Use of Force Final Project Report

Kaylhan Garcia, Adam Billen, and Phoebe Lin

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```
library(conflicted)
library(tidyverse)
```

```
## Warning: package 'purrr' was built under R version 4.3.2
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.3     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.3     v tibble    3.2.1
## v lubridate 1.9.2     v tidyr     1.3.0
## v purrr     1.0.2
```

```
library(nnet)
library(MASS)
library(rpart)
library(coefplot)
```

```
## Warning: package 'coefplot' was built under R version 4.3.2
```

```
conflicts_prefer(dplyr::filter)
```

```
## [conflicted] Will prefer dplyr::filter over any other package.
```

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Introduction:

Police have existed in America in some form for nearly its entire history. Police forces themselves have their philosophical origin in Patrick Colquhoun's 1797 "Treatise on the Police of the Metropolis" (Colquhoun 1797). These ideas first took form in London in 1829, but Colquhoun himself spent his early career as a British agent for cotton manufacturers. His conception of policing grew from his time spent enforcing slave codes and working with slave patrols in Virginia. The first hiring of police through legislative means was in Boston in 1838, but before then "police" simply referred to slave patrols (Potter 2022). North Carolina's first state police force was formed in order to stamp out the publishing of "The Liberator," William Lloyd Garrison's weekly abolitionist newspaper, soon after he was almost killed in a mob attack in Boston in 1835 (Lepore 2020). The modern American police force began and grew from these dark roots of American history.

The existing literature around racialized policing has established that Black, Hispanic and American Indian/Native Americans are disproportionately likely to be killed by police in America, especially at younger ages. One study using data from between 2013 and 2018 found that Black men are ~2.5 times more and Black women ~1.4 times more likely to be killed by police in their lifetime than white men and white women, respectively (Fryer 2019). This amounts to some 96 out of 100,000 Black men and boys, between 36 and 81 American Indian/Alaskan Native men and boys, and 53 out of 100,000 Latino men and boys being killed by police over their lifetime, as compared to about 39 out of 100,000 white men and boys being killed (Fryer 2019). The risk is substantially lower for women across all racial groups. Between 2.4 and 5.4 Black women and girls, 2.4 American Indian/Alaskan Native women and girls, and 2 Latino and white women and girls out of 100,000 are expected to be killed by police throughout their lifetime (Fryer 2019). This relationship holds even when controlling for uses of police violence against criminal vs non-criminal subjects (Ross et al. 2021). This existing set of literature focuses broadly on fatal violence inflicted by American police, often using national level data collected by the Washington Post (Washington Post). This data is, however, scattered and often inconsistent. The Washington Post's database, for example, relies on local news reports (Nix 2022). Official national level data compiled by the Bureau of Justice Statistics also fails to provide a full picture. There is no federal regulation mandating the format or way in which individual police departments collect data, and so America's 18,000+ police departments each have control over how, when, and where data is collected. Matthew Hickman, a professor and former Bureau of Justicts Statistics employee, described the situation as a "huge mess" wherein police departments can each do "whatever they want" (Katie 2019).

In the past decade, however, a new political force, the Black Lives Matter movement, rose up and sparked a conservation around the appropriate use of force by the police. The public began pushing for more transparency around the use of force, and policing generalky (Schwartz, 2020). A number of local governments have, at least partially, met this demand. These local governments have mandated that their local police forces provide public data on each case of a police officer using force against a civilian. The resulting datasets provide a way to analyze use of force more broadly, rather than soley fatal violence by the police. There has not, however, been a large wave of research exploring this data. Instead, local agencies, often Police Accountability Offices, typically produce a yearly report analyzing the past year's use of force data. While these reports tend to draw lots of public attention in the news, they are are generally relatively surface level. They tend to include general information about the number of uses of force and any clear disparities in the use of force. They do not, however, include more advanced methods such as regression. To expand on this existing literature, we will emplore more advances methods such as logistic multiple regression to explore the relationship between demographic factors such as subject or officer race and the severity of a given use of force.

Hypotheses:

We hypothesize that Black/African American subjects are more likely to have serious force used against them than other racial groups, particularly white subjects. While this is our primary topic of interest, we expect that other demographic groups for both subjects and officers will have varying degrees of likelihood to have serious force used against them as well. We will also explore whether particular races of officers are more or less likely to use serious force against particular races of subjects. We hypthesize that white officers will be more likely to use serious force against black subjects than black officers.

Methods:

By including all of the demographic information provided, we will build a clearer picture of exactly what demographic groups are more likely to have severe uses of force inflicted upon them. By subsetting our data to specific officer races, we will examine which particular combinations of demographic factors result in more severe uses of force, providing a fuller picture of how officers and citizens interact. We have chosen logistic multiple regression as it is the most applicable and interpretable model for this particular data. All of the data for each city is categorical, and we have thus created dummy variables for each key cateogrical variable in each dataset. We have chosen a regular logistic regression instead of an ordinal logistic regression because each categorical independent variable is unordered. Including categorical variables such as race as an ordered set of numbers would make certain races have a larger effect on the dependent variable, hurting the accuracy and interpretability of the resulting coefficients. We have created a binary dependent variable (described) below as our output.

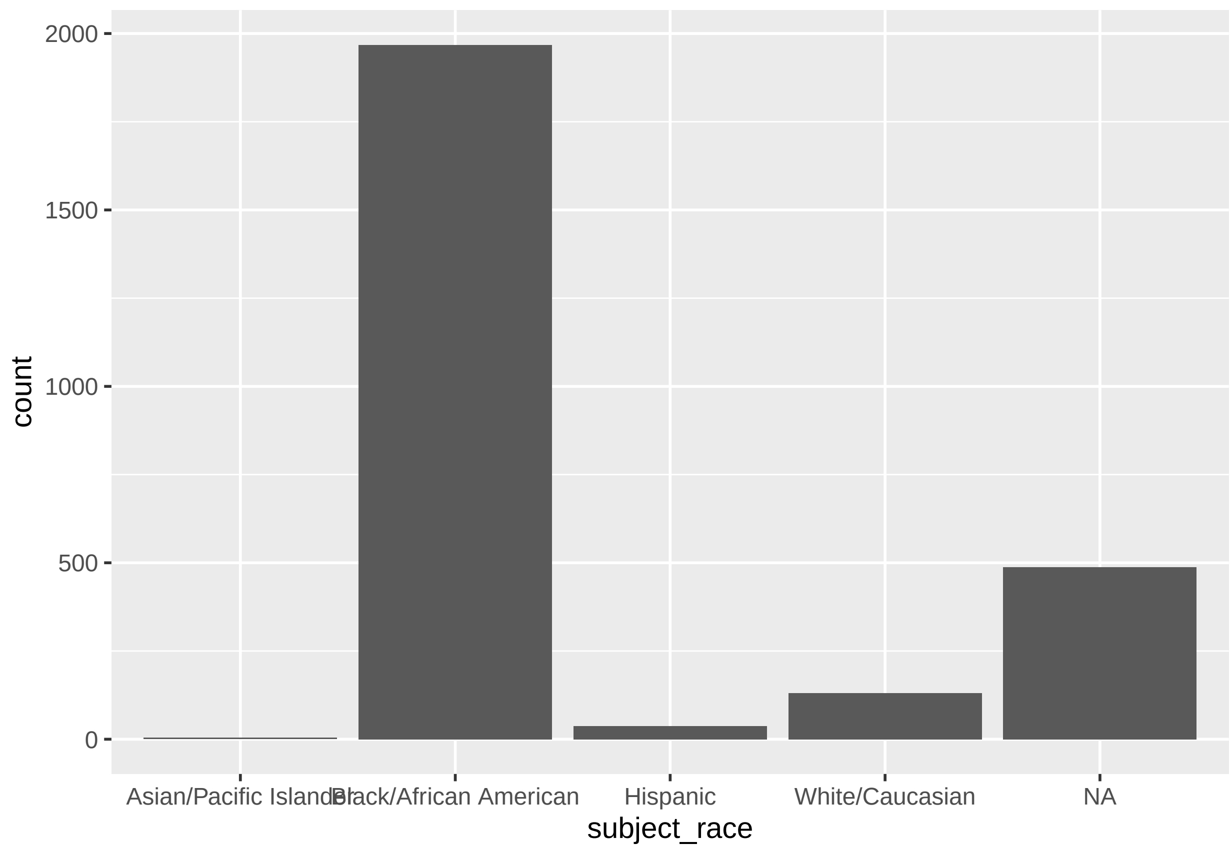
This study involves four unique American cities which vary widely in their locations and demographic makeup. We will study use of force data in Washington, DC (East Coast), Indianapolis (Midwest), Portland (West Coast), and Seattle (the Northwest). In order to compare these models we have created a binary Serious/non-Serious variable for each dataset. This variable is based on a pre-existing variable in the dataset for Washington, DC. This variable, "serious," is set to 1 when a use of force involves a firearm discharge, strike to the head, canine bite, neck restraint, results in a serious physical injury, or results in the risk of or loss of consciousness, death, or serious disfigurement. The data for Seattle includes a similar risk tier system from one to three, which we have simplified to a binary variable where levels two and three are serious and level one is non-serious. The data for Portland utilizes a four-tiered system, which we have simplified to make tiers two through four serious uses of force and tier four non-serious. The data for Indianapolis breaks down uses of force by individual type, which we have categorized as serious or non-serious to match the other cities. Still, these categories should not be read as precisely comparable. Systems of reporting and publishing data vary between cities, but this variable still provides a stronger point of reference between cities.

Data Exploration

Washington, DC

1. Distribution of Incident Counts by Subject Race Black/ African American have a significantly higher amount of incident counts in 2020. Conversely, Asian/Pacific Islander individuals appear to experience the least instances of use of force.

```
df <- read.csv("../data/UOF_DC_2020.csv")
mpd_dat <- df
ggplot(data = mpd_dat, mapping = aes(x = subject_race)) +
  geom_bar()
```



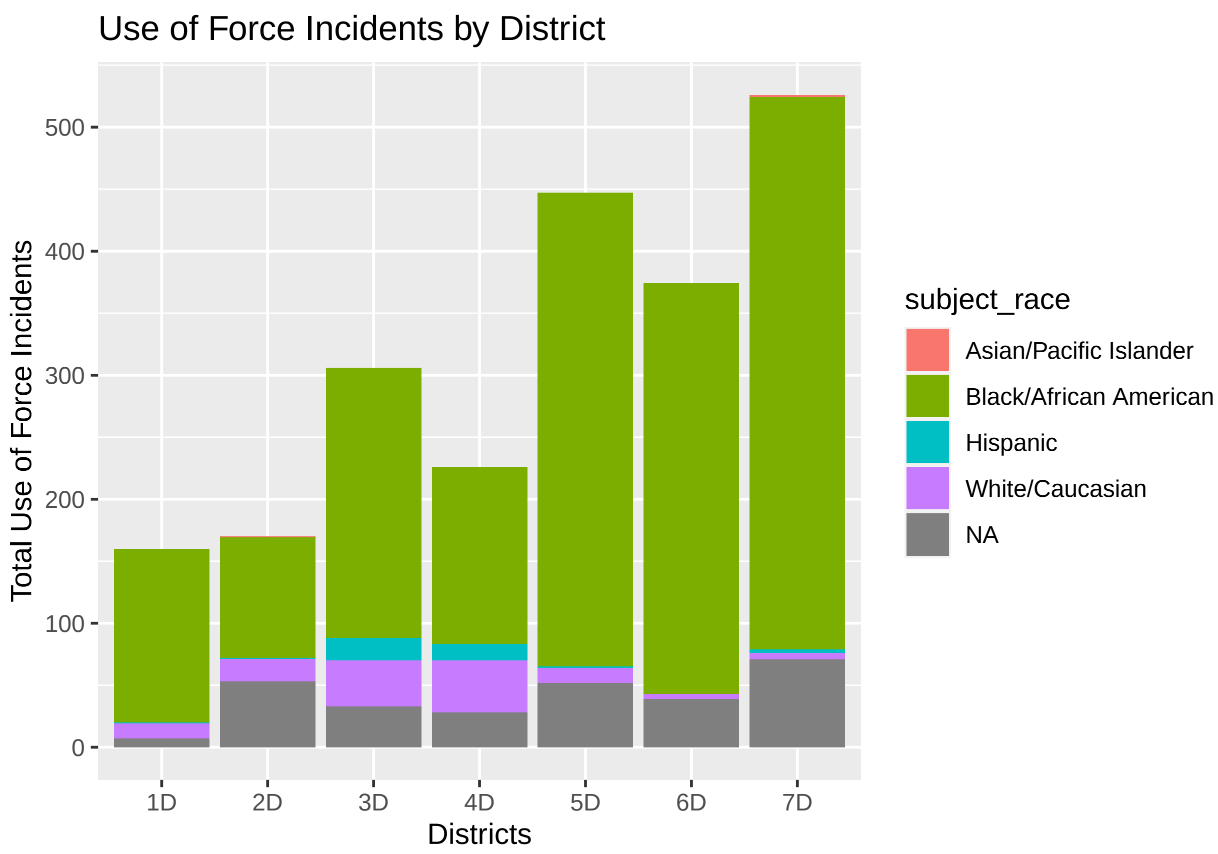
2. UOF Incident Counts by District and Subject Race Across all districts in DC, it is prevalent that Black/African Americans experience UOF at a higher rate than their counterparts.

7th District has the highest total UOF incidents out of all the DC districts.

```
force_by_district_race <- mpd_dat %>%
group_by(OfficerAssignment, subject_race) %>% summarize(Total_Use_of_Force = n()) #total num of cases o
```

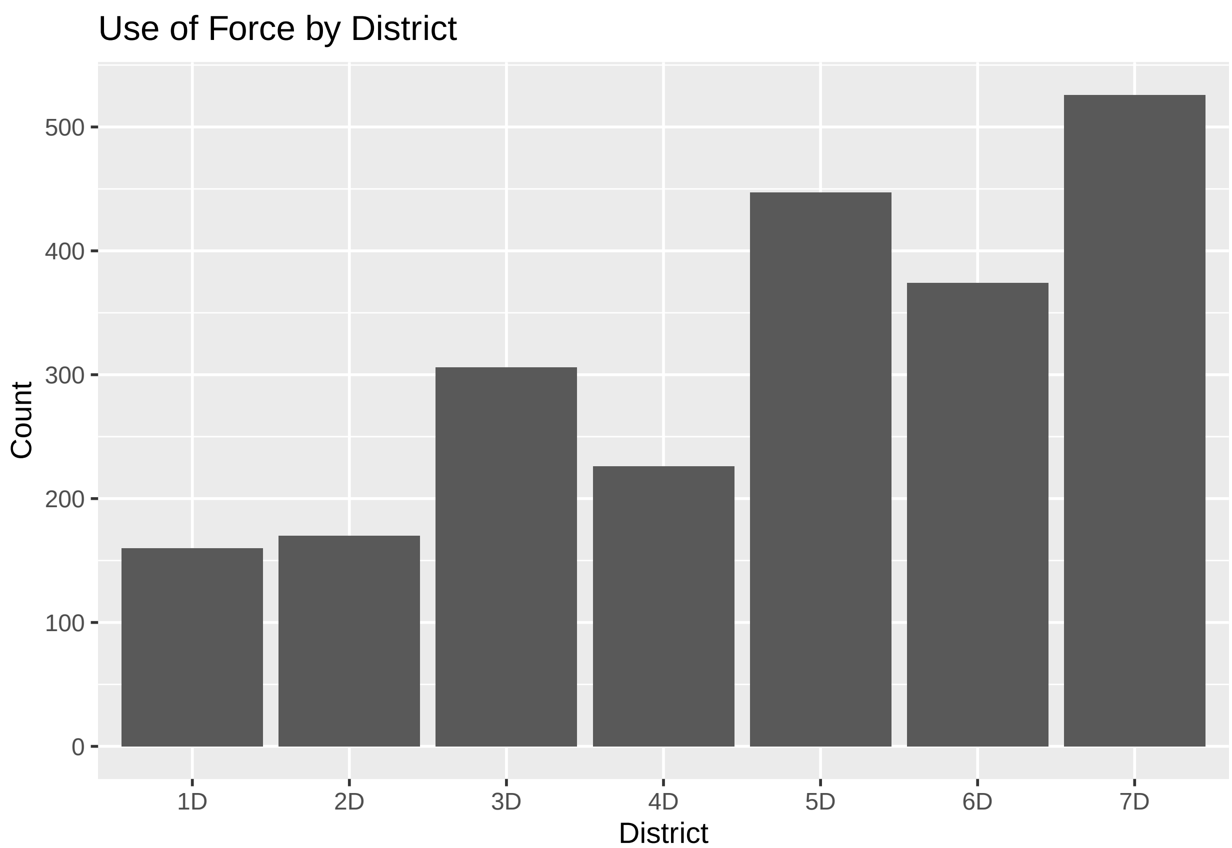
```
## `summarise()` has grouped output by 'OfficerAssignment'. You can override using
## the `.groups` argument.
```

```
ggplot(subset(force_by_district_race, OfficerAssignment %in% c("1D", "2D", "3D", "4D", "5D", "6D", "7D")
       aes(x = OfficerAssignment, y = Total_Use_of_Force, fill = subject_race)) +
  geom_bar(stat = "identity") +
  labs(title = "Use of Force Incidents by District") +
  xlab("Districts") +
  ylab("Total Use of Force Incidents")
```



3. Use of Force by District. 1D, 2D, and 3D are shown to be the safest districts in DC, whereas 7D is deemed to be the most dangerous.

