Preliminary Analyses

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Summary

The various results presented below show substantial variation by race, but little systematic variation by class. Descriptively, evaluations of the police in 5 separate dimensions, court fairness evaluations regardless of prompt, beliefs that respecting police improve interactions, and perceptions that police corruption is motivated less by bad apples all vary by race. But perhaps more importantly for our position, little variation exists *within* each racial group that seems attributable to class. Only court evaluations appear to have any meaningful variation by class in these cross-tabs.

On the court evaluations question, higher class whites are somewhat more likely to view them as fair in the class condition. In contrast, higher class blacks in both the class and race conditions view the courst as less fair, with a 14 point gap emerging between low and high class blacks in the class-prime condition.

For me, interesting differences emerge in some of the additional analyses. On the court fairness questionwording test, priming race leads to a polarization in beliefs by race. Blacks view the courts as less fair relative to the other prompts while whites see them as more fair.

Social connections, racial attitudes, government employment, and employment in the criminal justice system all explain variation in outcomes, too. Class fragility and specific CJS occupation appear to explain little meaningful variation. What varies is which racial group they matter for, on which outcomes, and with what effect. Social connections play an important role for whites, bringing their responses closer in line with blacks. Whites who have more peers with felony convictions evaluate the police at about the same level blacks. Relatedly, blacks employed in the government look more like whites in their responses to many items than do blacks employed elsewhere. Perhaps most interestingly, linked fate, regardless of racial groups, produces more negative views about the criminal justice system. In sharp contrast, racially resentful whites overwhemlingly believe the CJS to be fair and the police in their area to be good. These are all bivariate interactive relationships, but the results to me are suggestive.

Average Policy Differences By Race and Class

Police Fairness Evaluations

By race

Below I present the distribution for each of the individual police evaluation items. I include both the full sample, and then the white and black only samples respectively. Higher values denote more positive evaluations. Everything is in percentage points. I also report the results from a Chi^2 test on these distributions. Unsurprisingly, all of these are significant.

Of these individual items, blacks tend to offer the most negative ratings on the *equal treatment*, *excessive force*, and *accountability* items. For whites, the distribution of repsonses to these items does not appear to meaningfully differ from the rest, at least eyeballing the results.

Solving Crime

```
##             black
## p.crim.solve  0  1
##            0  5 19
##            1 11 20
```

```
##            2 35 36
##            3 36 17
##            4 13  7
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.crim.solve + black, d.all), 2) *     100)
## X-squared = 19.4, df = 4, p-value = 0.0006556
```

Protecting people like you from violent crime

```
##            black
## p.viol.crim  0  1
##           0  4 21
##           1  9 19
##           2 28 34
##           3 40 17
##           4 20  8
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.viol.crim + black, d.all), 2) *     100)
## X-squared = 30.119, df = 4, p-value = 4.63e-06
```

Treating racial and ethnic groups equally

```
##            black
## p.race.fair  0  1
##           0 12 43
##           1 13 18
##           2 30 23
##           3 29 11
##           4 16  6
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.race.fair + black, d.all), 2) *     100)
## X-squared = 31.845, df = 4, p-value = 2.058e-06
```

Not using excessive force on suspects

```
##              black
## p.exces.force  0  1
##             0  9 35
##             1 13 18
##             2 31 28
##             3 31 12
##             4 16  7
```

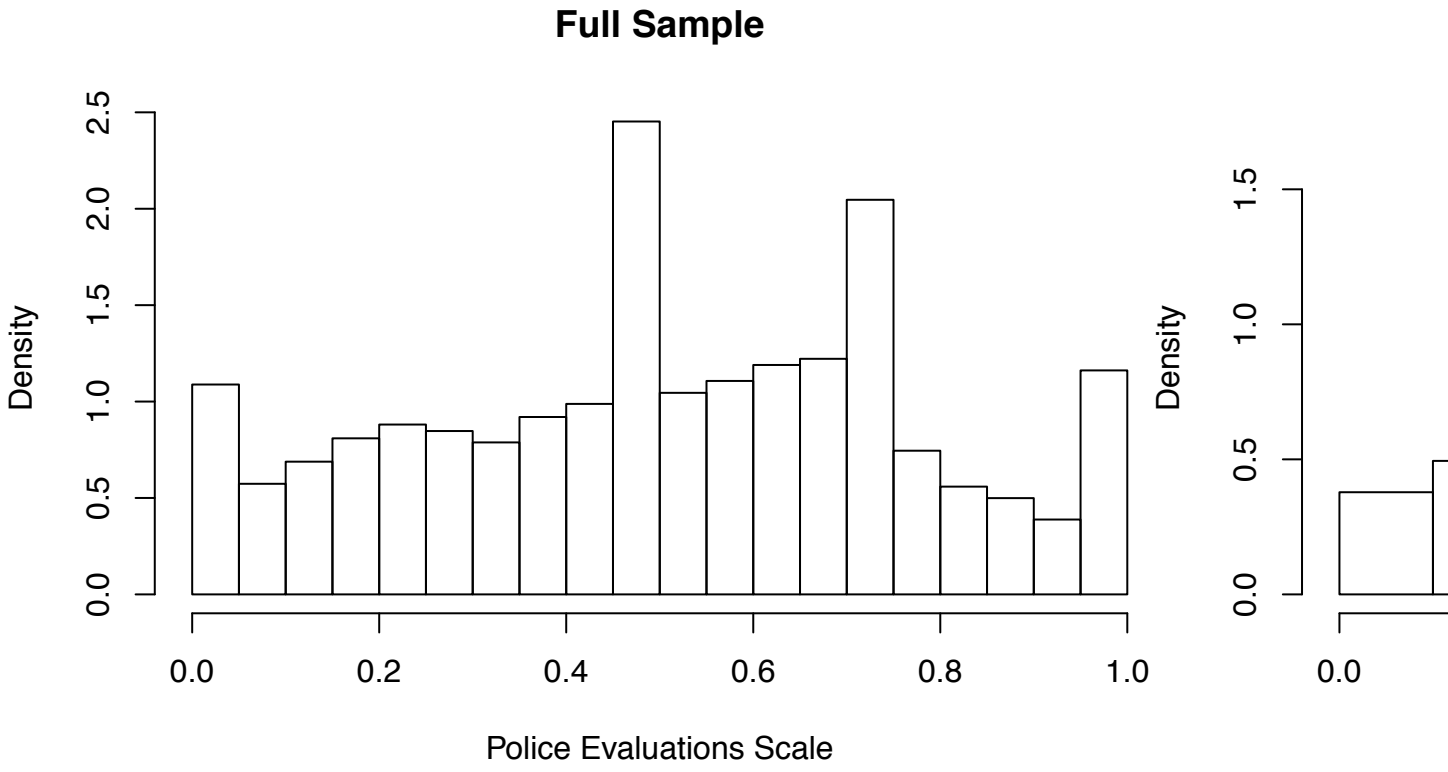
```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.exces.force + black, d.all), 2) *     100)
## X-squared = 28.24, df = 4, p-value = 1.115e-05
```

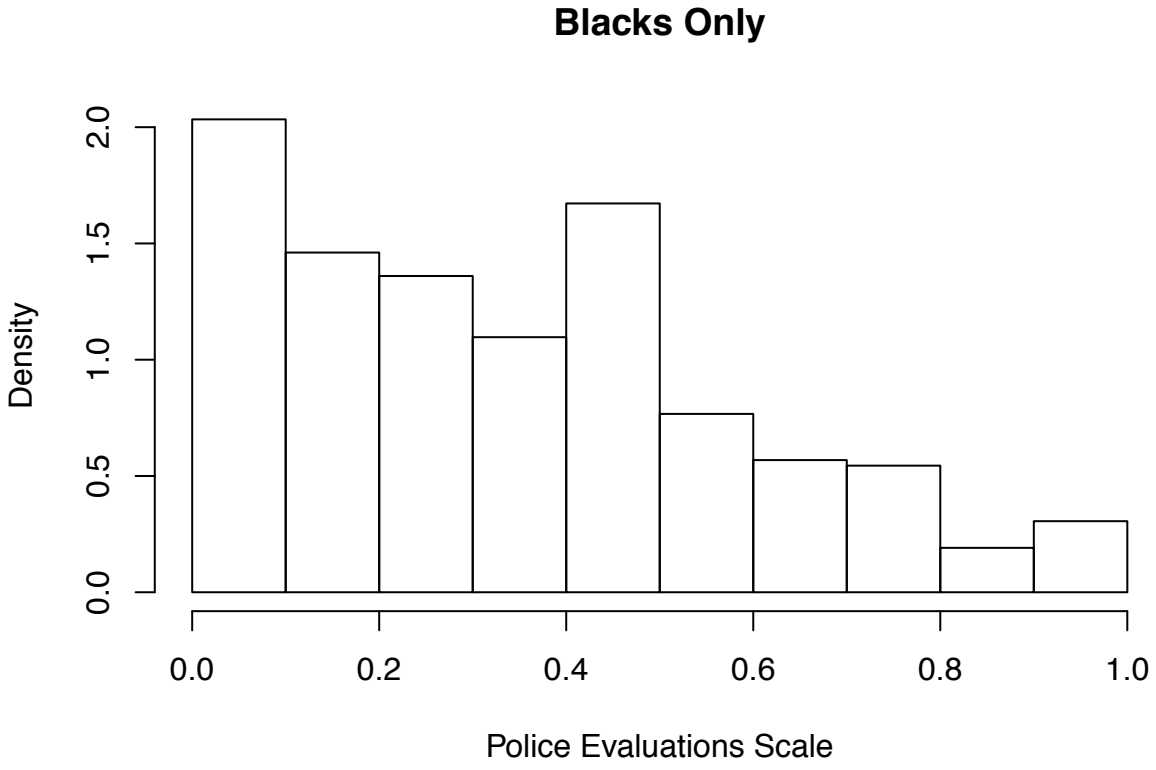
Holding police officers accountable for misconduct

```
##          black
## p.account  0  1
##         0 12 44
##         1 12 15
##         2 29 24
##         3 32 11
##         4 15  6
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.account + black, d.all), 2) * 100)
## X-squared = 33.204, df = 4, p-value = 1.085e-06
```

I also considered a summary evaluation index. I summed together the 5 evaluations and set the scale to run from 0-1, where higher values denote more positive evaluations. The mean for the full sample is 0.53, while for whites it is 0.59 and for blacks it is 0.37. Blacks clearly rate the police on average lower than whites, and this difference is significant at $p < 0.000$. I present the distribution for the scale for the full sample and by race below.





It's also potentially instructive to contrast whites and blacks in how these police evaluation items scale together. To get a sense for whether these capture summary evaluations across groups, I present alphas for the 5 items scaled together. Cronbach's alpha for whites is 0.90, while for black it is 0.89. Although a rough pass, the similarity suggests that blacks and whites use the same dimensions to evaluate the police. I could push further on this with some factor analyses if interested.

Race seems closely related to how people evaluate the police in their area. This manifests both in individual and summary item ratings. Importantly, the dimensions on which whites and blacks evaluate the police seem to matter the same.

By class

I created two separate measure of class based on tercile breakdowns of income and education. Each assigned repondents to an income or education tercile, however one version determined terciles based on the full weighted sample while the second looked within each racial group. Because the correlation between the two measures is 0.92 I use the class measure that's specific within each race to account for potential incomparabilities across groups. I again included a Chi^2 test for each distribution. None of these are significant. Class level does not appear to be related with evaluations of the police. Moreover, response distributions appear to be similar across items, too.

Solving Crime

```
##             class
## p.crim.solve  0 0.25 0.5 0.75  1
##            0 13   10   8    6  6
##            1 16   14  14   12 11
##            2 36   36  34   35 35
##            3 24   29  33   36 34
##            4 11   10  11   10 15
```

```
##
```

```
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.crim.solve + class, d.all), 2) *     100)
## X-squared = 9.6774, df = 16, p-value = 0.8829
```

Protecting people like you from violent crime

```
##            class
## p.viol.crim  0 0.25 0.5 0.75  1
##           0 12   10   8    6  5
##           1 16   13  11    9 11
##           2 32   32  29   29 25
##           3 25   31  35   40 38
##           4 15   15  17   16 21
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.viol.crim + class, d.all), 2) *     100)
## X-squared = 13.171, df = 16, p-value = 0.6602
```

Treating racial and ethnic groups equally

```
##            class
## p.race.fair  0 0.25 0.5 0.75  1
##           0 22   22  21   17 19
##           1 16   14  14   14 13
##           2 30   29  27   29 25
##           3 19   23  26   27 28
##           4 13   12  13   13 15
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.race.fair + class, d.all), 2) *     100)
## X-squared = 4.3657, df = 16, p-value = 0.9981
```

Not using excessive force on suspects

```
##              class
## p.exces.force  0 0.25 0.5 0.75  1
##             0 19   18  16   14 12
##             1 15   15  14   14 15
##             2 33   32  28   30 26
##             3 20   23  29   28 29
##             4 12   12  13   14 17
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.exces.force + class, d.all), 2) *     100)
## X-squared = 7.124, df = 16, p-value = 0.9708
```

Holding police officers accountable for misconduct

```
##          class
## p.account  0 0.25 0.5 0.75  1
##         0 25   22  21   18 17
##         1 13   14  12   12 12
```

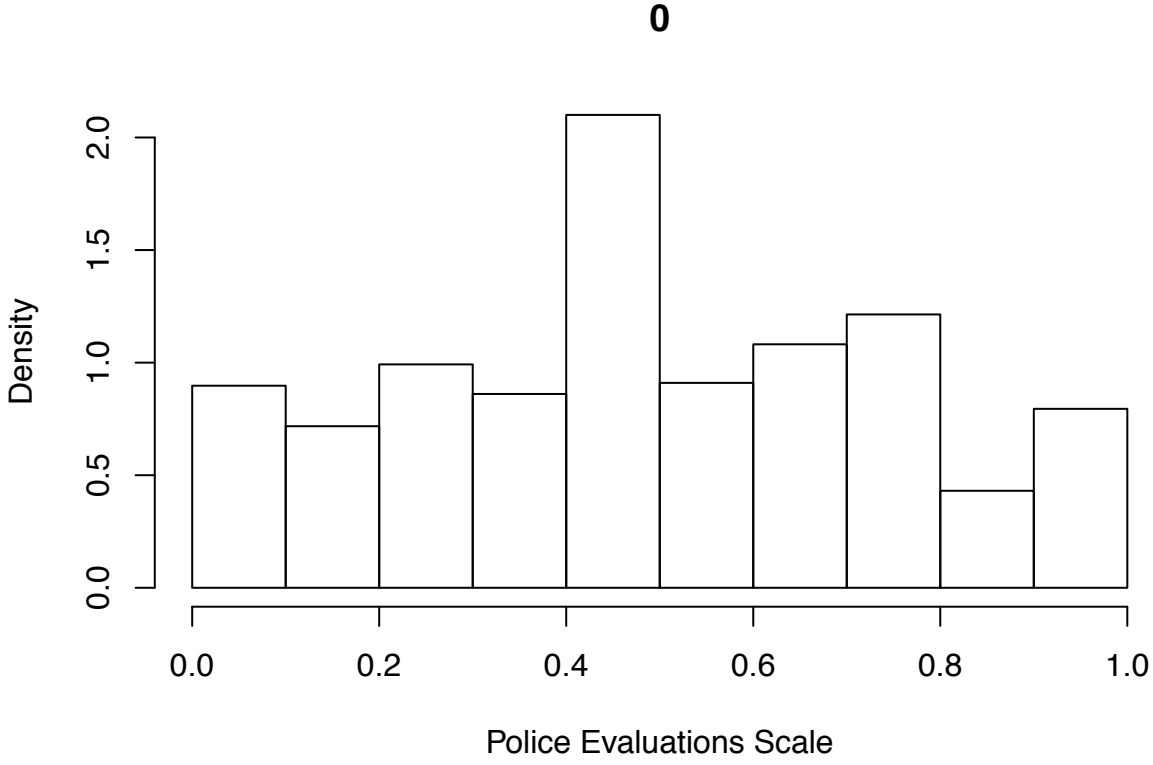
```
##         2 29   29  27   28 24
##         3 21   23  28   29 31
##         4 12   11  12   13 15
```

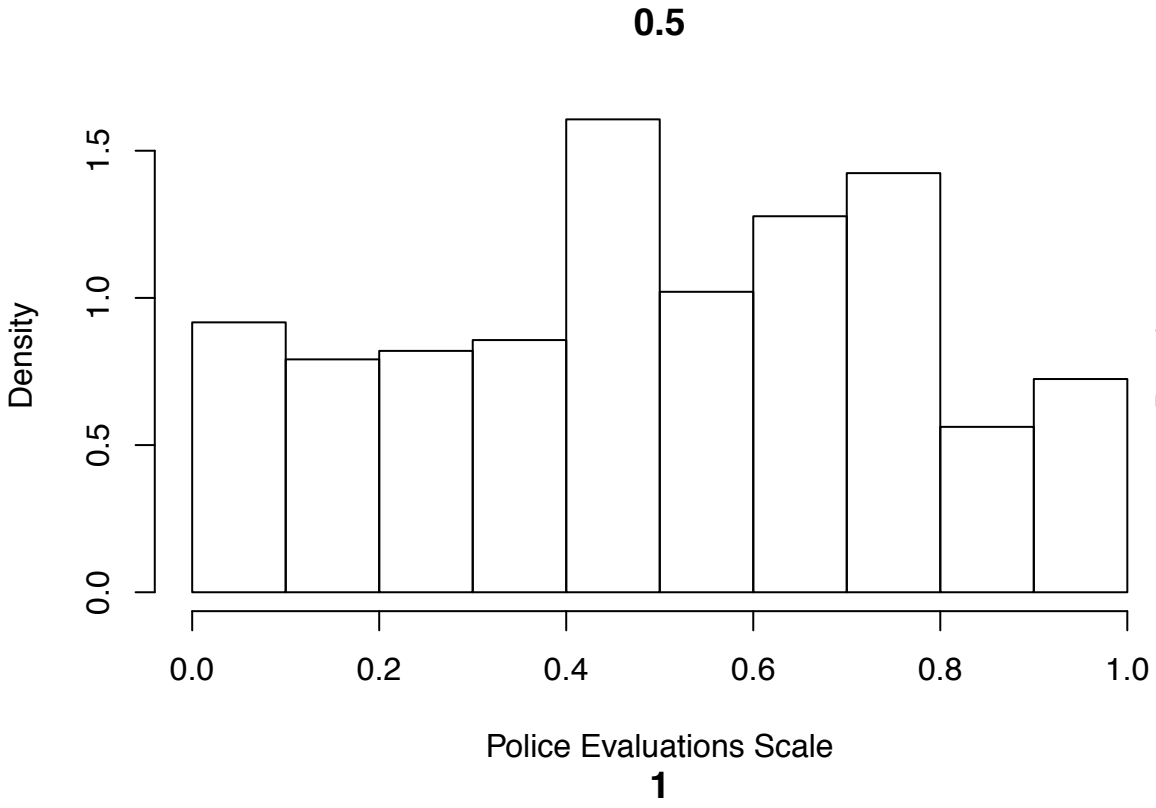
```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.account + class, d.all), 2) * 100)
## X-squared = 6.305, df = 16, p-value = 0.9845
```

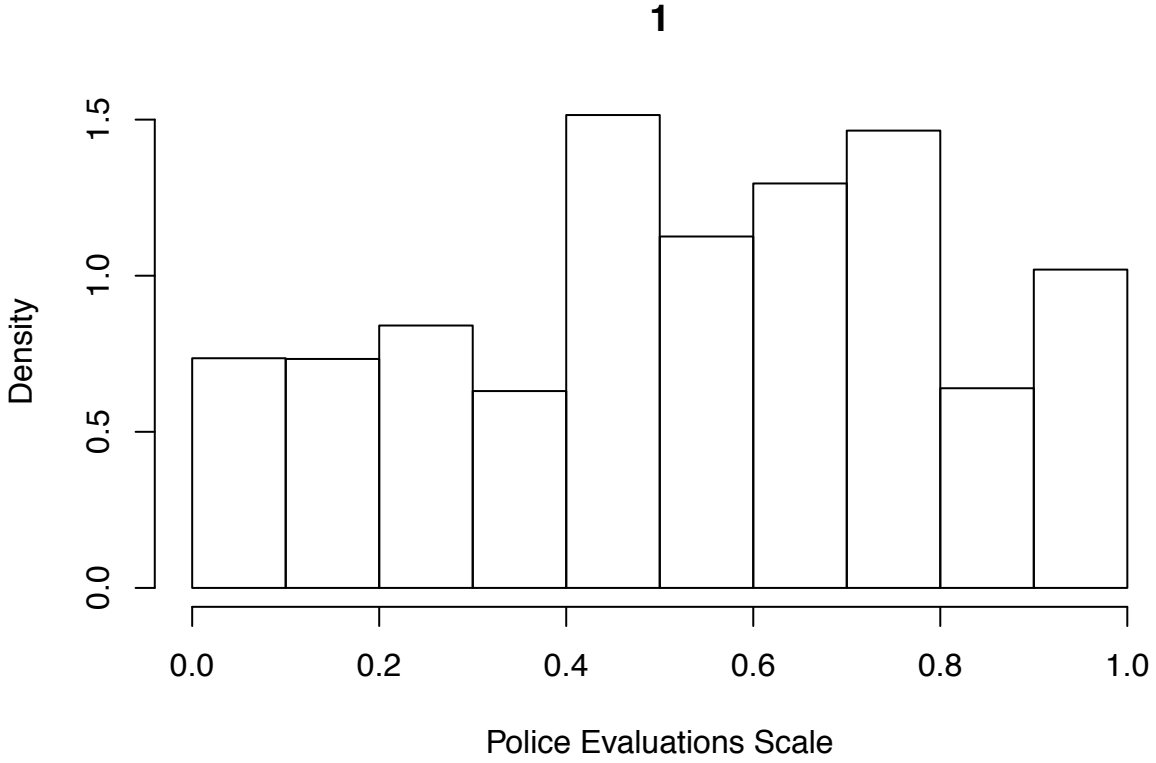
As for the summary evaluation index, the table below proveis the mean for each class category. Descriptively higher class individuals tend to evaluate the police more positively. A 5 point difference exists between the lowest and highest class individuals, one significant at $p < 0.000$.

```
##         0 0.25  0.5 0.75    1
## mean 0.51 0.52 0.53 0.54 0.56
```

The plots below present the distribution of summary police evaluations for each class level.







I return to the alpha measure to contrast class category groups' police evaluations. The table below presents these tallies. No meaningful variation exists by class category, suggesting class does not shape which dimensions people rely on for evaluating the police.

```
##            0  0.25   0.5  0.75     1
## alpha 0.915 0.907 0.914 0.914 0.919
```

To summarize, class appears unrelated to individuals' evaluations of the police. This holds for both the individual items and the summary index.

By Race and Class

Finally, for the race and class breakdown I present the item distributions again, but by class within each racial group. I again include Chi^2 tests to compare the distributions. None of these tests are significant, suggesting that the intersection of race and class does not affect evaluations of the police.

Whites: Solving Crime

```
##             class
## p.crim.solve  0 0.25 0.5 0.75  1
##            0  7    6   4    5  4
##            1 14   12  12   10 10
##            2 37   36  34   35 34
##            3 30   33  38   38 36
##            4 13   12  12   12 16
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.crim.solve + class, d.wht), 2) *     100)
## X-squared = 4.7253, df = 16, p-value = 0.997
```

Blacks: Solving Crime

```
##             class
## p.crim.solve  0 0.25 0.5 0.75  1
##            0 20   19  18   12 12
##            1 22   22  21   21 13
##            2 36   35  36   39 44
##            3 14   17  19   24 24
##            4  8    7   6    3  7
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.crim.solve + class, d.blk), 2) *     100)
## X-squared = 14.471, df = 16, p-value = 0.5636
```

Whites: Protecting people like you from violent crime

```
##            class
## p.viol.crim  0 0.25 0.5 0.75  1
##           0  6    5   3    4  1
##           1 13   11   9    7  8
##           2 31   32  29   26 23
##           3 32   35  40   44 43
##           4 19   18  19   19 24
```

```
## Warning in chisq.test(round(prop.table(svytable(~p.viol.crim + class,
## d.wht), : Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.viol.crim + class, d.wht), 2) *     100)
```

```
## X-squared = 12.146, df = 16, p-value = 0.7338
```

Blacks: Protecting people like you from violent crime

```
##             class
## p.viol.crim  0 0.25 0.5 0.75  1
##           0 20   21  20   16 21
##           1 22   19  17   18 20
##           2 36   33  34   39 31
##           3 12   21  20   22 19
##           4 10    7   9    4 10
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.viol.crim + class, d.blk), 2) *     100)
## X-squared = 9.3279, df = 16, p-value = 0.8993
```

Whites: Treating racial and ethnic groups equally

```
##             class
## p.race.fair  0 0.25 0.5 0.75  1
##           0 13   14  13   11 11
##           1 16   13  12   13 13
##           2 31   31  30   30 26
##           3 24   27  30   30 32
##           4 16   15  15   16 18
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.race.fair + class, d.wht), 2) *     100)
## X-squared = 3.5939, df = 16, p-value = 0.9994
```

Blacks: Treating racial and ethnic groups equally

```
##             class
## p.race.fair  0 0.25 0.5 0.75  1
##           0 37   40  44   40 51
##           1 18   17  20   24 15
##           2 28   25  21   23 18
##           3 10   11  12   12 10
##           4  7    6   4    2  6
```

```
## Warning in chisq.test(round(prop.table(svytable(~p.race.fair + class,
## d.blk), : Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.race.fair + class, d.blk), 2) *     100)
## X-squared = 11.3, df = 16, p-value = 0.7906
```

Whites: Not using excessive force on suspects

```
##              class
## p.exces.force  0 0.25 0.5 0.75  1
##             0 12   11  10    9  7
##             1 14   14  12   14 14
##             2 34   34  29   30 27
```

```
##             3 26   27  33   32 33
##             4 15   15  16   16 19
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.exces.force + class, d.wht), 2) *     100)
## X-squared = 5.2147, df = 16, p-value = 0.9946
```

Blacks: Not using excessive force on suspects

```
##              class
## p.exces.force  0 0.25 0.5 0.75  1
##             0 31   35  35   34 32
##             1 17   18  19   19 21
##             2 34   29  26   30 22
##             3 11   13  14   11 15
##             4  6    5   5    5  9
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.exces.force + class, d.blk), 2) *     100)
## X-squared = 6.7311, df = 16, p-value = 0.9781
```

Whites: Holding police officers accountable for misconduct

```
##          class
## p.account  0 0.25 0.5 0.75  1
##         0 16   14  12   12 10
##         1 13   14  11   12 12
##         2 30   31  30   28 25
##         3 26   27  33   34 36
##         4 14   13  14   15 17
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.account + class, d.wht), 2) * 100)
## X-squared = 5.9786, df = 16, p-value = 0.9883
```

Blacks: Holding police officers accountable for misconduct

```
##          class
## p.account  0 0.25 0.5 0.75  1
##         0 40   41  47   39 50
##         1 15   16  16   17 13
##         2 28   26  20   29 18
##         3 12   12  12   11 10
##         4  6    6   5    4  9
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~p.account + class, d.blk), 2) * 100)
## X-squared = 9.3722, df = 16, p-value = 0.8973
```

Returning to the summary evaluation index, the table below provides the means for each race/class category. Whereas the prior class-only results indicated that higher class individuals tended to evaluate the police

more positively, this seems driven by whites. A 7 point difference exists between the lowest and highest class whites, but this gap is only 2 points for blacks. The former is significant at $p < 0.000$ while the latter is not ($p = 0.703$).

```
##                  0 0.25  0.5 0.75    1
## mean - White 0.56 0.57 0.60 0.60 0.63
## mean - Black 0.35 0.38 0.35 0.37 0.37
```

Finally, I present the scale alphas in table below. The first row looks at whites across class, while the second looks at blacks by class. No meaningful variation exists according to class/race interaction, reinforcing the likelihood that people rely on the same dimensions for evaluating the police.

```
##                     0  0.25   0.5  0.75     1
## Alpha - Whites 0.906 0.901 0.897 0.903 0.898
## Alpha - Blacks 0.900 0.884 0.898 0.891 0.907
```

Court Fairness

By race

I break down each court fairness item based on the suffix. The first is whether the court will fairly apply the law, while the second two ask whether this is the case regardless of a person's class or race, resepctively. Again, I presented the response distribution in percentage points, broken down by race. The Chi^2 tests are again significant. Regardless of the prompt, blacks are on average less likely to think the courts in their area will be fair.

''fairly apply the law?"

```
##                    black
## court.fair           0  1
##   0                  5 16
##   0.333333333333333 14 29
##   0.666666666666667 52 43
##   1                 29 12
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair + black, d.all), 2) * 100)
## X-squared = 18.896, df = 3, p-value = 0.0002873
```

''fairly apply the law, regardless of a person's class?"

```
##                    black
## court.fair.class     0  1
##   0                  6 16
##   0.333333333333333 15 27
##   0.666666666666667 49 43
##   1                 30 14
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair.class + black, d.all),     2) * 100)
## X-squared = 14.184, df = 3, p-value = 0.002666
```

''fairly apply the law, regardless of a person's race?"

```
##                    black
## court.fair.race      0  1
##   0                  6 21
##   0.333333333333333 14 30
##   0.666666666666667 45 37
##   1                 35 12
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair.race + black, d.all), 2) *     100)
## X-squared = 26.187, df = 3, p-value = 8.714e-06
```

We also see interesting treatment effects within racial group. While there are no differences between the baseline condition and the class prime, the race prime decreases blacks' perceptions that courts will be fair. In contrast, the same prime increases whites' perceptions of fairness. These differences are small, however. The Cohen's D effect size for whites is 0.06, whole for blacks it is 0.12. Even so, because of the divergent effects, the black-white gap in fairness evaluations grows by 5 percentage points, from 18 to 23 points.

```
##
## Call:
## lm(formula = court.fair.all ~ court.fair.treat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.70289 -0.13145 -0.01167  0.21515  1.30115
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  0.681538   0.005430 125.504  < 2e-16 ***
## court.fair.treatRace         0.013662   0.007723   1.769 0.076919 .
## court.fair.treatClass       -0.004915   0.007688  -0.639 0.522699
## black                       -0.177522   0.010409 -17.055  < 2e-16 ***
## court.fair.treatRace:black  -0.048872   0.014807  -3.301 0.000967 ***
## court.fair.treatClass:black  0.020124   0.014756   1.364 0.172677
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2839 on 11156 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.08072,    Adjusted R-squared:  0.0803
## F-statistic: 195.9 on 5 and 11156 DF,  p-value: < 2.2e-16
```

By Class

Turning to class, the analyses below suggest little variation exists by class category in fairness percpetions. Moreover, this holds regardless of the prompt. Even when primed to think about class, low and high class respondents think the courts in their area will fairly apply the law. **"fairly apply the law?"**

```
##                    class.rac
## court.fair           0 0.25 0.5 0.75  1
##   0                 11    7   9    6  6
##   0.333333333333333 20   20  17   20 15
##   0.666666666666667 47   50  51   48 53
```

```
##   1                 22   23  24   27 26
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair + class.rac, d.all), 2) *     100)
## X-squared = 4.72, df = 12, p-value = 0.9667
```

"fairly apply the law, regardless of a person's class?"

```
##                    class.rac
## court.fair.class     0 0.25 0.5 0.75  1
##   0                 10    9   9    9  6
##   0.333333333333333 19   19  17   19 16
##   0.666666666666667 49   46  49   45 48
##   1                 22   25  24   27 31
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair.class + class.rac, d.all),     2) * 100)
## X-squared = 3.555, df = 12, p-value = 0.9902
```

"fairly apply the law, regardless of a person's race?"

```
##                    class.rac
## court.fair.race      0 0.25 0.5 0.75  1
##   0                 12   11   9    8  9
##   0.333333333333333 17   19  20   19 14
##   0.666666666666667 41   44  40   43 48
##   1                 30   25  30   30 29
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair.race + class.rac, d.all),     2) * 100)
## X-squared = 3.9198, df = 12, p-value = 0.9848
```

```
##
## Call:
## lm(formula = court.fair.all ~ court.fair.treat * class.rac, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.62974 -0.21365  0.02581  0.07588  0.91059
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    6.072e-01  8.221e-03  73.856  < 2e-16 ***
## court.fair.treatRace           7.624e-03  1.176e-02   0.648    0.517
## court.fair.treatClass          3.421e-05  1.164e-02   0.003    0.998
## class.rac                      5.662e-02  1.447e-02   3.913 9.19e-05 ***
## court.fair.treatRace:class.rac -1.513e-02  2.089e-02  -0.724    0.469
## court.fair.treatClass:class.rac  1.509e-03  2.046e-02   0.074    0.941
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.2956 on 11156 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.00349,    Adjusted R-squared:  0.003043
## F-statistic: 7.814 on 5 and 11156 DF,  p-value: 2.37e-07
```

By Race and Class

Finally, looking at the intersection of race and class, little variation again appears by class level. One interesting point is that for blacks, the class prime appears to have decreases the number of lower class blacks believing the courts in their area will fairly apply the law. The p-vale on the Chi^2 test is 0.082.

Whites: "fairly apply the law?"

```
##                    class.rac
## court.fair           0 0.25 0.5 0.75  1
##   0                  8    5   5    4  4
##   0.333333333333333 19   15  12   14 14
##   0.666666666666667 48   52  55   50 52
##   1                 26   27  28   32 29
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair + class.rac, d.wht), 2) *     100)
## X-squared = 5.0985, df = 12, p-value = 0.9546
```

Blacks: "fairly apply the law?"

```
##                    class.rac
## court.fair           0 0.25 0.5 0.75  1
##   0                 22   11  16   11 12
##   0.333333333333333 26   35  27   35 20
##   0.666666666666667 43   43  44   46 53
##   1                  9   12  13    8 15
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair + class.rac, d.blk), 2) *     100)
## X-squared = 16.43, df = 12, p-value = 0.1723
```

Whites: "fairly apply the law, regardless of a person's class?"

```
##                    class.rac
## court.fair.class     0 0.25 0.5 0.75  1
##   0                  6    8   7    7  2
##   0.333333333333333 20   18  13   13 10
##   0.666666666666667 50   46  50   48 51
##   1                 24   27  30   32 37
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair.class + class.rac, d.wht),     2) * 100)
## X-squared = 11.76, df = 12, p-value = 0.4651
```

Blacks: "fairly apply the law, regardless of a person's class?"

```
##                    class.rac
## court.fair.class     0 0.25 0.5 0.75  1
##   0                 25   12  16   15 15
##   0.333333333333333 16   23  29   34 29
##   0.666666666666667 46   45  47   38 41
##   1                 13   20   9   12 15
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair.class + class.rac, d.blk),     2) * 100)
## X-squared = 19.288, df = 12, p-value = 0.08181
```

Whites: "fairly apply the law, regardless of a person's race?"

```
##                    class.rac
## court.fair.race      0 0.25 0.5 0.75  1
##   0                  8    8   4    6  5
##   0.333333333333333 14   17  16   13 10
##   0.666666666666667 44   44  44   44 52
##   1                 34   30  36   37 33
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair.race + class.rac, d.wht),     2) * 100)
## X-squared = 6.2091, df = 12, p-value = 0.9052
```

Blacks: "fairly apply the law, regardless of a person's race?"

```
##                    class.rac
## court.fair.race      0 0.25 0.5 0.75  1
##   0                 28   20  19   14 21
##   0.333333333333333 25   24  32   36 32
##   0.666666666666667 33   44  36   45 35
##   1                 14   12  14    5 11
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~court.fair.race + class.rac, d.blk),     2) * 100)
## X-squared = 16.484, df = 12, p-value = 0.17
```

However, we get more nuance by looking at potential treatment effects. For whites in the class prime, higher class whites are marginally more likely to think the courts in their area are fair. The difference between low and high class whites here is 4 percentage points ($p = 0.066$). This is on top of a 5 point class difference in the baseline condition ($p < 0.000$).

```
##
## Call:
## lm(formula = court.fair.all ~ court.fair.treat * class.rac, data = cjs.df,
##     weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.75490 -0.04959 -0.00782  0.21841  0.78941
##
## Coefficients:
```

```
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                      0.650394   0.008860  73.406  < 2e-16 ***
## court.fair.treatRace             0.018690   0.012716   1.470 0.141656
## court.fair.treatClass           -0.020307   0.012447  -1.632 0.102814
## class.rac                        0.054297   0.015789   3.439 0.000587 ***
## court.fair.treatRace:class.rac  -0.006945   0.022665  -0.306 0.759291
## court.fair.treatClass:class.rac  0.040979   0.022318   1.836 0.066379 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2764 on 8084 degrees of freedom
##   (3076 observations deleted due to missingness)
## Multiple R-squared:  0.007835,   Adjusted R-squared:  0.007221
## F-statistic: 12.77 on 5 and 8084 DF,  p-value: 2.188e-12
```

As for blacks, a different picture emerges. The results below show a sharp divergence in fairness evaluations by class depending on the question wording. For those receiving the class prime, higher class blacks are 9 points less likely to believe the courts in their area are fair than their lower class counterparts ($p < 0.05$). Interestingly, a similar effect manifests for higher class blacks receiving the race prime, although the magnitude is smaller and imprecisely estimated ($\beta = -0.07$, $p < 0.1$).

```
##
## Call:
## lm(formula = court.fair.all ~ court.fair.treat * class.rac, data = cjs.df,
##     weights = wts_black)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -1.2594 -0.1636  0.1036  0.1649  1.2823
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                      0.47710    0.01575  30.286   <2e-16 ***
## court.fair.treatRace            -0.00398    0.02242  -0.178   0.8591
## court.fair.treatClass            0.04734    0.02291   2.066   0.0389 *
## class.rac                        0.07406    0.02865   2.585   0.0098 **
## court.fair.treatRace:class.rac  -0.07068    0.04217  -1.676   0.0939 .
## court.fair.treatClass:class.rac -0.09094    0.04075  -2.232   0.0257 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3043 on 3066 degrees of freedom
##   (8094 observations deleted due to missingness)
## Multiple R-squared:  0.005924,   Adjusted R-squared:  0.004303
## F-statistic: 3.654 on 5 and 3066 DF,  p-value: 0.002677
```

Police Respect

We also asked respondents whether give the police more respect would make civilian-police interactions go more smoothly. Higher values denote a belief that being more respectful would lead to more frequent positive interactions. The crosstabs by respondent characteristics suggest that race, not class, shapes these beliefs. Blacks are much less likely than whites to beleif respect leads to consistently positive interactions. 79% of whites believe respect leads to smooth interactions "most of the time" or "always." In contrast, only 46% of blacks believe this. Consequently, the Chi^2 p-value by race is 0.000. Moreover, within racial groups class

does not appear to offer any variation. Perpsectives on this item thus appear to follow more from racial background than class.

By race

```
##               black
## respect.police  0  1
##              0  2 10
##              1 18 44
##              2 49 34
##              3 30 12
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~respect.police + black, d.all), 2) *     100)
## X-squared = 26.657, df = 3, p-value = 6.946e-06
```

By Class

```
##               class.rac
## respect.police  0 0.25 0.5 0.75  1
##              0  6    4   5    3  4
##              1 24   25  26   25 27
##              2 45   46  43   46 46
##              3 25   25  27   26 24
```

```
## Warning in chisq.test(round(prop.table(svytable(~respect.police +
## class.rac, : Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~respect.police + class.rac, d.all),     2) * 100)
## X-squared = 1.7315, df = 12, p-value = 0.9997
```

By Race and Class

Whites

```
##               class.rac
## respect.police  0 0.25 0.5 0.75  1
##              0  3    2   2    2  2
##              1 20   20  18   16 17
##              2 48   49  47   51 51
##              3 29   29  33   31 30
```

```
## Warning in chisq.test(round(prop.table(svytable(~respect.police + class, :
## Chi-squared approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~respect.police + class, d.wht), 2) *     100)
## X-squared = 1.853, df = 12, p-value = 0.9996
```

Blacks

```
##                class.rac
## respect.police  0 0.25 0.5 0.75  1
##              0 15    9  11    6  6
##              1 34   39  47   52 53
##              2 37   39  31   32 32
##              3 14   13  11   10  9
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~respect.police + class, d.blk), 2) *     100)
## X-squared = 13.436, df = 12, p-value = 0.3382
```

Police Quality "Bad Apples"

Finally, respondents reported whether or not incidents of police corruption were systemic or just "bad apples." Again, responses vary substantially by race, but not class. 34% of black respondents see these incidents as systemic issues, 23% as bad apples, and 40% a little bit of both. In contrast, 49% of whites focus on bad apples, and only 19% respond that these issues reflect systemic problems. No such variation occurs across class categories. Each class group sees a little over 40% emphasizing bad apples, with between 20 and 26% reponding that it's a systemic issue. It's interesting to note that the emphasis on systemic problems rises by class, but the overall distribution doesn't meaningfully change.

By race

```
##              black
## pol.badapples  0  1
##             1 50 24
##             2 31 42
##             3 19 35
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~pol.badapples + black, d.all), 2) *     100)
## X-squared = 15.529, df = 2, p-value = 0.0004246
```

By Class

```
##              class.rac
## pol.badapples  0 0.25 0.5 0.75  1
##             1 43   43  43   44 42
##             2 37   34  33   32 31
##             3 20   23  24   24 27
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~pol.badapples + class.rac, d.all),     2) * 100)
## X-squared = 1.749, df = 8, p-value = 0.9878
```

By Race and Class

Turning to within-group differences, nothing signficantly varies. Even so, there's interesting descriptive variation within blacks. Higher class blacks are less likely to report that police corruption comes from bad apples, and are more likely to emphasize systemic issues, than are lower class blacks. The proportion reporting that both issues matter stays effectively the same.

Whites

```
##              class.rac
## pol.badapples  0 0.25 0.5 0.75  1
##             1 46   48  50   51 51
##             2 35   31  31   28 28
##             3 19   21  19   20 22
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~pol.badapples + class, d.wht), 2) *     100)
## X-squared = 1.9063, df = 8, p-value = 0.9837
```

Blacks

```
##              class.rac
## pol.badapples  0 0.25 0.5 0.75  1
##             1 28   26  23   21 18
##             2 45   44  42   41 40
##             3 27   30  35   37 42
```

```
##
##  Pearson's Chi-squared test
##
## data:  round(prop.table(svytable(~pol.badapples + class, d.blk), 2) *     100)
## X-squared = 11.005, df = 8, p-value = 0.2014
```

Explaining Item Variation

Police Fairness Evaluations

Social Experiences

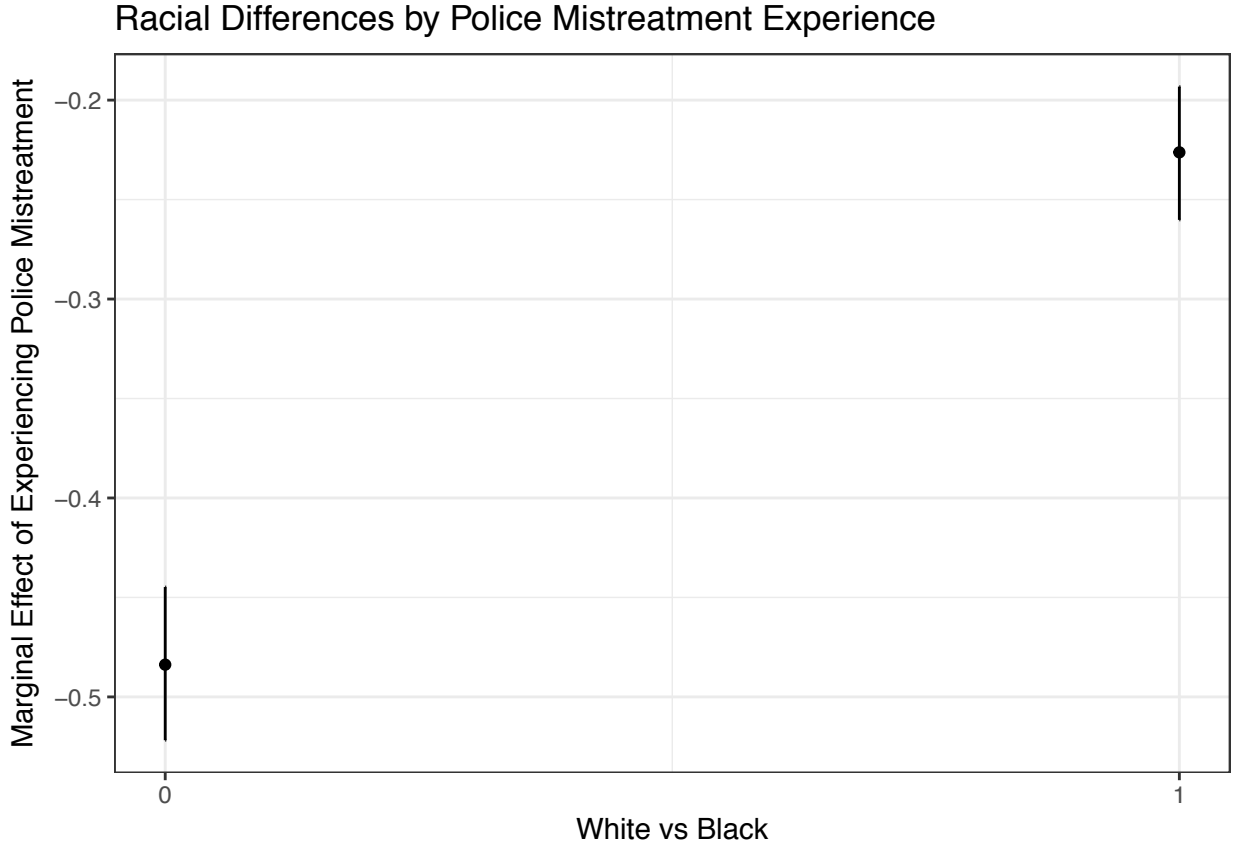
Police Abused Friends/Family

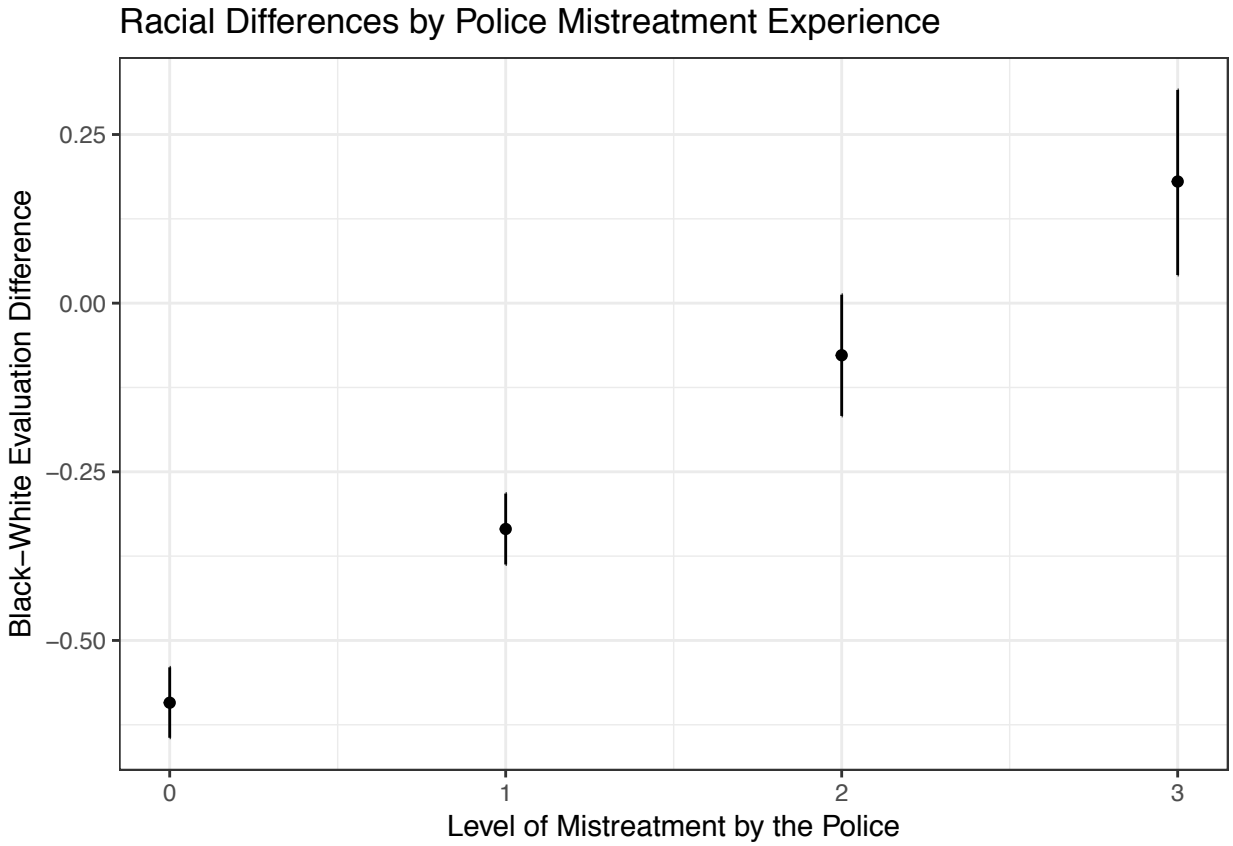
I being by looking at whether respondents report that they or their peers had been mistreated by the police. Across all items, respondents are less positive in their evaluations of the police. Perhaps more interestingly, across all items the black-white evaluation gap closes as the frequency of mistreatment increases. The gaps remain, but they grow smaller by varying degrees.

Solving Crime

```
##
## Call:
## lm(formula = p.crim.solve ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
```

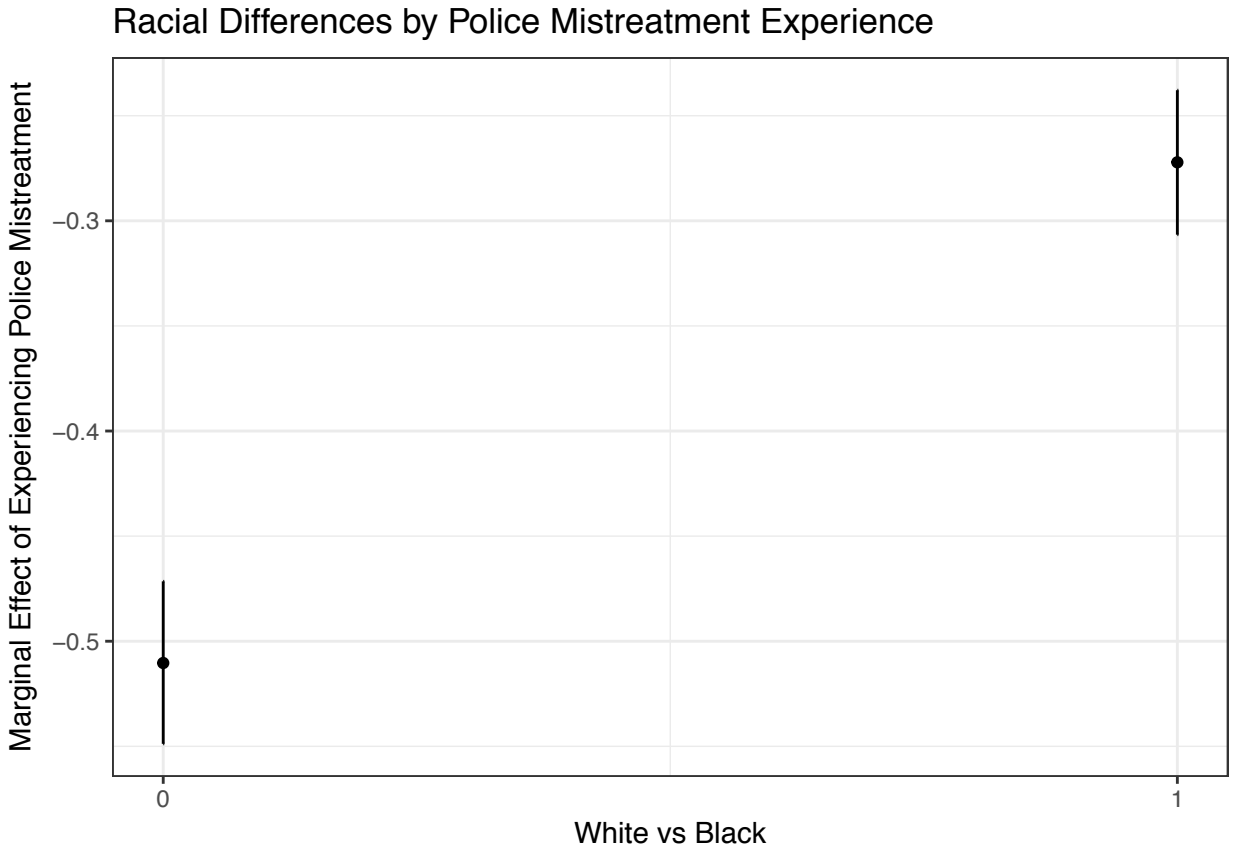
```
## -6.1744 -0.5717  0.0530  0.5370  5.9921
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          2.52071    0.01210 208.406   <2e-16 ***
## pol.mistreat        -0.48348    0.01944 -24.872   <2e-16 ***
## black               -0.59131    0.02641 -22.391   <2e-16 ***
## pol.mistreat:black   0.25704    0.02578   9.969   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.016 on 11154 degrees of freedom
##   (8 observations deleted due to missingness)
## Multiple R-squared:  0.1372, Adjusted R-squared:  0.137
## F-statistic: 591.4 on 3 and 11154 DF,  p-value: < 2.2e-16
```

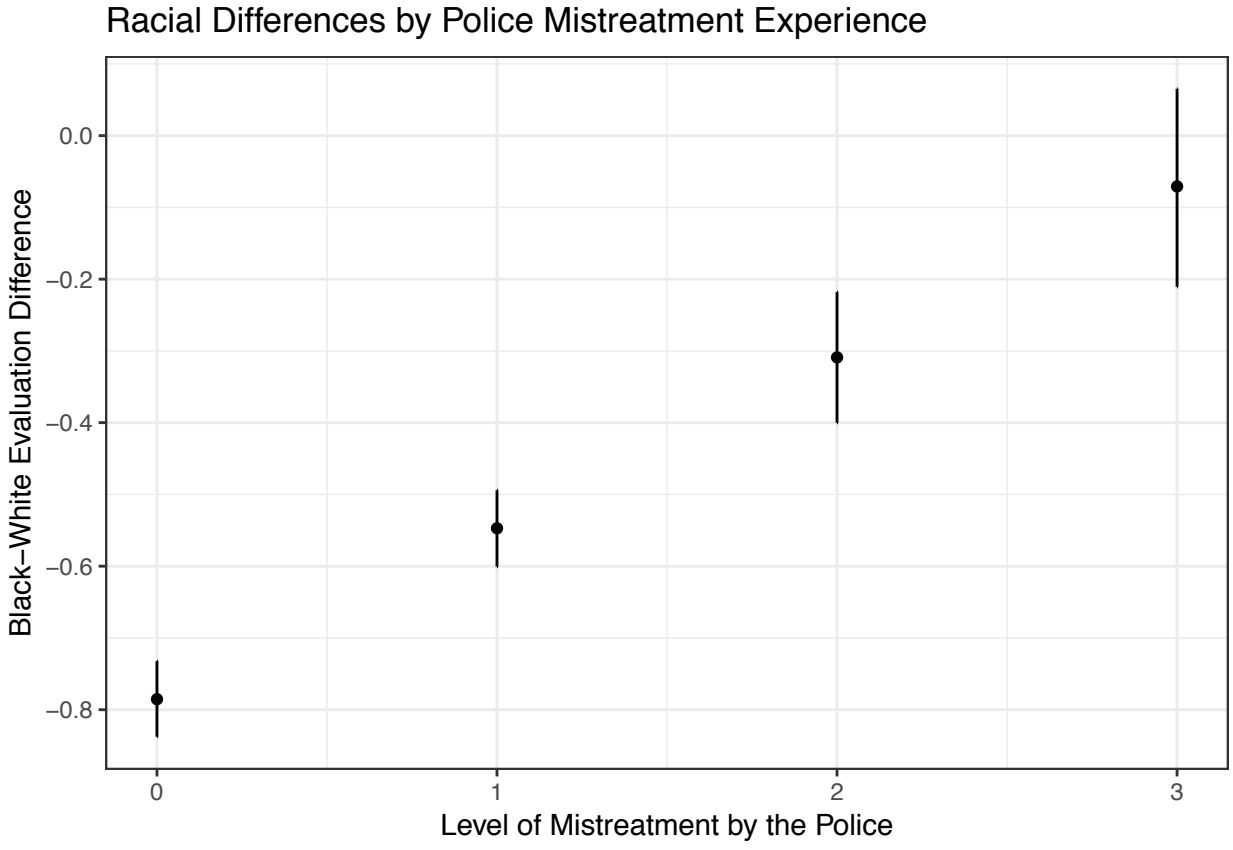




Protecting people like you from violent crime

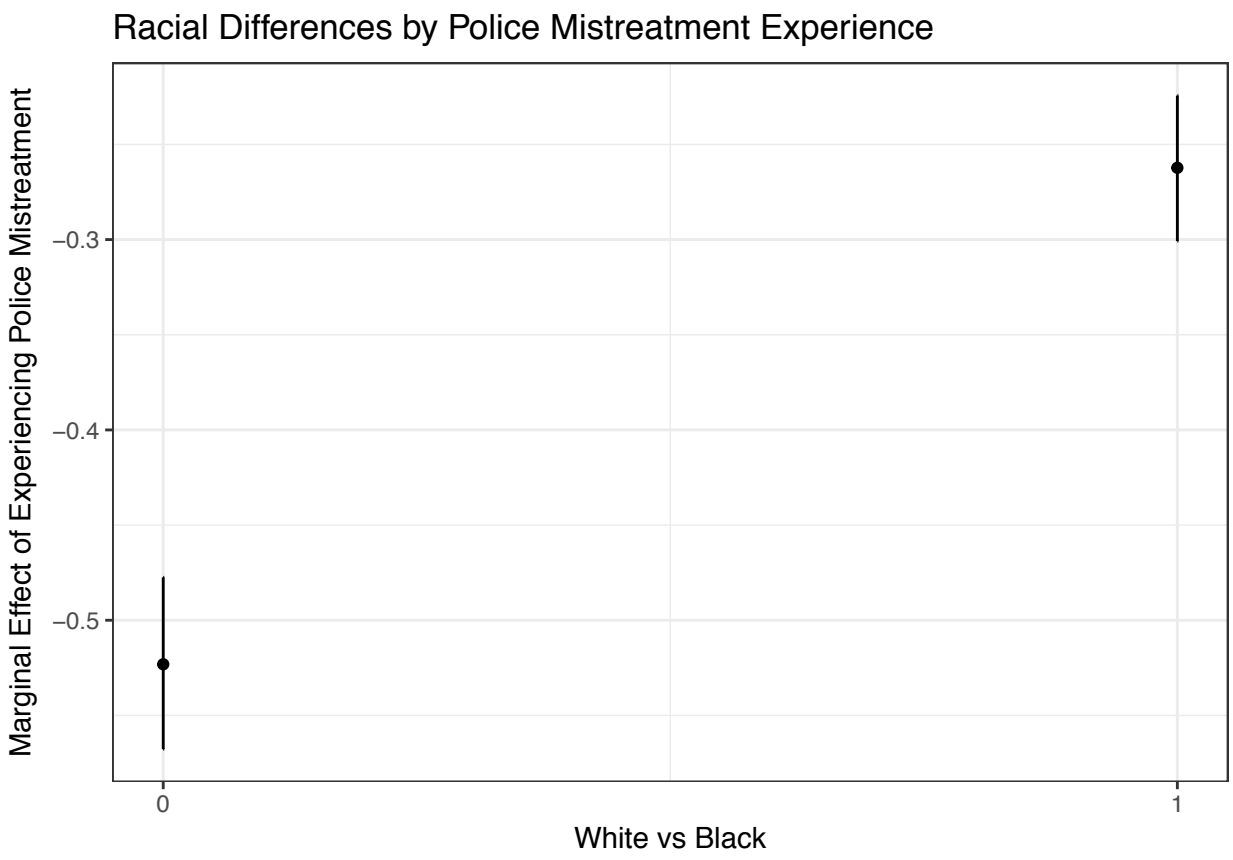
```
##
## Call:
## lm(formula = p.viol.crim ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.4641 -0.6743  0.1834  0.5440  6.6753
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)         2.74069    0.01224 223.942   <2e-16 ***
## pol.mistreat       -0.50998    0.01967 -25.930   <2e-16 ***
## black              -0.78437    0.02672 -29.351   <2e-16 ***
## pol.mistreat:black  0.23774    0.02609   9.113   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.028 on 11152 degrees of freedom
##   (10 observations deleted due to missingness)
## Multiple R-squared:  0.1905, Adjusted R-squared:  0.1903
## F-statistic: 874.7 on 3 and 11152 DF,  p-value: < 2.2e-16
```

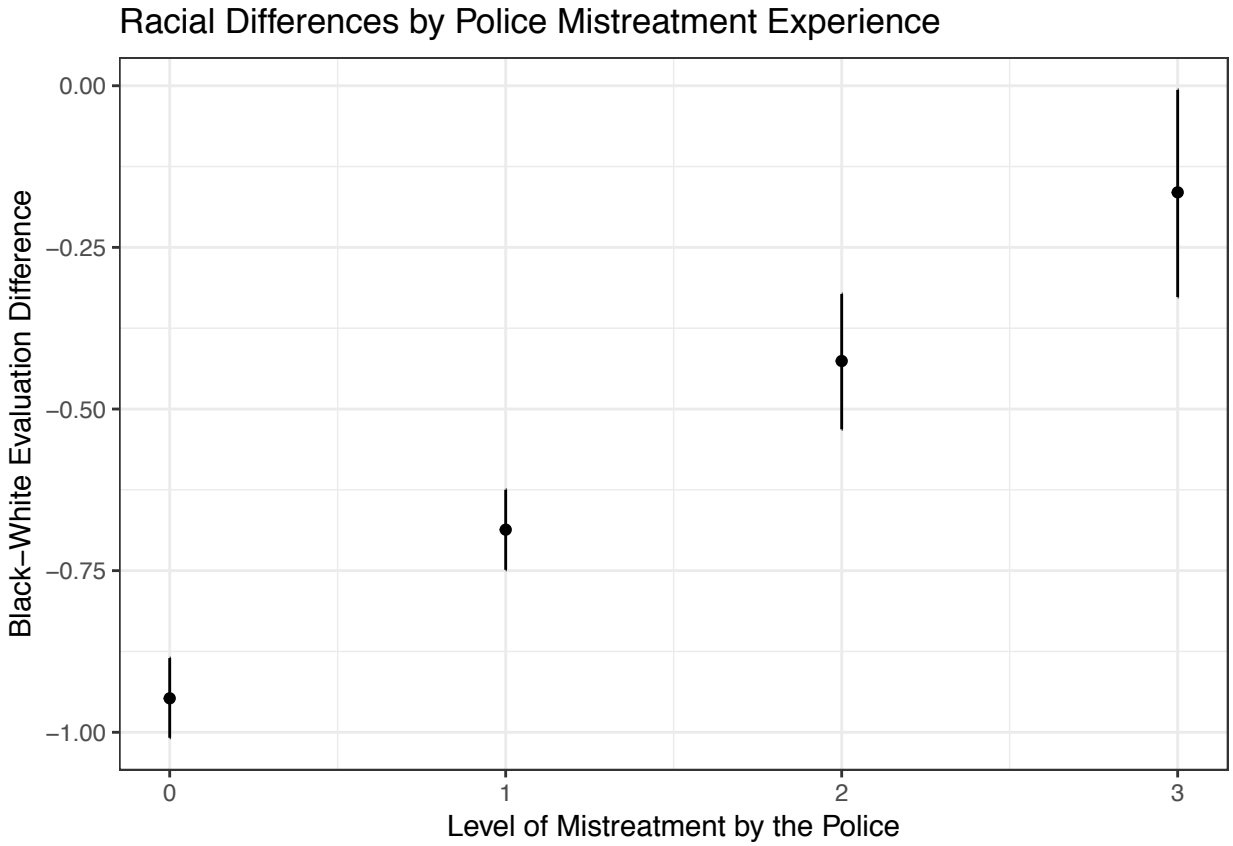

Racial Differences by Police Mistreatment Experience
Marginal Effect of Experiencing Police Mistreatment
−0.3
−0.4
−0.5
0
1
White vs Black


Racial Differences by Police Mistreatment Experience
Black−White Evaluation Difference
0.0
−0.2
−0.4
−0.6
−0.8
0
1
2
3
Level of Mistreatment by the Police

Treating racial and ethnic groups equally

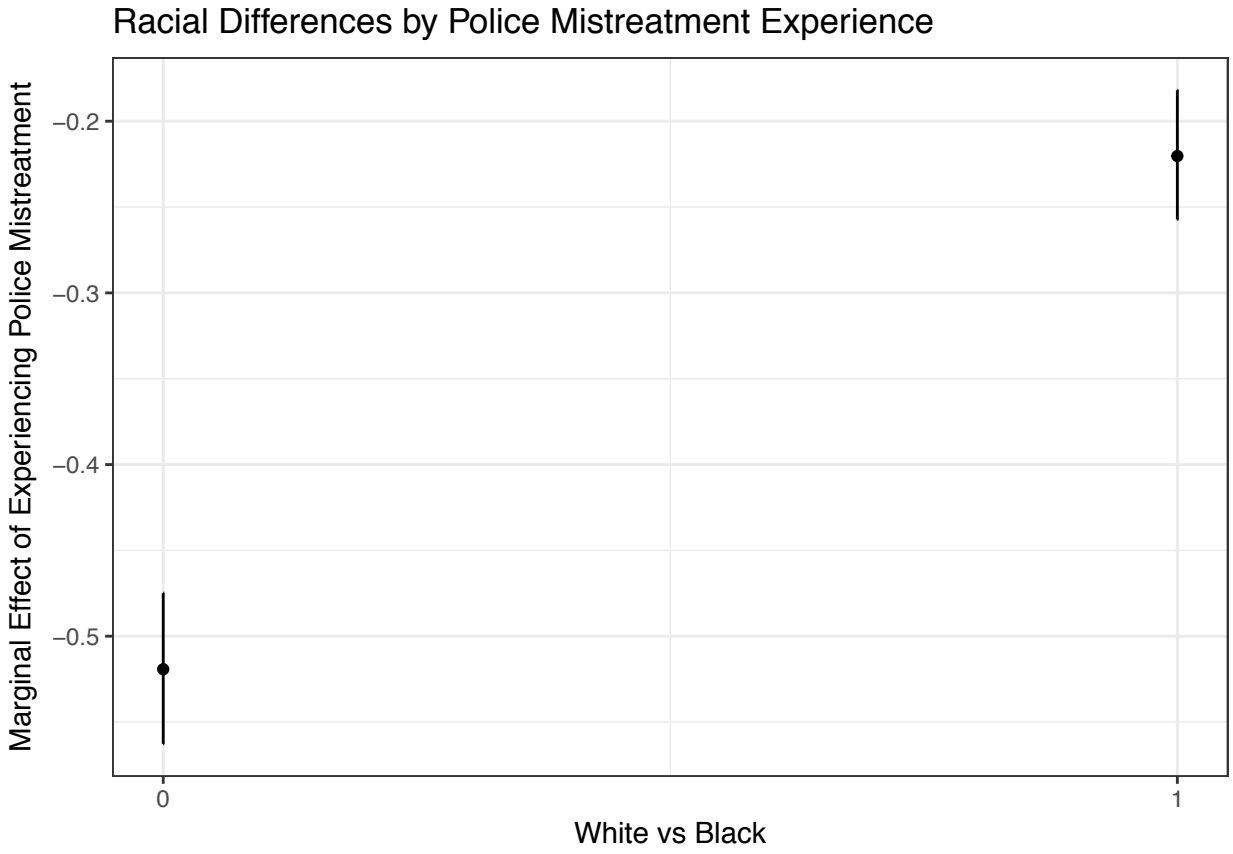
```
##
## Call:
## lm(formula = p.race.fair ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7739 -0.8841 -0.2526  0.6948  6.9844
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          2.35718    0.01416 166.417   <2e-16 ***
## pol.mistreat        -0.52268    0.02276 -22.970   <2e-16 ***
## black               -0.94631    0.03093 -30.598   <2e-16 ***
## pol.mistreat:black   0.26043    0.03019   8.627   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.19 on 11152 degrees of freedom
##   (10 observations deleted due to missingness)
## Multiple R-squared:  0.1789, Adjusted R-squared:  0.1787
## F-statistic: 809.9 on 3 and 11152 DF,  p-value: < 2.2e-16
```

