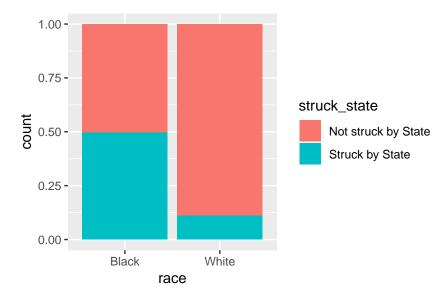
## StatChat013019

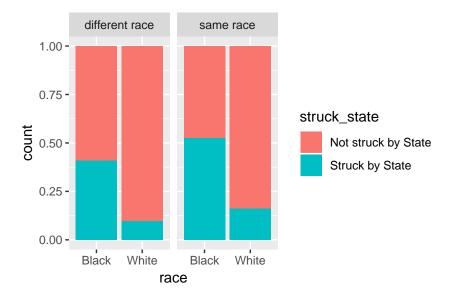
```
# Find raw disparities in preemptory strikes from 225 trials with race data
combo <- jurors %>%
 left_join(trials, by = c("trial__id" = "id")) %>%
 filter(race != "Unknown")
combo %>% summarise(num_trials = n_distinct(trial__id)) # 226
## # A tibble: 1 x 1
    num_trials
##
          <int>
## 1
            226
# Examine some categorical variables
combo %>% count(struck_by)
## # A tibble: 9 x 2
##
     struck_by
                                        n
     <chr>>
                                    <int>
## 1 Juror chosen as alternate
                                      240
## 2 Juror chosen to serve on jury
                                    2462
## 3 Juror excused/absent
                                       43
## 4 Juror not struck
                                     2902
## 5 Struck by the defense
                                    1467
## 6 Struck by the state
                                    1286
## 7 Struck for cause
                                     1342
## 8 Struck without notation
                                     362
## 9 Unknown
                                      18
combo %>% count(race)
## # A tibble: 4 x 2
##
     race
                n
     <chr>
           <int>
## 1 Asian
## 2 Black
             3877
## 3 Latino
## 4 White
             6241
combo %>% count(defendant_race)
## # A tibble: 4 x 2
##
   defendant_race
                        n
     <chr>>
                    <int>
## 1 Asian
                       54
## 2 Black
                     7819
## 3 Unknown
                      193
## 4 White
                     2056
combo %>% count(verdict)
## # A tibble: 4 x 2
   verdict
                                        n
##
     <chr>>
                                     <int>
## 1 Aquitted on all counts
                                      1529
```

```
## 2 Guilty on at least one offense 8045
## 3 Mistrial
                                      447
## 4 Unknown
                                      101
combo %>% count(strike_eligibility)
## # A tibble: 5 x 2
##
    strike_eligibility
                                n
##
    <chr>
                            <int>
## 1 Both State and Defense 3504
## 2 Defense
                              155
## 3 n/a
                             4700
## 4 Neither
                              136
## 5 State
                             1627
combo %>% count(def_attny_1)
## # A tibble: 92 x 2
##
     def_attny_1
                                   n
##
      <chr>>
                               <int>
## 1 A.E. (Rusty) Harlow, Jr.
                                  36
## 2 Aelicia L. Thomas
                                  58
                                 125
## 3 Alison Steiner
## 4 Andre de Gruy
                                  53
## 5 Antwayn Patrick
                                 115
## 6 Austin Vollor
                                 199
## 7 Azki Shah
                                  57
## 8 B. Leon Johnson
                                  63
## 9 Bennie L. Jones, Jr.
                                  70
## 10 Bernard C. Jones, Jr.
                                  98
## # ... with 82 more rows
combo %>% count(offense title 1)
## # A tibble: 81 x 2
##
      offense_title_1
                                                   n
##
      <chr>
                                               <int>
## 1 Accessory after the fact of murder
                                                  51
## 2 Aggravated assault
                                                1047
## 3 Aggravated Assault
                                                  51
## 4 Aggravated assault (attempt)
                                                  27
## 5 Aggravated driving under the influence
                                                 104
## 6 armed robbery
                                                  46
## 7 Armed robbery
                                                 817
## 8 Arson of state supported school building
                                                  70
## 9 Attempted building burglary
                                                  35
## 10 Attempted burglary of a dwelling
                                                  63
## # ... with 71 more rows
combo %>% count(cause_number)
## # A tibble: 218 x 2
##
      cause_number
                  <int>
      <chr>
## 1 1992-2061
                      21
## 2 1992-2087
                      21
## 3 1992-4399
                      14
```

