61.4 0.0991 0.155  
 Unemployed White 0.104 0.0183 5.70 <0.001 26.3 0.0683 0.140  
 Unemployed Black 0.113 0.0119 9.46 <0.001 68.1 0.0895 0.136  
  
Columns: f\_race, f\_employment, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_comparisons(mod\_race\_employment\_ipv, variables = "f\_race")

Term Contrast Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 f\_race Black - White 0.00884 0.0167 0.531 0.596 0.7 -0.0238 0.0415  
  
Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_predictions(mod\_race\_employment\_ipv, variables = "f\_employment")

f\_employment Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 Employed 0.123 0.00947 13.0 <0.001 125.3 0.1043 0.141  
 Unemployed 0.109 0.01266 8.6 <0.001 56.8 0.0841 0.134  
  
Columns: f\_employment, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_comparisons(mod\_race\_employment\_ipv, variables = "f\_employment")

Term Contrast Estimate Std. Error z Pr(>|z|) S  
 f\_employment Employed - Unemployed 0.0139 0.019 0.736 0.462 1.1  
 2.5 % 97.5 %  
 -0.0232 0.0511  
  
Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

And now without covariates

mod\_race\_employment\_ipv\_nocov <- survey::svyglm(  
 formula = ipv\_prop ~ f\_race + f\_employment,  
 design = dat\_weights,  
 family = "gaussian"  
)  
  
summary(mod\_race\_employment\_ipv\_nocov)

Call:  
survey::svyglm(formula = ipv\_prop ~ f\_race + f\_employment, design = dat\_weights,   
 family = "gaussian")  
  
Survey design:  
Called via srvyr  
  
Coefficients:  
 Estimate Std. Error t value Pr(>|t|)   
(Intercept) 0.108074 0.016719 6.464 3.84e-07 \*\*\*  
f\_raceBlack 0.026861 0.014262 1.883 0.0694 .   
f\_employmentEmployed -0.009731 0.015767 -0.617 0.5418   
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
  
(Dispersion parameter for gaussian family taken to be 27.04126)  
  
Number of Fisher Scoring iterations: 2

marginaleffects::avg\_predictions(mod\_race\_employment\_ipv\_nocov, variables = "f\_race")

f\_race Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 White 0.100 0.00683 14.6 <0.001 159.0 0.0867 0.113  
 Black 0.127 0.01087 11.7 <0.001 102.2 0.1056 0.148  
  
Columns: f\_race, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_predictions(mod\_race\_employment\_ipv\_nocov, variables = c("f\_race", "f\_employment"))

f\_employment f\_race Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 Employed White 0.0983 0.00639 15.40 <0.001 175.2 0.0858 0.111  
 Employed Black 0.1252 0.01279 9.79 <0.001 72.7 0.1001 0.150  
 Unemployed White 0.1081 0.01672 6.46 <0.001 33.2 0.0753 0.141  
 Unemployed Black 0.1349 0.01039 12.99 <0.001 125.7 0.1146 0.155  
  
Columns: f\_race, f\_employment, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_comparisons(mod\_race\_employment\_ipv\_nocov, variables = "f\_race")

Term Contrast Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 f\_race Black - White 0.0269 0.0143 1.88 0.0596 4.1 -0.00109 0.0548  
  
Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_predictions(mod\_race\_employment\_ipv\_nocov, variables = "f\_employment")

f\_employment Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 Employed 0.113 0.00758 14.9 <0.001 164.7 0.0982 0.128  
 Unemployed 0.123 0.01164 10.5 <0.001 83.9 0.0999 0.146  
  
Columns: f\_employment, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_comparisons(mod\_race\_employment\_ipv\_nocov, variables = "f\_employment")

Term Contrast Estimate Std. Error z Pr(>|z|) S  
 f\_employment Employed - Unemployed -0.00973 0.0158 -0.617 0.537 0.9  
 2.5 % 97.5 %  
 -0.0406 0.0212  
  
Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

## Race \* Employment -> IPV

When allowing race and employment to interact, how do they predict IPV?