```
districts <- c("1D", "2D", "3D", "4D", "5D", "6D", "7D")
mpd_dat_filtered <- mpd_dat[mpd_dat$OfficerAssignment %in% districts, ]

uof_counts <- mpd_dat_filtered %>%
  group_by(OfficerAssignment) %>%
  summarise(Count = n())

ggplot(uof_counts, aes(x = OfficerAssignment, y = Count)) +
  geom_bar(stat = "identity") +
  labs(title = "Use of Force by District",
       x = "District",
       y = "Count")
```



Seattle, Washington

```
seattle_2020 <- read_csv("../data/UOF_Seattle.csv")
```

```
## Rows: 16513 Columns: 11
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (8): ID, Incident_Type, Occured_date_time, Precinct, Sector, Beat, Subje...
## dbl (3): Incident_Num, Officer_ID, Subject_ID
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

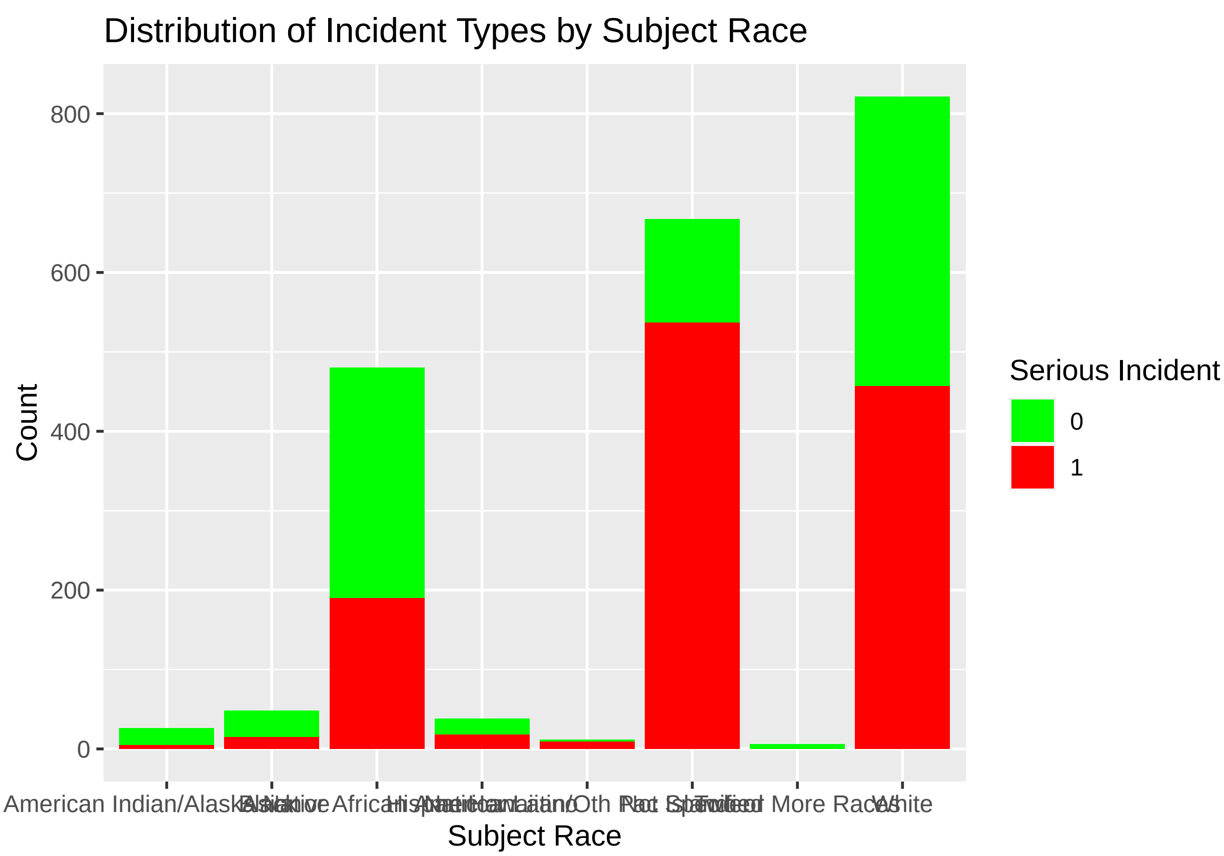
```
seattle_2020 <- seattle_2020 %>%
  mutate(datetime = mdy_hms(Occured_date_time)) %>%
  filter(year(datetime) == 2020) %>%
  drop_na(Incident_Type, Subject_Race, Subject_Gender, Precinct, Sector, Beat) %>%
  mutate(serious = ifelse(Incident_Type == "Level 1 - Use of Force", 0, 1))
```

4. Distribution of Incident Types by Subject Race There is a huge amount of 'Not Specified' values for this data visualization during the year 2020.

White people have a shared count amount of serious incidents regarding use of force my the police department.

The next following group that stands out is 'Black or African American,' with level 1 - Use of Force being greater than the other levels.

```
ggplot(seattle_2020, aes(x = Subject_Race, fill = factor(serious))) +
  geom_bar(position = "stack") +
  labs(
    title = "Distribution of Incident Types by Subject Race",
    x = "Subject Race",
    y = "Count",
    fill = "Incident Type"
  ) +
  scale_fill_manual(values = c("0" = "green", "1" = "red"), name = "Serious Incident")
```



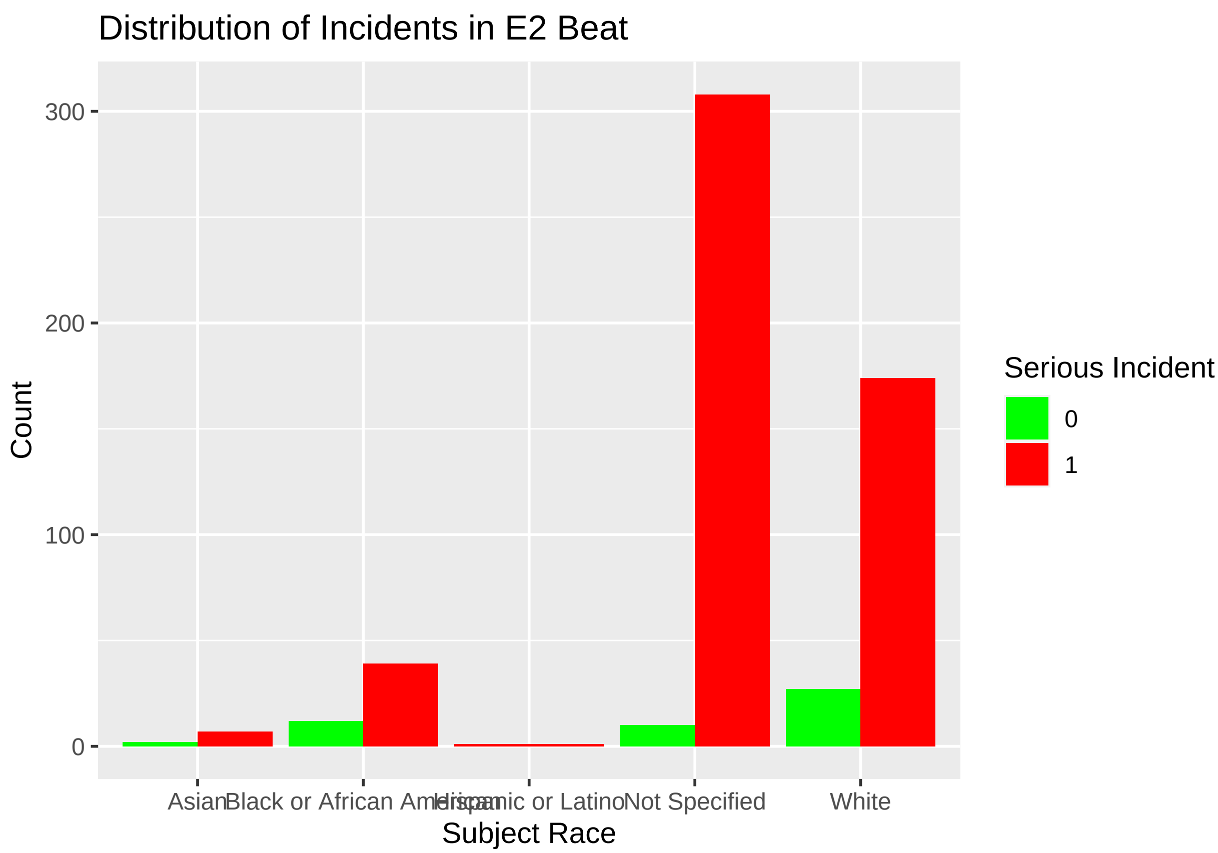
5. Comparative Analysis: Incidents in E2 by Subject Race E2 has the highest amount of incidents across all the other beats in Seattle. There are a total of 52 beats reported in the dataset.

Many of the 'Subject Race' is left unreported or 'Not Specified' in the year 2020. The next leading race that are subjected to incidents in the E2 beat are White, then it is Black or African American.

It is notable to mention that many of the serious incidents are reported as 'Not Specified' in the E2 beat.

```
e2_data <- subset(seattle_2020, Beat == "E2")

ggplot(e2_data, aes(x = Subject_Race, fill = factor(serious))) +
  geom_bar(position = "dodge", stat = "count") +
  labs(
```

```r
    title = "Distribution of Incidents in E2 Beat",
    x = "Subject Race",
    y = "Count",
    fill = "Serious Incident"
  ) +
  scale_fill_manual(values = c("0" = "green", "1" = "red"), name = "Serious Incident")
```



###Indianapolis, Indiana

In Indianapolis, 52.7% of the population are Whites, 28.5% are Black or African American and 3.82% are Asian. The presence of an 'Unknown' category for subject race suggests that data collection may not be complete or consistently conducted across all incidents. But overall, the "Black" category shows significantly higher number of incidents comparedito other races.

The seriousness of the cases seems to vary across races, but for those races with a significant number of incidents (Black and White categories), non-serious incidents outnumber serious incidents. This could indicate that while the use of force is more commonly reported as non-serious, serious use of force incidents still occur with notable frequency in these populations.

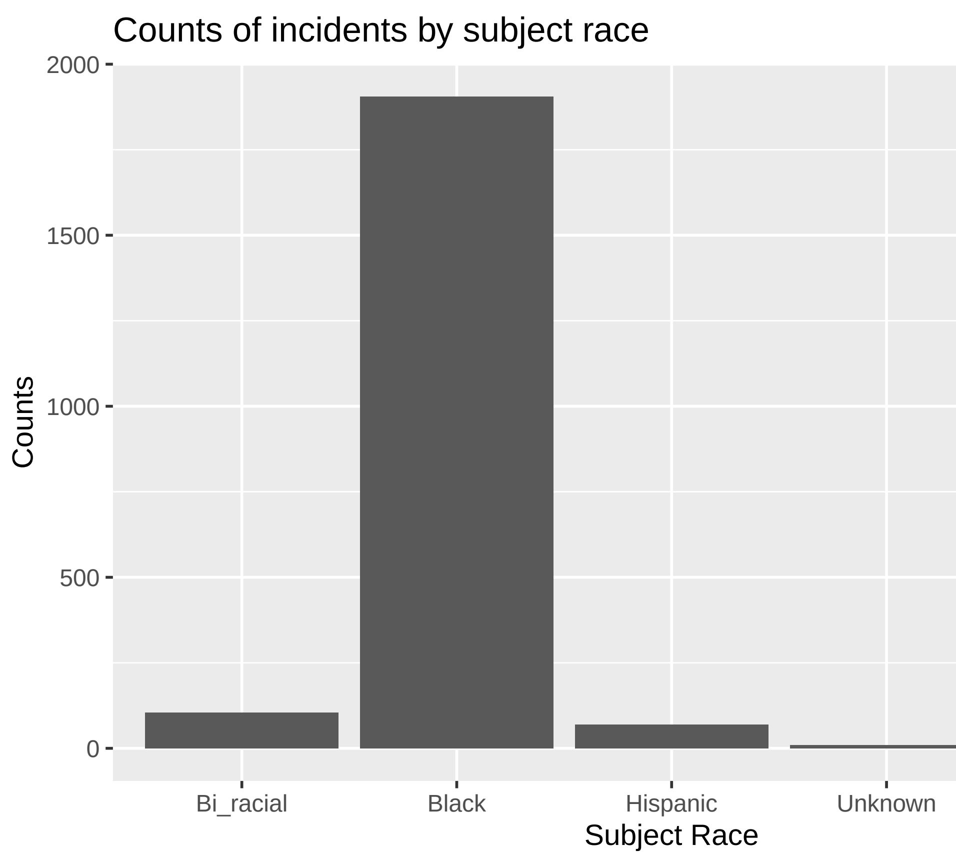
```r
ind_dat <- read_csv("../data/ind_dat_2020_final.csv")
```

```
## Rows: 2793 Columns: 59
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (30): OCCURRED_DT, OCCURRED_TM, UDTEXT24A, UDTEXT24B, UDTEXT24C, UDTEXT...
## dbl  (27): OBJECTID, INCNUM, CITNUM, CIT_AGE, OFFNUM, OFF_AGE, OFF_YR_EMPLOY...
## lgl   (1): CIT_WEAPON_TYPE
```

```
## date  (1): datetime
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

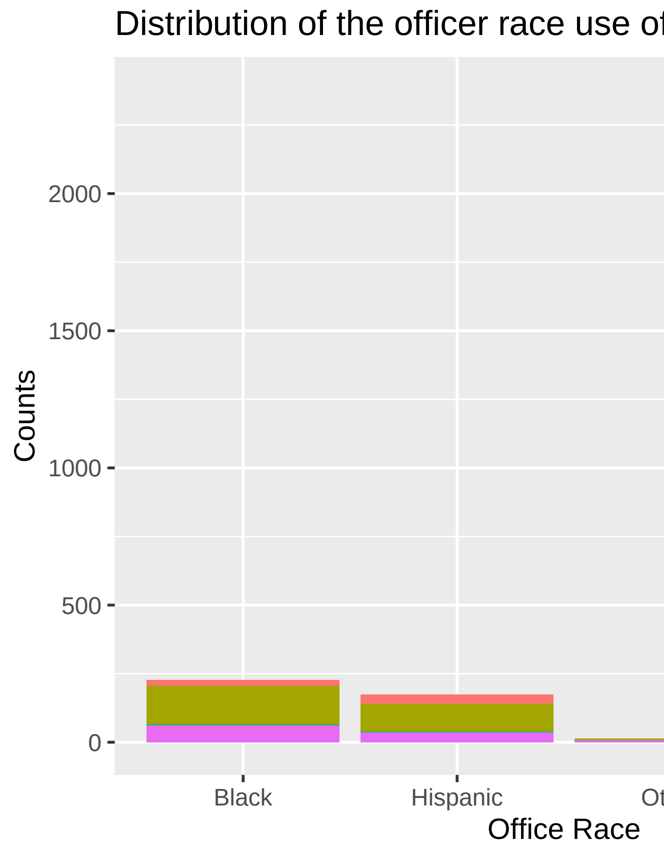
```
ind_dat$serious <- factor(ind_dat$serious)
```

```
ggplot(data = ind_dat, mapping = aes(x = RACE)) +
  geom_bar() +
  labs(title = "Counts of incidents by subject race",
       x = "Subject Race",
       y = "Counts")
```



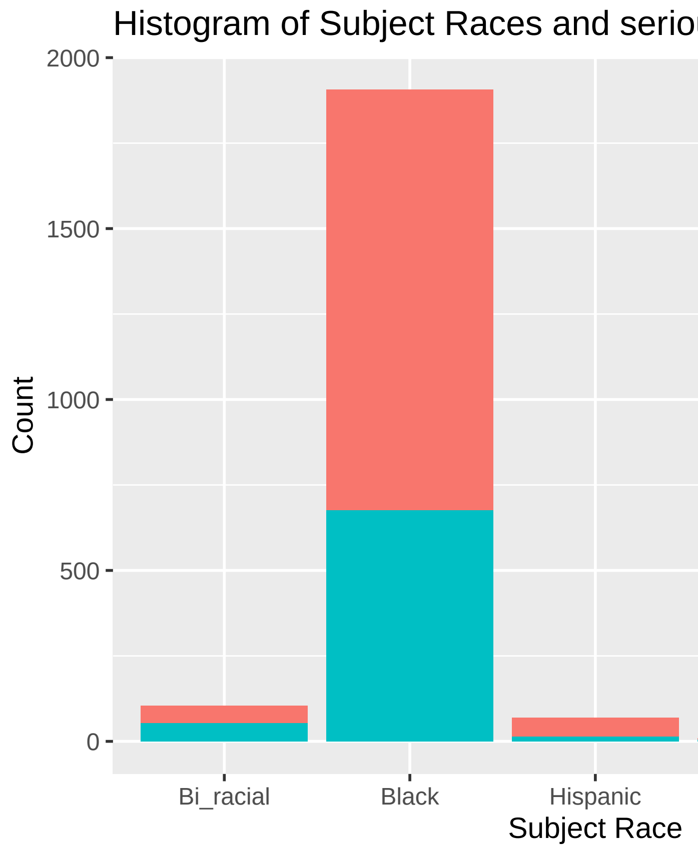
Counts of incidents by subject race
Based on the plot, the Blacks are experiencing the most UOF where over 10,000 incidents happened and followed by the White with counts less than 6,000.

