Regression Analysis

Corrrelationx Matrix

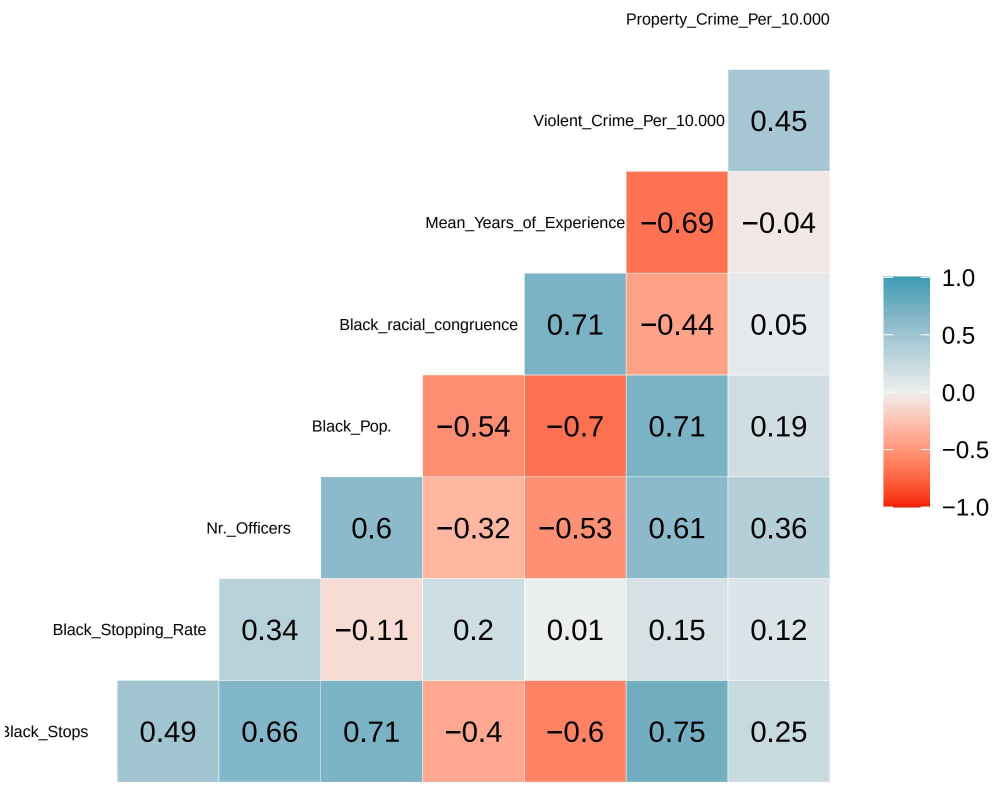
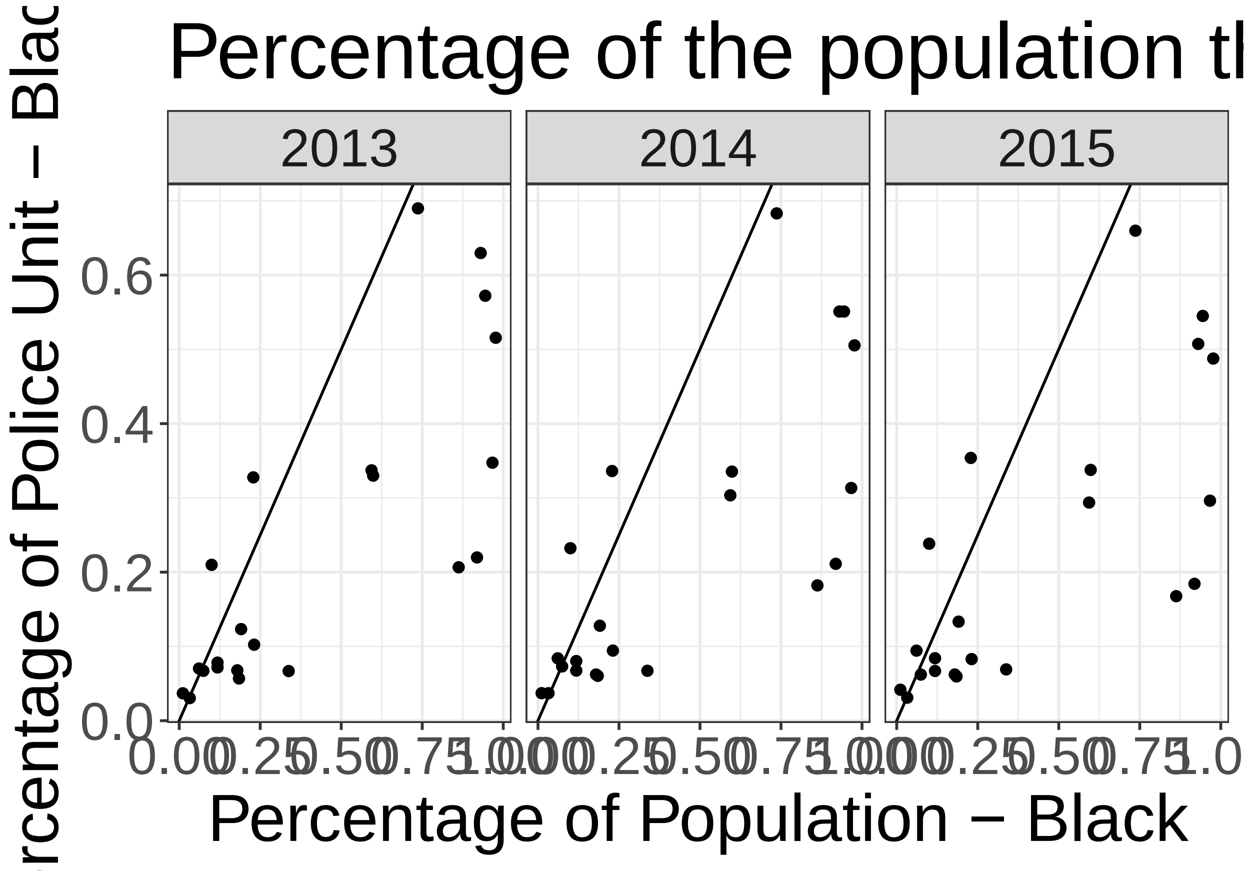
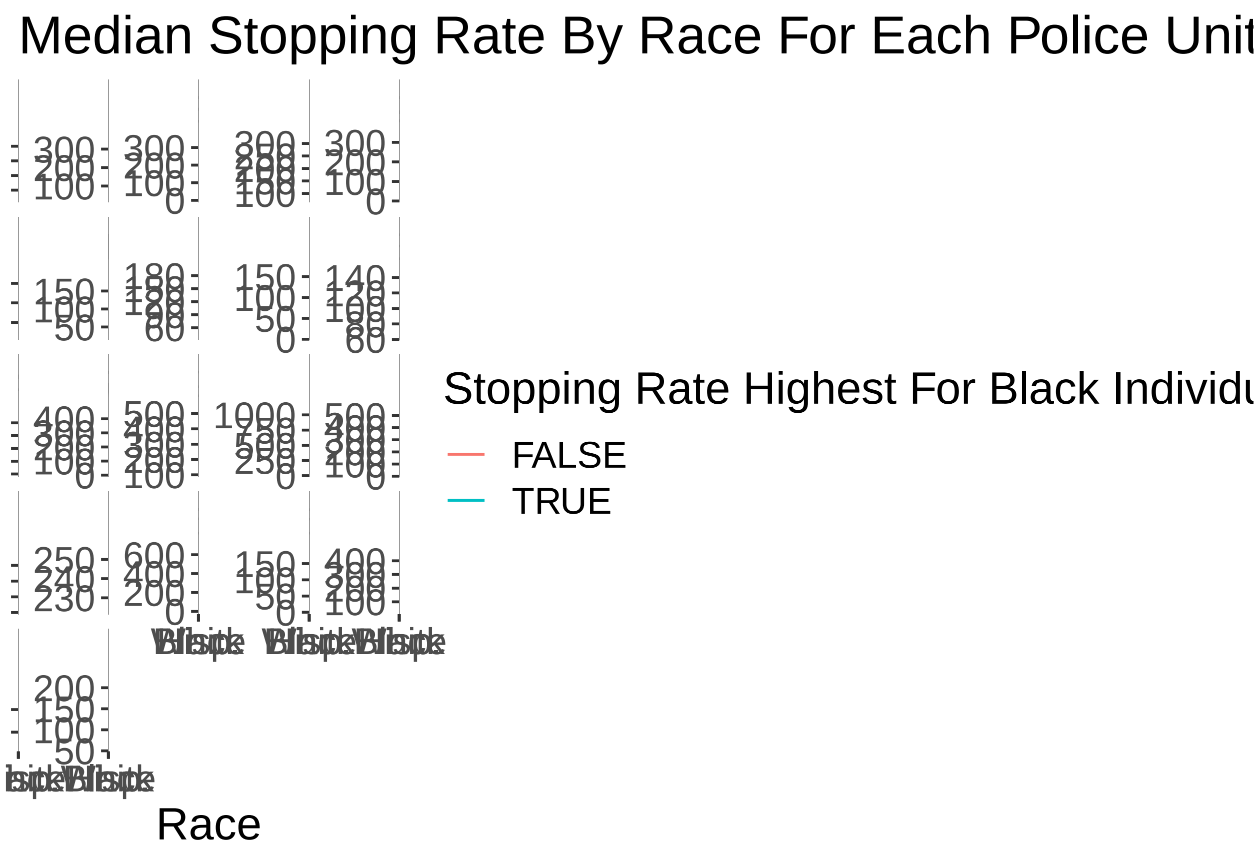