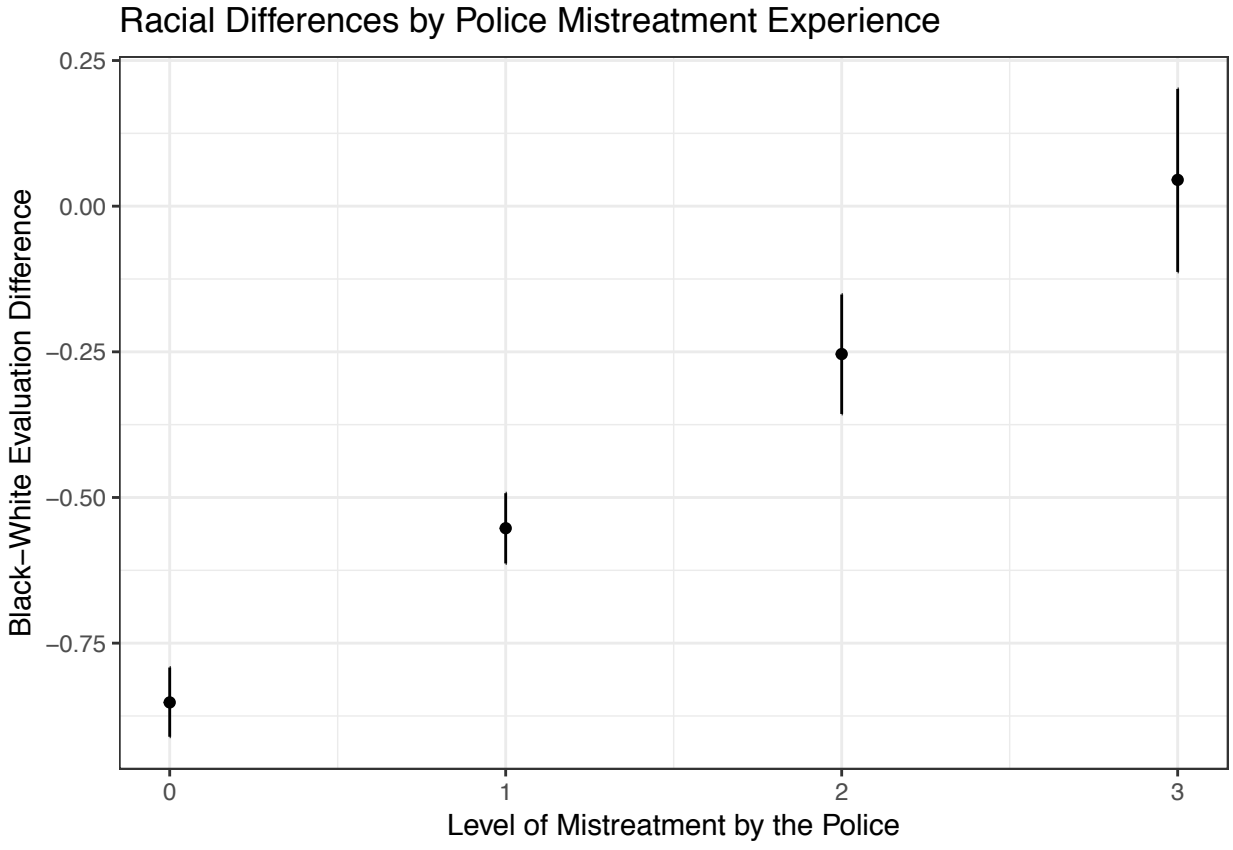




Not using excessive force on suspects

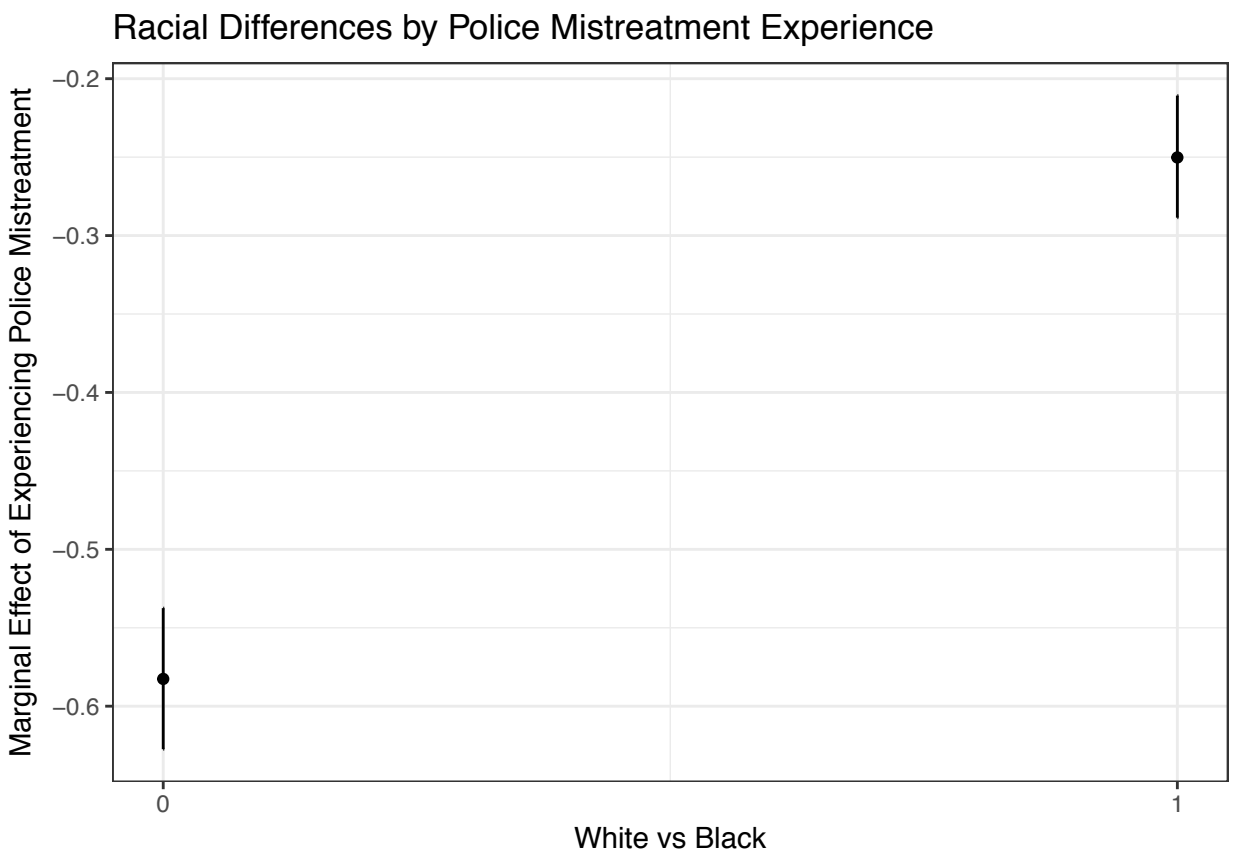
```
##
## Call:
## lm(formula = p.exces.force ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.9396 -0.7881 -0.2500  0.6481  7.2061
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)         2.42485    0.01378  175.99   <2e-16 ***
## pol.mistreat       -0.51897    0.02214  -23.44   <2e-16 ***
## black              -0.85057    0.03009  -28.27   <2e-16 ***
## pol.mistreat:black  0.29826    0.02937   10.15   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.158 on 11150 degrees of freedom
##   (12 observations deleted due to missingness)
## Multiple R-squared:  0.1573, Adjusted R-squared:  0.1571
## F-statistic: 693.7 on 3 and 11150 DF,  p-value: < 2.2e-16
```

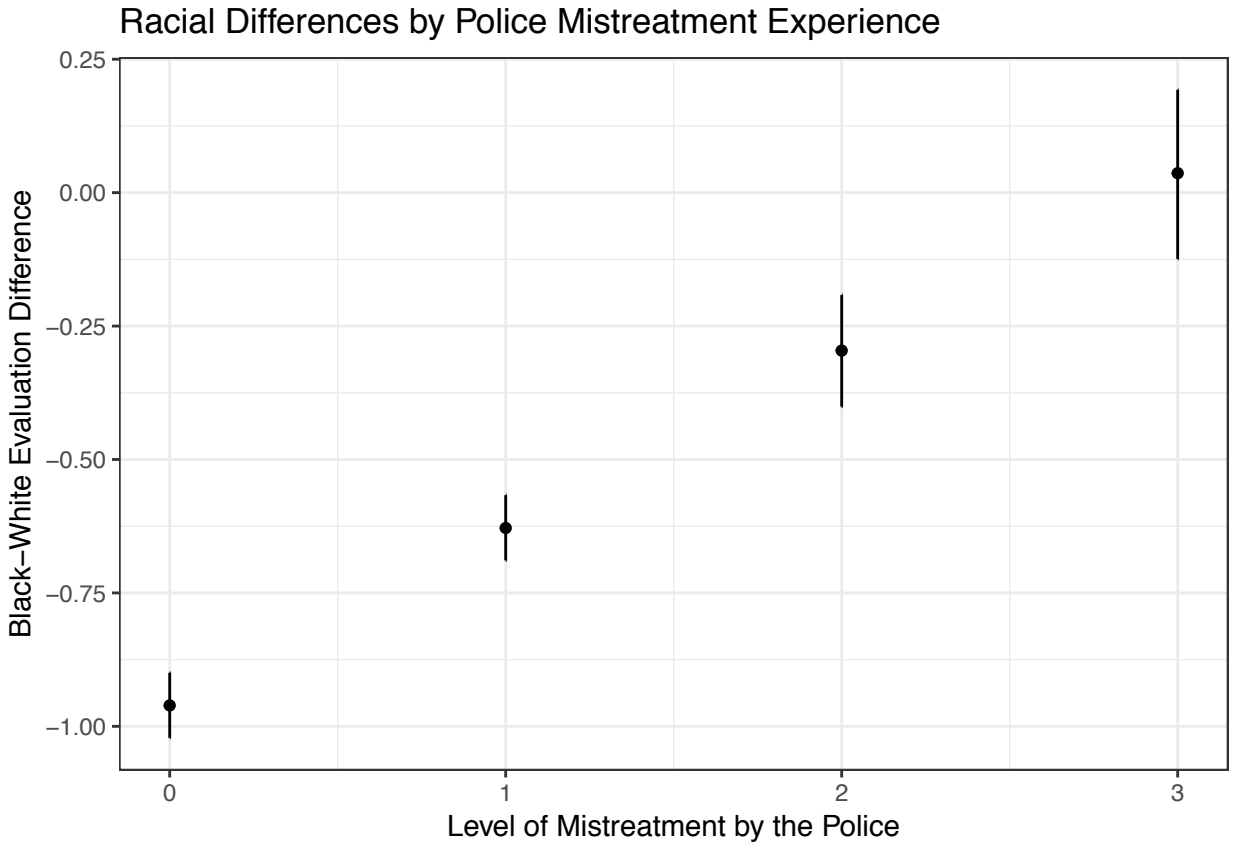

Racial Differences by Police Mistreatment Experience
Marginal Effect of Experiencing Police Mistreatment
−0.2
−0.3
−0.4
−0.5
0
1
White vs Black


Racial Differences by Police Mistreatment Experience
Black−White Evaluation Difference
0.25
0.00
−0.25
−0.50
−0.75
0
1
2
3
Level of Mistreatment by the Police

Holding police officers accountable for misconduct

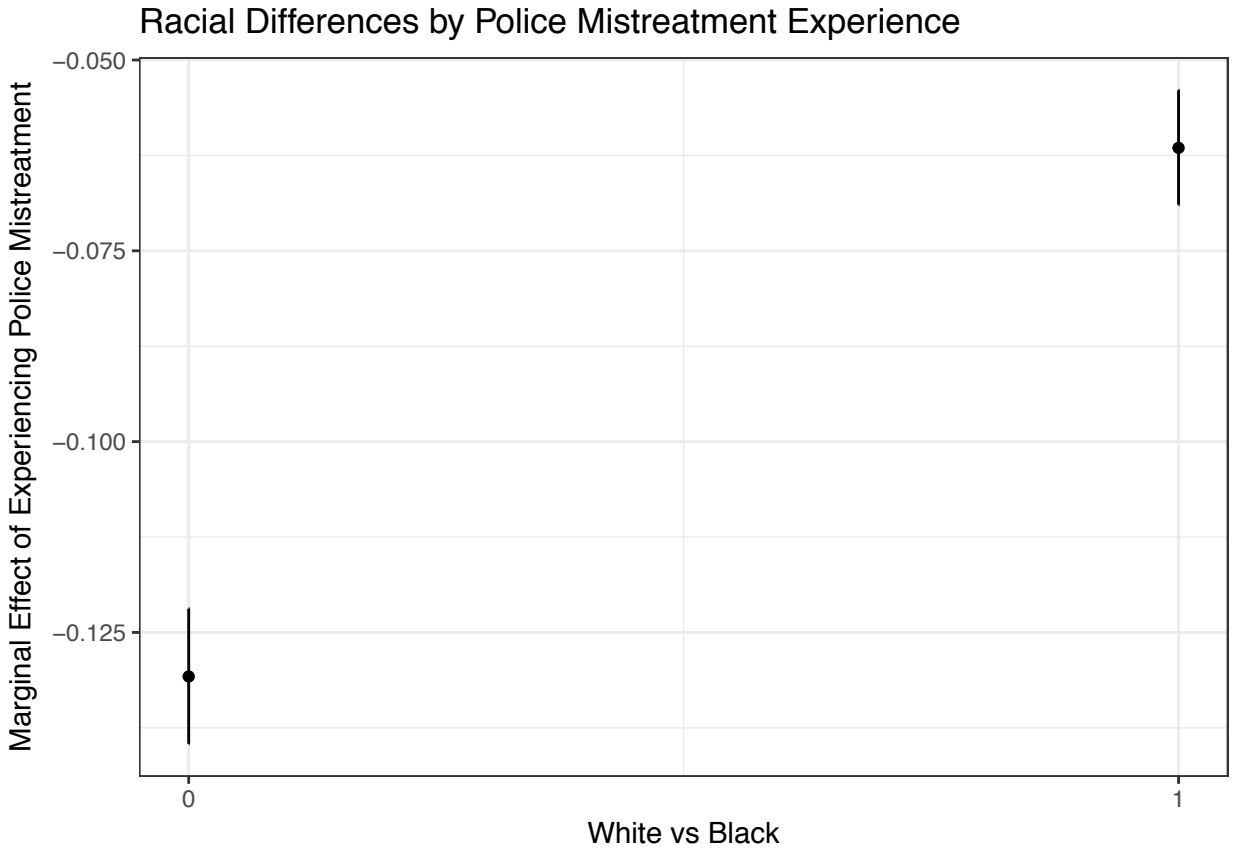
```
##
## Call:
## lm(formula = p.account ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.8363 -0.8614 -0.2706  0.6718  6.9254
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          2.38266    0.01407  169.36   <2e-16 ***
## pol.mistreat        -0.58220    0.02261  -25.75   <2e-16 ***
## black               -0.95956    0.03072  -31.23   <2e-16 ***
## pol.mistreat:black   0.33182    0.02999   11.06   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.182 on 11152 degrees of freedom
##   (10 observations deleted due to missingness)
## Multiple R-squared:  0.1856, Adjusted R-squared:  0.1853
## F-statistic: 846.9 on 3 and 11152 DF,  p-value: < 2.2e-16
```

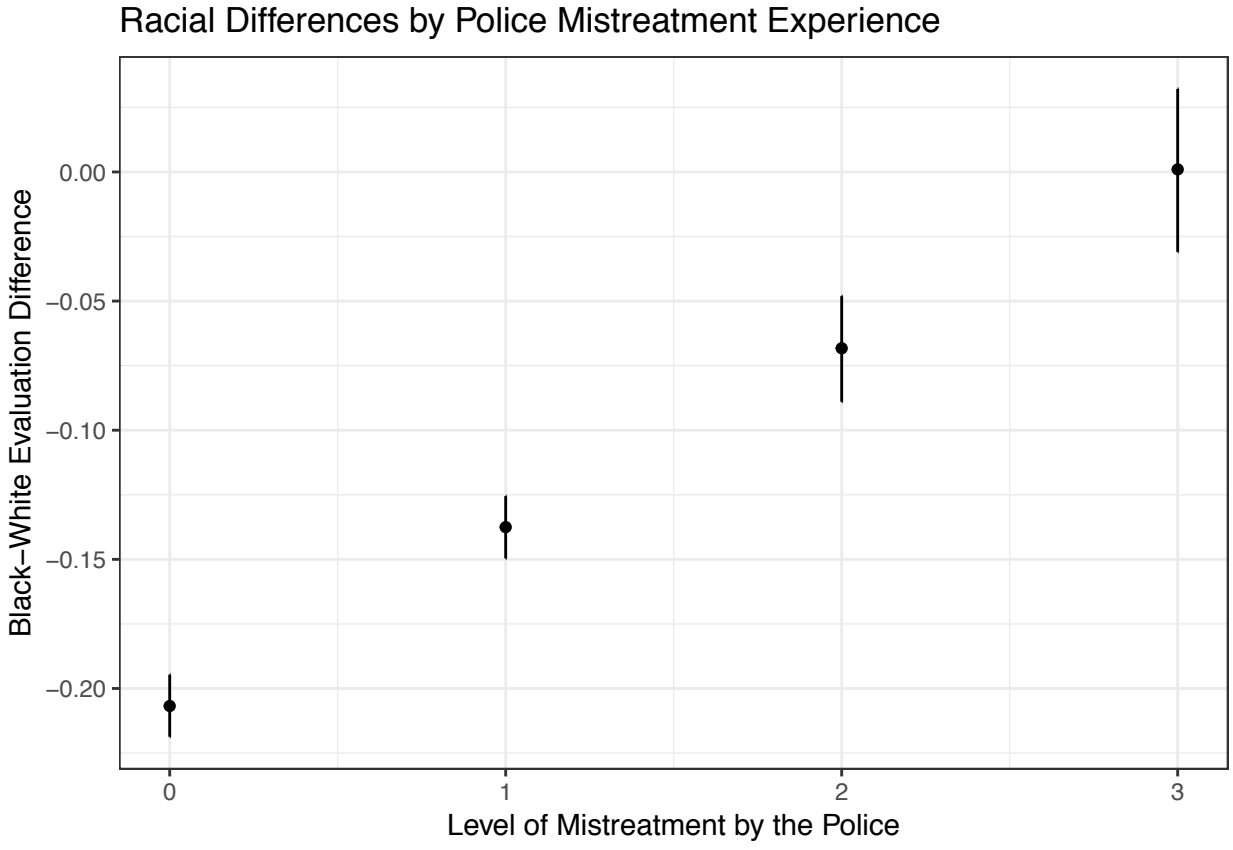




Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.23513 -0.15647 -0.01505  0.12969  1.58443
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.621289   0.002772  224.13   <2e-16 ***
## pol.mistreat       -0.130705   0.004454  -29.34   <2e-16 ***
## black              -0.206551   0.006052  -34.13   <2e-16 ***
## pol.mistreat:black  0.069126   0.005908   11.70   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2329 on 11146 degrees of freedom
##   (16 observations deleted due to missingness)
## Multiple R-squared:  0.2263, Adjusted R-squared:  0.2261
## F-statistic:  1087 on 3 and 11146 DF,  p-value: < 2.2e-16
```


Racial Differences by Police Mistreatment Experience
Marginal Effect of Experiencing Police Mistreatment
−0.050
−0.075
−0.100
−0.125
0
1
White vs Black

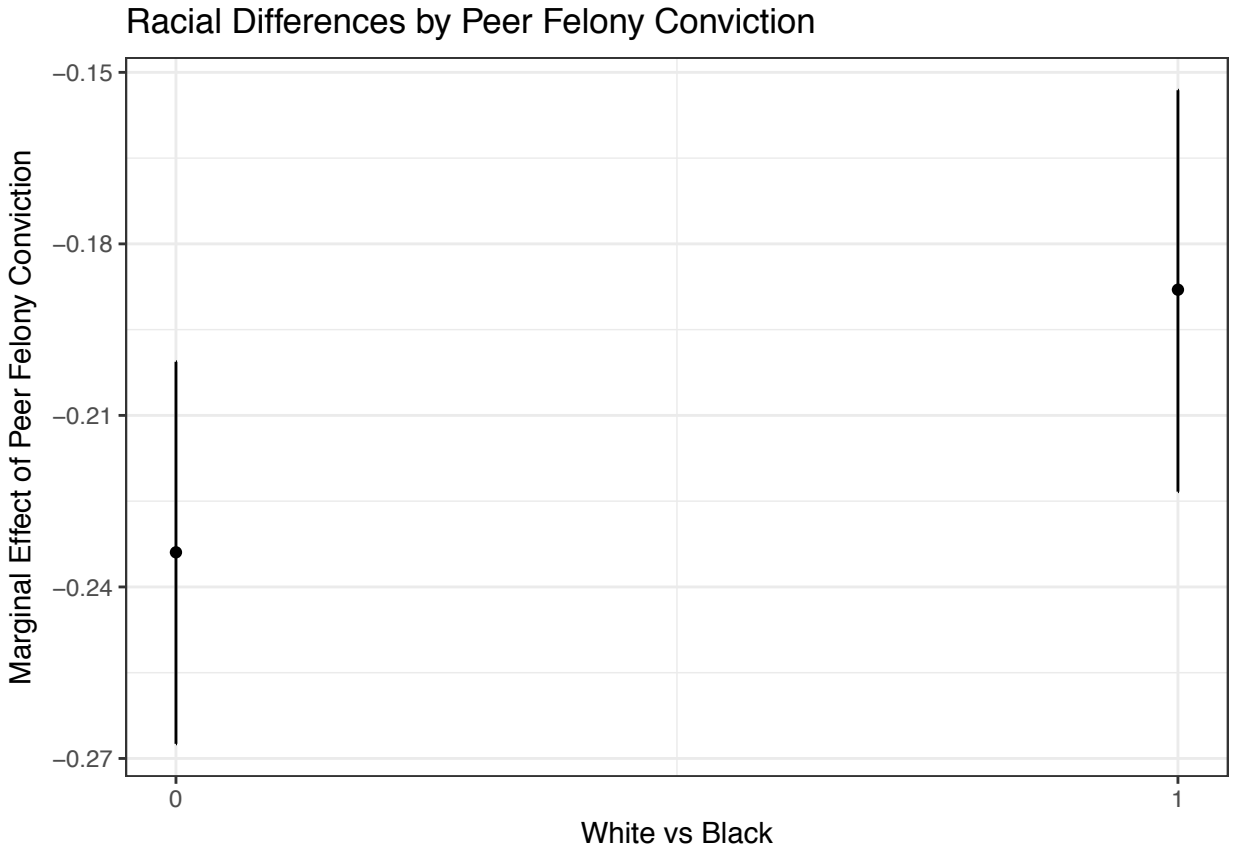

Racial Differences by Police Mistreatment Experience
Black−White Evaluation Difference
0.00
−0.05
−0.10
−0.15
−0.20
0
1
2
3
Level of Mistreatment by the Police

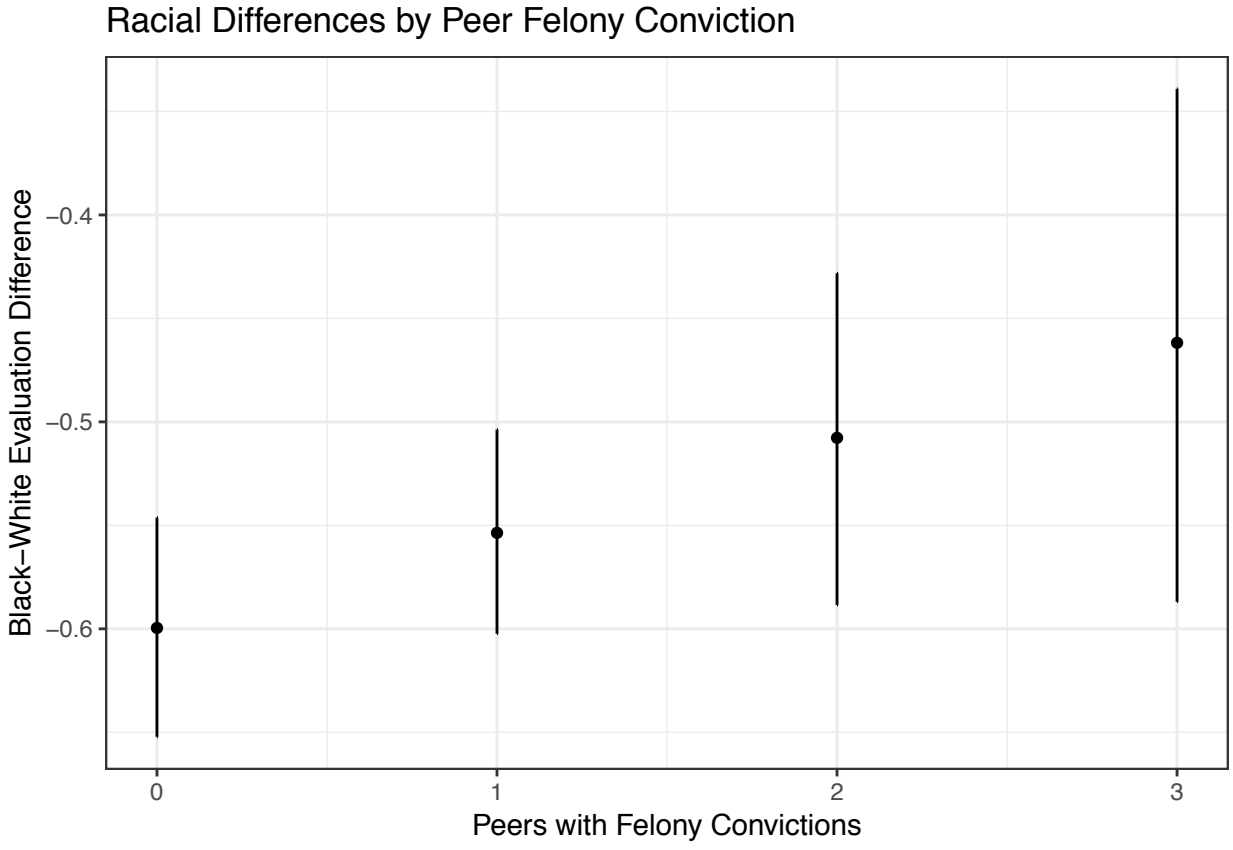
Peers convicted of a Felony

I now turn to conditioning on whether a respondent has friends or family with felony convictions. Across all items, respondents with peers who have experienced a felony are less positive in their evaluations of the police. As with the police mistreatment item, in many cases the black-white evaluation gap closes as the number of peers with convictions increases. The gaps remain, but they grow smaller by varying degrees. Finally, relative to being mistreated by the police, the effect of social connections with felony convictions is smaller.

Solving Crime

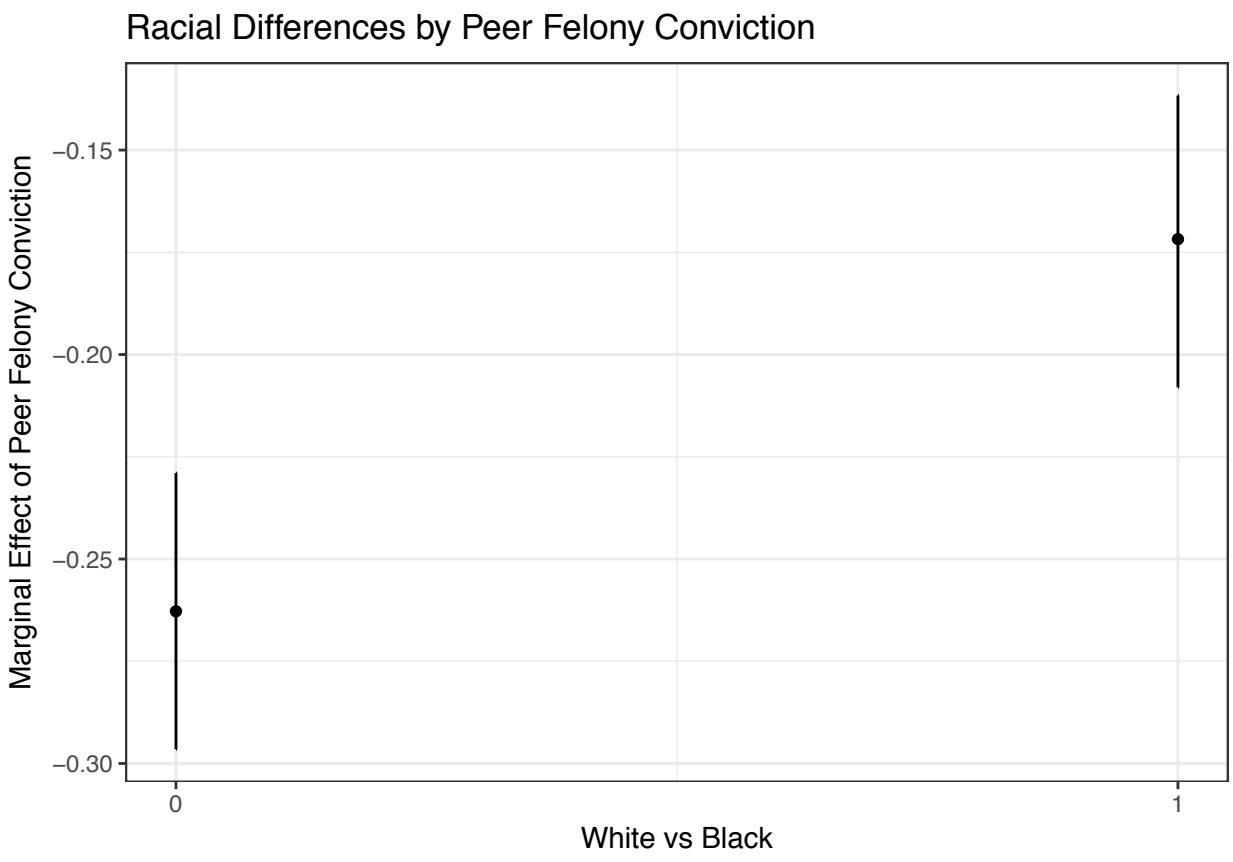
```
##
## Call:
## lm(formula = p.crim.solve ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.1040 -0.5601  0.0758  0.5627  5.6223
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.49197    0.01284 194.060   <2e-16 ***
## peer.felony       -0.23327    0.01655 -14.095   <2e-16 ***
## black             -0.59912    0.02723 -22.004   <2e-16 ***
## peer.felony:black  0.04514    0.02432   1.856   0.0634 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.038 on 11155 degrees of freedom
##   (7 observations deleted due to missingness)
## Multiple R-squared:  0.1005, Adjusted R-squared:  0.1003
## F-statistic: 415.6 on 3 and 11155 DF,  p-value: < 2.2e-16
```

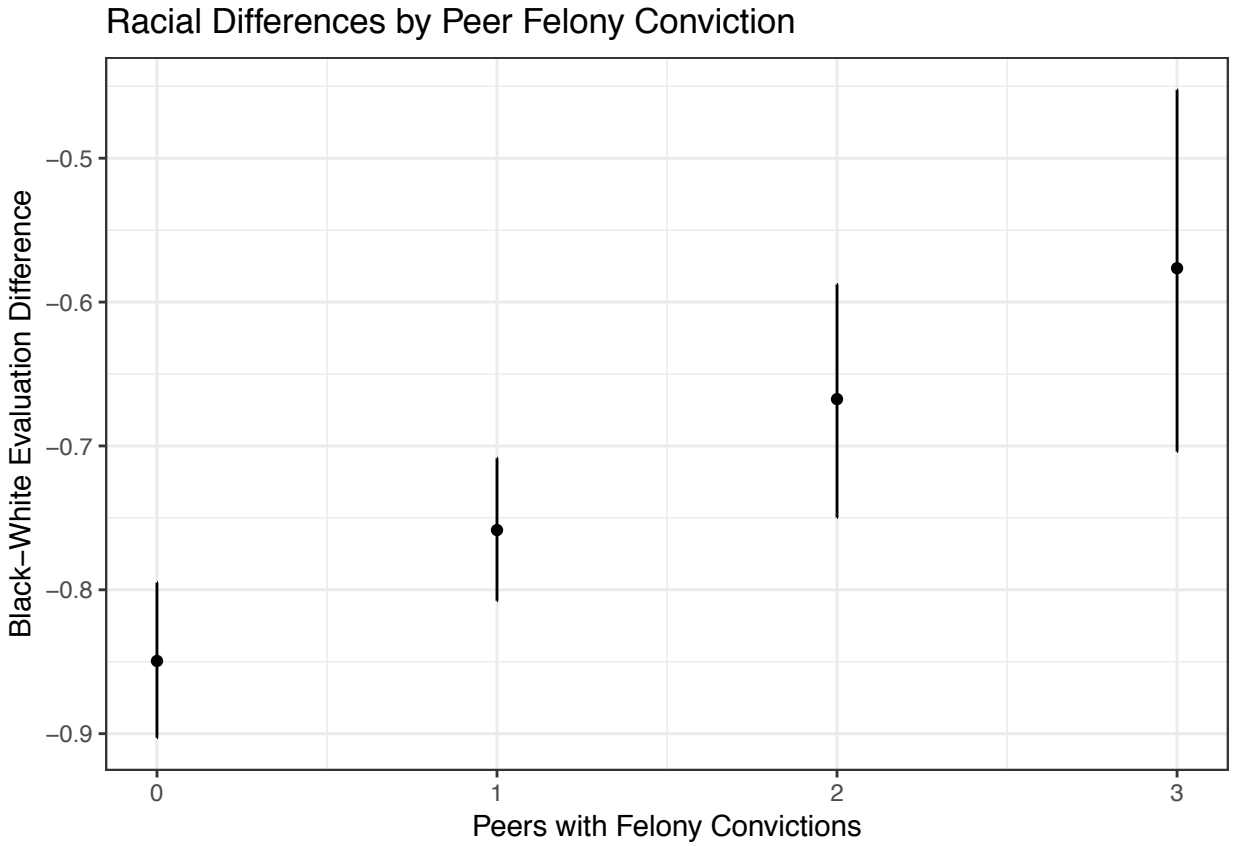

Racial Differences by Peer Felony Conviction
Marginal Effect of Peer Felony Conviction
−0.15
−0.18
−0.21
−0.24
−0.27
0
1
White vs Black


Racial Differences by Peer Felony Conviction
Black−White Evaluation Difference
−0.4
−0.5
−0.6
0
1
2
3
Peers with Felony Convictions

Protecting people like you from violent crime

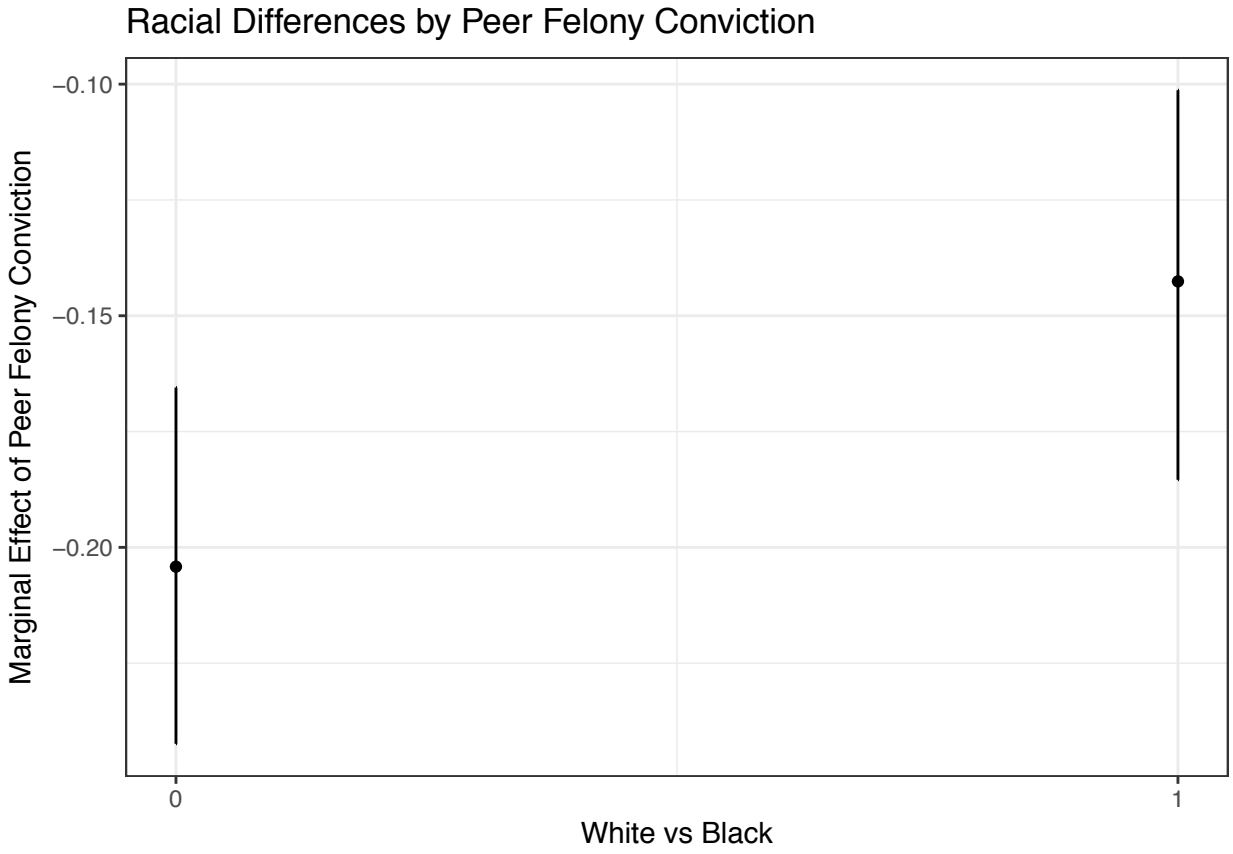
```
##
## Call:
## lm(formula = p.viol.crim ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.0102 -0.6415  0.2009  0.4893  6.1834
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)         2.71594    0.01305 208.139  < 2e-16 ***
## peer.felony        -0.26227    0.01682 -15.596  < 2e-16 ***
## black              -0.84897    0.02767 -30.684  < 2e-16 ***
## peer.felony:black   0.09007    0.02471   3.644 0.000269 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.054 on 11153 degrees of freedom
##   (9 observations deleted due to missingness)
## Multiple R-squared:  0.1488, Adjusted R-squared:  0.1486
## F-statistic: 650.1 on 3 and 11153 DF,  p-value: < 2.2e-16
```

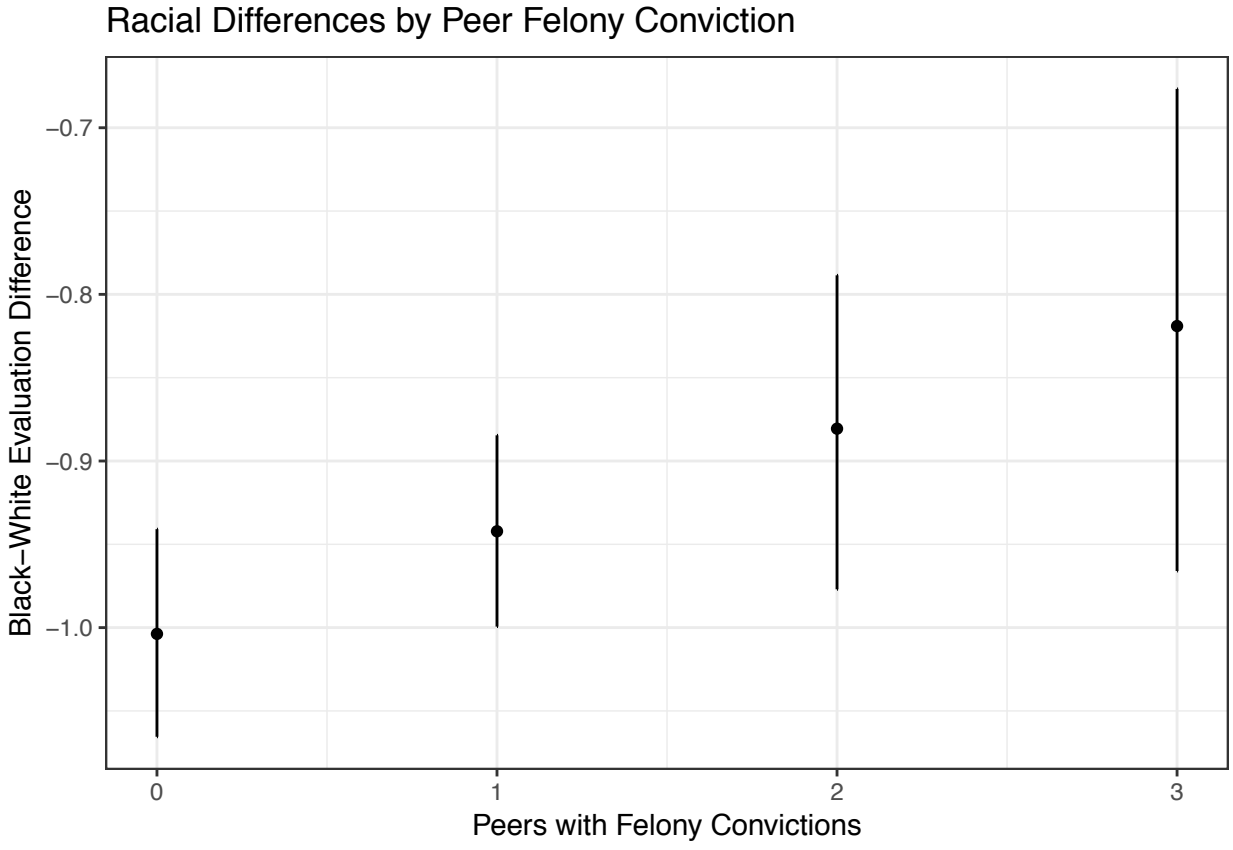




Treating racial and ethnic groups equally

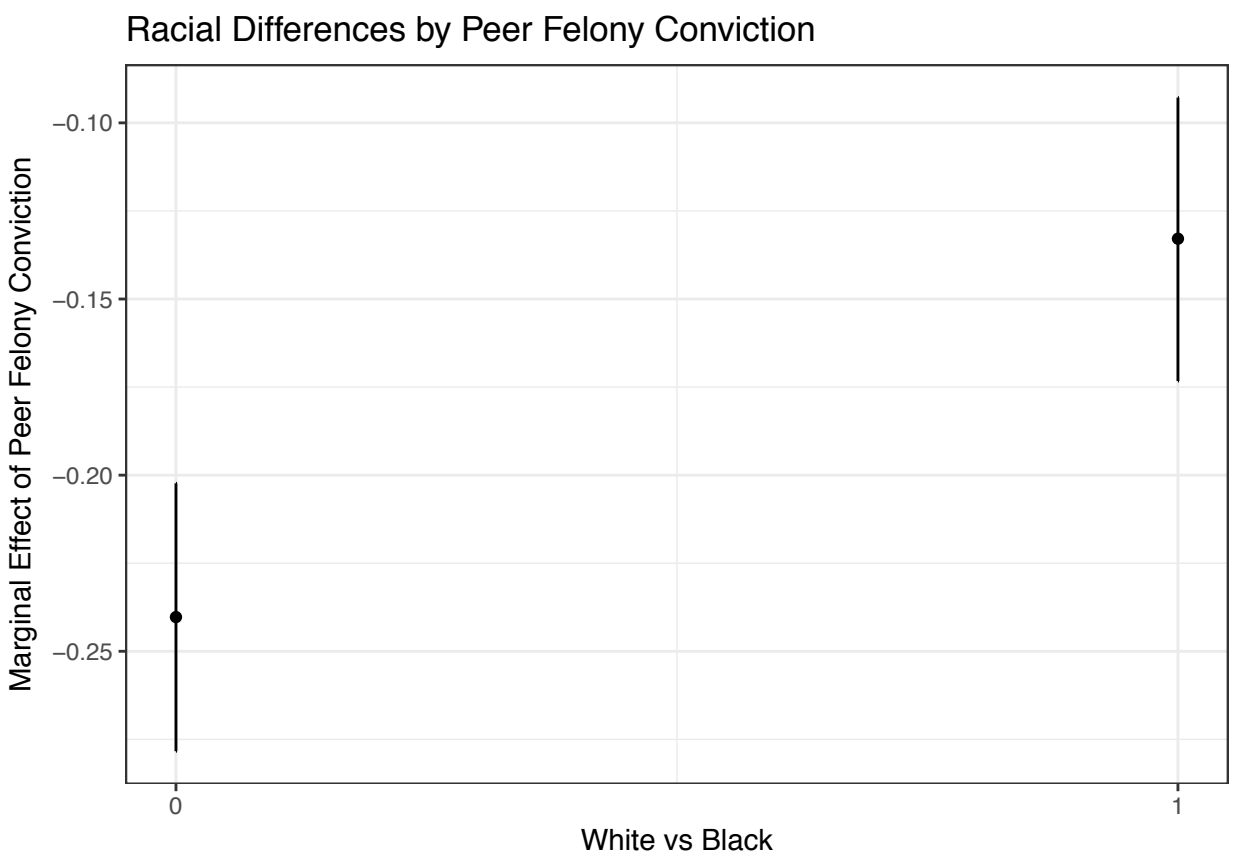
```
##
## Call:
## lm(formula = p.race.fair ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.6562 -0.9234 -0.2186  0.7366  6.9498
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.30912    0.01508 153.119   <2e-16 ***
## peer.felony       -0.20361    0.01942 -10.484   <2e-16 ***
## black             -1.00319    0.03197 -31.377   <2e-16 ***
## peer.felony:black  0.06045    0.02855   2.117   0.0343 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.218 on 11153 degrees of freedom
##   (9 observations deleted due to missingness)
## Multiple R-squared:  0.1392, Adjusted R-squared:  0.139
## F-statistic: 601.2 on 3 and 11153 DF,  p-value: < 2.2e-16
```

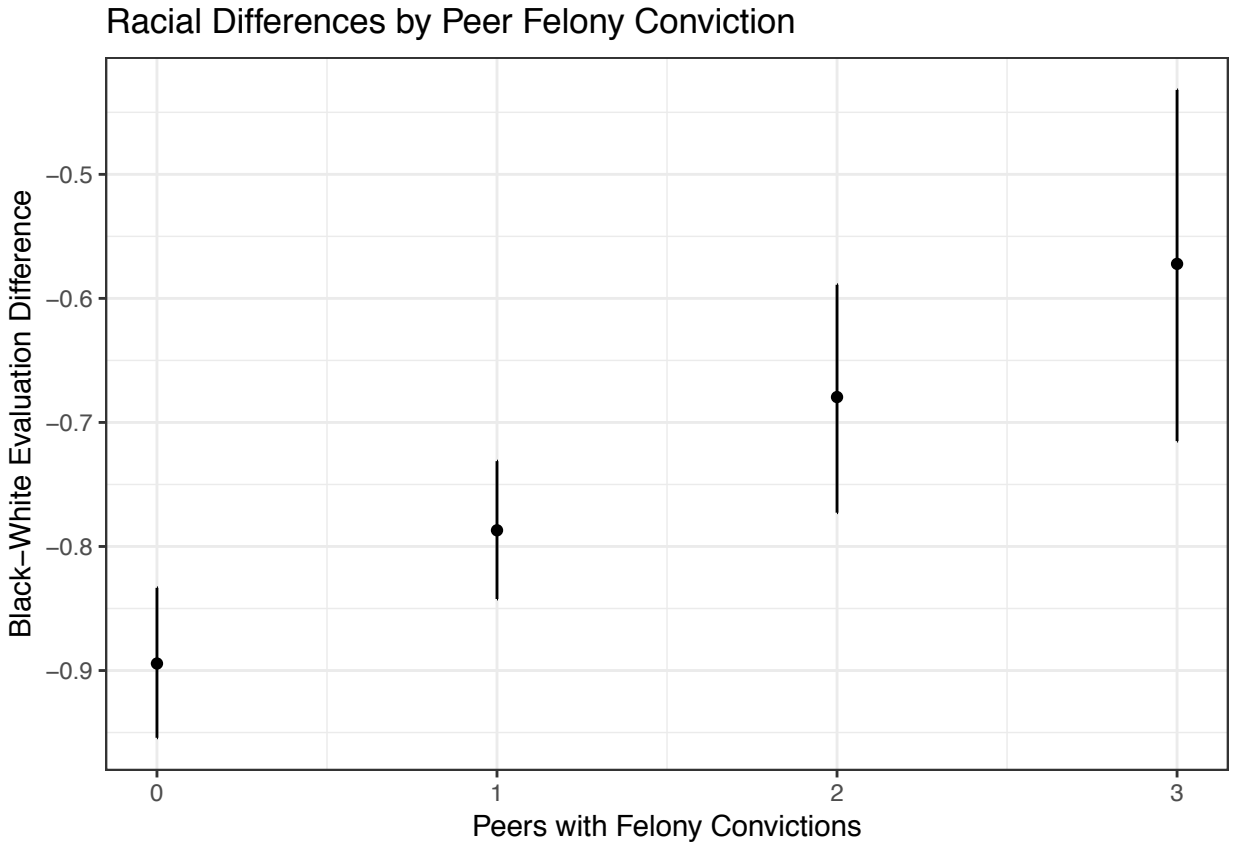

Racial Differences by Peer Felony Conviction
−0.10
−0.15
−0.20
Marginal Effect of Peer Felony Conviction
0
1
White vs Black


Racial Differences by Peer Felony Conviction
−0.7
−0.8
−0.9
−1.0
Black−White Evaluation Difference
0
1
2
3
Peers with Felony Convictions

Not using excessive force on suspects

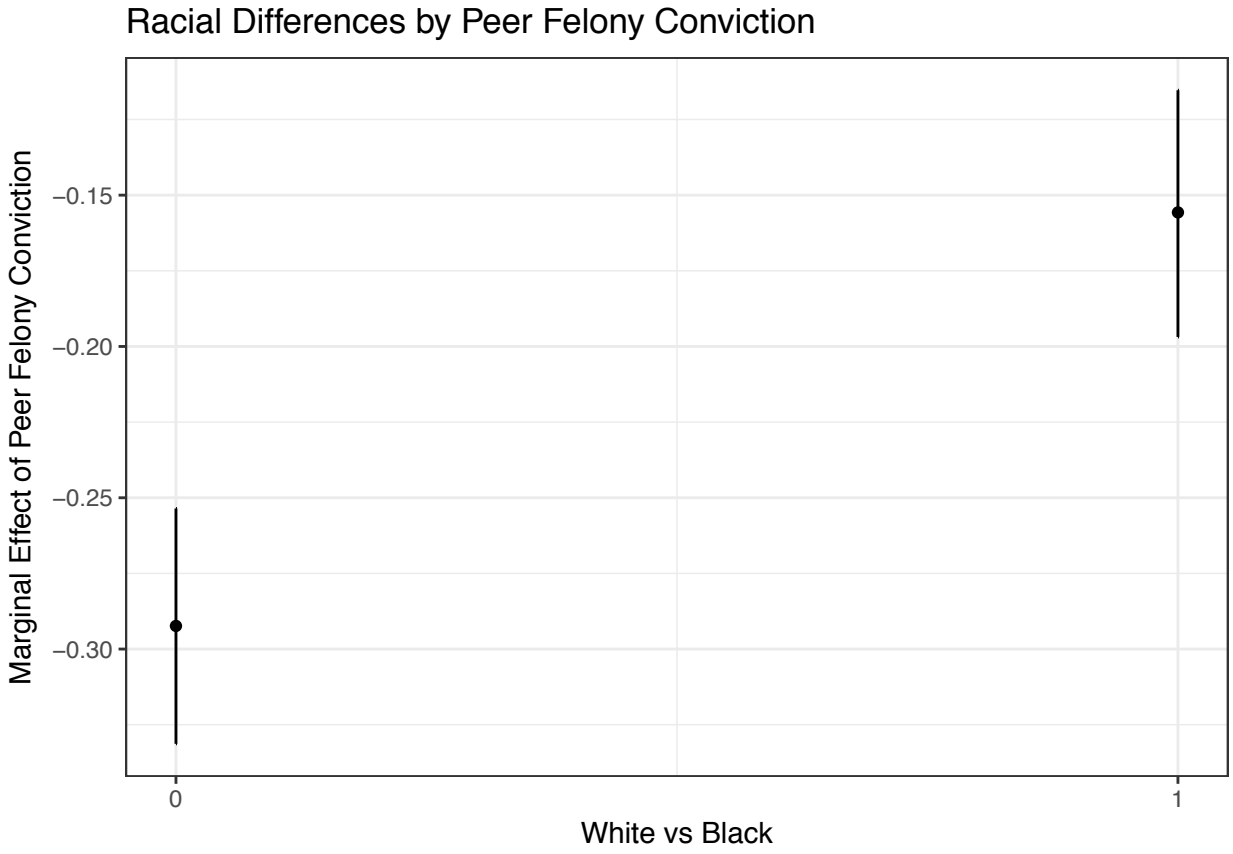
```
##
## Call:
## lm(formula = p.exces.force ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.8550 -0.8960 -0.1628  0.6672  6.7746
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)         2.39029    0.01462 163.455  < 2e-16 ***
## peer.felony        -0.23960    0.01885 -12.714  < 2e-16 ***
## black              -0.89382    0.03101 -28.826  < 2e-16 ***
## peer.felony:black   0.10645    0.02770   3.843 0.000122 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.182 on 11151 degrees of freedom
##   (11 observations deleted due to missingness)
## Multiple R-squared:  0.122,  Adjusted R-squared:  0.1217
## F-statistic: 516.4 on 3 and 11151 DF,  p-value: < 2.2e-16
```

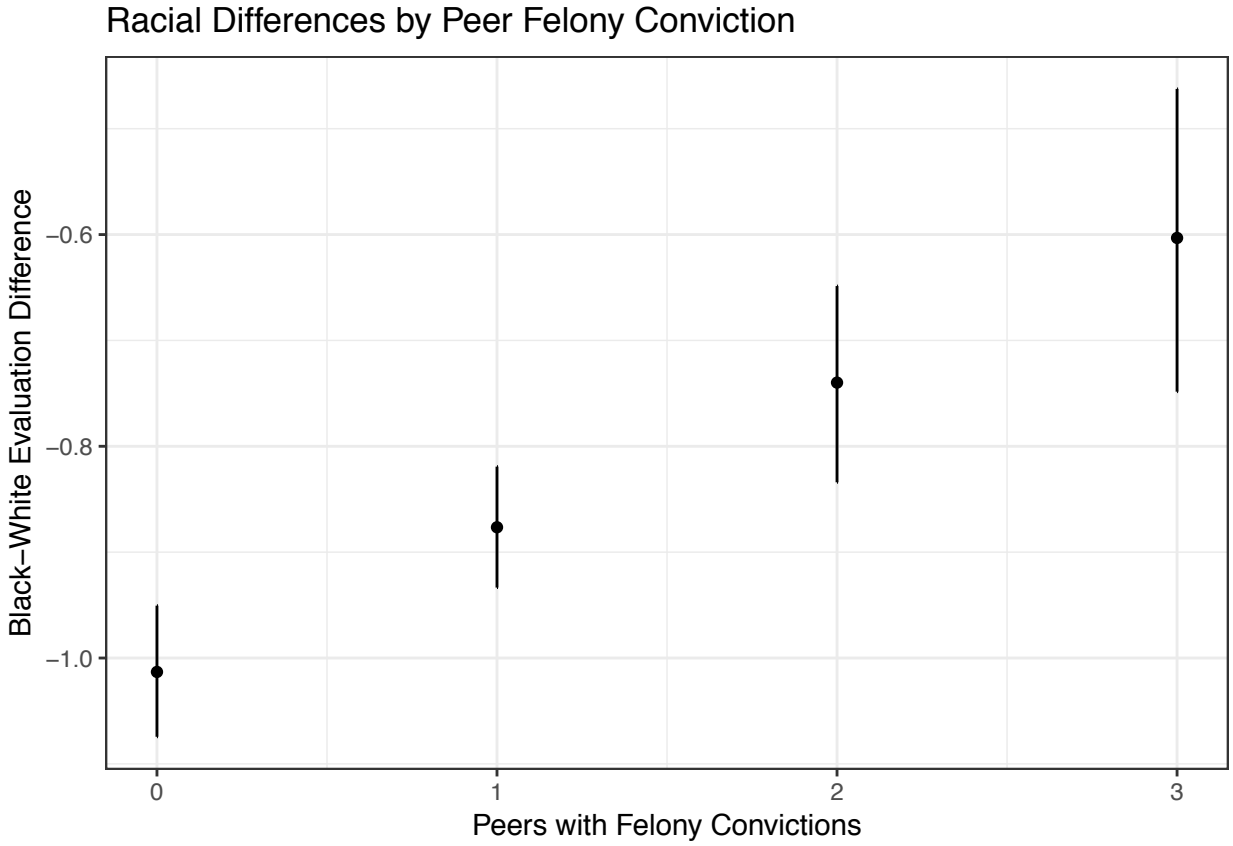




Holding police officers accountable for misconduct

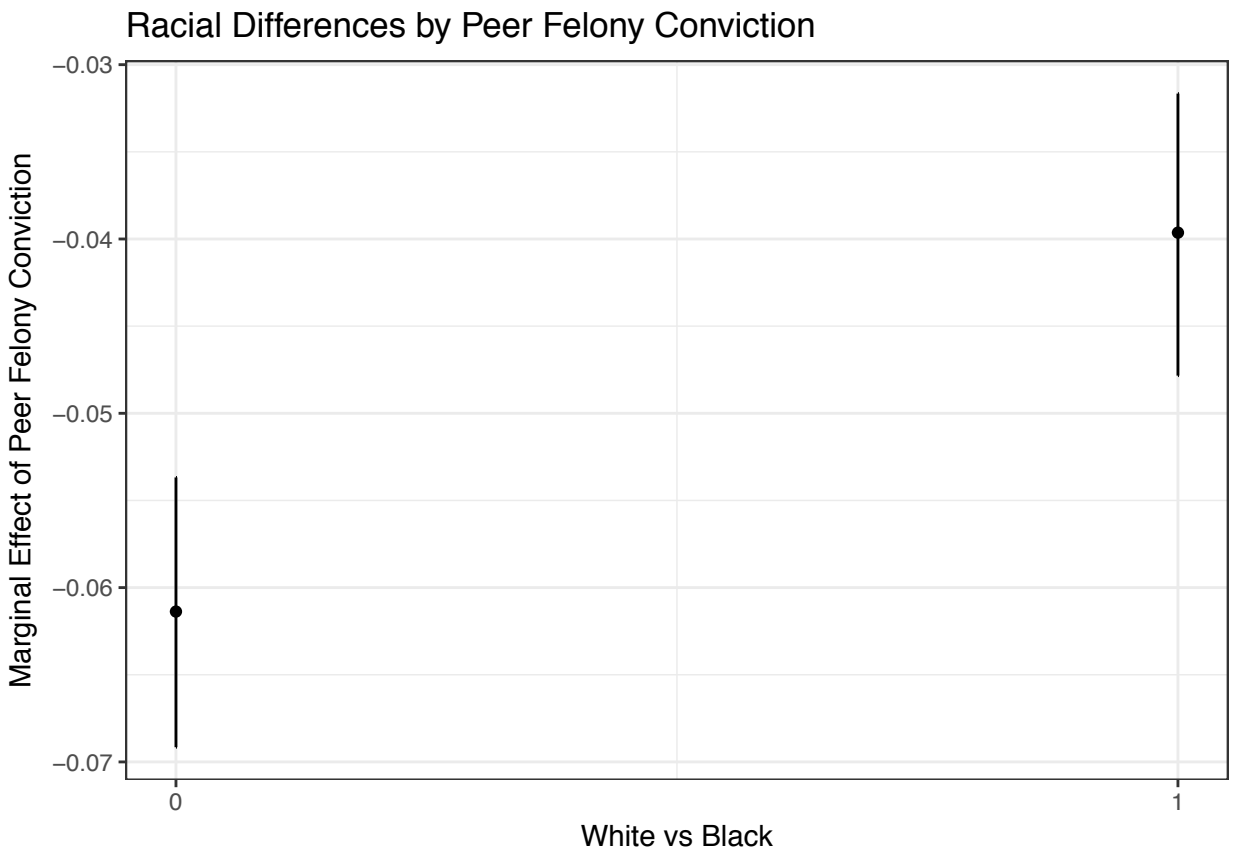
```
##
## Call:
## lm(formula = p.account ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7607 -0.9469 -0.2398  0.7082  6.9000
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.35178    0.01497 157.104  < 2e-16 ***
## peer.felony       -0.29171    0.01929 -15.120  < 2e-16 ***
## black             -1.01260    0.03175 -31.898  < 2e-16 ***
## peer.felony:black  0.13562    0.02835   4.783 1.75e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.21 on 11153 degrees of freedom
##   (9 observations deleted due to missingness)
## Multiple R-squared:  0.1471, Adjusted R-squared:  0.1469
## F-statistic: 641.3 on 3 and 11153 DF,  p-value: < 2.2e-16
```

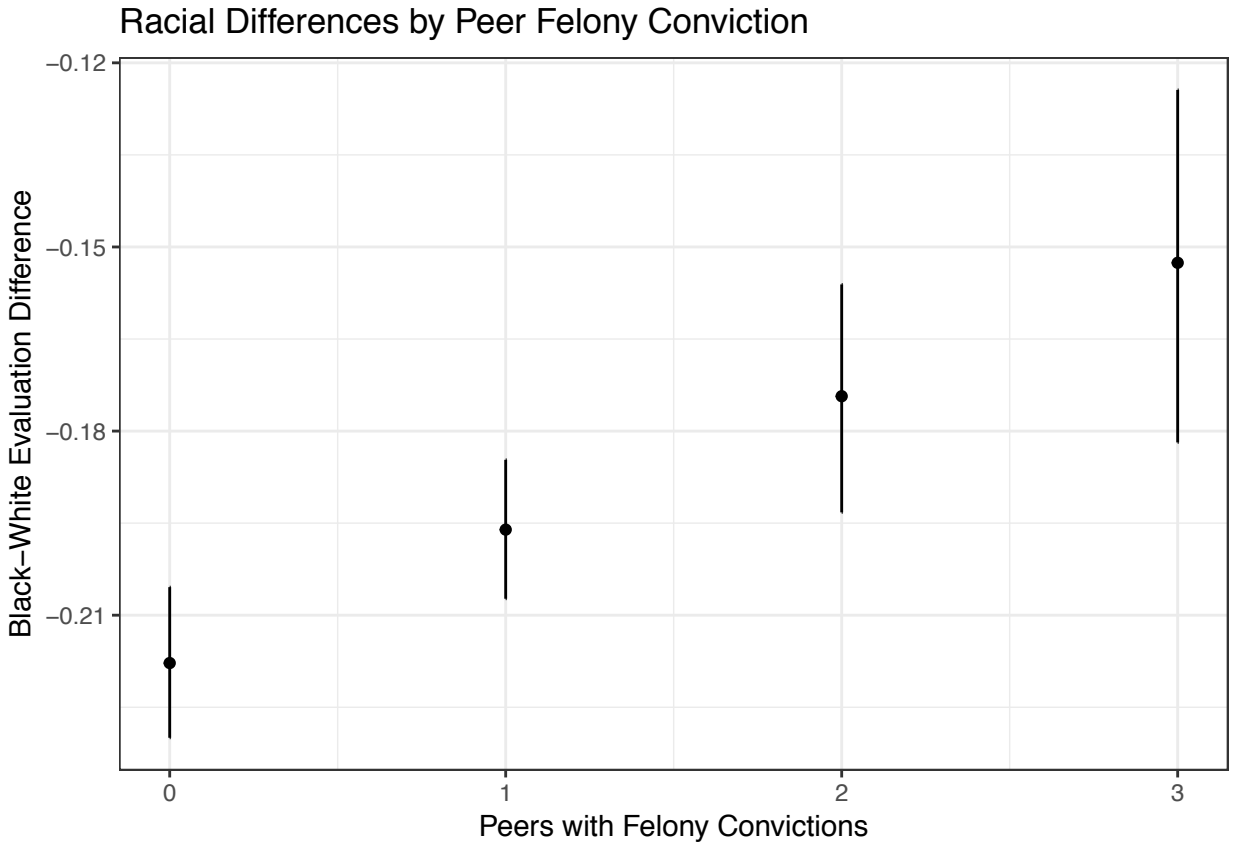

Racial Differences by Peer Felony Conviction
Marginal Effect of Peer Felony Conviction
−0.15
−0.20
−0.25
−0.30
0
1
White vs Black


Racial Differences by Peer Felony Conviction
Black−White Evaluation Difference
−0.6
−0.8
−1.0
0
1
2
3
Peers with Felony Convictions

Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.22872 -0.16369 -0.01091  0.13872  1.57875
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.612879   0.002977 205.881  < 2e-16 ***
## peer.felony        -0.061256   0.003837 -15.963  < 2e-16 ***
## black              -0.217679   0.006312 -34.488  < 2e-16 ***
## peer.felony:black   0.021532   0.005639   3.818 0.000135 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2405 on 11147 degrees of freedom
##   (15 observations deleted due to missingness)
## Multiple R-squared:  0.1747, Adjusted R-squared:  0.1745
## F-statistic: 786.8 on 3 and 11147 DF,  p-value: < 2.2e-16
```