We perform a weighted logistic regression, adjusting for all control variables.

mod\_race\_employment\_interaction\_ipv <- survey::svyglm(  
 formula = ipv\_prop ~ f\_race \* f\_employment +  
 f\_age + f\_education + f\_alcohol + f\_drugs +  
 f\_children + f\_poverty + f\_incarceration +  
 f\_home + f\_depression,  
 design = dat\_weights,  
 family = "gaussian"  
)  
  
summary(mod\_race\_employment\_interaction\_ipv)

Call:  
survey::svyglm(formula = ipv\_prop ~ f\_race \* f\_employment + f\_age +   
 f\_education + f\_alcohol + f\_drugs + f\_children + f\_poverty +   
 f\_incarceration + f\_home + f\_depression, design = dat\_weights,   
 family = "gaussian")  
  
Survey design:  
Called via srvyr  
  
Coefficients:  
 Estimate Std. Error t value Pr(>|t|)  
(Intercept) 0.1274130 0.0684108 1.862 0.0789  
f\_raceBlack -0.0140629 0.0387711 -0.363 0.7210  
f\_employmentEmployed -0.0026596 0.0319329 -0.083 0.9345  
f\_age -0.0001651 0.0016210 -0.102 0.9200  
f\_educationHS and above -0.0260339 0.0208651 -1.248 0.2281  
f\_alcohol<1 / month -0.0098439 0.0163060 -0.604 0.5536  
f\_alcohol>1 / month 0.0299121 0.0177837 1.682 0.1098  
f\_drugs<1 / month 0.0067767 0.0282438 0.240 0.8131  
f\_drugs>1 / month -0.0051379 0.0238741 -0.215 0.8320  
f\_children -0.0018367 0.0093587 -0.196 0.8466  
f\_poverty -0.0028406 0.0025286 -1.123 0.2760  
f\_incarcerationExperienced incarceration 0.0597784 0.0233314 2.562 0.0196  
f\_homeRented 0.0009762 0.0133464 0.073 0.9425  
f\_depression -0.0009790 0.0094508 -0.104 0.9186  
f\_raceBlack:f\_employmentEmployed 0.0260387 0.0382746 0.680 0.5050  
   
(Intercept) .  
f\_raceBlack   
f\_employmentEmployed   
f\_age   
f\_educationHS and above   
f\_alcohol<1 / month   
f\_alcohol>1 / month   
f\_drugs<1 / month   
f\_drugs>1 / month   
f\_children   
f\_poverty   
f\_incarcerationExperienced incarceration \*  
f\_homeRented   
f\_depression   
f\_raceBlack:f\_employmentEmployed   
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
  
(Dispersion parameter for gaussian family taken to be 25.37529)  
  
Number of Fisher Scoring iterations: 2

marginaleffects::avg\_predictions(  
 mod\_race\_employment\_interaction\_ipv,   
 variables = c("f\_race", "f\_employment")  
)

f\_employment f\_race Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 Employed White 0.117 0.0105 11.12 <0.001 93.0 0.0965 0.138  
 Employed Black 0.129 0.0145 8.93 <0.001 61.0 0.1007 0.157  
 Unemployed White 0.120 0.0310 3.86 <0.001 13.1 0.0590 0.181  
 Unemployed Black 0.106 0.0158 6.70 <0.001 35.5 0.0748 0.137  
  
Columns: f\_race, f\_employment, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_predictions(  
 mod\_race\_employment\_interaction\_ipv,   
 variables = c("f\_race", "f\_employment")  
) |>   
 dplyr::mutate(  
 across(.cols = -dplyr::starts\_with("f\_"), .fns = as.numeric)  
 ) |>   
 ggplot(aes(x = f\_race, y = estimate, ymin = conf.low, ymax = conf.high, color = f\_employment)) +  
 geom\_pointrange(position = position\_dodge(width = .5)) +  
 xlab("Race") +  
 ylab("IPV Index") +  
 scale\_color\_viridis\_d(option = "magma", begin = .2, end = .8)



marginaleffects::avg\_comparisons(  
 mod\_race\_employment\_interaction\_ipv,   
 variables = "f\_race",   
 by = "f\_employment"  
)