Table 1: Summary Statistics Across All Units Over All Years

Variable	N	Mean	Std. Dev.	Min	25th	Median	75th	Max
Total Number of Stops	792	1402.902	789.189	189	822	1288.5	1812.25	4665
Stops of Black Civilians	792	926.659	812.262	27	305.75	724	1268.25	4346
Stops of Black Civilians Per 10,000	792	243.598	126.299	57	144	216	315	690
Stops of White Civilians Per 10,000	792	167.366	250.91	1	10	71.5	217.25	1864
Stops of Hispanic Civilians Per 10,000	792	187.992	303.376	7	34	65	203	2459
Total Number of Officers	792	390.662	78.204	237	317	408	445.25	534
Total Number of Black Officers	792	95.965	88.96	6	25	67	137.25	352
Percent of Officers - Black	792	0.228	0.195	0.023	0.068	0.152	0.336	0.694
Total Population	792	120793.955	52189.454	55232	75501	109828	146656	245944
Black Population	792	39522.636	27159.15	2264	12494	36467.5	62487	94929
Percent of Population - Black	792	0.427	0.36	0.011	0.118	0.23	0.862	0.977
Black Racial Congruence	792	0.824	0.75	0.172	0.359	0.572	0.933	3.969
Mean Amount of Experience (Years)	792	14.503	2.346	10.824	12.542	14.158	16.526	19.885
Violent Crime Per 10,000 individuals	792	9.039	6.602	0.648	3.876	6.644	13.382	30.786
Property Crime Per 10,000 individuals	792	32.085	16.486	9.143	19.55	28.97	40.458	106.779

Summary Table





Unconditional Fixed Effects Negative Binomial Regression

- **Standard errors clustered on police unit**. We already allow for the error terms to be correlated across police units by including police unit as a dummy variable. I.e. We allow for observations to from the same unit to be correlated with themselves or more alike than we would expect if they were truly independent.
- However even within a police unit, observations are likely not truly independent of each other. Changes in unobserved factors are likely correlated over time. E.g. the police unit dummy variables represent time-invariant reasons why stops of Black civilians tend to be higher for some police units vs. others. However, **within a unit** there are likely time-varying unobserved reasons why the number of stops in one month is not truly independent of the previous month's or next month's number of stops.

Why am I using an Unconditional Fixed Effects Negative Binomial Regression?

- Dependent variable is a count variable.
- An offset is included for the size of the Black population.
- Evidence of overdispersion. The conditional variance is not equal to the conditional mean.
- Unconditional nonlinear regression models suffer from the incidental parameter problem when the number of time-periods observed is small compared to the number of cross-sectional units.
- I have T = 36 time observation periods and N = 22 police unit observations. I don't think incidental parameters should be an issue.
- But just in case…
- "On the other hand, a simulation study yields good results from applying an unconditional negative binomial regression estimator with dummy variables to represent the fixed effects. There is no evidence for any incidental parameters bias in the coefficients…" Allison and Waterman 2002.

	Stops of Black Civilians	Stops of Black Civilians
	Model 1	Model 2
Black Racial Congruence - Between Unit	0.437 (0.065)***	1.153 (0.094)+
Black Racial Congruence - Within Unit	0.336 (0.095)***	0.369 (0.111)***
year2014	1.219 (0.083)**	1.144 (0.092)+
year2015	0.975 (0.051)	0.912 (0.069)
Num.Obs.	792	792
Offset - Black Pop.	No	Yes
R2 Pseudo	0.025	0.094
AIC	12 087.3	11 232.0
BIC	12 110.6	11 255.4
Log.Lik.	−6038.628	−5611.017
Std.Errors	by: unit	by: unit

P-values are denoted by symbols: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Standard Errors in parentheses. Coefficients are incident rate ratios.

Not enough variation in independent variable of interest over time

- If there isn't enough variation in the independent variable over time, this can hurt the power of the model or its ability to detect a true effect. It can become too sensitive to small changes in the data (since the data only encompasses small changes).
- It also may not be detecting the true effect of the variable as its effect may get absorbed by the unit effects.
- I show the effect of the variable is robust to different model specifications (i.e. including more variables). Descriptively, I think there is a relationship to be explored and there seems to be some variation in some units. There is no test which can specify before running the model if there is enough variation.

Results

- Reported in log odds.
- Concerned with directionality not interpreting the coefficients.
- Use predictions from model to understand true effect size.