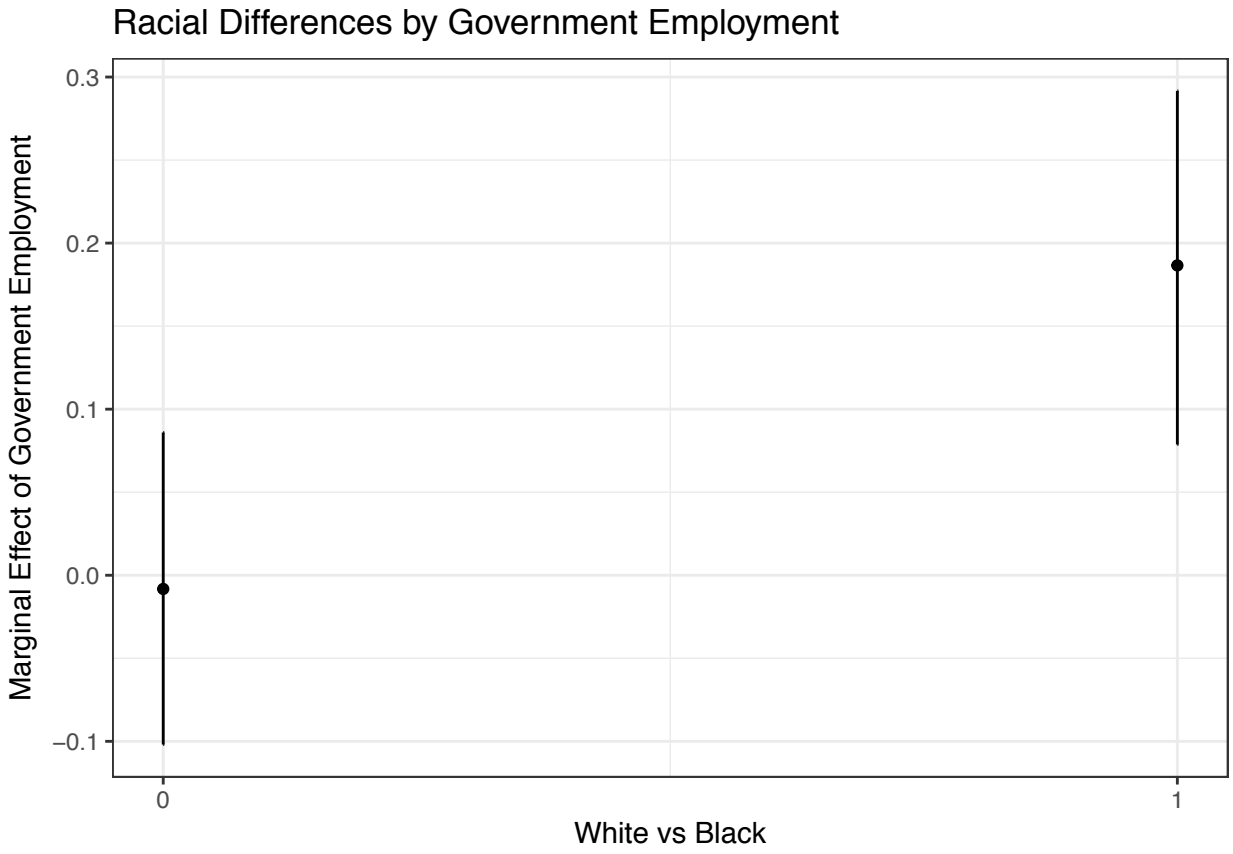
Employment

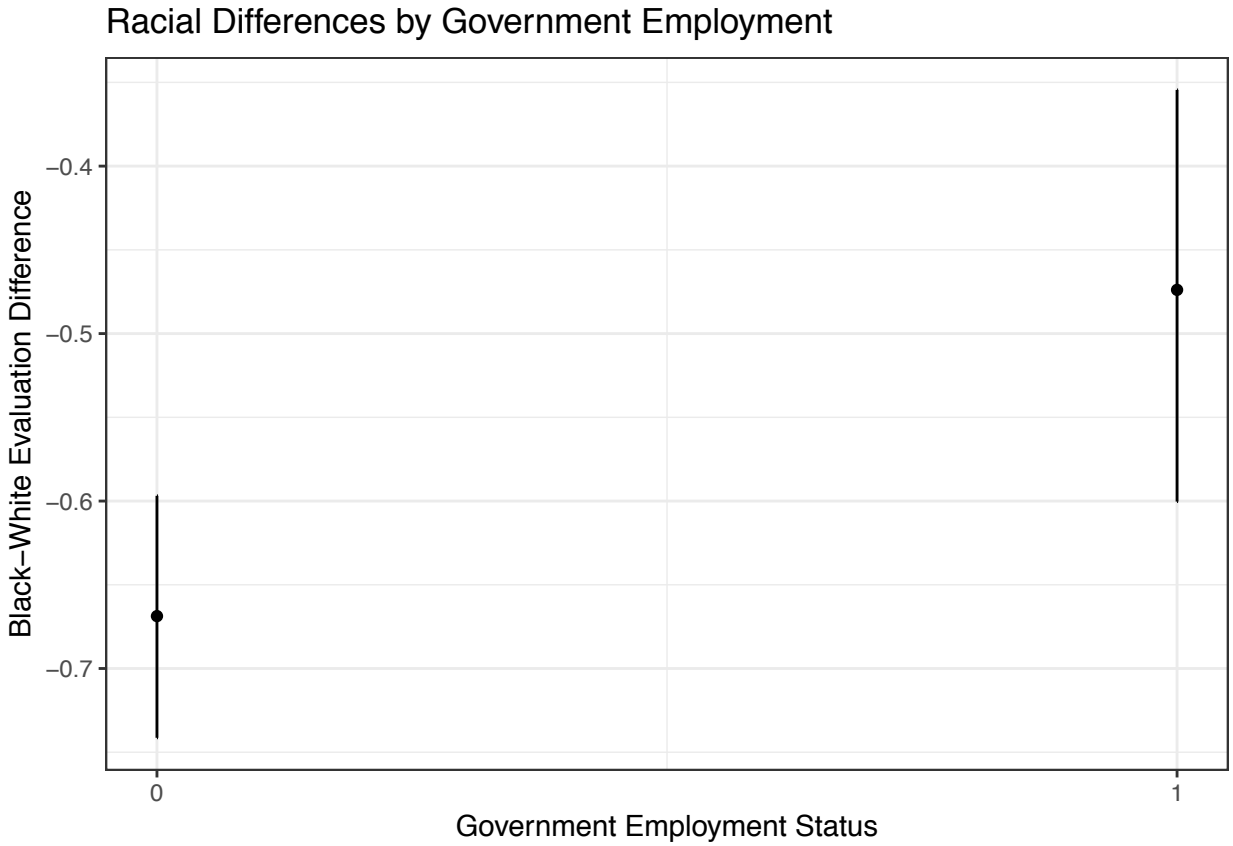
Employed in the Government

Government-employed individuals are generally more positive in their evaluations of the police, but these differences manifest only for blacks. Black respondents still on average evaluate the police worse, but those employed in government at some level more positive in varying degrees. What varies is the effect magnitude.
Solving Crime

```
##
## Call:
## lm(formula = p.crim.solve ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.6699 -0.5116 -0.2225  0.6094  5.7623
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.314718   0.018403 125.780  < 2e-16 ***
## employ.gov       -0.007131   0.047063  -0.152  0.87956
## black            -0.667175   0.036156 -18.452  < 2e-16 ***
## employ.gov:black  0.192333   0.071989   2.672  0.00757 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

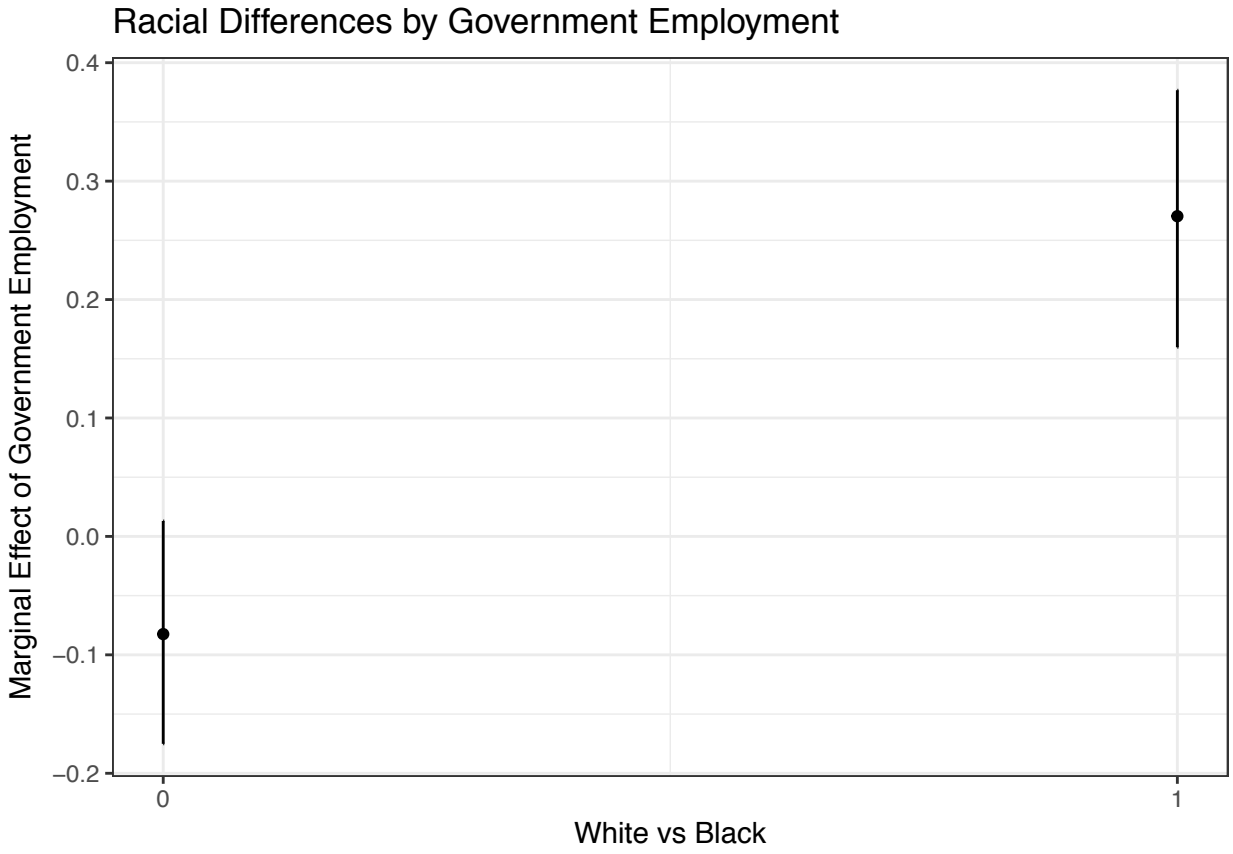
```
## Residual standard error: 1.056 on 5791 degrees of freedom
##   (5371 observations deleted due to missingness)
## Multiple R-squared:  0.06492,    Adjusted R-squared:  0.06444
## F-statistic:   134 on 3 and 5791 DF,  p-value: < 2.2e-16
```

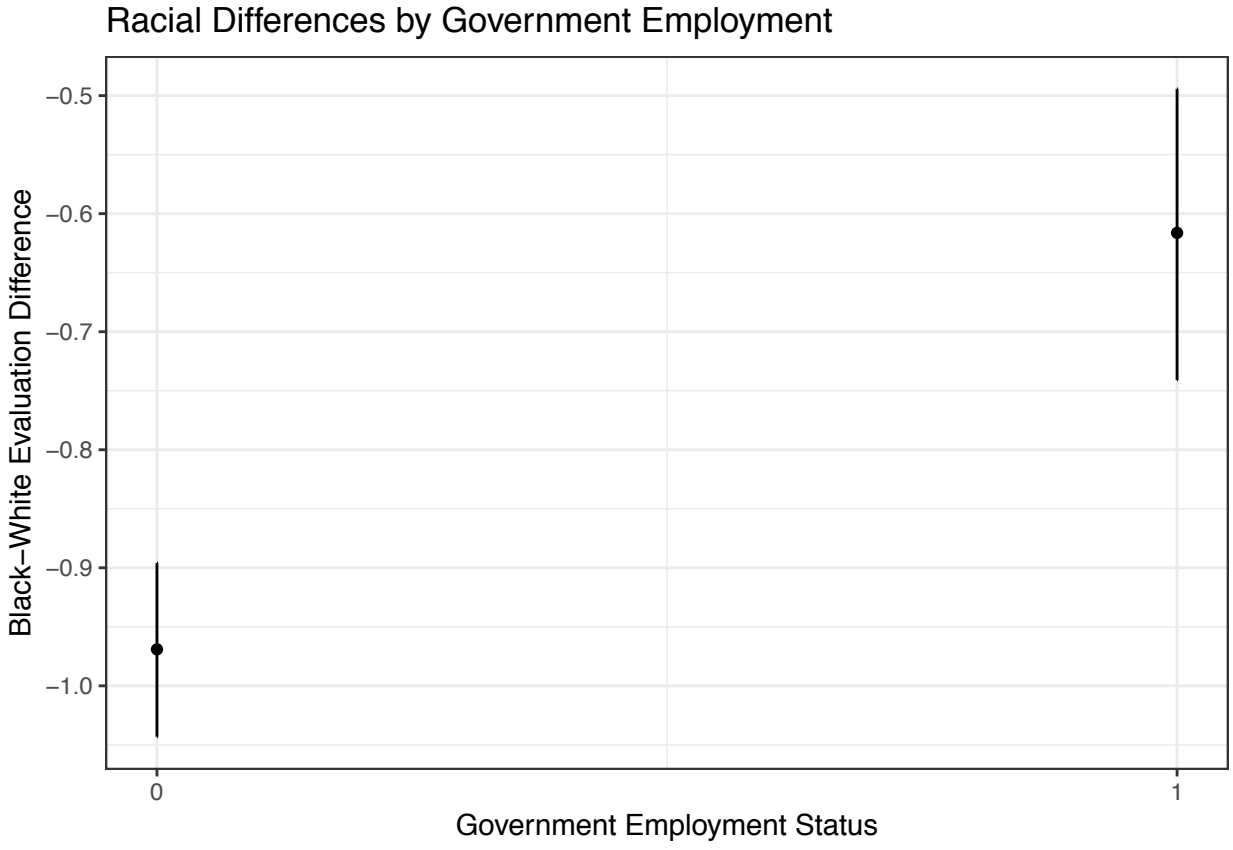




Protecting people like you from violent crime

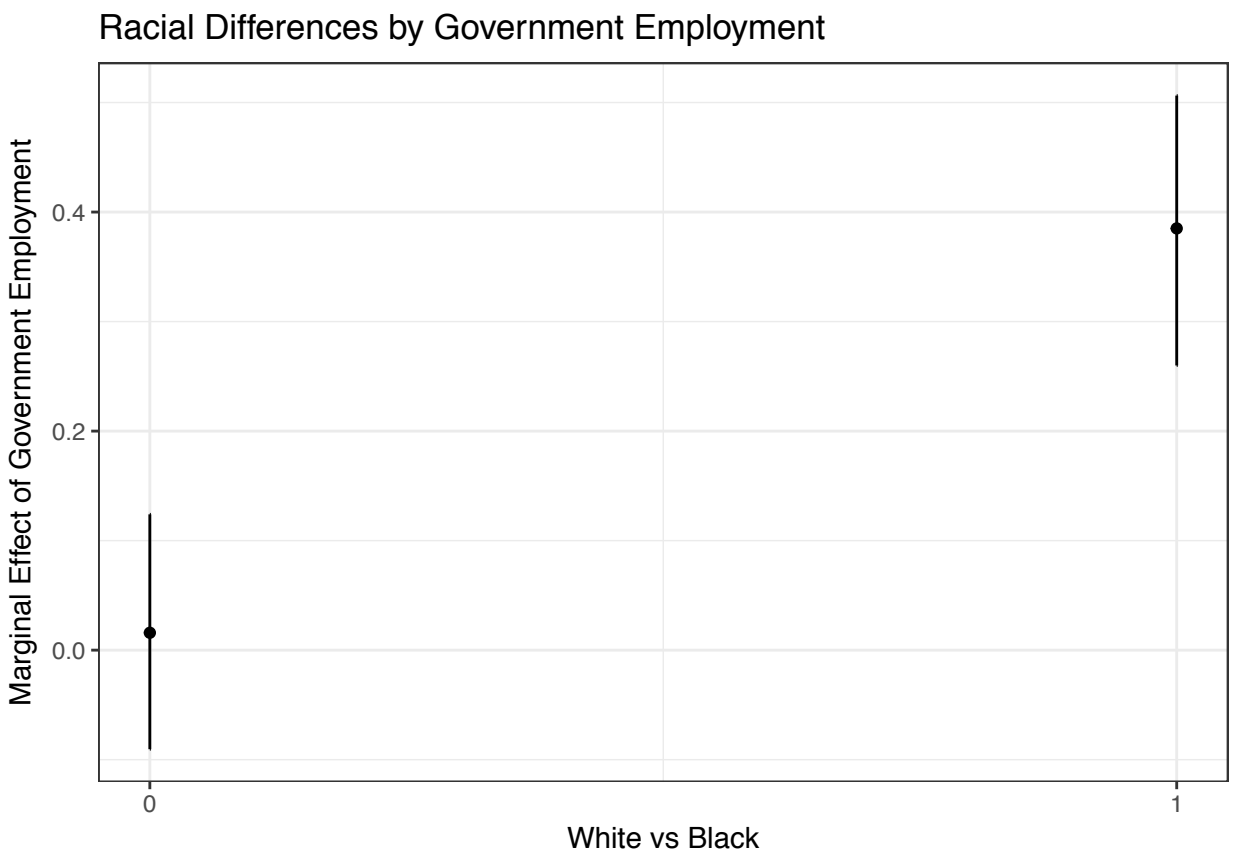
```
##
## Call:
## lm(formula = p.viol.crim ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.2926 -0.6052  0.3031  0.4990  5.8761
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.56895    0.01860 138.126  < 2e-16 ***
## employ.gov       -0.08178    0.04756  -1.720   0.0856 .
## black            -0.96785    0.03654 -26.488  < 2e-16 ***
## employ.gov:black  0.35093    0.07277   4.823 1.45e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.067 on 5789 degrees of freedom
##   (5373 observations deleted due to missingness)
## Multiple R-squared:  0.1229, Adjusted R-squared:  0.1225
## F-statistic: 270.4 on 3 and 5789 DF,  p-value: < 2.2e-16
```

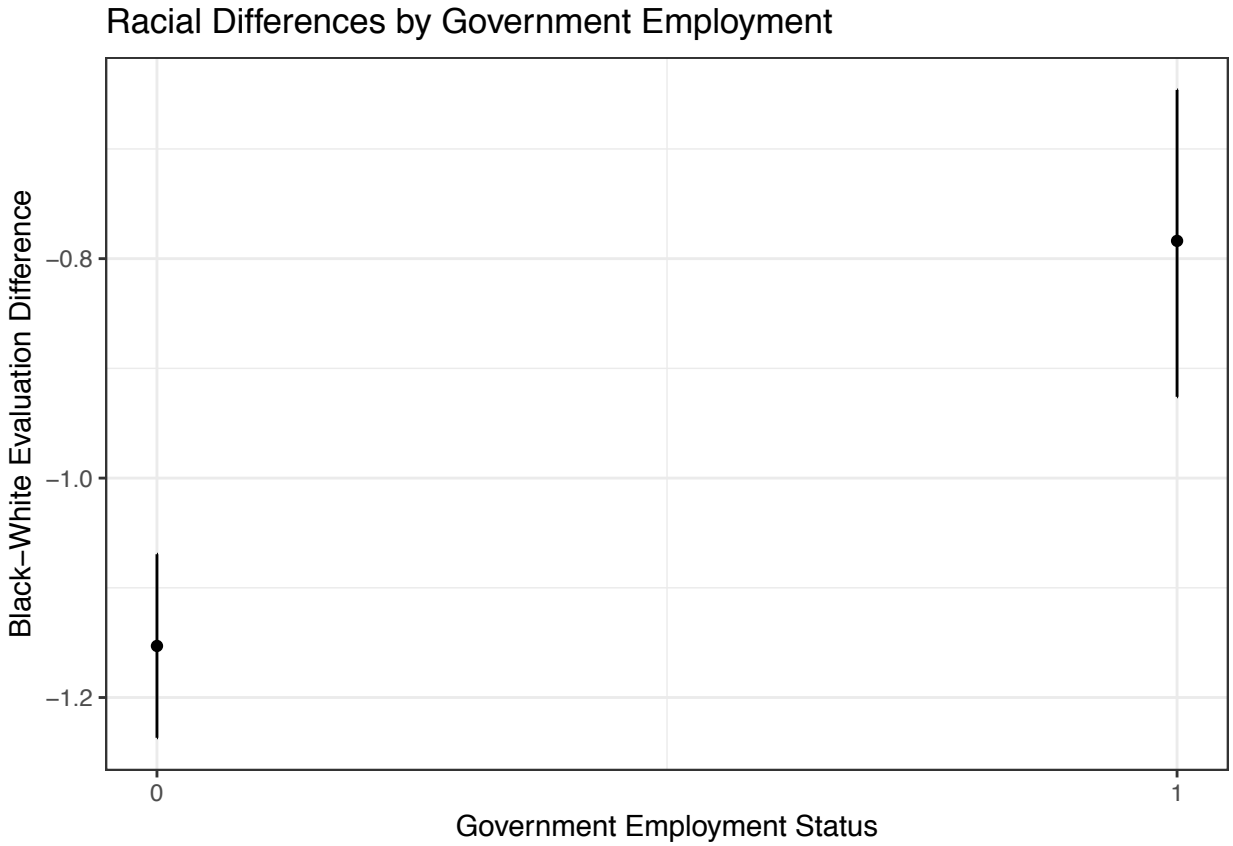

Racial Differences by Government Employment
Marginal Effect of Government Employment
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
0
1
White vs Black


Racial Differences by Government Employment
Black−White Evaluation Difference
−0.5
−0.6
−0.7
−0.8
−0.9
−1.0
0
1
Government Employment Status

Treating racial and ethnic groups equally

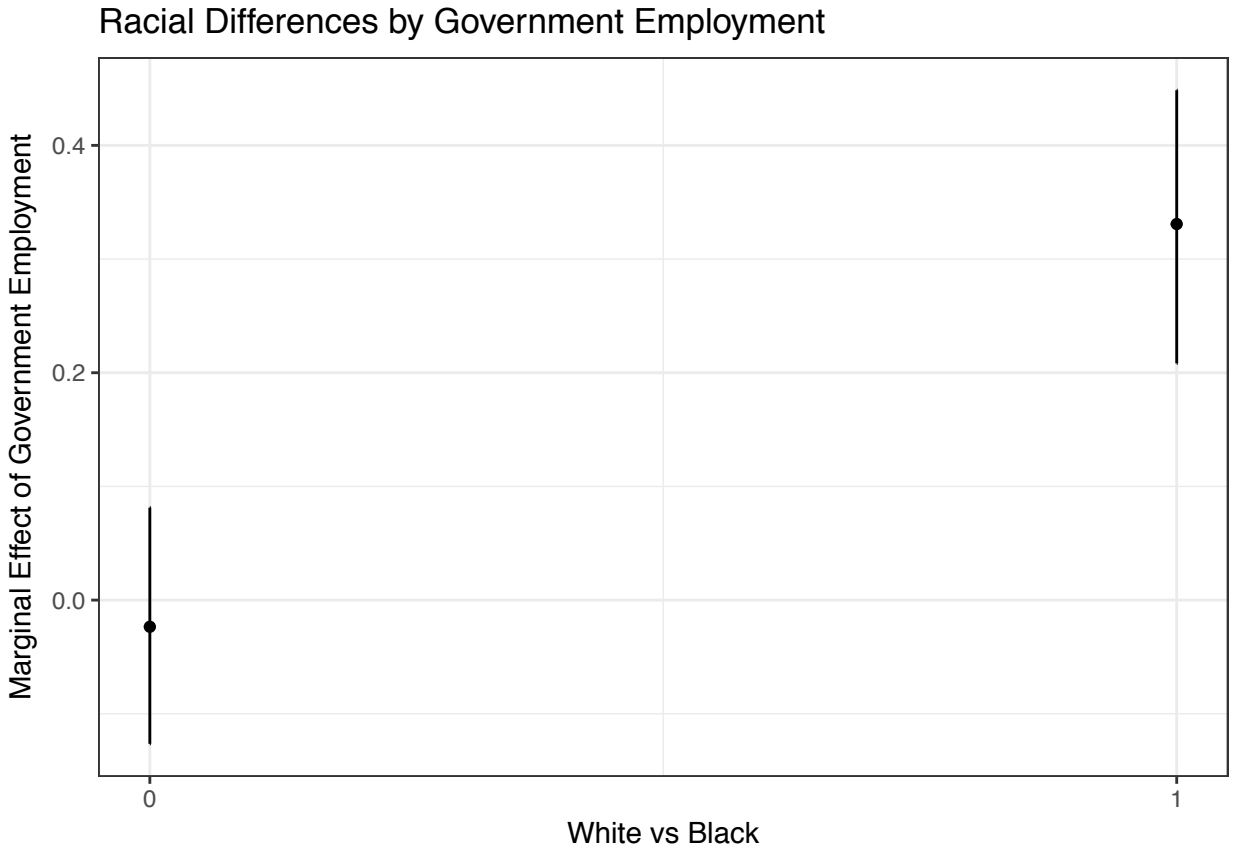
```
##
## Call:
## lm(formula = p.race.fair ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.3402 -0.9002 -0.1238  0.7597  7.3197
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.16312    0.02115 102.277  < 2e-16 ***
## employ.gov         0.01701    0.05397   0.315    0.753
## black             -1.15137    0.04155 -27.710  < 2e-16 ***
## employ.gov:black   0.36631    0.08267   4.431 9.56e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.213 on 5790 degrees of freedom
##   (5372 observations deleted due to missingness)
## Multiple R-squared:  0.1334, Adjusted R-squared:  0.1329
## F-statistic:   297 on 3 and 5790 DF,  p-value: < 2.2e-16
```

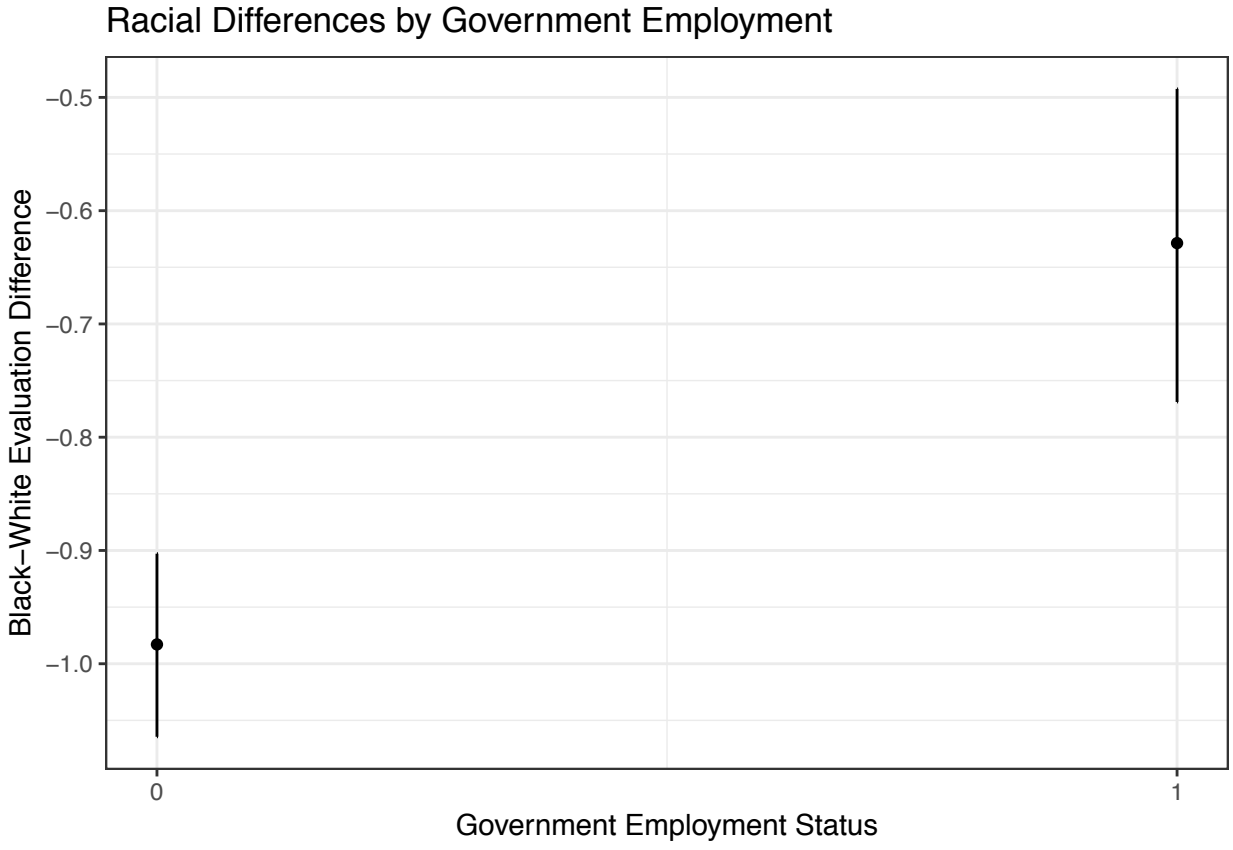




Not using excessive force on suspects

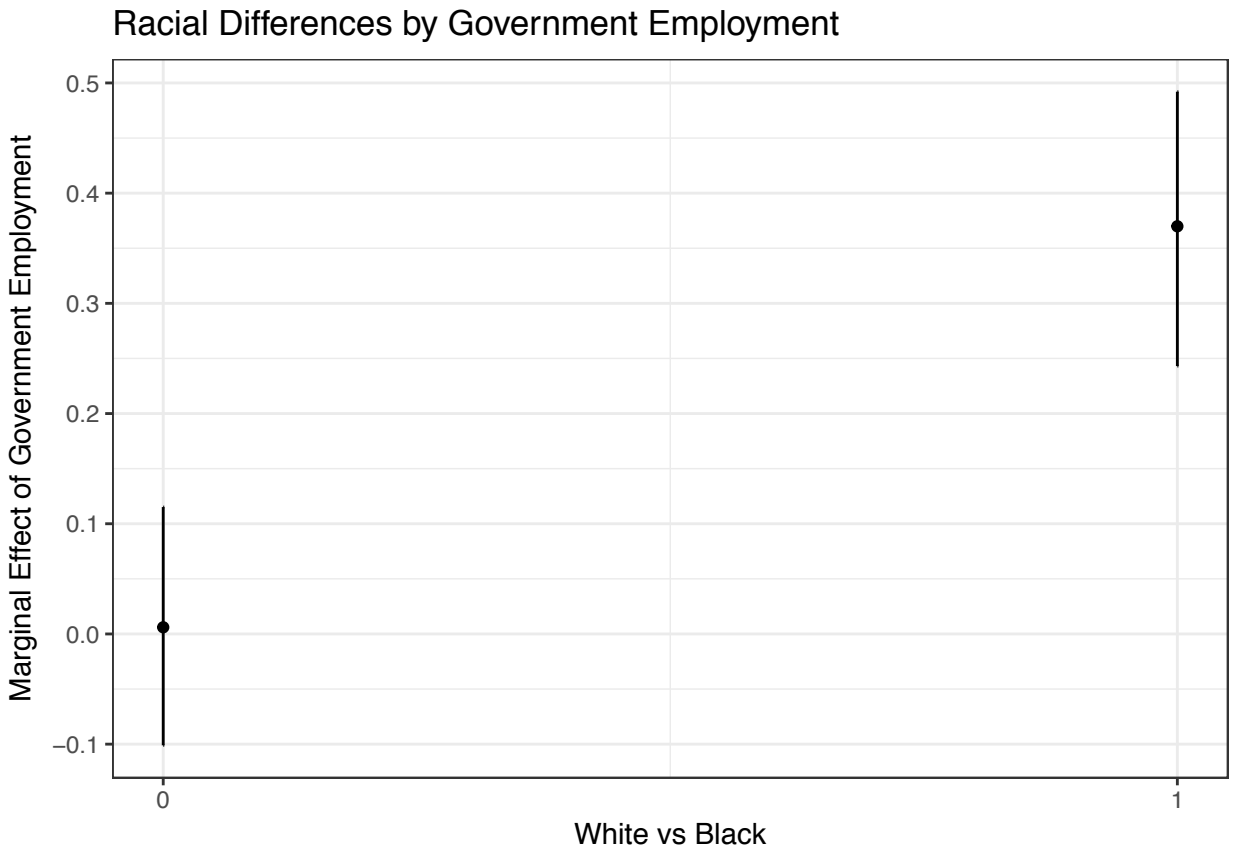
```
##
## Call:
## lm(formula = p.exces.force ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.4980 -0.8932 -0.1729  0.7058  6.7037
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.24453    0.02058 109.049  < 2e-16 ***
## employ.gov       -0.02236    0.05264  -0.425    0.671
## black            -0.98132    0.04045 -24.261  < 2e-16 ***
## employ.gov:black  0.35174    0.08054   4.367 1.28e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.181 on 5789 degrees of freedom
##   (5373 observations deleted due to missingness)
## Multiple R-squared:  0.1043, Adjusted R-squared:  0.1038
## F-statistic: 224.6 on 3 and 5789 DF,  p-value: < 2.2e-16
```

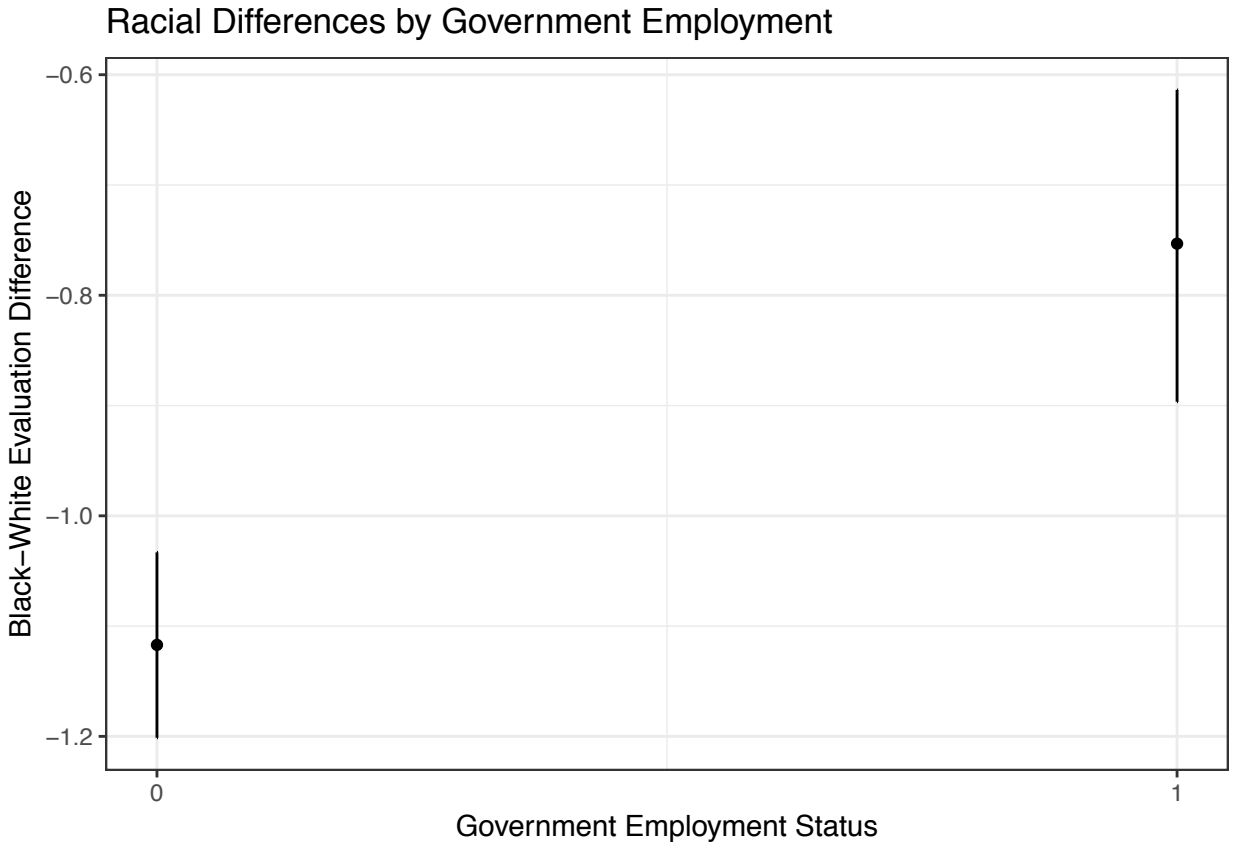

Racial Differences by Government Employment
Marginal Effect of Government Employment
0.4
0.2
0.0
0
1
White vs Black


Racial Differences by Government Employment
Black–White Evaluation Difference
−0.5
−0.6
−0.7
−0.8
−0.9
−1.0
0
1
Government Employment Status

Holding police officers accountable for misconduct

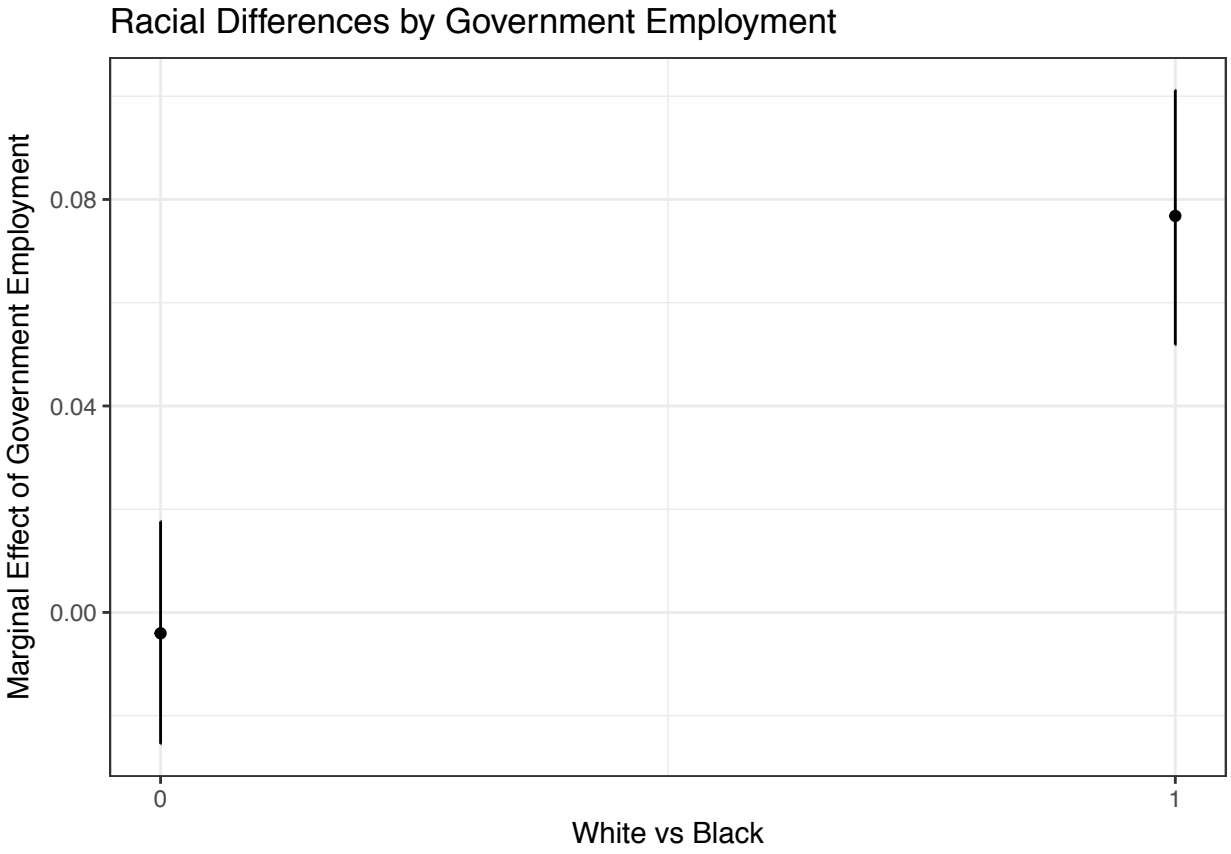
```
##
## Call:
## lm(formula = p.account ~ employ.gov * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2572 -0.8935 -0.1034  0.7627  7.2906
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.139002   0.021297 100.439  < 2e-16 ***
## employ.gov        0.007221   0.054463   0.133    0.895
## black            -1.115376   0.041849 -26.652  < 2e-16 ***
## employ.gov:black  0.361184   0.083332   4.334 1.49e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.222 on 5789 degrees of freedom
##   (5373 observations deleted due to missingness)
## Multiple R-squared:  0.1244, Adjusted R-squared:  0.124
## F-statistic: 274.3 on 3 and 5789 DF,  p-value: < 2.2e-16
```

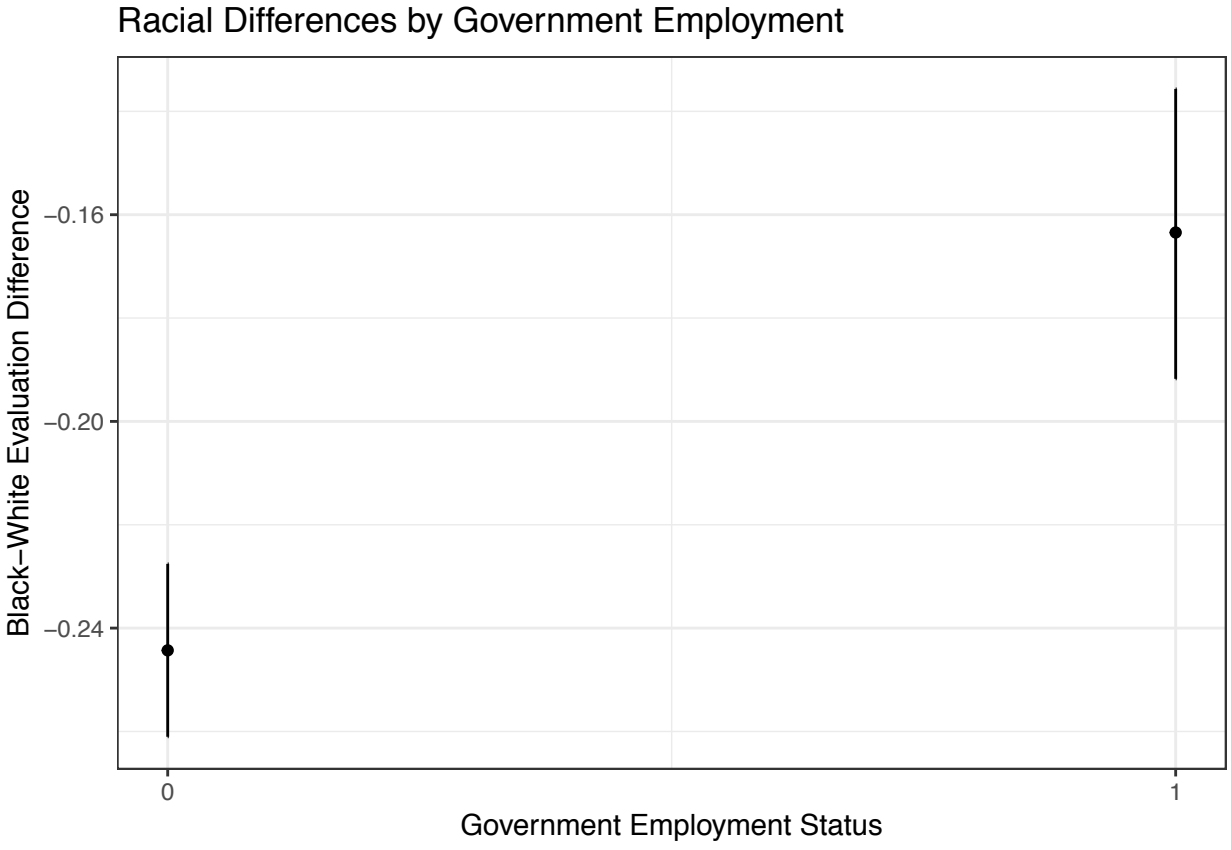




Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.27749 -0.16585 -0.01812  0.14101  1.64710
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.571532   0.004234 134.990  < 2e-16 ***
## employ.gov       -0.003811   0.010826  -0.352    0.725
## black            -0.243960   0.008321 -29.320  < 2e-16 ***
## employ.gov:black  0.080362   0.016565   4.851 1.26e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2429 on 5786 degrees of freedom
##   (5376 observations deleted due to missingness)
## Multiple R-squared:  0.1469, Adjusted R-squared:  0.1464
## F-statistic: 332.1 on 3 and 5786 DF,  p-value: < 2.2e-16
```

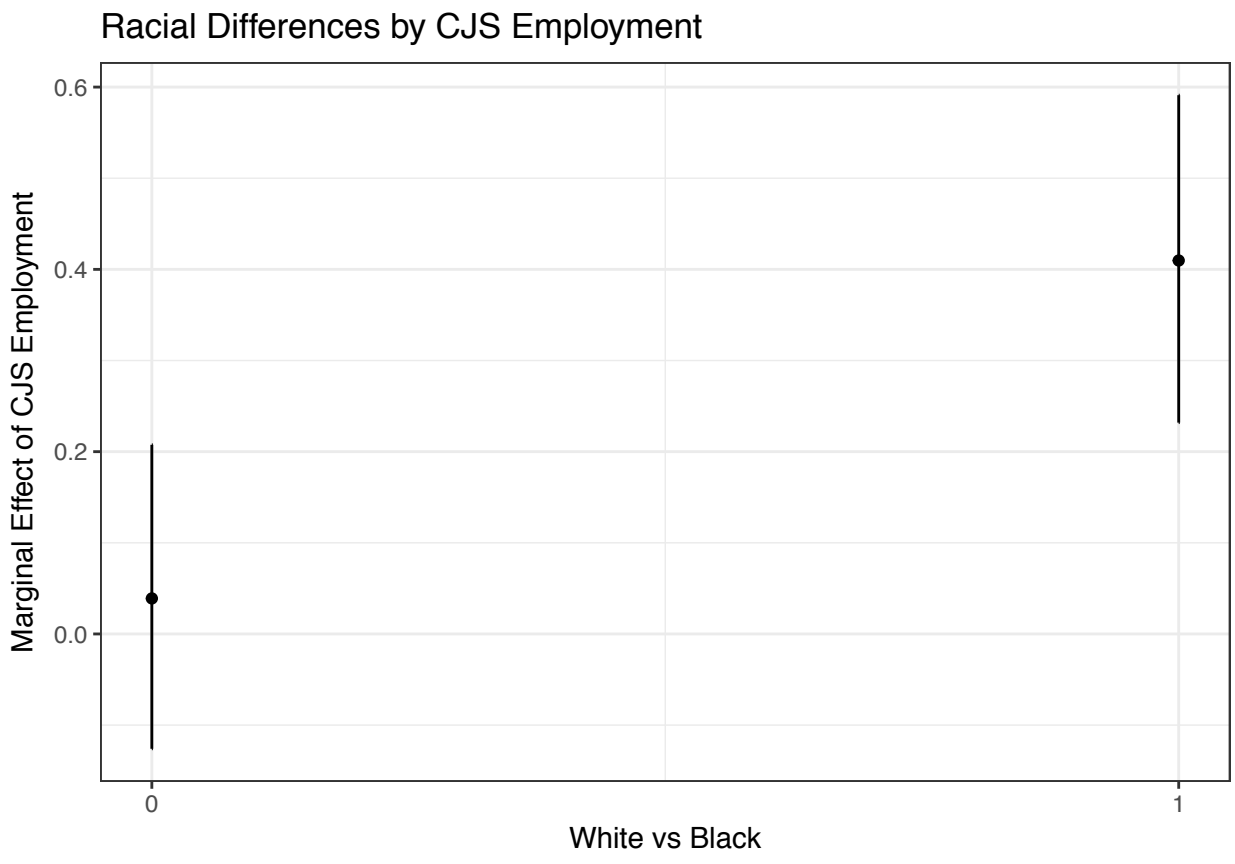

Racial Differences by Government Employment
Marginal Effect of Government Employment
0.08
0.04
0.00
0
1
White vs Black

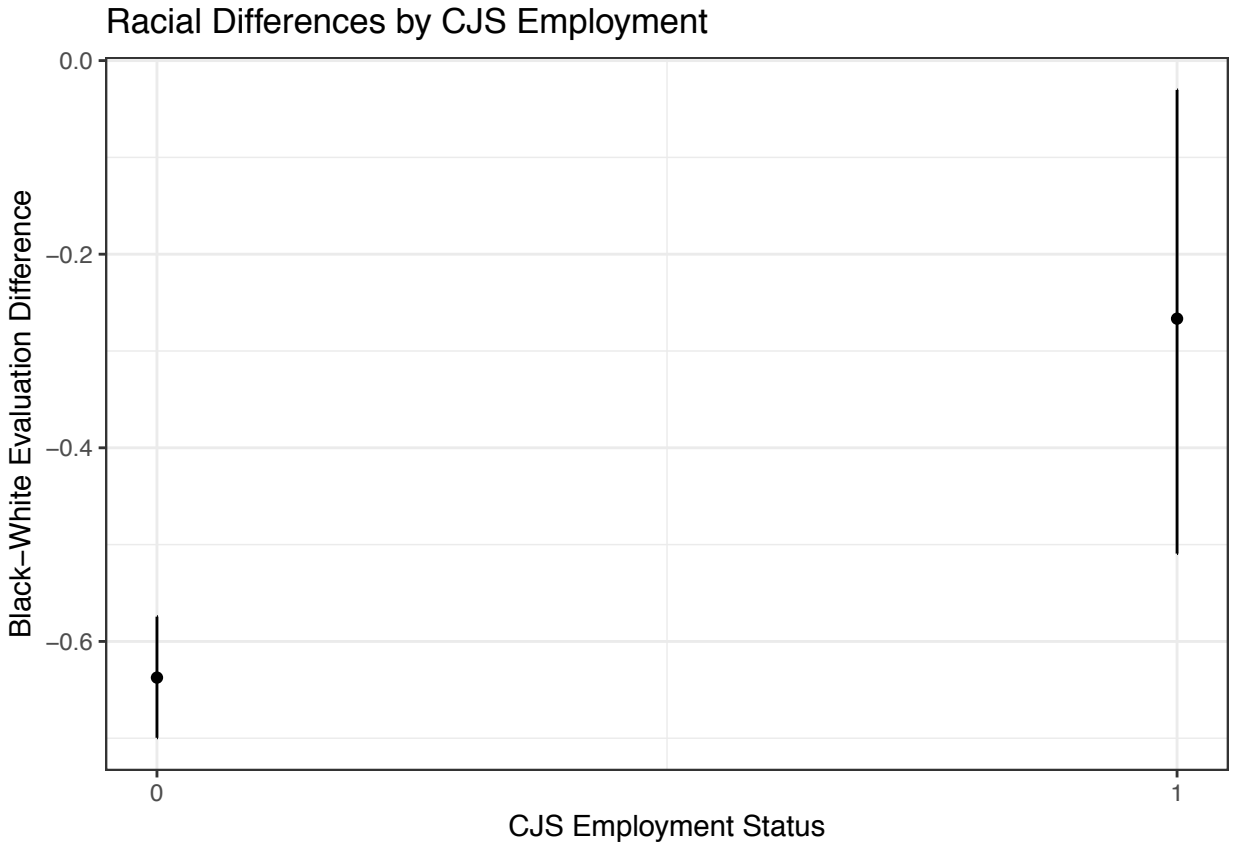

Racial Differences by Government Employment
Black–White Evaluation Difference
−0.16
−0.20
−0.24
0
1
Government Employment Status

Employed in the Criminal Justice System

A similar pattern holds when looking at whether or not respondents are employed in the criminal justice system. Black respondents employed in the criminal justice system evaluate the police more positively. CJS employement does not appear to have a systematic influence on whites' attitudes. **Solving Crime**

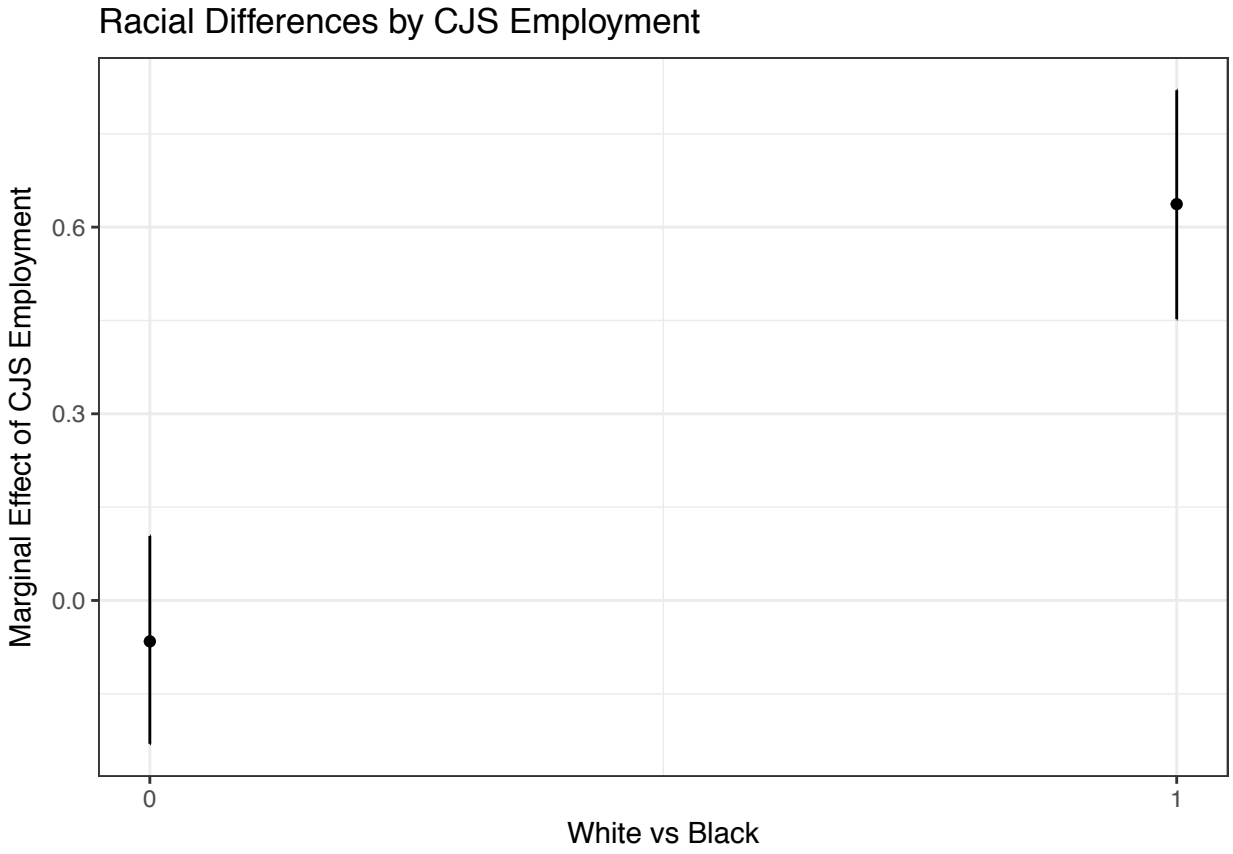
```
##
## Call:
## lm(formula = p.crim.solve ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7619 -0.4771 -0.2200  0.6100  5.6958
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.31110    0.01728 133.749  < 2e-16 ***
## employ.cjs         0.04119    0.08517   0.484  0.62870
## black             -0.63640    0.03180 -20.013  < 2e-16 ***
## employ.cjs:black   0.36536    0.12486   2.926  0.00345 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.055 on 5787 degrees of freedom
##   (5375 observations deleted due to missingness)
## Multiple R-squared:  0.06588,    Adjusted R-squared:  0.0654
## F-statistic: 136.1 on 3 and 5787 DF,  p-value: < 2.2e-16
```

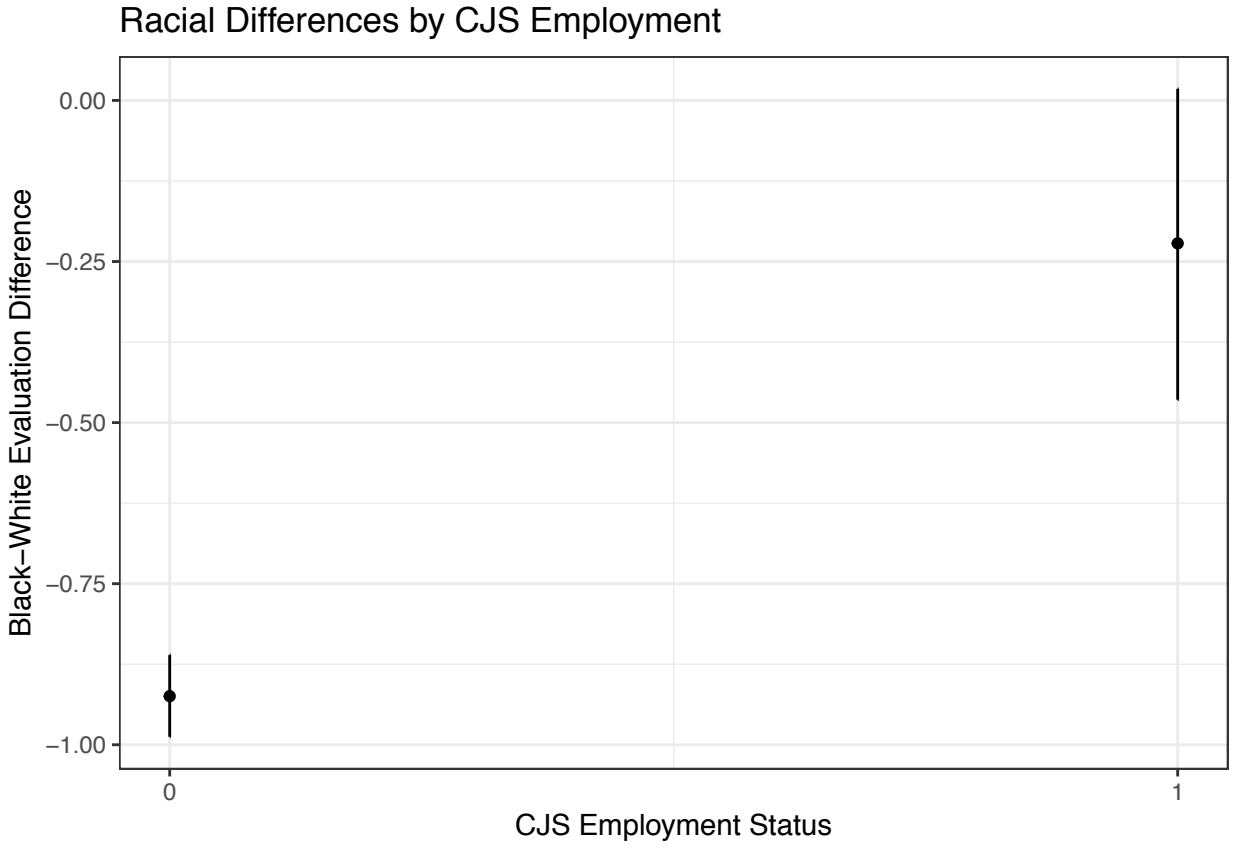




Protecting people like you from violent crime

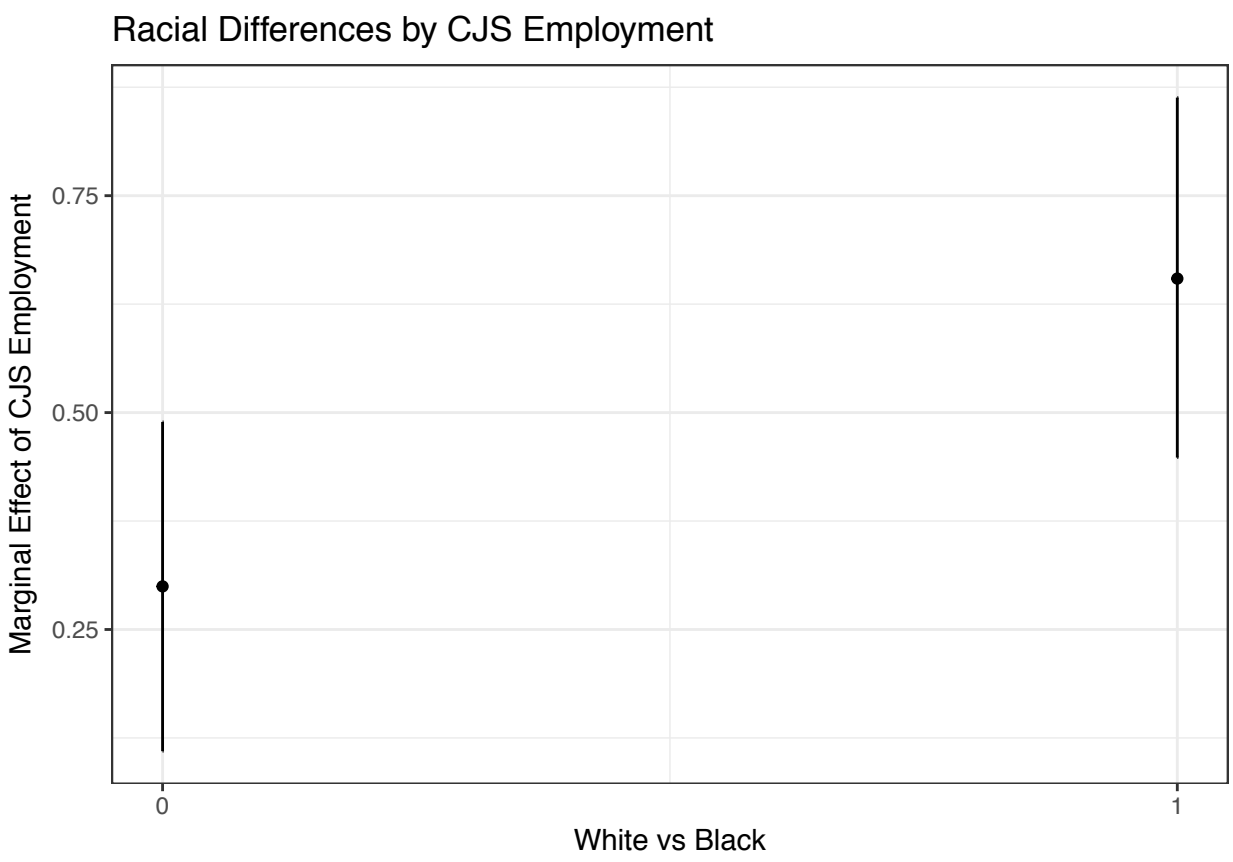
```
##
## Call:
## lm(formula = p.viol.crim ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.2668 -0.5808  0.3123  0.5033  5.7937
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.55839    0.01745 146.612  < 2e-16 ***
## employ.cjs       -0.06439    0.08601  -0.749    0.454
## black            -0.92367    0.03212 -28.761  < 2e-16 ***
## employ.cjs:black  0.69866    0.12609   5.541 3.14e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.065 on 5785 degrees of freedom
##   (5377 observations deleted due to missingness)
## Multiple R-squared:  0.1259, Adjusted R-squared:  0.1254
## F-statistic: 277.7 on 3 and 5785 DF,  p-value: < 2.2e-16
```

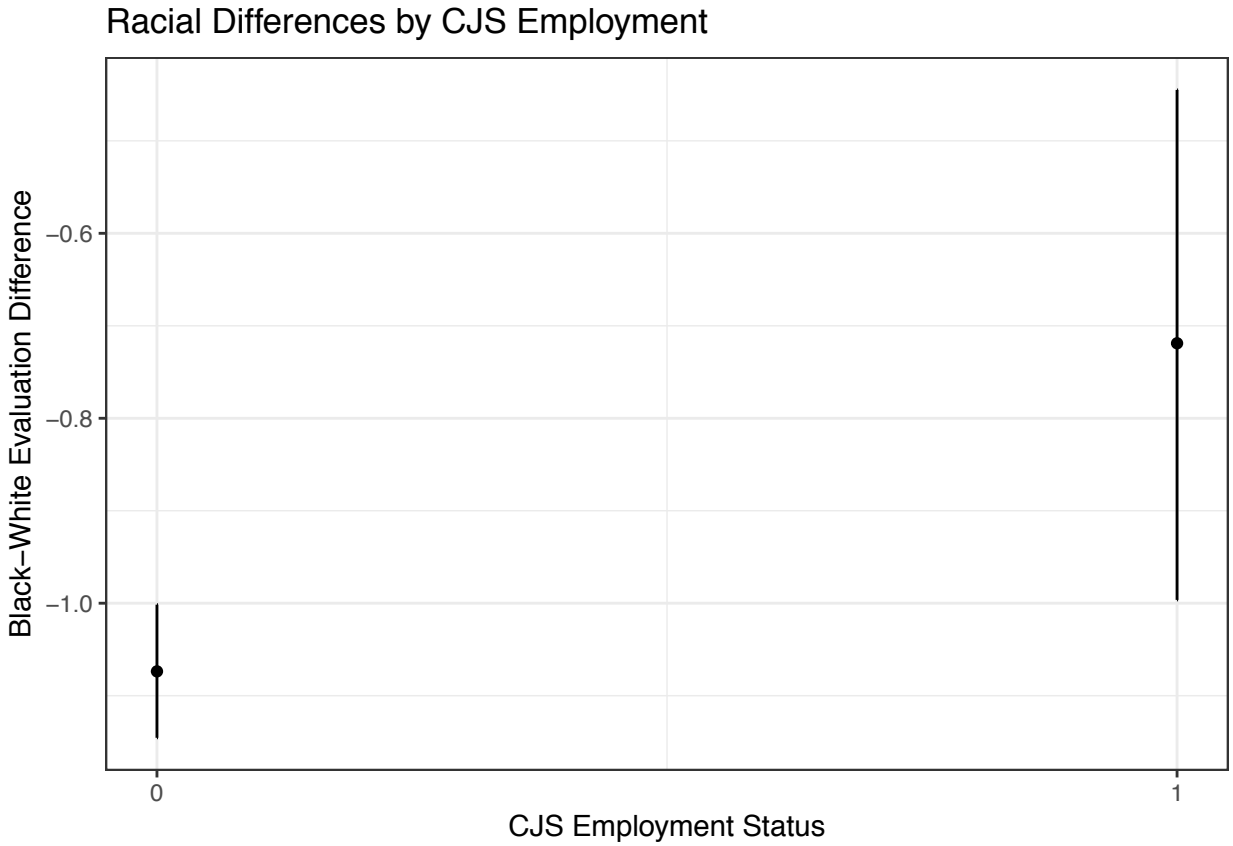

Racial Differences by CJS Employment
Marginal Effect of CJS Employment
0.6
0.3
0.0
0
1
White vs Black


Racial Differences by CJS Employment
Black–White Evaluation Difference
0.00
−0.25
−0.50
−0.75
−1.00
0
1
CJS Employment Status

Treating racial and ethnic groups equally

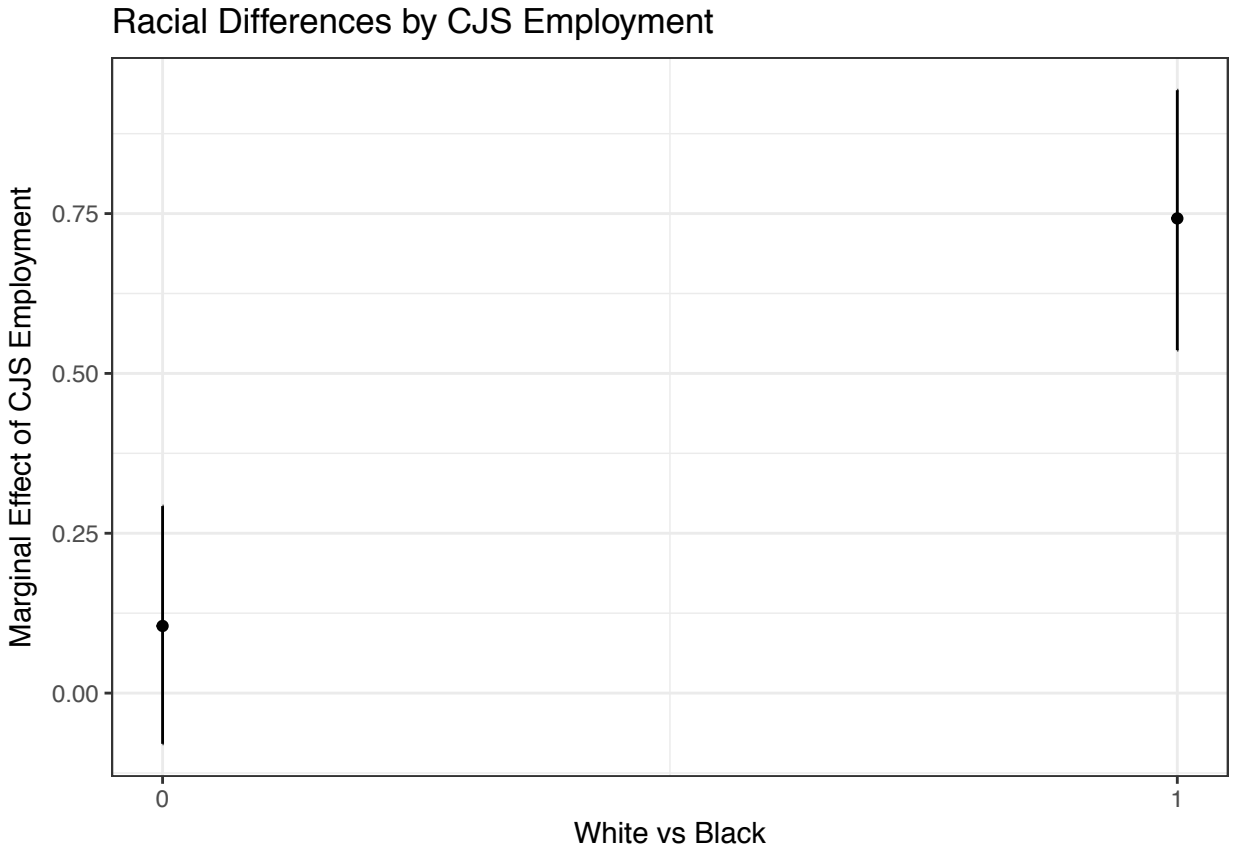
```
##
## Call:
## lm(formula = p.race.fair ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.0124 -0.8696 -0.1090  0.7700  7.1491
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.15416    0.01984 108.560  < 2e-16 ***
## employ.cjs         0.30040    0.09780   3.071  0.00214 **
## black             -1.07275    0.03652 -29.374  < 2e-16 ***
## employ.cjs:black   0.35139    0.14338   2.451  0.01428 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.211 on 5785 degrees of freedom
##   (5377 observations deleted due to missingness)
## Multiple R-squared:  0.1352, Adjusted R-squared:  0.1348
## F-statistic: 301.5 on 3 and 5785 DF,  p-value: < 2.2e-16
```

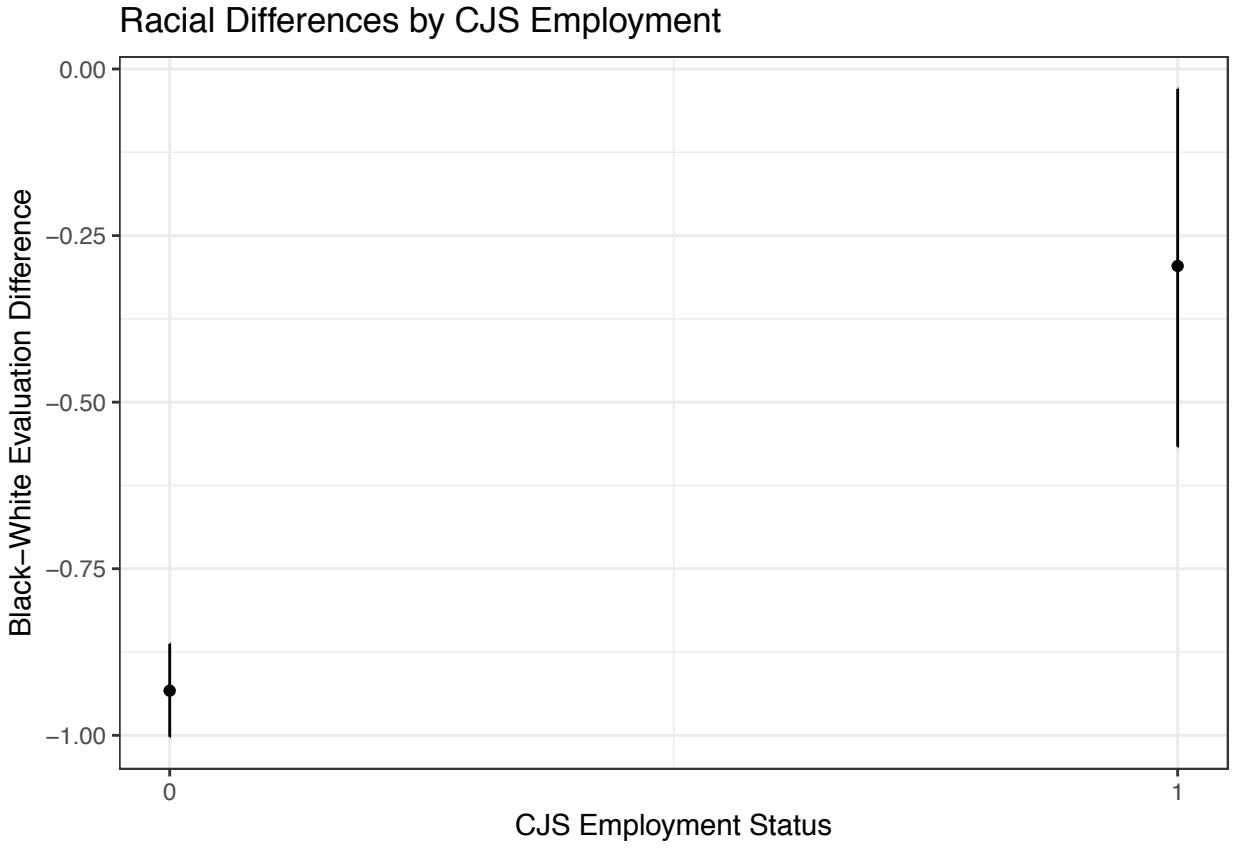




Not using excessive force on suspects

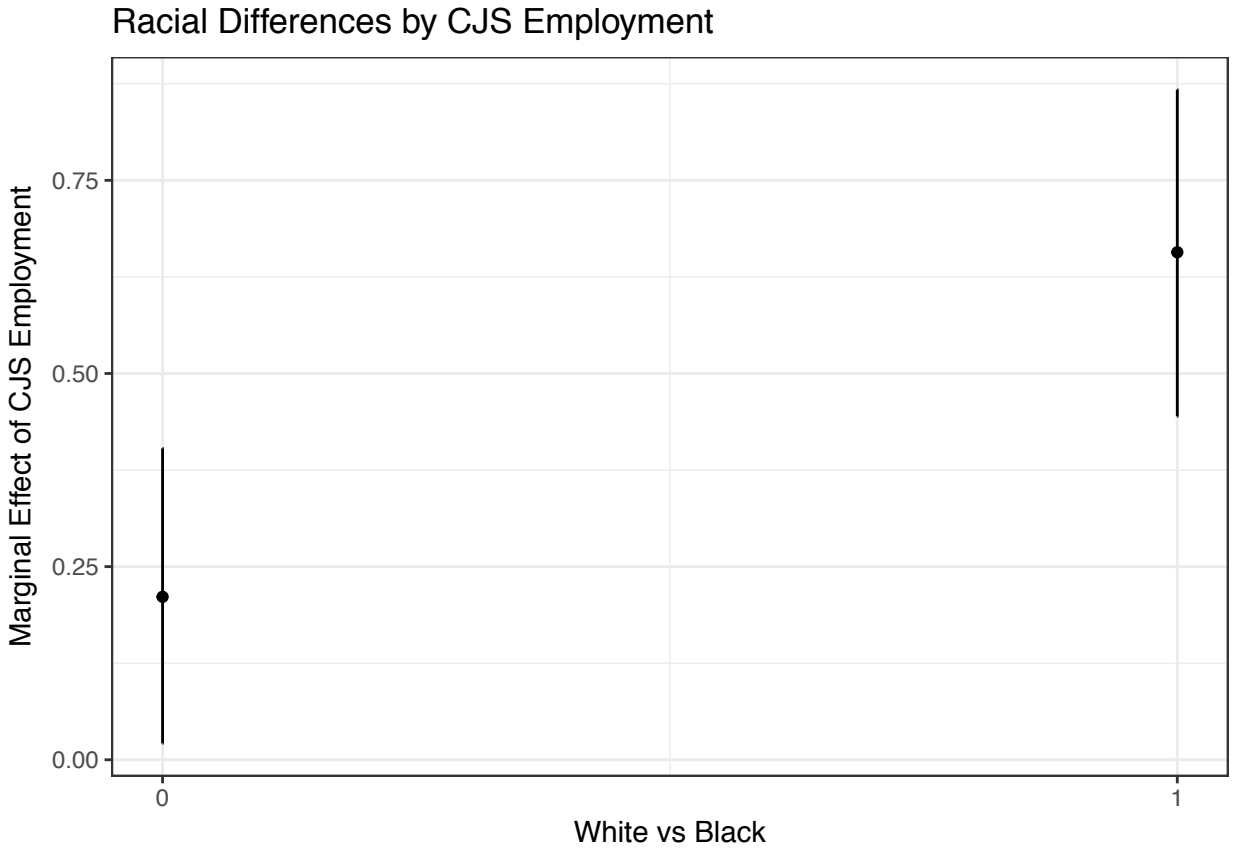
```
##
## Call:
## lm(formula = p.exces.force ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7395 -0.9219 -0.1668  0.7082  6.6043
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.23583    0.01929 115.903  < 2e-16 ***
## employ.cjs        0.10729    0.09509   1.128    0.259
## black            -0.93204    0.03551 -26.247  < 2e-16 ***
## employ.cjs:black  0.63243    0.13940   4.537 5.83e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.177 on 5785 degrees of freedom
##   (5377 observations deleted due to missingness)
## Multiple R-squared:  0.1087, Adjusted R-squared:  0.1083
## F-statistic: 235.3 on 3 and 5785 DF,  p-value: < 2.2e-16
```

