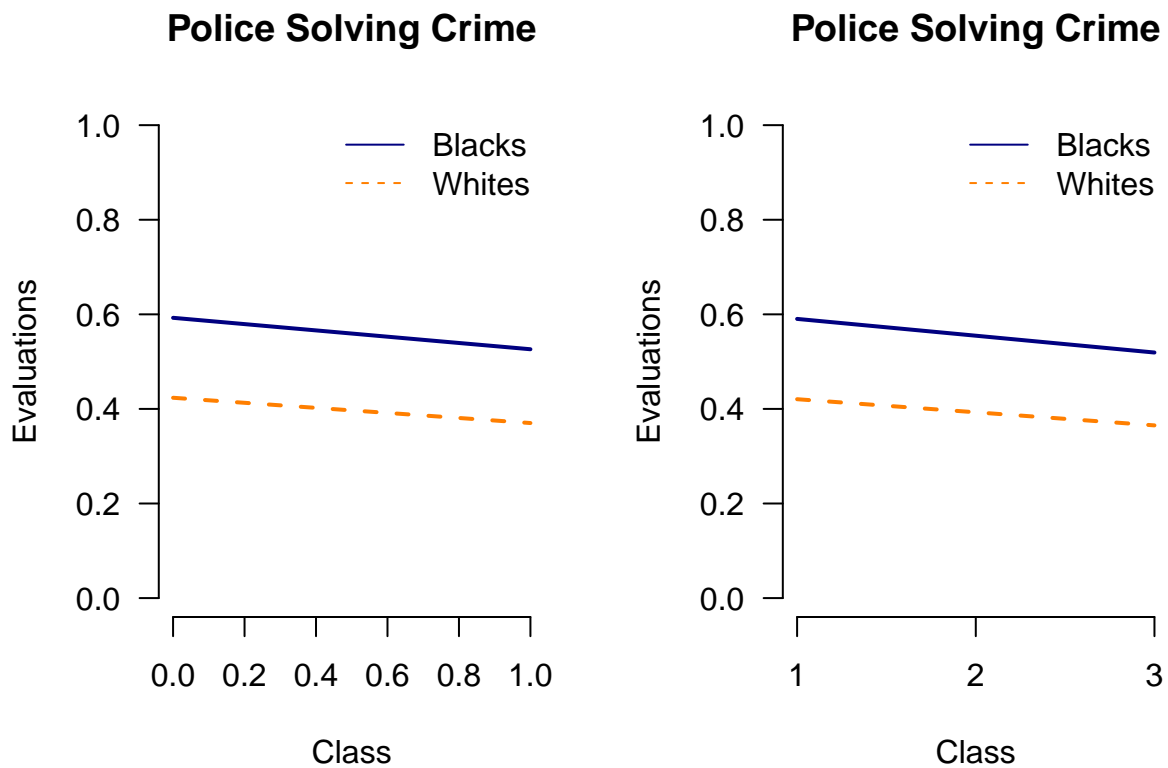


CJS Evaluations

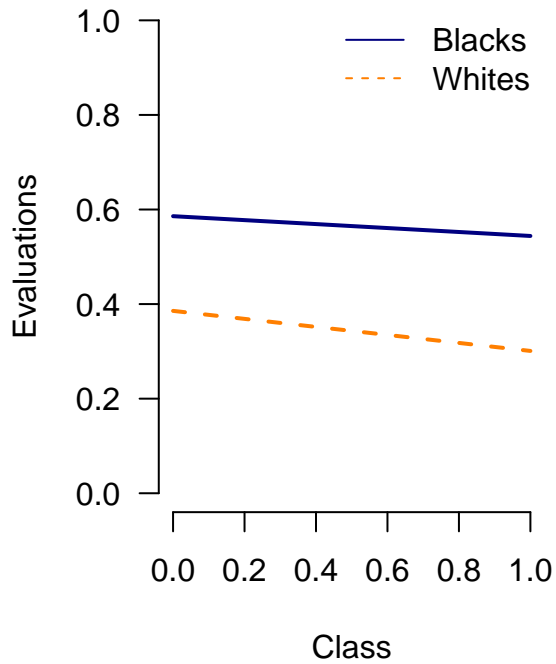
Drew Engelhardt

Part I: Descriptive Relationship between Race, Class, and CJS Evaluations

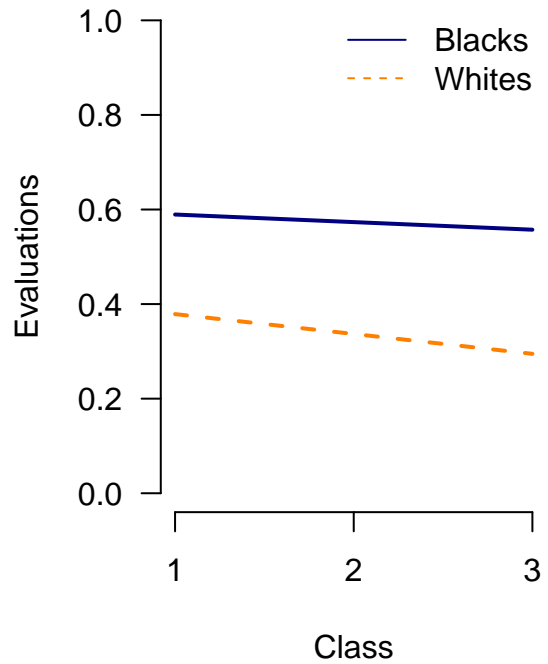
As most of the figures below indicate, the racial gap in police evaluations grows as class increases. On all items except the police's capacity to solve crime, higher