Between vs. within

```
## Warning: To compile a LaTeX document with this table, the following commands must be placed in the d
##
## \usepackage{booktabs}
## \usepackage{siunitx}
## \newcolumntype{d}{S[input-symbols = ()]}
##
## To disable `siunitx` and prevent `modelsummary` from wrapping numeric entries in `\num{}`, call:
##
## options("modelsummary_format_numeric_latex" = "plain")
##  This warning appears once per session.
```

Plotting number of stops

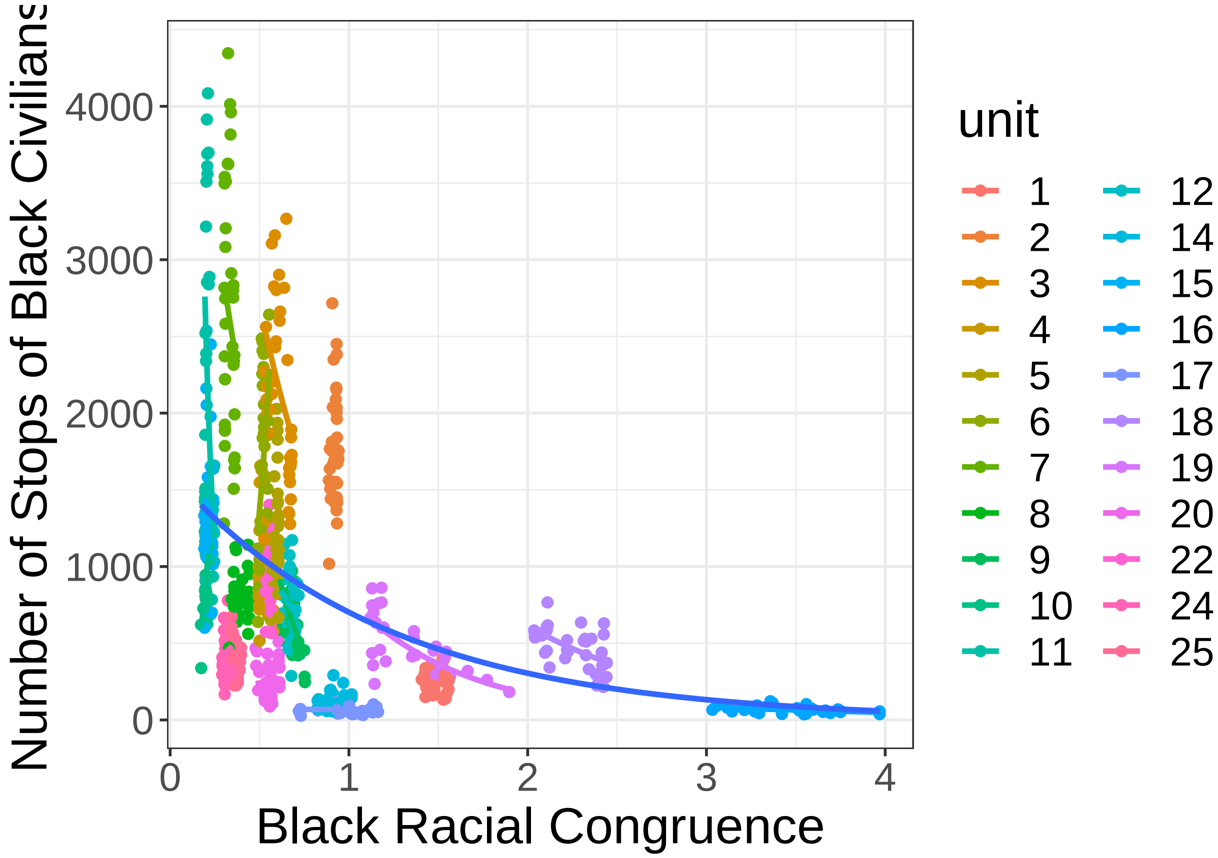
- Scatterplot of Black Racial Congruence Vs. Number of Stops of Black Civilians.
- Overall trend suggests a negative relationship wherein increasing Black Racial Congruence is correlated with less stops of Black civilians.
- Differences in the the within unit trend though. Some units exhibit a negative relationship while other units exhibit no relationship. The variation in racial congruence also *varies* by unit making it hard to

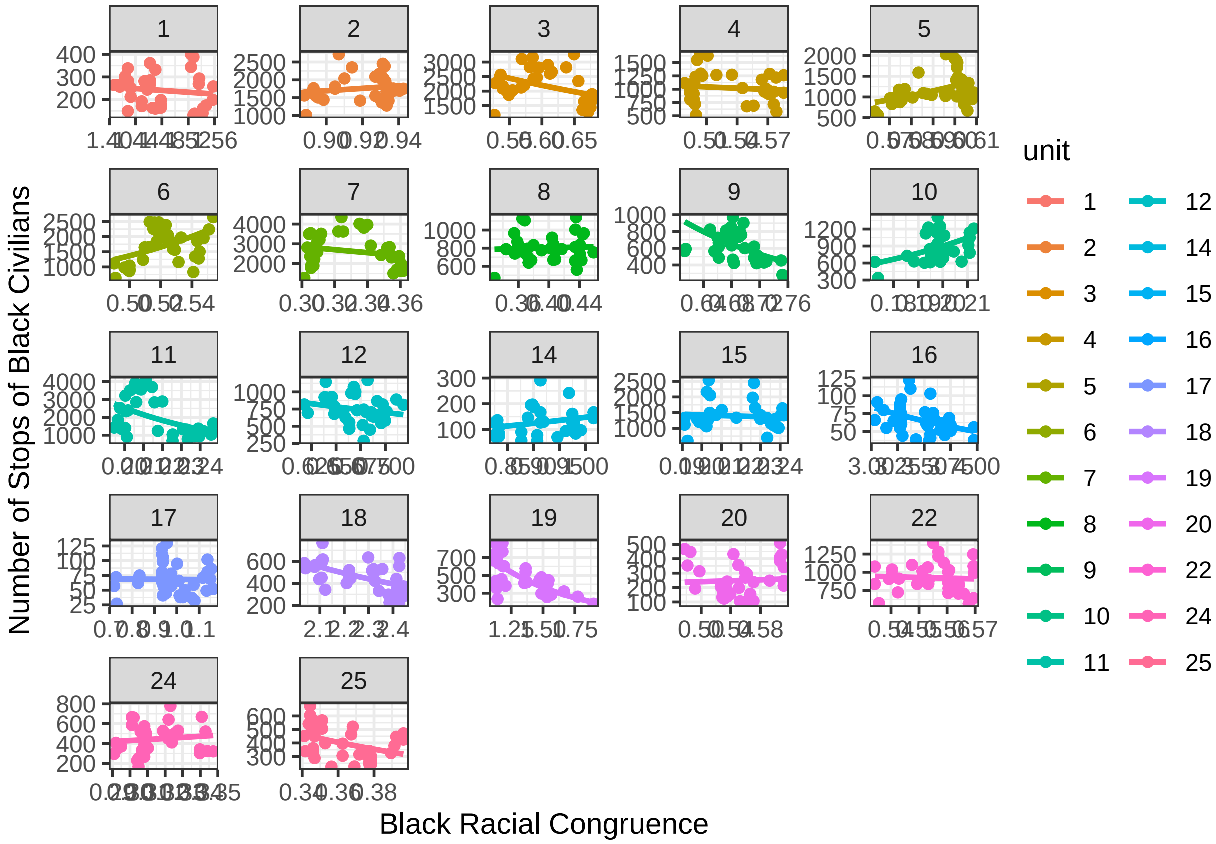
	Stops of Black Civilians	Stops of Black Civilians
	Model 3	Model 4
Black Racial Congruence	0.499 (0.131)**	0.619 (0.207)
Violent Crime Per 10,000	0.995 (0.009)	0.989 (0.008)
Property Crime Per 10,000	0.994 (0.002)**	0.998 (0.003)
Log of the Total Number of Officers	3.413 (2.686)	1.045 (0.694)
year2014	1.011 (0.080)	1.107 (0.072)
year2015	0.824 (0.070)*	0.892 (0.057)+
Mean Amount of Experience (Years)		0.807 (0.046)***
Offset - Black Pop.	Yes	Yes
Num.Obs.	792	792
R2 Pseudo	0.156	0.160
AIC	10 516.3	10 459.0
BIC	10 647.2	10 594.6
Log.Lik.	−5230.137	−5200.497
Std.Errors	by: unit	by: unit
FE: unit	X	X

P-values are denoted by symbols: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Standard Errors in parentheses. Coefficients are incident rate ratios.

discern the trend (if any) in some of the units.