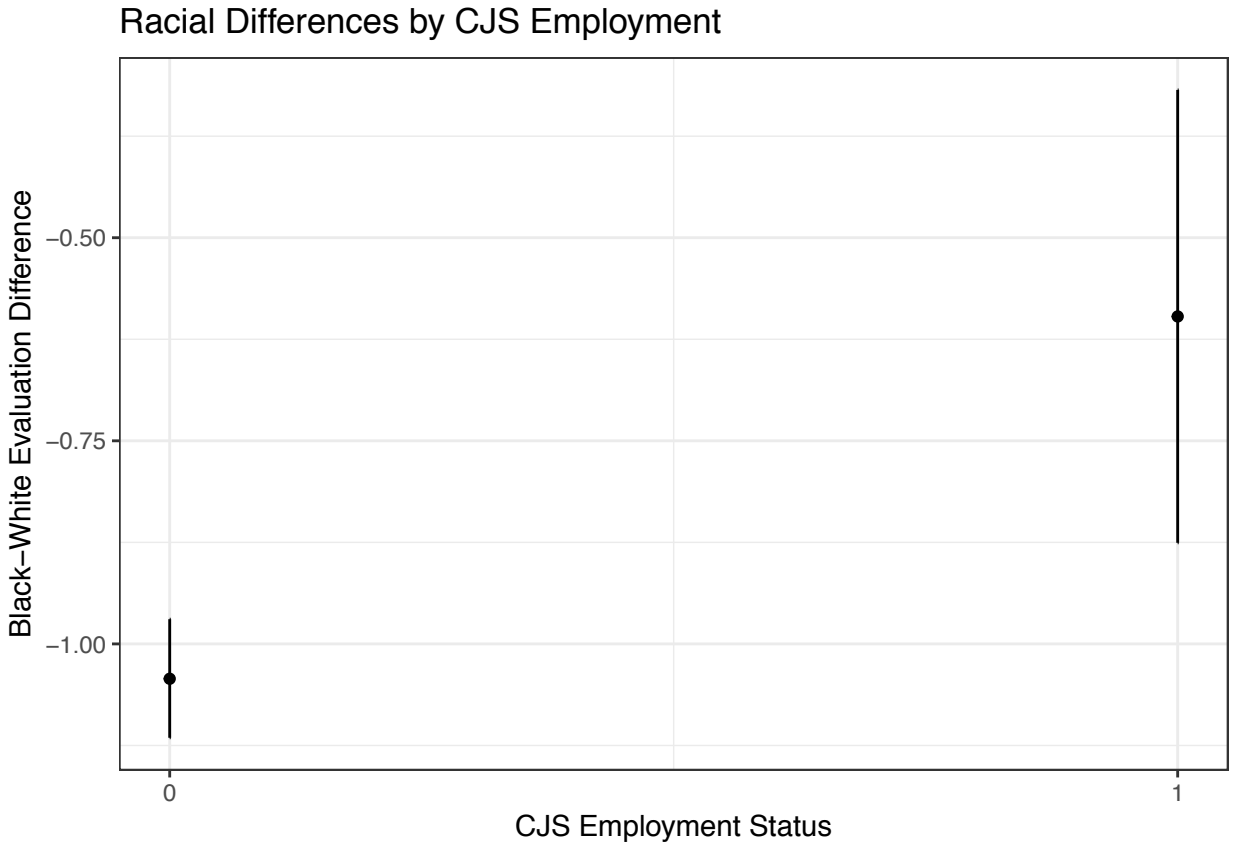

Racial Differences by CJS Employment
Marginal Effect of CJS Employment
0.75
0.50
0.25
0.00
0
1
White vs Black


Racial Differences by CJS Employment
Black–White Evaluation Difference
0.00
−0.25
−0.50
−0.75
−1.00
0
1
CJS Employment Status

Holding police officers accountable for misconduct

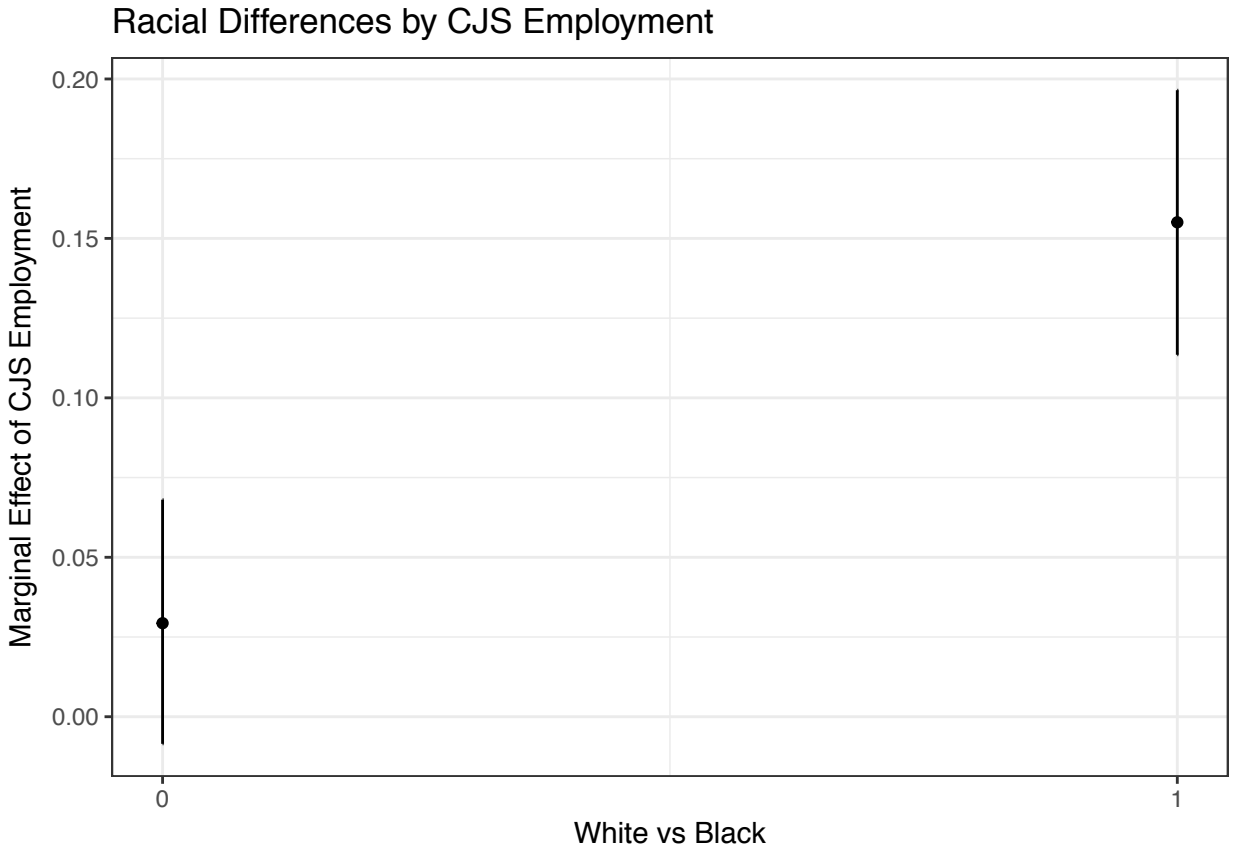
```
##
## Call:
## lm(formula = p.account ~ employ.cjs * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.7375 -0.8728 -0.0941  0.7818  7.1317
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.13048    0.02000 106.516  < 2e-16 ***
## employ.cjs        0.21183    0.09859   2.149  0.03170 *
## black            -1.04197    0.03682 -28.300  < 2e-16 ***
## employ.cjs:black  0.44287    0.14453   3.064  0.00219 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.221 on 5785 degrees of freedom
##   (5377 observations deleted due to missingness)
## Multiple R-squared:  0.1255, Adjusted R-squared:  0.125
## F-statistic: 276.6 on 3 and 5785 DF,  p-value: < 2.2e-16
```

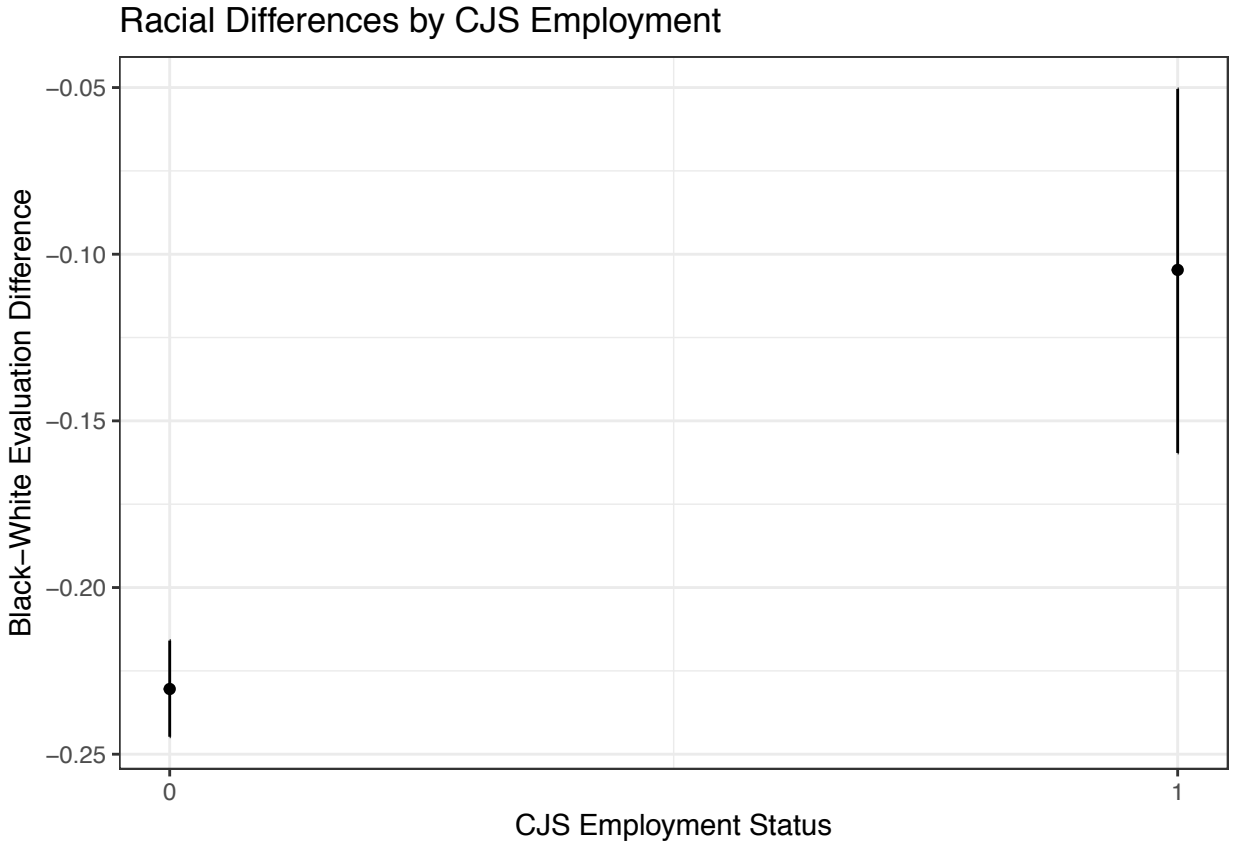




Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.34554 -0.16922 -0.01712  0.14524  1.61835
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.569512   0.003972 143.368  < 2e-16 ***
## employ.cjs        0.029802   0.019578   1.522    0.128
## black            -0.230200   0.007313 -31.480  < 2e-16 ***
## employ.cjs:black  0.124394   0.028702   4.334 1.49e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2424 on 5782 degrees of freedom
##   (5380 observations deleted due to missingness)
## Multiple R-squared:  0.1495, Adjusted R-squared:  0.1491
## F-statistic: 338.8 on 3 and 5782 DF,  p-value: < 2.2e-16
```


Racial Differences by CJS Employment
Marginal Effect of CJS Employment
0.20
0.15
0.10
0.05
0.00
0
1
White vs Black


Racial Differences by CJS Employment
Black–White Evaluation Difference
−0.05
−0.10
−0.15
−0.20
−0.25
0
1
CJS Employment Status

Criminal Justice System Profession

Finally, considering the specific position in the criminal justice system, nothing systematic appears to manifest. Some items and some occupations light up, but that varies. Moreover, nothing systematically varies between whites and blacks.

Solving Crime

```
##
## Call:
## lm(formula = p.crim.solve ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9600 -0.6924  0.0575  0.8133  4.7264
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 1.94392    0.29358   6.621 2.22e-10 ***
## as.factor(cjs.pos)2        -0.75343    0.54216  -1.390  0.16588
## as.factor(cjs.pos)3         0.19956    0.57831   0.345  0.73034
## as.factor(cjs.pos)4         0.68918    0.43538   1.583  0.11472
## as.factor(cjs.pos)5         0.57009    0.46298   1.231  0.21937
## as.factor(cjs.pos)6        -0.32726    0.41718  -0.784  0.43352
## as.factor(cjs.pos)7        -0.39260    0.51685  -0.760  0.44821
## as.factor(cjs.pos)8         0.97470    0.33840   2.880  0.00432 **
## black                       0.26642    0.40195   0.663  0.50807
## as.factor(cjs.pos)2:black   0.86121    0.68971   1.249  0.21297
## as.factor(cjs.pos)3:black  -0.70239    0.85900  -0.818  0.41433
## as.factor(cjs.pos)4:black  -1.15456    0.64009  -1.804  0.07249 .
## as.factor(cjs.pos)5:black  -1.27171    0.66309  -1.918  0.05629 .
## as.factor(cjs.pos)6:black   0.37986    0.59692   0.636  0.52513
## as.factor(cjs.pos)7:black   0.03347    0.74609   0.045  0.96426
## as.factor(cjs.pos)8:black  -1.00989    0.47378  -2.132  0.03403 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.332 on 246 degrees of freedom
##   (10904 observations deleted due to missingness)
## Multiple R-squared:  0.136,  Adjusted R-squared:  0.08329
## F-statistic: 2.581 on 15 and 246 DF,  p-value: 0.001314
```

Protecting people like you from violent crime

```
##
## Call:
## lm(formula = p.viol.crim ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.7800 -0.7547 -0.0397  0.7453  4.3570
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)                2.61314    0.27882   9.372  < 2e-16 ***
## as.factor(cjs.pos)2       -1.52942    0.51489  -2.970 0.003269 **
## as.factor(cjs.pos)3       -0.47673    0.54922  -0.868 0.386233
## as.factor(cjs.pos)4       -0.10490    0.41348  -0.254 0.799948
## as.factor(cjs.pos)5        0.06704    0.43969   0.152 0.878947
## as.factor(cjs.pos)6       -0.59434    0.39619  -1.500 0.134863
## as.factor(cjs.pos)7       -1.85144    0.49085  -3.772 0.000203 ***
## as.factor(cjs.pos)8        0.45414    0.32138   1.413 0.158889
## black                     -0.10778    0.38173  -0.282 0.777914
## as.factor(cjs.pos)2:black  1.43836    0.65502   2.196 0.029031 *
## as.factor(cjs.pos)3:black -0.38936    0.81579  -0.477 0.633585
## as.factor(cjs.pos)4:black -0.19321    0.60789  -0.318 0.750877
## as.factor(cjs.pos)5:black  0.57775    0.62974   0.917 0.359802
## as.factor(cjs.pos)6:black  0.31025    0.56689   0.547 0.584680
## as.factor(cjs.pos)7:black  1.41133    0.70856   1.992 0.047496 *
## as.factor(cjs.pos)8:black -0.91990    0.44994  -2.044 0.041972 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.265 on 246 degrees of freedom
##   (10904 observations deleted due to missingness)
## Multiple R-squared:  0.1915, Adjusted R-squared:  0.1422
## F-statistic: 3.884 on 15 and 246 DF,  p-value: 3.015e-06
```

Treating racial and ethnic groups equally

```
##
## Call:
## lm(formula = p.race.fair ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5203 -0.9713  0.0199  0.7315  4.8233
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                2.783662   0.306565   9.080  < 2e-16 ***
## as.factor(cjs.pos)2       -0.890435   0.566135  -1.573  0.11704
## as.factor(cjs.pos)3       -1.359927   0.603882  -2.252  0.02521 *
## as.factor(cjs.pos)4        0.050144   0.454634   0.110  0.91226
## as.factor(cjs.pos)5        0.004057   0.483451   0.008  0.99331
## as.factor(cjs.pos)6       -1.614620   0.435621  -3.706  0.00026 ***
## as.factor(cjs.pos)7        0.471693   0.539700   0.874  0.38298
## as.factor(cjs.pos)8       -0.131516   0.353365  -0.372  0.71008
## black                     -0.800878   0.419723  -1.908  0.05754 .
## as.factor(cjs.pos)2:black  0.753053   0.720205   1.046  0.29677
## as.factor(cjs.pos)3:black  0.814693   0.896980   0.908  0.36463
## as.factor(cjs.pos)4:black -0.536356   0.668390  -0.802  0.42306
## as.factor(cjs.pos)5:black  0.972901   0.692410   1.405  0.16125
## as.factor(cjs.pos)6:black  1.662712   0.623312   2.668  0.00815 **
## as.factor(cjs.pos)7:black -0.876036   0.779081  -1.124  0.26192
## as.factor(cjs.pos)8:black -0.535426   0.494725  -1.082  0.28019
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 1.391 on 246 degrees of freedom
##   (10904 observations deleted due to missingness)
## Multiple R-squared:  0.214,  Adjusted R-squared:  0.1661
## F-statistic: 4.465 on 15 and 246 DF,  p-value: 1.865e-07
```

Not using excessive force on suspects

```
##
## Call:
## lm(formula = p.exces.force ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9082 -1.0052  0.1641  0.9156  5.2148
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 2.47759    0.30606   8.095 2.64e-14 ***
## as.factor(cjs.pos)2        -1.28710    0.56520  -2.277   0.0236 *
## as.factor(cjs.pos)3        -0.91614    0.60288  -1.520   0.1299
## as.factor(cjs.pos)4         0.29157    0.45388   0.642   0.5212
## as.factor(cjs.pos)5         0.19237    0.48265   0.399   0.6906
## as.factor(cjs.pos)6        -1.10725    0.43490  -2.546   0.0115 *
## as.factor(cjs.pos)7        -0.35880    0.53880  -0.666   0.5061
## as.factor(cjs.pos)8         0.22750    0.35278   0.645   0.5196
## black                      -0.21850    0.41903  -0.521   0.6025
## as.factor(cjs.pos)2:black   1.51345    0.71901   2.105   0.0363 *
## as.factor(cjs.pos)3:black   0.21741    0.89549   0.243   0.8084
## as.factor(cjs.pos)4:black  -0.99315    0.66728  -1.488   0.1379
## as.factor(cjs.pos)5:black   0.12092    0.69126   0.175   0.8613
## as.factor(cjs.pos)6:black   1.14682    0.62228   1.843   0.0665 .
## as.factor(cjs.pos)7:black  -0.03286    0.77779  -0.042   0.9663
## as.factor(cjs.pos)8:black  -0.69461    0.49390  -1.406   0.1609
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.388 on 246 degrees of freedom
##   (10904 observations deleted due to missingness)
## Multiple R-squared:  0.1314, Adjusted R-squared:  0.07841
## F-statistic: 2.481 on 15 and 246 DF,  p-value: 0.002053
```

Holding police officers accountable for misconduct

```
##
## Call:
## lm(formula = p.account ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -4.1653 -1.1120  0.2037  0.8785  4.7634
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)                2.37710    0.31435   7.562 7.88e-13 ***
## as.factor(cjs.pos)2       -0.48387    0.58051  -0.834 0.405358
## as.factor(cjs.pos)3       -0.06782    0.61922  -0.110 0.912873
## as.factor(cjs.pos)4        0.20457    0.46618   0.439 0.661176
## as.factor(cjs.pos)5        0.20268    0.49573   0.409 0.683002
## as.factor(cjs.pos)6       -1.60228    0.44668  -3.587 0.000403 ***
## as.factor(cjs.pos)7        1.31078    0.55340   2.369 0.018630 *
## as.factor(cjs.pos)8        0.19549    0.36234   0.540 0.590008
## black                     -0.27181    0.43038  -0.632 0.528266
## as.factor(cjs.pos)2:black  0.07906    0.73849   0.107 0.914835
## as.factor(cjs.pos)3:black -0.40581    0.91976  -0.441 0.659444
## as.factor(cjs.pos)4:black -0.76770    0.68536  -1.120 0.263750
## as.factor(cjs.pos)5:black -0.30728    0.70999  -0.433 0.665542
## as.factor(cjs.pos)6:black  1.55234    0.63914   2.429 0.015867 *
## as.factor(cjs.pos)7:black -2.68783    0.79886  -3.365 0.000889 ***
## as.factor(cjs.pos)8:black -0.64647    0.50729  -1.274 0.203734
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.426 on 246 degrees of freedom
##   (10904 observations deleted due to missingness)
## Multiple R-squared:  0.189,  Adjusted R-squared:  0.1396
## F-statistic: 3.822 on 15 and 246 DF,  p-value: 4.054e-06
```

Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -0.86981 -0.17071  0.00107  0.14440  1.11830
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                0.609770   0.063762   9.563  < 2e-16 ***
## as.factor(cjs.pos)2       -0.247213   0.117750  -2.099  0.03679 *
## as.factor(cjs.pos)3       -0.131053   0.125601  -1.043  0.29778
## as.factor(cjs.pos)4        0.056528   0.094559   0.598  0.55052
## as.factor(cjs.pos)5        0.051812   0.100553   0.515  0.60683
## as.factor(cjs.pos)6       -0.262287   0.090605  -2.895  0.00413 **
## as.factor(cjs.pos)7       -0.041018   0.112252  -0.365  0.71512
## as.factor(cjs.pos)8        0.086016   0.073496   1.170  0.24299
## black                     -0.056627   0.087298  -0.649  0.51716
## as.factor(cjs.pos)2:black  0.232257   0.149795   1.550  0.12231
## as.factor(cjs.pos)3:black -0.023273   0.186563  -0.125  0.90083
## as.factor(cjs.pos)4:black -0.182249   0.139018  -1.311  0.19109
## as.factor(cjs.pos)5:black  0.004629   0.144014   0.032  0.97439
## as.factor(cjs.pos)6:black  0.252599   0.129643   1.948  0.05250 .
## as.factor(cjs.pos)7:black -0.107596   0.162041  -0.664  0.50731
## as.factor(cjs.pos)8:black -0.190315   0.102898  -1.850  0.06558 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 0.2893 on 246 degrees of freedom
##   (10904 observations deleted due to missingness)
## Multiple R-squared:  0.1637, Adjusted R-squared:  0.1127
## F-statistic: 3.211 on 15 and 246 DF,  p-value: 7.326e-05
```

Racial Group Views

Racial Resentment

Whites' racial attitudes help explain their evaluations of the police. More resentful whites evaluate the police more positively. Importantly, however, these attitudes' influence varies by the outcome. Racial resentment is more important relative to evaluations of police accountability, using excessive force, and perceptions of whether the police treat racial groups equally. **Solving Crime**

```
##
## Call:
## lm(formula = p.crim.solve ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.0722 -0.4541 -0.0790  0.5838  4.5253
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.98937    0.02942   67.62   <2e-16 ***
## rr_sc        0.65279    0.04485   14.55   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.009 on 8069 degrees of freedom
##   (22 observations deleted due to missingness)
## Multiple R-squared:  0.02558,    Adjusted R-squared:  0.02546
## F-statistic: 211.8 on 1 and 8069 DF,  p-value: < 2.2e-16
```

Protecting people like you from violent crime

```
##
## Call:
## lm(formula = p.viol.crim ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.6308 -0.5551  0.1836  0.5434  4.0590
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.16089    0.02952   73.20   <2e-16 ***
## rr_sc        0.72815    0.04501   16.18   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.013 on 8068 degrees of freedom
```

```
##   (23 observations deleted due to missingness)
## Multiple R-squared:  0.03142,    Adjusted R-squared:  0.0313
## F-statistic: 261.7 on 1 and 8068 DF,  p-value: < 2.2e-16
```

Treating racial and ethnic groups equally

```
##
## Call:
## lm(formula = p.race.fair ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5237 -0.7615  0.0305  0.7376  5.7070
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.08526    0.03311   32.78   <2e-16 ***
## rr_sc        1.87165    0.05048   37.07   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.136 on 8068 degrees of freedom
##   (23 observations deleted due to missingness)
## Multiple R-squared:  0.1456, Adjusted R-squared:  0.1455
## F-statistic:  1374 on 1 and 8068 DF,  p-value: < 2.2e-16
```

Not using excessive force on suspects

```
##
## Call:
## lm(formula = p.exces.force ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.0737 -0.6884  0.0153  0.7111  5.3611
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.47720    0.03286   44.96   <2e-16 ***
## rr_sc        1.33650    0.05010   26.68   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.127 on 8068 degrees of freedom
##   (23 observations deleted due to missingness)
## Multiple R-squared:  0.08107,    Adjusted R-squared:  0.08095
## F-statistic: 711.8 on 1 and 8068 DF,  p-value: < 2.2e-16
```

Holding police officers accountable for misconduct

```
##
## Call:
## lm(formula = p.account ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
```

```
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.9245 -0.7437  0.0104  0.7186  5.3517
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.38413    0.03404   40.67   <2e-16 ***
## rr_sc        1.37940    0.05189   26.58   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.168 on 8069 degrees of freedom
##   (22 observations deleted due to missingness)
## Multiple R-squared:  0.08052,    Adjusted R-squared:  0.0804
## F-statistic: 706.6 on 1 and 8069 DF,  p-value: < 2.2e-16
```

Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.41736 -0.14010 -0.00291  0.13851  1.17398
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.40508    0.00669   60.55   <2e-16 ***
## rr_sc        0.29807    0.01020   29.22   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2295 on 8065 degrees of freedom
##   (26 observations deleted due to missingness)
## Multiple R-squared:  0.09576,    Adjusted R-squared:  0.09564
## F-statistic:   854 on 1 and 8065 DF,  p-value: < 2.2e-16
```

White Linked Fate

Interestingly, whites' linked fate also appears to explain their evaluations of police. Higher levels of linked fate relate to worse evaluations of the police. Its influence also varies by outcome. Importantly, though, its effect seems relatively small. The effect for a min-max difference in linked fate is between 1/5 and 2/5 a category on the outcome. **Solving Crime**

```
##
## Call:
## lm(formula = p.crim.solve ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.0872 -0.4396 -0.1619  0.5938  4.3382
##
```

```
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.48510    0.01604 154.889   <2e-16 ***
## wht.lfate.sc -0.25617    0.02923  -8.763   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.018 on 8076 degrees of freedom
##   (15 observations deleted due to missingness)
## Multiple R-squared:  0.009419,   Adjusted R-squared:  0.009296
## F-statistic: 76.79 on 1 and 8076 DF,  p-value: < 2.2e-16
```

Protecting people like you from violent crime

```
##
## Call:
## lm(formula = p.viol.crim ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.2143 -0.5578  0.2513  0.4822  3.7746
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.69290    0.01615 166.768  < 2e-16 ***
## wht.lfate.sc -0.23389    0.02942  -7.949 2.13e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.024 on 8075 degrees of freedom
##   (16 observations deleted due to missingness)
## Multiple R-squared:  0.007765,   Adjusted R-squared:  0.007642
## F-statistic: 63.19 on 1 and 8075 DF,  p-value: 2.127e-15
```

Treating racial and ethnic groups equally

```
##
## Call:
## lm(formula = p.race.fair ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.8764 -0.7701 -0.0672  0.7663  5.0604
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.39902    0.01918  125.07   <2e-16 ***
## wht.lfate.sc -0.46494    0.03493  -13.31   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.216 on 8075 degrees of freedom
##   (16 observations deleted due to missingness)
## Multiple R-squared:  0.02148,    Adjusted R-squared:  0.02135
```

```
## F-statistic: 177.2 on 1 and 8075 DF,  p-value: < 2.2e-16
```

Not using excessive force on suspects

```
##
## Call:
## lm(formula = p.exces.force ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.9980 -0.7302 -0.1212  0.7036  4.8189
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.44867    0.01838  133.25   <2e-16 ***
## wht.lfate.sc -0.41599    0.03348  -12.43   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.165 on 8075 degrees of freedom
##   (16 observations deleted due to missingness)
## Multiple R-squared:  0.01876,    Adjusted R-squared:  0.01864
## F-statistic: 154.4 on 1 and 8075 DF,  p-value: < 2.2e-16
```

Holding police officers accountable for misconduct

```
##
## Call:
## lm(formula = p.account ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.8450 -0.7790 -0.0719  0.7473  4.9983
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.38622    0.01903  125.42   <2e-16 ***
## wht.lfate.sc -0.42677    0.03466  -12.31   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.207 on 8076 degrees of freedom
##   (15 observations deleted due to missingness)
## Multiple R-squared:  0.01842,    Adjusted R-squared:  0.0183
## F-statistic: 151.6 on 1 and 8076 DF,  p-value: < 2.2e-16
```

Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -1.39769 -0.14901 -0.00888  0.14653  1.14930
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.620606   0.003766  164.81   <2e-16 ***
## wht.lfate.sc -0.089807   0.006860  -13.09   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2387 on 8072 degrees of freedom
##   (19 observations deleted due to missingness)
## Multiple R-squared:  0.02079,    Adjusted R-squared:  0.02067
## F-statistic: 171.4 on 1 and 8072 DF,  p-value: < 2.2e-16
```

Black Linked Fate

The pattern of results is similar when looking at blacks' linked fate. The effects vary between 1/5 and 3/5 a scale point. Higher levels of linked fate relate to worse evaluations of the police. **Solving Crime**

```
##
## Call:
## lm(formula = p.crim.solve ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5564 -0.7118  0.1718  0.4441  5.7933
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.86014    0.03178  58.537  < 2e-16 ***
## blk.lfate.sc -0.22526    0.05049  -4.461 8.43e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.133 on 3067 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.006448,   Adjusted R-squared:  0.006124
## F-statistic:  19.9 on 1 and 3067 DF,  p-value: 8.434e-06
```

Protecting people like you from violent crime

```
##
## Call:
## lm(formula = p.viol.crim ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -4.7888 -0.8231  0.0498  0.7389  6.0492
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.95503    0.03311  59.048  < 2e-16 ***
## blk.lfate.sc -0.42462    0.05260  -8.072  9.8e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.181 on 3066 degrees of freedom
##   (5 observations deleted due to missingness)
## Multiple R-squared:  0.02081,    Adjusted R-squared:  0.02049
## F-statistic: 65.16 on 1 and 3066 DF,  p-value: 9.802e-16
```

Treating racial and ethnic groups equally

```
##
## Call:
## lm(formula = p.race.fair ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5388 -0.8975 -0.2611  0.7437  7.4754
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.44469    0.03410  42.365   <2e-16 ***
## blk.lfate.sc -0.49650    0.05418  -9.164   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.216 on 3066 degrees of freedom
##   (5 observations deleted due to missingness)
## Multiple R-squared:  0.02666,    Adjusted R-squared:  0.02634
## F-statistic: 83.98 on 1 and 3066 DF,  p-value: < 2.2e-16
```

Not using excessive force on suspects

```
##
## Call:
## lm(formula = p.exces.force ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.7931 -0.9635 -0.2306  0.6640  6.8222
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.54853    0.03436   45.06  < 2e-16 ***
## blk.lfate.sc -0.33366    0.05460   -6.11 1.12e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.225 on 3064 degrees of freedom
##   (7 observations deleted due to missingness)
## Multiple R-squared:  0.01204,    Adjusted R-squared:  0.01172
## F-statistic: 37.34 on 1 and 3064 DF,  p-value: 1.119e-09
```

Holding police officers accountable for misconduct

```
##
```

```
## Call:
## lm(formula = p.account ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.4667 -0.9531 -0.2561  0.7404  7.3314
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.41526    0.03515   40.27  < 2e-16 ***
## blk.lfate.sc -0.40827    0.05585   -7.31 3.39e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.253 on 3065 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.01714,    Adjusted R-squared:  0.01681
## F-statistic: 53.43 on 1 and 3065 DF,  p-value: 3.395e-13
```

Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -0.85341 -0.18239 -0.03423  0.13357  1.67286
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.411097   0.007053  58.283   <2e-16 ***
## blk.lfate.sc -0.094038   0.011210  -8.389   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2515 on 3063 degrees of freedom
##   (8 observations deleted due to missingness)
## Multiple R-squared:  0.02246,    Adjusted R-squared:  0.02214
## F-statistic: 70.37 on 1 and 3063 DF,  p-value: < 2.2e-16
```

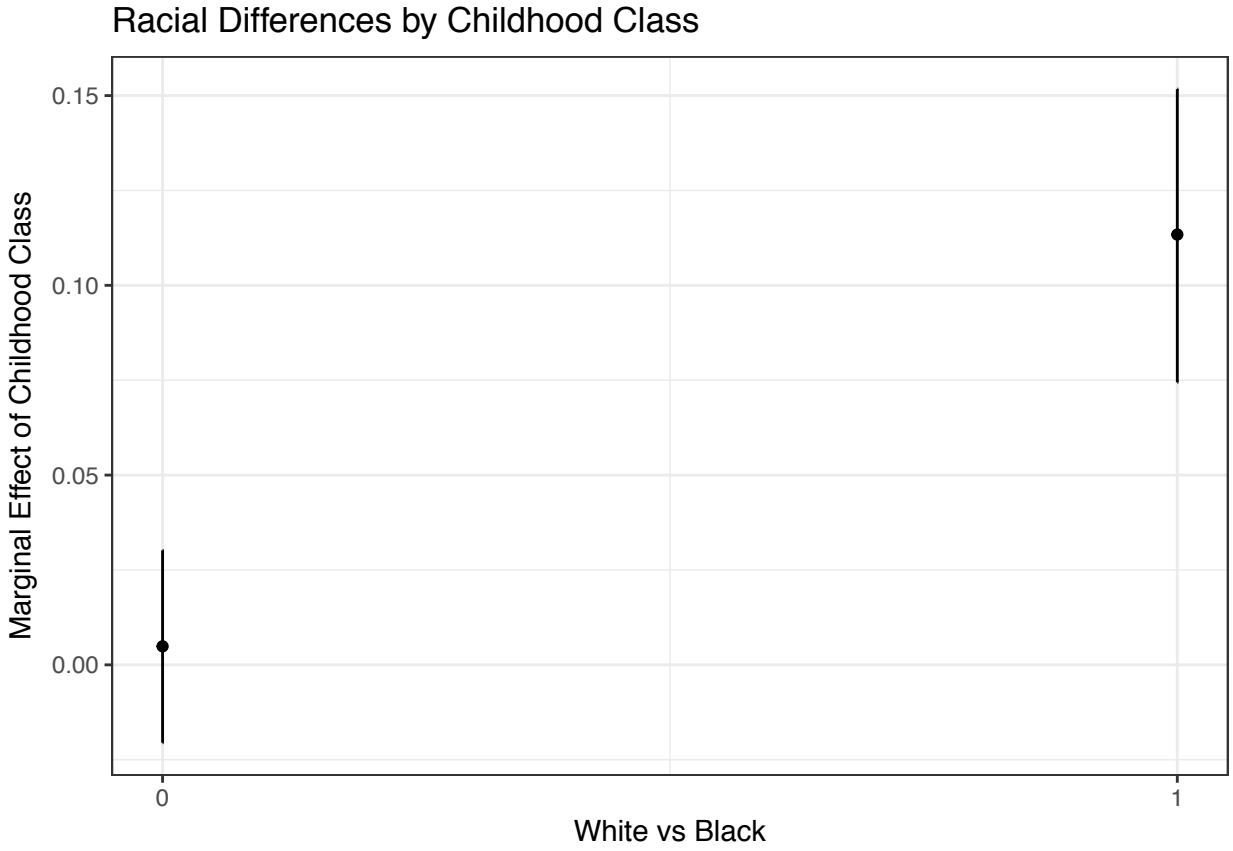
Class Fragility

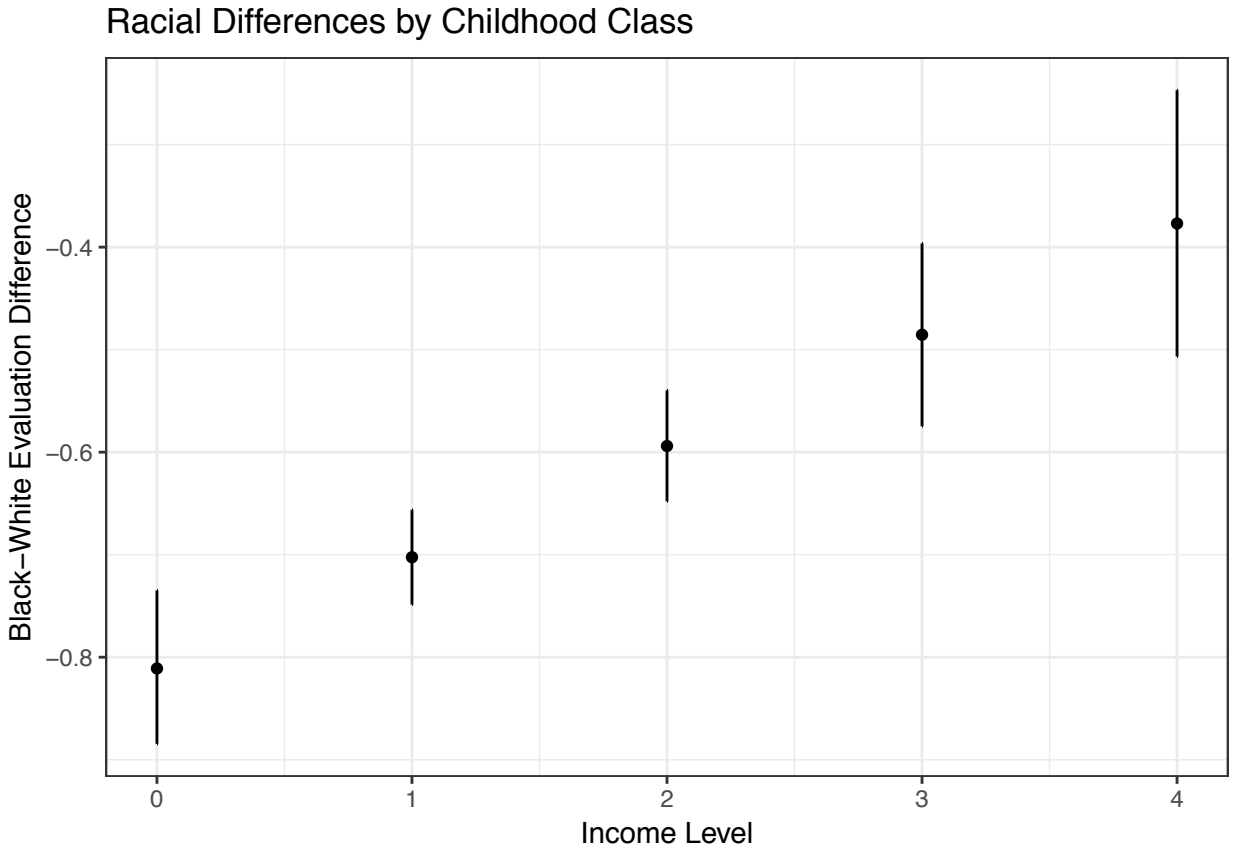
Family class growing up

Exploring variation in class background as measured by childhood class background offers some interesting insights. Class operationalized this way matters for police evaluations, btu only systematically for black respondents. Higher class black respondents evaluate the police more positively on all outcomes. **Solving Crime**

```
##
## Call:
## lm(formula = p.crim.solve ~ chood.class * black, data = cjs.df,
```

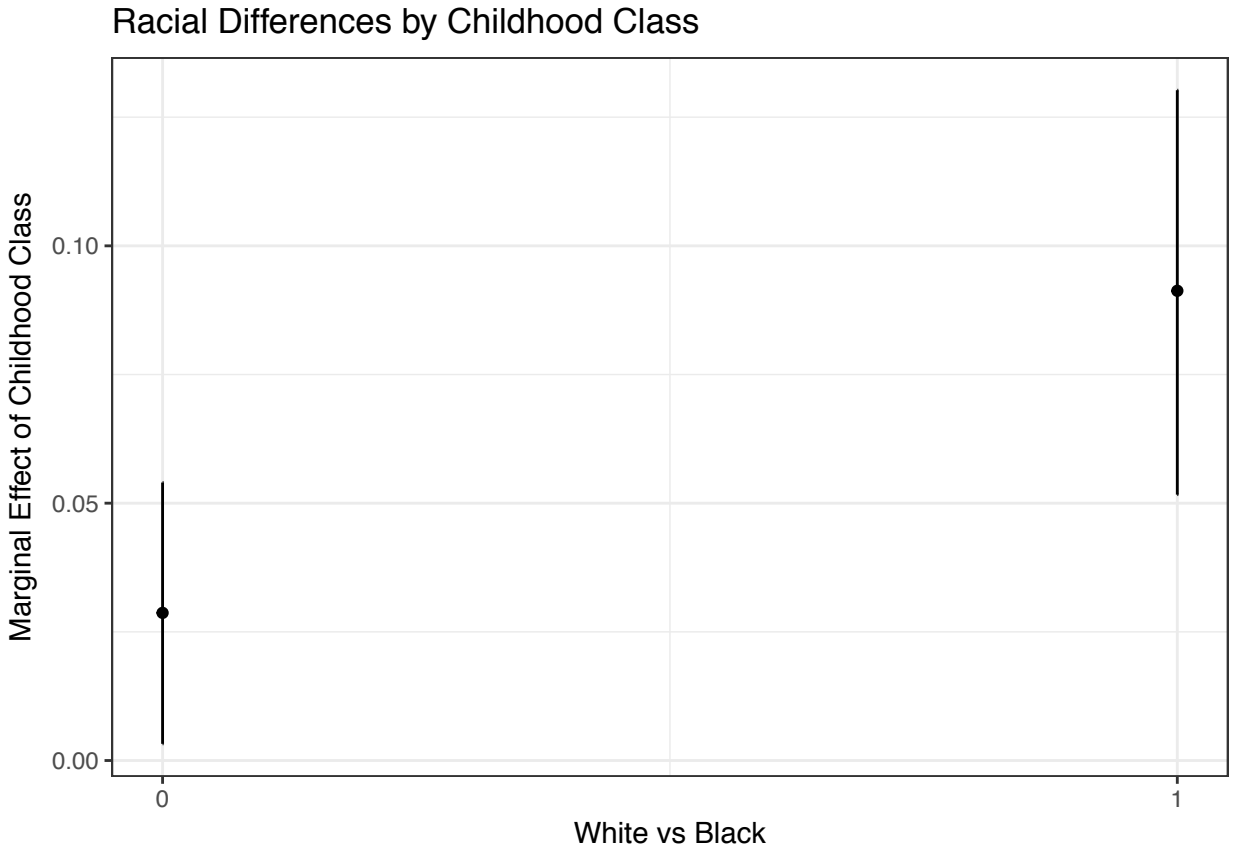
```
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.9414 -0.5132  0.1271  0.5706  5.3392
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.404416   0.021334 112.704  < 2e-16 ***
## chood.class        0.005288   0.012492   0.423    0.672
## black             -0.810002   0.037656 -21.510  < 2e-16 ***
## chood.class:black  0.107653   0.023137   4.653 3.31e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.05 on 11153 degrees of freedom
##   (9 observations deleted due to missingness)
## Multiple R-squared:  0.07826,    Adjusted R-squared:  0.07802
## F-statistic: 315.7 on 3 and 11153 DF,  p-value: < 2.2e-16
```

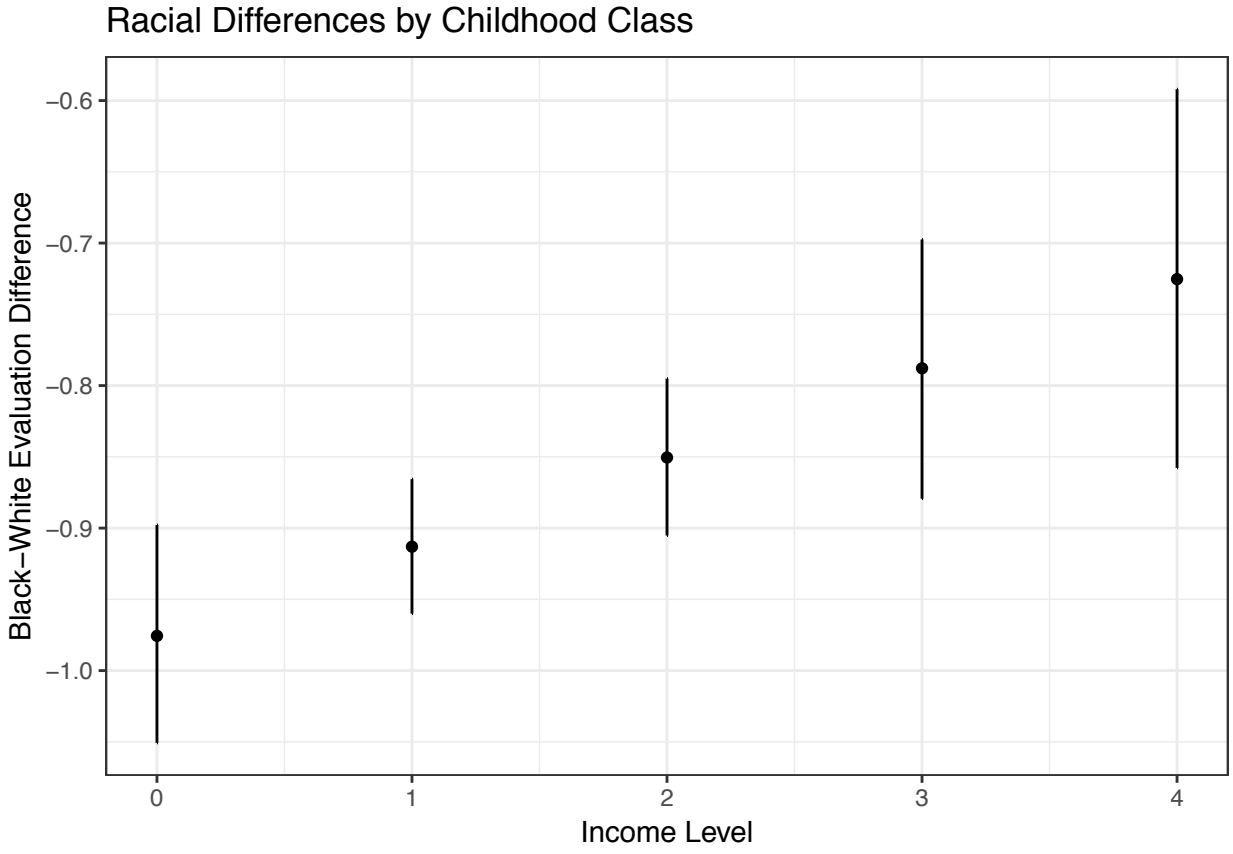




Protecting people like you from violent crime

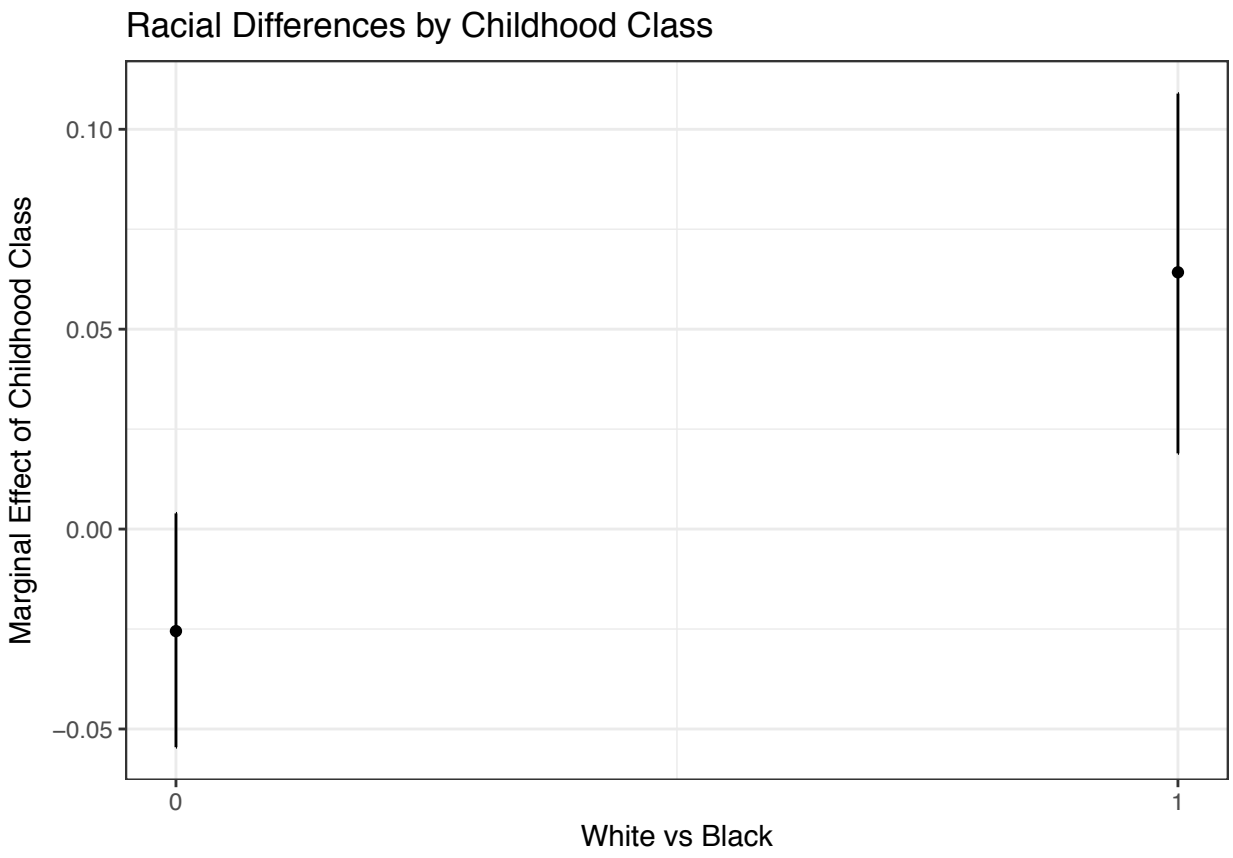
```
##
## Call:
## lm(formula = p.viol.crim ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.5442 -0.6163  0.2528  0.4628  5.6326
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)         2.58434    0.02171 119.054  < 2e-16 ***
## chood.class         0.02910    0.01271   2.290  0.02206 *
## black              -0.97463    0.03832 -25.436  < 2e-16 ***
## chood.class:black   0.06170    0.02354   2.621  0.00879 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.069 on 11151 degrees of freedom
##   (11 observations deleted due to missingness)
## Multiple R-squared:  0.1254, Adjusted R-squared:  0.1251
## F-statistic: 532.8 on 3 and 11151 DF,  p-value: < 2.2e-16
```

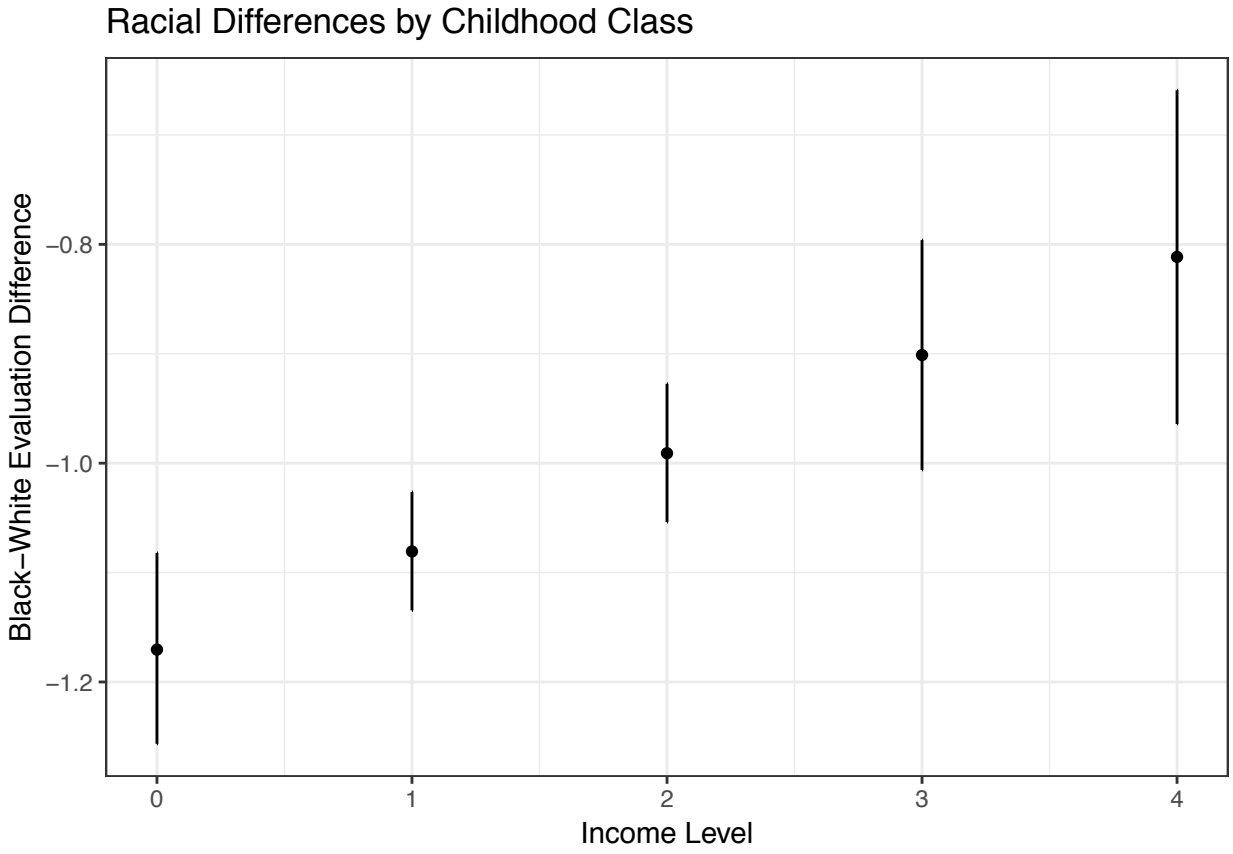

Racial Differences by Childhood Class
Marginal Effect of Childhood Class
0.10
0.05
0.00
0
1
White vs Black


Racial Differences by Childhood Class
Black–White Evaluation Difference
−0.6
−0.7
−0.8
−0.9
−1.0
0
1
2
3
4
Income Level

Treating racial and ethnic groups equally

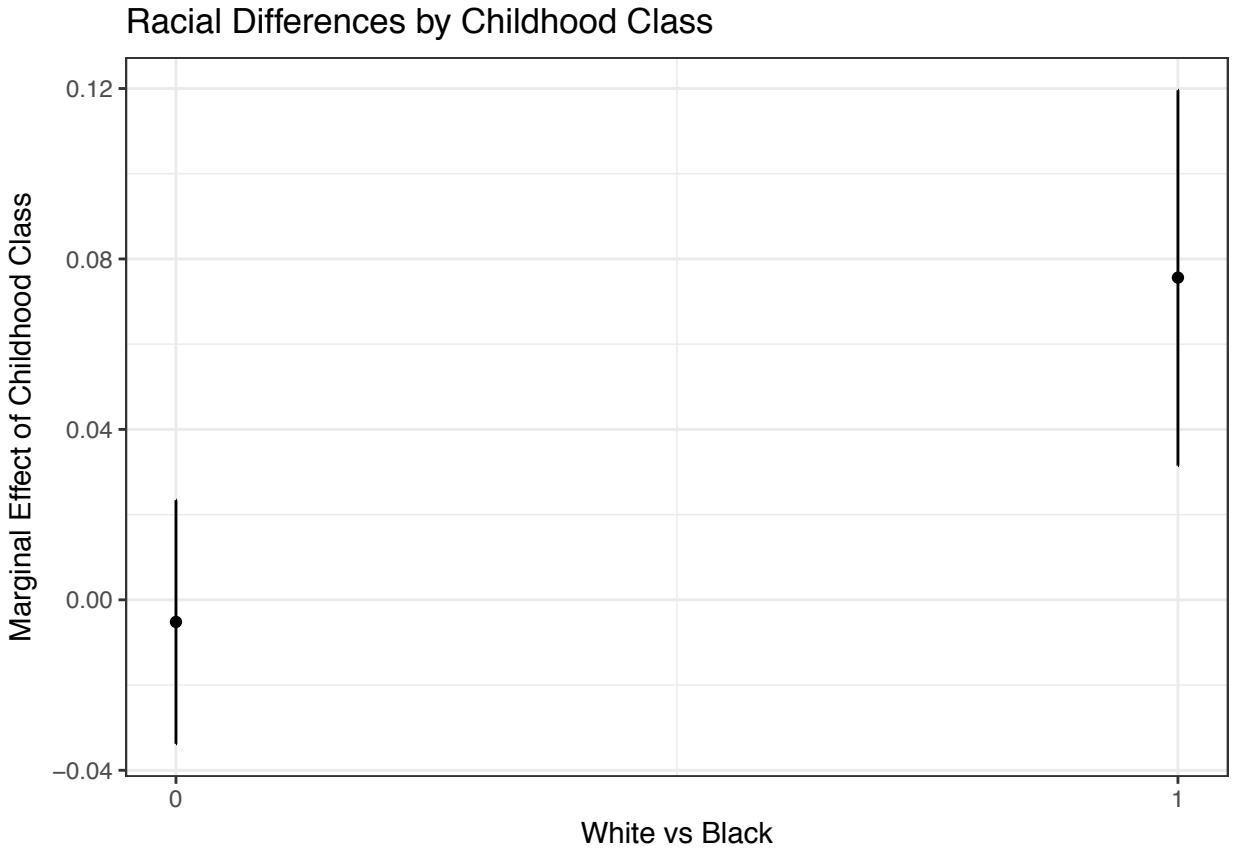
```
##
## Call:
## lm(formula = p.race.fair ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5731 -0.8839 -0.1768  0.7534  6.7773
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.27521    0.02489  91.396  < 2e-16 ***
## chood.class       -0.02513    0.01456  -1.726  0.08441 .
## black             -1.16920    0.04396 -26.600  < 2e-16 ***
## chood.class:black  0.08871    0.02700   3.286  0.00102 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.226 on 11151 degrees of freedom
##   (11 observations deleted due to missingness)
## Multiple R-squared:  0.1281, Adjusted R-squared:  0.1279
## F-statistic: 546.3 on 3 and 11151 DF,  p-value: < 2.2e-16
```

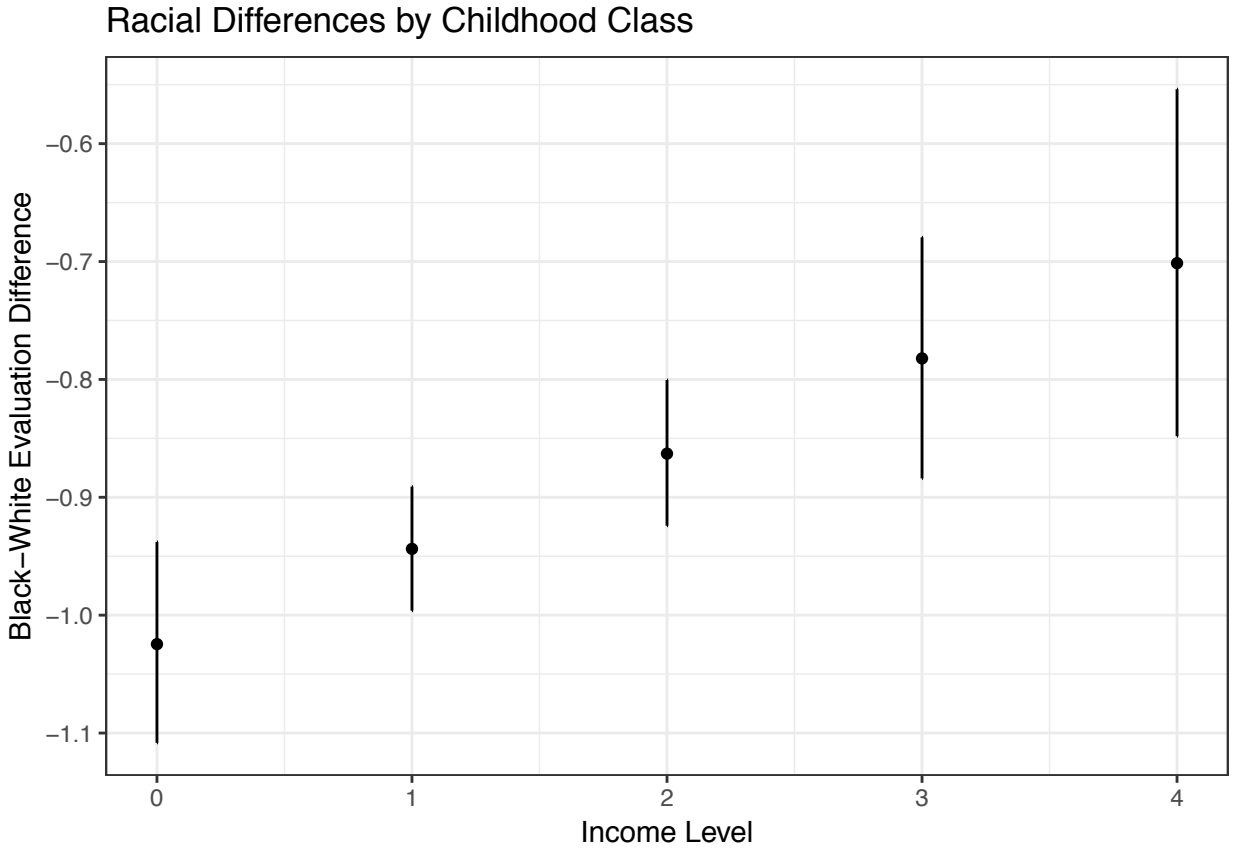




Not using excessive force on suspects

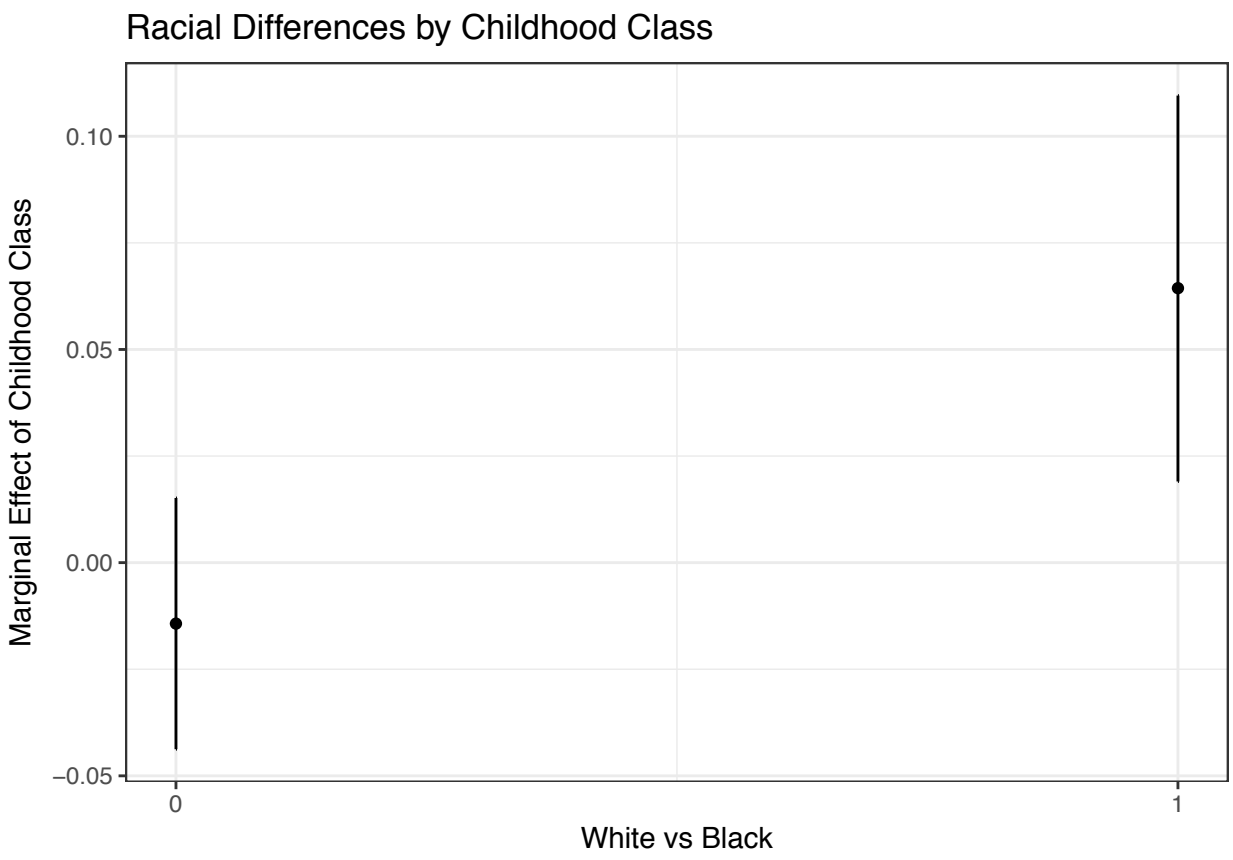
```
##
## Call:
## lm(formula = p.exces.force ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.6701 -0.9264 -0.2193  0.6876  6.2666
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.314826   0.024213  95.604  < 2e-16 ***
## chood.class       -0.004691   0.014176  -0.331  0.74073
## black             -1.023465   0.042735 -23.949  < 2e-16 ***
## chood.class:black  0.079852   0.026255   3.041  0.00236 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.192 on 11149 degrees of freedom
##   (13 observations deleted due to missingness)
## Multiple R-squared:  0.1068, Adjusted R-squared:  0.1065
## F-statistic: 444.2 on 3 and 11149 DF,  p-value: < 2.2e-16
```

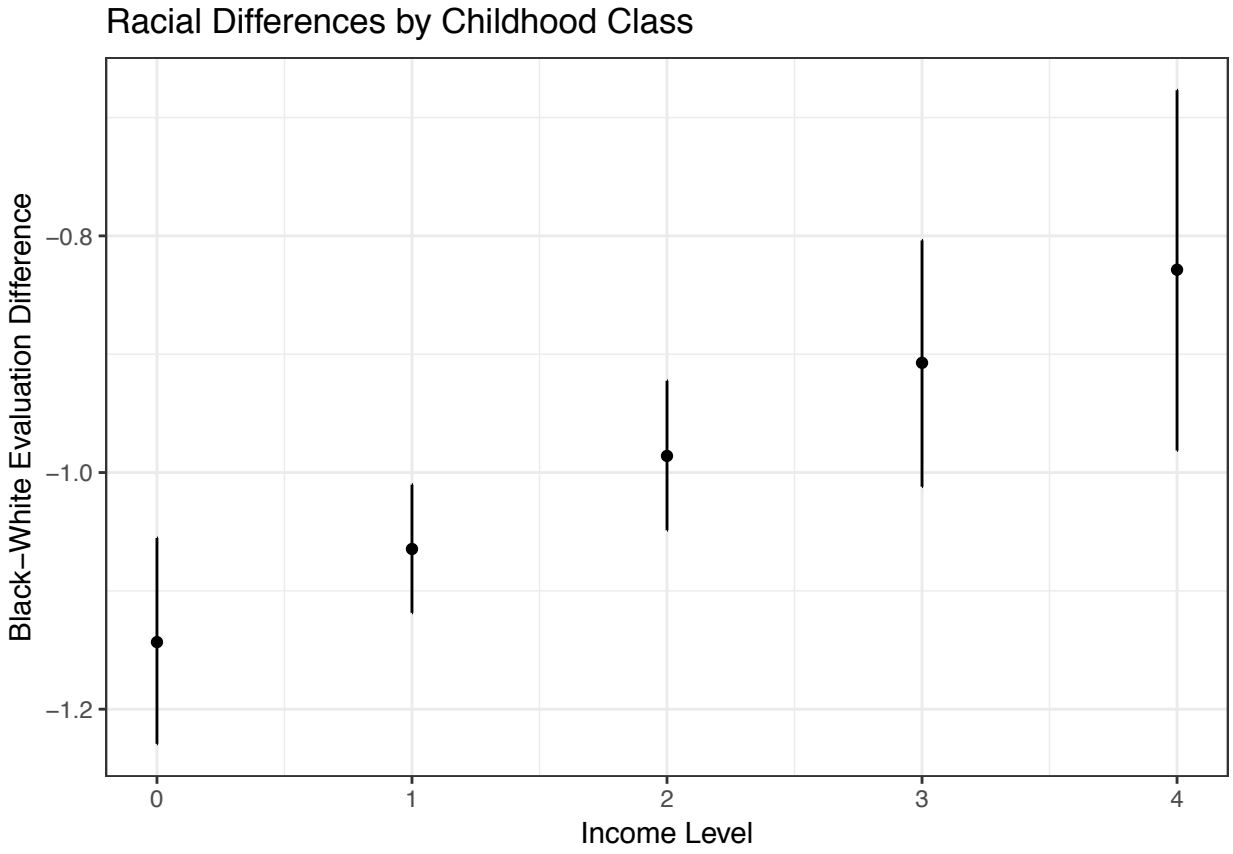

Racial Differences by Childhood Class
Marginal Effect of Childhood Class
0.12
0.08
0.04
0.00
−0.04
0
1
White vs Black


Racial Differences by Childhood Class
Black−White Evaluation Difference
−0.6
−0.7
−0.8
−0.9
−1.0
−1.1
0
1
2
3
4
Income Level

Holding police officers accountable for misconduct

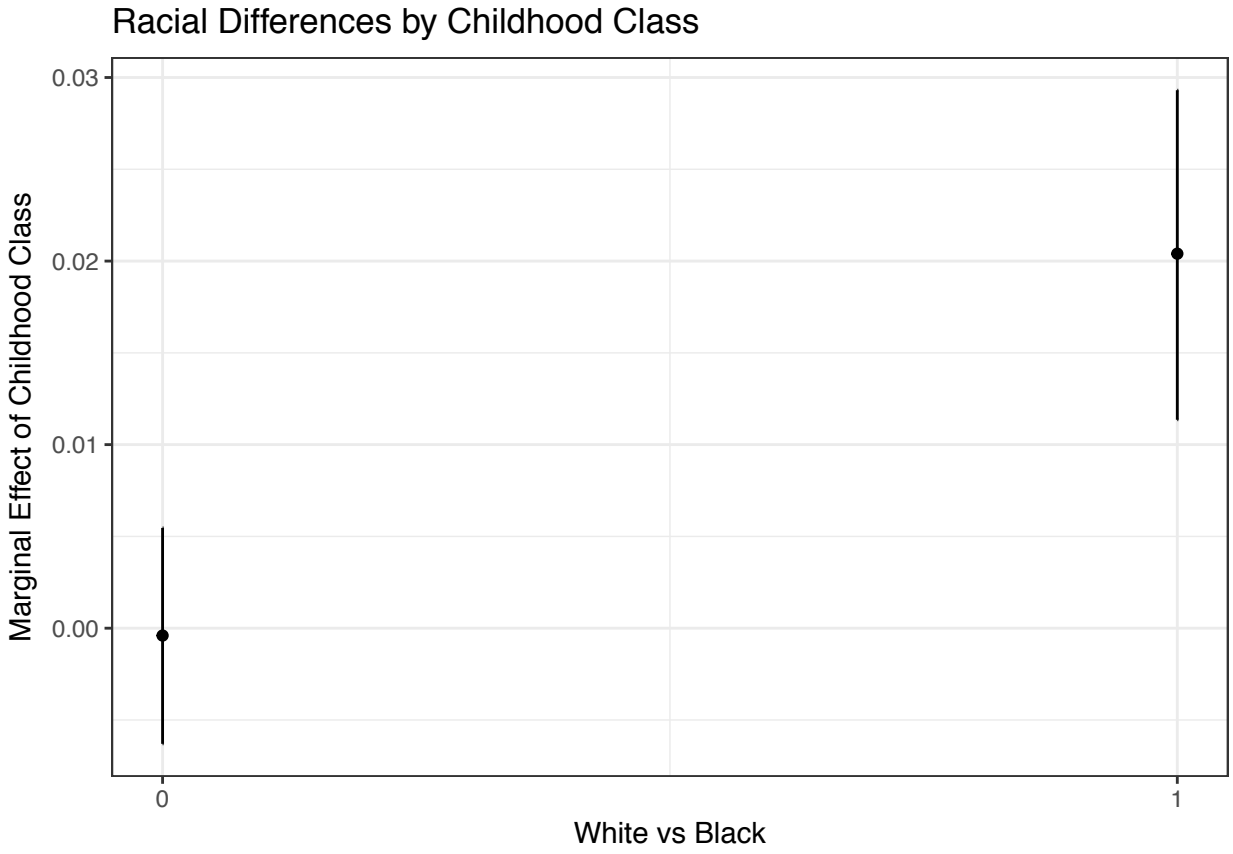
```
##
## Call:
## lm(formula = p.account ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5634 -0.8892 -0.1821  0.7361  6.7187
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.27125    0.02487  91.318  < 2e-16 ***
## chood.class       -0.01367    0.01456  -0.939  0.34776
## black             -1.14225    0.04391 -26.016  < 2e-16 ***
## chood.class:black  0.07773    0.02697   2.882  0.00396 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.225 on 11151 degrees of freedom
##   (11 observations deleted due to missingness)
## Multiple R-squared:  0.1259, Adjusted R-squared:  0.1257
## F-statistic: 535.6 on 3 and 11151 DF,  p-value: < 2.2e-16
```

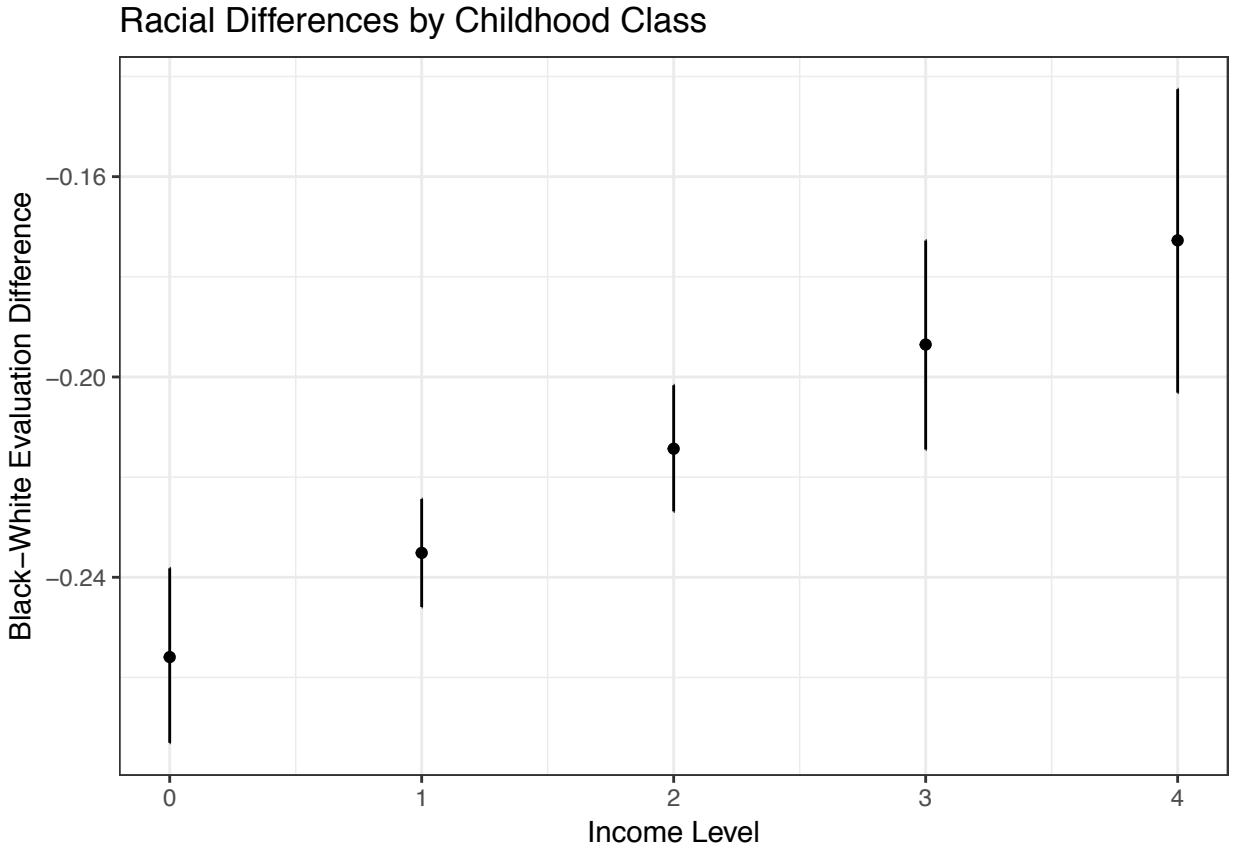




Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.32687 -0.17072 -0.00784  0.14453  1.52548
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.5923258  0.0049574 119.484  < 2e-16 ***
## chood.class       -0.0003172  0.0029023  -0.109 0.912961
## black             -0.2556859  0.0087489 -29.225  < 2e-16 ***
## chood.class:black  0.0206092  0.0053749   3.834 0.000127 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.244 on 11145 degrees of freedom
##   (17 observations deleted due to missingness)
## Multiple R-squared:  0.1506, Adjusted R-squared:  0.1503
## F-statistic: 658.5 on 3 and 11145 DF,  p-value: < 2.2e-16
```