class blacks hold more negative evaluations of the police than higher class whites. These increases range from about 0.03-0.12 points on outcomes scaled 0-1. Moreover, the patterns hold both from the additive class measure and the tripartite low-low – high-high class measure.



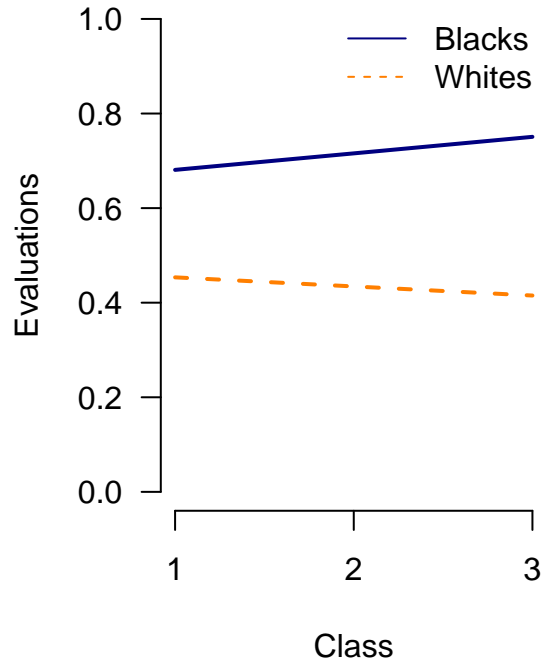
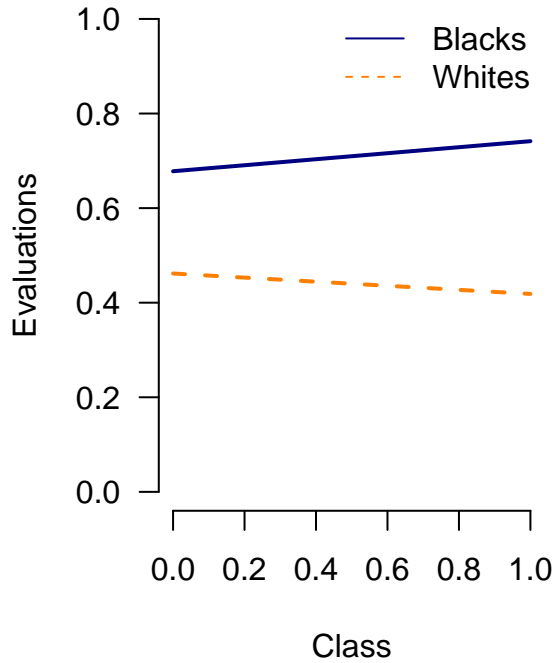
Protect From Violent Crime