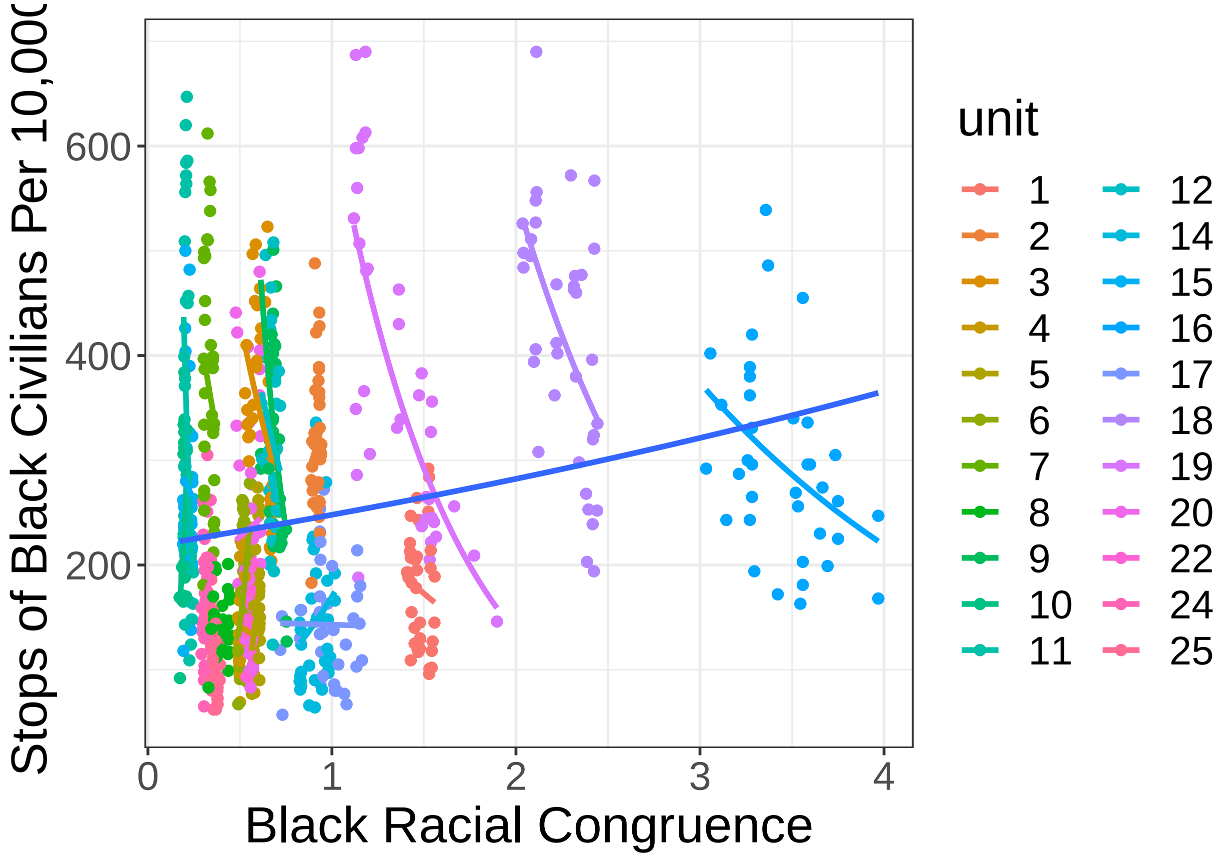
- The bottom graph makes it easier to see trends **within-unit**. There a few units with a positive relationship and there are a few others with no relationship, but most units demonstrate a slight to moderately negative relationship.
- As above table suggests though, there are a lot of moving parts. Black officers are being hired (or in some cases leaving), and the total size of the police force is changing **all** relative to the share of the population that is Black.
- Interpreting this graph, there is an association between the share of the police force that is Black and the share of population that is Black such that as this ratio increases (indicating parity and in a few cases over-representation), the number of stops of Black civilians declines.

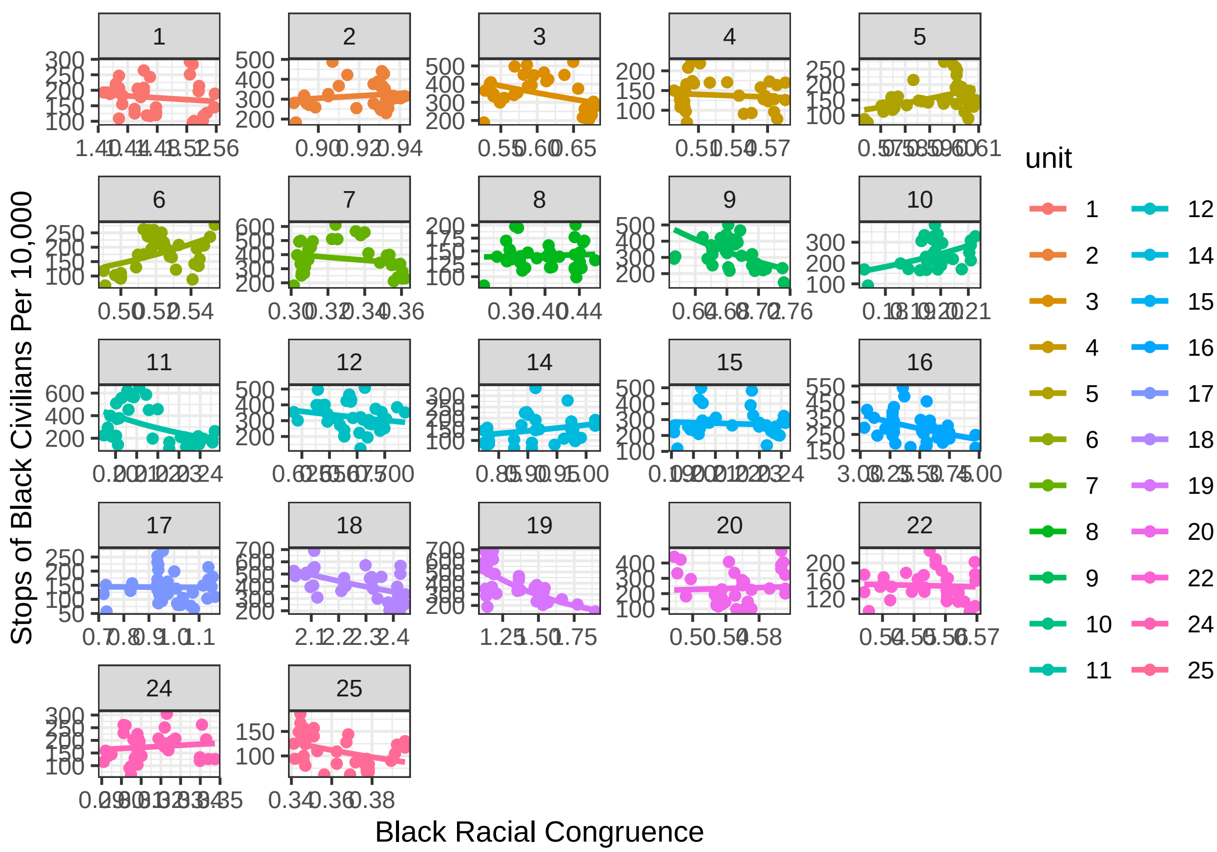

Number of Stops of Black Civilians
Black Racial Congruence
0
1000
2000
3000
4000
0
1
2
3
4
unit
1
2
3
4
5
6
7
8
9
10
11
12
14
15
16
17
18
19
20
22
24
25