Term Contrast f\_employment Estimate Std. Error z  
 f\_race mean(Black) - mean(White) Unemployed -0.0141 0.0388 -0.363  
 f\_race mean(Black) - mean(White) Employed 0.0120 0.0173 0.694  
 Pr(>|z|) S 2.5 % 97.5 %  
 0.717 0.5 -0.0901 0.0619  
 0.488 1.0 -0.0219 0.0458  
  
Columns: term, contrast, f\_employment, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high, predicted\_lo, predicted\_hi, predicted   
Type: response

# (BE - WE) - (BU - WU)  
marginaleffects::avg\_comparisons(  
 mod\_race\_employment\_interaction\_ipv,  
 variables = "f\_race",   
 by = "f\_employment",  
 hypothesis = "pairwise"  
)

Term Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 Unemployed - Employed -0.026 0.0383 -0.68 0.496 1.0 -0.101 0.049  
  
Columns: term, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_comparisons(  
 mod\_race\_employment\_interaction\_ipv,   
 variables = "f\_employment",   
 by = "f\_race"  
)

Term Contrast f\_race Estimate Std. Error  
 f\_employment mean(Employed) - mean(Unemployed) White -0.00266 0.0319  
 f\_employment mean(Employed) - mean(Unemployed) Black 0.02338 0.0230  
 z Pr(>|z|) S 2.5 % 97.5 %  
 -0.0833 0.934 0.1 -0.0652 0.0599  
 1.0179 0.309 1.7 -0.0216 0.0684  
  
Columns: term, contrast, f\_race, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high, predicted\_lo, predicted\_hi, predicted   
Type: response

# (WE - WU) - (BE - BU) (simply the other comparison multiplied by -1)  
marginaleffects::avg\_comparisons(  
 mod\_race\_employment\_interaction\_ipv,  
 variables = "f\_employment", by = "f\_race",  
 hypothesis = "pairwise"  
)

Term Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 White - Black -0.026 0.0383 -0.68 0.496 1.0 -0.101 0.049  
  
Columns: term, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

And now without covariates

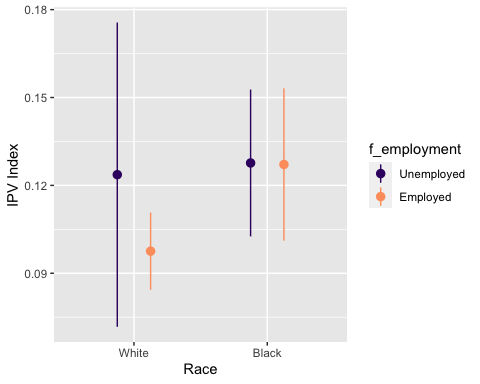
mod\_race\_employment\_interaction\_ipv\_nocov <- survey::svyglm(  
 formula = ipv\_prop ~ f\_race \* f\_employment,  
 design = dat\_weights,  
 family = "gaussian"  
)  
  
summary(mod\_race\_employment\_interaction\_ipv\_nocov)

Call:  
survey::svyglm(formula = ipv\_prop ~ f\_race \* f\_employment, design = dat\_weights,   
 family = "gaussian")  
  
Survey design:  
Called via srvyr  
  
Coefficients:  
 Estimate Std. Error t value Pr(>|t|)   
(Intercept) 0.123663 0.026499 4.667 6.4e-05 \*\*\*  
f\_raceBlack 0.003993 0.031322 0.127 0.899   
f\_employmentEmployed -0.026110 0.027706 -0.942 0.354   
f\_raceBlack:f\_employmentEmployed 0.025594 0.033577 0.762 0.452   
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
  
(Dispersion parameter for gaussian family taken to be 27.02082)  
  