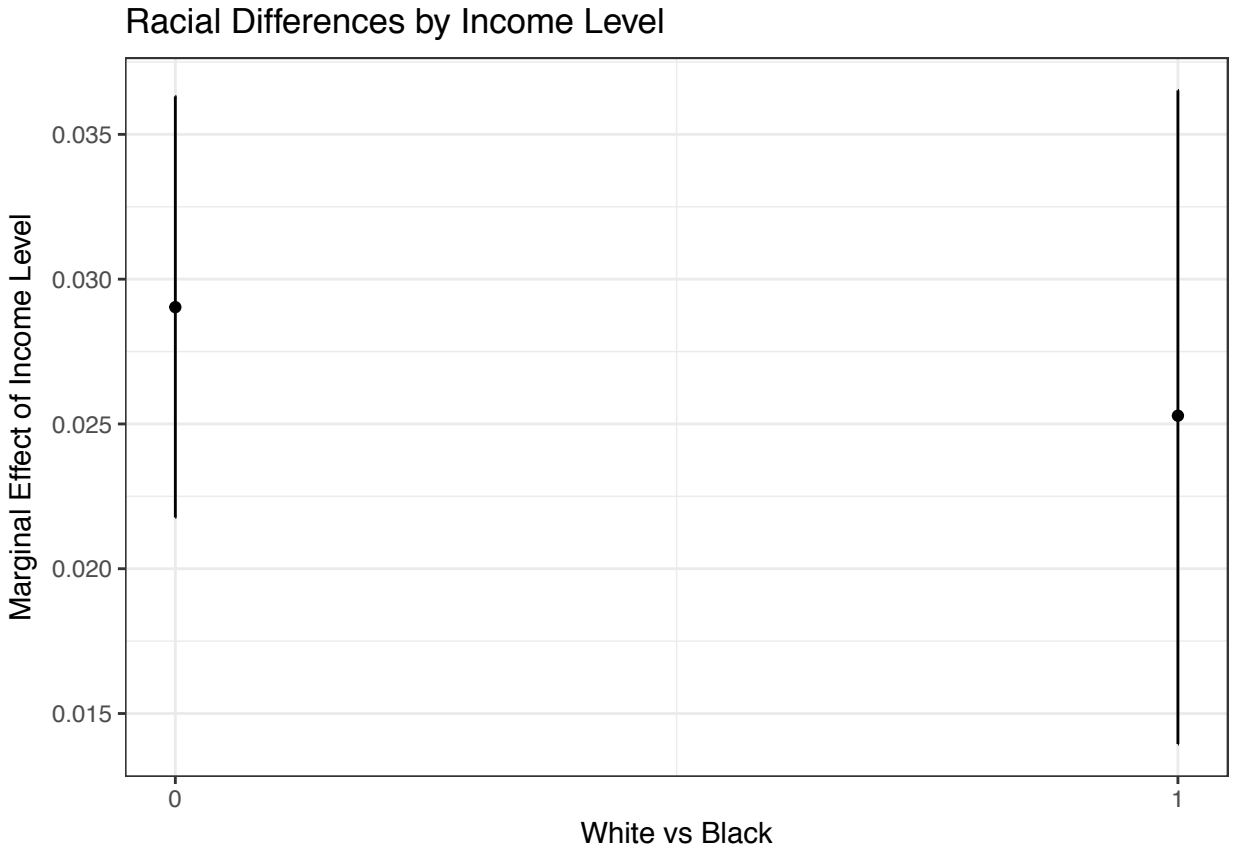

Racial Differences by Childhood Class
Marginal Effect of Childhood Class
0.03
0.02
0.01
0.00
0
1
White vs Black

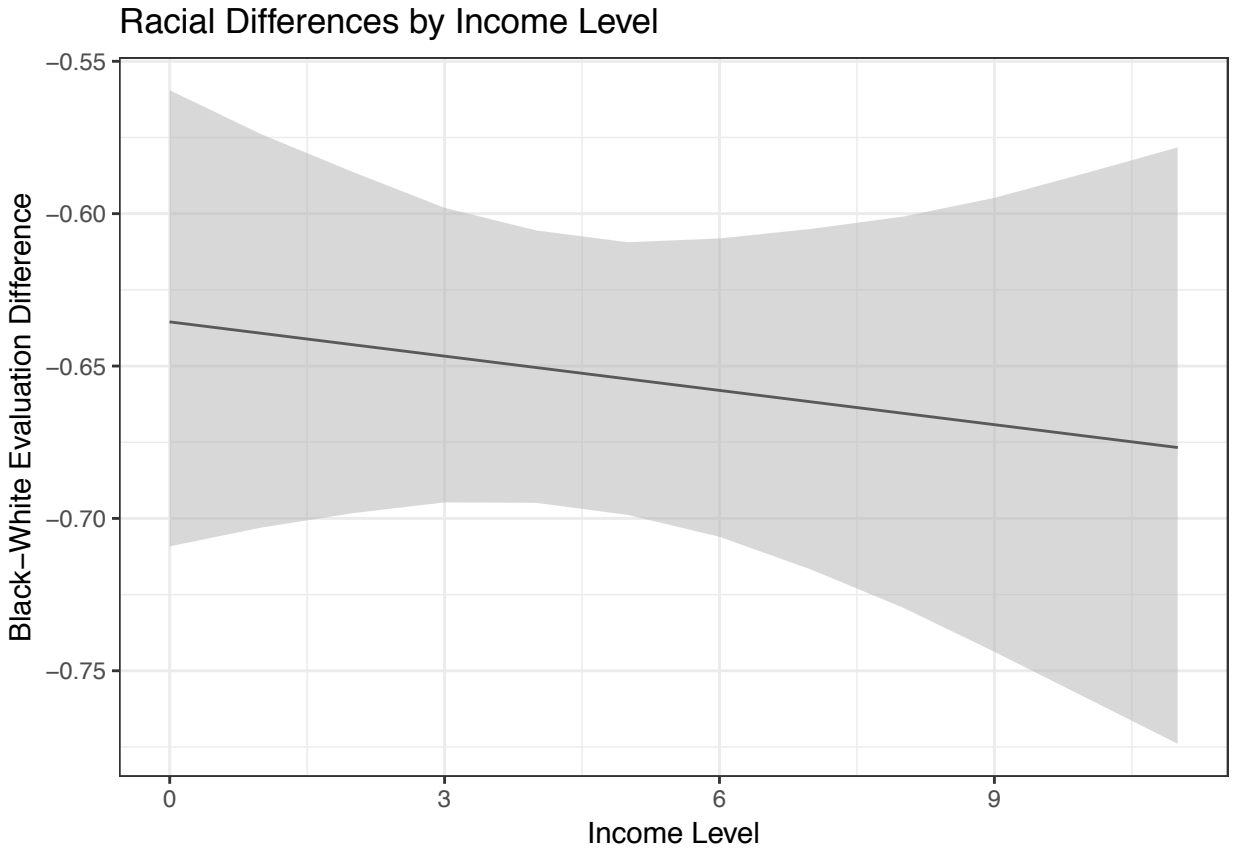

Racial Differences by Childhood Class
Black–White Evaluation Difference
−0.16
−0.20
−0.24
0
1
2
3
4
Income Level

Current income

As measured by income, class fragility also seems to matter on some outcomes. Higher income individuals tend to evaluate the police more positively, but this seems more influetial for whites. **Solving Crime**

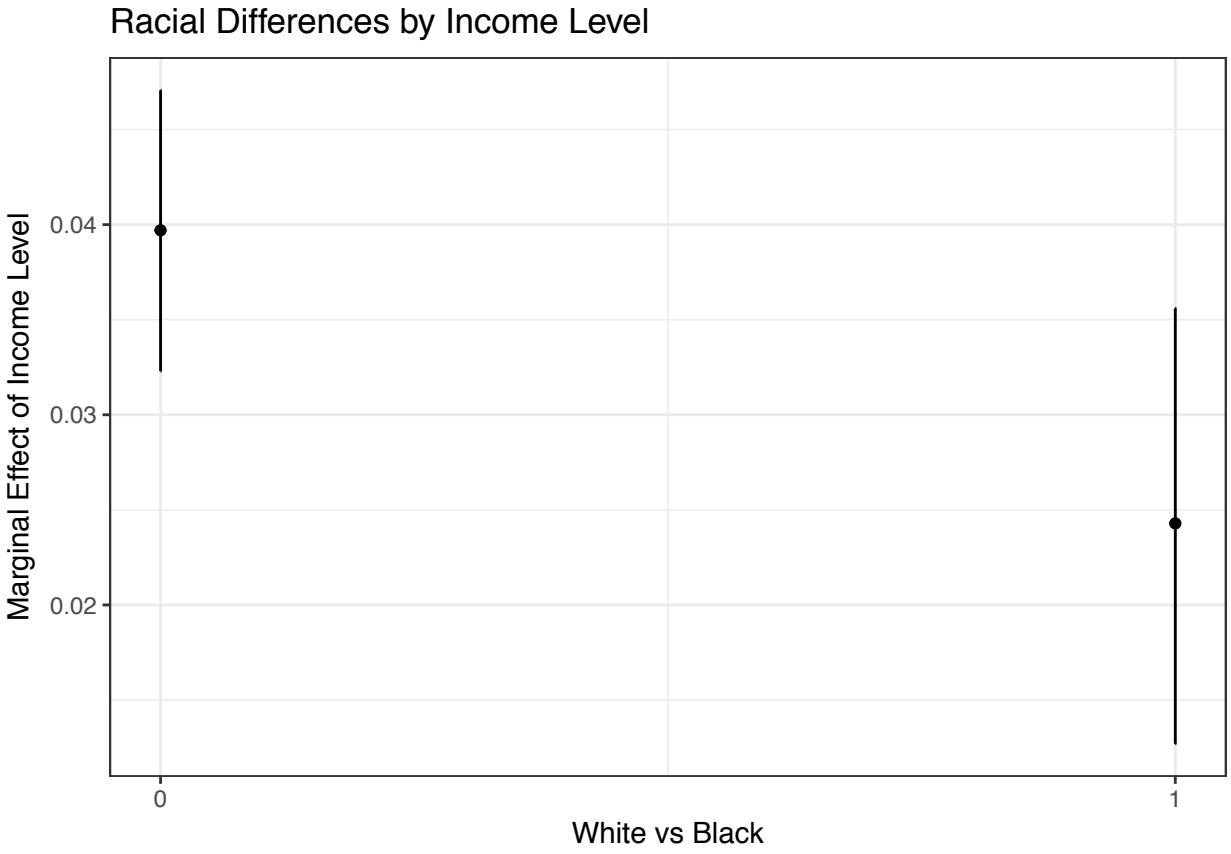
```
##
## Call:
## lm(formula = p.crim.solve ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.3285 -0.5333  0.1382  0.5750  5.2546
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.262919   0.021782 103.888  < 2e-16 ***
## inc          0.029151   0.003607   8.083 6.98e-16 ***
## black       -0.634405   0.037770 -16.796  < 2e-16 ***
## inc:black   -0.004004   0.006738  -0.594    0.552
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.048 on 11156 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.08251,    Adjusted R-squared:  0.08226
## F-statistic: 334.4 on 3 and 11156 DF,  p-value: < 2.2e-16
```

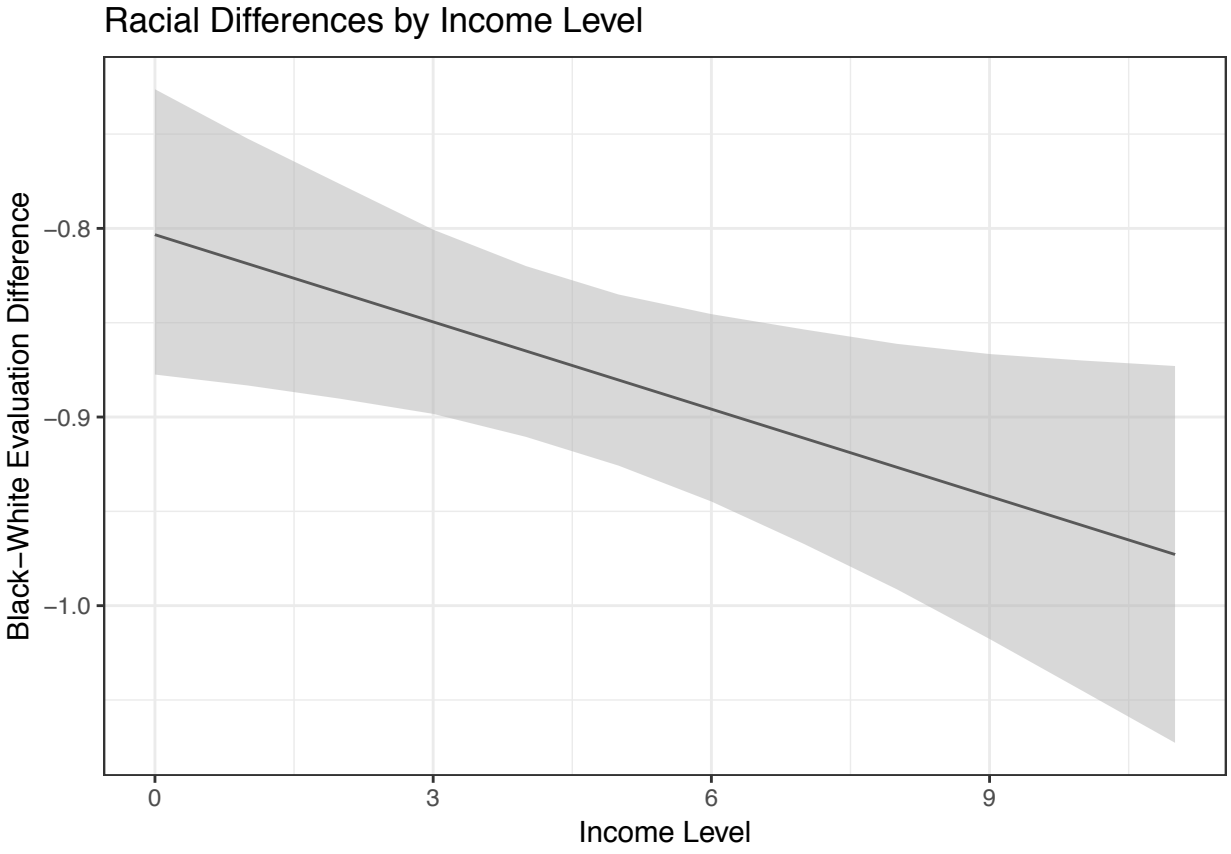




Protecting people like you from violent crime

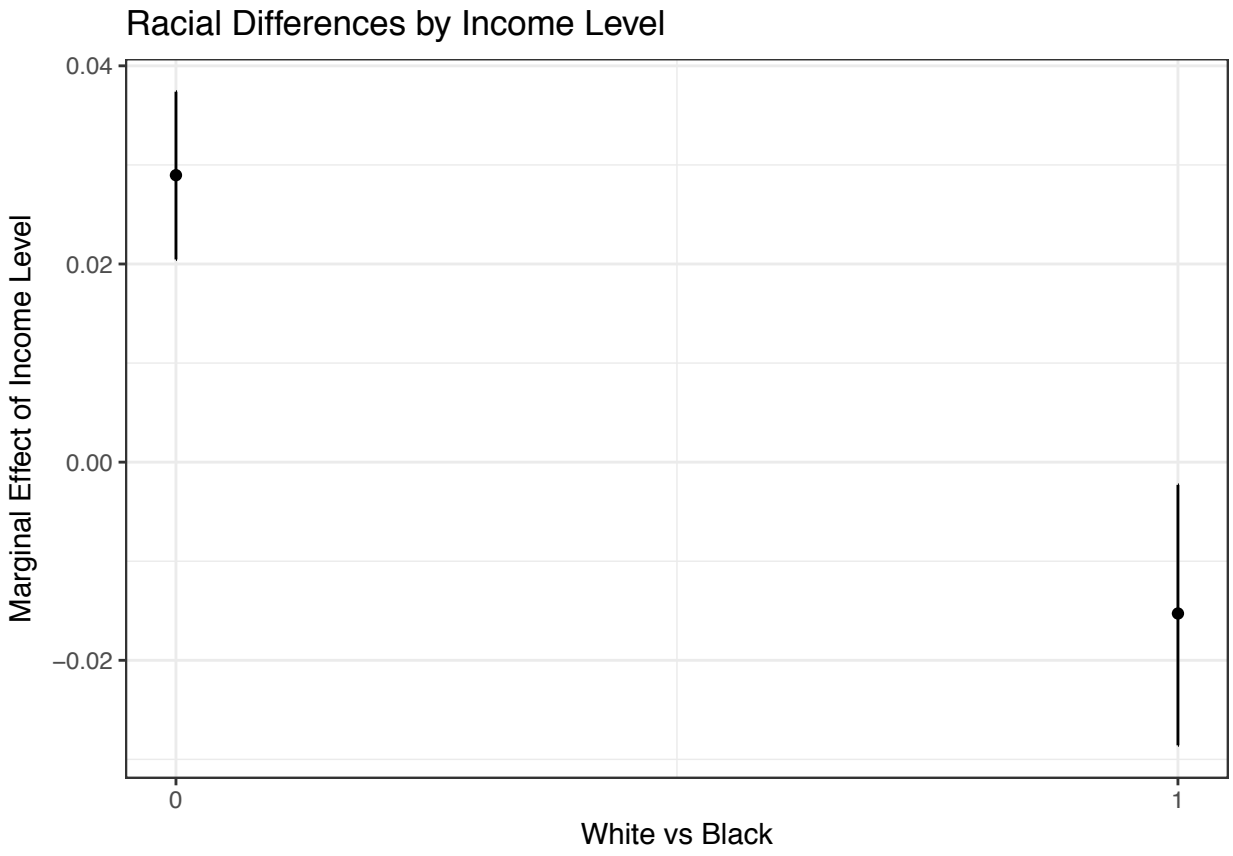
```
##
## Call:
## lm(formula = p.viol.crim ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.5189 -0.5908  0.2344  0.4729  5.3556
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.422358   0.022106 109.582   <2e-16 ***
## inc          0.039830   0.003660  10.882   <2e-16 ***
## black       -0.802259   0.038336 -20.927   <2e-16 ***
## inc:black   -0.015645   0.006838  -2.288   0.0222 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.064 on 11154 degrees of freedom
##   (8 observations deleted due to missingness)
## Multiple R-squared:  0.1339, Adjusted R-squared:  0.1337
## F-statistic:   575 on 3 and 11154 DF,  p-value: < 2.2e-16
```

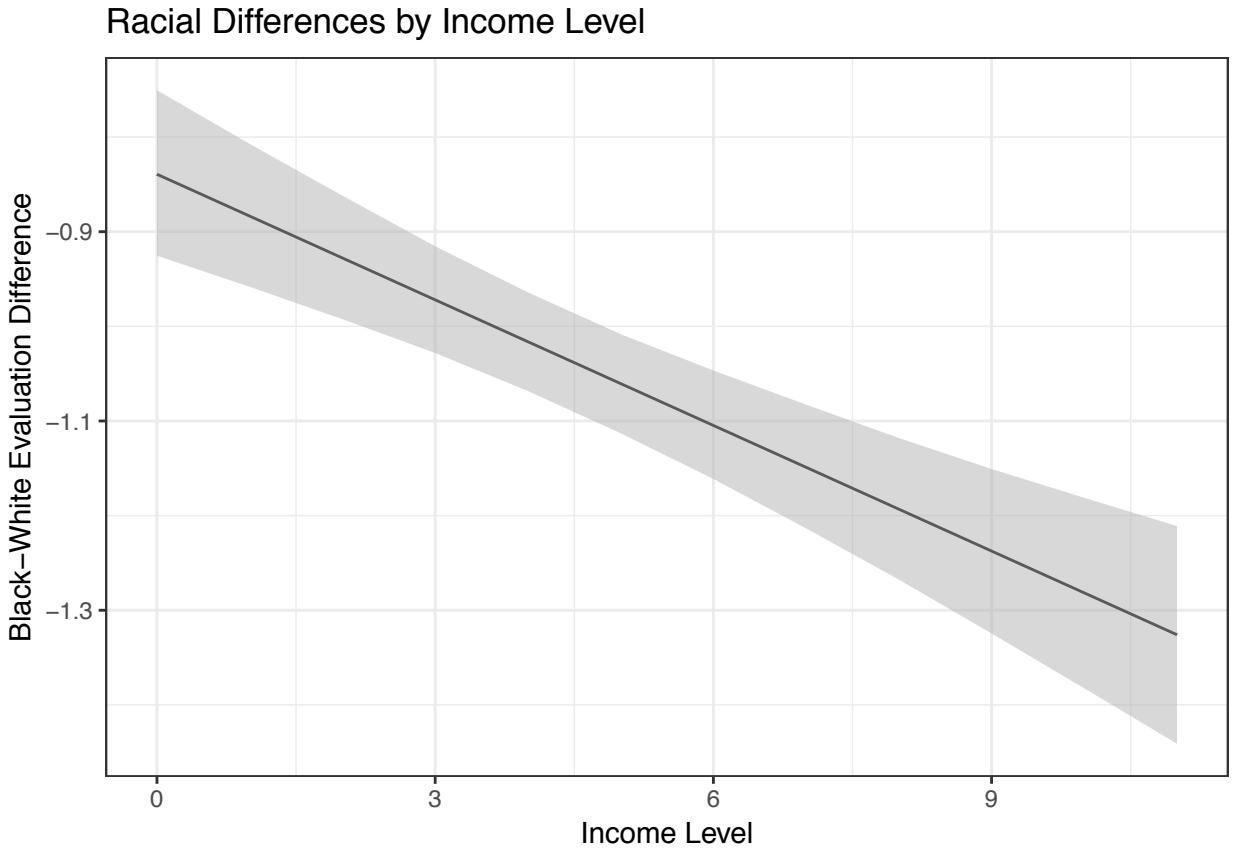

Racial Differences by Income Level
Marginal Effect of Income Level
0.04
0.03
0.02
0
1
White vs Black


Racial Differences by Income Level
Black–White Evaluation Difference
−0.8
−0.9
−1.0
0
3
6
9
Income Level

Treating racial and ethnic groups equally

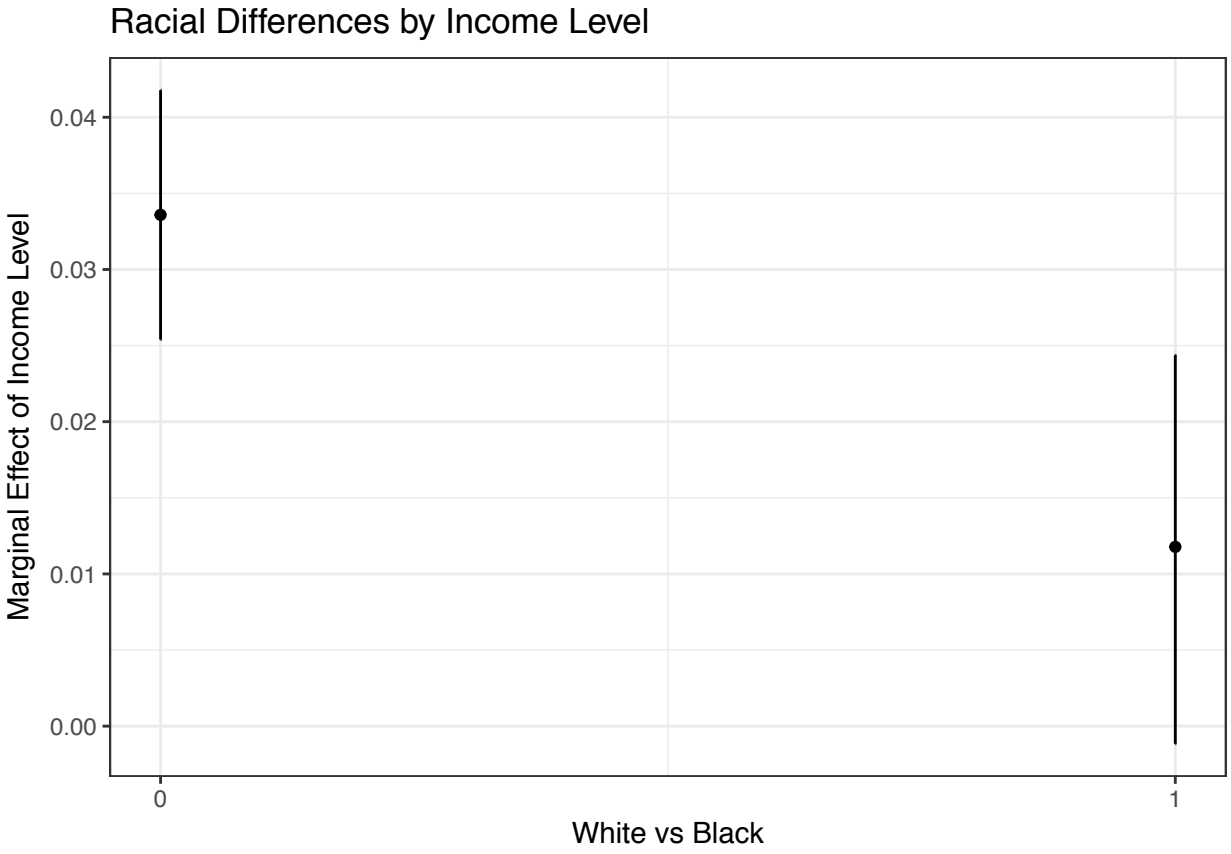
```
##
## Call:
## lm(formula = p.race.fair ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.9044 -0.8869 -0.1442  0.7451  7.1458
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.090297   0.025448  82.140  < 2e-16 ***
## inc          0.029107   0.004211   6.912 5.03e-12 ***
## black       -0.838035   0.044124 -18.993  < 2e-16 ***
## inc:black   -0.044518   0.007869  -5.657 1.58e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.224 on 11154 degrees of freedom
##   (8 observations deleted due to missingness)
## Multiple R-squared:  0.1313, Adjusted R-squared:  0.131
## F-statistic: 561.7 on 3 and 11154 DF,  p-value: < 2.2e-16
```

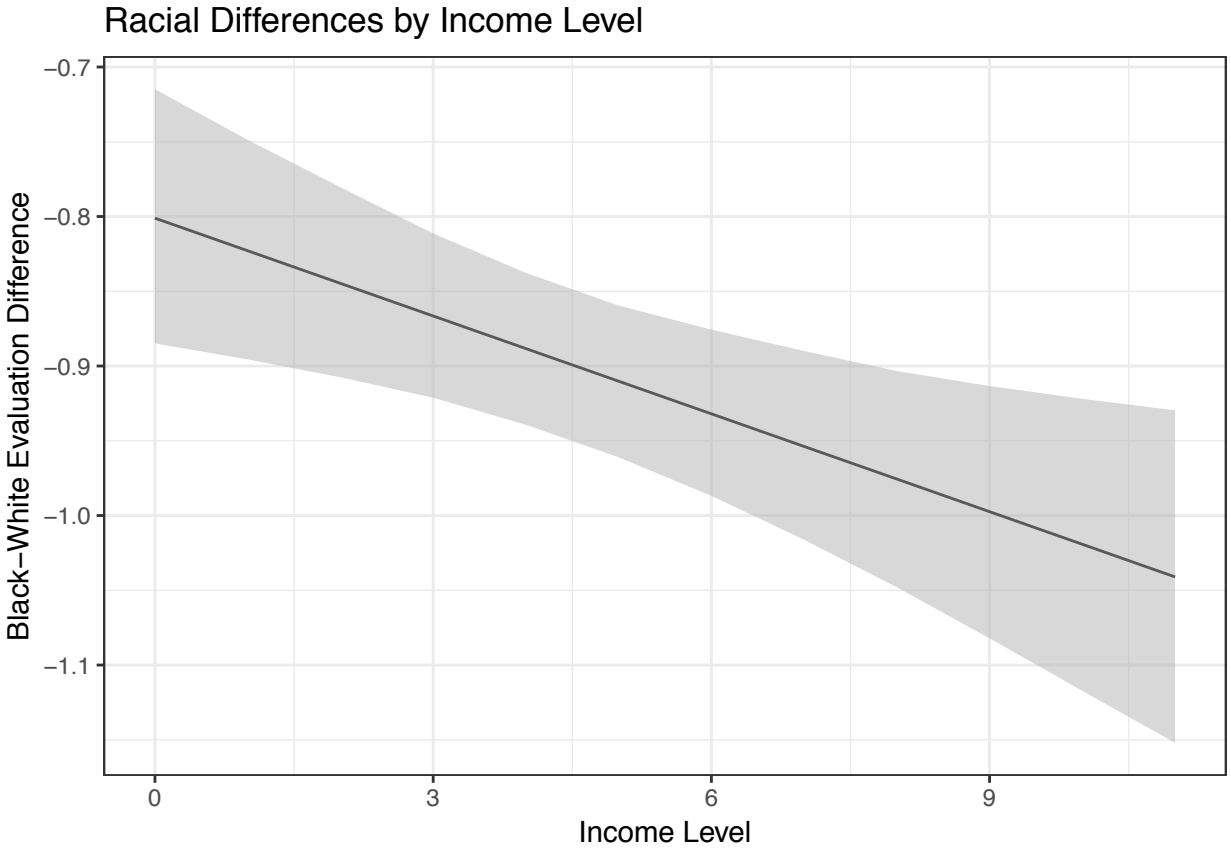




Not using excessive force on suspects

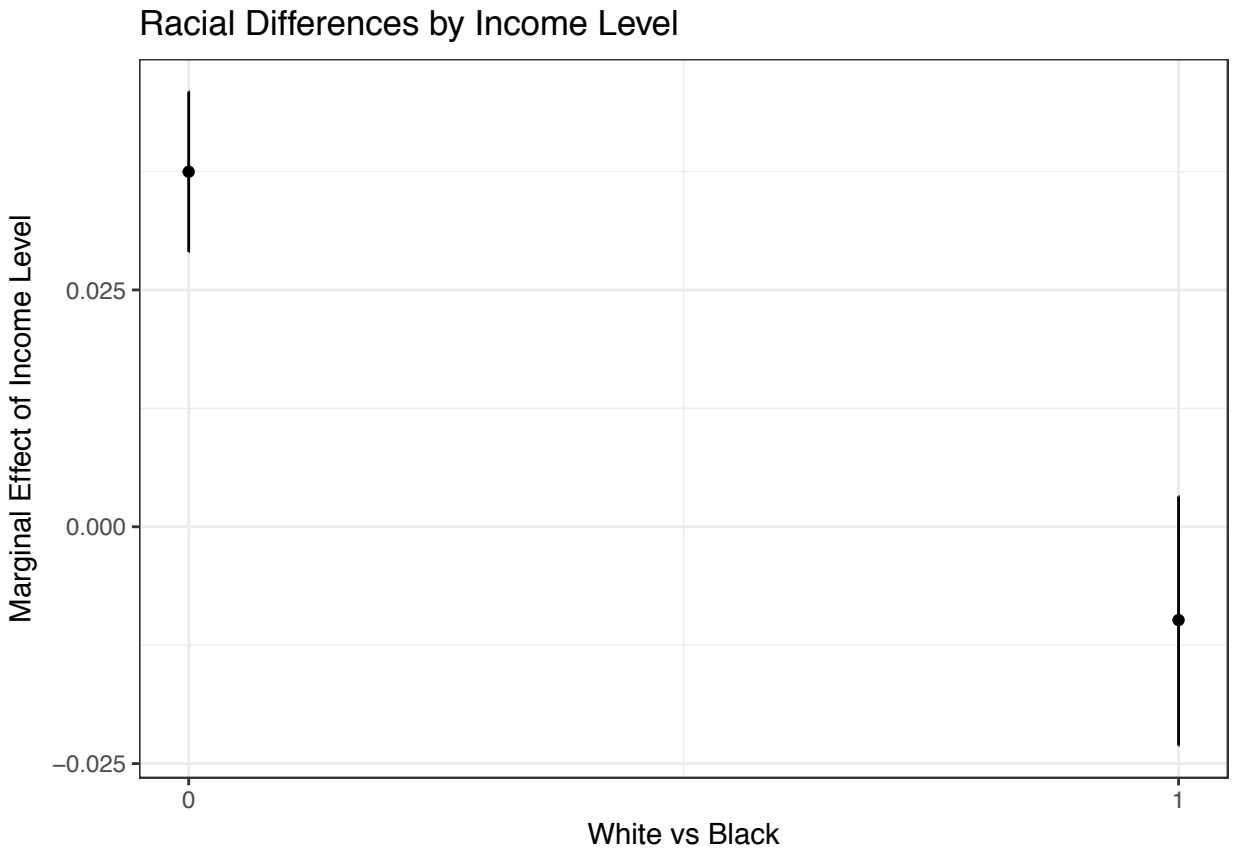
```
##
## Call:
## lm(formula = p.exces.force ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.1400 -0.9223 -0.1675  0.6859  6.2981
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.135674   0.024710  86.429  < 2e-16 ***
## inc          0.033724   0.004091   8.244  < 2e-16 ***
## black       -0.799849   0.042854 -18.665  < 2e-16 ***
## inc:black   -0.022099   0.007643  -2.891  0.00384 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.189 on 11152 degrees of freedom
##   (10 observations deleted due to missingness)
## Multiple R-squared:  0.1116, Adjusted R-squared:  0.1113
## F-statistic: 466.8 on 3 and 11152 DF,  p-value: < 2.2e-16
```

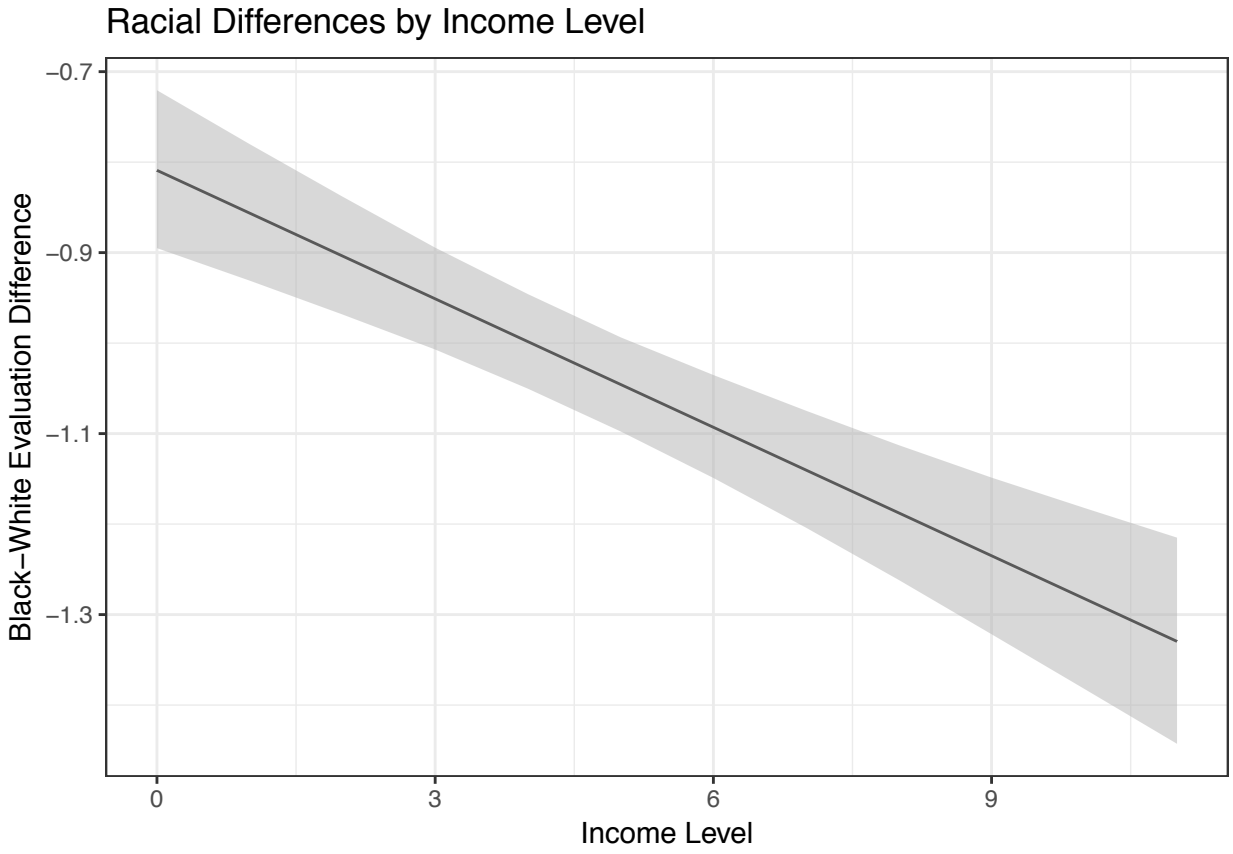

Racial Differences by Income Level
Marginal Effect of Income Level
0.04
0.03
0.02
0.01
0.00
0
1
White vs Black


Racial Differences by Income Level
Black–White Evaluation Difference
−0.7
−0.8
−0.9
−1.0
−1.1
0
3
6
9
Income Level

Holding police officers accountable for misconduct

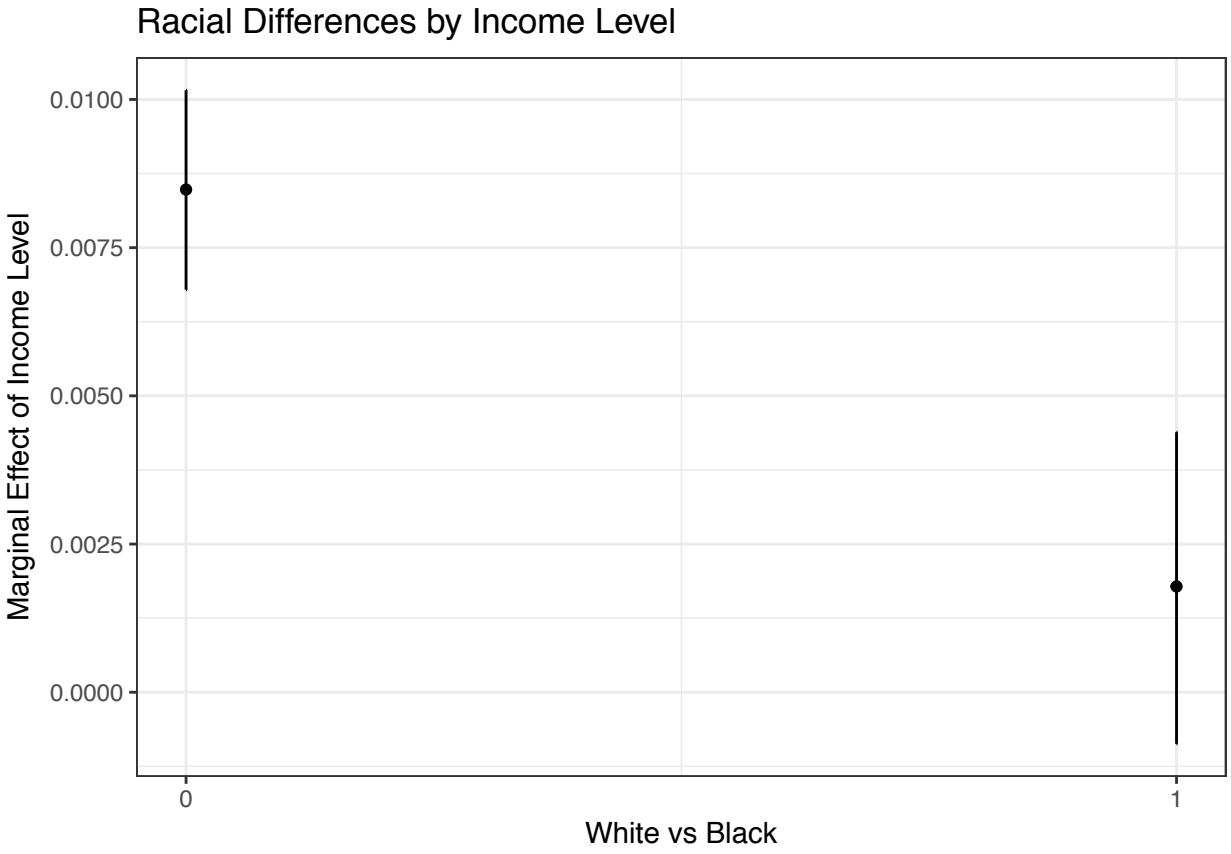
```
##
## Call:
## lm(formula = p.account ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -6.0581 -0.8850 -0.1317  0.7295  7.0016
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.059390   0.025367  81.183  < 2e-16 ***
## inc          0.037618   0.004200   8.957  < 2e-16 ***
## black       -0.807757   0.043995 -18.360  < 2e-16 ***
## inc:black   -0.047622   0.007847  -6.069 1.33e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.221 on 11154 degrees of freedom
##   (8 observations deleted due to missingness)
## Multiple R-squared:  0.1318, Adjusted R-squared:  0.1315
## F-statistic: 564.2 on 3 and 11154 DF,  p-value: < 2.2e-16
```

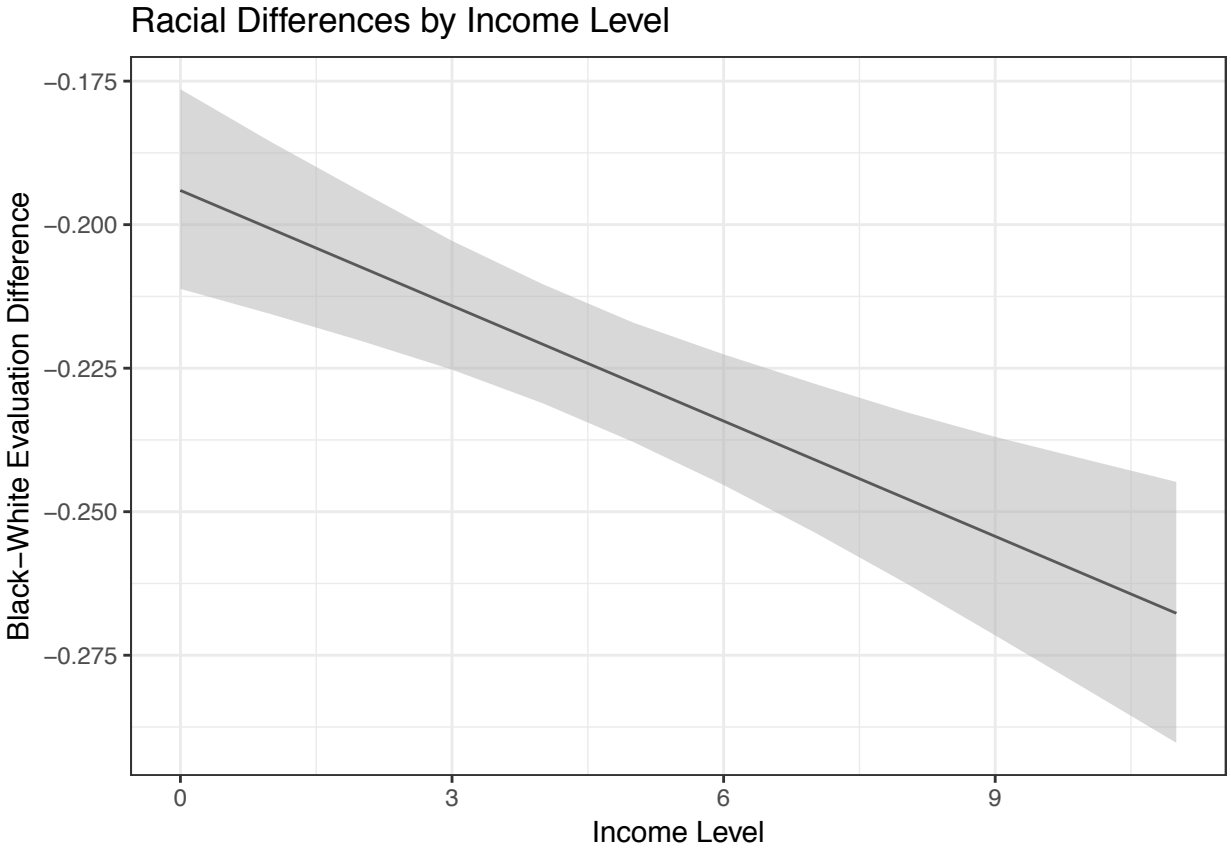




Summary Evaluation Index

```
##
## Call:
## lm(formula = police.rate.sc ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.44997 -0.16515 -0.01087  0.14313  1.54222
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.5483522  0.0050555 108.466  < 2e-16 ***
## inc          0.0085088  0.0008369  10.167  < 2e-16 ***
## black       -0.1937908  0.0087651 -22.109  < 2e-16 ***
## inc:black   -0.0067497  0.0015631  -4.318 1.59e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2431 on 11148 degrees of freedom
##   (14 observations deleted due to missingness)
## Multiple R-squared:  0.157,  Adjusted R-squared:  0.1568
## F-statistic: 692.1 on 3 and 11148 DF,  p-value: < 2.2e-16
```


Racial Differences by Income Level
0.0100
0.0075
0.0050
0.0025
0.0000
Marginal Effect of Income Level
0
1
White vs Black


Racial Differences by Income Level
−0.175
−0.200
−0.225
−0.250
−0.275
Black−White Evaluation Difference
0
3
6
9
Income Level

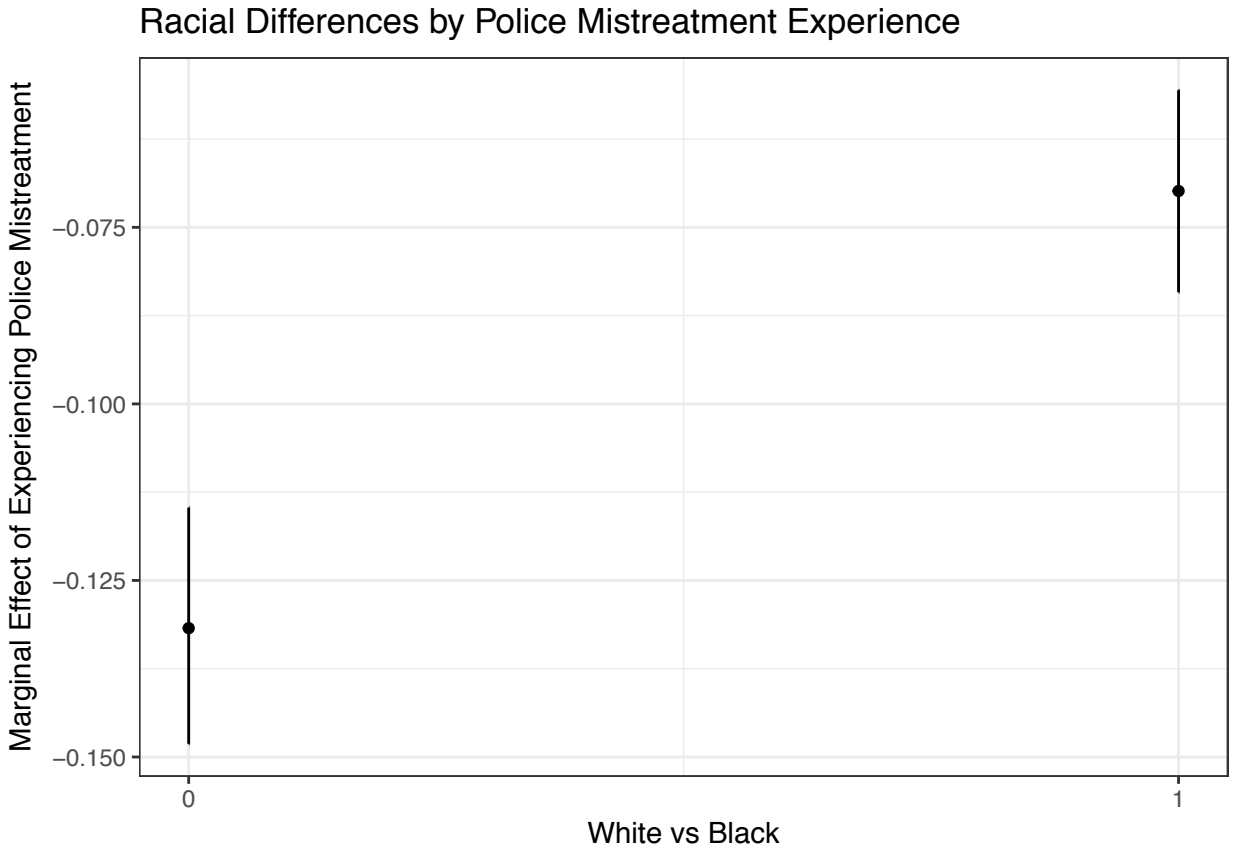
Court Fairness

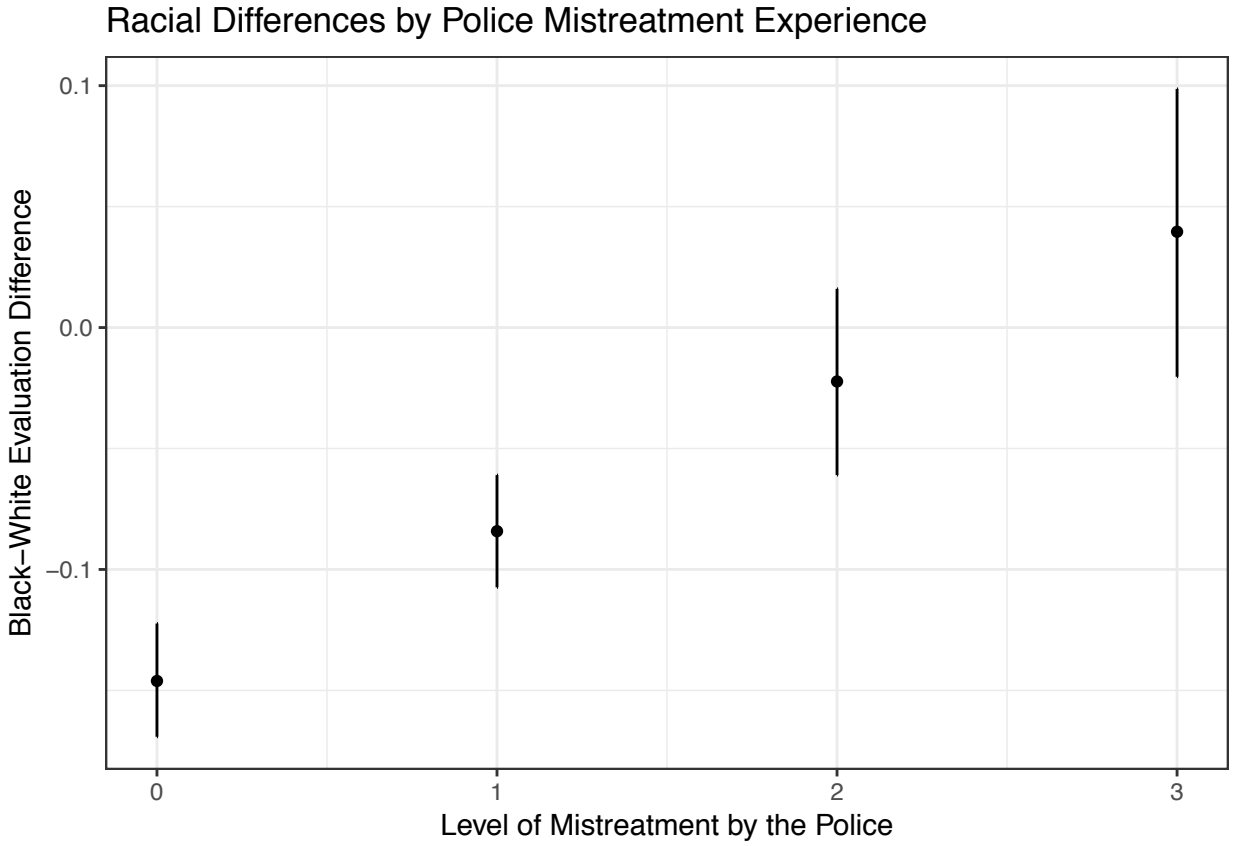
Social Experiences

Police Abused Friends/Family

Having peers abused by the police shapes evaluations of the court system. This effect is larger for white rather than black respondents, but regardless, the more friends and family a respondent has who have been mistreated by the police motivates a belief that the courts will not be fair. Moreover, these experiences reduce the gap in fairness beliefs between whites and blacks. Perhaps most interestingly, this pattern holds regardless of the frame presented. What varies is the relative influence these social experiences have. **''fairly apply the law?"**

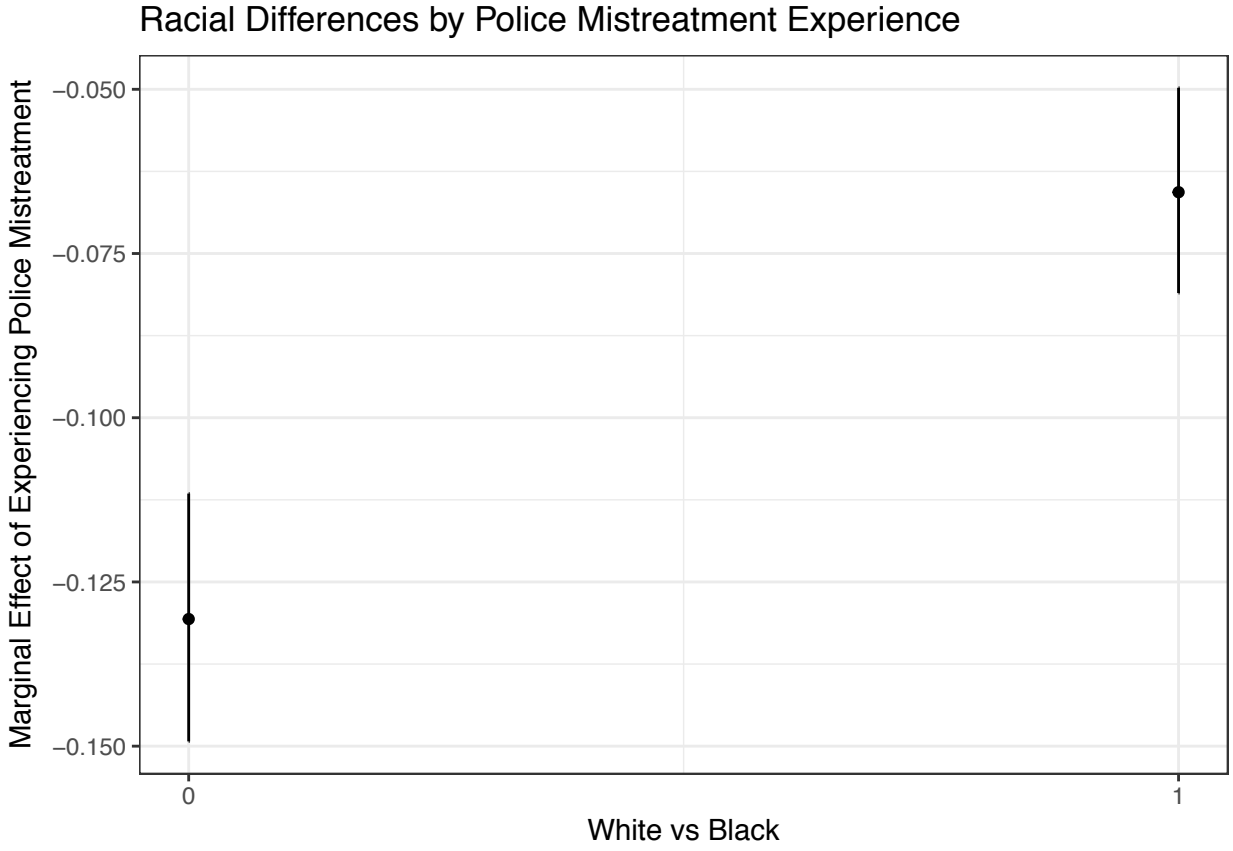
```
##
## Call:
## lm(formula = court.fair ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.47383 -0.08447 -0.03163  0.17360  1.23493
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.711395   0.005394 131.895  < 2e-16 ***
## pol.mistreat       -0.131574   0.008479 -15.518  < 2e-16 ***
## black              -0.145652   0.011817 -12.326  < 2e-16 ***
## pol.mistreat:black  0.061671   0.011252   5.481 4.51e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2635 on 3738 degrees of freedom
##   (7424 observations deleted due to missingness)
## Multiple R-squared:  0.1516, Adjusted R-squared:  0.1509
## F-statistic: 222.7 on 3 and 3738 DF,  p-value: < 2.2e-16
```

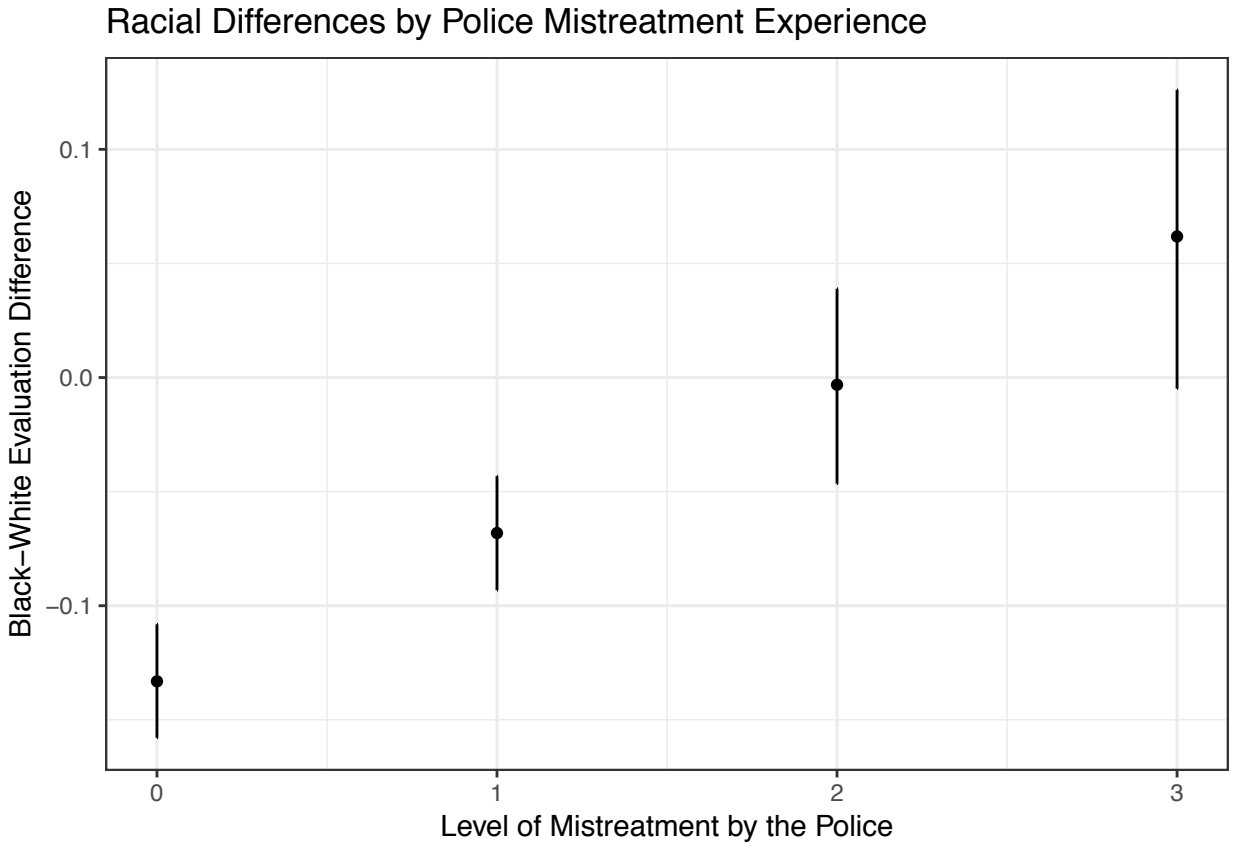




''fairly apply the law, regardless of a person's class?"