Number of Stops of Black Civilians
Black Racial Congruence
unit

Plotting Rate of Stops





	Stops of Black Civilians	Stops of Black Civilians
	Model 5	Model 6
Black Racial Congruence	0.385 (0.109)***	
Residualized Mean Amount of Experience	0.807 (0.046)***	
Violent Crime Per 10,000	0.989 (0.008)	0.989 (0.008)
Property Crime Per 10,000	0.998 (0.003)	0.998 (0.003)
Log of the Total Number of Officers	1.045 (0.694)	1.045 (0.694)
year2014	1.107 (0.072)	1.107 (0.072)
year2015	0.892 (0.057)+	0.892 (0.057)+
Residualized Black Racial Congruence		0.619 (0.207)
Mean Amount of Experience (Years)		0.724 (0.047)***
Offset - Black Pop.	Yes	Yes
Num.Obs.	792	792
R2 Pseudo	0.160	0.160
AIC	10 459.0	10 459.0
BIC	10 594.6	10 594.6
Log.Lik.	−5200.497	−5200.497
Std.Errors	by: unit	by: unit
FE: unit	X	X

P-values are denoted by symbols: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard Errors in parentheses. Coefficients are incident rate ratios.

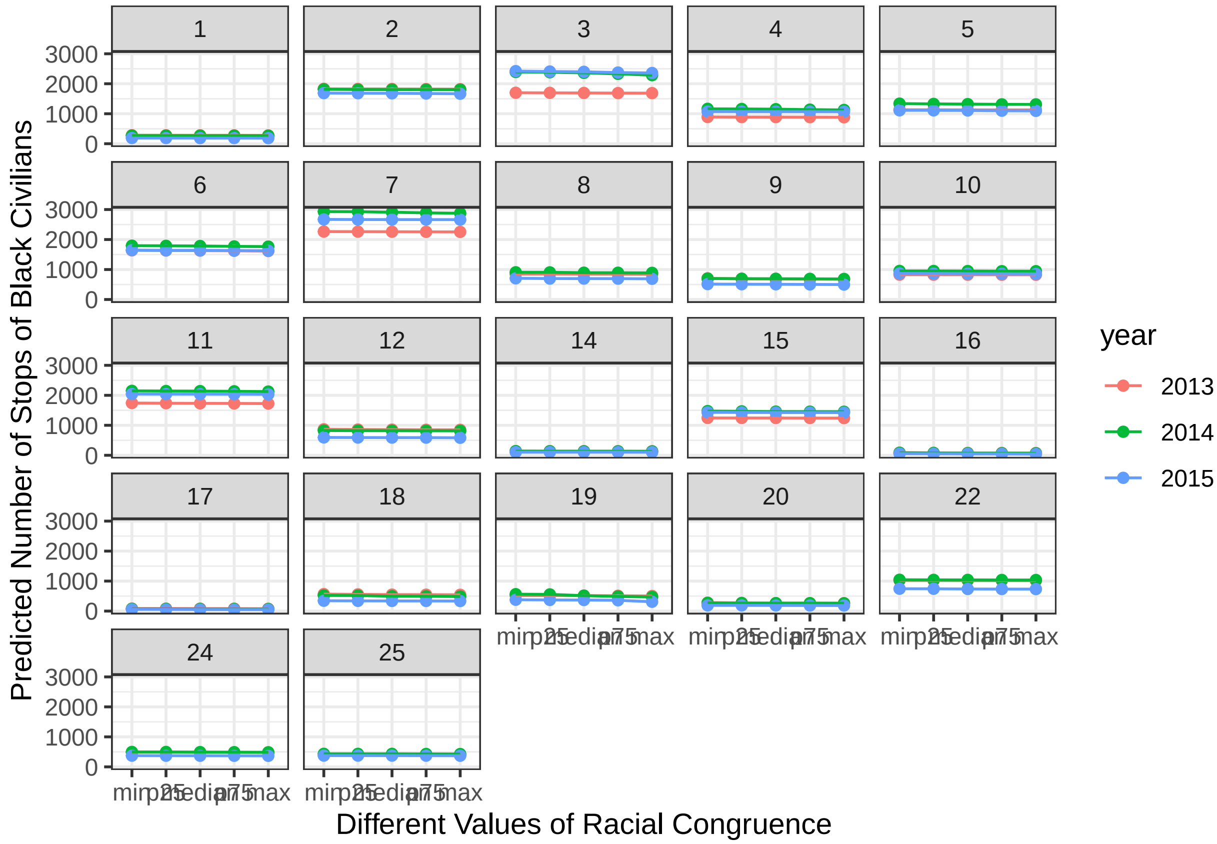
Residualized Regression

Predictions To Aid In Interpretation of Coefficients

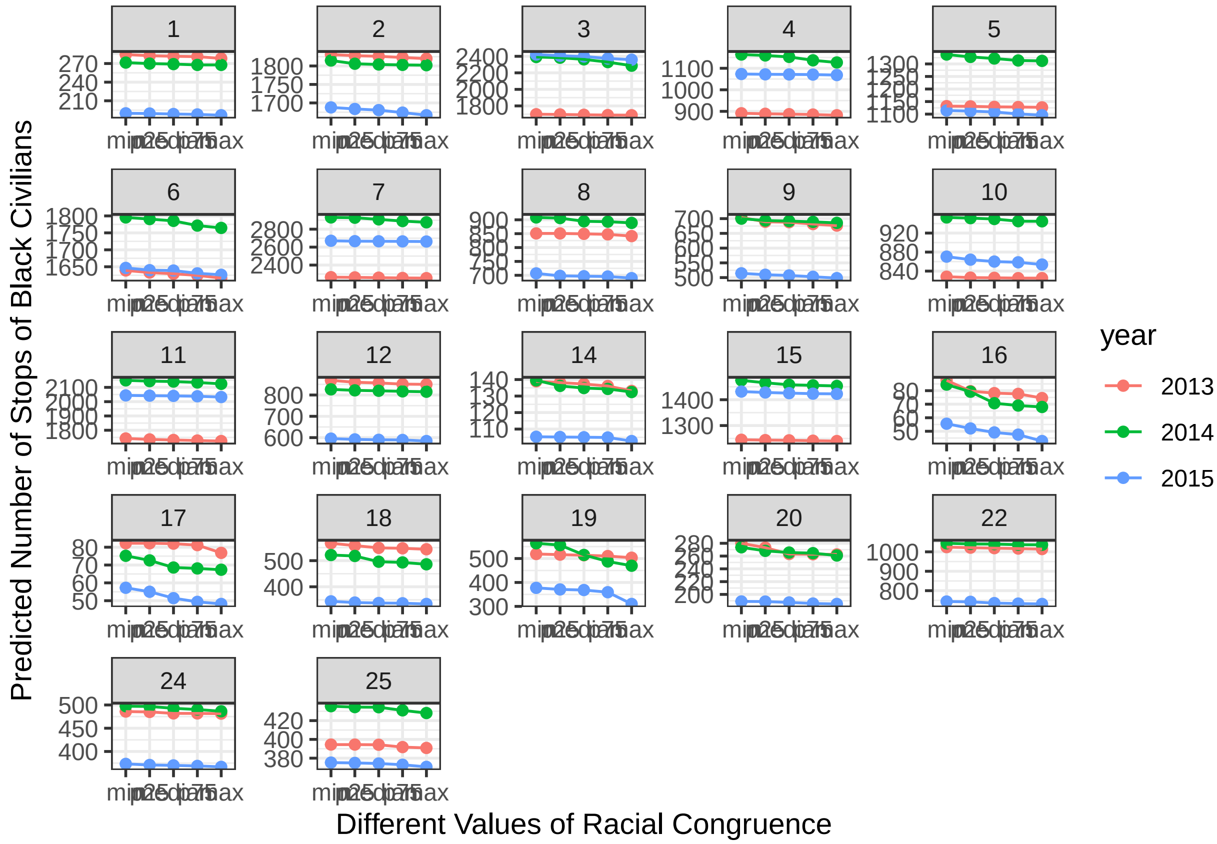
- Standardized coefficients do not make much sense to use in aiding in the interpretation of panel regressions. Should one standardize using the **total** mean and standard deviation? Within time unit mean and standard deviation? Within police unit? Within police unit crossed by time unit? Furthermore such interpretations in the context of a fixed effects regression remain unclear.
- To aid in the interpretation of the regression models, I systematically vary the value of the Black Racial Congruence variable (e.g. using maximum and minimum observed values for each unit within each year) while holding all other variables constant at their mean. I then do the same for the Mean Amount of Experience (Years) as a comparison point.