Number of Fisher Scoring iterations: 2

marginaleffects::avg\_predictions(  
 mod\_race\_employment\_interaction\_ipv\_nocov,   
 variables = c("f\_race", "f\_employment")  
)

f\_employment f\_race Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 Employed White 0.0976 0.00673 14.50 <0.001 155.9 0.0844 0.111  
 Employed Black 0.1271 0.01326 9.59 <0.001 69.9 0.1011 0.153  
 Unemployed White 0.1237 0.02650 4.67 <0.001 18.3 0.0717 0.176  
 Unemployed Black 0.1277 0.01279 9.98 <0.001 75.5 0.1026 0.153  
  
Columns: f\_race, f\_employment, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_predictions(  
 mod\_race\_employment\_interaction\_ipv\_nocov,   
 variables = c("f\_race", "f\_employment")  
) |>   
 dplyr::mutate(  
 across(.cols = -dplyr::starts\_with("f\_"), .fns = as.numeric)  
 ) |>   
 ggplot(aes(x = f\_race, y = estimate, ymin = conf.low, ymax = conf.high, color = f\_employment)) +  
 geom\_pointrange(position = position\_dodge(width = .5)) +  
 xlab("Race") +  
 ylab("IPV Index") +  
 scale\_color\_viridis\_d(option = "magma", begin = .2, end = .8)



marginaleffects::avg\_comparisons(  
 mod\_race\_employment\_interaction\_ipv\_nocov,   
 variables = "f\_race",   
 by = "f\_employment"  
)

Term Contrast f\_employment Estimate Std. Error z  
 f\_race mean(Black) - mean(White) Unemployed 0.00399 0.0313 0.127  
 f\_race mean(Black) - mean(White) Employed 0.02959 0.0154 1.926  
 Pr(>|z|) S 2.5 % 97.5 %  
 0.8986 0.2 -0.057398 0.0654  
 0.0541 4.2 -0.000515 0.0597  
  
Columns: term, contrast, f\_employment, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high, predicted\_lo, predicted\_hi, predicted   
Type: response

# (BE - WE) - (BU - WU)  
marginaleffects::avg\_comparisons(  
 mod\_race\_employment\_interaction\_ipv\_nocov,  
 variables = "f\_race",   
 by = "f\_employment",  
 hypothesis = "pairwise"  
)

Term Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 Unemployed - Employed -0.0256 0.0336 -0.762 0.446 1.2 -0.0914 0.0402  
  
Columns: term, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

marginaleffects::avg\_comparisons(  
 mod\_race\_employment\_interaction\_ipv\_nocov,   
 variables = "f\_employment",   
 by = "f\_race"  
)

Term Contrast f\_race Estimate Std. Error  
 f\_employment mean(Employed) - mean(Unemployed) White -0.026110 0.0277  
 f\_employment mean(Employed) - mean(Unemployed) Black -0.000516 0.0194  
 z Pr(>|z|) S 2.5 % 97.5 %  
 -0.9424 0.346 1.5 -0.0804 0.0282  
 -0.0267 0.979 0.0 -0.0384 0.0374  
  
Columns: term, contrast, f\_race, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high, predicted\_lo, predicted\_hi, predicted   
Type: response

# (WE - WU) - (BE - BU) (simply the other comparison multiplied by -1)  
marginaleffects::avg\_comparisons(  
 mod\_race\_employment\_interaction\_ipv\_nocov,  
 variables = "f\_employment", by = "f\_race",  
 hypothesis = "pairwise"  
)

Term Estimate Std. Error z Pr(>|z|) S 2.5 % 97.5 %  
 White - Black -0.0256 0.0336 -0.762 0.446 1.2 -0.0914 0.0402  
  
Columns: term, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high   
Type: response