```
ggplot(data = ind_dat, mapping = aes(x = OFF_RACE, fill = RACE)) +
  geom_bar() +
  labs(title = "Distribution of the officer race use of force frequency",
       x = "Office Race",
       y = "Counts")
```



The Distribution of the officer race use of force frequency.
In this case, the White officers are using the most use of force in an incident with highest number of Black being targeted.

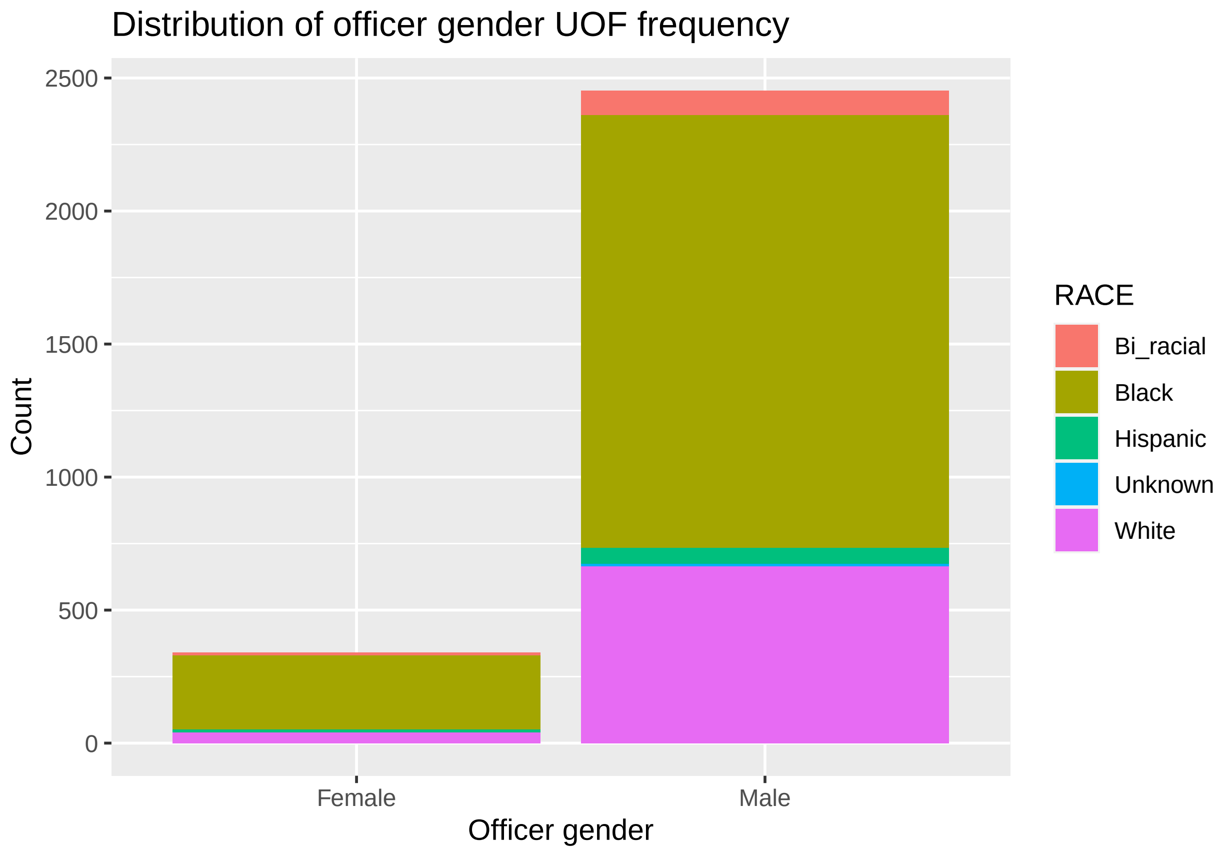
```
ggplot(data = ind_dat, mapping = aes(x = RACE, fill = serious)) +
 geom_bar() +
 labs(title = "Histogram of Subject Races and serious incidents", x = "Subject Race", y = "Count")
```



The counts of serious incidents relative to subject race.
Based on the plot, Black experiencing use of force occurred the most, over 10,000 counts. White experiencing almost less than half of the incidents of the Blacks.

```
ggplot(data = ind_dat, mapping = aes(x = SEX, fill = RACE)) +
 geom_bar() +
 labs(title = "Distribution of officer gender UOF frequency", x = "Officer gender", y = "Count")
```

The counts of officer gender use of force frequency in relation to the subject race.



This plots shows the distribution of the counts of the use of force cases among male and female officers. From the chart, it appears that there are significantly more incidents involving males officer than females officer.

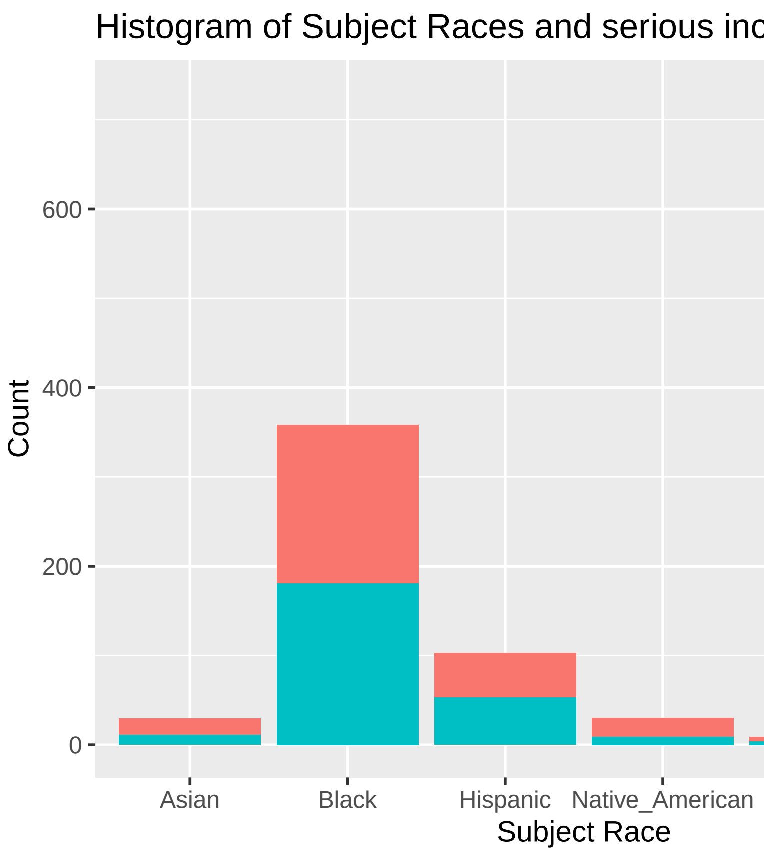
Portland, Oregon

Portland's population is made up of 635,067 of people where 73.8% are White, 5.6% are Black or African American, 8.5% are Asian. Overall, the Whites are experiencing the highest number of incidents in Portland 2020.

```
port_dat <- read_csv("../data/pdx_dat_2020_final.csv")
```

```
## Rows: 1260 Columns: 75
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (41): Blunt_Object, Category_of_Force_Event__Measured_at_Event_Level, Di...
## dbl (34): Officer, Officer_Tenure, Record_ID, Subject, Subject_Age, Subject_...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
port_dat$serious <- factor(port_dat$serious)

ggplot(data = port_dat, mapping = aes(x = Subject__Race, fill = serious)) +
 geom_bar() +
 labs(title = "Histogram of Subject Races and serious incidents", x = "Subject Race", y = "Count")
```



Histogram of Subject Races and serious incidents

Based on the plot, the race with the highest number of incidents is White, with a notable number of both serious and not serious incidents. This might due to the reason that Portland's population have over 70% Whites with only 5.6% of Blacks or African American. For all races, there are more incidents that are not serious (0) than serious (1), as indicated by the size of the colored sections.

Data driven hypotheses:

Our data exploration shows that Black/African American community members across each city are subject to a disproportionate amount of serious force, as compared to white community members. We can also see that particular wards and districts in some cities see a disproprionate amount of use of force generally. Our previous hypotheses remain relevant. We will use the methods described above to further explore these relationships. Given the disproportionate representation of Black/African Americans in cases of use of force, we expect subject race to be highly predictive in the model. We also expect some locations and districts to be highly predictive, as well as officer race.

Results/

Reading in data

```
mpd_dat_2020 <- read.csv('../data/UOF_DC_2020.csv')
sea_dat_2020 <- read.csv('../data/UOF_Seattle.csv')
pdx_dat_2020 <- read_csv("../data/UOF_Portland.csv")
```

```
## New names:
## Rows: 10037 Columns: 49
## -- Column specification
## -------------------------------------------------------- Delimiter: "," chr
## (40): Blunt Object, Category of Force Event - Measured at Event Level, D... dbl
## (9): Officer, Officer Tenure, Record ID, Subject, Subject Age, Subject ...
## i Use `spec()` to retrieve the full column specification for this data. i
## Specify the column types or set `show_col_types = FALSE` to quiet this message.
## * `Record Count` -> `Record Count...48`
## * `Record Count` -> `Record Count...49`
```

```
ind_dat_2020 <- read_csv("../data/UOF_Indianapolis.csv")
```

```
## Rows: 63151 Columns: 35
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (26): OCCURRED_DT, UDTEXT24A, UDTEXT24B, UDTEXT24C, UDTEXT24D, DISPOSIT...
## dbl   (7): OBJECTID, INCNUM, CITNUM, CIT_AGE, OFFNUM, OFF_AGE, OFF_YR_EMPLOY
## lgl   (1): CIT_WEAPON_TYPE
## time  (1): OCCURRED_TM
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Setting up the data for DC

```
age_breaks <- c(18, 25, 35, 45, 55, 65, 100)

mpd_dat_2020 <- mpd_dat_2020 %>%
  mutate(
    subject_age = as.numeric(subject_age),
    AgeBands = cut(subject_age, breaks = age_breaks, labels = c("18_24", "25_34", "35_44", "45_54", "55_
                   include.lowest = TRUE, right = FALSE)) %>%
  drop_na(uof_type, IncidentDistrict, OfficerGender, OfficerRace, AgeBands, subject_race, subject_gende
  mutate(OfficerRace = str_replace_all(OfficerRace, "/", "_")) %>%
  mutate(OfficerRace = str_replace_all(OfficerRace, " ", "_")) %>%
  mutate(subject_race = str_replace_all(subject_race, " ", "_")) %>%
  mutate(subject_race = str_replace_all(subject_race, "/", "_"))
```

```
## Warning: There was 1 warning in `mutate()`.
## i In argument: `subject_age = as.numeric(subject_age)`.
## Caused by warning:
## ! NAs introduced by coercion
```

```r
mpd_dat_2020$IncidentDistrict <- factor(mpd_dat_2020$IncidentDistrict)
mpd_dat_2020$IncidentDistrict <- relevel(mpd_dat_2020$IncidentDistrict, ref = "1D")
mpd_dat_2020$OfficerGender <- factor(mpd_dat_2020$OfficerGender)
mpd_dat_2020$OfficerGender <- relevel(mpd_dat_2020$OfficerGender, ref = "Male")
mpd_dat_2020$OfficerRace <- factor(mpd_dat_2020$OfficerRace)
mpd_dat_2020$OfficerRace <- relevel(mpd_dat_2020$OfficerRace, ref = "White_Caucasian")
mpd_dat_2020$AgeBands <- factor(mpd_dat_2020$AgeBands)
mpd_dat_2020$AgeBands <- relevel(mpd_dat_2020$AgeBands, ref = "18_24")
mpd_dat_2020$subject_race <- factor(mpd_dat_2020$subject_race)
mpd_dat_2020$subject_race <- relevel(mpd_dat_2020$subject_race, ref = "White_Caucasian")
mpd_dat_2020$subject_gender <- factor(mpd_dat_2020$subject_gender)
mpd_dat_2020$subject_gender <- relevel(mpd_dat_2020$subject_gender, ref = "Male")

encoded_data_2020 <- model.matrix(~ IncidentDistrict + OfficerGender + OfficerRace + AgeBands + subject_

mpd_dat_enc_2020 <- cbind(mpd_dat_2020, encoded_data_2020)
```

DC overall regression

The results for our regression classifying serious vs non-serious use of force based on location, officer race, subject age, subject race and subject gender in DC for the year 2020 are shown below. For this regression, districts are compared to District 1 as the reference, officer and subject race are compared to white as the reference, subject age is compared to 18-24 as the reference, and subject gender is compared to male as the reference. The negative coefficient for subjects aged 55-65, for example, indicates that those in that age bracket are less likely to have serious force used against them than those in the 18-24 age bracket. These "reference" variables are rows in the dataset where a given row has all 0s for a given set of variables. This is the result of making our categorical variables into dummy variables.

The results of this regression indicate that our hypothesis that Black/African American subject would be more likely to be subject to a serious use of force may be incorrect, because the variable for subject race = Black/African American has a non-positive P value (.3). This does not, however, indicate that Black/African American residents are less likely to have force used against them than white subject in general, only that they are not more likely to have serious force used against them then white subjects. This is important to understand for our analysis of each of the regressions in this study.

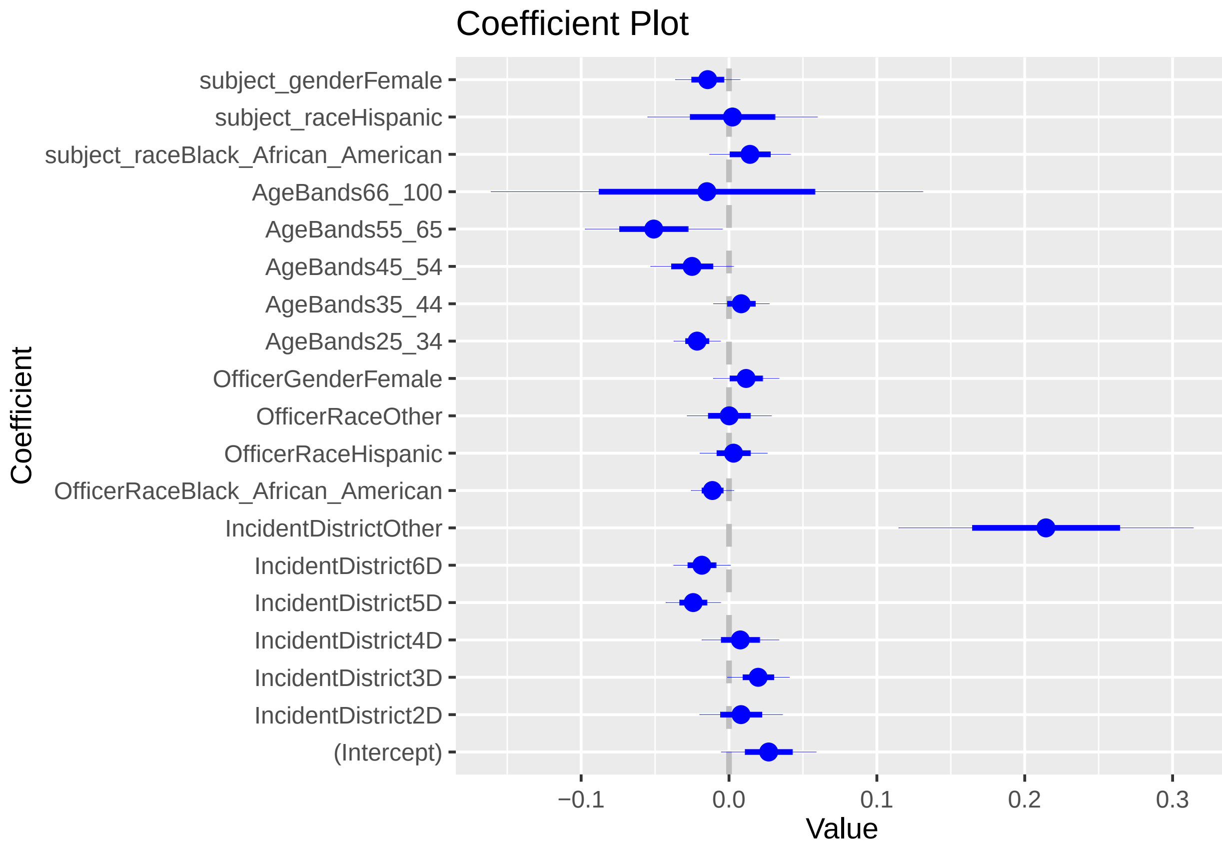
Other variables of interest, however, do show significance. In district 5, for example, serious force is 1.8% less likely to be used than in district 1 (p = .008). Subjects aged 25 to 34 are 2.2% less likely to have serious forced used against them than are subjects aged 18-24 (p = .006). Subjects aged 55 to 65 are 5.1% less likely to have serious force used against them thatn subjects aged 18-24 (p = .02).

```r
model_mpd_2020 <- glm(serious ~ IncidentDistrict2D + IncidentDistrict3D + IncidentDistrict4D + Incident
               data = mpd_dat_enc_2020)

summary(model_mpd_2020)
```

```
##
## Call:
## glm(formula = serious ~ IncidentDistrict2D + IncidentDistrict3D +
##     IncidentDistrict4D + IncidentDistrict5D + IncidentDistrict6D +
##     IncidentDistrictOther + OfficerRaceBlack_African_American +
##     OfficerRaceHispanic + OfficerRaceOther + OfficerGenderFemale +
##     AgeBands25_34 + AgeBands35_44 + AgeBands45_54 + AgeBands55_65 +
##     AgeBands66_100 + subject_raceBlack_African_American + subject_raceHispanic +
```

```
##     subject_genderFemale, data = mpd_dat_enc_2020)
##
## Coefficients:
##                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       0.0268214  0.0160077   1.676  0.09399 .
## IncidentDistrict2D                0.0081125  0.0140112   0.579  0.56265
## IncidentDistrict3D                0.0197266  0.0104725   1.884  0.05976 .
## IncidentDistrict4D                0.0076422  0.0130105   0.587  0.55701
## IncidentDistrict5D               -0.0242273  0.0092516  -2.619  0.00889 **
## IncidentDistrict6D               -0.0183856  0.0095872  -1.918  0.05529 .
## IncidentDistrictOther             0.2143488  0.0498187   4.303 1.77e-05 ***
## OfficerRaceBlack_African_American -0.0112253 0.0072042  -1.558  0.11935
## OfficerRaceHispanic               0.0030355  0.0113752   0.267  0.78961
## OfficerRaceOther                  0.0001299  0.0142572   0.009  0.99273
## OfficerGenderFemale               0.0115627  0.0110954   1.042  0.29748
## AgeBands25_34                    -0.0215921  0.0078973  -2.734  0.00631 **
## AgeBands35_44                     0.0082553  0.0094316   0.875  0.38153
## AgeBands45_54                    -0.0250014  0.0140251  -1.783  0.07480 .
## AgeBands55_65                    -0.0509218  0.0232159  -2.193  0.02839 *
## AgeBands66_100                   -0.0149708  0.0730176  -0.205  0.83757
## subject_raceBlack_African_American 0.0141636  0.0136904   1.035  0.30100
## subject_raceHispanic              0.0023417  0.0286974   0.082  0.93497
## subject_genderFemale             -0.0144387  0.0109316  -1.321  0.18671
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02095595)
##
##     Null deviance: 43.037  on 2009  degrees of freedom
## Residual deviance: 41.723  on 1991  degrees of freedom
## AIC: -2044.3
##
## Number of Fisher Scoring iterations: 2
```

```
coefplot(model_mpd_2020)
```



White officers in Washington, DC This regression utilizes the same variables and setup as the full DC regression, but includes only white officers.