The effect of moving from the least amount of racial congruence to the most for each year for each unit

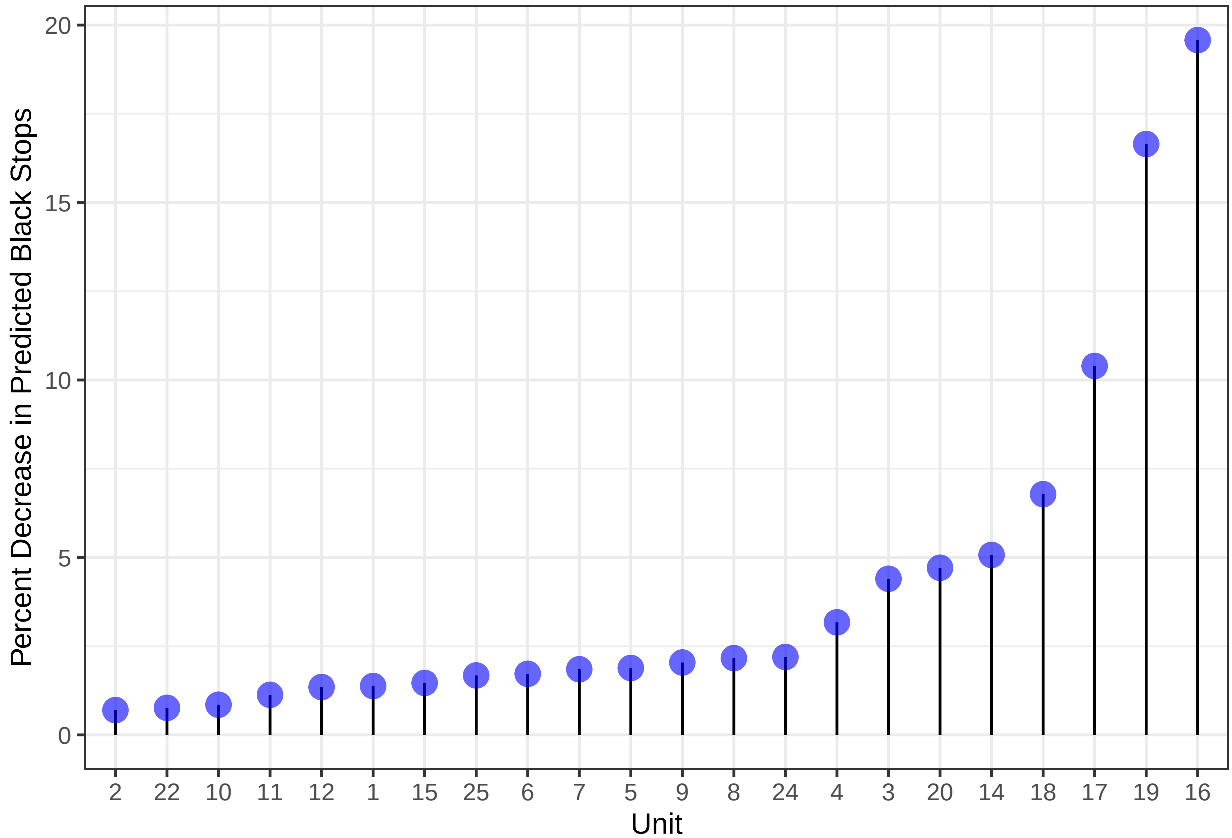
As mentioned above, I hold all other values constant at their means (for each unit in each year). I then systematically vary the value of Black racial congruence using the minimum value (for that unit in that year), the 25th percentile, the median, the 75th percentile, and the maximum value.



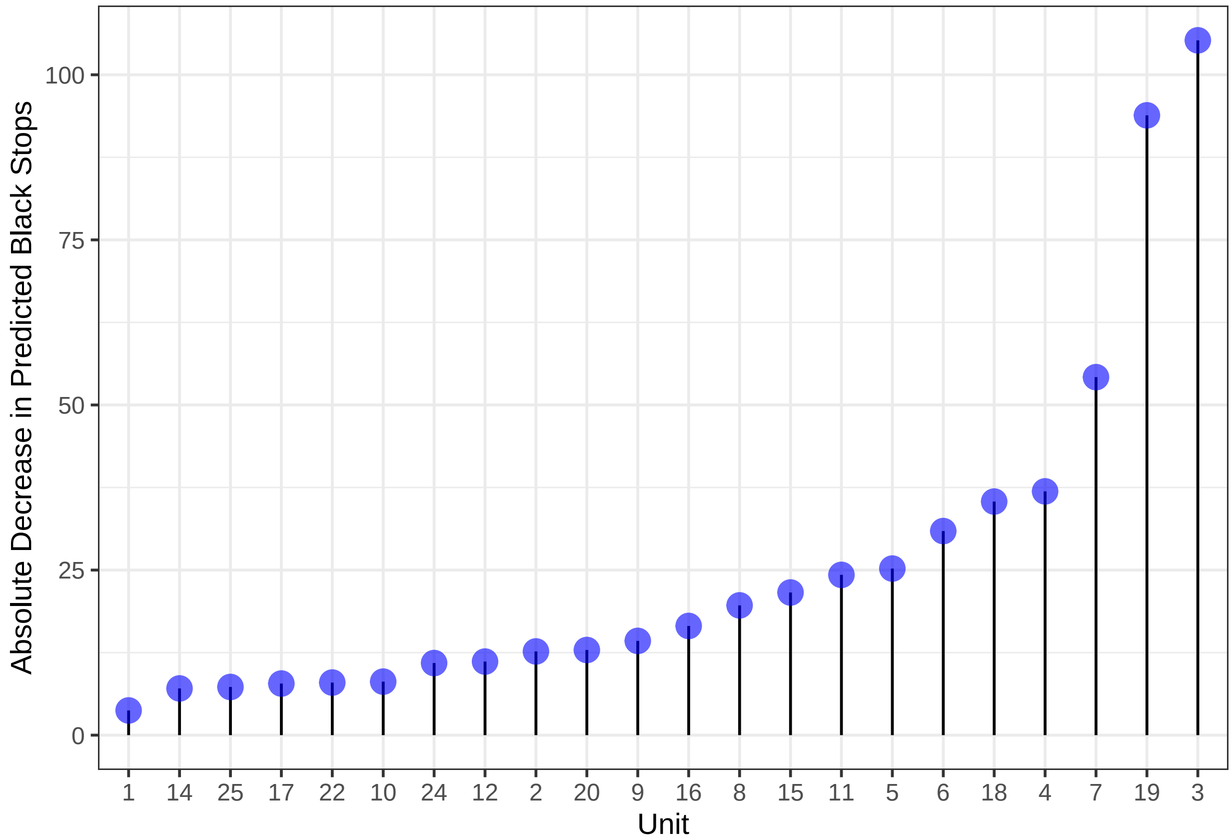
In this first graph where the same scale is used for all observations, it's impossible to discern or see the changes because the changes are small and need to be contextualized within the unit in which they're happening.