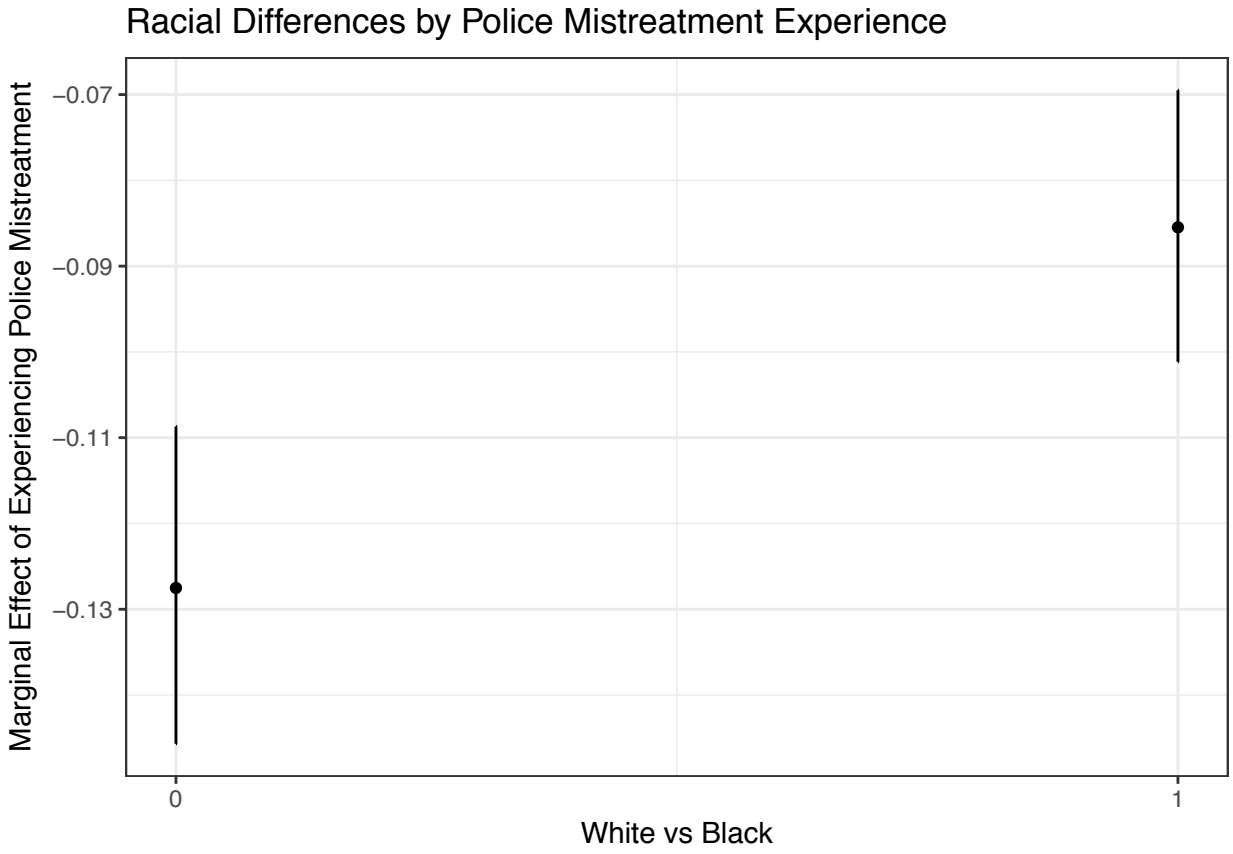
```
##
## Call:
## lm(formula = court.fair.class ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.72945 -0.14778 -0.02784  0.20786  1.35918
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.706045   0.005740 122.996  < 2e-16 ***
## pol.mistreat       -0.130464   0.009479 -13.763  < 2e-16 ***
## black              -0.132705   0.012436 -10.671  < 2e-16 ***
## pol.mistreat:black  0.064696   0.012520   5.168  2.5e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2779 on 3675 degrees of freedom
##   (7487 observations deleted due to missingness)
## Multiple R-squared:  0.1178, Adjusted R-squared:  0.117
## F-statistic: 163.5 on 3 and 3675 DF,  p-value: < 2.2e-16
```

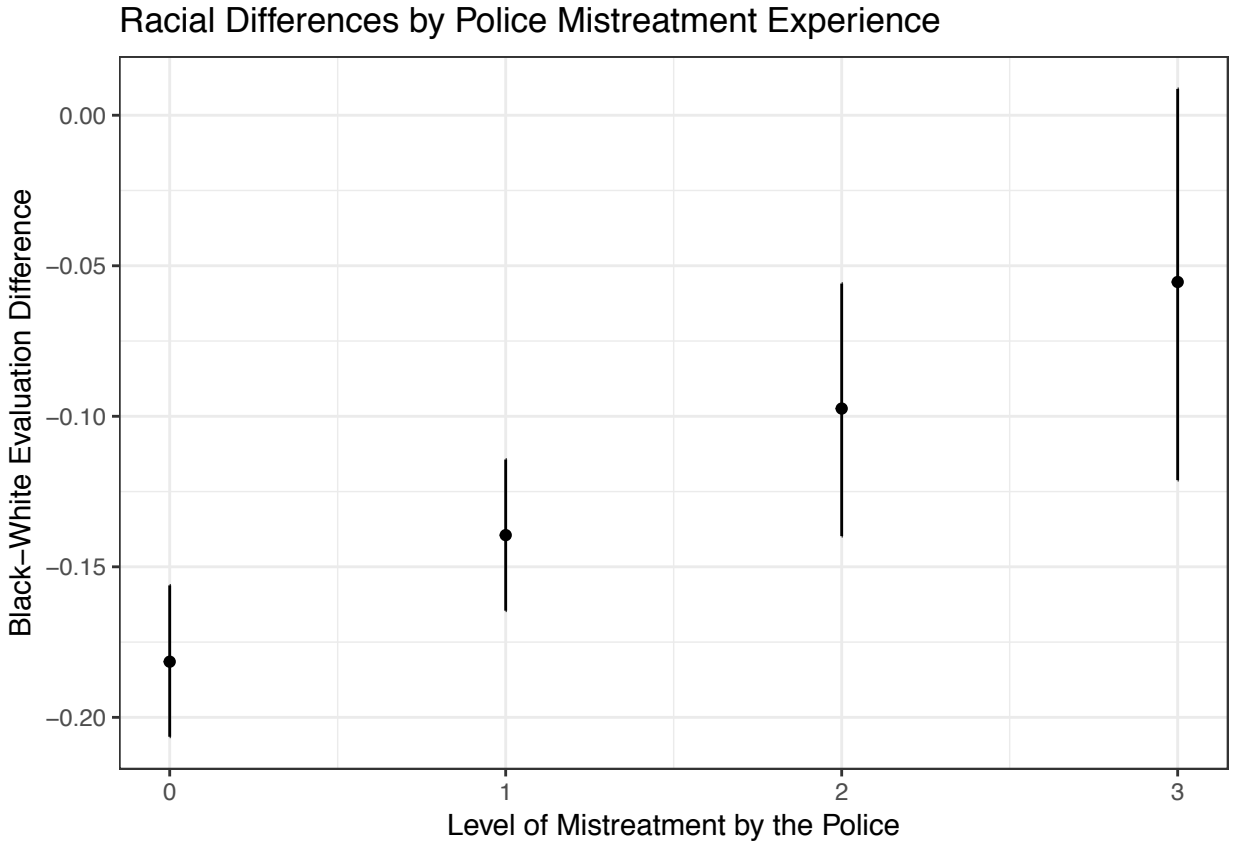




''fairly apply the law, regardless of a person's race?"

```
##
## Call:
## lm(formula = court.fair.race ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.77232 -0.11119 -0.04022  0.19548  1.12068
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.723546   0.005775 125.287  < 2e-16 ***
## pol.mistreat        -0.127347   0.009288 -13.710  < 2e-16 ***
## black               -0.181061   0.012658 -14.304  < 2e-16 ***
## pol.mistreat:black   0.041785   0.012347   3.384 0.000721 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2788 on 3735 degrees of freedom
##   (7427 observations deleted due to missingness)
## Multiple R-squared:  0.1723, Adjusted R-squared:  0.1716
## F-statistic: 259.1 on 3 and 3735 DF,  p-value: < 2.2e-16
```

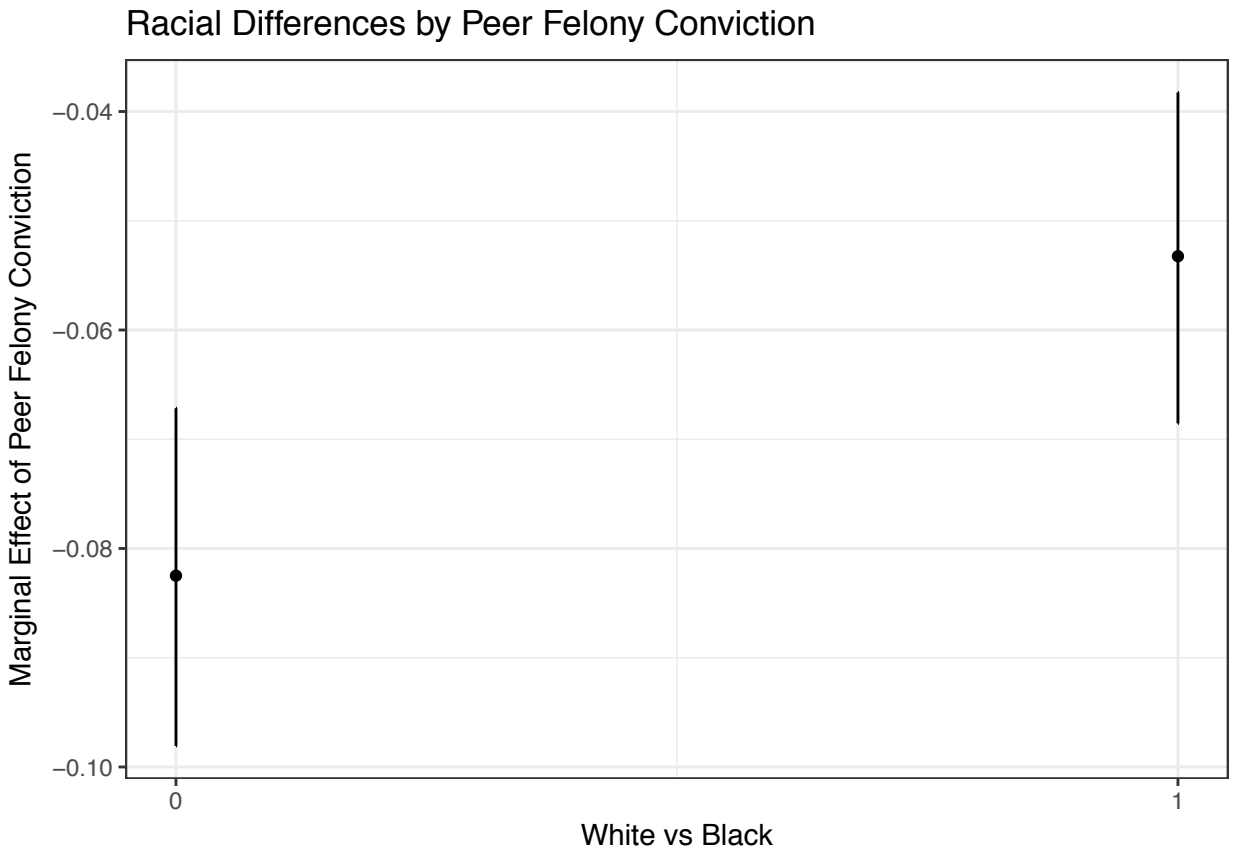


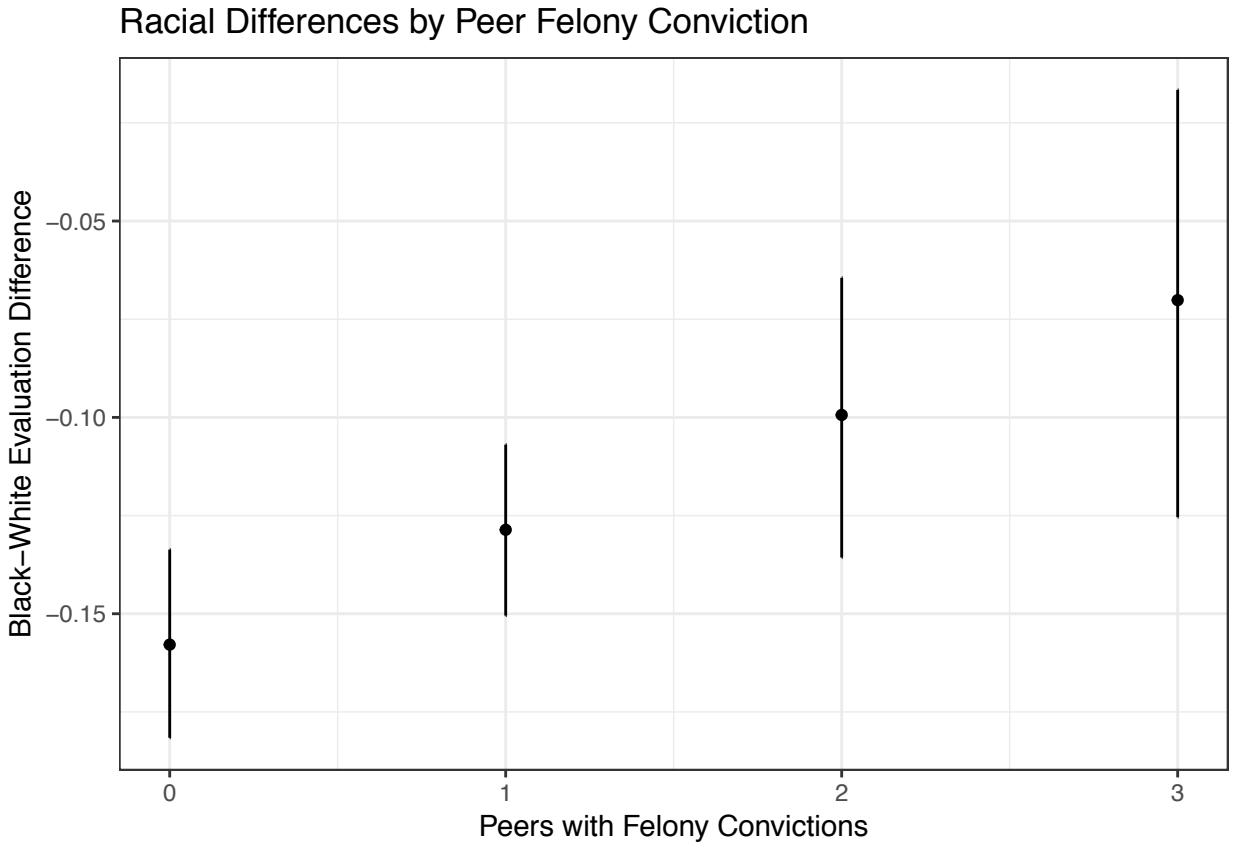


####Peers convicted of a Felony A similar pattern holds with social experiences are measured by peers

with felony convictions. These connections are more influential for whites, and the black-white gap in evaluations grows smaller as the number of connections increases. Finally, as before, these patterns hold across outcomes even as the magnitudes vary. **''fairly apply the law?"**

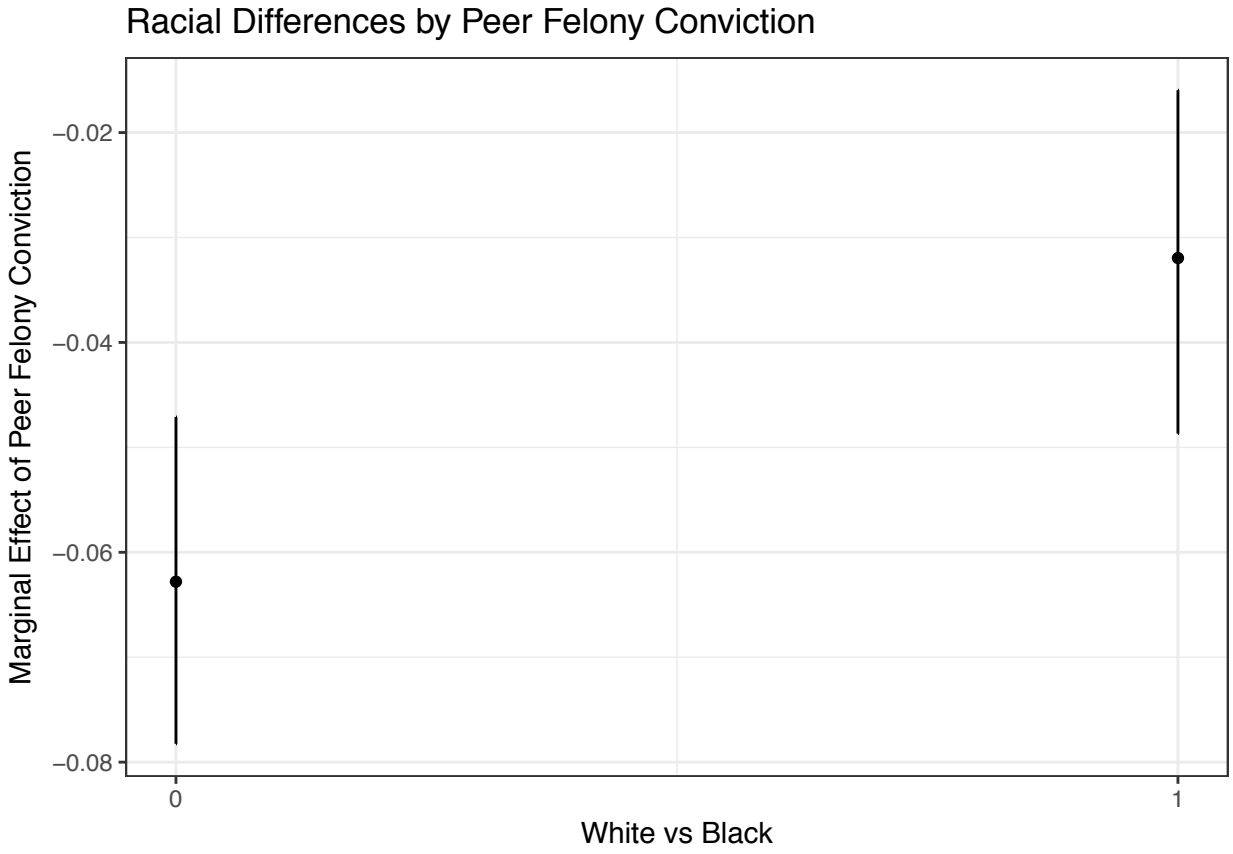
```
##
## Call:
## lm(formula = court.fair ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.46863 -0.10251 -0.02985  0.17248  1.36089
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.708883   0.005738 123.534  < 2e-16 ***
## peer.felony        -0.082262   0.007622 -10.793  < 2e-16 ***
## black              -0.157626   0.012307 -12.808  < 2e-16 ***
## peer.felony:black   0.028842   0.010915   2.642  0.00826 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2691 on 3737 degrees of freedom
##   (7425 observations deleted due to missingness)
## Multiple R-squared:  0.1153, Adjusted R-squared:  0.1146
## F-statistic: 162.3 on 3 and 3737 DF,  p-value: < 2.2e-16
```

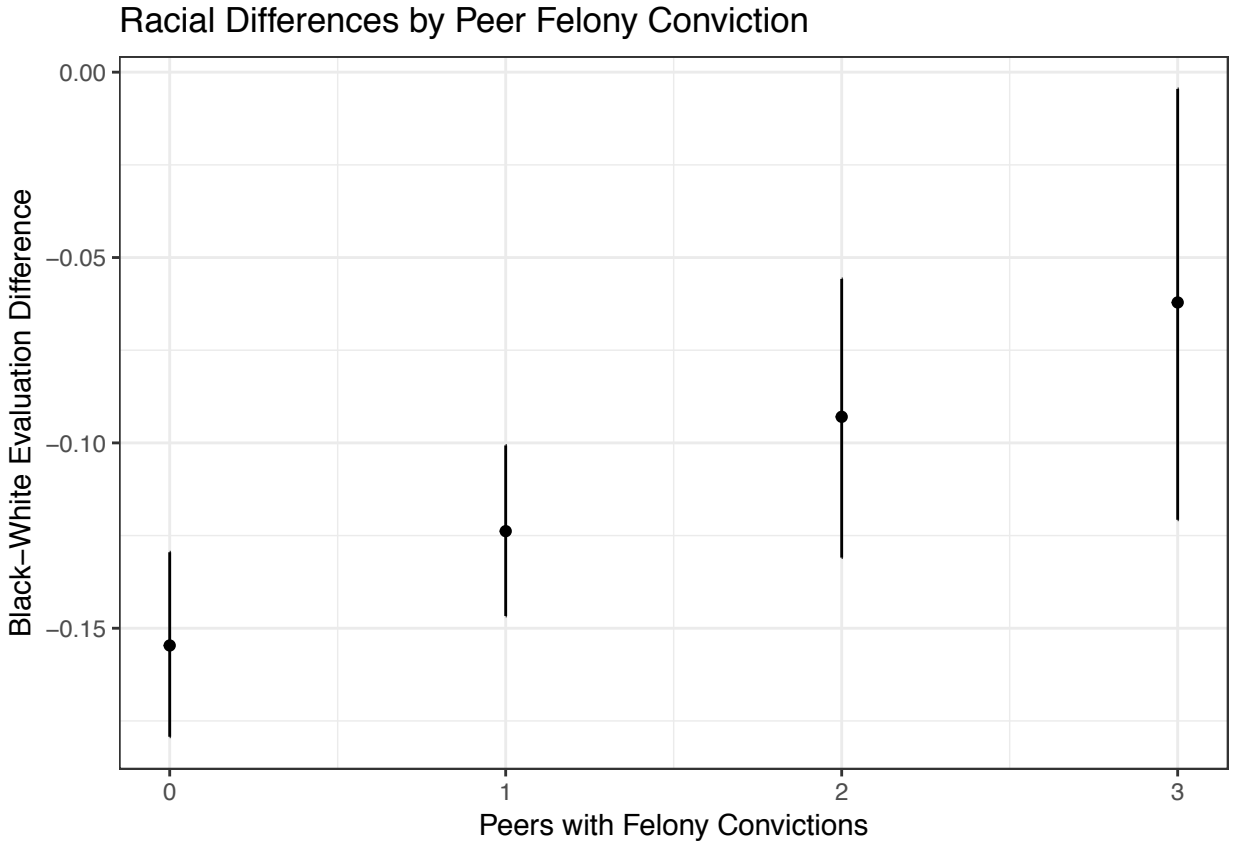




''fairly apply the law, regardless of a person's class?"

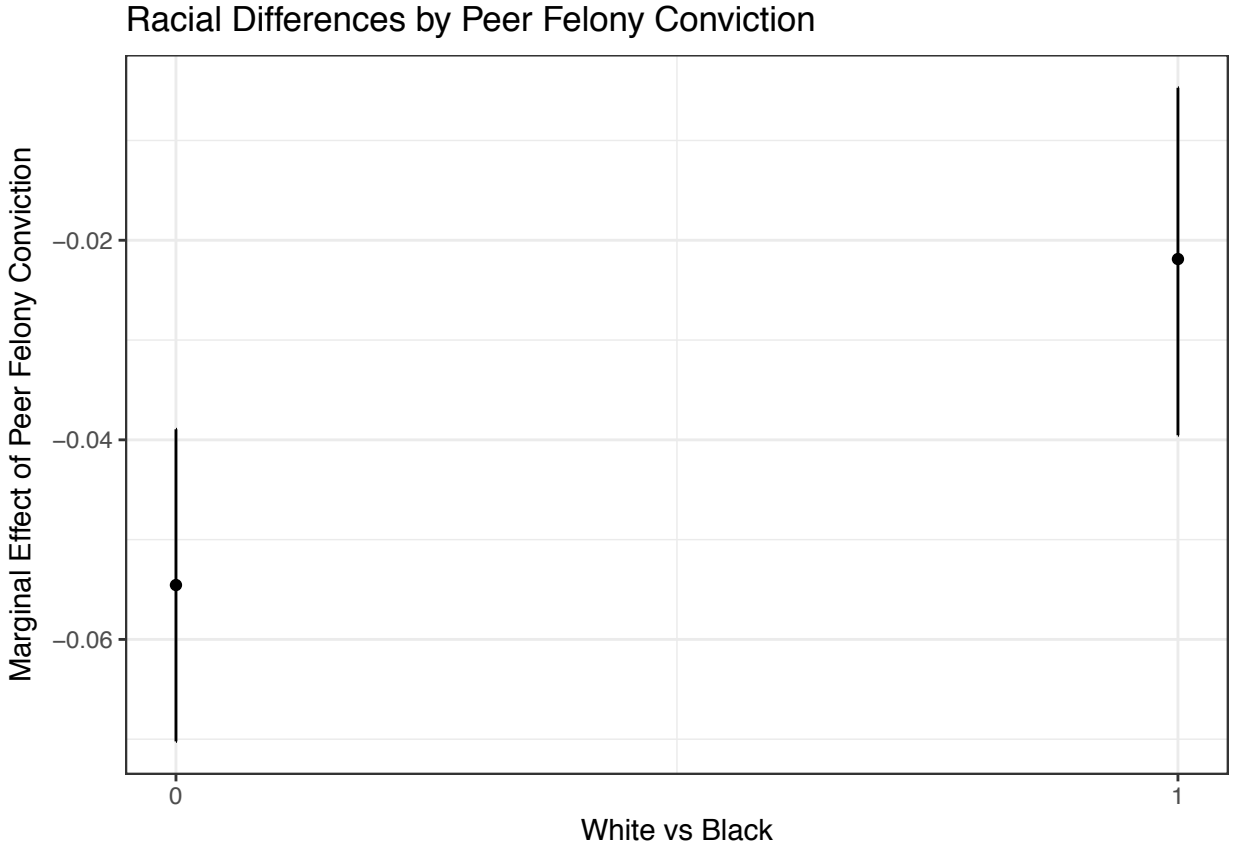
```
##
## Call:
## lm(formula = court.fair.class ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.71328 -0.14971 -0.02318  0.19041  1.19611
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.699445   0.006135 114.016  < 2e-16 ***
## peer.felony        -0.062585   0.007734  -8.092 7.87e-16 ***
## black              -0.154389   0.012789 -12.072  < 2e-16 ***
## peer.felony:black   0.030437   0.011447   2.659  0.00787 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2842 on 3676 degrees of freedom
##   (7486 observations deleted due to missingness)
## Multiple R-squared:  0.07684,    Adjusted R-squared:  0.07609
## F-statistic:   102 on 3 and 3676 DF,  p-value: < 2.2e-16
```

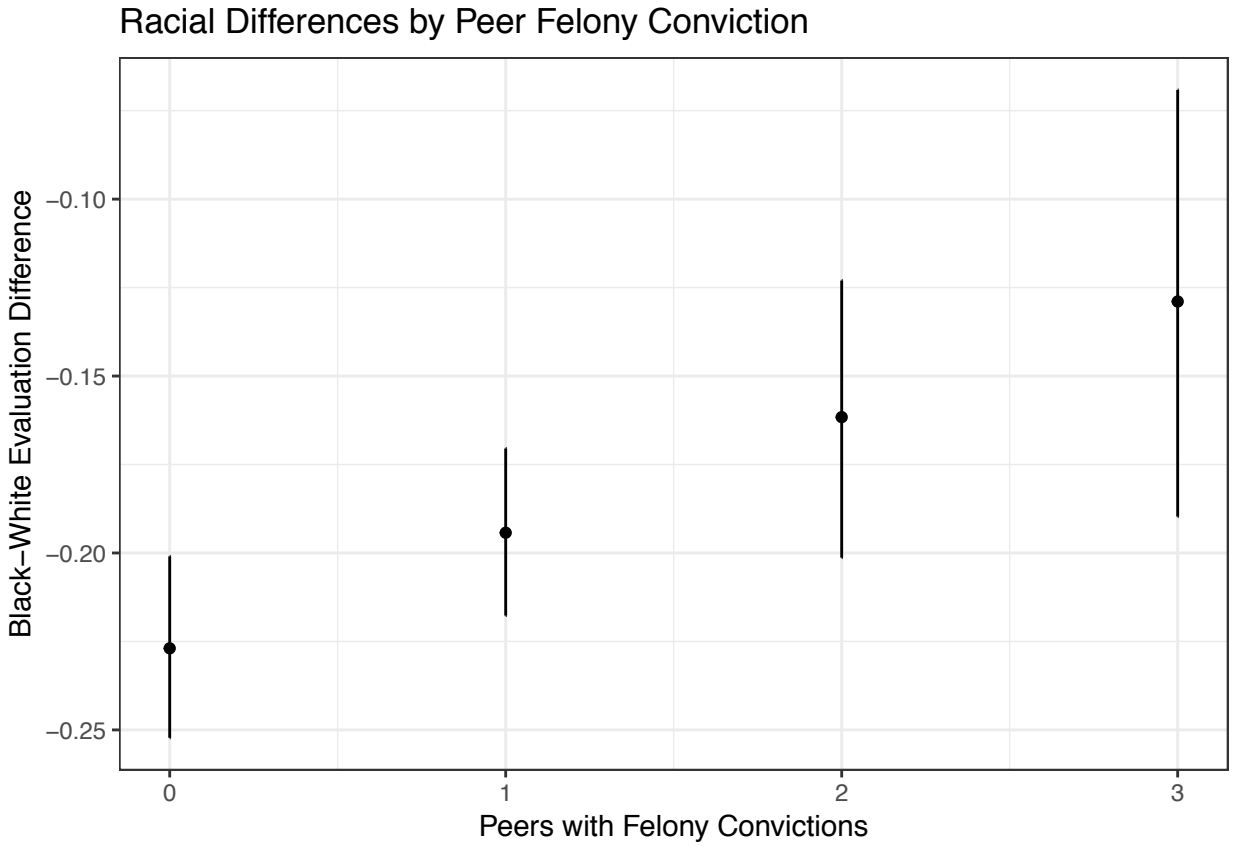




''fairly apply the law, regardless of a person's race?"

```
##
## Call:
## lm(formula = court.fair.race ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.74746 -0.11616 -0.03304  0.20266  1.25730
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         0.713396   0.006156 115.895  < 2e-16 ***
## peer.felony        -0.054271   0.007859  -6.906 5.84e-12 ***
## black              -0.226687   0.013120 -17.278  < 2e-16 ***
## peer.felony:black   0.032288   0.011799   2.737  0.00624 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2877 on 3736 degrees of freedom
##   (7426 observations deleted due to missingness)
## Multiple R-squared:  0.1189, Adjusted R-squared:  0.1182
## F-statistic: 168.1 on 3 and 3736 DF,  p-value: < 2.2e-16
```





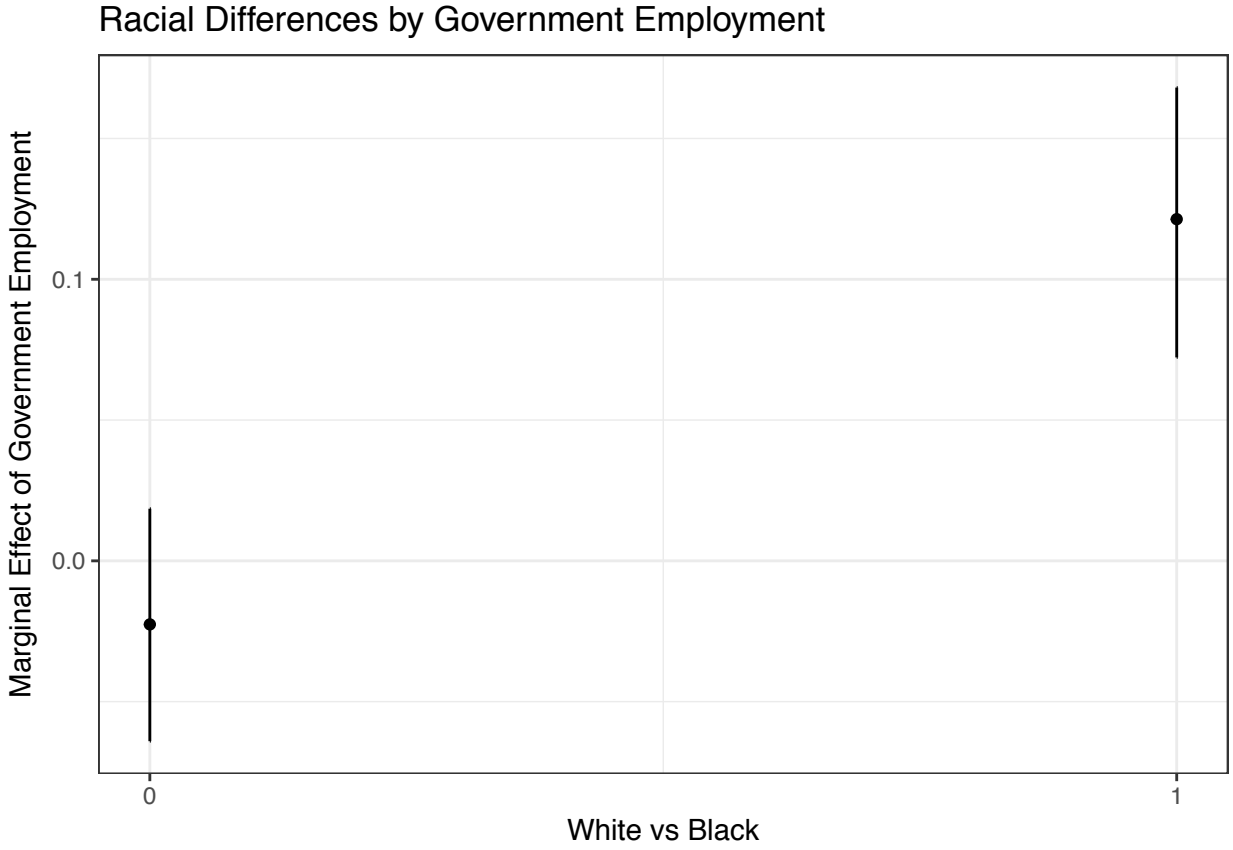
Employment

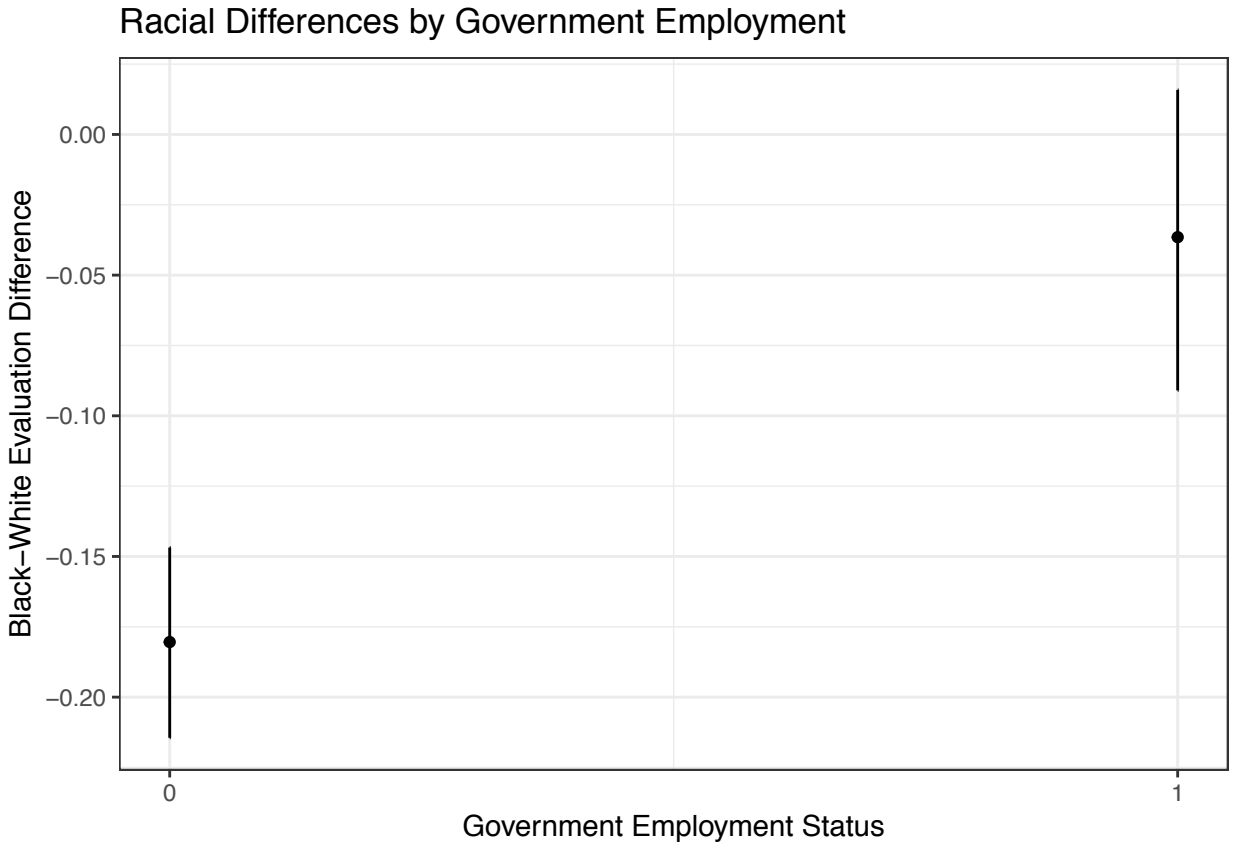
Employed in the Government

Government employment appears to shape evaluations of the court system. But what its influence varies by question wording. For the neutral and racial prime conditions, government employment does not shape whites' evaluations. For blacks, it matters. Blacks employed by the government hold more positive evaluations of the courts in both conditions such that the black-white evaluation gap disappears in the neutral condition and grows smaller in the race-prime condition. In the class condition, government employment motivates blacks and whites to view the courts more positively, but nothing shifts the racial gap in evaluations. **''fairly apply the law?"**

```
##
## Call:
## lm(formula = court.fair ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.58396 -0.12050 -0.00148  0.14334  0.95523
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.668758   0.008354  80.050  < 2e-16 ***
## employ.gov       -0.022108   0.020635  -1.071    0.284
## black            -0.179769   0.016680 -10.778  < 2e-16 ***
## employ.gov:black  0.143146   0.032014   4.471 8.23e-06 ***
```

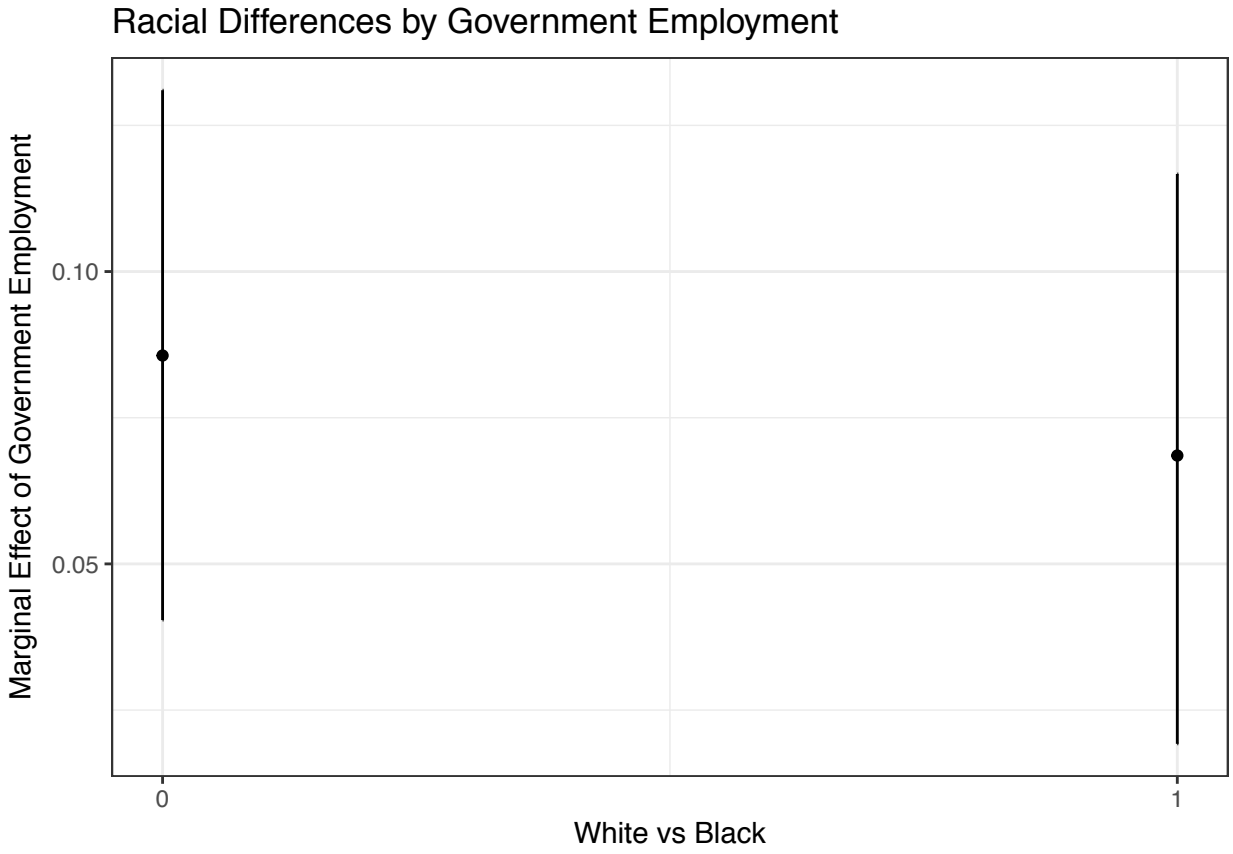
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2739 on 1922 degrees of freedom
##   (9240 observations deleted due to missingness)
## Multiple R-squared:  0.05788,    Adjusted R-squared:  0.05641
## F-statistic: 39.36 on 3 and 1922 DF,  p-value: < 2.2e-16
```

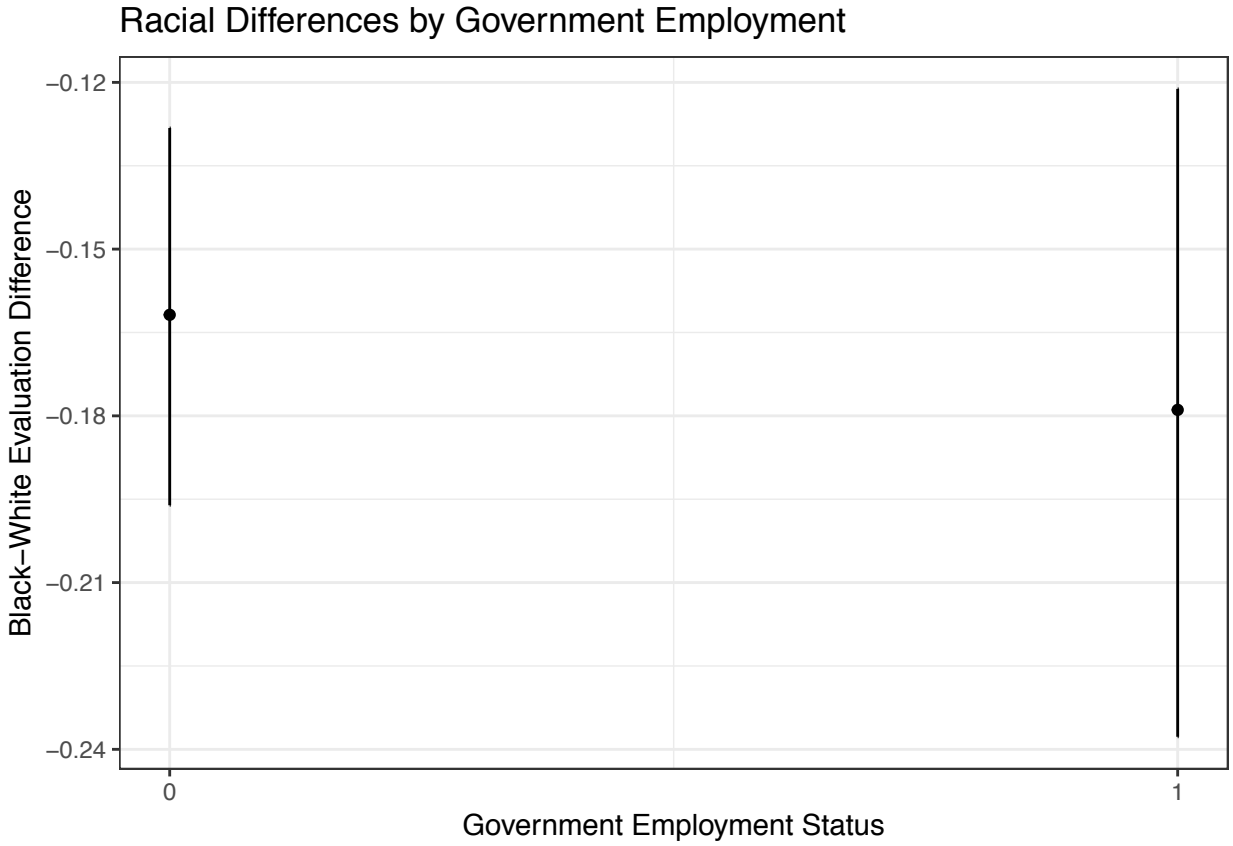




''fairly apply the law, regardless of a person's class?"

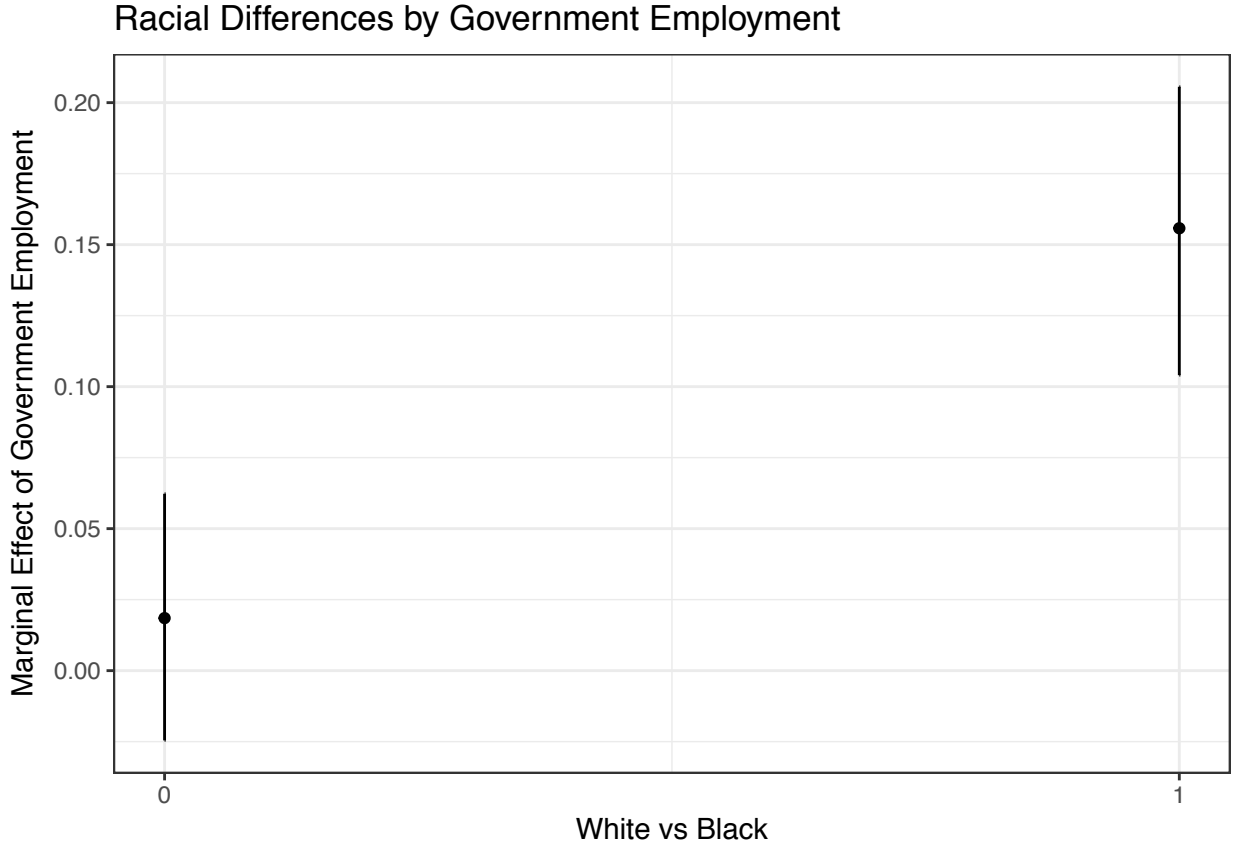
```
##
## Call:
## lm(formula = court.fair.class ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.59303 -0.16615  0.01347  0.16924  1.25147
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.650353   0.008565  75.933  < 2e-16 ***
## employ.gov         0.086042   0.022797   3.774 0.000165 ***
## black             -0.161262   0.016831  -9.581  < 2e-16 ***
## employ.gov:black -0.017873   0.033954  -0.526 0.598691
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2879 on 1902 degrees of freedom
##   (9260 observations deleted due to missingness)
## Multiple R-squared:  0.06556,    Adjusted R-squared:  0.06408
## F-statistic: 44.48 on 3 and 1902 DF,  p-value: < 2.2e-16
```

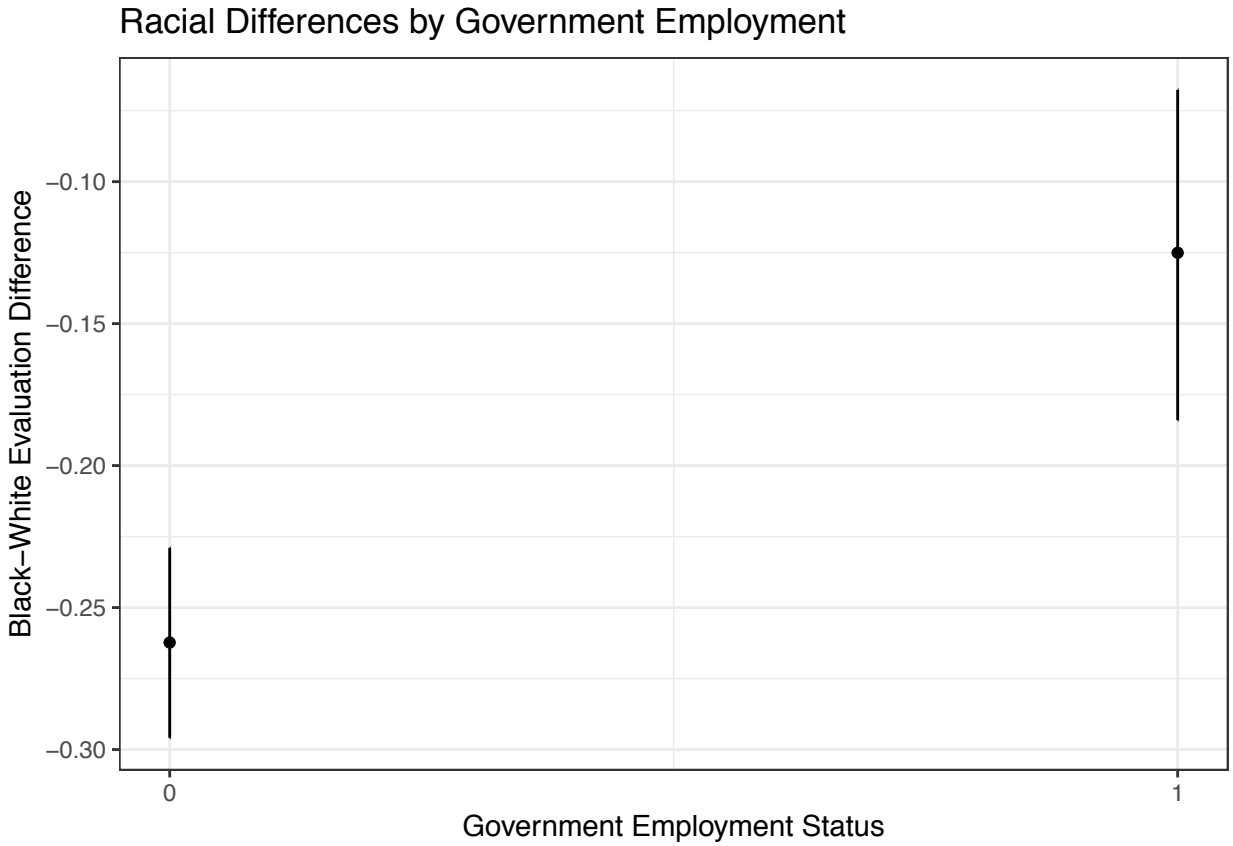




''fairly apply the law, regardless of a person's race?"

```
##
## Call:
## lm(formula = court.fair.race ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.65797 -0.09342 -0.00840  0.22849  1.43258
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.676862   0.008597  78.728  < 2e-16 ***
## employ.gov        0.018849   0.021778   0.866    0.387
## black            -0.261712   0.016638 -15.729  < 2e-16 ***
## employ.gov:black  0.136677   0.033917   4.030  5.8e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2836 on 1961 degrees of freedom
##   (9201 observations deleted due to missingness)
## Multiple R-squared:  0.1206, Adjusted R-squared:  0.1193
## F-statistic: 89.65 on 3 and 1961 DF,  p-value: < 2.2e-16
```

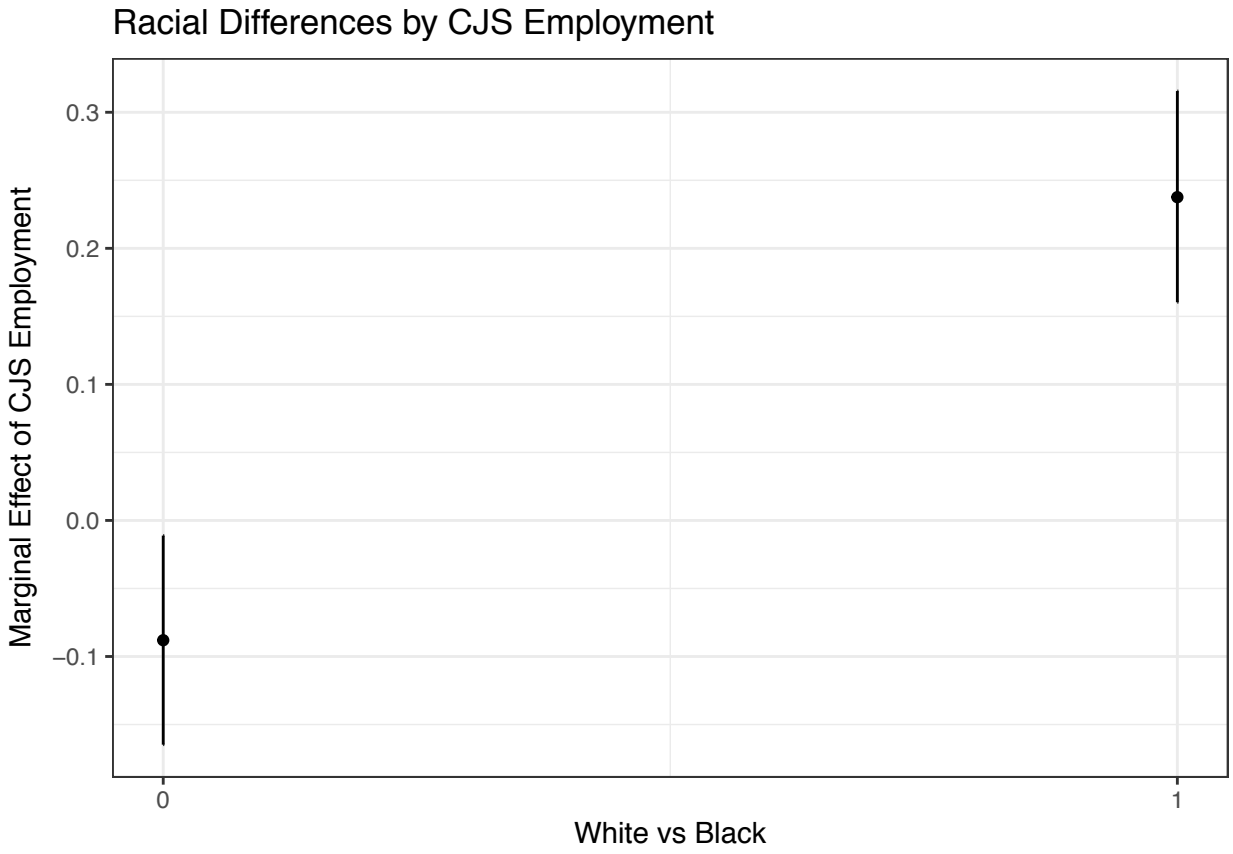


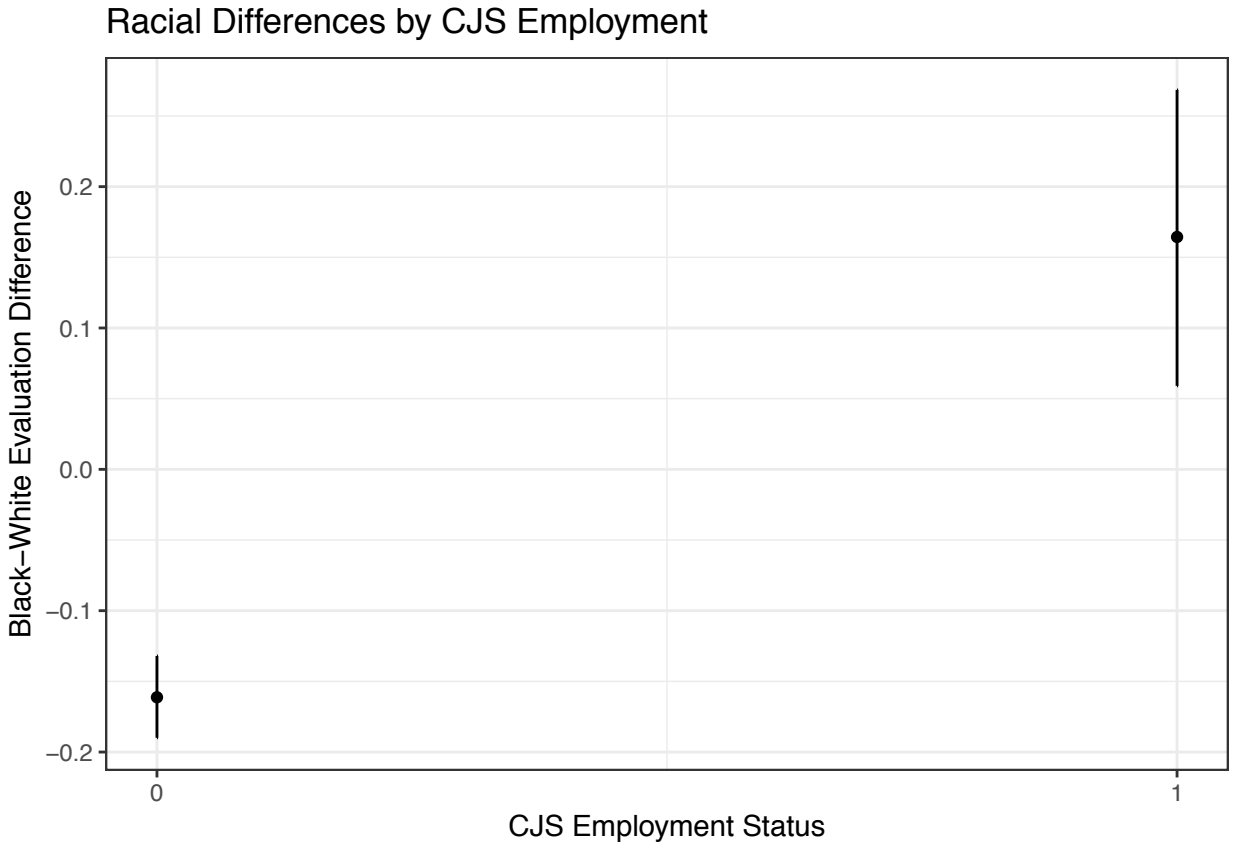


####Employed in the Criminal Justice System Employment in the criminal justice system also matters. But its influence varies by the prime. In the neutral prime, whites employed by the criminal justice sytem believe the courts to be less fair, but the opposite is true for blacks. Consequently, the racial gap in evaluations is smaller among those not employed in the CJS, and larger among those employed. Similarly, in the race-prime condition, both CJS employment status matters more for blacks than whites. For those employed in the criminal justice system, the black-white evaluation gap disappears. Finally, there are no difference by employment status or gaps by race in evaluations in the class-prime condition. **''fairly apply the law?"**

```
##
## Call:
## lm(formula = court.fair ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.42247 -0.12323 -0.00133  0.14670  1.17839
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.668380   0.007763  86.097  < 2e-16 ***
## employ.cjs        -0.087657   0.039095  -2.242   0.0251 *
## black             -0.160775   0.014486 -11.099  < 2e-16 ***
## employ.cjs:black   0.324563   0.055109   5.889 4.56e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2727 on 1921 degrees of freedom
```

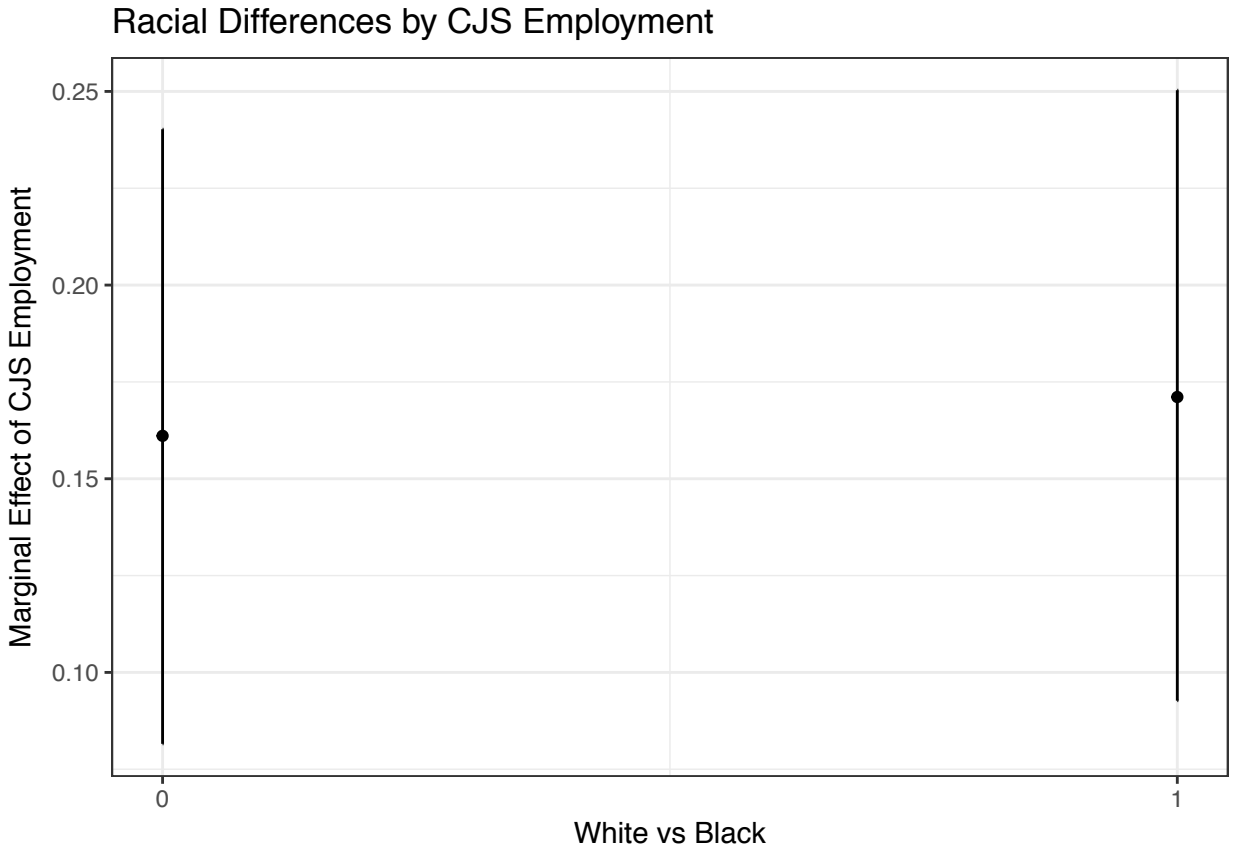
```
##   (9241 observations deleted due to missingness)
## Multiple R-squared:  0.06575,    Adjusted R-squared:  0.0643
## F-statistic: 45.07 on 3 and 1921 DF,  p-value: < 2.2e-16
```

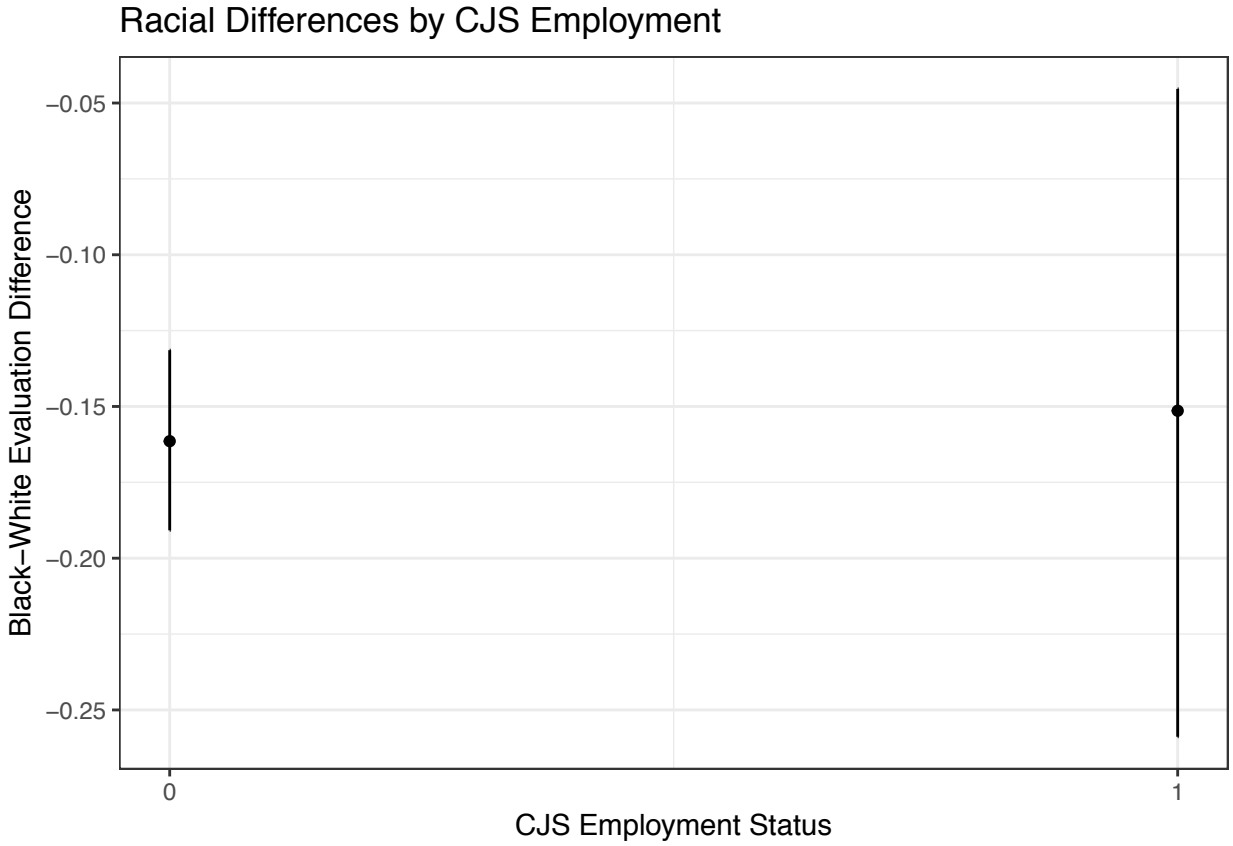




''fairly apply the law, regardless of a person's class?"

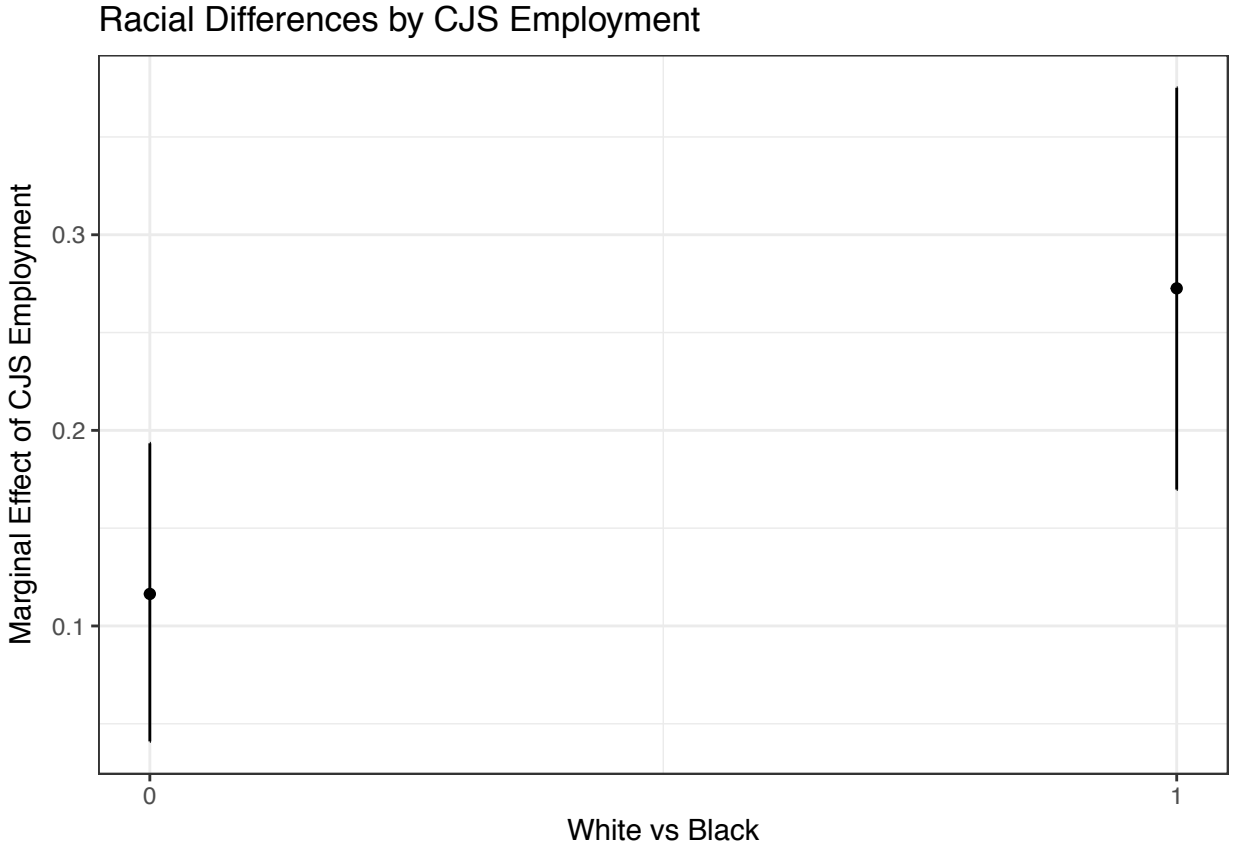
```
##
## Call:
## lm(formula = court.fair.class ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.60607 -0.16322  0.00943  0.17135  1.23755
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.655677   0.008088  81.064  < 2e-16 ***
## employ.cjs        0.161691   0.040250   4.017 6.12e-05 ***
## black            -0.160903   0.014865 -10.825  < 2e-16 ***
## employ.cjs:black  0.008499   0.056318   0.151     0.88
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.287 on 1898 degrees of freedom
##   (9264 observations deleted due to missingness)
## Multiple R-squared:  0.07159,    Adjusted R-squared:  0.07012
## F-statistic: 48.78 on 3 and 1898 DF,  p-value: < 2.2e-16
```

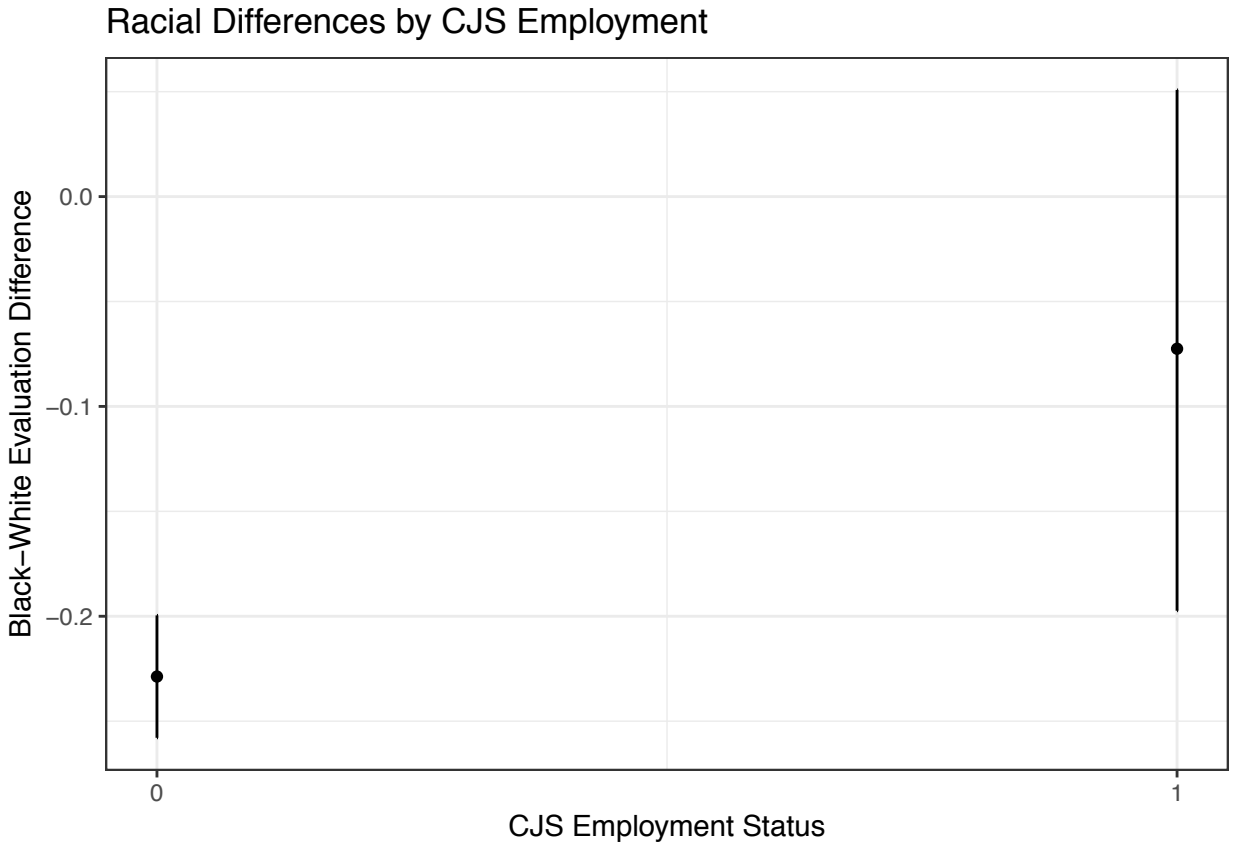




''fairly apply the law, regardless of a person's race?"

```
##
## Call:
## lm(formula = court.fair.race ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -1.6525 -0.1091 -0.0064  0.2296  1.3560
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.674640   0.008078  83.516  < 2e-16 ***
## employ.cjs        0.117159   0.038490   3.044  0.00237 **
## black            -0.228233   0.014689 -15.537  < 2e-16 ***
## employ.cjs:black  0.154354   0.064276   2.401  0.01642 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2835 on 1961 degrees of freedom
##   (9201 observations deleted due to missingness)
## Multiple R-squared:  0.1209, Adjusted R-squared:  0.1195
## F-statistic: 89.86 on 3 and 1961 DF,  p-value: < 2.2e-16
```





####Criminal Justice System Profession Finally, not much in a respondent's specific position in the CJS seems to systematically explain fairness evaluations. What does hold consistently is there's no relationship between any employment position and evaluations in the race-prime condition. **''fairly apply the law?"**

```
##
## Call:
## lm(formula = court.fair ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -0.8021 -0.1178  0.0000  0.1905  0.6500
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 0.518621   0.104850   4.946 5.63e-06 ***
## as.factor(cjs.pos)2         0.148045   0.373108   0.397   0.6928
## as.factor(cjs.pos)3         0.427313   0.211634   2.019   0.0476 *
## as.factor(cjs.pos)4         0.162393   0.265658   0.611   0.5431
## as.factor(cjs.pos)5         0.148045   0.468353   0.316   0.7529
## as.factor(cjs.pos)6        -0.191152   0.142812  -1.338   0.1854
## as.factor(cjs.pos)7        -0.004516   0.151755  -0.030   0.9763
## as.factor(cjs.pos)8         0.229321   0.133437   1.719   0.0905 .
## black                       0.203697   0.165485   1.231   0.2228
## as.factor(cjs.pos)2:black   0.087098   0.404657   0.215   0.8303
## as.factor(cjs.pos)3:black -0.482965   0.336244  -1.436   0.1557
## as.factor(cjs.pos)4:black -0.034723   0.319769  -0.109   0.9139
## as.factor(cjs.pos)5:black -0.037030   0.583032  -0.064   0.9496
```

```
## as.factor(cjs.pos)6:black  0.418131   0.224448   1.863   0.0670 .
## as.factor(cjs.pos)7:black -0.322519   0.260752  -1.237   0.2206
## as.factor(cjs.pos)8:black -0.451604   0.203500  -2.219   0.0300 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3228 on 65 degrees of freedom
##   (11085 observations deleted due to missingness)
## Multiple R-squared:  0.4079, Adjusted R-squared:  0.2713
## F-statistic: 2.986 on 15 and 65 DF,  p-value: 0.00116
```

''fairly apply the law, regardless of a person's class?"