Our results indicate that white officers in DC are no more likely to use serious force against one racial group than against another. The subject race variables each have insignificant p values. Our results do indicate that white officers in DC are 4% less likely to use force in District 5 than in District 1 (p = .018) force against subjects aged 55 to 65 than against those aged 18-24 (p = .047).

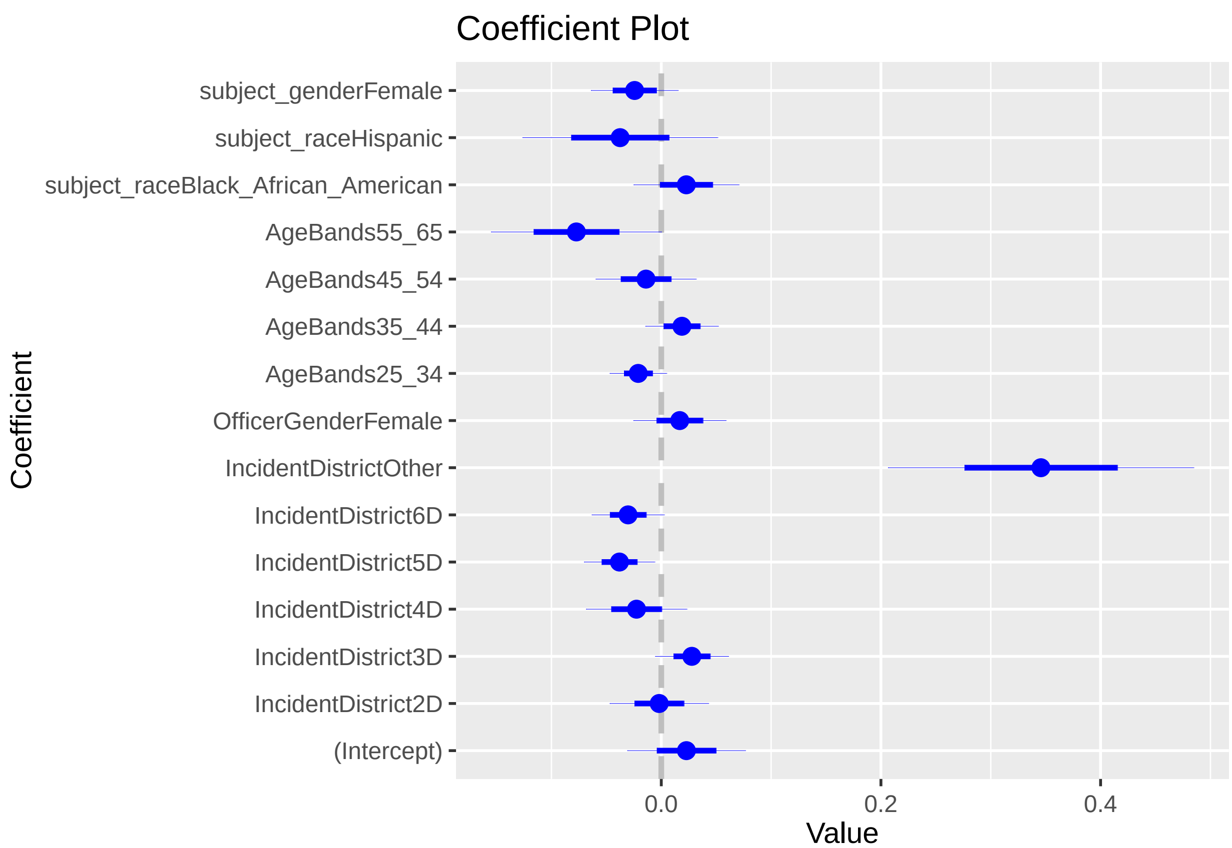
Full results for individual officer race breakdowns for Washington, DC are available under "Officer race breakdowns DC" in the appendix.

```
mpd_dat_whiteoff <- mpd_dat_enc_2020 %>%
  filter(OfficerRace == "White_Caucasian")

model_mpd_whiteoff_2020 <- glm(serious ~ IncidentDistrict2D + IncidentDistrict3D + IncidentDistrict4D +
               data = mpd_dat_whiteoff)

summary(model_mpd_whiteoff_2020)
```

```
##
## Call:
## glm(formula = serious ~ IncidentDistrict2D + IncidentDistrict3D +
##     IncidentDistrict4D + IncidentDistrict5D + IncidentDistrict6D +
##     IncidentDistrictOther + OfficerGenderFemale + AgeBands25_34 +
##     AgeBands35_44 + AgeBands45_54 + AgeBands55_65 + subject_raceBlack_African_American +
##     subject_raceHispanic + subject_genderFemale, data = mpd_dat_whiteoff)
##
```

```
## Coefficients:
##                                   Estimate Std. Error t value Pr(>|t|)    
## (Intercept)                        0.022882   0.026886   0.851   0.3950    
## IncidentDistrict2D                -0.001909   0.022485  -0.085   0.9324    
## IncidentDistrict3D                 0.027805   0.016692   1.666   0.0961 .  
## IncidentDistrict4D                -0.022542   0.022920  -0.984   0.3256    
## IncidentDistrict5D                -0.038091   0.016097  -2.366   0.0182 *  
## IncidentDistrict6D                -0.030231   0.016502  -1.832   0.0673 .  
## IncidentDistrictOther              0.345674   0.069574   4.968 8.15e-07 ***
## OfficerGenderFemale                0.016784   0.021076   0.796   0.4260    
## AgeBands25_34                     -0.020994   0.012945  -1.622   0.1052    
## AgeBands35_44                      0.018787   0.016588   1.133   0.2577    
## AgeBands45_54                     -0.013932   0.022880  -0.609   0.5427    
## AgeBands55_65                     -0.077323   0.038789  -1.993   0.0465 *  
## subject_raceBlack_African_American  0.022781   0.023960   0.951   0.3420    
## subject_raceHispanic              -0.037481   0.044455  -0.843   0.3994    
## subject_genderFemale              -0.024280   0.019837  -1.224   0.2213    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for gaussian family taken to be 0.02564137)
## 
##     Null deviance: 23.341  on 873  degrees of freedom
## Residual deviance: 22.026  on 859  degrees of freedom
## AIC: -704.77
## 
## Number of Fisher Scoring iterations: 2
```

```
coefplot(model_mpd_whiteoff_2020)
```



Officer + subject race combination counts in DC Getting the counts

```
mpd_dat_blackoff <- mpd_dat_enc_2020 %>%
  filter(OfficerRace == "Black_African_American")

mpd_dat_hispanicoff <- mpd_dat_enc_2020 %>%
  filter(OfficerRace == "Hispanic")

mpd_dat_whiteoff %>%
  filter(subject_race == "White_Caucasian") %>%
  nrow()
```

```
## [1] 55
```

```
mpd_dat_whiteoff %>%
  filter(subject_race == "Black_African_American") %>%
  nrow()
```

```
## [1] 800
```

```
mpd_dat_whiteoff %>%
  filter(subject_race == "Asian_Pacific_Islander") %>%
  nrow()
```

```
## [1] 2
```

```r
mpd_dat_whiteoff %>%
  filter(subject_race == "Hispanic") %>%
  nrow()
```

```
## [1] 17
```

```r
mpd_dat_blackoff %>%
  filter(subject_race == "White_Caucasian") %>%
  nrow()
```

```
## [1] 50
```

```r
mpd_dat_blackoff %>%
  filter(subject_race == "Black_African_American") %>%
  nrow()
```

```
## [1] 757
```

```r
mpd_dat_blackoff %>%
  filter(subject_race == "Asian_Pacific_Islander") %>%
  nrow()
```

```
## [1] 2
```

```r
mpd_dat_blackoff %>%
  filter(subject_race == "Hispanic") %>%
  nrow()
```

```
## [1] 7
```

```r
mpd_dat_hispanicoff %>%
  filter(subject_race == "White_Caucasian") %>%
  nrow()
```

```
## [1] 14
```

```r
mpd_dat_hispanicoff %>%
  filter(subject_race == "Black_African_American") %>%
  nrow()
```

```
## [1] 181
```

```r
mpd_dat_hispanicoff %>%
  filter(subject_race == "Asian_Pacific_Islander") %>%
  nrow()
```

```
## [1] 0
```

```r
mpd_dat_hispanicoff %>%
  filter(subject_race == "Hispanic") %>%
  nrow()
```

```
## [1] 7
```

```r
mpd_dat_hispanicoff %>%
  filter(subject_race == "White_Caucasian") %>%
  nrow()
```

```
## [1] 14
```

```r
mpd_dat_hispanicoff %>%
  filter(subject_race == "Black_African_American") %>%
  nrow()
```

```
## [1] 181
```

```r
mpd_dat_hispanicoff %>%
  filter(subject_race == "Asian_Pacific_Islander") %>%
  nrow()
```

```
## [1] 0
```

```r
mpd_dat_hispanicoff %>%
  filter(subject_race == "Hispanic") %>%
  nrow()
```

```
## [1] 7
```

The below matrix shows the combination counts of officer + subject race for each possible combination. We analyzed this relationship by developing the regressions for specific officer races, as shown above in the regression for just white officers in DC For the full results of those regressions, view "Officer race breakdowns DC" in the appendix.

```r
matrix_data_mpd <- matrix(c(
  55, 50, 14,
  800, 757, 181,
  2, 2, 0,
  17, 7, 7
), ncol = 3, byrow = TRUE)

row_names_mpd <- c("White subject", "Black subject", "Hispanic subject", "Asian subject")
col_names_mpd <- c("White officer", "Black officer", "Hispanic officer")

data_df_mpd <- as.data.frame(matrix_data_mpd)
rownames(data_df_mpd) <- row_names_mpd
colnames(data_df_mpd) <- col_names_mpd

print(data_df_mpd)
```

```
##                    White officer Black officer Hispanic officer
## White subject                 55            50               14
## Black subject                800           757              181
## Hispanic subject               2             2                0
## Asian subject                 17             7                7
```

Setting up the data for Seattle

```r
sea_dat_2020 <- sea_dat_2020 %>%
  mutate(datetime = mdy_hms(Occured_date_time)) %>%
  filter(year(datetime) == 2020) %>%
  drop_na(Incident_Type, Subject_Race, Subject_Gender, Precinct, Sector, Beat) %>%
  mutate(serious = ifelse(Incident_Type == "Level 1 - Use of Force", 0, 1)) %>%
  mutate(Subject_Race = str_replace_all(Subject_Race, "/", "_")) %>%
  mutate(Subject_Race = str_replace_all(Subject_Race, " ", "_")) %>%
  mutate(Subject_Gender = str_replace_all(Subject_Gender, " ", "_")) %>%
  mutate(Subject_Gender = str_replace_all(Subject_Gender, "/", "_")) %>%
  mutate(Subject_Gender = str_replace_all(Subject_Gender, "-", "_"))

sea_dat_2020$Subject_Race <- factor(sea_dat_2020$Subject_Race)
sea_dat_2020$Subject_Race <- relevel(sea_dat_2020$Subject_Race, ref = "White")
sea_dat_2020$Subject_Gender <- factor(sea_dat_2020$Subject_Gender)
sea_dat_2020$Subject_Gender <- relevel(sea_dat_2020$Subject_Gender, ref = "Male")
sea_dat_2020$Precinct <- factor(sea_dat_2020$Precinct)
sea_dat_2020$Precinct <- relevel(sea_dat_2020$Precinct, ref = "West")

encoded_seattle_2020 <- model.matrix(~ Subject_Race + Subject_Gender + Precinct, data = sea_dat_2020)

sea_dat_2020_final <- cbind(sea_dat_2020, encoded_seattle_2020)
```

Overall regression for Seattle

The results for our regression classifying serious vs non-serious use of force based on subject race, subject, gender, and location for Seattle for the year 2020 are below. For this regression, subject race is compared to white, subject gender is compared to male, and precinct is compared to the West precinct. These function the same as described in the DC regression. It is important to note that key demographic variables such as officer race and gender are not included in Seattle's reported data, which may affect the results of other variables and makes this city's results more difficult to compare with the results of other cities.

The results of this regression also indicate that our hypothesis that Black/ African American subjects would be more likely to be subject to a serious use of force may be incorrect. Our results indicate that Black/African American subjects may be 12.3% less likely to be subject to a serious use of force than white subjects ($p = 2.45e-07$). Our results indicate that Asian subjects are 16.6% less likely to be subject to a serious use of force than white subjects ($p = .007$). American Indian/Alaska Native subjects appear to be 21.6% less likely to be subject to a serious use of force than white subjects ($p = .001$).