In this second graph where the y-axis is allowed to freely change with the unit, we can discern changes. This allows us to see how different vales of racial congruence lead to a declining number of stops of Black civilians.



Percent Decrease in Predicted Black Stops
20
15
10
5
0
2 22 10 11 12 1 15 25 6 7 5 9 8 24 4 3 20 14 18 17 19 16
Unit

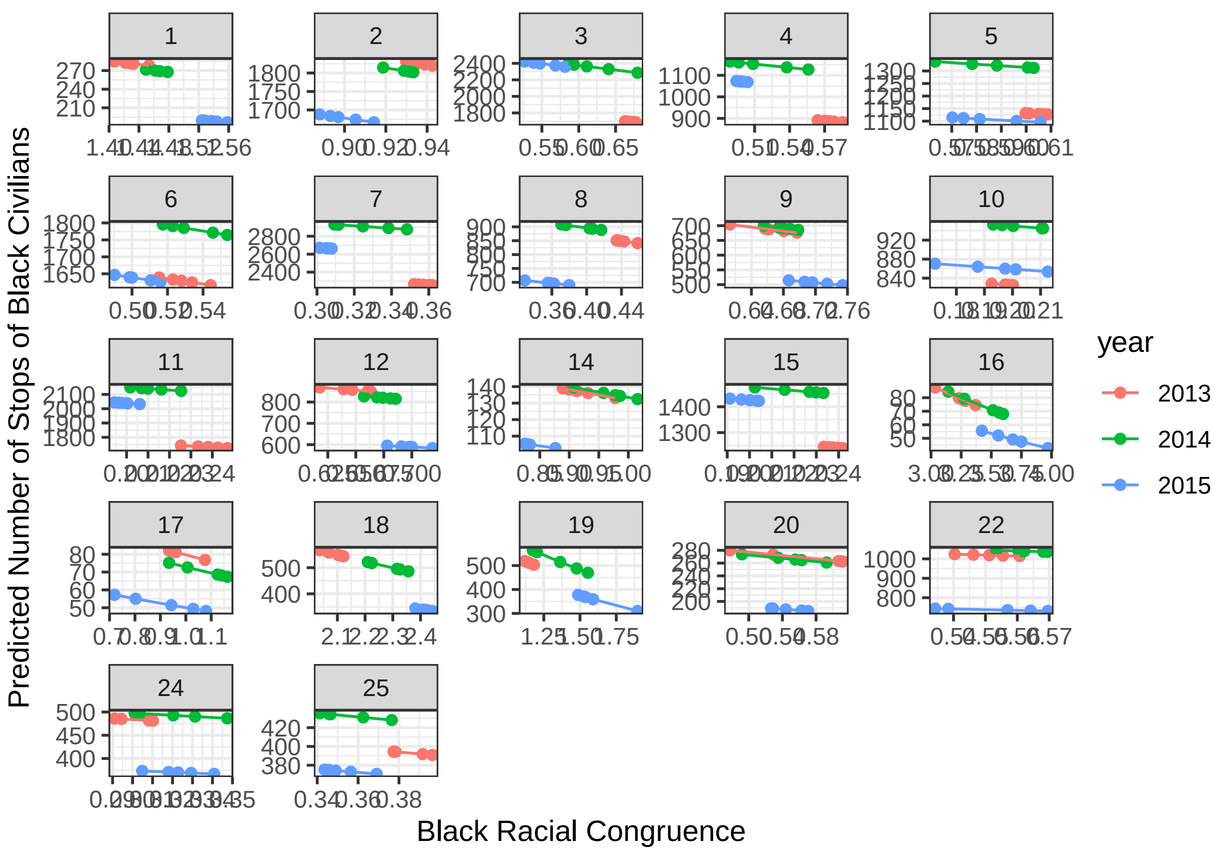


The bar graphs demonstrate the percentage and absolute change in the number of stops within each unit for each year when the racial congruence measure starts at its minimum value but is then increased to its maximum value.

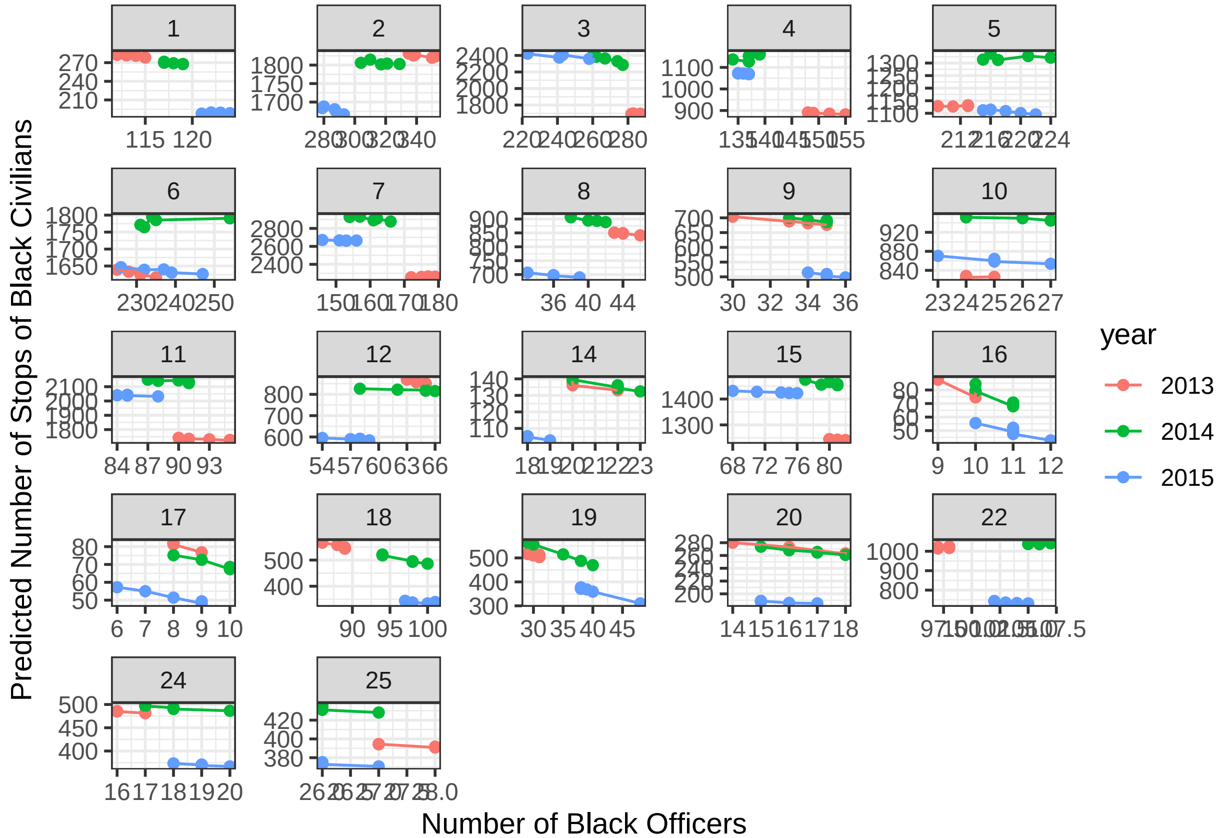
Here is a table trying to link together changes in racial congruence, the predicted number of stops of Black civilians, and changes in the absolute number of Black officers.