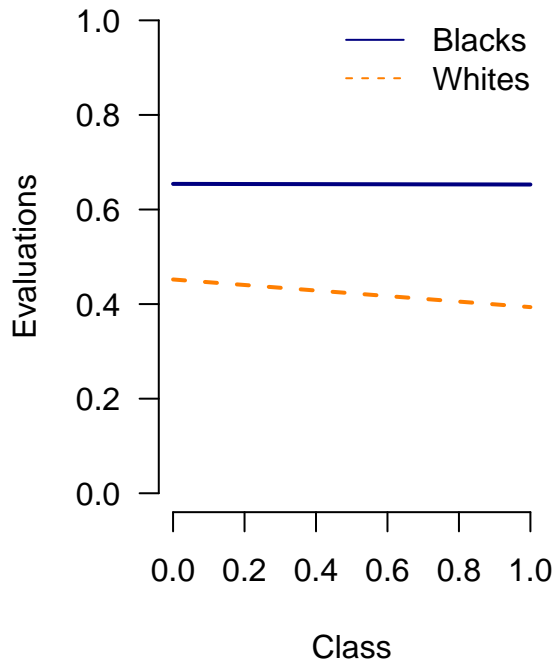
Protect From Violent Crime



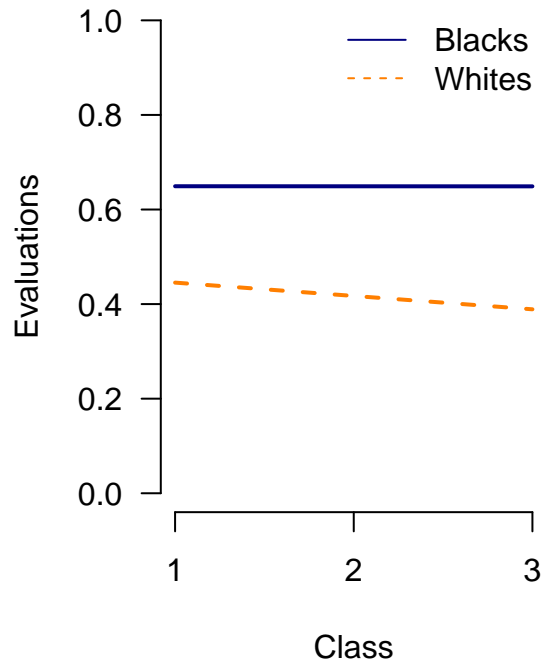
Treat racial and ethnic groups equ



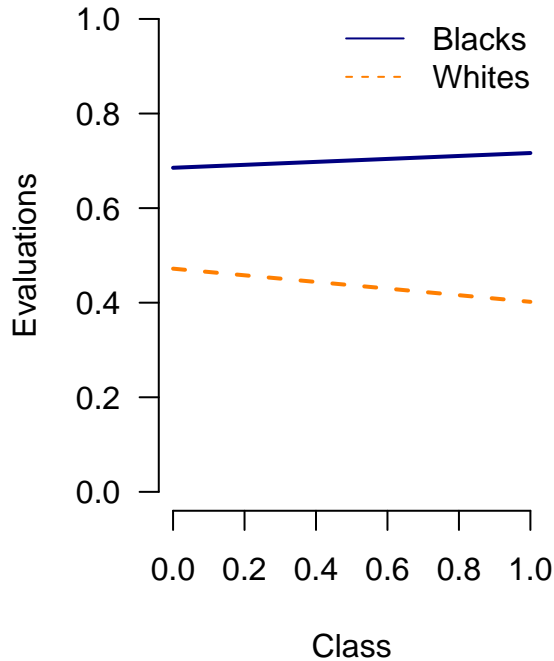