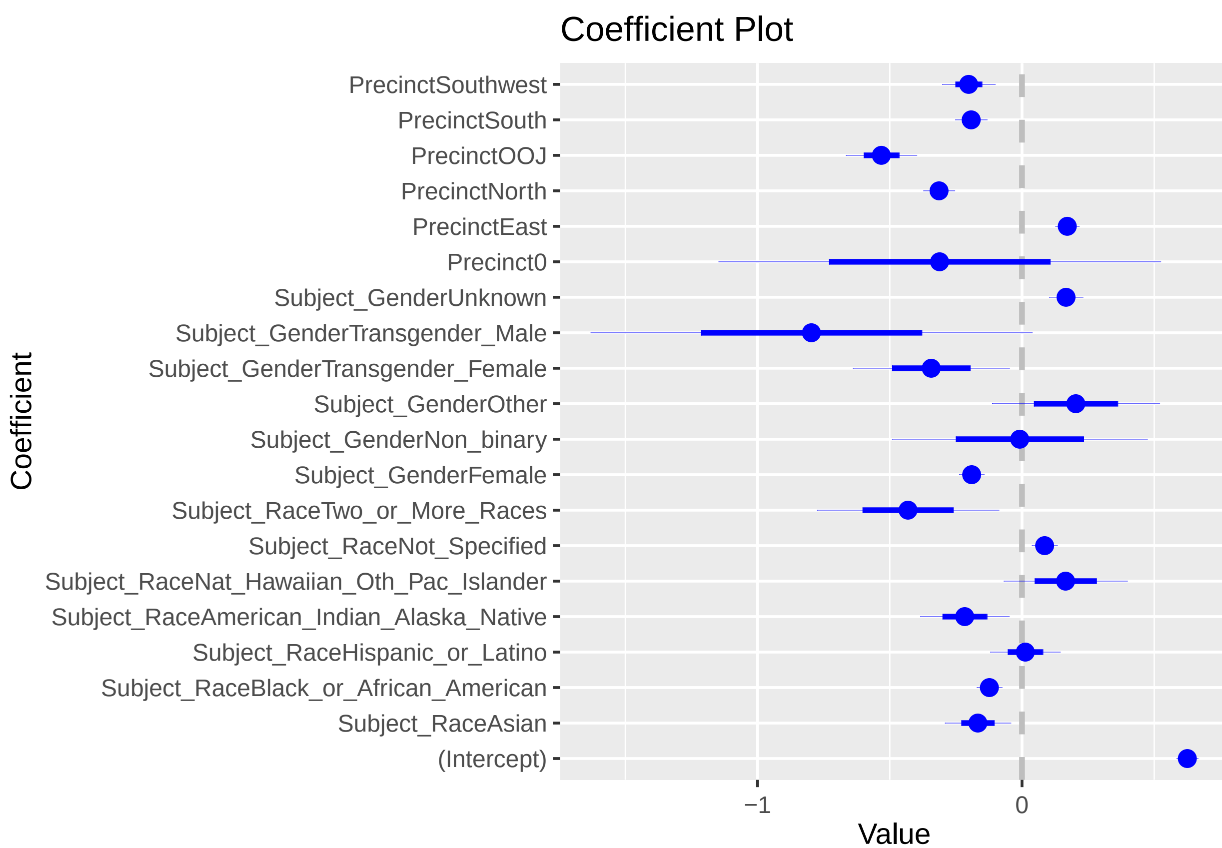
In terms of other variables, our results indicate that women are 19% less likely to be subject to a serious use of force than are men ($p = 1.35e-15$). Finally, the North, South, OJJ, South, and Southwest precincts each appear to be less likely to have serious uses of force occur within them than the West precinct. In contrast, serious uses of force appear to be 17% more likely to occur in the East precinct, where large-scale protests occured, than in the West precinct ($p = 2.77e-14$).

```r
model_seattle_2020 <- glm(serious ~ Subject_RaceAsian + Subject_RaceBlack_or_African_American + Subject_

summary(model_seattle_2020)
```

```
##
## Call:
## glm(formula = serious ~ Subject_RaceAsian + Subject_RaceBlack_or_African_American +
##     Subject_RaceHispanic_or_Latino + Subject_RaceAmerican_Indian_Alaska_Native +
##     Subject_RaceNat_Hawaiian_Oth_Pac_Islander + Subject_RaceNot_Specified +
##     Subject_RaceTwo_or_More_Races + Subject_GenderFemale + Subject_GenderNon_binary +
##     Subject_GenderOther + Subject_GenderTransgender_Female +
##     Subject_GenderTransgender_Male + Subject_GenderUnknown +
##     Precinct0 + PrecinctEast + PrecinctNorth + PrecinctOOJ +
##     PrecinctSouth + PrecinctSouthwest, data = sea_dat_2020_final)
##
## Coefficients:
##                                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                                0.625230   0.020224  30.915  < 2e-16
## Subject_RaceAsian                         -0.166947   0.062229  -2.683 0.007358
## Subject_RaceBlack_or_African_American     -0.123328   0.023826  -5.176 2.48e-07
## Subject_RaceHispanic_or_Latino             0.012506   0.066177   0.189 0.850127
## Subject_RaceAmerican_Indian_Alaska_Native -0.216579   0.083953  -2.580 0.009953
## Subject_RaceNat_Hawaiian_Oth_Pac_Islander  0.164827   0.116898   1.410 0.158684
## Subject_RaceNot_Specified                  0.085625   0.024136   3.548 0.000397
## Subject_RaceTwo_or_More_Races             -0.431160   0.171830  -2.509 0.012173
## Subject_GenderFemale                      -0.190272   0.023635  -8.050 1.35e-15
## Subject_GenderNon_binary                  -0.008613   0.241461  -0.036 0.971548
## Subject_GenderOther                        0.203586   0.158326   1.286 0.198629
## Subject_GenderTransgender_Female          -0.343263   0.148017  -2.319 0.020485
## Subject_GenderTransgender_Male            -0.796388   0.417466  -1.908 0.056567
## Subject_GenderUnknown                      0.166532   0.031909   5.219 1.97e-07
## Precinct0                                 -0.311631   0.417933  -0.746 0.455962
## PrecinctEast                               0.171159   0.022341   7.661 2.77e-14
## PrecinctNorth                             -0.313694   0.029514 -10.629  < 2e-16
## PrecinctOOJ                               -0.531919   0.066854  -7.956 2.84e-15
## PrecinctSouth                             -0.192167   0.029932  -6.420 1.67e-10
## PrecinctSouthwest                         -0.201666   0.049937  -4.038 5.57e-05
##
## (Intercept)                               ***
## Subject_RaceAsian                         **
## Subject_RaceBlack_or_African_American     ***
## Subject_RaceHispanic_or_Latino
## Subject_RaceAmerican_Indian_Alaska_Native **
## Subject_RaceNat_Hawaiian_Oth_Pac_Islander
## Subject_RaceNot_Specified                 ***
## Subject_RaceTwo_or_More_Races             *
## Subject_GenderFemale                      ***
## Subject_GenderNon_binary
## Subject_GenderOther
## Subject_GenderTransgender_Female          *
## Subject_GenderTransgender_Male            .
## Subject_GenderUnknown                     ***
## Precinct0
```

```
## PrecinctEast                                 ***
## PrecinctNorth                                ***
## PrecinctOOJ                                  ***
## PrecinctSouth                                ***
## PrecinctSouthwest                            ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.1738626)
##
##     Null deviance: 527.73  on 2160  degrees of freedom
## Residual deviance: 372.24  on 2141  degrees of freedom
## AIC: 2373.9
##
## Number of Fisher Scoring iterations: 2
```

```r
coefplot(model_seattle_2020)
```



Setting up the data for Portland

```r
pdx_dat_2020 <- pdx_dat_2020 %>%
  filter(Year == 2020) %>%
  mutate_all(~str_replace_all(., "/", "_")) %>%
  mutate_all(~str_replace_all(., " ", "_")) %>%
  mutate_all(~str_replace_all(., "-", "_")) %>%
  mutate_all(~str_replace_all(., "\\(|\\)", "")) %>%
```

```r
  rename_all(~str_replace_all(., " ", "_")) %>%
  rename_all(~str_replace_all(., "-", "")) %>%
  rename_all(~str_replace_all(., "/", "_")) %>%
  mutate(Subject_Age = as.numeric(Subject_Age),
    AgeBands = cut(Subject_Age, breaks = age_breaks, labels = c("18_24", "25_34", "35_44", "45_54", "55_
                   include.lowest = TRUE, right = FALSE)) %>%
  drop_na(Category_of_Force_Event__Measured_at_Event_Level, Officer_Precinct, Subject__Race, Subject__Se
  mutate(serious = ifelse(Category_of_Force_Event__Measured_at_Event_Level == "IV", 0, 1))

pdx_dat_2020$Officer_Precinct <- factor(pdx_dat_2020$Officer_Precinct)
pdx_dat_2020$Officer_Precinct <- relevel(pdx_dat_2020$Officer_Precinct, ref = "Central_Precinct")
pdx_dat_2020$Subject__Race <- factor(pdx_dat_2020$Subject__Race)
pdx_dat_2020$Subject__Race <- relevel(pdx_dat_2020$Subject__Race, ref = "White")
pdx_dat_2020$Subject__Sex <- factor(pdx_dat_2020$Subject__Sex)
pdx_dat_2020$Subject__Sex <- relevel(pdx_dat_2020$Subject__Sex, ref = "Male")
pdx_dat_2020$AgeBands <- factor(pdx_dat_2020$AgeBands)
pdx_dat_2020$AgeBands <- relevel(pdx_dat_2020$AgeBands, ref = "18_24")

encoded_pdx_2020 <- model.matrix(~ Officer_Precinct + Subject__Race + Subject__Sex + Subject__Transient

pdx_dat_2020_final <- cbind(pdx_dat_2020, encoded_pdx_2020)
```

Full regression for Portland

The results for our regression classifying serious vs non-serious uses of force based on officer precinct, subject race, subject gender, and subject age for Portland for the year 2020 are below. For this regression, officer precinct is compared to the central precinct, subject race is compared to white, subject sex is compared to male, and subject age is compared to the 18-24 bracket. It is important to note that, as in Seattle, some key demographic variables such as officer race and gender are not included in the Portland data, which may affect the results of other variables and makes this city's results more difficult to compare with the results of other cities.

As in Seattle and DC, the results of this regression also indicate that our hypothesis that Black/African American subjects are more likely to be subject to a serious use of force may be incorrect. None of the variables for subject race have a statistically significant coefficient, indicating that no one racial group is more likely to have forced used against them than any other in Portland.

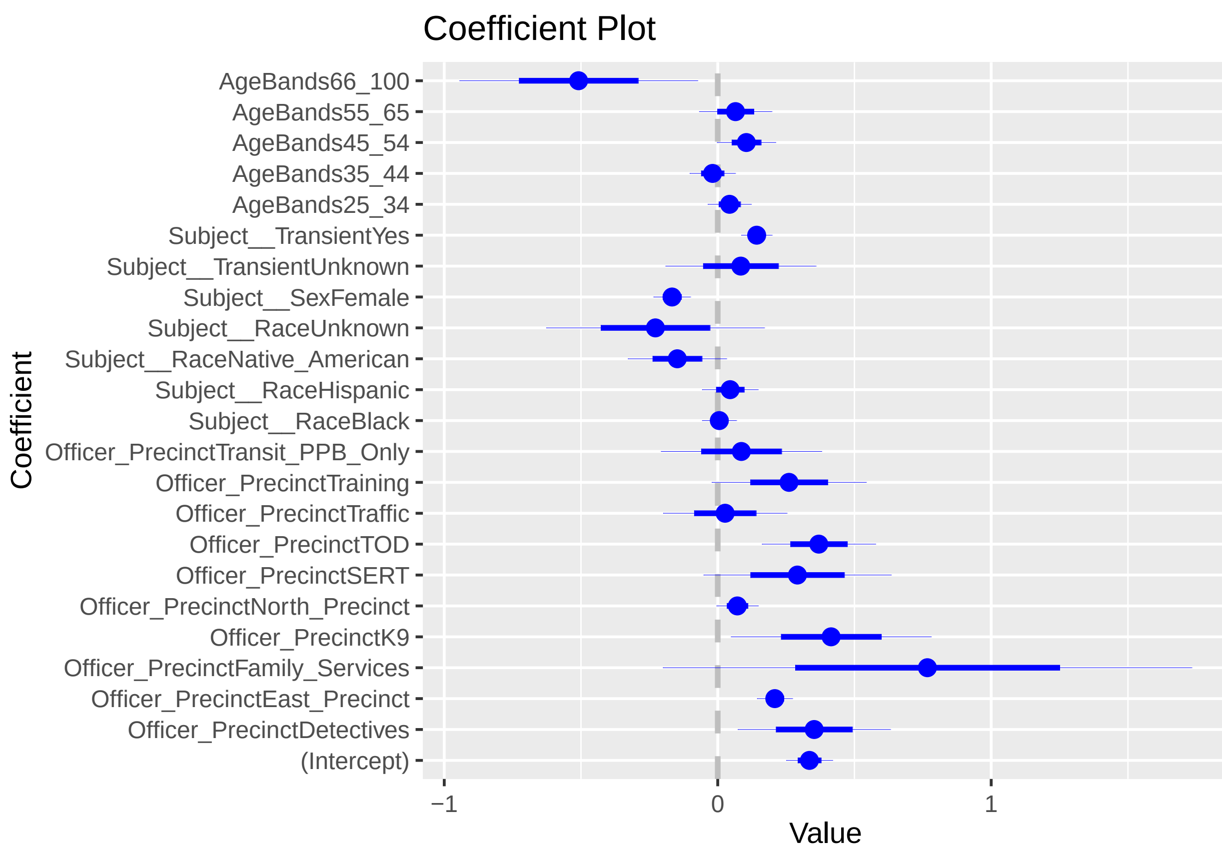
Other variables do show clear relationships, however. Our results indicate that serious uses of force are more 35% likely to occur in the Detectives Precinct (p = .01), 21% more likely to occur in the East Precinct (p = 1.61e-10), 41.5% more likely to occur in the K9 precinct (p = .02), and 37% more likely to occur in the TOD precinct (p = .00039). Our results also indicate that women are 17% less likely than men to have serious force used against them (p = 8.36e-07), that subject classified as transient are 14% more likely than non-transient subjects to have forced used against them (p = 4.50e-07), and that those aged 66 to 100 are 50% less likely to have force used against them (p = .02).

```r
model_portland_2020 <- glm(serious ~ Officer_PrecinctDetectives + Officer_PrecinctEast_Precinct + Offic

summary(model_portland_2020)
```

```
##
## Call:
## glm(formula = serious ~ Officer_PrecinctDetectives + Officer_PrecinctEast_Precinct +
##     Officer_PrecinctFamily_Services + Officer_PrecinctK9 + Officer_PrecinctNorth_Precinct +
```

```
##     Officer_PrecinctSERT + Officer_PrecinctTOD + Officer_PrecinctTraffic +
##     Officer_PrecinctTraining + Officer_PrecinctTransit_PPB_Only +
##     Subject__RaceBlack + Subject__RaceHispanic + Subject__RaceNative_American +
##     Subject__RaceUnknown + Subject__SexFemale + Subject__TransientUnknown +
##     Subject__TransientYes + AgeBands25_34 + AgeBands35_44 + AgeBands45_54 +
##     AgeBands55_65 + AgeBands66_100, data = pdx_dat_2020_final)
##
## Coefficients:
##                                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       0.335347   0.042389   7.911 5.62e-15 ***
## Officer_PrecinctDetectives        0.352590   0.139463   2.528 0.011588 *
## Officer_PrecinctEast_Precinct     0.208699   0.032361   6.449 1.61e-10 ***
## Officer_PrecinctFamily_Services   0.766666   0.483352   1.586 0.112962
## Officer_PrecinctK9                0.414573   0.182990   2.266 0.023651 *
## Officer_PrecinctNorth_Precinct    0.071772   0.038102   1.884 0.059843 .
## Officer_PrecinctSERT              0.291294   0.171438   1.699 0.089548 .
## Officer_PrecinctTOD               0.369611   0.103819   3.560 0.000385 ***
## Officer_PrecinctTraffic           0.026949   0.113118   0.238 0.811738
## Officer_PrecinctTraining          0.260655   0.141169   1.846 0.065072 .
## Officer_PrecinctTransit_PPB_Only  0.086352   0.146828   0.588 0.556562
## Subject__RaceBlack                0.005783   0.031373   0.184 0.853786
## Subject__RaceHispanic             0.045301   0.051158   0.886 0.376049
## Subject__RaceNative_American     -0.147907   0.090108  -1.641 0.100962
## Subject__RaceUnknown             -0.227911   0.199360  -1.143 0.253172
## Subject__SexFemale               -0.167067   0.033736  -4.952 8.36e-07 ***
## Subject__TransientUnknown         0.084212   0.137525   0.612 0.540428
## Subject__TransientYes             0.142413   0.028070   5.073 4.50e-07 ***
## AgeBands25_34                     0.043266   0.039677   1.090 0.275727
## AgeBands35_44                    -0.018903   0.041728  -0.453 0.650631
## AgeBands45_54                     0.104659   0.053594   1.953 0.051066 .
## AgeBands55_65                     0.065054   0.066456   0.979 0.327826
## AgeBands66_100                   -0.508783   0.217695  -2.337 0.019591 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2290336)
##
##     Null deviance: 315.00  on 1259  degrees of freedom
## Residual deviance: 283.31  on 1237  degrees of freedom
## AIC: 1743.4
##
## Number of Fisher Scoring iterations: 2
```

```
coefplot(model_portland_2020)
```



Setting up the data for Indianapolis

```
ind_dat_2020 <- read_csv("../data/UOF_Indianapolis.csv")
```

```
## Rows: 63151 Columns: 35
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (26): OCCURRED_DT, UDTEXT24A, UDTEXT24B, UDTEXT24C, UDTEXT24D, DISPOSIT...
## dbl   (7): OBJECTID, INCNUM, CITNUM, CIT_AGE, OFFNUM, OFF_AGE, OFF_YR_EMPLOY
## lgl   (1): CIT_WEAPON_TYPE
## time  (1): OCCURRED_TM
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
ind_dat_2020 <- ind_dat_2020 %>%
  mutate_all(~str_replace_all(., "/", "_")) %>%
  mutate_all(~str_replace_all(., " ", "_")) %>%
  mutate_all(~str_replace_all(., ",", "_")) %>%
  mutate_all(~str_replace_all(., "-", "_")) %>%
  mutate_all(~str_replace_all(., "\\(|\\)", "")) %>%
  mutate_all(~str_replace_all(., ":", "_")) %>%
  mutate_all(~str_replace_all(., "__", "_")) %>%
  mutate(DISTRICT = UDTEXT24B) %>%
  mutate(datetime = mdy(OCCURRED_DT)) %>%
  filter(year(datetime) == 2020) %>%
```

```
  mutate(OFF_AGE = as.numeric(OFF_AGE),
    OFF_AGE_BANDS = cut(OFF_AGE, breaks = age_breaks, labels = c("18_24", "25_34", "35_44", "45_54", "55
                    include.lowest = TRUE, right = FALSE)) %>%
  mutate(CIT_AGE = as.numeric(CIT_AGE),
    CIT_AGE_BANDS = cut(CIT_AGE, breaks = age_breaks, labels = c("18_24", "25_34", "35_44", "45_54", "55
                    include.lowest = TRUE, right = FALSE)) %>%
  drop_na(RACE, SEX, OFF_RACE, OFF_SEX, OFF_AGE, OFF_AGE_BANDS, CIT_AGE_BANDS, UOF_FORCE_TYPE)

serious_cats <- c("Less_Lethal_Pepperball", "Lethal_Handgun", "Canine_Bite", "Less_Lethal_Bean_Bag", "Ph
                  "Less_Lethal_CS_OC", "Physical_Kick", "Less_Lethal_CS_Fogger", "Physical_Leg_Sweep",
                  "Physical_Fist_Strike", "Less_Lethal_Taser", "Physical_Knee_Strike", "Physical_Elbow_S
                  "Physical_Palm_Strike", "Less_Lethal_Clearout_OC", "Lethal_Rifle", "Less_Lethal_Baton
                  "Less_Lethal_BPS_Gas", "Less_Lethal_Burning_CS", "Lethal_Shotgun", "Less_Lethal_CS_Gre

ind_dat_2020 <- ind_dat_2020 %>%
  mutate(serious = as.integer(UOF_FORCE_TYPE %in% serious_cats))

ind_dat_2020$RACE <- factor(ind_dat_2020$RACE)
ind_dat_2020$RACE <- relevel(ind_dat_2020$RACE, ref = "White")
ind_dat_2020$SEX <- factor(ind_dat_2020$SEX)
ind_dat_2020$SEX <- relevel(ind_dat_2020$SEX, ref = "Male")
ind_dat_2020$OFF_RACE <- factor(ind_dat_2020$OFF_RACE)
ind_dat_2020$OFF_RACE <- relevel(ind_dat_2020$OFF_RACE, ref = "White")
ind_dat_2020$OFF_SEX <- factor(ind_dat_2020$OFF_SEX)
ind_dat_2020$OFF_SEX <- relevel(ind_dat_2020$OFF_SEX, ref = "Male")
ind_dat_2020$OFF_AGE_BANDS <- factor(ind_dat_2020$OFF_AGE_BANDS)
ind_dat_2020$OFF_AGE_BANDS <- relevel(ind_dat_2020$OFF_AGE_BANDS, ref = "18_24")
ind_dat_2020$CIT_AGE_BANDS <- factor(ind_dat_2020$CIT_AGE_BANDS)
ind_dat_2020$CIT_AGE_BANDS <- relevel(ind_dat_2020$CIT_AGE_BANDS, ref = "18_24")

encoded_ind_2020 <- model.matrix(~ RACE + SEX + OFF_RACE + OFF_SEX + OFF_AGE_BANDS + CIT_AGE_BANDS, data

ind_dat_2020_final <- cbind(ind_dat_2020, encoded_ind_2020)
```

Full regression for Indianapolis

The results for our regression classifying serious vs non-serious uses of force based on subject race, subject sex, subject age, officer race, officer sex, and officer age for Indiana in 2020 are below. For this regression, race is compared to white, sex is compared male, and age is compared to 18-24.