```
##
## Call:
## lm(formula = court.fair.class ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -0.7606 -0.1748  0.0000  0.1858  0.7441
##
## Coefficients: (1 not defined because of singularities)
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                1.000e+00  1.180e-01   8.477 1.02e-12 ***
## as.factor(cjs.pos)2        4.838e-16  3.419e-01   0.000  1.00000
## as.factor(cjs.pos)3       -1.876e-01  2.302e-01  -0.815  0.41749
## as.factor(cjs.pos)4       -2.163e-02  1.578e-01  -0.137  0.89130
## as.factor(cjs.pos)5       -2.351e-01  1.545e-01  -1.522  0.13200
## as.factor(cjs.pos)6       -5.402e-01  1.907e-01  -2.832  0.00586 **
## as.factor(cjs.pos)7       -5.321e-01  2.353e-01  -2.261  0.02649 *
## as.factor(cjs.pos)8       -2.199e-01  1.358e-01  -1.619  0.10941
## black                     -2.963e-01  1.448e-01  -2.046  0.04412 *
## as.factor(cjs.pos)2:black  2.963e-01  4.012e-01   0.739  0.46233
## as.factor(cjs.pos)3:black  1.506e-01  3.062e-01   0.492  0.62430
## as.factor(cjs.pos)4:black -5.639e-02  2.653e-01  -0.213  0.83225
## as.factor(cjs.pos)5:black  4.827e-01  2.050e-01   2.355  0.02101 *
## as.factor(cjs.pos)6:black  3.488e-01  2.368e-01   1.473  0.14477
## as.factor(cjs.pos)7:black         NA         NA      NA       NA
## as.factor(cjs.pos)8:black  1.012e-01  1.737e-01   0.583  0.56164
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3064 on 79 degrees of freedom
##   (11072 observations deleted due to missingness)
## Multiple R-squared:  0.3201, Adjusted R-squared:  0.1996
## F-statistic: 2.657 on 14 and 79 DF,  p-value: 0.003199
```

''fairly apply the law, regardless of a person's race?"

```
##
## Call:
## lm(formula = court.fair.race ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -0.7423 -0.1045  0.0000  0.1582  0.5717
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 0.75558    0.13001   5.812 1.56e-07 ***
## as.factor(cjs.pos)2         0.24442    0.16647   1.468    0.146
## as.factor(cjs.pos)3         0.24442    0.24759   0.987    0.327
## as.factor(cjs.pos)4        -0.08891    0.16623  -0.535    0.594
## as.factor(cjs.pos)5         0.14904    0.18914   0.788    0.433
## as.factor(cjs.pos)6        -0.02133    0.17843  -0.120    0.905
## as.factor(cjs.pos)7        -0.19007    0.24822  -0.766    0.446
## as.factor(cjs.pos)8         0.01625    0.14026   0.116    0.908
## black                       0.13777    0.18936   0.728    0.469
## as.factor(cjs.pos)2:black -0.13777    0.31840  -0.433    0.667
## as.factor(cjs.pos)3:black -0.47110    0.44717  -1.054    0.296
## as.factor(cjs.pos)4:black -0.03122    0.26682  -0.117    0.907
## as.factor(cjs.pos)5:black -0.44022    0.29313  -1.502    0.138
## as.factor(cjs.pos)6:black -0.09424    0.31607  -0.298    0.766
## as.factor(cjs.pos)7:black  0.22627    0.32850   0.689    0.493
## as.factor(cjs.pos)8:black -0.28603    0.20742  -1.379    0.172
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2714 on 72 degrees of freedom
##   (11078 observations deleted due to missingness)
## Multiple R-squared:  0.1966, Adjusted R-squared:  0.02924
## F-statistic: 1.175 on 15 and 72 DF,  p-value: 0.311
```

Racial Group Views

Racial Resentment

Whites racial attitudes also explain court fairness evaluations. The more racially resentful see the courts in their area more fairly. More interestingly, this effect is larger in the class and race conditions than the neutral condition. **''fairly apply the law?"**

```
##
## Call:
## lm(formula = court.fair ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.65687 -0.03295  0.00070  0.20603  0.87155
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.62271    0.01304  47.750  < 2e-16 ***
## rr_sc        0.08592    0.01990   4.317 1.64e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2666 on 2716 degrees of freedom
```

```
##   (5375 observations deleted due to missingness)
## Multiple R-squared:  0.006816,   Adjusted R-squared:  0.00645
## F-statistic: 18.64 on 1 and 2716 DF,  p-value: 1.637e-05
```

‘’fairly apply the law, regardless of a person’s class?”

```
##
## Call:
## lm(formula = court.fair.class ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.71971 -0.09500  0.01185  0.20421  0.88951
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.54557    0.01413  38.605   <2e-16 ***
## rr_sc        0.20867    0.02158   9.671   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2762 on 2661 degrees of freedom
##   (5430 observations deleted due to missingness)
## Multiple R-squared:  0.03396,    Adjusted R-squared:  0.03359
## F-statistic: 93.54 on 1 and 2661 DF,  p-value: < 2.2e-16
```

‘’fairly apply the law, regardless of a person’s race?”

```
##
## Call:
## lm(formula = court.fair.race ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.62429 -0.09963  0.00435  0.19081  0.95621
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.52354    0.01414   37.02   <2e-16 ***
## rr_sc        0.27550    0.02151   12.81   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2746 on 2687 degrees of freedom
##   (5404 observations deleted due to missingness)
## Multiple R-squared:  0.05752,    Adjusted R-squared:  0.05717
## F-statistic:   164 on 1 and 2687 DF,  p-value: < 2.2e-16
```

White Linked Fate

Whites levels of linked fate are also related to their evaluations of the court system. Higher levels of linked fate relate to less fair views of the courts. Moreover, unlike their racial attitudes, linked fate functions the same across condition. **‘’fairly apply the law?”**

```
##
## Call:
## lm(formula = court.fair ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.72718 -0.04372  0.00929  0.20851  0.91187
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.70512    0.00732  96.324  < 2e-16 ***
## wht.lfate.sc -0.07739    0.01326  -5.837 5.95e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2663 on 2719 degrees of freedom
##   (5372 observations deleted due to missingness)
## Multiple R-squared:  0.01237,    Adjusted R-squared:  0.01201
## F-statistic: 34.07 on 1 and 2719 DF,  p-value: 5.953e-09
```

''fairly apply the law, regardless of a person's class?"

```
##
## Call:
## lm(formula = court.fair.class ~ wht.lfate.sc, data = cjs.df,
##     subset = black == 0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.65824 -0.05512  0.01148  0.20965  0.92127
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.703516   0.007575  92.874  < 2e-16 ***
## wht.lfate.sc -0.079625   0.013669  -5.825 6.39e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2787 on 2664 degrees of freedom
##   (5427 observations deleted due to missingness)
## Multiple R-squared:  0.01258,    Adjusted R-squared:  0.01221
## F-statistic: 33.93 on 1 and 2664 DF,  p-value: 6.385e-09
```

''fairly apply the law, regardless of a person's race?"

```
##
## Call:
## lm(formula = court.fair.race ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.72287 -0.06632 -0.00106  0.22898  0.83966
##
## Coefficients:
```

```
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.721023   0.007695  93.697  < 2e-16 ***
## wht.lfate.sc -0.079899   0.014209  -5.623 2.07e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2819 on 2690 degrees of freedom
##   (5401 observations deleted due to missingness)
## Multiple R-squared:  0.01162,    Adjusted R-squared:  0.01125
## F-statistic: 31.62 on 1 and 2690 DF,  p-value: 2.068e-08
```

Black Linked Fate

For blacks, linked fate matters, too. Individuals reporting greater linked fate view the courts in their area less fairly. As with whites, this effect doesn't vary by treatment condition. **''fairly apply the law?"**

```
##
## Call:
## lm(formula = court.fair ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.21487 -0.15204  0.08909  0.15678  1.29879
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.54836    0.01424  38.500  < 2e-16 ***
## blk.lfate.sc -0.07858    0.02235  -3.515 0.000459 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2926 on 1016 degrees of freedom
##   (2055 observations deleted due to missingness)
## Multiple R-squared:  0.01202,    Adjusted R-squared:  0.01104
## F-statistic: 12.36 on 1 and 1016 DF,  p-value: 0.0004586
```

''fairly apply the law, regardless of a person's class?"

```
##
## Call:
## lm(formula = court.fair.class ~ blk.lfate.sc, data = cjs.df,
##     subset = black == 1, weights = wts_black)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.38082 -0.18066  0.07824  0.14953  1.31130
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.56372    0.01485  37.966  < 2e-16 ***
## blk.lfate.sc -0.09905    0.02359  -4.199 2.92e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.3038 on 1006 degrees of freedom
##   (2065 observations deleted due to missingness)
## Multiple R-squared:  0.01722,    Adjusted R-squared:  0.01625
## F-statistic: 17.63 on 1 and 1006 DF,  p-value: 2.92e-05
```

''fairly apply the law, regardless of a person's race?"

```
##
## Call:
## lm(formula = court.fair.race ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -1.1185 -0.1614  0.1049  0.1864  1.3247
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.51833    0.01494  34.694  < 2e-16 ***
## blk.lfate.sc -0.09256    0.02405  -3.849 0.000126 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3104 on 1041 degrees of freedom
##   (2030 observations deleted due to missingness)
## Multiple R-squared:  0.01403,    Adjusted R-squared:  0.01308
## F-statistic: 14.81 on 1 and 1041 DF,  p-value: 0.0001261
```

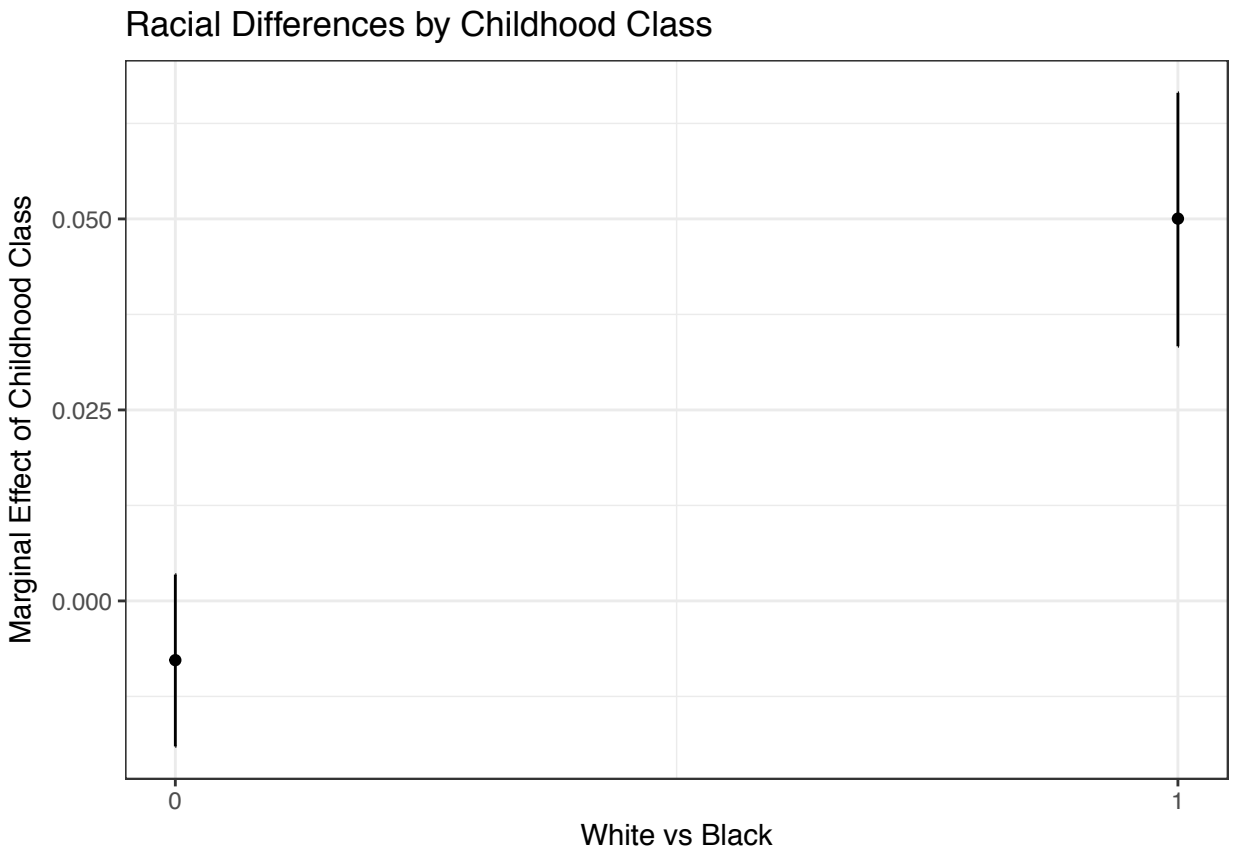
Class Fragility

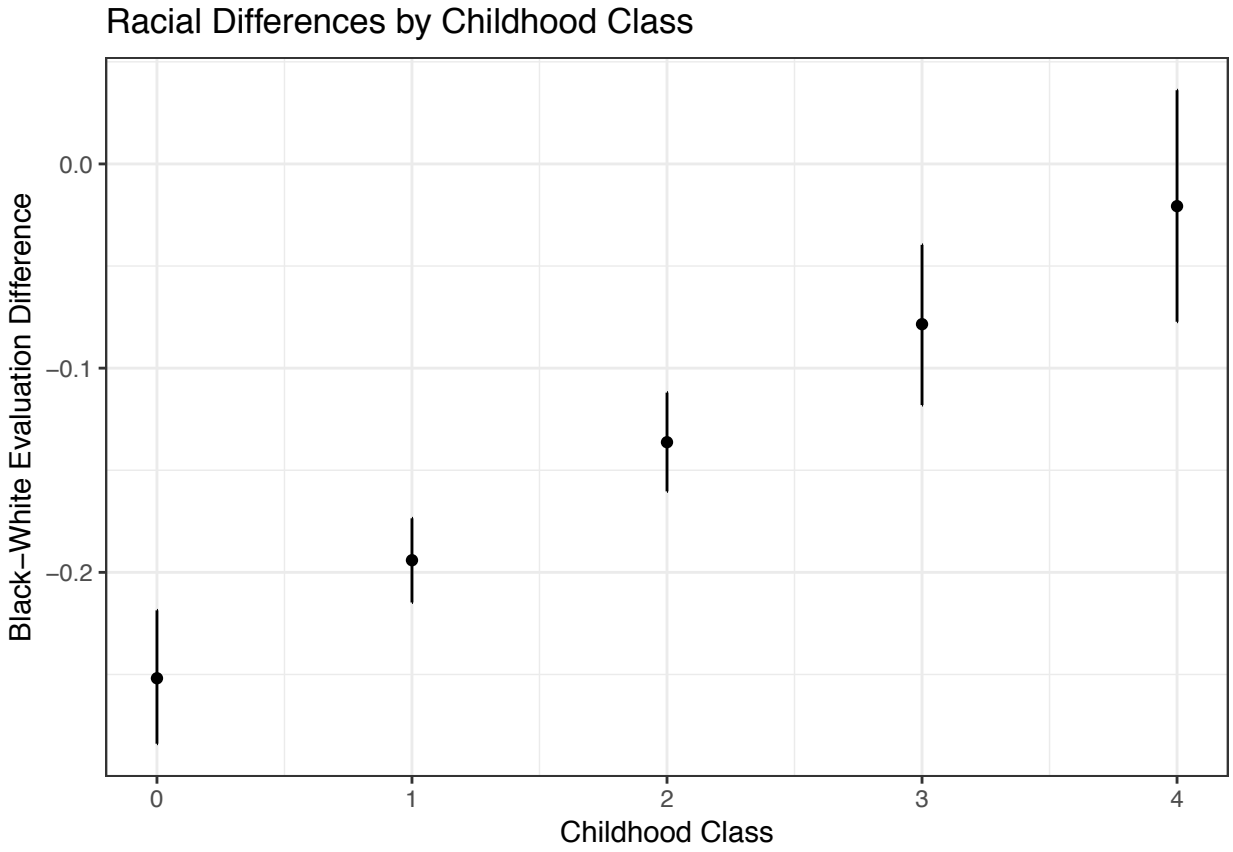
Family class growing up

Class fragility, operationalized by perceived childhood social class, shapes court evaluations to a degree, but this functions only for blacks, and not on all outcomes. For the neutral prompt, highest class blacks don't look different from whites in their evaluations of the court system's fairness. For the class prompt, class still matters for blacks, but the gap between racial groups doesn't meaningfully change. Finally, the race prompt sees no effect for class fragility here. Nothing differentiates blacks or whites. **''fairly apply the law?"**

```
##
## Call:
## lm(formula = court.fair ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -1.6217 -0.1113 -0.0128  0.1729  1.1251
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.692335   0.009441  73.335  < 2e-16 ***
## chood.class       -0.007569   0.005547  -1.365    0.172
## black             -0.251419   0.016531 -15.209  < 2e-16 ***
## chood.class:black  0.057442   0.010051   5.715 1.18e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

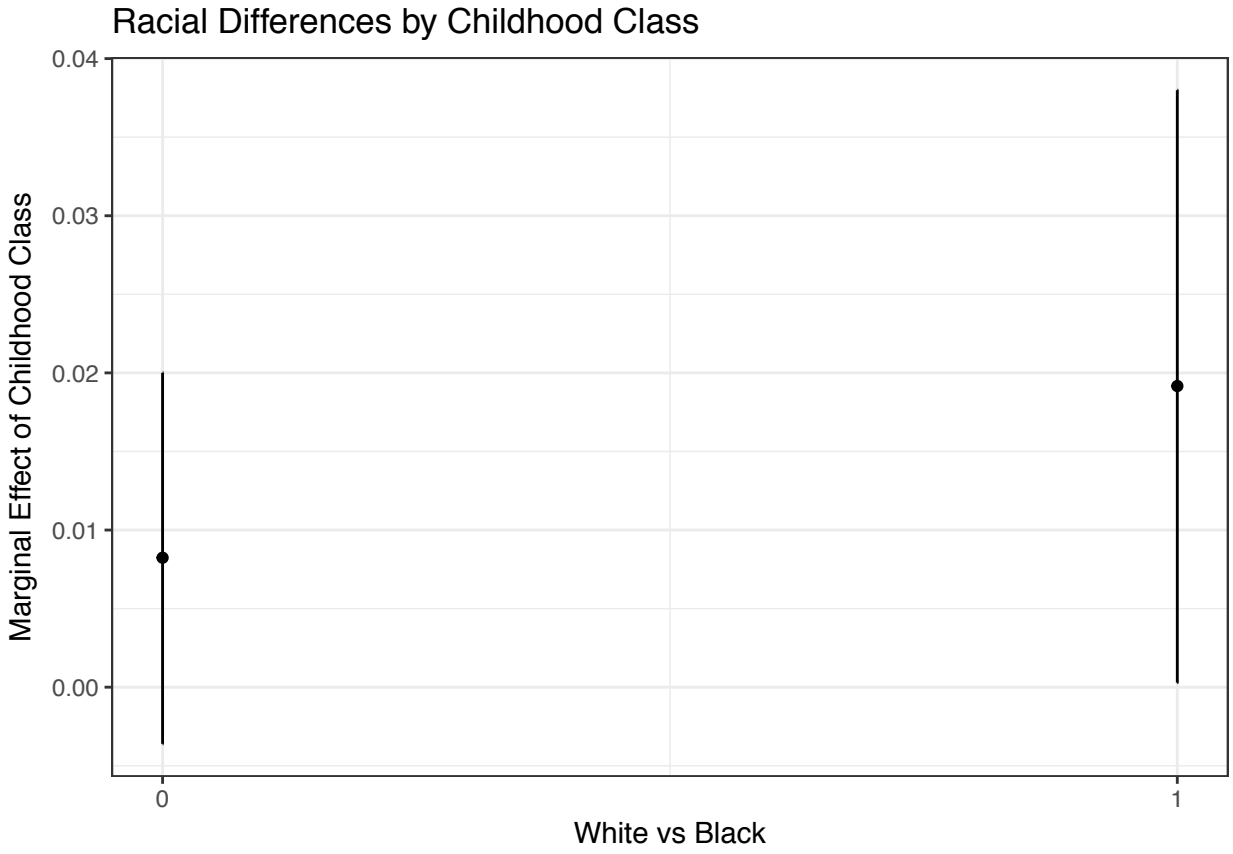
```
##
## Residual standard error: 0.2734 on 3736 degrees of freedom
##   (7426 observations deleted due to missingness)
## Multiple R-squared:  0.08621,    Adjusted R-squared:  0.08547
## F-statistic: 117.5 on 3 and 3736 DF,  p-value: < 2.2e-16
```

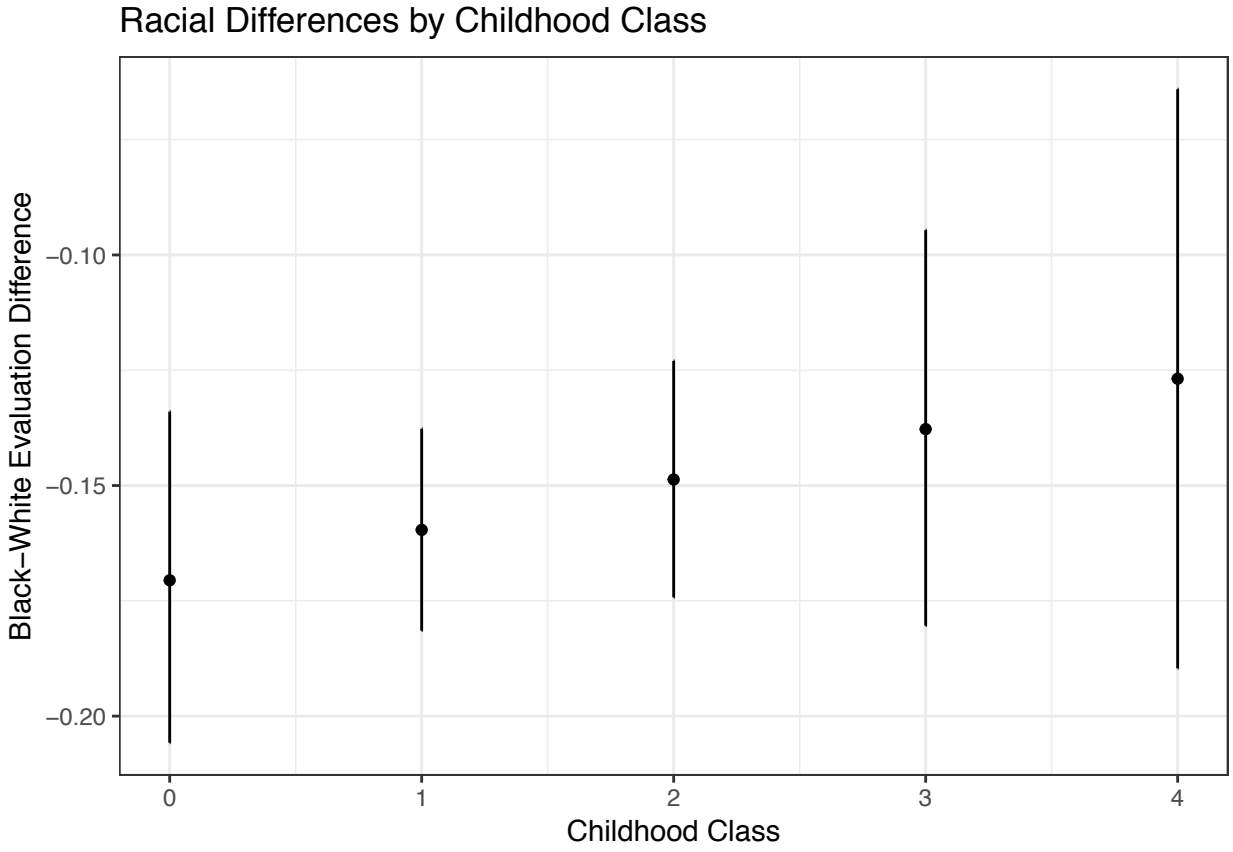




''fairly apply the law, regardless of a person's class?"

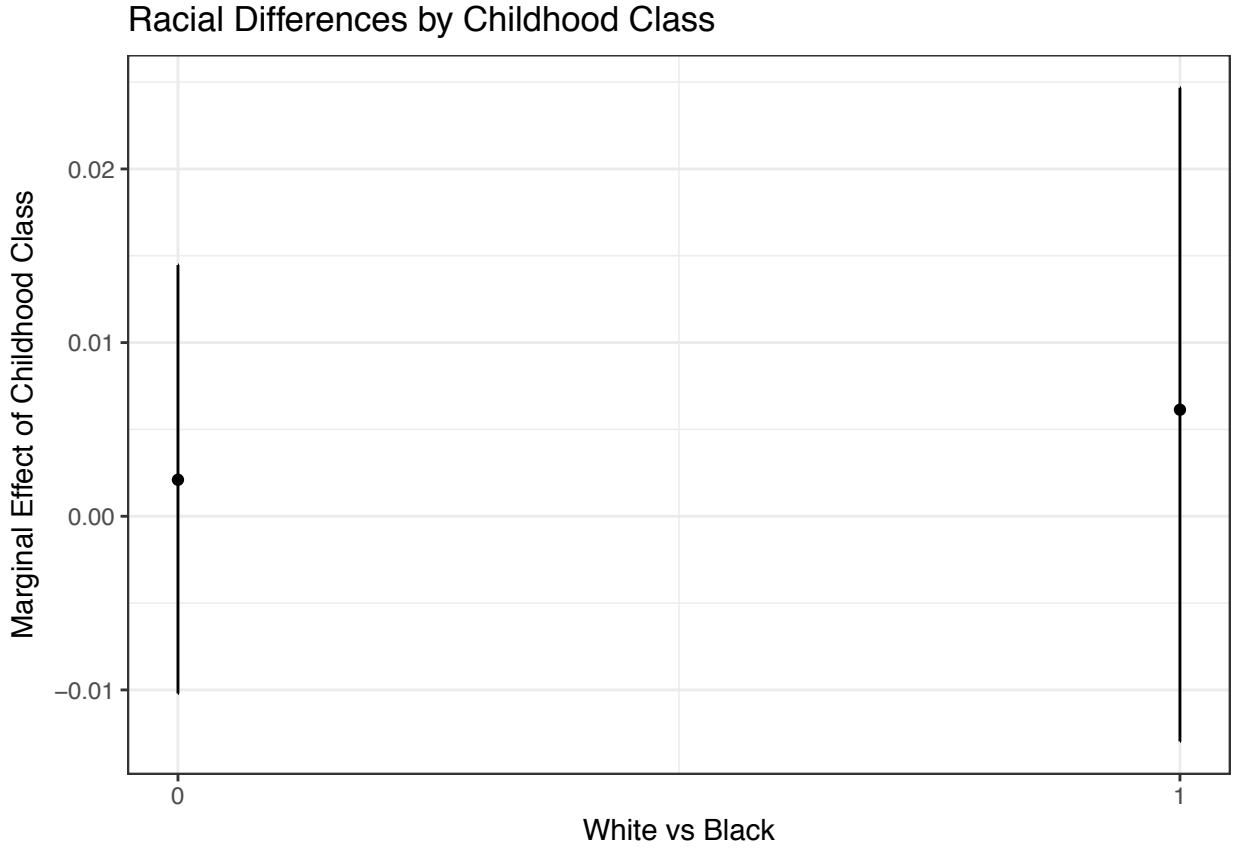
```
##
## Call:
## lm(formula = court.fair.class ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.66987 -0.15624 -0.00682  0.17553  1.19092
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.664928   0.009879  67.306   <2e-16 ***
## chood.class        0.008396   0.005890   1.425    0.154
## black             -0.170031   0.018100  -9.394   <2e-16 ***
## chood.class:black  0.010517   0.011154   0.943    0.346
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2871 on 3676 degrees of freedom
##   (7486 observations deleted due to missingness)
## Multiple R-squared:  0.0583, Adjusted R-squared:  0.05753
## F-statistic: 75.85 on 3 and 3676 DF,  p-value: < 2.2e-16
```

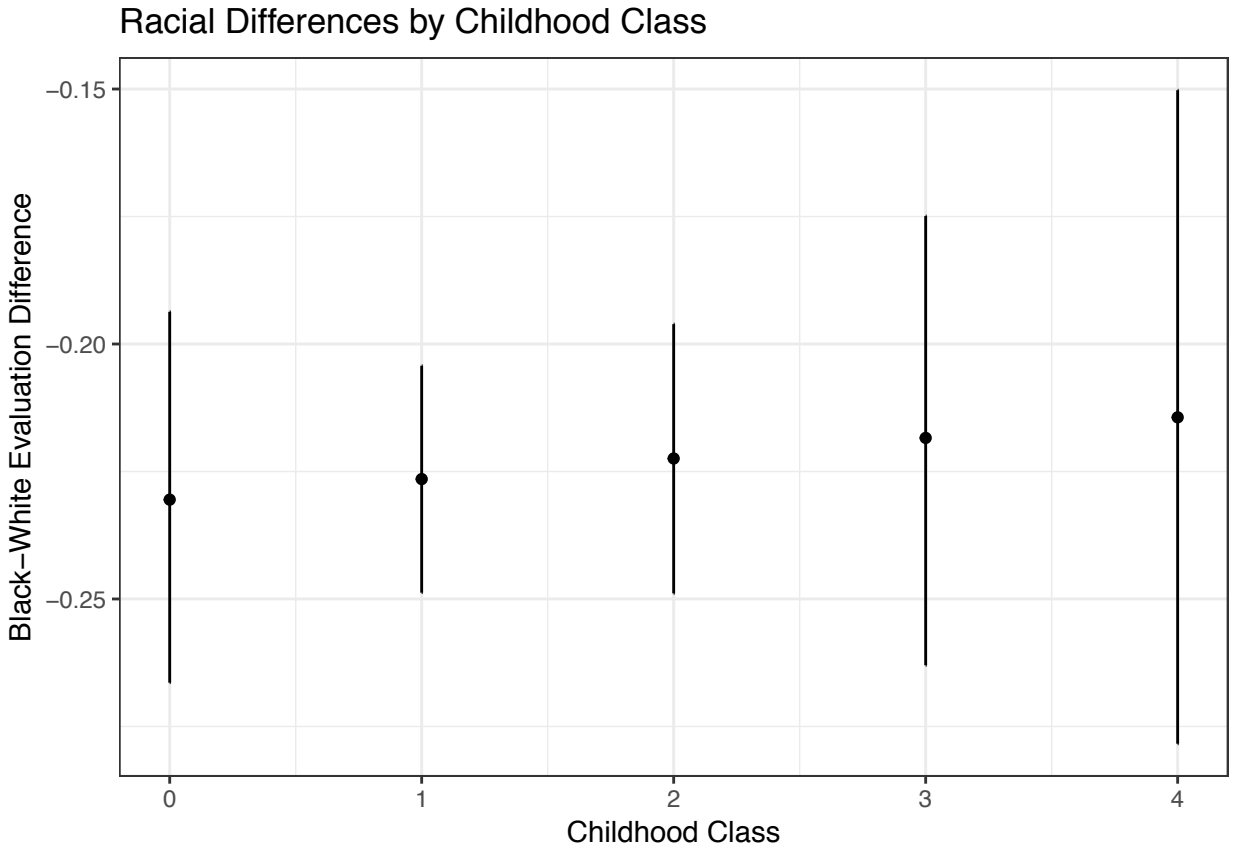




''fairly apply the law, regardless of a person's race?"

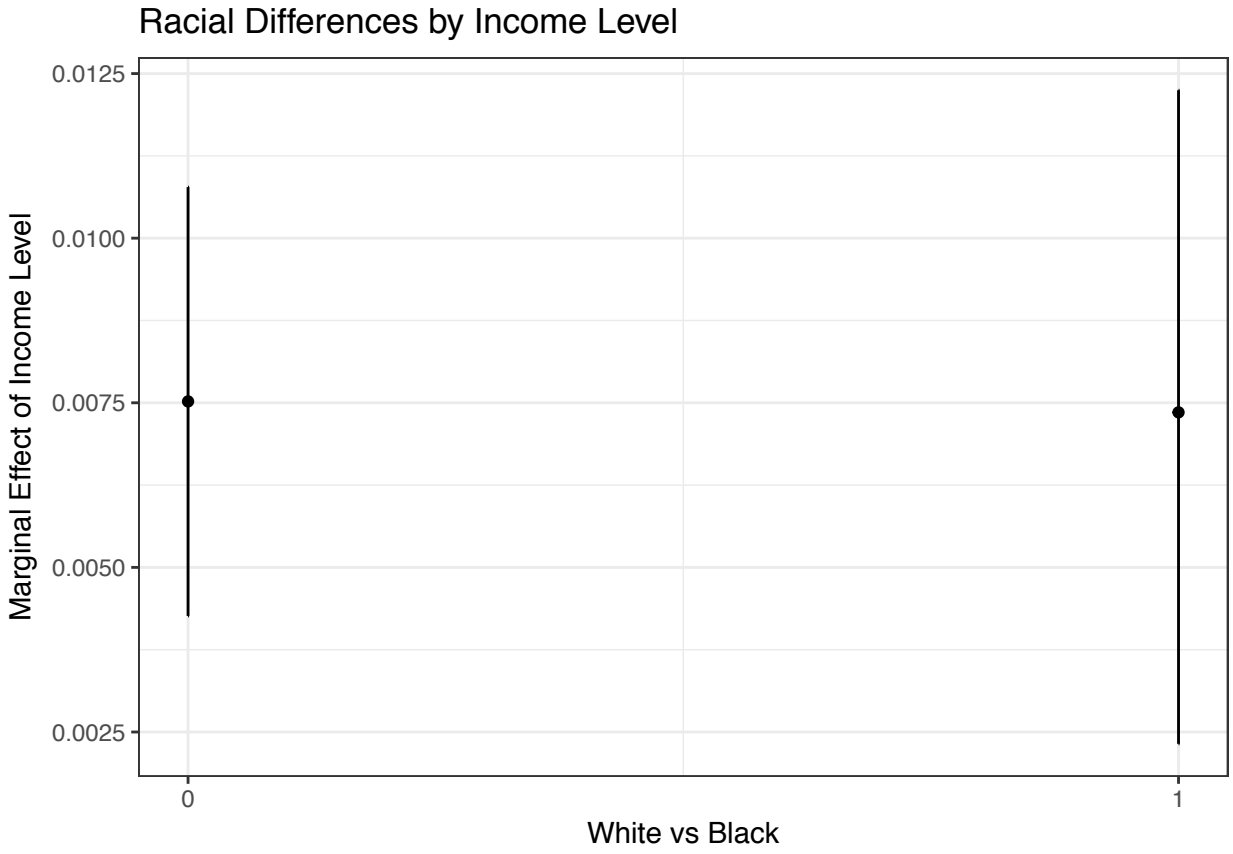
```
##
## Call:
## lm(formula = court.fair.race ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.70573 -0.11838 -0.02218  0.21470  1.28941
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        0.691848   0.010622  65.133   <2e-16 ***
## chood.class        0.002257   0.006076   0.372    0.710
## black             -0.230000   0.018245 -12.606   <2e-16 ***
## chood.class:black  0.003620   0.011298   0.320    0.749
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2897 on 3735 degrees of freedom
##   (7427 observations deleted due to missingness)
## Multiple R-squared:  0.1061, Adjusted R-squared:  0.1054
## F-statistic: 147.8 on 3 and 3735 DF,  p-value: < 2.2e-16
```

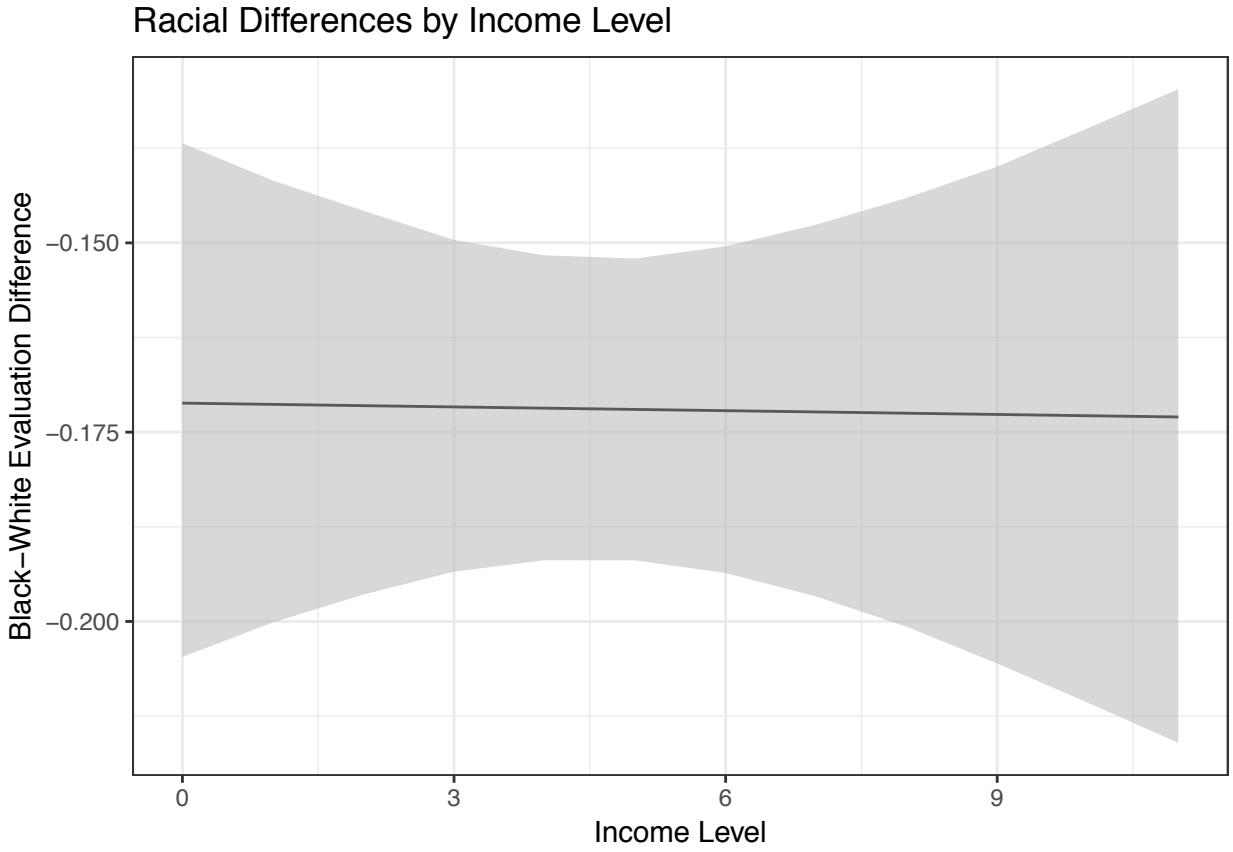




####Current income When operationalizing class fragility with current income, income shapes views, but prompt matters for how its influence maps. In the neutral prompt, both higher income whites and blacks view the courts more positively. When incorporating class into the prompt, higher income whites view the courts more positively, increasing the gap between blacks and whites in their fairness evaluations. A similar effect holds for the race prompt, but the effects are smaller. **''fairly apply the law?"**

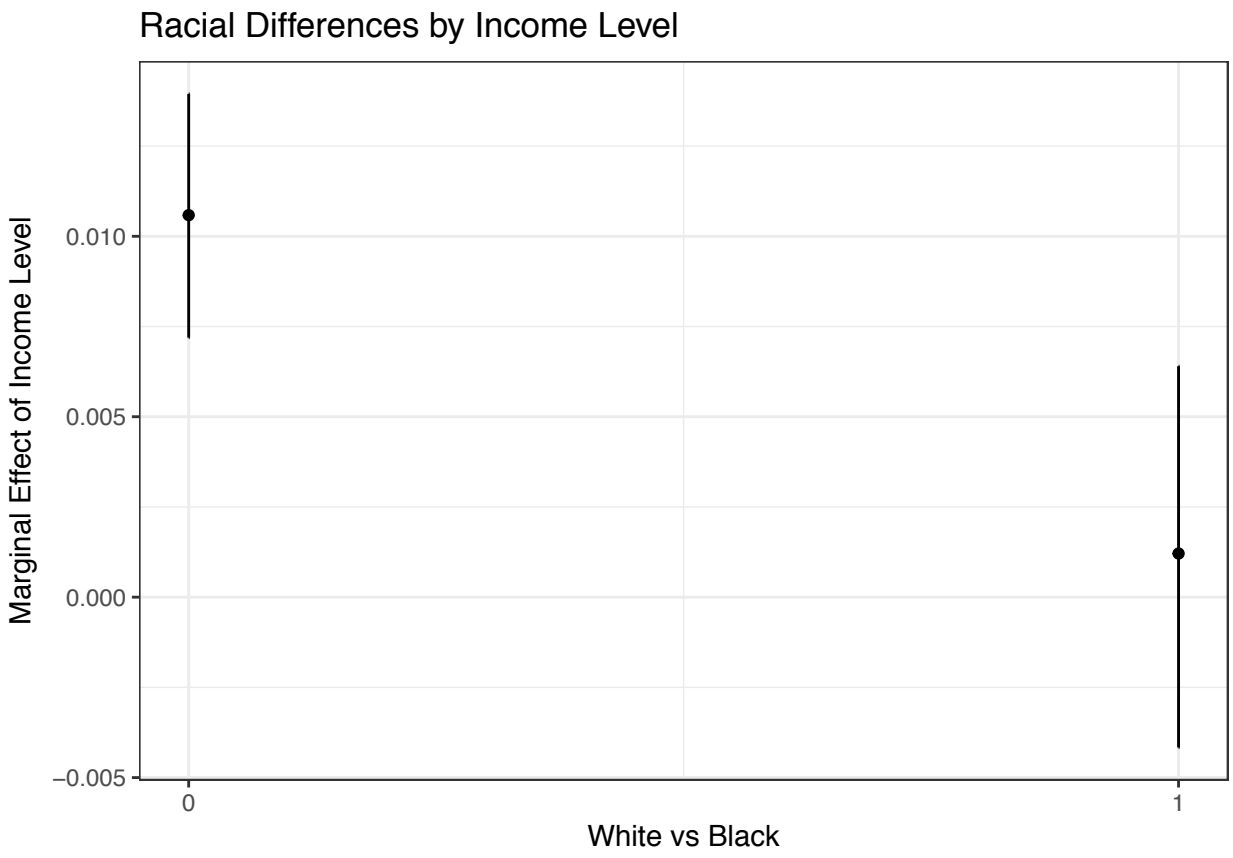
```
##
## Call:
## lm(formula = court.fair ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.77858 -0.11528  0.00078  0.17047  1.23926
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.6428571  0.0098204  65.461  < 2e-16 ***
## inc          0.0075677  0.0016255   4.656 3.34e-06 ***
## black       -0.1706508  0.0170199 -10.027  < 2e-16 ***
## inc:black   -0.0002789  0.0029899  -0.093    0.926
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2738 on 3738 degrees of freedom
##   (7424 observations deleted due to missingness)
## Multiple R-squared:  0.08406,    Adjusted R-squared:  0.08332
## F-statistic: 114.3 on 3 and 3738 DF,  p-value: < 2.2e-16
```

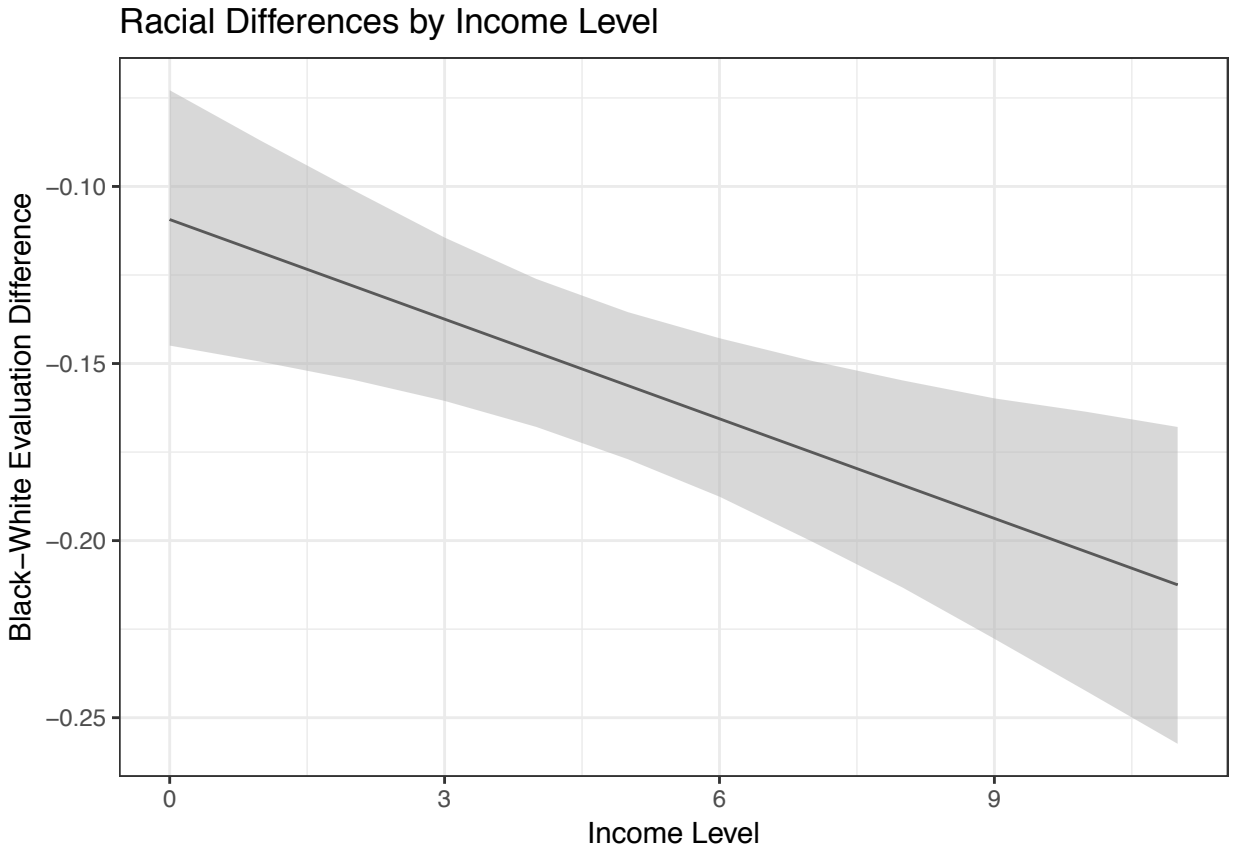




''fairly apply the law, regardless of a person's class?"

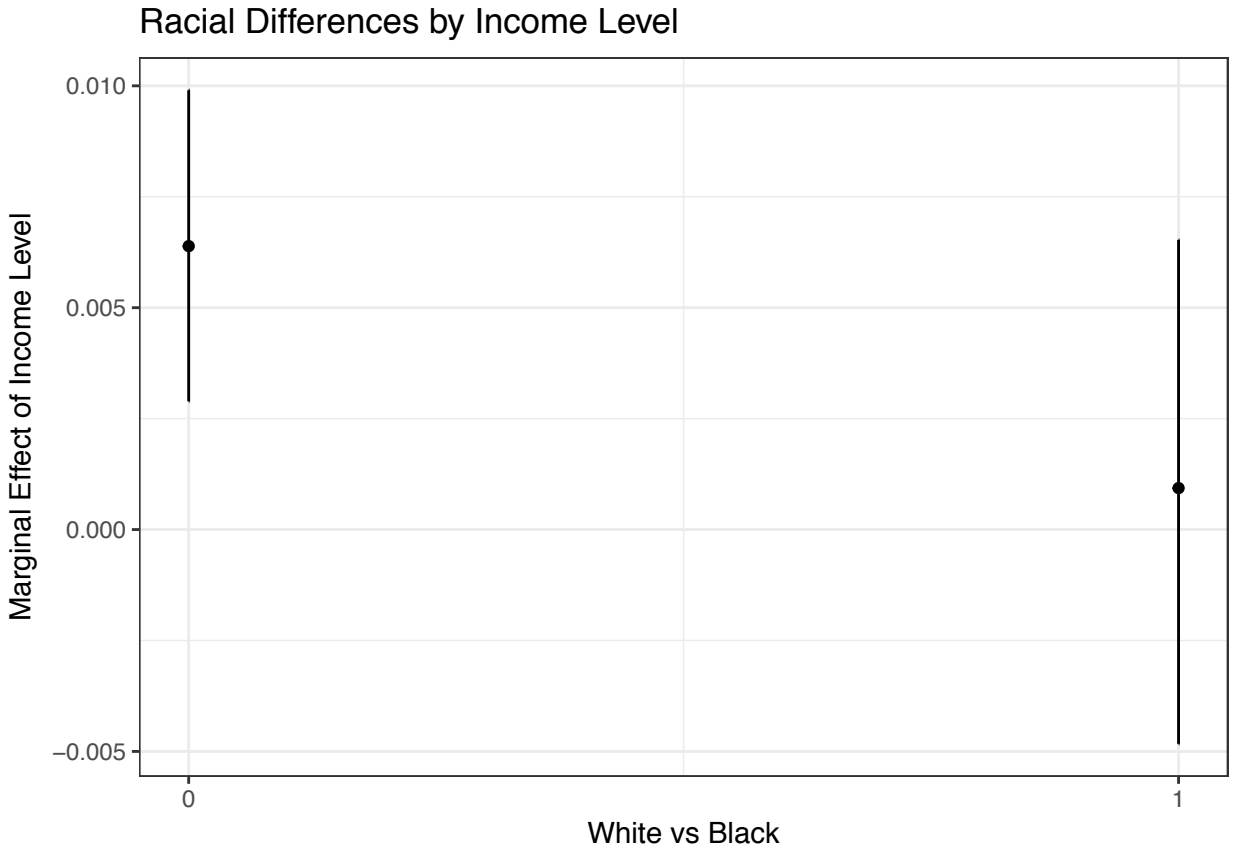
```
##
## Call:
## lm(formula = court.fair.class ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.68196 -0.15736  0.00843  0.17336  1.18473
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.622836   0.010125  61.516  < 2e-16 ***
## inc          0.010637   0.001684   6.316 3.00e-10 ***
## black       -0.108792   0.018092  -6.013 1.99e-09 ***
## inc:black   -0.009490   0.003144  -3.019  0.00255 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2857 on 3676 degrees of freedom
##   (7486 observations deleted due to missingness)
## Multiple R-squared:  0.06693,    Adjusted R-squared:  0.06617
## F-statistic: 87.89 on 3 and 3676 DF,  p-value: < 2.2e-16
```

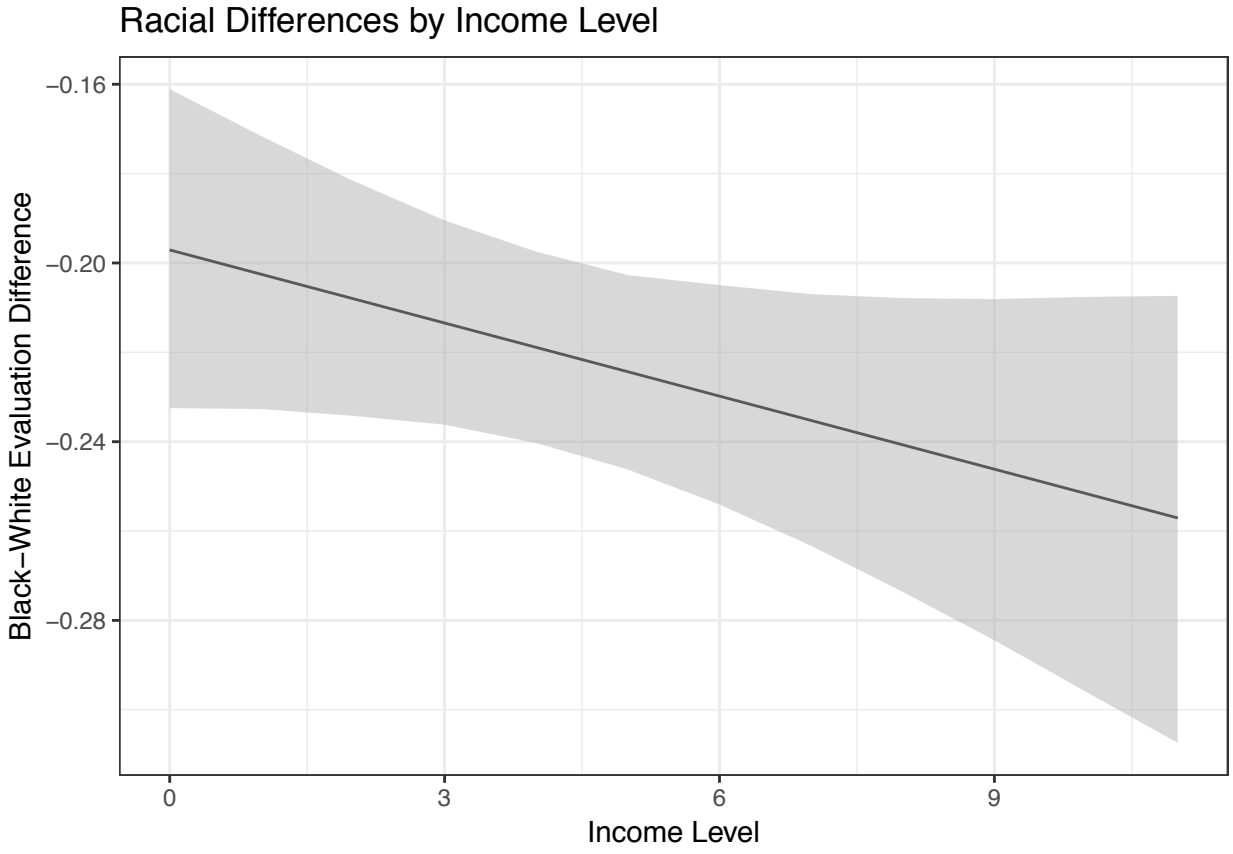




''fairly apply the law, regardless of a person's race?"

```
##
## Call:
## lm(formula = court.fair.race ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.76347 -0.12119 -0.01369  0.22082  1.28591
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.661944   0.010612  62.375  < 2e-16 ***
## inc          0.006443   0.001747   3.687  0.00023 ***
## black       -0.196563   0.017916 -10.972  < 2e-16 ***
## inc:black   -0.005566   0.003350  -1.661  0.09671 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2892 on 3736 degrees of freedom
##   (7426 observations deleted due to missingness)
## Multiple R-squared:  0.1095, Adjusted R-squared:  0.1087
## F-statistic: 153.1 on 3 and 3736 DF,  p-value: < 2.2e-16
```

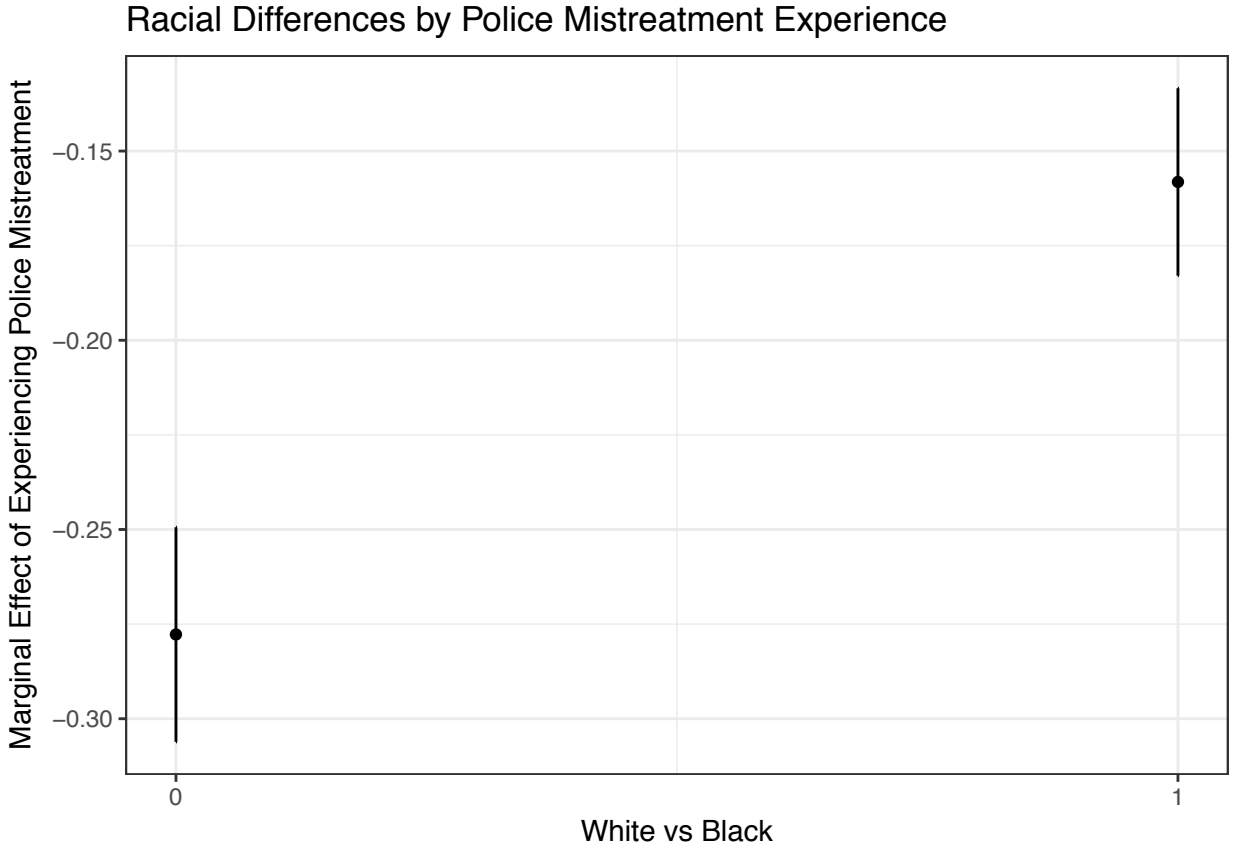


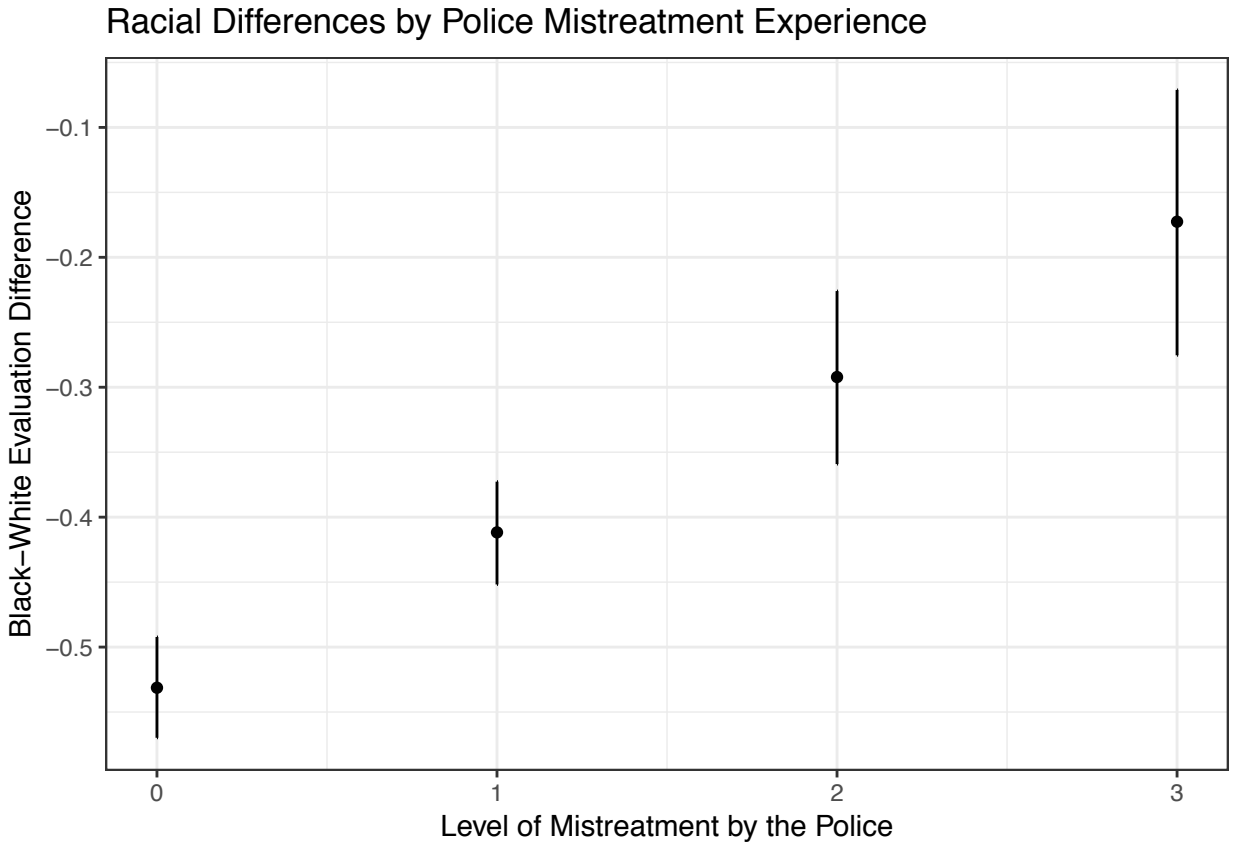


##Police Respect ###Social Experiences ####Police Abused Friends/Family Having peers who have

been mistreated by the police helps explain variation in perceptions about whether or not beleiving that respecting the police makes civilian-police interactions smoother. Mistreating by the police decreases belief that respecting the police makes interactions smoother. This works for both whites and blacks, but whites are more responsive. Moreover, the black-white gap in the outcome grows smaller as mistreatement increases.

```
##
## Call:
## lm(formula = respect.police ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2489 -0.4330 -0.1127  0.6061  3.7868
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         2.142847   0.008974 238.791  < 2e-16 ***
## pol.mistreat       -0.277480   0.014416 -19.248  < 2e-16 ***
## black              -0.530524   0.019589 -27.083  < 2e-16 ***
## pol.mistreat:black  0.119200   0.019124   6.233 4.75e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7541 on 11159 degrees of freedom
##   (3 observations deleted due to missingness)
## Multiple R-squared:  0.1483, Adjusted R-squared:  0.148
## F-statistic: 647.6 on 3 and 11159 DF,  p-value: < 2.2e-16
```



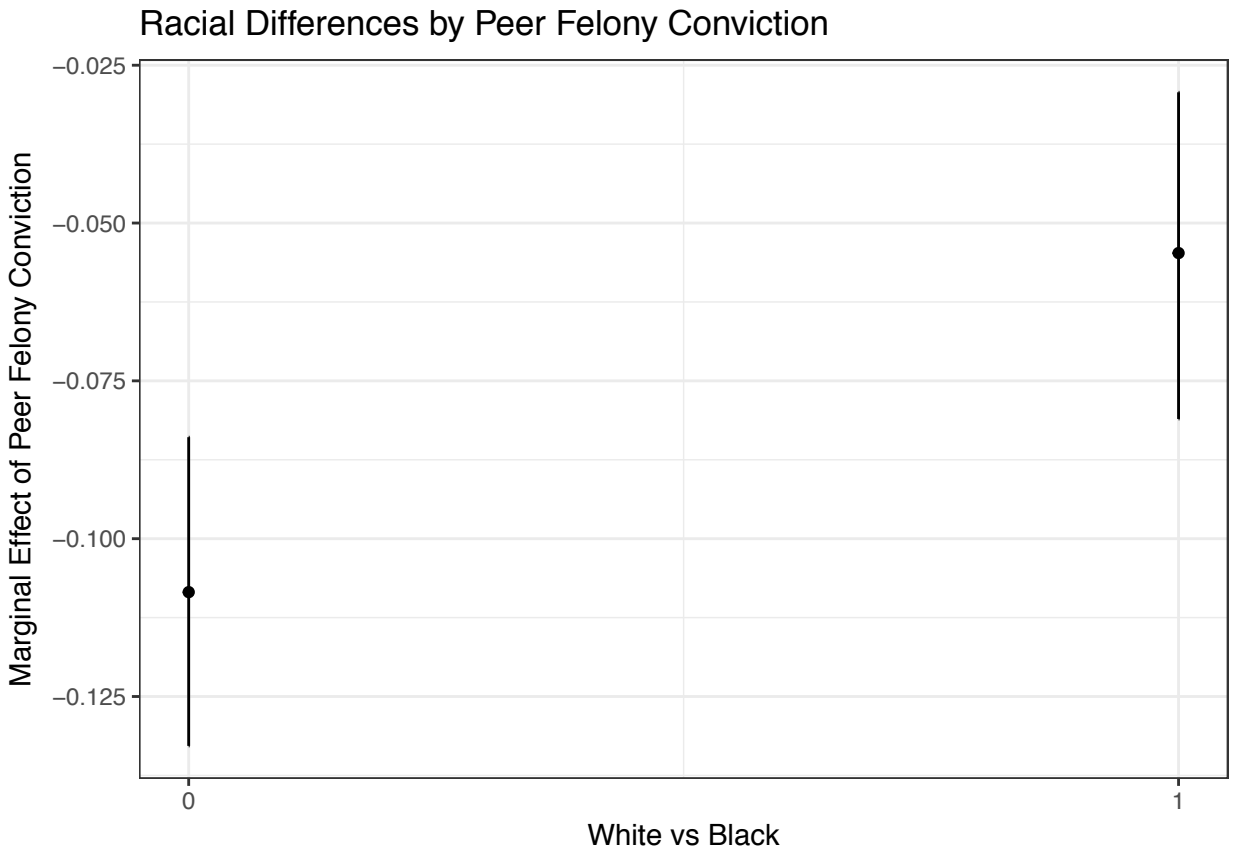


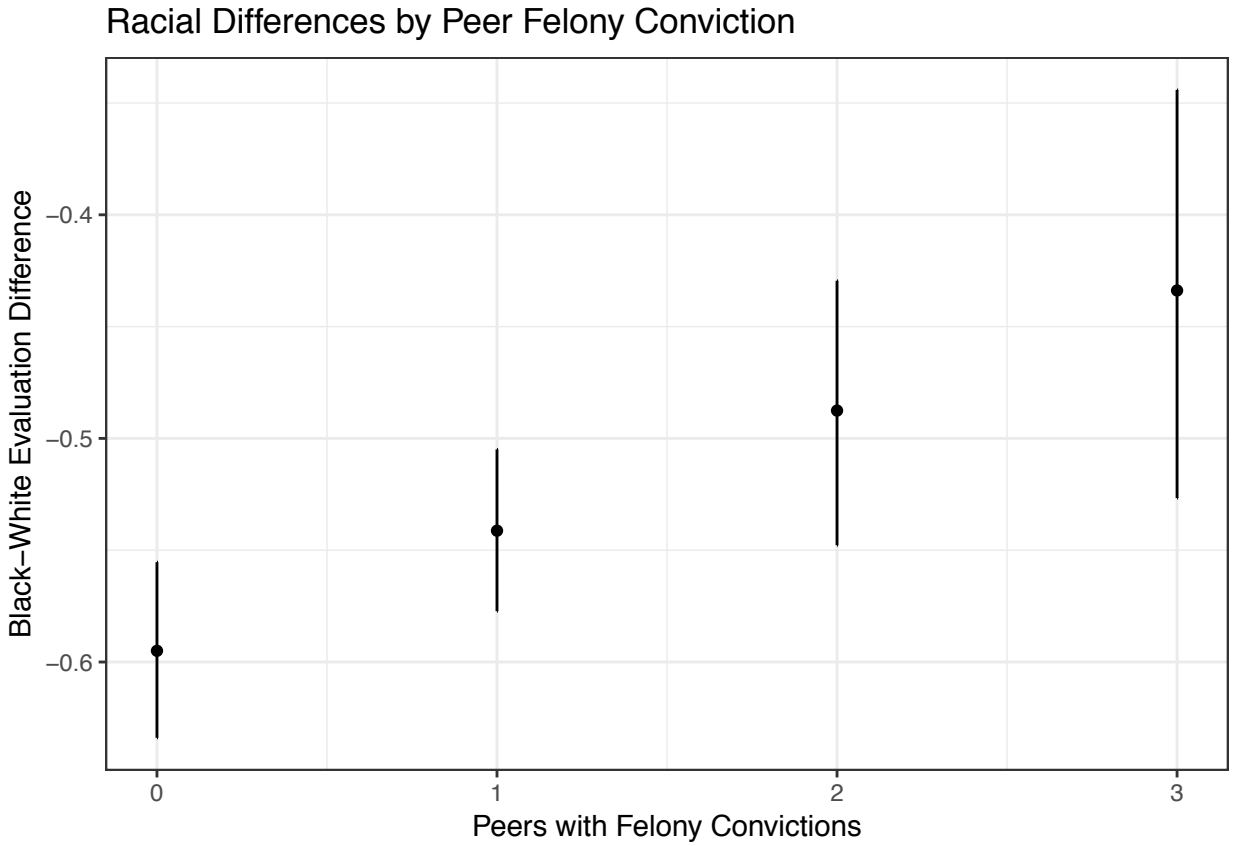
Peers convicted of a Felony

A similar effect holds when turning to whether or not a respondent has peers with felony convictions. Here, while racial difference in responsiveness exist, the gap is smaller. Moreover, the racial gap on the outcome grows slightly smaller as peers with convictions increase.

```
##
## Call:
## lm(formula = respect.police ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.1869 -0.4211 -0.0892  0.6240  3.7529
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.11753    0.00951 222.663  < 2e-16 ***
## peer.felony       -0.10808    0.01224  -8.829  < 2e-16 ***
## black             -0.59462    0.02016 -29.496  < 2e-16 ***
## peer.felony:black  0.05304    0.01800   2.947  0.00321 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7685 on 11160 degrees of freedom
##   (2 observations deleted due to missingness)
## Multiple R-squared:  0.1154, Adjusted R-squared:  0.1152
```

```
## F-statistic: 485.5 on 3 and 11160 DF,  p-value: < 2.2e-16
```