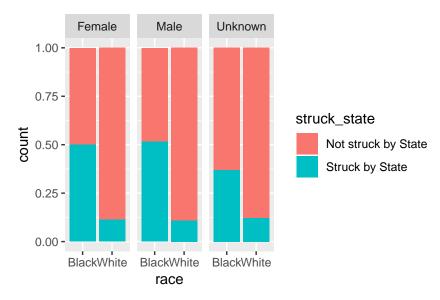
```
## 4 1992-9708
## 5 1993-2114
                      34
                      40
## 6 1993-2156
## 7 1993-2165
                     70
## 8 1993-3106
                      33
## 9 1993-4141
                      12
## 10 1993-4516
## # ... with 208 more rows
# Smaller version of combo to look at a few variables that might be associated
# with being struck by the state (assuming eligible to be struck by state)
combo_small <- combo %>%
  select(id, trial__id, struck_by, race, gender, defendant_race,
         strike_eligibility, cause_number) %>%
  filter(strike_eligibility == "Both State and Defense" |
          strike_eligibility == "State") %>%
 filter(race == "Black" | race == "White") %>%
  mutate(same_race = ifelse(race == defendant_race, "same race",
                            "different race"),
         struck_state = ifelse(struck_by == "Struck by the state",
                               "Struck by State", "Not struck by State"),
         year = parse_number(str_sub(cause_number)))
# Ratio of black prob to white prob is 4.45 = .498 / .112 (matches report)
combo_small %>%
  group_by(race) %>%
  summarise(prop_struck = mean(struck_state == "Struck by State"),
            num_struck = sum(struck_state == "Struck by State"),
            total = n()
## # A tibble: 2 x 4
     race prop_struck num_struck total
##
                           <int> <int>
     <chr>>
                 <dbl>
## 1 Black
                 0.498
                              902 1811
                              372 3318
## 2 White
                 0.112
ggplot(combo_small) +
 geom_bar(aes(x = race, fill = struck_state), position = "fill")
```



```
ggplot(combo_small) +
  geom_bar(aes(x = race, fill = struck_state), position = "fill") +
  facet_grid(. ~ same_race)
```



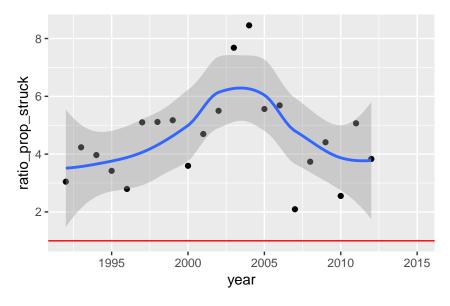
```
ggplot(combo_small) +
  geom_bar(aes(x = race, fill = struck_state), position = "fill") +
  facet_grid(. ~ gender)
```

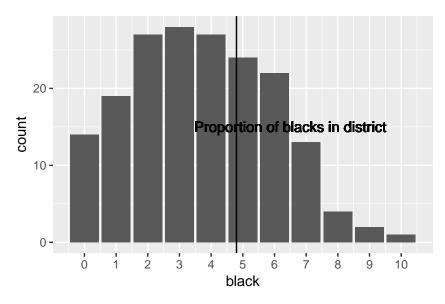


```
# Look at patterns over time in strike ratio
combo_small %>%
  group_by(year, race) %>%
  summarise(prop_struck = mean(struck_state == "Struck by State")) %>%
  spread(key = "race", value = "prop_struck") %>%
  mutate(ratio_prop_struck = Black / White) %>%
  ggplot(aes(x = year, y = ratio_prop_struck)) +
  geom_point() +
  geom_smooth() +
  geom_hline(yintercept = 1, color = "red")
```

## `geom\_smooth()` using method = 'loess' and formula 'y ~ x'
## Warning: Removed 1 rows containing non-finite values (stat\_smooth).

## Warning: Removed 1 rows containing missing values (geom\_point).





```
# Logistic regression analysis with voirdire data added
# 89 trials represented in voirdire (not counting 1 with trial_id = NA),
# although 2 have n=1
print(voirdire %>% count(juror_id__trial__id) %>% arrange(n), n = Inf)
```

```
## # A tibble: 90 x 2
##
      juror_id__trial__id
##
                     <dbl> <int>
##
   1
                        78
##
   2
                       270
                               1
##
   3
                        NA
                               1
##
   4
                        18
                              21
##
   5
                        72
                              22
                              22
##
   6
                       153
##
   7
                              24
                         1
                        13
                              25
##
  8
## 9
                        73
                              25
                         3
                              26
## 10
                        31
                              26
## 11
## 12
                       101
                              26
```