Unit	Change - Pred. Black Stops	Min to Max, Racial Con.	Change - Black Officers	Diff - Stops	Diff - Officers
1	271 to 268	1.45 to 1.48	117 to 119	4	2
2	1815 to 1802	0.92 to 0.93	310 to 317	13	7
3	2392 to 2287	0.59 to 0.68	260 to 277	105	17
4	1164 to 1127	0.49 to 0.56	139 to 137	37	-2
5	1337 to 1312	0.56 to 0.6	216 to 217	25	1
6	1795 to 1765	0.52 to 0.55	234 to 232	31	-2
7	2931 to 2877	0.31 to 0.35	157 to 166	54	9
8	908 to 889	0.37 to 0.42	38 to 42	20	4
9	700 to 686	0.66 to 0.7	33 to 35	14	2
10	953 to 945	0.19 to 0.21	24 to 27	8	3
11	2149 to 2125	0.2 to 0.23	87 to 91	24	4
12	826 to 815	0.66 to 0.69	58 to 66	11	8
14	140 to 132	0.91 to 1.02	20 to 23	7	3
15	1475 to 1453	0.2 to 0.23	77 to 81	22	4
16	84 to 68	3.14 to 3.6	10 to 11	17	1
17	75 to 67	0.93 to 1.16	8 to 10	8	2
18	521 to 486	2.21 to 2.36	94 to 100	35	6
19	564 to 470	1.17 to 1.55	29 to 40	94	11
20	274 to 261	0.49 to 0.59	15 to 18	13	3
22	1044 to 1036	0.55 to 0.57	107 to 106	8	-1
24	497 to 486	0.3 to 0.35	17 to 20	11	3
25	435 to 428	0.34 to 0.38	26 to 27	7	1

Appendix results

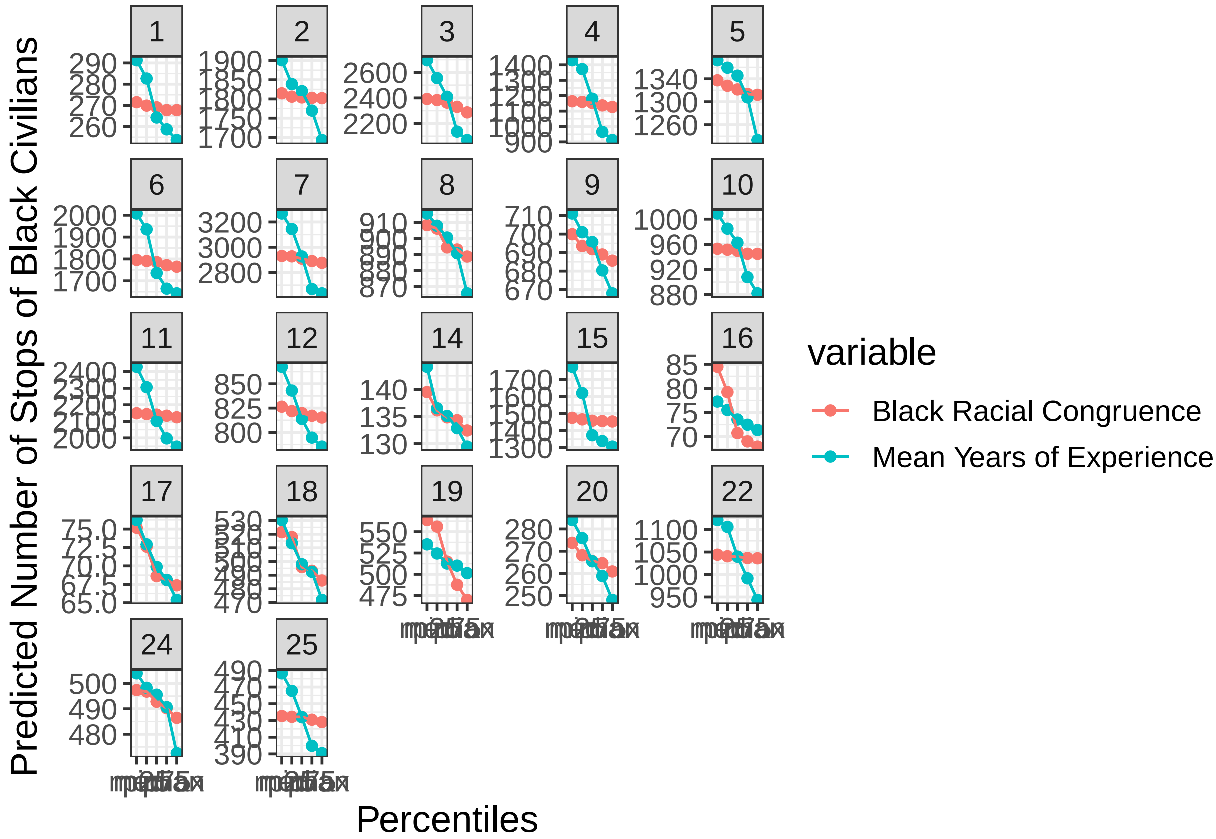


Here instead of having the x-axis be categorical, I use the associated Black Racial Congruence measure. So each dot on a line moving from left to right (or lowest to highest Racial Congruence) represents the minimum, 25th percentile, median, 75th percentile, and maximum racial congruence for that unit in that year.



This graph is a bit more complicated. The x-axis is the **rough** association of the number of Black officers to the corresponding values of racial congruence. I say rough because there isn't always an **exact** match to the racial congruence measures because the 25th percentile is averaged between two values, the median is averaged between two values, and the 75th percentile is averaged between two values.

In general, an increasing number of Black officers is associated with less stops of Black civilians. Occasionally though, an increasing number of Black officers is associated with an increasing number of stops of Black civilians. This has to do with the fact that even though the number of Black officers increased, the racial congruence decreased. I.e. the total number of officers increased at a higher rate than the rate of increase for Black officers. Their share or percentage of the force was diluted.



Demonstrates how racial congruence compares to the mean amount of experience in a police unit within a given year and how strongly associated each variable is with the decrease in the number of stops of Black civilians. Experience has the stronger association.