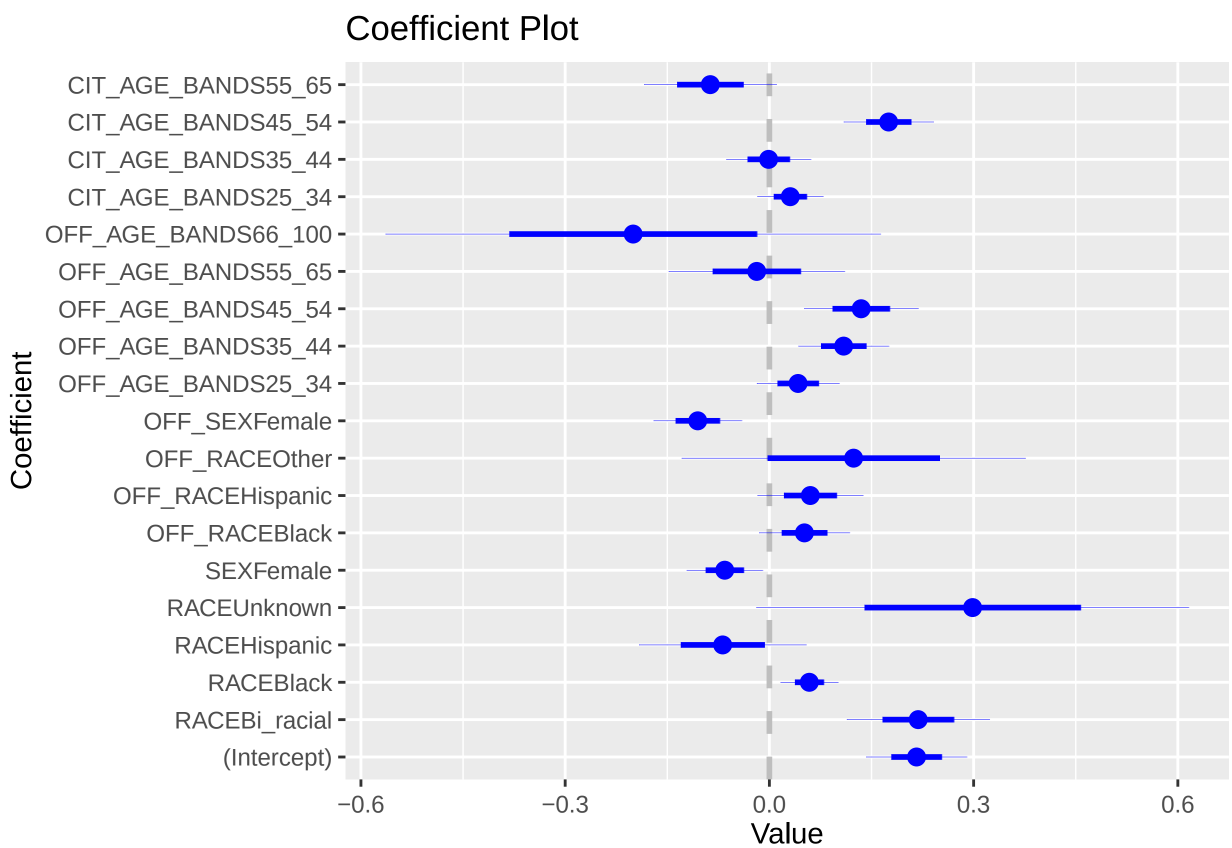
Indianapolis is the only city in our analysis where our results match our initial hypothesis that Black/African American subjects are more likely to be subject to a serious use of ofrce than white subjects. Our results indicate that Black/African American subjects are 6% more likely to be subjected to serious force than white subjects ($p = .006$) and that Biracial subjects are 22% more likely to be subject to serious force than white subjects ($p = 3.11e-05$).

Other variables also show a clear relationship with serious force. Our results indicate that women are 6.5% less likely to be subjected to serious force than men ($p = .018$) and that female officers are 10.5% less likely to use serious force than male officers ($p = .011$). Our results also indicate that citizens aged 45 to 54 are 18% more likely to be subjected to serious force than citizens aged 18-24 ($p = 1.14e-07$), that officers aged 35 to 44 are 11% more likely to use serious force than officers aged 18-24, and that officers aged 45 to 54 are 13% more likely to use serious force than officers aged 18-24.

```r
model_indianapolis_2020 <- glm(serious ~ RACEBi_racial + RACEBlack + RACEHispanic + RACEUnknown + SEXFem

summary(model_indianapolis_2020)
```

```
##
## Call:
## glm(formula = serious ~ RACEBi_racial + RACEBlack + RACEHispanic +
##     RACEUnknown + SEXFemale + OFF_RACEBlack + OFF_RACEHispanic +
##     OFF_RACEOther + OFF_SEXFemale + OFF_AGE_BANDS25_34 + OFF_AGE_BANDS35_44 +
##     OFF_AGE_BANDS45_54 + OFF_AGE_BANDS55_65 + OFF_AGE_BANDS66_100 +
##     CIT_AGE_BANDS25_34 + CIT_AGE_BANDS35_44 + CIT_AGE_BANDS45_54 +
##     CIT_AGE_BANDS55_65, data = ind_dat_2020_final)
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.216149   0.036936   5.852 5.43e-09 ***
## RACEBi_racial        0.218580   0.052390   4.172 3.11e-05 ***
## RACEBlack            0.058655   0.021155   2.773  0.00560 **
## RACEHispanic        -0.068657   0.061390  -1.118  0.26351
## RACEUnknown          0.298466   0.158754   1.880  0.06020 .
## SEXFemale           -0.065616   0.027896  -2.352  0.01873 *
## OFF_RACEBlack        0.051423   0.033235   1.547  0.12192
## OFF_RACEHispanic     0.060095   0.038731   1.552  0.12087
## OFF_RACEOther        0.123658   0.126192   0.980  0.32721
## OFF_SEXFemale       -0.105289   0.032358  -3.254  0.00115 **
## OFF_AGE_BANDS25_34   0.042105   0.030235   1.393  0.16386
## OFF_AGE_BANDS35_44   0.109057   0.033181   3.287  0.00103 **
## OFF_AGE_BANDS45_54   0.134792   0.041981   3.211  0.00134 **
## OFF_AGE_BANDS55_65  -0.018629   0.064594  -0.288  0.77306
## OFF_AGE_BANDS66_100 -0.200181   0.181776  -1.101  0.27088
## CIT_AGE_BANDS25_34   0.030666   0.024178   1.268  0.20478
## CIT_AGE_BANDS35_44  -0.001164   0.031008  -0.038  0.97005
## CIT_AGE_BANDS45_54   0.175143   0.032939   5.317 1.14e-07 ***
## CIT_AGE_BANDS55_65  -0.086850   0.048600  -1.787  0.07404 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2189251)
##
##     Null deviance: 632.82  on 2792  degrees of freedom
## Residual deviance: 607.30  on 2774  degrees of freedom
## AIC: 3704.5
##
## Number of Fisher Scoring iterations: 2
```

```r
coefplot(model_indianapolis_2020)
```



Officer race subsetted regressions for Indianapolis #### White officers in Indianapolis This regression utilizes the same variables and setup as the full Indianapolis regression, but includes only white officers.

Our results indicate that white officers are 19% more likely to use serious force against biracial subjects than white subjects (p = 1.57e-09) and 6.5% more likely to use serious force against Black/African American subjects than white subjects (p = .008). Our results also indicate that white officers are 12.8% less likely to use force against female subjects than against male subjects (p = .0005). Our results also indicate that white officers aged 35 to 44 are 13% more likely to use serious force than those aged 18-24 (p = .0002), as are those aged 34 to 54 (p = .003). Finally, white officers are 17% more likely to use serious force against citizens aged 45-54 than those aged 18-24 (p = 8.99e-07) and 13% less likely to use force against those aged 55 to 65 (p= .01).

Full results for individual officer race breakdowns for Indianapolis are available under "Officer race breakdowns Indianapolis" in the appendix.

```
ind_dat_whiteoff <- ind_dat_2020_final %>%
  filter(OFF_RACE == "White")

model_ind_whiteoff_2020 <- glm(serious ~ RACEBi_racial + RACEBlack + RACEHispanic + RACEUnknown + SEXFe

summary(model_ind_whiteoff_2020)
```

```
##
## Call:
## glm(formula = serious ~ RACEBi_racial + RACEBlack + RACEHispanic +
##     RACEUnknown + SEXFemale + OFF_SEXFemale + OFF_AGE_BANDS25_34 +
```

```
##     OFF_AGE_BANDS35_44 + OFF_AGE_BANDS45_54 + OFF_AGE_BANDS55_65 +
##     OFF_AGE_BANDS66_100 + CIT_AGE_BANDS25_34 + CIT_AGE_BANDS35_44 +
##     CIT_AGE_BANDS45_54 + CIT_AGE_BANDS55_65, data = ind_dat_whiteoff)
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.231264   0.038157   6.061 1.57e-09 ***
## RACEBi_racial        0.191726   0.071689   2.674 0.007537 **
## RACEBlack            0.065475   0.022558   2.903 0.003736 **
## RACEHispanic        -0.071005   0.064173  -1.106 0.268643
## RACEUnknown          0.334953   0.157506   2.127 0.033556 *
## SEXFemale           -0.062114   0.029927  -2.076 0.038047 *
## OFF_SEXFemale       -0.127519   0.036449  -3.499 0.000476 ***
## OFF_AGE_BANDS25_34   0.032527   0.030459   1.068 0.285683
## OFF_AGE_BANDS35_44   0.125956   0.033824   3.724 0.000201 ***
## OFF_AGE_BANDS45_54   0.128619   0.043710   2.943 0.003287 **
## OFF_AGE_BANDS55_65   0.080447   0.071921   1.119 0.263451
## OFF_AGE_BANDS66_100 -0.178009   0.180677  -0.985 0.324610
## CIT_AGE_BANDS25_34   0.008789   0.025993   0.338 0.735308
## CIT_AGE_BANDS35_44  -0.043188   0.033511  -1.289 0.197606
## CIT_AGE_BANDS45_54   0.173044   0.035131   4.926 8.99e-07 ***
## CIT_AGE_BANDS55_65  -0.125976   0.051151  -2.463 0.013855 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2143535)
##
##     Null deviance: 529.88  on 2377  degrees of freedom
## Residual deviance: 506.30  on 2362  degrees of freedom
## AIC: 3104
##
## Number of Fisher Scoring iterations: 2
```

Matrix of officer + subject race combination conuts

Getting the counts

```r
ind_dat_blackoff <- ind_dat_2020_final %>%
  filter(OFF_RACE == "Black")

ind_dat_hispanicoff <- ind_dat_2020_final %>%
  filter(OFF_RACE == "Hispanic")


ind_dat_whiteoff %>%
  filter(RACE == "White") %>%
  nrow()
```

```
## [1] 601
```

```r
ind_dat_whiteoff %>%
  filter(RACE == "Black") %>%
  nrow()
```

```
## [1] 1659
```

```r
ind_dat_whiteoff %>%
  filter(RACE == "Hispanic") %>%
  nrow()
```

```
## [1] 63
```

```r
ind_dat_blackoff %>%
  filter(RACE == "White") %>%
  nrow()
```

```
## [1] 62
```

```r
ind_dat_blackoff %>%
  filter(RACE == "Black") %>%
  nrow()
```

```
## [1] 139
```

```r
ind_dat_blackoff %>%
  filter(RACE == "Hispanic") %>%
  nrow()
```

```
## [1] 3
```

```r
ind_dat_hispanicoff %>%
  filter(RACE == "White") %>%
  nrow()
```

```
## [1] 36
```

```r
ind_dat_hispanicoff %>%
  filter(RACE == "Black") %>%
  nrow()
```

```
## [1] 100
```

```r
ind_dat_hispanicoff %>%
  filter(RACE == "Hispanic") %>%
  nrow()
```

```
## [1] 3
```

The below matrix shows the combination counts of officer + subject race for each possible combination. We analyzed this relationship by developing the regressions for specific officer races, as shown above in the regression for just white officers in Indianapolis. For the fullr results of those regressions, view "Officer race breakdowns Indianapolis" in the appendix.

```r
matrix_data <- matrix(c(
  601, 1659, 63,
  62, 139, 3,
  36, 100, 3
), ncol = 3, byrow = TRUE)

row_names <- c("White subject", "Black subject", "Hispanic subject")
col_names <- c("White officer", "Black officer", "Hispanic officer")

data_df <- as.data.frame(matrix_data)
rownames(data_df) <- row_names
colnames(data_df) <- col_names

print(data_df)
```

```
##                  White officer Black officer Hispanic officer
## White subject              601          1659               63
## Black subject               62           139                3
## Hispanic subject            36           100                3
```

Discussion:

Our research fills a gap in the existing literature by using advanved methods to analyze localized police use of force data, rather than focusing on fatal use of force based on national data or employing only basic methods, as in city level reports. Our results indicate that our hypothesis that Black/African American subjects are more likely to be subjected to serious force is true for only one of the cities studied; Indianapolis. Our results also indicate that for Indianapolis, white officers are particularly likely to use serious force against Black/African American or Biracial subjects. Beyond subject race, the majority of our regressions showed that women and older subjects are less likely to have force used against them than men and younger subjects. In addition, certain precincts and districts in each city showed a higher likelihood for force to be used. This could be a result of the type of crime or police-subject interactions that occur in this part of the city. If, for example, murders are much more common in one district than another, it would make sense that officers would be more likely to utilize force in responding to incidents in said district than in others.

Limitations

Our research is limited primarily by the data itself. As is true for national data, collection and reporting is not standardized at the local level. Different cities in our study may employ different techniques and standards for when to report the use of force. It is also possible that the data is influenced by how likely different groups are to report negative interactions with the police. For the data used in this study, if a citizen chooses to report an inappropriate use of force by an officer, that complaint will be added to the dataset. If one racial group or gender is more likely to report negative interactions with the police, that may skew the data in a way that makes them seem more or less likely to be subject to various types of force.

Appendix All other regression outputs, including our exploration of individual relationships, are included below. We did this in order to make the results section smaller and easier to read.