##	13	24	27
##	14	30	27
##	15	21	28
##	16	27	28
##	17	57	28
##	18	96	28
##	19	19	29
##	20	53	30
##	21	109	30
##	22	134	30
##	23	164	30
##	24	201	30
##	25	4	31
## ##	26 27	5 1 E	31
##		15 16	31
##	28	16	31
##	29 30	39 60	31
##	31	60 64	31 31
##	32	68	31
##	33	93	31
##	34	107	31
##	35	132	31
##	36	177	31
##	37	62	32
##	38	71	32
##	39	91	32
##	40	133	32
##	41	169	32
##	42	9	33
##	43	168	34
##	44	14	35
##	45	48	35
##	46	175	35
##	47	191	35
##	48	55	36
##	49	197	36
##	50	70	37
##	51	100	37
##	52	139	37
##	53	166	37
##	54	65	38
##	55	85	38
##	56	108	39
##	57	110	39
##	58	104	40
##	59	28	41
##	60	33	41
##	61	92	41
##	62	162	41
##	63	140	42
##	64	90	43
##	65	128	43
##	66	42	44

```
## 67
                       135
                              44
## 68
                       186
                              44
## 69
                         6
                              45
## 70
                        12
                              45
## 71
                         8
                              46
## 72
                        22
                              46
## 73
                       77
                              46
## 74
                       189
                              47
## 75
                       182
                              49
## 76
                       152
                              51
## 77
                       141
                              52
                        26
## 78
                              55
## 79
                        98
                              55
## 80
                        88
                              57
## 81
                       10
                              60
## 82
                       144
                              62
## 83
                       301
                              62
## 84
                       163
                              64
## 85
                        47
                              69
## 86
                         7
                              73
## 87
                       102
                              88
## 88
                        95
                              97
## 89
                       255
                             105
## 90
                       268
                             130
# all data for jurors in 89 trials with complete voir dire transcript
master <- voirdire %>%
 left_join(trials, by = c("juror_id__trial__id" = "id")) %>%
 filter(!is.na(juror_id__trial__id)) %>%
  left_join(jurors, by = c("juror_id" = "id"))
# Confirm 89 trials
master %>% summarise(num_trials = n_distinct(trial__id))
## # A tibble: 1 x 1
##
     num_trials
##
          <int>
## 1
             89
# Examine some categorical variables
master %>% count(struck_by)
## # A tibble: 9 x 2
##
     struck_by
                                         n
##
     <chr>>
                                     <int>
## 1 Juror chosen as alternate
                                       112
## 2 Juror chosen to serve on jury
                                     1037
## 3 Juror excused/absent
                                        53
## 4 Juror not struck
                                       141
## 5 Struck by the defense
                                       696
## 6 Struck by the state
                                       573
## 7 Struck for cause
                                       912
## 8 Struck without notation
                                       20
## 9 Unknown
                                         1
```

```
master %>% count(race)
## # A tibble: 3 x 2
## race n
## <chr> <int>
## 1 Black 1290
## 2 Unknown 87
## 3 White 2168
master %>% count(defendant_race)
## # A tibble: 4 x 2
## defendant_race n
## <chr> <int>
## 1 Asian
                  31
## 2 Black
                2792
## 3 Unknown
                  77
## 4 White
                  645
master %>% count(strike_eligibility)
## # A tibble: 5 x 2
## strike_eligibility
## <chr>
## 1 Both State and Defense 1569
## 2 Defense
## 3 n/a
                        1122
## 4 Neither
                         67
## 5 State
                         726
master %>% count(accused)
## # A tibble: 2 x 2
## accused n
## <lgl> <int>
## 1 FALSE 3495
## 2 TRUE 50
master %>% count(fam_accused)
## # A tibble: 2 x 2
## fam_accused n
## <lgl> <int>
## 1 FALSE
             3078
## 2 TRUE
               467
master %>% count(death_hesitation)
## # A tibble: 2 x 2
## death_hesitation n
## <lgl> <int>
                   3514
## 1 FALSE
## 2 TRUE
master %>% count(know_def)
## # A tibble: 2 x 2
## know_def
```

```
## <lgl>
              <int>
## 1 FALSE
               3079
## 2 TRUE
                466
master %>% count(fam_law_enforcement)
## # A tibble: 2 x 2
##
     fam_law_enforcement
                             n
##
     <1g1>
                         <int>
## 1 FALSE
                          2822
## 2 TRUE
                           723
# Logistic regression data (note they combine White and Unknown races)
master_logistic <- master %>%
  select(juror_id, trial__id, struck_by, race, defendant_race, accused,
         fam_accused, know_def, fam_law_enforcement, death_hesitation,
         strike_eligibility) %>%
  filter(strike_eligibility == "Both State and Defense" |