Not use Excessive Force



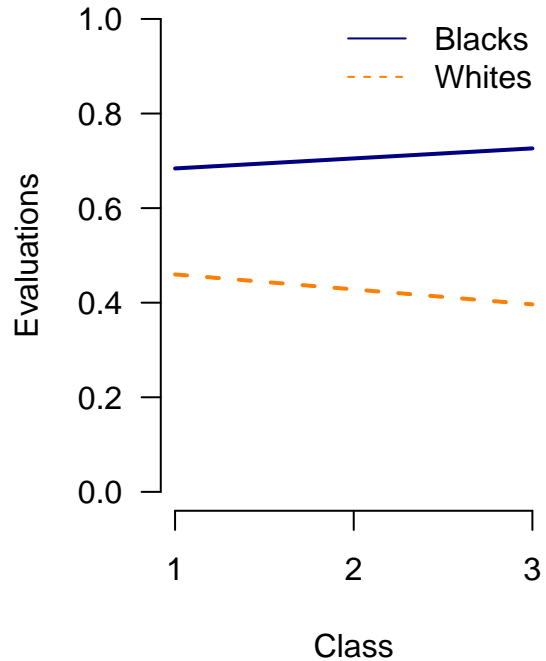
Not use Excessive Force



Holding Officers Accountable

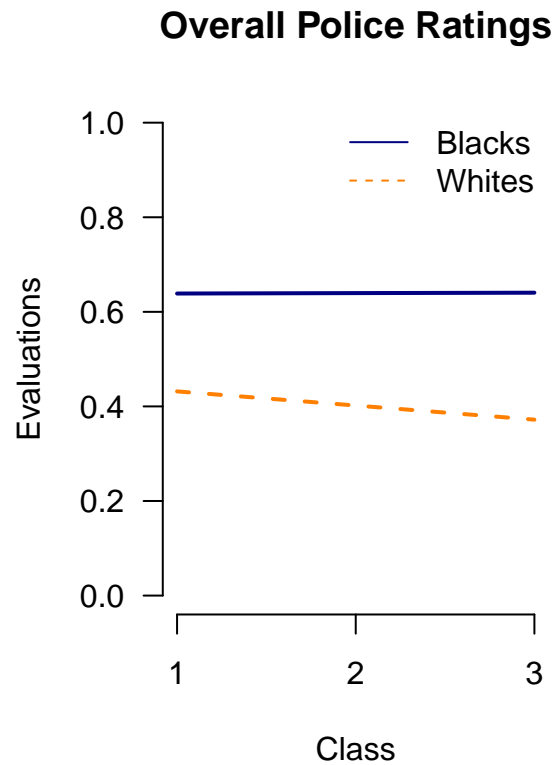
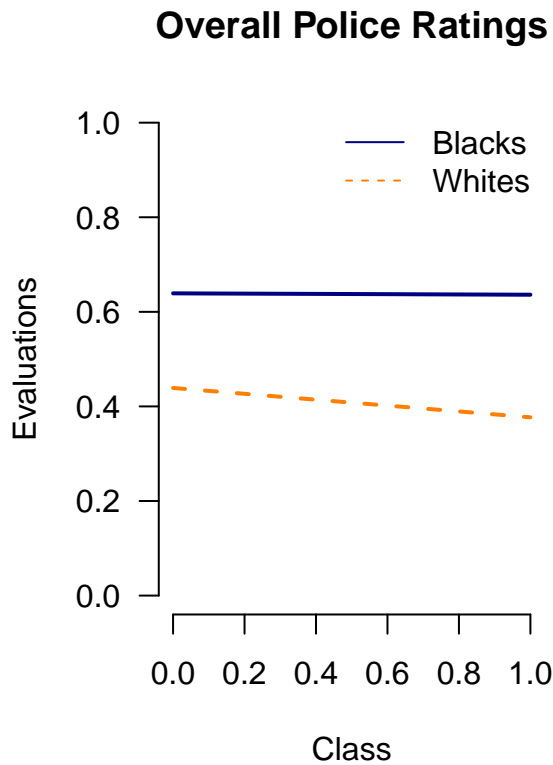