Individual variable/dependent relationships for DC.

```r
model_mpd_district <- glm(serious ~ IncidentDistrict2D + IncidentDistrict3D + IncidentDistrict4D + Inci
                data = mpd_dat_enc_2020)
summary(model_mpd_district)
```

```
##
## Call:
## glm(formula = serious ~ IncidentDistrict2D + IncidentDistrict3D +
##     IncidentDistrict4D + IncidentDistrict5D + IncidentDistrict6D +
##     IncidentDistrictOther, data = mpd_dat_enc_2020)
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)            0.024961   0.005738   4.350 1.43e-05 ***
## IncidentDistrict2D     0.005573   0.013930   0.400   0.6891
## IncidentDistrict3D     0.020022   0.010294   1.945   0.0519 .
## IncidentDistrict4D     0.003941   0.012447   0.317   0.7516
## IncidentDistrict5D    -0.022492   0.009222  -2.439   0.0148 *
## IncidentDistrict6D    -0.016674   0.009552  -1.746   0.0810 .
## IncidentDistrictOther  0.197261   0.048766   4.045 5.43e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02110705)
##
##     Null deviance: 43.037  on 2009  degrees of freedom
## Residual deviance: 42.277  on 2003  degrees of freedom
## AIC: -2041.8
##
## Number of Fisher Scoring iterations: 2
```

```r
model_mpd_offrace <- glm(serious ~ OfficerRaceBlack_African_American + OfficerRaceHispanic + OfficerRac
                         data = mpd_dat_enc_2020)
summary(model_mpd_offrace)
```

```
##
## Call:
## glm(formula = serious ~ OfficerRaceBlack_African_American + OfficerRaceHispanic +
##     OfficerRaceOther, data = mpd_dat_enc_2020)
##
## Coefficients:
##                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)                        0.027460   0.004949   5.549 3.26e-08 ***
## OfficerRaceBlack_African_American -0.013980   0.007122  -1.963   0.0498 *
## OfficerRaceHispanic                0.002243   0.011422   0.196   0.8443
## OfficerRaceOther                  -0.002036   0.014349  -0.142   0.8872
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02140488)
##
##     Null deviance: 43.037  on 2009  degrees of freedom
## Residual deviance: 42.938  on 2006  degrees of freedom
## AIC: -2016.6
##
## Number of Fisher Scoring iterations: 2
```

```r
model_mpd_offgender <- glm(serious ~ OfficerGenderFemale, data = mpd_dat_enc_2020)
summary(model_mpd_offgender)
```

```
##
## Call:
## glm(formula = serious ~ OfficerGenderFemale, data = mpd_dat_enc_2020)
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.021488   0.003436   6.253  4.9e-10 ***
## OfficerGenderFemale 0.004153   0.011032   0.376    0.707
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02143116)
##
##     Null deviance: 43.037  on 2009  degrees of freedom
## Residual deviance: 43.034  on 2008  degrees of freedom
## AIC: -2016.1
##
## Number of Fisher Scoring iterations: 2
```

```r
model_mpd_age <- glm(serious ~ AgeBands25_34 + AgeBands35_44 + AgeBands45_54 + AgeBands55_65 + AgeBands6
                     data = mpd_dat_enc_2020)
summary(model_mpd_age)
```

```
##
## Call:
## glm(formula = serious ~ AgeBands25_34 + AgeBands35_44 + AgeBands45_54 +
##     AgeBands55_65 + AgeBands66_100, data = mpd_dat_enc_2020)
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)     0.031858   0.006142   5.187 2.35e-07 ***
## AgeBands25_34  -0.021258   0.007926  -2.682  0.00738 **
## AgeBands35_44   0.006603   0.009431   0.700  0.48393
## AgeBands45_54  -0.024340   0.014070  -1.730  0.08380 .
## AgeBands55_65  -0.031858   0.023094  -1.380  0.16789
## AgeBands66_100 -0.031858   0.073250  -0.435  0.66366
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.0213115)
##
##     Null deviance: 43.037  on 2009  degrees of freedom
## Residual deviance: 42.708  on 2004  degrees of freedom
## AIC: -2023.4
##
## Number of Fisher Scoring iterations: 2
```

```r
model_mpd_subrace <- glm(serious ~ subject_raceBlack_African_American + subject_raceHispanic,
                     data = mpd_dat_enc_2020)
summary(model_mpd_subrace)
```

```
##
## Call:
## glm(formula = serious ~ subject_raceBlack_African_American +
##     subject_raceHispanic, data = mpd_dat_enc_2020)
##
## Coefficients:
##                                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)                        0.0223881  0.0126497   1.770   0.0769 .
## subject_raceBlack_African_American -0.0006961  0.0131012  -0.053   0.9576
## subject_raceHispanic               0.0088619  0.0288110   0.308   0.7584
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02144191)
##
##     Null deviance: 43.037  on 2009  degrees of freedom
## Residual deviance: 43.034  on 2007  degrees of freedom
## AIC: -2014.1
##
## Number of Fisher Scoring iterations: 2
```

```
model_mpd_subgender <- glm(serious ~ subject_genderFemale,
                     data = mpd_dat_enc_2020)
summary(model_mpd_subgender)
```

```
##
## Call:
## glm(formula = serious ~ subject_genderFemale, data = mpd_dat_enc_2020)
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.02377    0.00344   6.911 6.44e-12 ***
## subject_genderFemale -0.01879    0.01088  -1.728   0.0841 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02140085)
##
##     Null deviance: 43.037  on 2009  degrees of freedom
## Residual deviance: 42.973  on 2008  degrees of freedom
## AIC: -2019
##
## Number of Fisher Scoring iterations: 2
```

Officer race breakdowns DC

```
mpd_dat_blackoff <- mpd_dat_enc_2020 %>%
  filter(OfficerRace == "Black_African_American")

model_mpd_blackoff_2020 <- glm(serious ~ IncidentDistrict2D + IncidentDistrict3D + IncidentDistrict4D +
               data = mpd_dat_enc_2020)
```

```r
summary(model_mpd_blackoff_2020)
```

```
##
## Call:
## glm(formula = serious ~ IncidentDistrict2D + IncidentDistrict3D +
##     IncidentDistrict4D + IncidentDistrict5D + IncidentDistrict6D +
##     IncidentDistrictOther + OfficerGenderFemale + AgeBands25_34 +
##     AgeBands35_44 + AgeBands45_54 + AgeBands55_65 + AgeBands66_100 +
##     subject_raceBlack_African_American + subject_raceHispanic +
##     subject_genderFemale, data = mpd_dat_enc_2020)
##
## Coefficients:
##                                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)                         0.023493   0.015680   1.498  0.13421
## IncidentDistrict2D                  0.007539   0.013999   0.539  0.59026
## IncidentDistrict3D                  0.020828   0.010444   1.994  0.04626 *
## IncidentDistrict4D                  0.007617   0.012978   0.587  0.55735
## IncidentDistrict5D                 -0.024973   0.009222  -2.708  0.00683 **
## IncidentDistrict6D                 -0.019578   0.009558  -2.048  0.04066 *
## IncidentDistrictOther               0.215305   0.049806   4.323 1.62e-05 ***
## OfficerGenderFemale                 0.009651   0.011021   0.876  0.38130
## AgeBands25_34                      -0.021905   0.007894  -2.775  0.00557 **
## AgeBands35_44                       0.006606   0.009381   0.704  0.48140
## AgeBands45_54                      -0.025221   0.014024  -1.798  0.07226 .
## AgeBands55_65                      -0.050748   0.023194  -2.188  0.02879 *
## AgeBands66_100                     -0.021889   0.072907  -0.300  0.76403
## subject_raceBlack_African_American  0.014312   0.013685   1.046  0.29577
## subject_raceHispanic                0.003933   0.028662   0.137  0.89087
## subject_genderFemale               -0.015959   0.010896  -1.465  0.14316
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02095705)
##
##     Null deviance: 43.037  on 2009  degrees of freedom
## Residual deviance: 41.788  on 1994  degrees of freedom
## AIC: -2047.1
##
## Number of Fisher Scoring iterations: 2
```

```r
mpd_dat_hispanicoff <- mpd_dat_enc_2020 %>%
  filter(OfficerRace == "Hispanic")

model_dat_hispanicoff_2020 <- glm(serious ~ IncidentDistrict2D + IncidentDistrict3D + IncidentDistrict4D
               data = mpd_dat_hispanicoff)

summary(model_dat_hispanicoff_2020)
```

```
##
## Call:
## glm(formula = serious ~ IncidentDistrict2D + IncidentDistrict3D +
##     IncidentDistrict4D + IncidentDistrict5D + IncidentDistrict6D +
```

```
##     IncidentDistrictOther + OfficerGenderFemale + AgeBands25_34 +
##     AgeBands35_44 + AgeBands45_54 + AgeBands55_65 + AgeBands66_100 +
##     subject_raceBlack_African_American + subject_raceHispanic +
##     subject_genderFemale, data = mpd_dat_hispanicoff)
##
## Coefficients: (1 not defined because of singularities)
##                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)                         0.01117    0.05697   0.196   0.8447
## IncidentDistrict2D                 -0.03986    0.08142  -0.490   0.6250
## IncidentDistrict3D                  0.02214    0.03622   0.611   0.5417
## IncidentDistrict4D                  0.02943    0.03967   0.742   0.4590
## IncidentDistrict5D                 -0.04394    0.03378  -1.301   0.1949
## IncidentDistrict6D                 -0.02032    0.03979  -0.511   0.6101
## IncidentDistrictOther               0.05137    0.18540   0.277   0.7820
## OfficerGenderFemale                -0.02518    0.04573  -0.551   0.5826
## AgeBands25_34                      -0.04322    0.02880  -1.500   0.1352
## AgeBands35_44                       0.07180    0.03604   1.992   0.0478 *
## AgeBands45_54                      -0.06285    0.05201  -1.208   0.2284
## AgeBands55_65                      -0.06254    0.06833  -0.915   0.3612
## AgeBands66_100                           NA         NA      NA       NA
## subject_raceBlack_African_American  0.03266    0.05123   0.637   0.5246
## subject_raceHispanic                0.14483    0.07988   1.813   0.0714 .
## subject_genderFemale                0.07943    0.05628   1.411   0.1598
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02756711)
##
##     Null deviance: 5.8218  on 201  degrees of freedom
## Residual deviance: 5.1551  on 187  degrees of freedom
## AIC: -135.74
##
## Number of Fisher Scoring iterations: 2
```

Individual variable/dependent relationships for Seattle.

```
model_seattle_subrace <- glm(serious ~ Subject_RaceAsian + Subject_RaceBlack_or_African_American + Subj
summary(model_seattle_subrace)
```

```
##
## Call:
## glm(formula = serious ~ Subject_RaceAsian + Subject_RaceBlack_or_African_American +
##     Subject_RaceHispanic_or_Latino + Subject_RaceAmerican_Indian_Alaska_Native +
##     Subject_RaceNat_Hawaiian_Oth_Pac_Islander + Subject_RaceNot_Specified +
##     Subject_RaceTwo_or_More_Races, data = sea_dat_2020_final)
##
## Coefficients:
##                                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)                                0.55263    0.01606  34.415  < 2e-16
## Subject_RaceAsian                         -0.24013    0.06891  -3.485 0.000503
## Subject_RaceBlack_or_African_American     -0.17318    0.02615  -6.622 4.45e-11
## Subject_RaceHispanic_or_Latino            -0.13403    0.07260  -1.846 0.065025
```

```
## Subject_RaceAmerican_Indian_Alaska_Native -0.36032    0.09246  -3.897 0.000100
## Subject_RaceNat_Hawaiian_Oth_Pac_Islander  0.13968    0.12977   1.076 0.281899
## Subject_RaceNot_Specified                  0.24385    0.02395  10.183  < 2e-16
## Subject_RaceTwo_or_More_Races             -0.55263    0.19023  -2.905 0.003709
##
## (Intercept)                               ***
## Subject_RaceAsian                         ***
## Subject_RaceBlack_or_African_American     ***
## Subject_RaceHispanic_or_Latino            .
## Subject_RaceAmerican_Indian_Alaska_Native ***
## Subject_RaceNat_Hawaiian_Oth_Pac_Islander
## Subject_RaceNot_Specified                 ***
## Subject_RaceTwo_or_More_Races             **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2155724)
##
##     Null deviance: 527.73  on 2160  degrees of freedom
## Residual deviance: 464.13  on 2153  degrees of freedom
## AIC: 2826.7
##
## Number of Fisher Scoring iterations: 2
```

```
model_seattle_subgender <- glm(serious ~ Subject_GenderFemale + Subject_GenderNon_binary + Subject_Gende
summary(model_seattle_subgender)
```

```
##
## Call:
## glm(formula = serious ~ Subject_GenderFemale + Subject_GenderNon_binary +
##     Subject_GenderOther + Subject_GenderTransgender_Female +
##     Subject_GenderTransgender_Male + Subject_GenderUnknown, data = sea_dat_2020_final)
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       0.57192    0.01217  46.988   <2e-16 ***
## Subject_GenderFemale             -0.21615    0.02590  -8.347   <2e-16 ***
## Subject_GenderNon_binary          0.09475    0.26943   0.352   0.7251
## Subject_GenderOther               0.42808    0.17662   2.424   0.0154 *
## Subject_GenderTransgender_Female -0.32192    0.16527  -1.948   0.0516 .
## Subject_GenderTransgender_Male   -0.57192    0.46634  -1.226   0.2202
## Subject_GenderUnknown             0.38175    0.03142  12.150   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2173258)
##
##     Null deviance: 527.73  on 2160  degrees of freedom
## Residual deviance: 468.12  on 2154  degrees of freedom
## AIC: 2843.2
##
## Number of Fisher Scoring iterations: 2
```

```r
model_seattle_precinct <- glm(serious ~ Precinct0 + PrecinctEast + PrecinctNorth + PrecinctOOJ + Precin
summary(model_seattle_precinct)
```

```
##
## Call:
## glm(formula = serious ~ Precinct0 + PrecinctEast + PrecinctNorth +
##     PrecinctOOJ + PrecinctSouth + PrecinctSouthwest, data = sea_dat_2020_final)
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.57967    0.01636  35.422  < 2e-16 ***
## Precinct0         -0.57967    0.44185  -1.312     0.19
## PrecinctEast       0.24814    0.02294  10.819  < 2e-16 ***
## PrecinctNorth     -0.33499    0.03097 -10.816  < 2e-16 ***
## PrecinctOOJ       -0.53205    0.07007  -7.593 4.62e-14 ***
## PrecinctSouth     -0.20238    0.03134  -6.458 1.30e-10 ***
## PrecinctSouthwest -0.27967    0.05201  -5.377 8.37e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.1949656)
##
##     Null deviance: 527.73  on 2160  degrees of freedom
## Residual deviance: 419.96  on 2154  degrees of freedom
## AIC: 2608.6
##
## Number of Fisher Scoring iterations: 2
```

Individual variable/dependent relationships for Portland.

```r
model_portland_precinct <- glm(serious ~ Officer_PrecinctDetectives + Officer_PrecinctEast_Precinct + Of
summary(model_portland_precinct)
```

```
##
## Call:
## glm(formula = serious ~ Officer_PrecinctDetectives + Officer_PrecinctEast_Precinct +
##     Officer_PrecinctFamily_Services + Officer_PrecinctK9 + Officer_PrecinctNorth_Precinct +
##     Officer_PrecinctSERT + Officer_PrecinctTOD + Officer_PrecinctTraffic +
##     Officer_PrecinctTraining + Officer_PrecinctTransit_PPB_Only,
##     data = pdx_dat_2020_final)
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                      0.39602    0.02311  17.135  < 2e-16 ***
## Officer_PrecinctDetectives       0.31827    0.13334   2.387 0.017140 *
## Officer_PrecinctEast_Precinct    0.19828    0.03261   6.080  1.6e-09 ***
## Officer_PrecinctFamily_Services  0.60398    0.49191   1.228 0.219738
## Officer_PrecinctK9               0.46113    0.18715   2.464 0.013876 *
## Officer_PrecinctNorth_Precinct   0.07091    0.03839   1.847 0.064958 .
## Officer_PrecinctSERT             0.22898    0.17525   1.307 0.191597
## Officer_PrecinctTOD              0.38659    0.10503   3.681 0.000242 ***
```

```
## Officer_PrecinctTraffic           0.02503    0.11507   0.218 0.827807
## Officer_PrecinctTraining          0.27065    0.14371   1.883 0.059900 .
## Officer_PrecinctTransit_PPB_Only  0.14944    0.14994   0.997 0.319141
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2414369)
##
##     Null deviance: 315.00  on 1259  degrees of freedom
## Residual deviance: 301.55  on 1249  degrees of freedom
## AIC: 1798
##
## Number of Fisher Scoring iterations: 2
```

```r
model_portland_race <- glm(serious ~ Subject__RaceBlack + Subject__RaceHispanic + Subject__RaceNative_Ar
summary(model_portland_race)
```

```
##
## Call:
## glm(formula = serious ~ Subject__RaceBlack + Subject__RaceHispanic +
##     Subject__RaceNative_American + Subject__RaceUnknown, data = pdx_dat_2020_final)
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   0.5065789  0.0181356  27.933   <2e-16 ***
## Subject__RaceBlack           -0.0009924  0.0320488  -0.031   0.9753
## Subject__RaceHispanic         0.0079842  0.0524952   0.152   0.8791
## Subject__RaceNative_American -0.2065789  0.0930649  -2.220   0.0266 *
## Subject__RaceUnknown         -0.0621345  0.1676389  -0.371   0.7110
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2499652)
##
##     Null deviance: 315.00  on 1259  degrees of freedom
## Residual deviance: 313.71  on 1255  degrees of freedom
## AIC: 1835.8
##
## Number of Fisher Scoring iterations: 2
```

```r
model_portland_sex <- glm(serious ~ Subject__SexFemale, data = pdx_dat_2020_final)
summary(model_portland_sex)
```

```
##
## Call:
## glm(formula = serious ~ Subject__SexFemale, data = pdx_dat_2020_final)
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.54694    0.01575  34.720  < 2e-16 ***
## Subject__SexFemale -0.20408    0.03342  -6.107 1.35e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## (Dispersion parameter for gaussian family taken to be 0.2431848)
##
##     Null deviance: 315.00  on 1259  degrees of freedom
## Residual deviance: 305.93  on 1258  degrees of freedom
## AIC: 1798.2
##
## Number of Fisher Scoring iterations: 2
```

```
model_portland_transient <- glm(serious ~ Subject__TransientUnknown + Subject__TransientYes, data = pdx_
summary(model_portland_transient)
```

```
##
## Call:
## glm(formula = serious ~ Subject__TransientUnknown + Subject__TransientYes,
##     data = pdx_dat_2020_final)
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)                0.43651    0.01977  22.074   <2e-16 ***
## Subject__TransientUnknown  0.11905    0.11865   1.003    0.316
## Subject__TransientYes      0.13049    0.02817   4.632    4e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2463469)
##
##     Null deviance: 315.00  on 1259  degrees of freedom
## Residual deviance: 309.66  on 1257  degrees of freedom
## AIC: 1815.4
##
## Number of Fisher Scoring iterations: 2
```

```
model_portland_age <- glm(serious ~ AgeBands25_34 + AgeBands35_44 + AgeBands45_54 + AgeBands55_65 + Age
summary(model_portland_age)
```

```
##
## Call:
## glm(formula = serious ~ AgeBands25_34 + AgeBands35_44 + AgeBands45_54 +
##     AgeBands55_65 + AgeBands66_100, data = pdx_dat_2020_final)
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     0.43805    0.03312  13.228  < 2e-16 ***
## AgeBands25_34   0.09260    0.04026   2.300  0.02160 *
## AgeBands35_44   0.02937    0.04241   0.692  0.48877
## AgeBands45_54   0.15286    0.05454   2.803  0.00514 **
## AgeBands55_65   0.11124    0.06773   1.642  0.10075
## AgeBands66_100 -0.43805    0.22509  -1.946  0.05186 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.247847)
```

```
##
##     Null deviance: 315.0  on 1259  degrees of freedom
## Residual deviance: 310.8  on 1254  degrees of freedom
## AIC: 1826.1
##
## Number of Fisher Scoring iterations: 2
```