           strike eligibility == "State") %>%
  mutate(same_race = ifelse(race == defendant_race, TRUE, FALSE),
         struck state = ifelse(struck by == "Struck by the state", 1, 0),
         is_black = ifelse(race == "Black", TRUE, FALSE))
# Ratio of black prob to white prob is 4.68 = .534 / .114 (matches report)
master_logistic %>%
  group_by(is_black) %>%
  summarise(prop_struck = mean(struck_state == 1),
            num_struck = sum(struck_state == 1),
           total = n()
## # A tibble: 2 x 4
     is_black prop_struck num_struck total
     <1g1>
                    <dbl>
                             <int> <int>
## 1 FALSE
                    0.114
                                 177 1554
## 2 TRUE
                    0.534
                                 396
                                       741
# logistic regression model
model1 <- glm(struck_state ~ accused + is_black + fam_accused +</pre>
 death_hesitation + know_def + same_race + fam_law_enforcement,
 family = binomial, data = master_logistic)
summary(model1)
##
## Call:
## glm(formula = struck_state ~ accused + is_black + fam_accused +
##
       death_hesitation + know_def + same_race + fam_law_enforcement,
##
       family = binomial, data = master_logistic)
##
## Deviance Residuals:
                     Median
       Min
                1Q
                                   3Q
                                           Max
## -2.4693 -0.4874 -0.4107 -0.3127
                                        2.4667
##
## Coefficients:
                           Estimate Std. Error z value Pr(>|z|)
##
## (Intercept)
                            -2.4307
                                        0.1012 -24.017 < 2e-16 ***
                                        0.5455 4.606 4.10e-06 ***
## accusedTRUE
                             2.5128
```

```
## is blackTRUE
                             1.8972
                                        0.1411 13.443 < 2e-16 ***
## fam_accusedTRUE
                                        0.1620 11.402 < 2e-16 ***
                             1.8476
                             1.8243
                                                3.084 0.002044 **
## death hesitationTRUE
                                        0.5916
## know_defTRUE
                             1.3257
                                        0.2233
                                                 5.937 2.91e-09 ***
## same raceTRUE
                             0.3603
                                        0.1399
                                                 2.575 0.010036 *
## fam law enforcementTRUE -0.5627
                                        0.1622 -3.468 0.000524 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##
       Null deviance: 2579.5 on 2294 degrees of freedom
## Residual deviance: 1887.6 on 2287
                                       degrees of freedom
## AIC: 1903.6
##
## Number of Fisher Scoring iterations: 5
exp(coef(model1))
##
               (Intercept)
                                       accusedTRUE
                                                              is_blackTRUE
##
                0.08797419
                                       12.33917920
                                                                6.66695515
##
          fam accusedTRUE
                              death_hesitationTRUE
                                                              know defTRUE
##
                6.34456105
                                        6.19872633
                                                                3.76480682
##
             same_raceTRUE fam_law_enforcementTRUE
                1.43369659
                                        0.56968121
exp(confint(model1))
## Waiting for profiling to be done...
##
                                2.5 %
                                         97.5 %
                           0.07182462 0.106826
## (Intercept)
## accusedTRUE
                           4.57474511 40.090813
## is_blackTRUE
                           5.06788006 8.815129
## fam_accusedTRUE
                           4.62782800 8.738251
## death_hesitationTRUE
                           2.01793799 20.917259
## know defTRUE
                           2.43708908 5.854130
                           1.08819022 1.883933
## same_raceTRUE
## fam_law_enforcementTRUE 0.41209408 0.778917
# get Wald CIs to match report
SE = summary(model1)$coefficients[,2]
beta = summary(model1)$coefficients[,1]
lower = beta - 1.96*SE
upper = beta + 1.96*SE
exp(cbind(lower, upper))
                                lower
                                           upper
## (Intercept)
                           0.07214457 0.1072771
## accusedTRUE
                           4.23601835 35.9430321
## is_blackTRUE
                           5.05587652 8.7914115
## fam_accusedTRUE
                           4.61821801 8.7162310
## death_hesitationTRUE
                           1.94411943 19.7643249
## know_defTRUE
                           2.43032142 5.8320559
## same_raceTRUE
                           1.08980275
                                       1.8861082
## fam_law_enforcementTRUE 0.41451088 0.7829389
```