Holding Officers Accountable

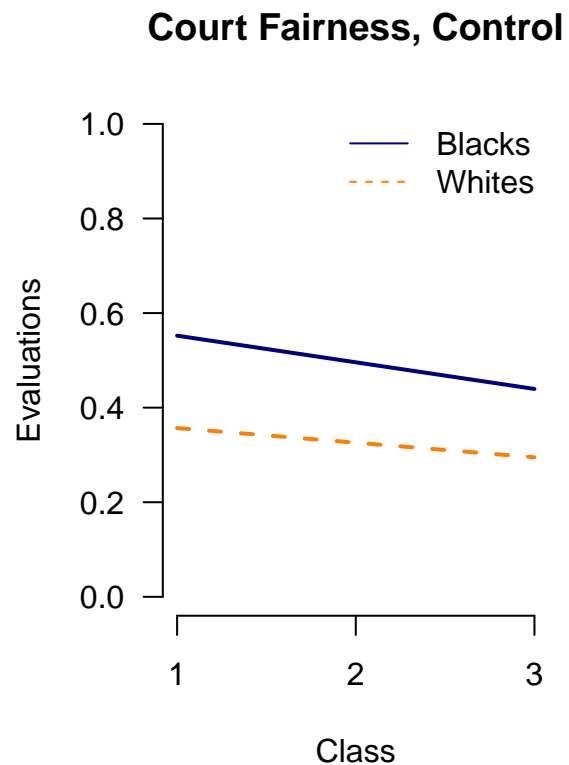
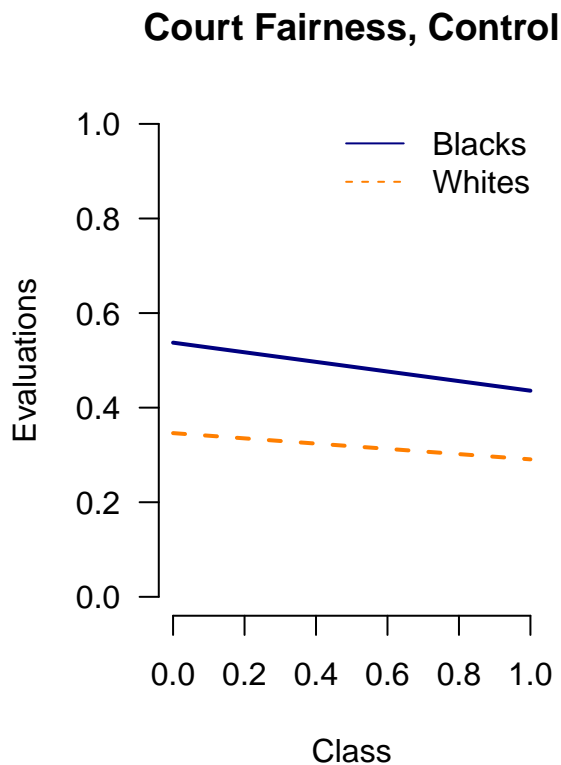


We can also model the relationship with these items by scaling the outcomes together. This seems reasonable given that all but the *solving crime* item have the same positive relationship. All items scale well together, too. I scale the outcome 0-1, with higher values again denoting more negative evaluations. The results indicate that the racial gap in evaluations increases as class increases. Higher class blacks on both operationalizations hold more negative views than higher class blacks, a larger gap than between low class blacks and whites.

The margin increases from 0.05 points, to 0.065 points.



Finally, turning to evaluations of court fairness, class does nothing to chaping the racial gap. A slight negative relationship exists, with the racial gap shrinking among higher class individuals. This difference is not significant, however. Blacks regardless of their class status hold more negative views of the capacity for courts in their area to treat everyone fairly, a gap between 0.15 and 0.18 points on the 0-1 outcome.



Part II: Explaining CJS Evaluations with Linked Fate

Across all items, linked fate matters. Moreover, it matters for whites and blacks and to roughly the same degree. The output from the regression models supporting this are below. All items are scaled 0-1, and I use the tripartite class measure. The results are the same with the additive measure. The difference in evaluations between blacks the least and most believing in linked fate ranges from 0.02 to 0.12 points.

```
##
## Call:
## lm(formula = p.crim.solve ~ lfate + class3, data = cjs.df, subset = black ==
##      1, weights = wts_black)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.2846 -0.1301 -0.0353  0.1907  1.1649
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.610155   0.018309  33.325 < 2e-16 ***
## lfate        0.045659   0.018669   2.446  0.0146 *
## class3      -0.043791   0.009787  -4.475 8.26e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2934 on 1448 degrees of freedom
## (1622 observations deleted due to missingness)
## Multiple R-squared:  0.01544,    Adjusted R-squared:  0.01408
## F-statistic: 11.35 on 2 and 1448 DF,  p-value: 1.283e-05
##
## Call:
## lm(formula = p.crim.solve ~ lfate + class3, data = cjs.df, subset = black ==
##      0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.09783 -0.14265  0.04477  0.11153  1.61151
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.439715   0.011373  38.664 < 2e-16 ***
## lfate        0.062045   0.011104   5.588 2.47e-08 ***
## class3      -0.032537   0.005109  -6.368 2.15e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2583 on 3599 degrees of freedom
## (4491 observations deleted due to missingness)
## Multiple R-squared:  0.01764,    Adjusted R-squared:  0.0171
## F-statistic: 32.32 on 2 and 3599 DF,  p-value: 1.227e-14
##
## Call:
## lm(formula = p.viol.crim ~ lfate + class3, data = cjs.df, subset = black ==
##      1, weights = wts_black)
```

```

##
## Weighted Residuals:
##      Min      1Q   Median      3Q      Max
## -1.46945 -0.14336 -0.03034  0.23583  1.22971
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.55854    0.01928  28.977 < 2e-16 ***
## lfate        0.09232    0.01965   4.698 2.87e-06 ***
## class3      -0.02019    0.01030  -1.960  0.0502 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3088 on 1447 degrees of freedom
## (1623 observations deleted due to missingness)
## Multiple R-squared:  0.01584,    Adjusted R-squared:  0.01448
## F-statistic: 11.64 on 2 and 1447 DF,  p-value: 9.621e-06

##
## Call:
## lm(formula = p.viol.crim ~ lfate + class3, data = cjs.df, subset = black ==
##      0, weights = wts_white)
##
## Weighted Residuals:
##      Min      1Q   Median      3Q      Max
## -0.99025 -0.13125 -0.05006  0.13544  1.25276
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.417559    0.011311  36.917 < 2e-16 ***
## lfate        0.054061    0.011043   4.895 1.02e-06 ***
## class3      -0.048379    0.005081  -9.521 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2569 on 3599 degrees of freedom
## (4491 observations deleted due to missingness)
## Multiple R-squared:  0.02848,    Adjusted R-squared:  0.02794
## F-statistic: 52.76 on 2 and 3599 DF,  p-value: < 2.2e-16

##
## Call:
## lm(formula = p.race.fair ~ lfate + class3, data = cjs.df, subset = black ==
##      1, weights = wts_black)
##
## Weighted Residuals:
##      Min      1Q   Median      3Q      Max
## -1.91989 -0.18148  0.06132  0.23578  0.88733
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.60894    0.01985  30.683 < 2e-16 ***
## lfate        0.08843    0.02023   4.371 1.33e-05 ***
## class3       0.02881    0.01060   2.717  0.00668 **
## ---