Individual variable/dependent relationships for Indianapolis

```r
model_indianapolis_subrace <- glm(serious ~ RACEBi_racial + RACEBlack + RACEHispanic + RACEUnknown, data
summary(model_indianapolis_subrace)
```

```
##
## Call:
## glm(formula = serious ~ RACEBi_racial + RACEBlack + RACEHispanic +
##     RACEUnknown, data = ind_dat_2020_final)
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     0.31206    0.01786  17.473  < 2e-16 ***
## RACEBi_racial   0.20717    0.04981   4.159 3.29e-05 ***
## RACEBlack       0.04261    0.02090   2.039   0.0416 *
## RACEHispanic   -0.10916    0.05982  -1.825   0.0681 .
## RACEUnknown     0.24350    0.15907   1.531   0.1259
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2248688)
##
##     Null deviance: 632.82  on 2792  degrees of freedom
## Residual deviance: 626.93  on 2788  degrees of freedom
## AIC: 3765.4
##
## Number of Fisher Scoring iterations: 2
```

```r
model_indianapolis_subsex <- glm(serious ~ SEXFemale, data=ind_dat_2020_final)
summary(model_indianapolis_subsex)
```

```
##
## Call:
## glm(formula = serious ~ SEXFemale, data = ind_dat_2020_final)
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.351958   0.009612  36.616   <2e-16 ***
## SEXFemale   -0.041107   0.027510  -1.494    0.135
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2265534)
##
```

```
##     Null deviance: 632.82  on 2792  degrees of freedom
## Residual deviance: 632.31  on 2791  degrees of freedom
## AIC: 3783.2
##
## Number of Fisher Scoring iterations: 2
```

```r
model_indianapolis_offrace <- glm(serious ~  OFF_RACEBlack + OFF_RACEHispanic + OFF_RACEOther, data=ind_
summary(model_indianapolis_offrace)
```

```
##
## Call:
## glm(formula = serious ~ OFF_RACEBlack + OFF_RACEHispanic + OFF_RACEOther,
##     data = ind_dat_2020_final)
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.33516    0.00975  34.374   <2e-16 ***
## OFF_RACEBlack     0.06573    0.03303   1.990   0.0467 *
## OFF_RACEHispanic  0.09588    0.03734   2.568   0.0103 *
## OFF_RACEOther     0.09342    0.12745   0.733   0.4636
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2260673)
##
##     Null deviance: 632.82  on 2792  degrees of freedom
## Residual deviance: 630.50  on 2789  degrees of freedom
## AIC: 3779.2
##
## Number of Fisher Scoring iterations: 2
```

```r
model_indianapolis_offsex <- glm(serious ~ OFF_SEXFemale, data=ind_dat_2020_final)
summary(model_indianapolis_offsex)
```

```
##
## Call:
## glm(formula = serious ~ OFF_SEXFemale, data = ind_dat_2020_final)
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.35470    0.00943  37.615  < 2e-16 ***
## OFF_SEXFemale -0.08670    0.03152  -2.751  0.00598 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2261216)
##
##     Null deviance: 632.82  on 2792  degrees of freedom
## Residual deviance: 631.11  on 2791  degrees of freedom
## AIC: 3777.9
##
## Number of Fisher Scoring iterations: 2
```

```r
model_indianapolis_offage <- glm(serious ~ OFF_AGE_BANDS25_34 + OFF_AGE_BANDS35_44 + OFF_AGE_BANDS45_54
summary(model_indianapolis_offage)
```

```
##
## Call:
## glm(formula = serious ~ OFF_AGE_BANDS25_34 + OFF_AGE_BANDS35_44 +
##     OFF_AGE_BANDS45_54 + OFF_AGE_BANDS55_65 + OFF_AGE_BANDS66_100,
##     data = ind_dat_2020_final)
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.27333    0.02736   9.991  < 2e-16 ***
## OFF_AGE_BANDS25_34   0.05889    0.02996   1.966 0.049435 *
## OFF_AGE_BANDS35_44   0.12229    0.03281   3.728 0.000197 ***
## OFF_AGE_BANDS45_54   0.16335    0.04158   3.928 8.76e-05 ***
## OFF_AGE_BANDS55_65  -0.03453    0.06403  -0.539 0.589758
## OFF_AGE_BANDS66_100 -0.27333    0.18118  -1.509 0.131497
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2245323)
##
##     Null deviance: 632.82  on 2792  degrees of freedom
## Residual deviance: 625.77  on 2787  degrees of freedom
## AIC: 3762.2
##
## Number of Fisher Scoring iterations: 2
```

```r
model_indianapolis_subage <- glm(serious ~ CIT_AGE_BANDS25_34 + CIT_AGE_BANDS35_44 + CIT_AGE_BANDS45_54
summary(model_indianapolis_subage)
```

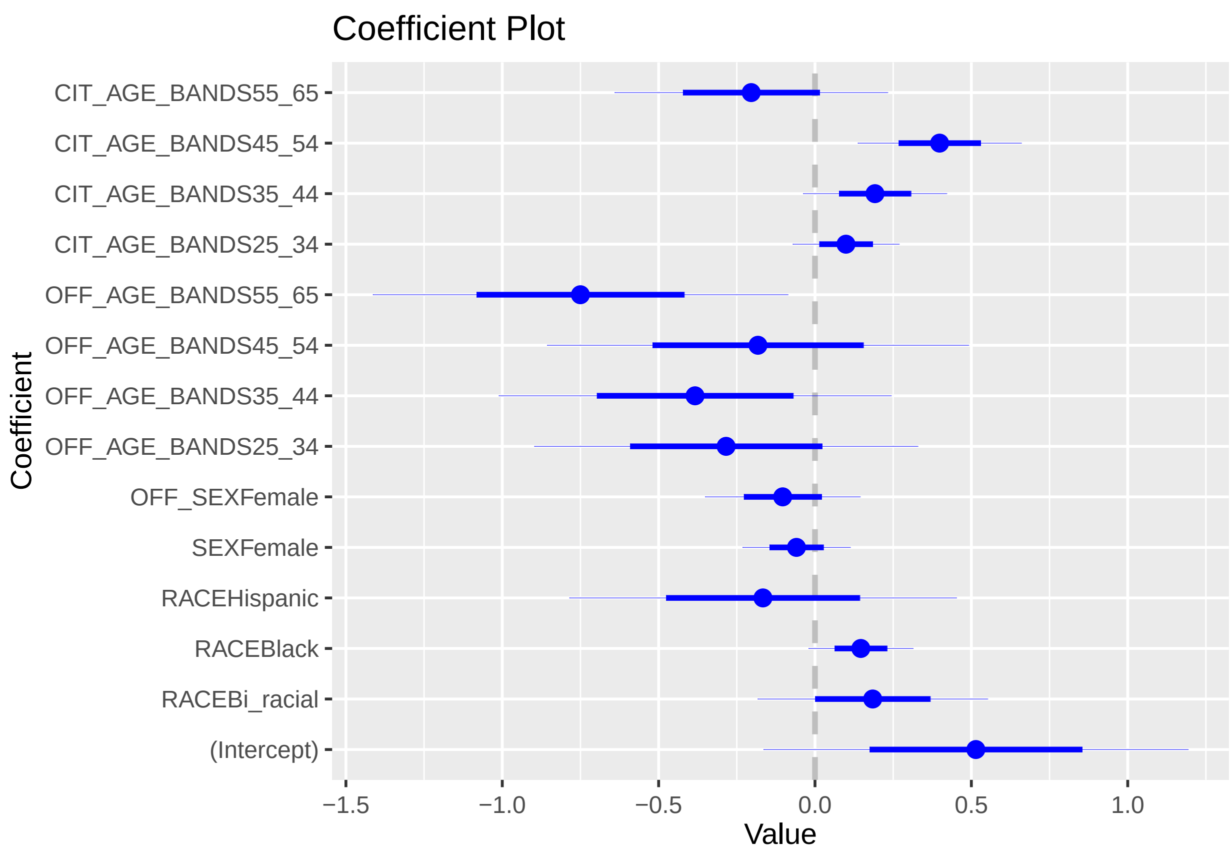
```
##
## Call:
## glm(formula = serious ~ CIT_AGE_BANDS25_34 + CIT_AGE_BANDS35_44 +
##     CIT_AGE_BANDS45_54 + CIT_AGE_BANDS55_65, data = ind_dat_2020_final)
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.318739   0.019811  16.089  < 2e-16 ***
## CIT_AGE_BANDS25_34  0.026114   0.023682   1.103    0.270
## CIT_AGE_BANDS35_44 -0.006385   0.030246  -0.211    0.833
## CIT_AGE_BANDS45_54  0.158272   0.032194   4.916 9.33e-07 ***
## CIT_AGE_BANDS55_65 -0.073125   0.048562  -1.506    0.132
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.224098)
##
##     Null deviance: 632.82  on 2792  degrees of freedom
## Residual deviance: 624.79  on 2788  degrees of freedom
## AIC: 3755.8
##
## Number of Fisher Scoring iterations: 2
```

Officer race breakdowns Indianapolis

```r
ind_dat_blackoff <- ind_dat_2020_final %>%
  filter(OFF_RACE == "Black")

model_ind_blackoff_2020 <- glm(serious ~ RACEBi_racial + RACEBlack + RACEHispanic + RACEUnknown + SEXFem

summary(model_ind_blackoff_2020)
```

```
##
## Call:
## glm(formula = serious ~ RACEBi_racial + RACEBlack + RACEHispanic +
##     RACEUnknown + SEXFemale + OFF_SEXFemale + OFF_AGE_BANDS25_34 +
##     OFF_AGE_BANDS35_44 + OFF_AGE_BANDS45_54 + OFF_AGE_BANDS55_65 +
##     OFF_AGE_BANDS66_100 + CIT_AGE_BANDS25_34 + CIT_AGE_BANDS35_44 +
##     CIT_AGE_BANDS45_54 + CIT_AGE_BANDS55_65, data = ind_dat_blackoff)
##
## Coefficients: (2 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.51434    0.33940   1.515   0.1311
## RACEBi_racial        0.18450    0.18383   1.004   0.3167
## RACEBlack            0.14651    0.08351   1.754   0.0808 .
## RACEHispanic        -0.16645    0.30940  -0.538   0.5912
## RACEUnknown               NA         NA      NA       NA
## SEXFemale           -0.05927    0.08610  -0.688   0.4919
## OFF_SEXFemale       -0.10331    0.12396  -0.833   0.4056
## OFF_AGE_BANDS25_34  -0.28429    0.30657  -0.927   0.3548
## OFF_AGE_BANDS35_44  -0.38362    0.31375  -1.223   0.2228
## OFF_AGE_BANDS45_54  -0.18240    0.33695  -0.541   0.5888
## OFF_AGE_BANDS55_65  -0.75013    0.33179  -2.261   0.0248 *
## OFF_AGE_BANDS66_100       NA         NA      NA       NA
## CIT_AGE_BANDS25_34   0.09898    0.08500   1.164   0.2455
## CIT_AGE_BANDS35_44   0.19177    0.11474   1.671   0.0961 .
## CIT_AGE_BANDS45_54   0.39843    0.13073   3.048   0.0026 **
## CIT_AGE_BANDS55_65  -0.20398    0.21826  -0.935   0.3511
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2170585)
##
##     Null deviance: 54.520  on 226  degrees of freedom
## Residual deviance: 46.233  on 213  degrees of freedom
## AIC: 312.99
##
## Number of Fisher Scoring iterations: 2
```

```r
coefplot(model_ind_blackoff_2020)
```

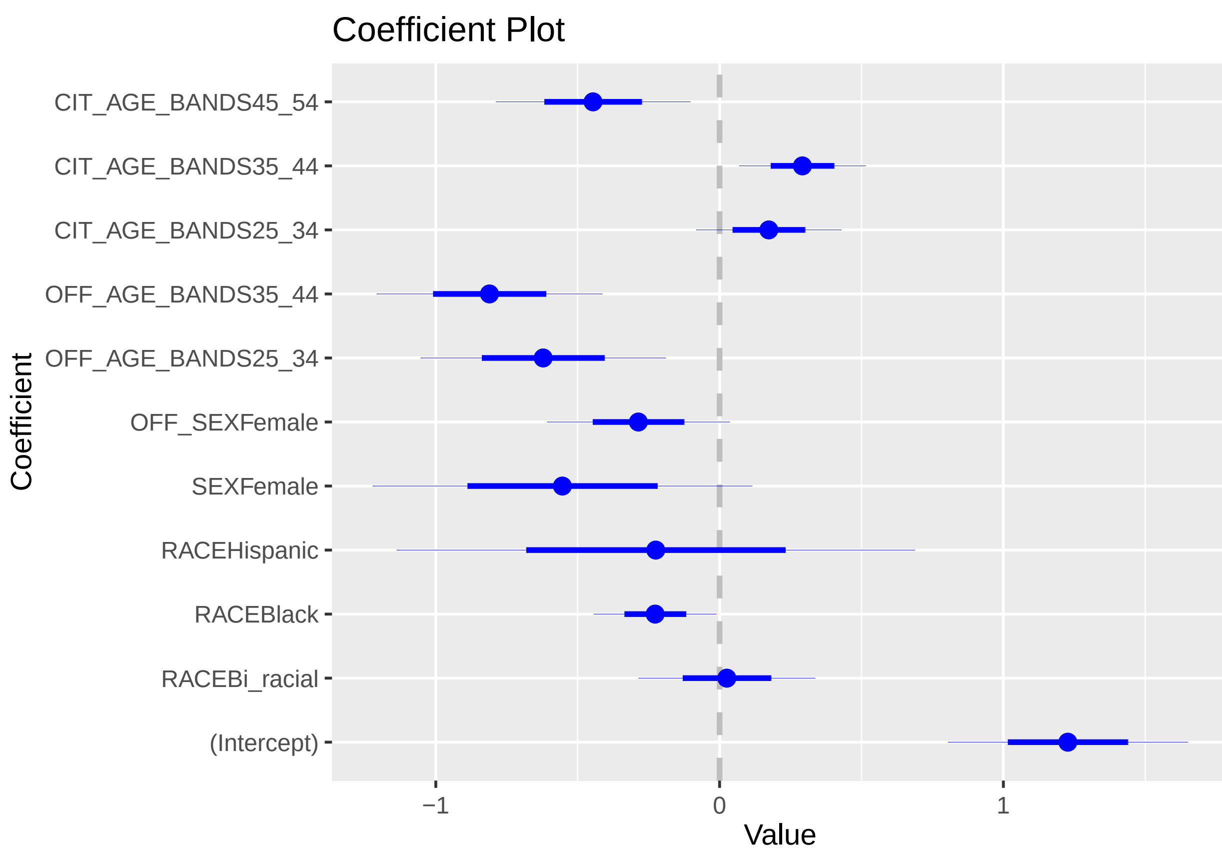



```
ind_dat_hispanicoff <- ind_dat_2020_final %>%
  filter(OFF_RACE == "Hispanic")

model_ind_hispanicoff_2020 <- glm(serious ~ RACEBi_racial + RACEBlack + RACEHispanic + RACEUnknown + SE

summary(model_ind_hispanicoff_2020)
```

```
##
## Call:
## glm(formula = serious ~ RACEBi_racial + RACEBlack + RACEHispanic +
##     RACEUnknown + SEXFemale + OFF_SEXFemale + OFF_AGE_BANDS25_34 +
##     OFF_AGE_BANDS35_44 + OFF_AGE_BANDS45_54 + OFF_AGE_BANDS55_65 +
##     OFF_AGE_BANDS66_100 + CIT_AGE_BANDS25_34 + CIT_AGE_BANDS35_44 +
##     CIT_AGE_BANDS45_54 + CIT_AGE_BANDS55_65, data = ind_dat_hispanicoff)
##
## Coefficients: (5 not defined because of singularities)
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            1.22708    0.21108   5.813 3.14e-08 ***
## RACEBi_racial          0.02557    0.15525   0.165  0.86940
## RACEBlack             -0.22708    0.10782  -2.106  0.03674 *
## RACEHispanic          -0.22496    0.45619  -0.493  0.62259
## RACEUnknown                 NA         NA      NA       NA
## SEXFemale             -0.55396    0.33409  -1.658  0.09922 .
## OFF_SEXFemale         -0.28615    0.16062  -1.781  0.07669 .
## OFF_AGE_BANDS25_34    -0.62155    0.21561  -2.883  0.00447 **
```

```
## OFF_AGE_BANDS35_44  -0.81082    0.19838  -4.087 6.84e-05 ***
## OFF_AGE_BANDS45_54        NA         NA      NA       NA
## OFF_AGE_BANDS55_65        NA         NA      NA       NA
## OFF_AGE_BANDS66_100       NA         NA      NA       NA
## CIT_AGE_BANDS25_34   0.17338    0.12745   1.360  0.17558
## CIT_AGE_BANDS35_44   0.29187    0.11119   2.625  0.00949 **
## CIT_AGE_BANDS45_54  -0.44604    0.17116  -2.606  0.01001 *
## CIT_AGE_BANDS55_65        NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.1975715)
##
##     Null deviance: 42.672  on 173  degrees of freedom
## Residual deviance: 32.204  on 163  degrees of freedom
## AIC: 224.26
##
## Number of Fisher Scoring iterations: 2
```

```
coefplot(model_ind_hispanicoff_2020)
```



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