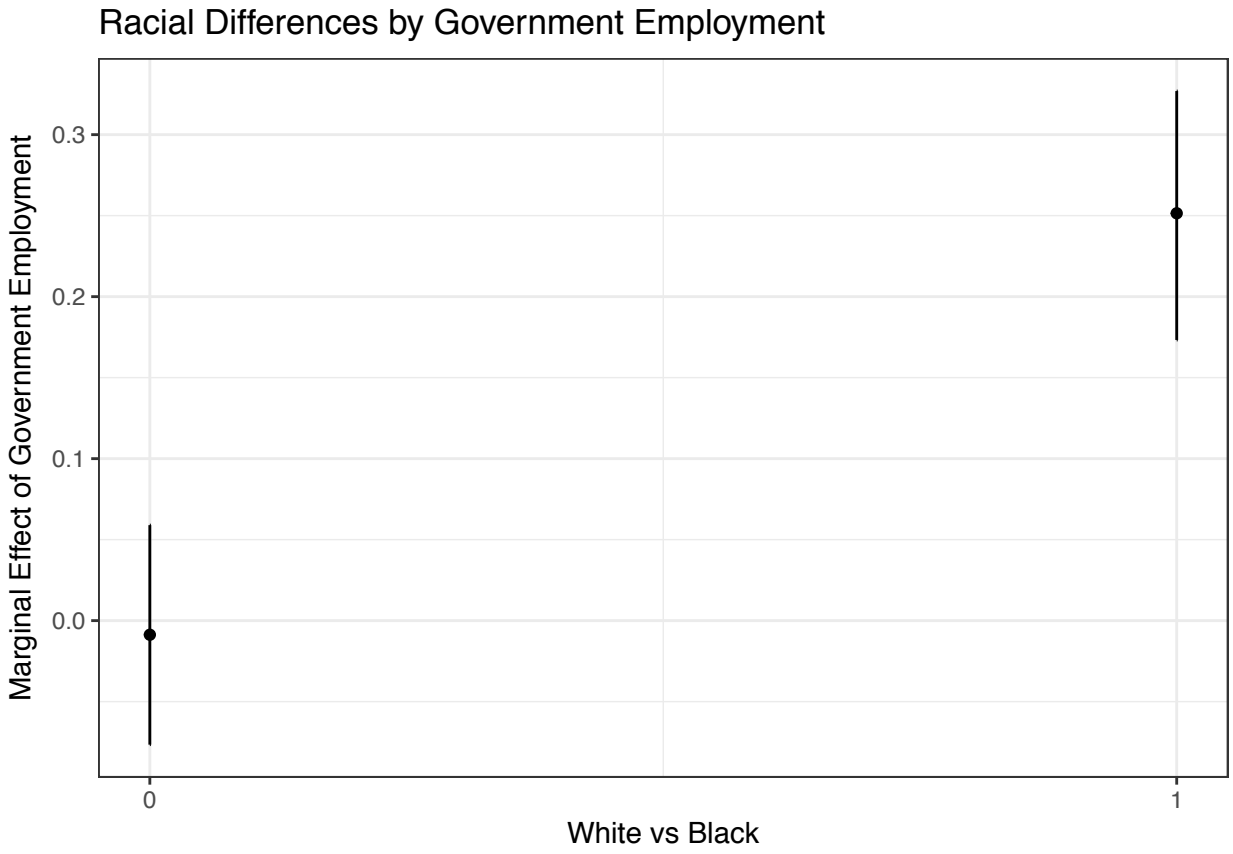
Employment

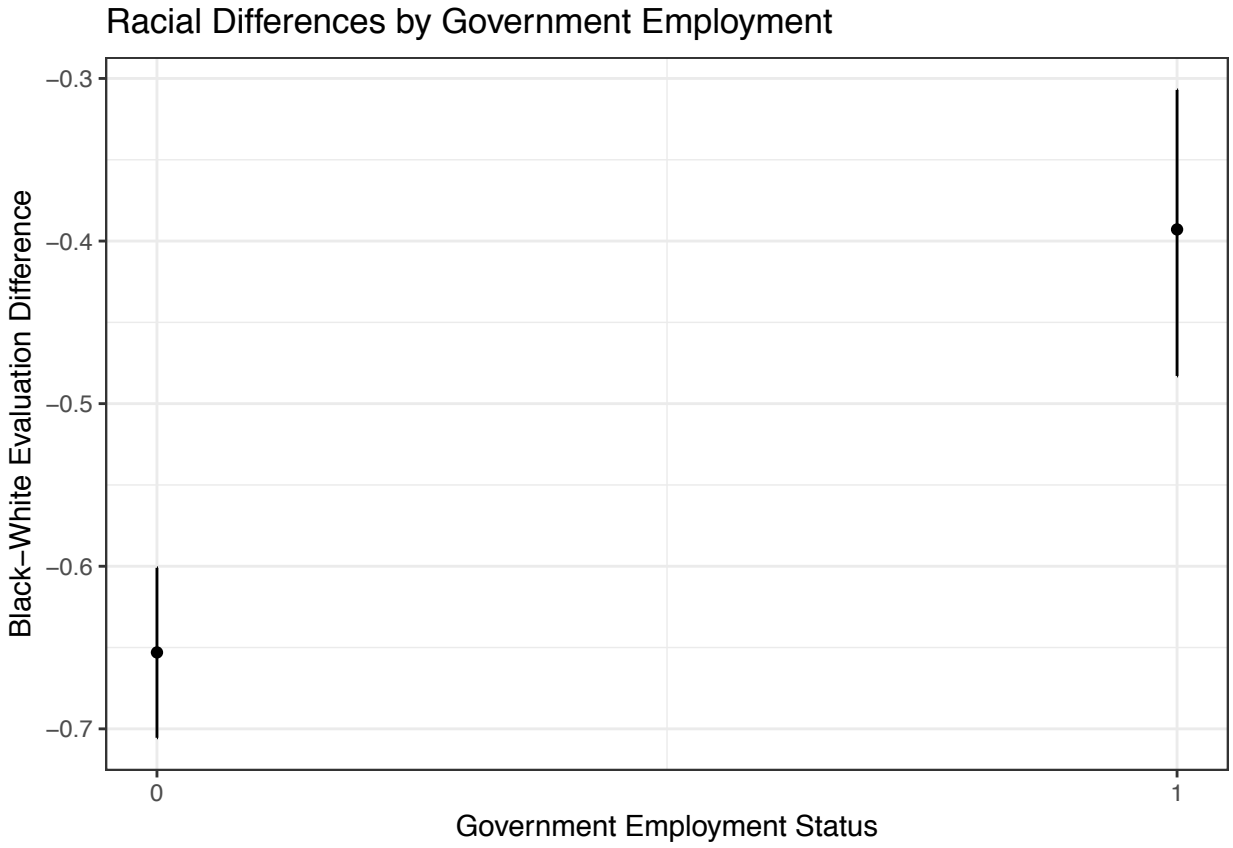
Employed in the Government

Being employed in some level of government helps explain the black-white gap on this outcome as well. First, the marginal effect of employment is larger for blacks than whites. Second, the black-white gap grows smaller for those employed by the government.

```
##
## Call:
## lm(formula = respect.police ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.0178 -0.4574 -0.0417  0.5684  3.9277
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.048507   0.013215 155.010  < 2e-16 ***
## employ.gov       -0.007958   0.033726  -0.236    0.813
## black            -0.651980   0.025966 -25.109  < 2e-16 ***
## employ.gov:black  0.258299   0.051652   5.001 5.88e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7583 on 5793 degrees of freedom
```

```
##   (5369 observations deleted due to missingness)
## Multiple R-squared:  0.1091, Adjusted R-squared:  0.1087
## F-statistic: 236.5 on 3 and 5793 DF,  p-value: < 2.2e-16
```



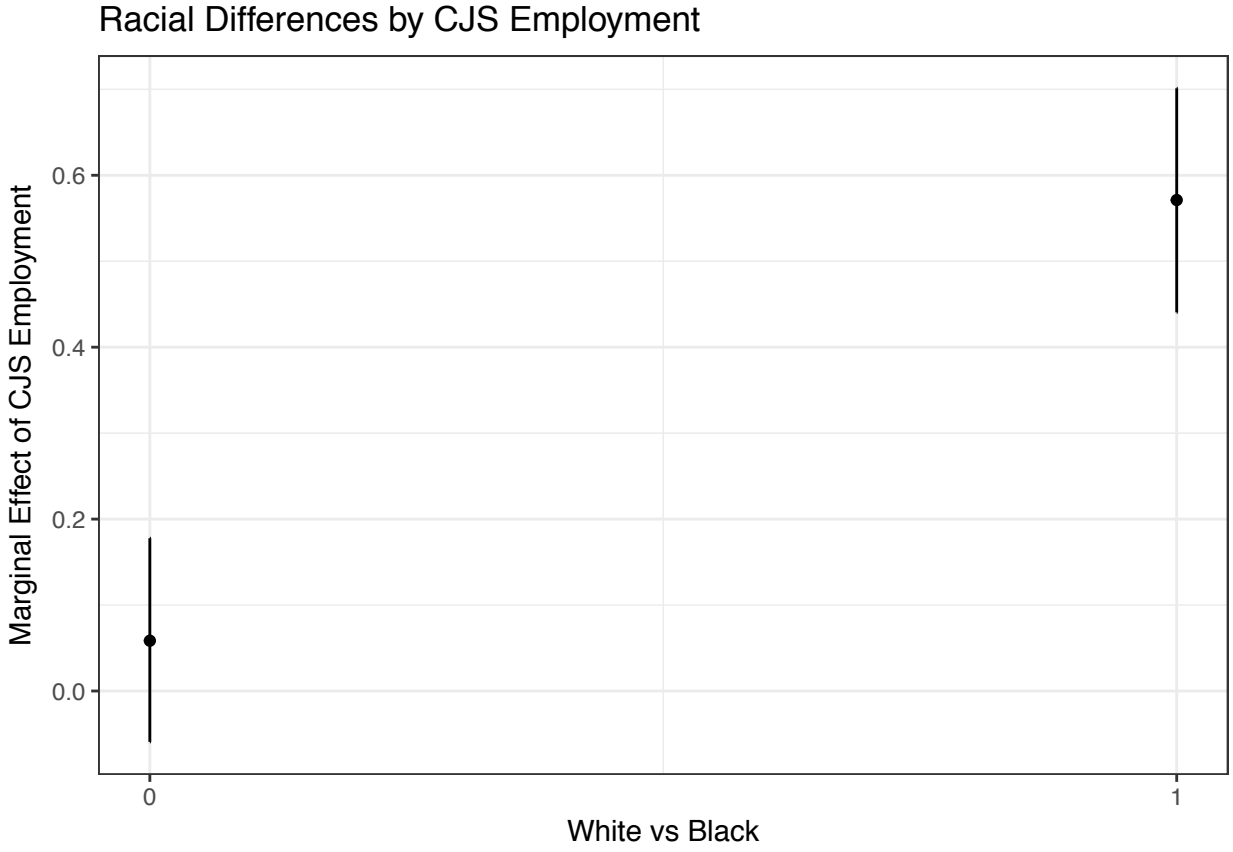


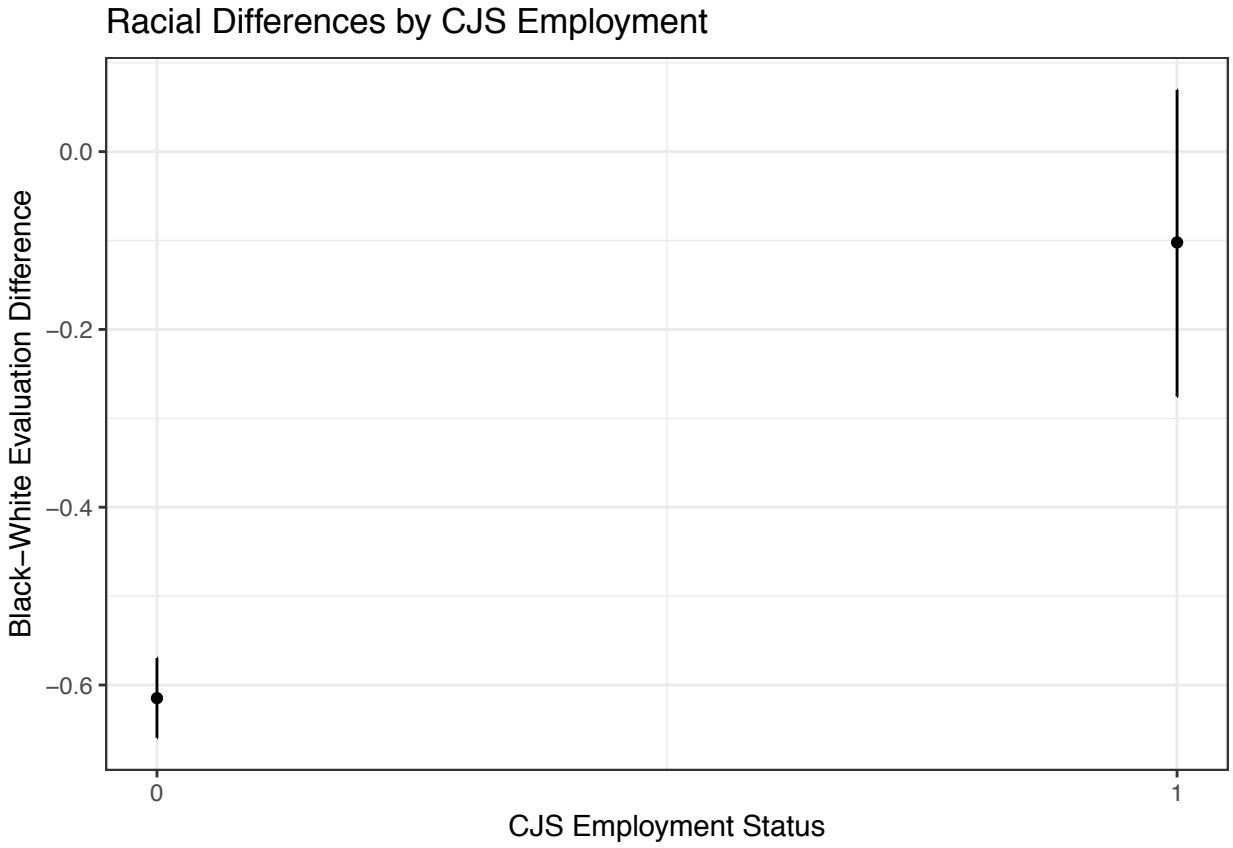
Employed in the Criminal Justice System

A similar pattern holds when looking at variation by whether or not respondents are employed in the criminal justice system. Employment here matters solely for blacks. Employment improves perspectives on respecting the police by half a scale point. The racial gap in evaluations effectively disappears.

```
##
## Call:
## lm(formula = respect.police ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.1531 -0.4157 -0.0395  0.5776  3.8458
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        2.04410    0.01239 165.021  < 2e-16 ***
## employ.cjs         0.05965    0.06096   0.978    0.328
## black             -0.61414    0.02280 -26.942  < 2e-16 ***
## employ.cjs:black   0.50946    0.08945   5.696 1.29e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.756 on 5788 degrees of freedom
##   (5374 observations deleted due to missingness)
## Multiple R-squared:  0.1141, Adjusted R-squared:  0.1137
```

```
## F-statistic: 248.6 on 3 and 5788 DF,  p-value: < 2.2e-16
```





Criminal Justice System Profession

Finally, little systematically varies by a respondent's specific position in the criminal justice system.

```
##
## Call:
## lm(formula = respect.police ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -3.04788 -0.46703 -0.05506  0.59481  2.25875
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 2.24026    0.18808  11.911  < 2e-16 ***
## as.factor(cjs.pos)2         0.05701    0.34732   0.164 0.869761
## as.factor(cjs.pos)3        -0.31558    0.37048  -0.852 0.395149
## as.factor(cjs.pos)4        -0.52406    0.27892  -1.879 0.061435 .
## as.factor(cjs.pos)5         0.02360    0.29660   0.080 0.936648
## as.factor(cjs.pos)6        -0.99597    0.26725  -3.727 0.000241 ***
## as.factor(cjs.pos)7        -0.22889    0.32562  -0.703 0.482753
## as.factor(cjs.pos)8         0.17583    0.21679   0.811 0.418107
## black                       0.22968    0.25750   0.892 0.373275
## as.factor(cjs.pos)2:black -0.45529    0.44185  -1.030 0.303820
## as.factor(cjs.pos)3:black -0.04564    0.55030  -0.083 0.933966
## as.factor(cjs.pos)4:black  0.20533    0.41006   0.501 0.617002
```

```
## as.factor(cjs.pos)5:black -0.02532    0.42479  -0.060 0.952509
## as.factor(cjs.pos)6:black  0.60389    0.38240   1.579 0.115568
## as.factor(cjs.pos)7:black  0.30792    0.47418   0.649 0.516700
## as.factor(cjs.pos)8:black -1.15663    0.30351  -3.811 0.000175 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8532 on 247 degrees of freedom
##   (10903 observations deleted due to missingness)
## Multiple R-squared:  0.2176, Adjusted R-squared:  0.1701
## F-statistic: 4.581 on 15 and 247 DF,  p-value: 1.061e-07
```

Racial Group Views

Racial Resentment

Whites' levels of racial resentment help explain beliefs about respecting the police. Min-max changes in racial resentment amount to over a category shift in the outcome.

```
##
## Call:
## lm(formula = respect.police ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.1292 -0.4023 -0.0171  0.4494  3.2456
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.39566    0.02035   68.57   <2e-16 ***
## rr_sc        1.11734    0.03104   36.00   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6988 on 8070 degrees of freedom
##   (21 observations deleted due to missingness)
## Multiple R-squared:  0.1384, Adjusted R-squared:  0.1383
## F-statistic:  1296 on 1 and 8070 DF,  p-value: < 2.2e-16
```

White Linked Fate

Whites' linked fate also helps explain the outcome, but the magnitude is small. A min-max change amounts to roughly a 1/7 a category change in the outcome.

```
##
## Call:
## lm(formula = respect.police ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2244 -0.1935 -0.0398  0.6132  2.5013
##
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.13284    0.01185 180.050  < 2e-16 ***
## wht.lfate.sc -0.15397    0.02156  -7.141 1.01e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7512 on 8079 degrees of freedom
##   (12 observations deleted due to missingness)
## Multiple R-squared:  0.006273,   Adjusted R-squared:  0.00615
## F-statistic:    51 on 1 and 8079 DF,  p-value: 1.005e-12
```

Black Linked Fate

A similar effect holds for black linked fate. A min-max change amounts to nearly a 1/5 of a category change in the outcome.

```
##
## Call:
## lm(formula = respect.police ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.8306 -0.4650 -0.2734  0.4766  3.9696
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.56385    0.02301  67.961  < 2e-16 ***
## blk.lfate.sc -0.18443    0.03656  -5.044 4.83e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8209 on 3068 degrees of freedom
##   (3 observations deleted due to missingness)
## Multiple R-squared:  0.008224,   Adjusted R-squared:  0.007901
## F-statistic: 25.44 on 1 and 3068 DF,  p-value: 4.827e-07
```

Class Fragility

Family class growing up

Considering variation based on family background, little varies. Blacks on average have less positive views, but nothing varies based on childhood class by either racial group.

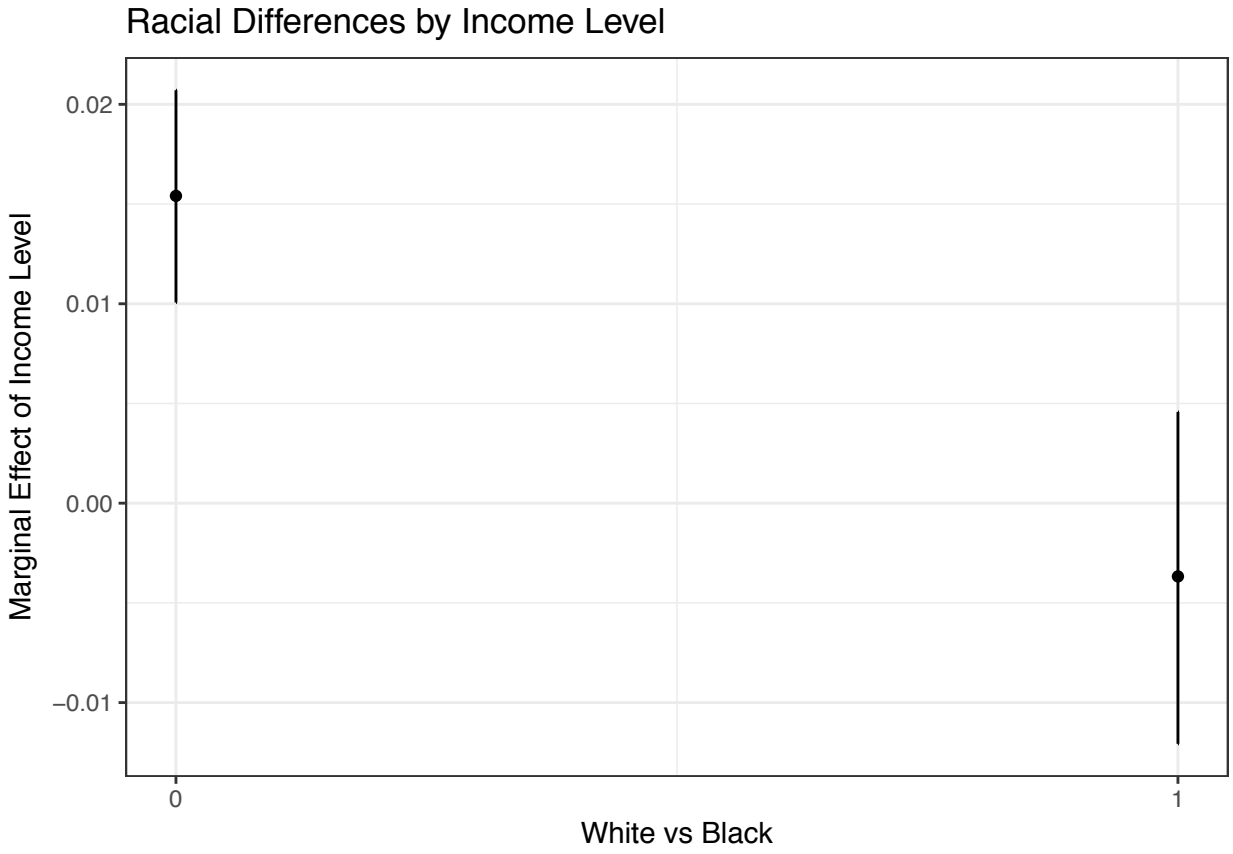
```
##
## Call:
## lm(formula = respect.police ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.0789 -0.4330 -0.0692  0.6145  3.7524
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
```

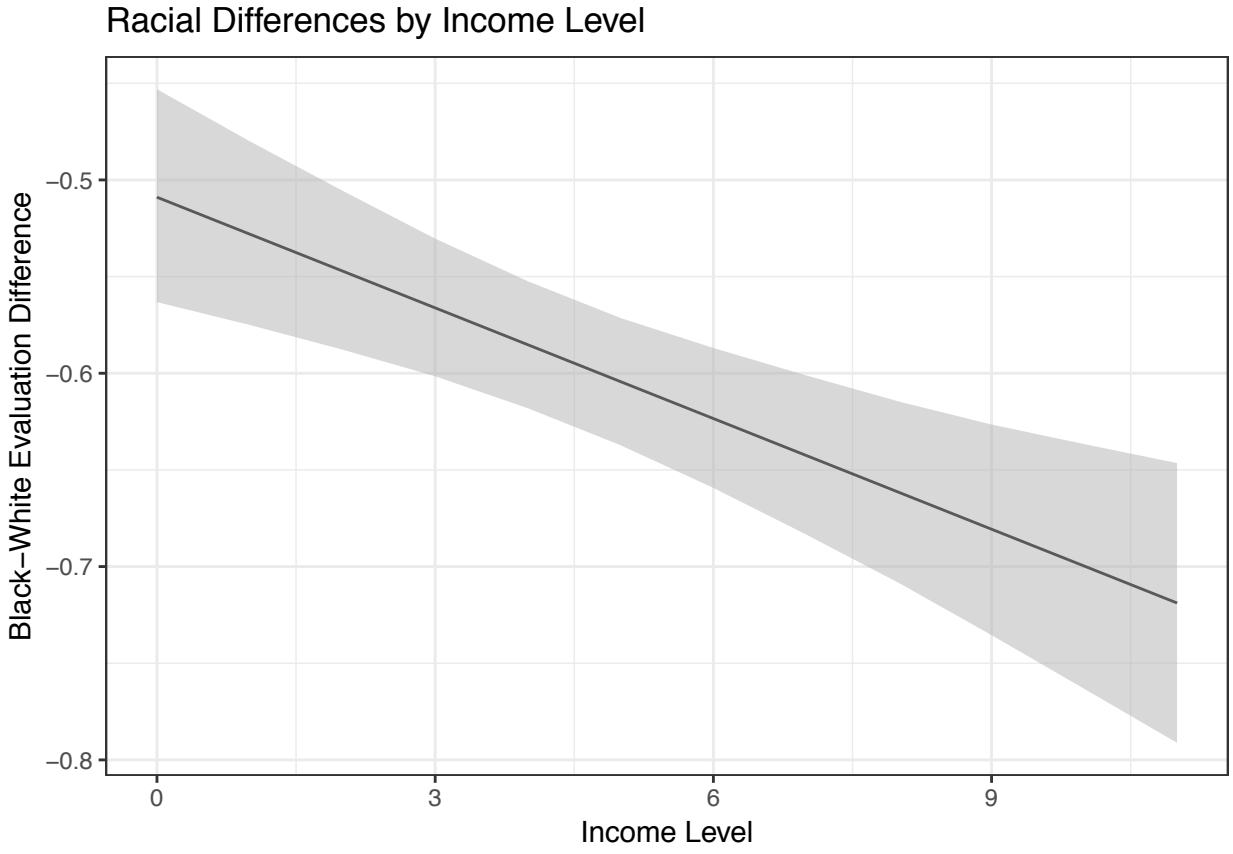
```
## (Intercept)        2.097891   0.015662 133.947   <2e-16 ***
## chood.class       -0.012217   0.009162  -1.333    0.182
## black             -0.629802   0.027648 -22.779   <2e-16 ***
## chood.class:black  0.019815   0.016986   1.167    0.243
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7716 on 11158 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.1079, Adjusted R-squared:  0.1077
## F-statistic: 449.8 on 3 and 11158 DF,  p-value: < 2.2e-16
```

Current income

Income does more to shape perspectives on respecting the police. Income matters more among whites than blacks, with higher income whites holding more positive views about respecting the police. Income doesn't matter for blacks. Consequently, with higher income whites becoming increasingly positive, the black-white racial gap increases as income increases.

```
##
## Call:
## lm(formula = respect.police ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -5.3192 -0.4384 -0.0556  0.6215  3.7927
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.001154   0.016013 124.969  < 2e-16 ***
## inc          0.015492   0.002650   5.846 5.18e-09 ***
## black       -0.508128   0.027757 -18.306  < 2e-16 ***
## inc:black   -0.019256   0.004952  -3.889 0.000101 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7705 on 11161 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.1107, Adjusted R-squared:  0.1104
## F-statistic:   463 on 3 and 11161 DF,  p-value: < 2.2e-16
```


Racial Differences by Income Level
Marginal Effect of Income Level
0.02
0.01
0.00
−0.01
0
1
White vs Black


Racial Differences by Income Level
Black−White Evaluation Difference
−0.5
−0.6
−0.7
−0.8
0
3
6
9
Income Level

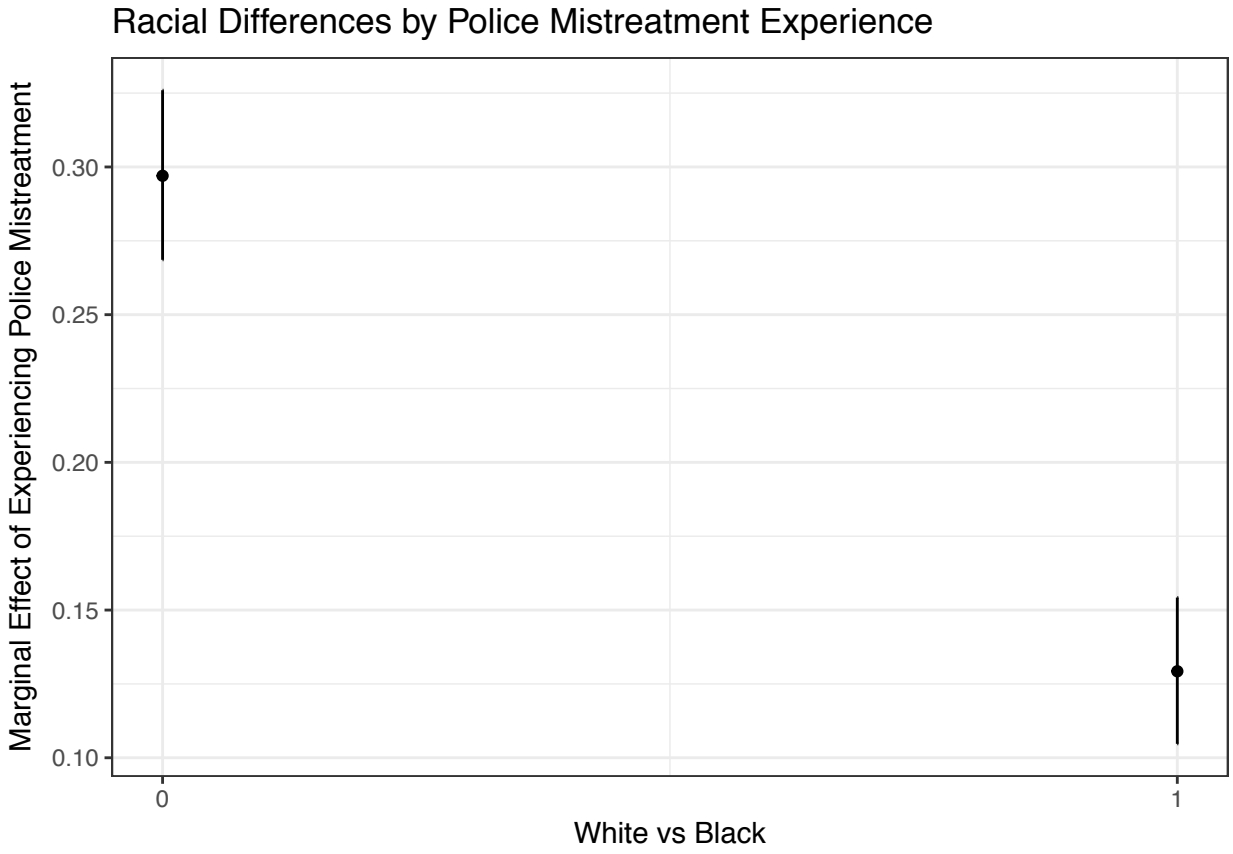
Police Quality "Bad Apples"

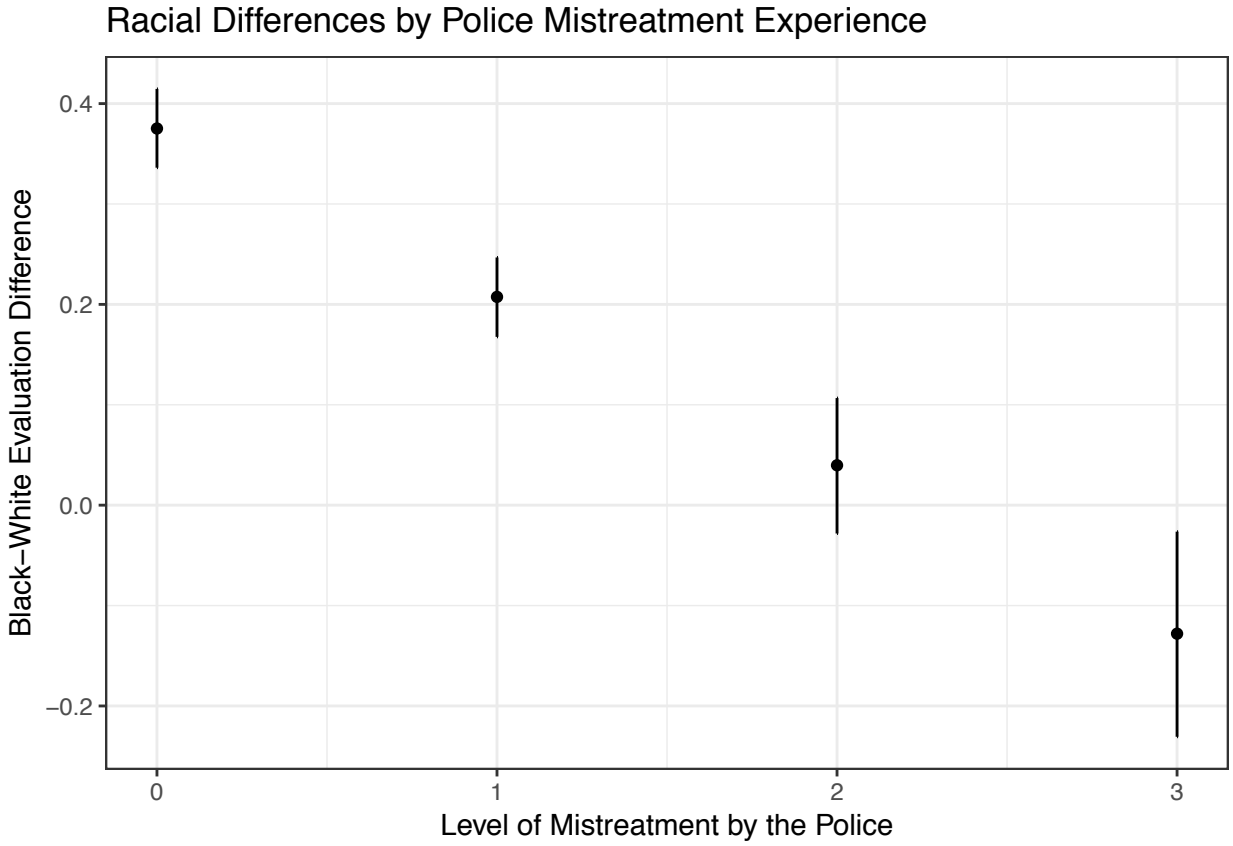
Social Experiences

Police Abused Friends/Family

Police mistreatment shapes explanations for police negligence and corruption. This effect matters more for whites than blacks, with whites having a peer being mistreated by the police being less likely to endorse a "bad apples" perspective.

```
##
## Call:
## lm(formula = pol.badapples ~ pol.mistreat * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.4059 -0.5690 -0.0025  0.4948  3.3627
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         1.627194   0.009015 180.494   <2e-16 ***
## pol.mistreat        0.297230   0.014537  20.447   <2e-16 ***
## black               0.375946   0.019846  18.943   <2e-16 ***
## pol.mistreat:black -0.168132   0.019333  -8.697   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.752 on 10916 degrees of freedom
##   (246 observations deleted due to missingness)
## Multiple R-squared:  0.09792,    Adjusted R-squared:  0.09767
## F-statistic:   395 on 3 and 10916 DF,  p-value: < 2.2e-16
```

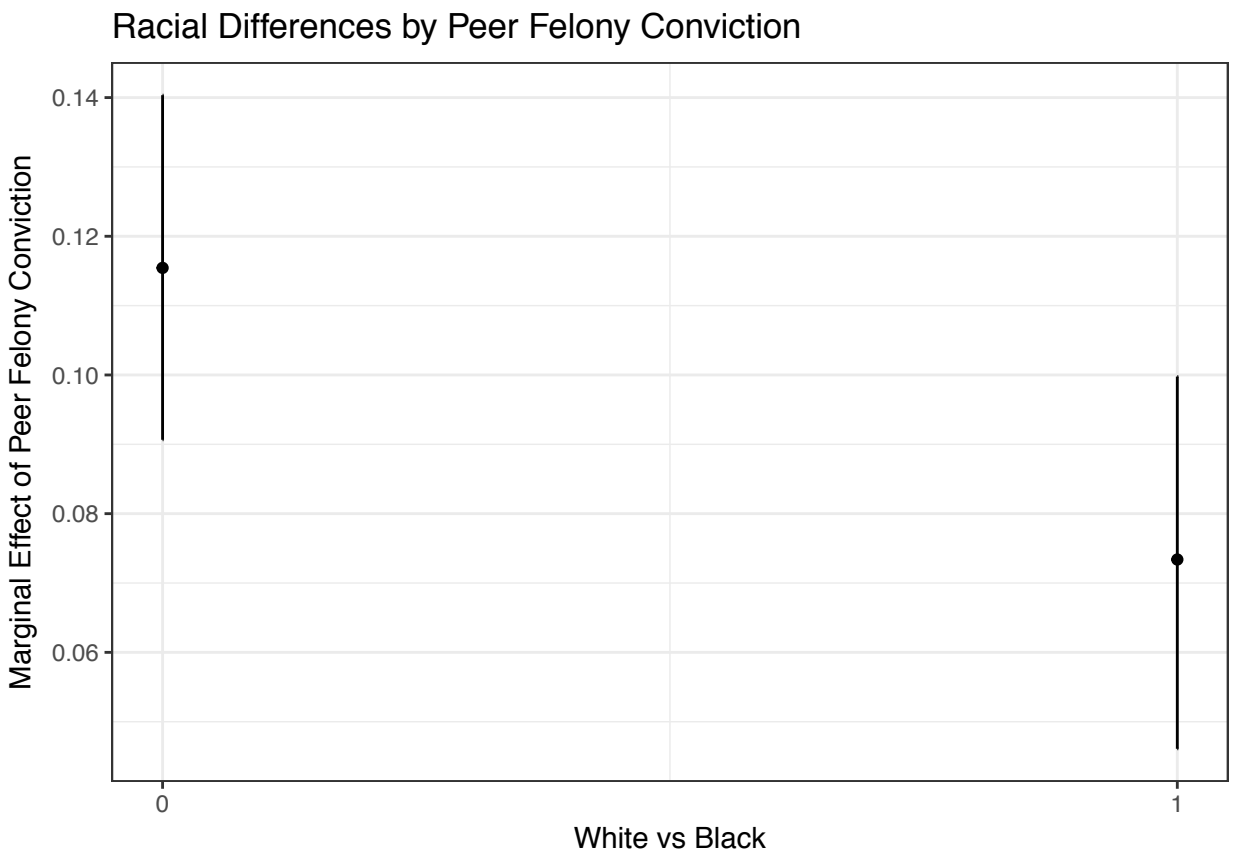

Racial Differences by Police Mistreatment Experience
Marginal Effect of Experiencing Police Mistreatment
0.30
0.25
0.20
0.15
0.10
0
1
White vs Black

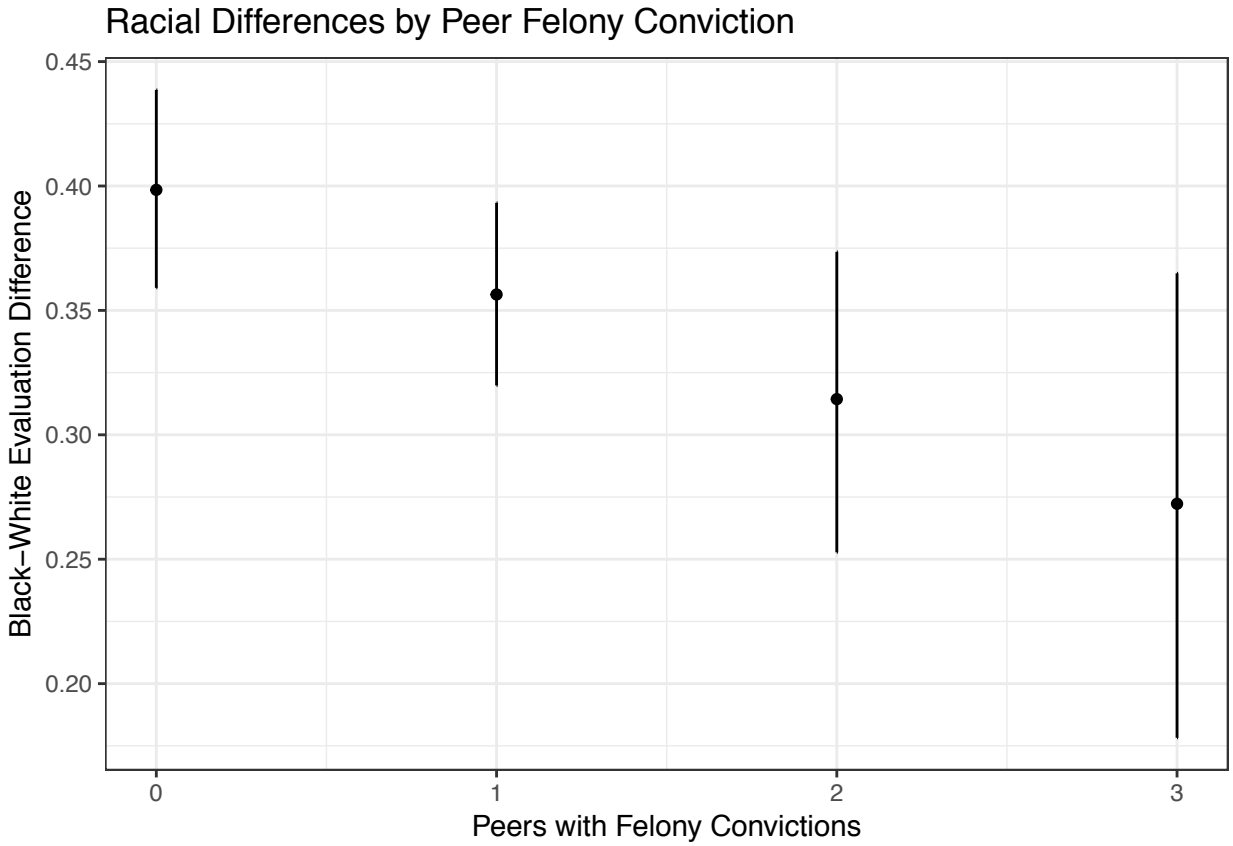

Racial Differences by Police Mistreatment Experience
Black–White Evaluation Difference
0.4
0.2
0.0
−0.2
0
1
2
3
Level of Mistreatment by the Police

Peers convicted of a Felony

Having peers with felony convictions similarly shapes attitudes. More peers moves individuals to endorse at least a mixed view of the causes of police negligence. Again, the effect is larger for whites than blacks, and the gap between blacks and whites in their attitudes grows smaller as the number of peers increses.

```
##
## Call:
## lm(formula = pol.badapples ~ peer.felony * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9377 -0.5934 -0.0374  0.5252  3.2968
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         1.654093   0.009547 173.256   <2e-16 ***
## peer.felony         0.115881   0.012304   9.418   <2e-16 ***
## black               0.398821   0.020421  19.530   <2e-16 ***
## peer.felony:black -0.042686   0.018280  -2.335   0.0196 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7656 on 10917 degrees of freedom
##   (245 observations deleted due to missingness)
## Multiple R-squared:  0.06501,    Adjusted R-squared:  0.06475
## F-statistic:   253 on 3 and 10917 DF,  p-value: < 2.2e-16
```





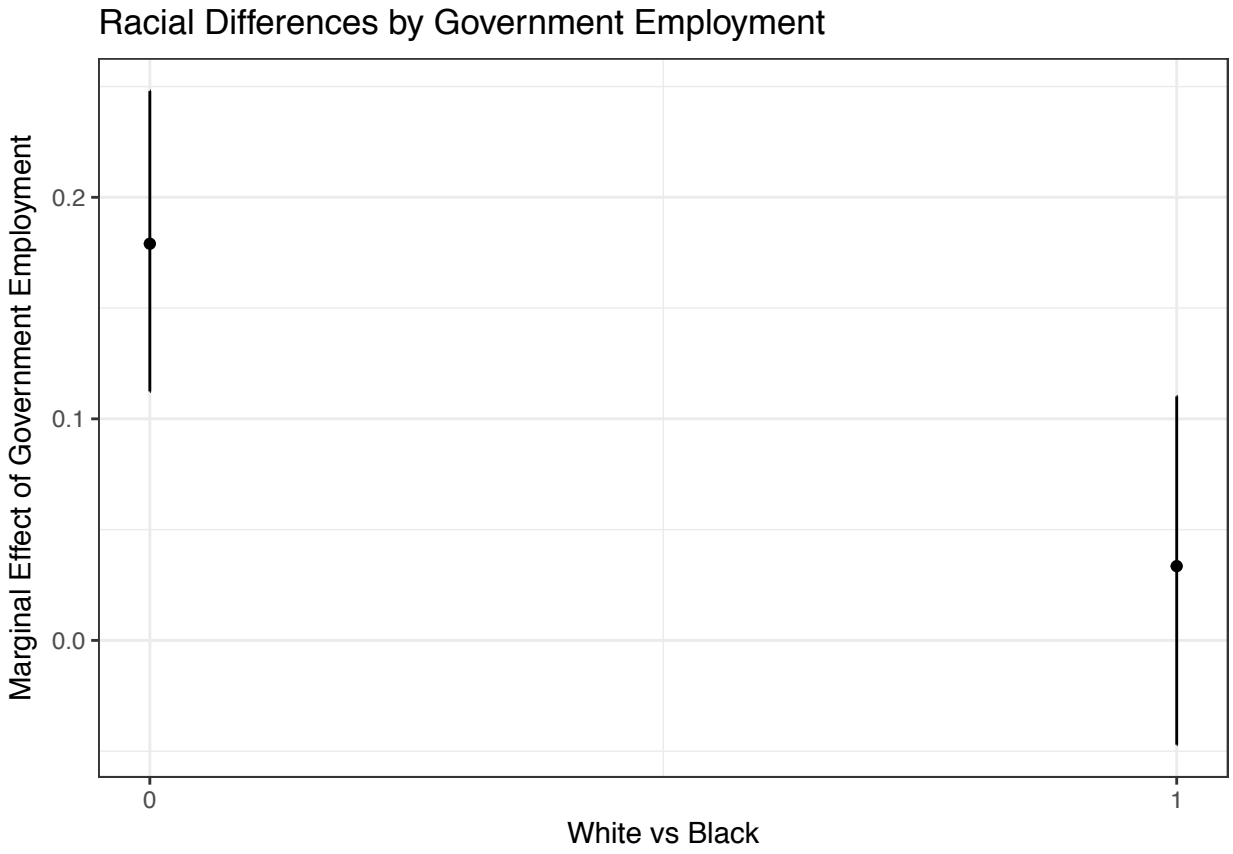
Employment

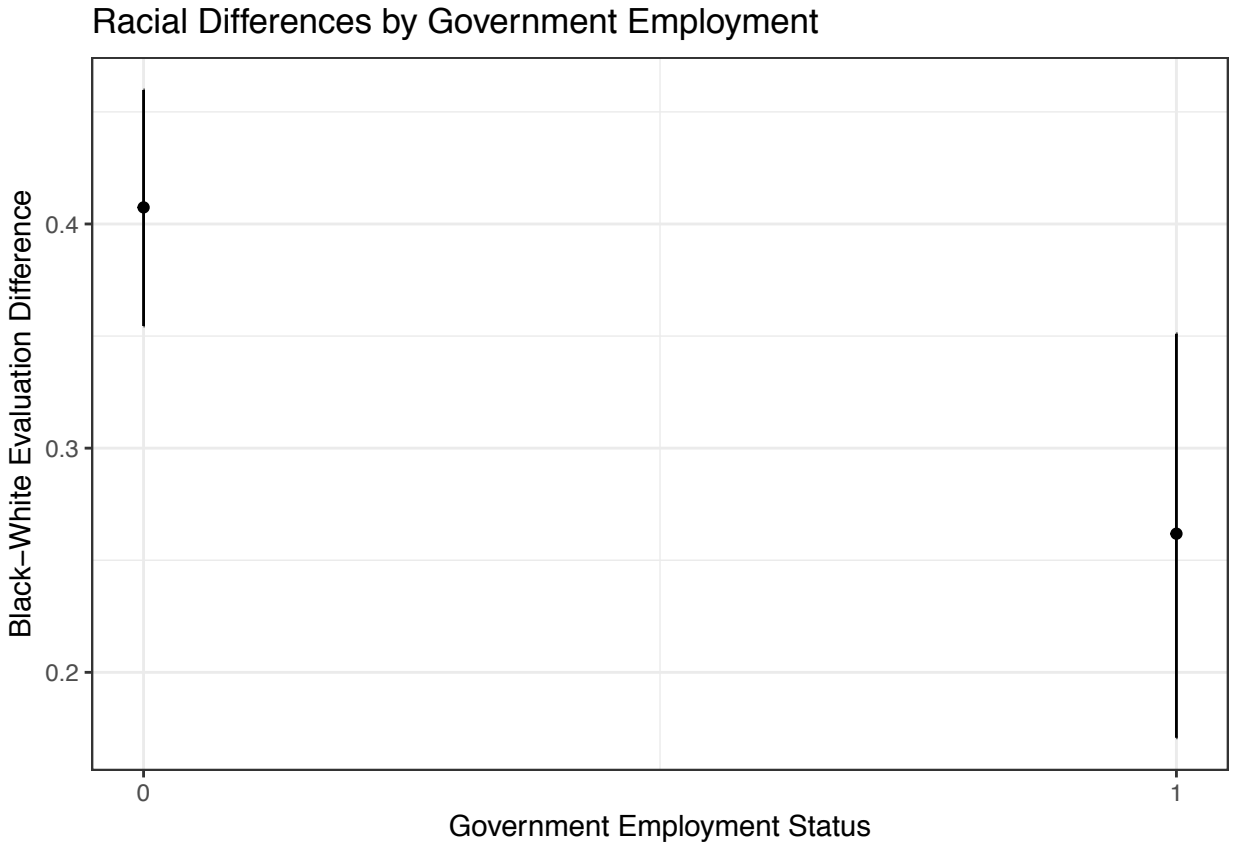
Employed in the Government

Employment in the government shapes views on police negligence, but mostly for whites. Whites employed in the government are less likely to endorse a "bad apples" perspective. The gap between whites and blacks employed in government is smaller than those not employed in government.

```
##
## Call:
## lm(formula = pol.badapples ~ employ.gov * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -2.89074 -0.61038  0.07025  0.60277  3.08832
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        1.73920    0.01335 130.275  < 2e-16 ***
## employ.gov         0.17964    0.03425   5.245 1.62e-07 ***
## black              0.40836    0.02631  15.522  < 2e-16 ***
## employ.gov:black -0.14706    0.05267  -2.792  0.00525 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7621 on 5690 degrees of freedom
```

```
##   (5472 observations deleted due to missingness)
## Multiple R-squared:  0.05555,    Adjusted R-squared:  0.05505
## F-statistic: 111.6 on 3 and 5690 DF,  p-value: < 2.2e-16
```

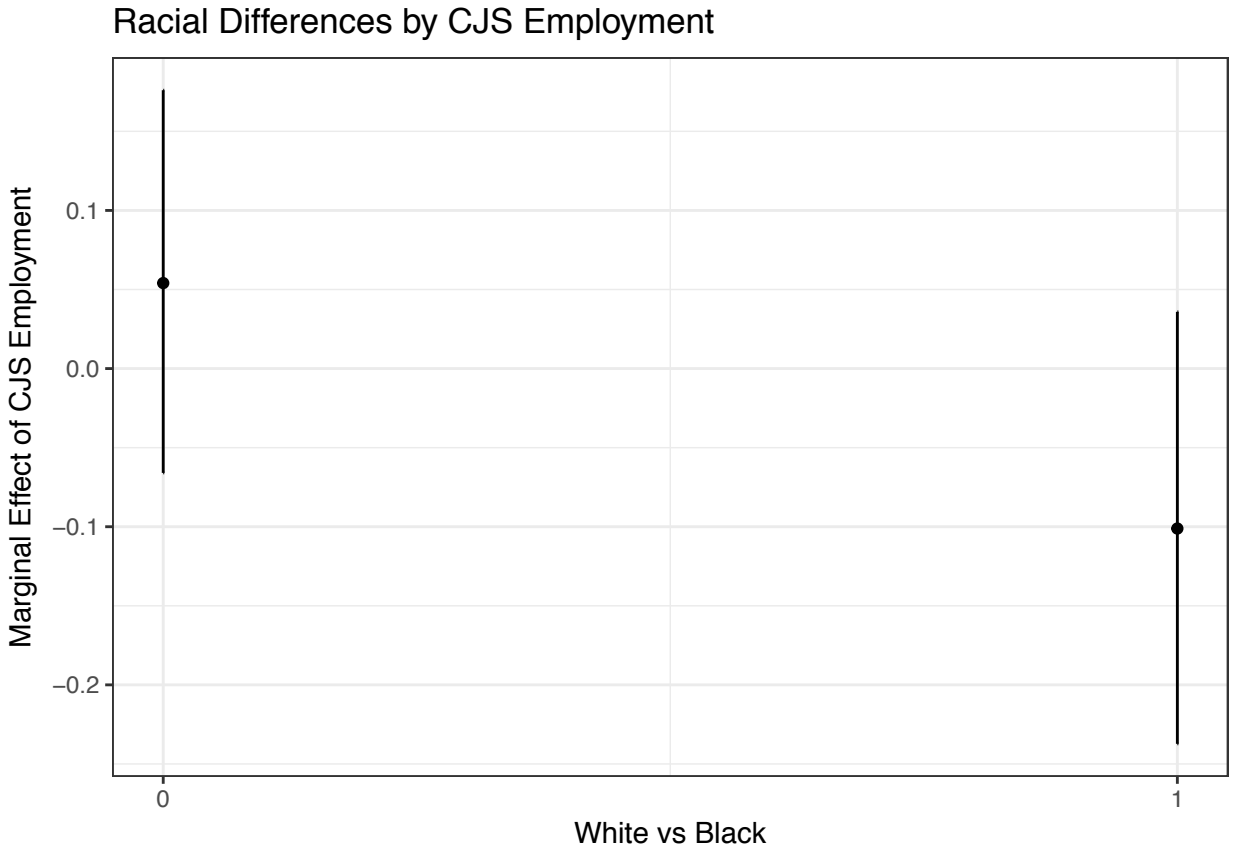


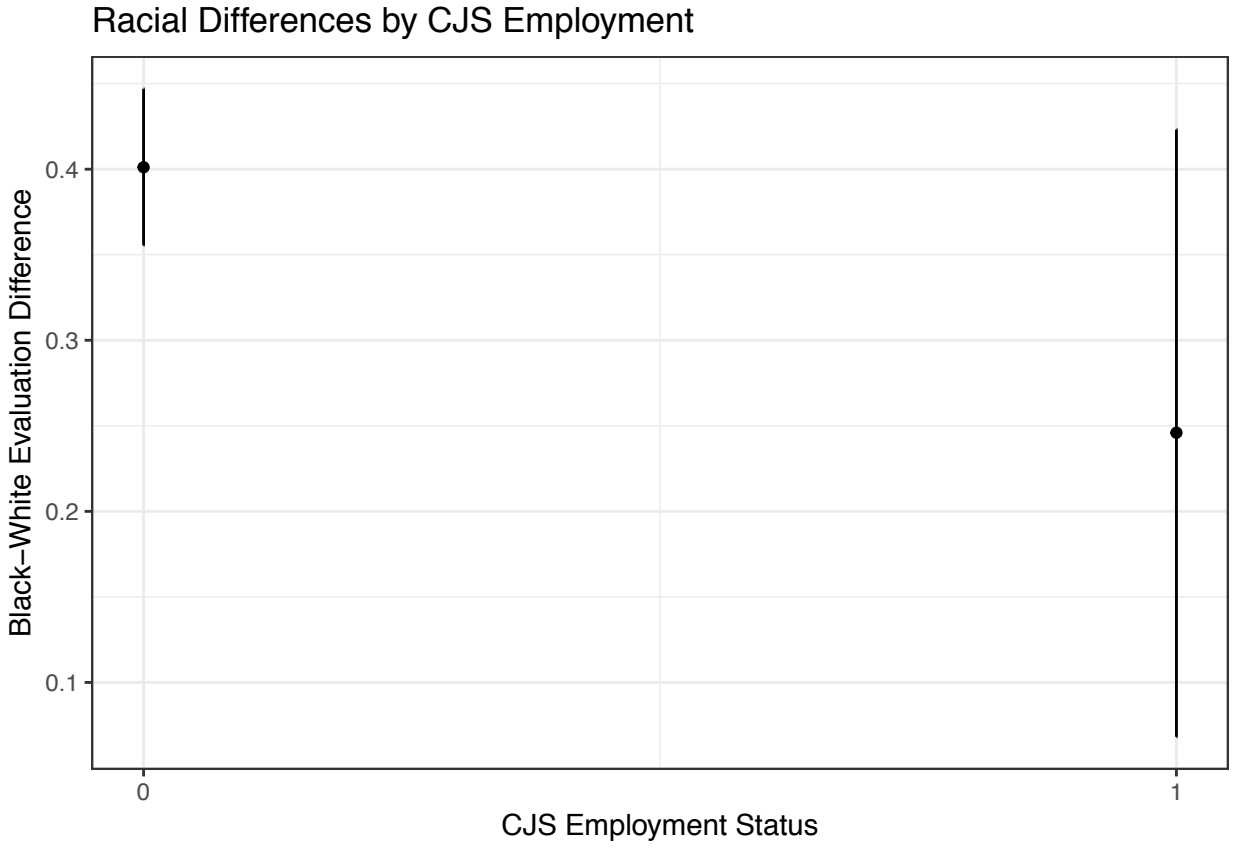


Employed in the Criminal Justice System

Less varies by whether or not the respondent is employed in the criminal justice system. CJS employment does not appear to meaningfully differentiate whites or blacks with respect to their attitudes.

```
##
## Call:
## lm(formula = pol.badapples ~ employ.cjs * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -2.8578 -0.5957  0.1662  0.5892  3.0253
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1.76493    0.01259 140.166   <2e-16 ***
## employ.cjs        0.05516    0.06210   0.888   0.3744
## black             0.40176    0.02326  17.273   <2e-16 ***
## employ.cjs:black -0.15810    0.09227  -1.713   0.0867 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7639 on 5685 degrees of freedom
##   (5477 observations deleted due to missingness)
## Multiple R-squared:  0.05124,    Adjusted R-squared:  0.05074
## F-statistic: 102.3 on 3 and 5685 DF,  p-value: < 2.2e-16
```


Racial Differences by CJS Employment
Marginal Effect of CJS Employment
0.1
0.0
−0.1
−0.2
0
1
White vs Black


Racial Differences by CJS Employment
Black−White Evaluation Difference
0.4
0.3
0.2
0.1
0
1
CJS Employment Status

Criminal Justice System Profession

Finally, little seems to systematically vary by position within the criminal justice system.

```
##
## Call:
## lm(formula = pol.badapples ~ as.factor(cjs.pos) * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -2.43094 -0.51918  0.02774  0.60749  2.46804
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 2.17183    0.18959  11.456  < 2e-16 ***
## as.factor(cjs.pos)2        -0.25555    0.34709  -0.736  0.46229
## as.factor(cjs.pos)3         0.27564    0.37007   0.745  0.45710
## as.factor(cjs.pos)4        -0.17940    0.27929  -0.642  0.52125
## as.factor(cjs.pos)5        -0.78373    0.29680  -2.641  0.00882 **
## as.factor(cjs.pos)6        -0.44966    0.26774  -1.679  0.09437 .
## as.factor(cjs.pos)7         0.35738    0.32556   1.098  0.27342
## as.factor(cjs.pos)8        -0.59410    0.21878  -2.716  0.00710 **
## black                      -0.25112    0.26437  -0.950  0.34314
## as.factor(cjs.pos)2:black   1.05832    0.44464   2.380  0.01809 *
## as.factor(cjs.pos)3:black   0.32010    0.55171   0.580  0.56232
## as.factor(cjs.pos)4:black   0.04209    0.41335   0.102  0.91898
## as.factor(cjs.pos)5:black   0.39678    0.42785   0.927  0.35467
## as.factor(cjs.pos)6:black   0.66982    0.41686   1.607  0.10941
## as.factor(cjs.pos)7:black   0.14862    0.47652   0.312  0.75540
## as.factor(cjs.pos)8:black   0.64691    0.31016   2.086  0.03806 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8495 on 239 degrees of freedom
##   (10911 observations deleted due to missingness)
## Multiple R-squared:  0.1742, Adjusted R-squared:  0.1224
## F-statistic: 3.362 on 15 and 239 DF,  p-value: 3.724e-05
```

Racial Group Views

Racial Resentment

Whites' racial attitudes motivate them to view police negligence as incidents of bad apples. The gap between the least and most racially resentful is roughly a full category.

```
##
## Call:
## lm(formula = pol.badapples ~ rr_sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -2.7814 -0.5339 -0.1111  0.4539  3.5951
##
```

```
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.35811    0.02148  109.81   <2e-16 ***
## rr_sc       -1.07201    0.03277  -32.72   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7315 on 7937 degrees of freedom
##   (154 observations deleted due to missingness)
## Multiple R-squared:  0.1188, Adjusted R-squared:  0.1187
## F-statistic:  1070 on 1 and 7937 DF,  p-value: < 2.2e-16
```

White Linked Fate

Whites' linked fate motivates them to view police negligence as less about bad apples. Higher levels of linked fate relate to a more systemic perspective.

```
##
## Call:
## lm(formula = pol.badapples ~ wht.lfate.sc, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -2.0929 -0.6042  0.1219  0.3776  3.3857
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.61781    0.01231  131.39   <2e-16 ***
## wht.lfate.sc  0.23662    0.02240   10.56   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7743 on 7946 degrees of freedom
##   (145 observations deleted due to missingness)
## Multiple R-squared:  0.01385,    Adjusted R-squared:  0.01372
## F-statistic: 111.6 on 1 and 7946 DF,  p-value: < 2.2e-16
```

Black Linked Fate

Blacks' linked fate functions similarly to whites. Higher levels of linked fate motivate endorse a more systematic reason for police negligence. Moreover, the effect is larger for blacks than whites.

```
##
## Call:
## lm(formula = pol.badapples ~ blk.lfate.sc, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -3.16077 -0.27726  0.06303  0.59123  2.66784
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.91086    0.02117   90.27   <2e-16 ***
```

```
## blk.lfate.sc  0.37952    0.03355   11.31   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7373 on 2958 degrees of freedom
##   (113 observations deleted due to missingness)
## Multiple R-squared:  0.04147,    Adjusted R-squared:  0.04115
## F-statistic:   128 on 1 and 2958 DF,  p-value: < 2.2e-16
```

Class Fragility

Family class growing up

Individuals' class background motivates their views as well, but the effect doesn't vary by race. Individuals from higher class backgrounds, regardless of race, are less likely to endorse a "bad apples" view.

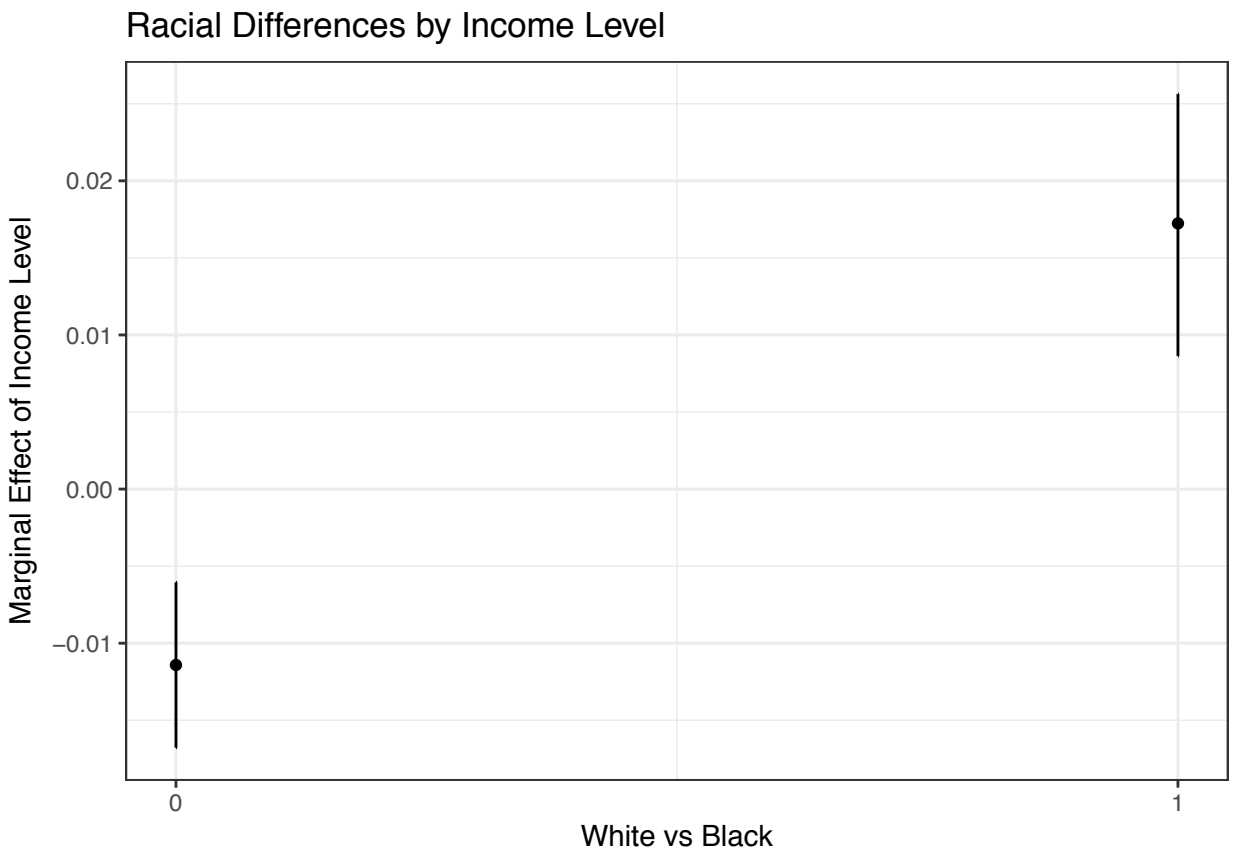
```
##
## Call:
## lm(formula = pol.badapples ~ chood.class * black, data = cjs.df,
##     weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9265 -0.5960 -0.0461  0.5694  3.2534
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         1.620786   0.015734 103.009  < 2e-16 ***
## chood.class         0.051021   0.009190   5.552 2.89e-08 ***
## black               0.435873   0.028110  15.506  < 2e-16 ***
## chood.class:black -0.004998   0.017516  -0.285    0.775
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7683 on 10916 degrees of freedom
##   (246 observations deleted due to missingness)
## Multiple R-squared:  0.05844,    Adjusted R-squared:  0.05819
## F-statistic: 225.9 on 3 and 10916 DF,  p-value: < 2.2e-16
```

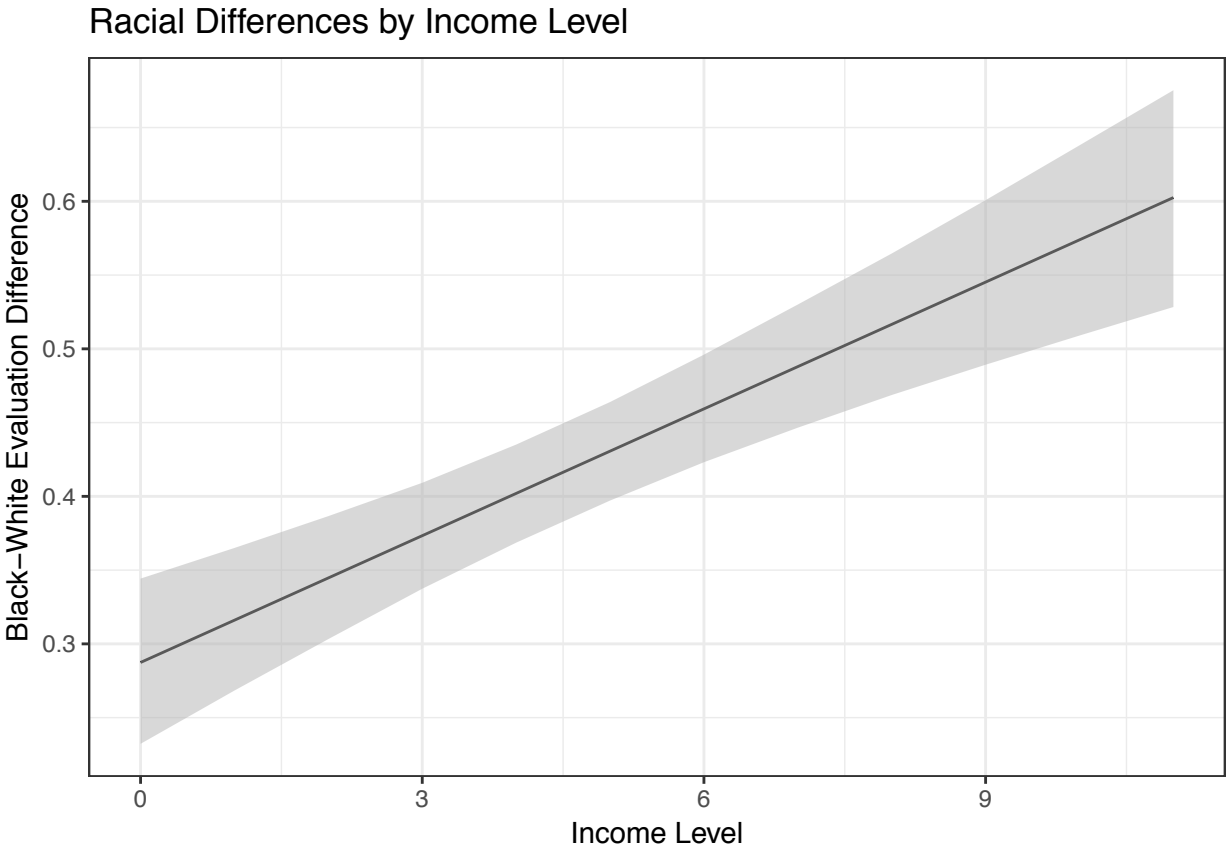
Current income

A similar story holds for income, but the effects also vary by race. Higher income whites are less likely do endorse a systemic explanation for police ngeligence. The opposite is true for blacks. Consequently, the differ between blacks and whites increases as income increases.

```
##
## Call:
## lm(formula = pol.badapples ~ inc * black, data = cjs.df, weights = wts_whole)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -3.0103 -0.6059 -0.0406  0.5937  3.3620
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)  1.752076   0.016121 108.680  < 2e-16 ***
## inc         -0.011330   0.002663  -4.254 2.12e-05 ***
## black        0.288220   0.028223  10.212  < 2e-16 ***
## inc:black    0.028478   0.005048   5.642 1.73e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7685 on 10918 degrees of freedom
##   (244 observations deleted due to missingness)
## Multiple R-squared:  0.05786,    Adjusted R-squared:  0.0576
## F-statistic: 223.5 on 3 and 10918 DF,  p-value: < 2.2e-16
```




Racial Differences by Income Level
Black–White Evaluation Difference
0.6
0.5
0.4
0.3
0
3
6
9
Income Level