```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.318 on 1447 degrees of freedom
## (1623 observations deleted due to missingness)
## Multiple R-squared:  0.02166,    Adjusted R-squared:  0.02031
## F-statistic: 16.02 on 2 and 1447 DF,  p-value: 1.317e-07
##
## Call:
## lm(formula = p.race.fair ~ lfate + class3, data = cjs.df, subset = black ==
##     0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.26542 -0.19828  0.01863  0.19540  1.54826
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.453883   0.013620  33.325 < 2e-16 ***
## lfate        0.115620   0.013290   8.700 < 2e-16 ***
## class3      -0.028652   0.006116  -4.685 2.9e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3091 on 3597 degrees of freedom
## (4493 observations deleted due to missingness)
## Multiple R-squared:  0.02433,    Adjusted R-squared:  0.02379
## F-statistic: 44.85 on 2 and 3597 DF,  p-value: < 2.2e-16
##
## Call:
## lm(formula = p.exces.force ~ lfate + class3, data = cjs.df, subset = black ==
##     1, weights = wts_black)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.65968 -0.16219  0.06478  0.25017  0.95564
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.620027   0.019803  31.309 < 2e-16 ***
## lfate        0.067700   0.020194   3.353 0.000822 ***
## class3      -0.003389   0.010583  -0.320 0.748840
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3173 on 1446 degrees of freedom
## (1624 observations deleted due to missingness)
## Multiple R-squared:  0.007779,    Adjusted R-squared:  0.006407
## F-statistic: 5.668 on 2 and 1446 DF,  p-value: 0.00353
##
## Call:
## lm(formula = p.exces.force ~ lfate + class3, data = cjs.df, subset = black ==
##     0, weights = wts_white)

```

```
##
## Weighted Residuals:
##      Min      1Q   Median      3Q      Max
## -1.2374 -0.1762  0.0089   0.1820  1.6103
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.451617   0.013017  34.694 < 2e-16 ***
## lfate        0.113593   0.012706   8.940 < 2e-16 ***
## class3       -0.036337   0.005847  -6.215 5.72e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2956 on 3598 degrees of freedom
## (4492 observations deleted due to missingness)
## Multiple R-squared:  0.02901,    Adjusted R-squared:  0.02848
## F-statistic: 53.76 on 2 and 3598 DF,  p-value: < 2.2e-16

##
## Call:
## lm(formula = p.account ~ lfate + class3, data = cjs.df, subset = black ==
##      1, weights = wts_black)
##
## Weighted Residuals:
##      Min      1Q   Median      3Q      Max
## -1.85959 -0.18681  0.07452  0.24123  0.86112
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.63489    0.02055  30.902 < 2e-16 ***
## lfate        0.08362    0.02095   3.991 6.92e-05 ***
## class3       0.01355    0.01098   1.235  0.217
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3291 on 1446 degrees of freedom
## (1624 observations deleted due to missingness)
## Multiple R-squared:  0.01363,    Adjusted R-squared:  0.01227
## F-statistic: 9.992 on 2 and 1446 DF,  p-value: 4.899e-05