# Models side by side

modelsummary::modelsummary(  
 models = list(  
 "IPV on race" = mod\_race\_ipv,  
 "IPV on race and employment" = mod\_race\_employment\_ipv,  
 "IPV on race by employment" = mod\_race\_employment\_interaction\_ipv  
 ),  
 estimate = "estimate",  
 stars = TRUE,  
 statistic = c("conf.int", "p.value")  
)

|  | IPV on race | IPV on race and employment | IPV on race by employment |
| --- | --- | --- | --- |
| (Intercept) | 0.121\* | 0.110+ | 0.127+ |
|  | [0.003, 0.238] | [-0.012, 0.232] | [-0.016, 0.271] |
|  | (0.044) | (0.075) | (0.079) |
| f\_raceBlack | 0.007 | 0.009 | -0.014 |
|  | [-0.026, 0.040] | [-0.026, 0.044] | [-0.096, 0.067] |
|  | (0.646) | (0.602) | (0.721) |
| f\_age | 0.000 | 0.000 | 0.000 |
|  | [-0.003, 0.003] | [-0.003, 0.003] | [-0.004, 0.003] |
|  | (0.953) | (0.946) | (0.920) |
| f\_educationHS and above | -0.024 | -0.026 | -0.026 |
|  | [-0.066, 0.017] | [-0.069, 0.018] | [-0.070, 0.018] |
|  | (0.237) | (0.230) | (0.228) |
| f\_alcohol<1 / month | -0.010 | -0.010 | -0.010 |
|  | [-0.044, 0.024] | [-0.044, 0.024] | [-0.044, 0.024] |
|  | (0.543) | (0.548) | (0.554) |
| f\_alcohol>1 / month | 0.030 | 0.029 | 0.030 |
|  | [-0.007, 0.067] | [-0.008, 0.066] | [-0.007, 0.067] |
|  | (0.111) | (0.113) | (0.110) |
| f\_drugs<1 / month | 0.007 | 0.008 | 0.007 |
|  | [-0.051, 0.065] | [-0.050, 0.066] | [-0.053, 0.066] |
|  | (0.803) | (0.778) | (0.813) |
| f\_drugs>1 / month | -0.007 | -0.006 | -0.005 |
|  | [-0.056, 0.042] | [-0.055, 0.044] | [-0.055, 0.045] |
|  | (0.771) | (0.813) | (0.832) |
| f\_children | -0.001 | -0.002 | -0.002 |
|  | [-0.021, 0.018] | [-0.021, 0.018] | [-0.021, 0.018] |
|  | (0.894) | (0.862) | (0.847) |
| f\_poverty | -0.003 | -0.003 | -0.003 |
|  | [-0.008, 0.002] | [-0.008, 0.002] | [-0.008, 0.002] |
|  | (0.285) | (0.256) | (0.276) |
| f\_incarcerationExperienced incarceration | 0.058\* | 0.060\* | 0.060\* |
|  | [0.010, 0.106] | [0.011, 0.108] | [0.011, 0.109] |
|  | (0.019) | (0.018) | (0.020) |
| f\_homeRented | 0.001 | 0.001 | 0.001 |
|  | [-0.026, 0.029] | [-0.026, 0.029] | [-0.027, 0.029] |
|  | (0.920) | (0.914) | (0.943) |
| f\_depression | -0.001 | -0.001 | -0.001 |
|  | [-0.020, 0.019] | [-0.021, 0.019] | [-0.021, 0.019] |
|  | (0.935) | (0.919) | (0.919) |
| f\_employmentEmployed |  | 0.014 | -0.003 |
|  |  | [-0.026, 0.054] | [-0.070, 0.064] |
|  |  | (0.471) | (0.935) |
| f\_raceBlack × f\_employmentEmployed |  |  | 0.026 |
|  |  |  | [-0.054, 0.106] |
|  |  |  | (0.505) |
| Num.Obs. | 1585 | 1585 | 1585 |
| R2 | 0.070 | 0.071 | 0.072 |
| R2 Adj. | -72.644 | -76.448 | -80.684 |
| BIC | 8395.2 | 8318.9 | 8238.7 |
| Log.Lik. | -4146.028 | -4104.185 | -4060.380 |
| F | 3.912 | 3.638 | 3.356 |
| RMSE | 0.15 | 0.15 | 0.15 |
| + p < 0.1, \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001 | | | |