##
## Call:
## lm(formula = p.account ~ lfate + class3, data = cjs.df, subset = black ==
##      0, weights = wts_white)
##
## Weighted Residuals:
##      Min      1Q   Median      3Q      Max
## -1.29008 -0.18392 -0.00655  0.19625  1.59526
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.475119   0.013403  35.450 < 2e-16 ***
## lfate        0.118398   0.013086   9.048 < 2e-16 ***
## class3       -0.042127   0.006021  -6.997 3.12e-12 ***
## ---
```



```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3044 on 3599 degrees of freedom
## (4491 observations deleted due to missingness)
## Multiple R-squared:  0.03179,    Adjusted R-squared:  0.03125
## F-statistic: 59.08 on 2 and 3599 DF,  p-value: < 2.2e-16

##
## Call:
## lm(formula = police.rate.sc ~ lfate + class3, data = cjs.df,
##     subset = black == 1, weights = wts_black)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.63345 -0.13763  0.04173  0.19348  0.79764
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.606621   0.016551  36.651 < 2e-16 ***
## lfate        0.075247   0.016884   4.457 8.96e-06 ***
## class3      -0.005005   0.008844  -0.566  0.572
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2652 on 1445 degrees of freedom
## (1625 observations deleted due to missingness)
## Multiple R-squared:  0.01361,    Adjusted R-squared:  0.01224
## F-statistic: 9.968 on 2 and 1445 DF,  p-value: 5.016e-05

##
## Call:
## lm(formula = police.rate.sc ~ lfate + class3, data = cjs.df,
##     subset = black == 0, weights = wts_white)
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -1.1764 -0.1474 -0.0023  0.1502  1.5073
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.447670   0.010708  41.806 < 2e-16 ***
## lfate        0.092816   0.010446   8.886 < 2e-16 ***
## class3      -0.037677   0.004807  -7.838 5.99e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2429 on 3596 degrees of freedom
## (4494 observations deleted due to missingness)
## Multiple R-squared:  0.03399,    Adjusted R-squared:  0.03345
## F-statistic: 63.26 on 2 and 3596 DF,  p-value: < 2.2e-16

```

We can also look at the independent relationship between linked fate, class, and court fairness evaluations.

```

##
## Call:
## lm(formula = court.fair ~ lfate + class3, data = cjs.df, subset = black ==

```

```
##      1, weights = wts_black)
##
## Weighted Residuals:
##      Min      1Q   Median      3Q      Max
## -1.13635 -0.17153 -0.07611  0.15959  1.04534
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.55909    0.03332  16.781 < 2e-16 ***
## lfate         0.06882    0.03330   2.067  0.03927 *
## class3       -0.05467    0.01756  -3.113  0.00196 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3068 on 490 degrees of freedom
## (2580 observations deleted due to missingness)
## Multiple R-squared:  0.02443,    Adjusted R-squared:  0.02044
## F-statistic: 6.134 on 2 and 490 DF,  p-value: 0.002338
##
## Call:
## lm(formula = court.fair ~ lfate + class3, data = cjs.df, subset = black ==
##      0, weights = wts_white)
##
## Weighted Residuals:
##      Min      1Q   Median      3Q      Max
## -0.78097 -0.11002 -0.00682  0.06147  1.80217
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.376765   0.020714  18.189 < 2e-16 ***
## lfate         0.081844   0.019975   4.097 4.46e-05 ***
## class3       -0.037499   0.009186  -4.082 4.75e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2708 on 1221 degrees of freedom
## (6869 observations deleted due to missingness)
## Multiple R-squared:  0.02465,    Adjusted R-squared:  0.02305
## F-statistic: 15.43 on 2 and 1221 DF,  p-value: 2.417e-07
```

Class's Moderating Role

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
 % Date and time: Wed, Oct 18, 2017 - 14:55:09

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 % Date and time: Wed, Oct 18, 2017 - 14:55:09

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
 % Date and time: Wed, Oct 18, 2017 - 14:55:09

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
 % Date and time: Wed, Oct 18, 2017 - 14:55:09

Table 1: Relationship between Linked Fate, Class, and Police Protecting From Violent Crime

	<i>Dependent variable:</i>	
	Protect From Violent Crime Blacks	Whites
Linked Fate	0.040 (0.045)	0.041 (0.029)
Class	-0.038** (0.017)	-0.051*** (0.007)
Linked Fate * Class	0.034 (0.026)	0.006 (0.013)
Constant	0.585*** (0.028)	0.422*** (0.015)
Observations	1,450	3,602
R ²	0.017	0.029
Residual Std. Error	0.309 (df = 1446)	0.257 (df = 3598)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

Table 2: Relationship between Linked Fate, Class, and Police Protecting From Violent Crime

	<i>Dependent variable:</i>	
	Protect From Violent Crime Blacks	Whites
Linked Fate	0.040 (0.045)	0.041 (0.029)
Class	-0.038** (0.017)	-0.051*** (0.007)
Linked Fate * Class	0.034 (0.026)	0.006 (0.013)
Constant	0.585*** (0.028)	0.422*** (0.015)
Observations	1,450	3,602
R ²	0.017	0.029
Residual Std. Error	0.309 (df = 1446)	0.257 (df = 3598)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

Table 3: Relationship between Linked Fate, Class, and Police Treating Racial Groups Fairly

	<i>Dependent variable:</i>	
	Police Treating Racial Groups Fairly Blacks	Whites
Linked Fate	0.088* (0.046)	0.048 (0.034)
Class	0.029 (0.018)	-0.041*** (0.008)
Linked Fate * Class	0.0004 (0.027)	0.034** (0.016)
Constant	0.609*** (0.029)	0.478*** (0.018)
Observations	1,450	3,600
R ²	0.022	0.026
Residual Std. Error	0.318 (df = 1446)	0.309 (df = 3596)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

Table 4: Relationship between Linked Fate, Class, and Police Using Excess Force

	<i>Dependent variable:</i>	
	Police Using Excessive Force Blacks	Whites
Linked Fate	0.055 (0.046)	0.060* (0.033)
Class	-0.008 (0.018)	-0.046*** (0.008)
Linked Fate * Class	0.008 (0.027)	0.027* (0.015)
Constant	0.627*** (0.029)	0.471*** (0.017)
Observations	1,449	3,601
R ²	0.008	0.030
Residual Std. Error	0.317 (df = 1445)	0.295 (df = 3597)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
 % Date and time: Wed, Oct 18, 2017 - 14:55:09

Table 5: Relationship between Linked Fate, Class, and Police Accountability

	<i>Dependent variable:</i>	
	Blacks	Whites
Linked Fate	0.009 (0.048)	0.008 (0.034)
Class	-0.012 (0.018)	-0.063*** (0.008)
Linked Fate * Class	0.048* (0.027)	0.055*** (0.016)
Constant	0.672*** (0.030)	0.514*** (0.017)
Observations	1,449	3,602
R ²	0.016	0.035
Residual Std. Error	0.329 (df = 1445)	0.304 (df = 3598)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
 % Date and time: Wed, Oct 18, 2017 - 14:55:09

Table 6: Relationship between Linked Fate, Class, and Police Evaluations

	<i>Dependent variable:</i>	
	Blacks	Whites
Linked Fate	0.033 (0.038)	0.027 (0.027)
Class	-0.020 (0.015)	-0.050*** (0.007)
Linked Fate * Class	0.027 (0.022)	0.033*** (0.012)
Constant	0.628*** (0.024)	0.471*** (0.014)
Observations	1,448	3,599
R ²	0.015	0.036
Residual Std. Error	0.265 (df = 1444)	0.243 (df = 3595)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		

We can also look at the independent relationship between linked fate, class, and court fairness evaluations. Again, there appears to be no moderating role for class on linked fate's relationship with the outcome. Moreover, this holds between whites and blacks.

% Table created by stargazer v.5.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
 % Date and time: Wed, Oct 18, 2017 - 14:55:09

Table 7: Relationship between Linked Fate, Class, and Court Evaluations

	<i>Dependent variable:</i>	
	Court Evaluations	
	Blacks	Whites
Linked Fate	0.171** (0.075)	0.130** (0.052)
Class	-0.019 (0.029)	-0.028** (0.013)
Linked Fate * Class	-0.065 (0.042)	-0.024 (0.024)
Constant	0.506*** (0.048)	0.359*** (0.027)
Observations	493	1,224
R ²	0.029	0.025
Residual Std. Error	0.306 (df = 489)	0.271 (df = 1220)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01		