Predictive Priors

Investigating Prior Points and their Use as Code in North Carolina

Luke Cain

POLI 490H, Prof. Baumgartner
UNC-Chapel Hill, Fall 2019

Abstract

This paper investigates prior points in North Carolina. First, it looks at North Carolina's punitive grid. Then it gives a brief overview on relevant literature. Next it describes the makeup of different prior point grouping across different identity factors, including race, sex, their intersects, district, and attorney type. Then, it attempts to predict prior point levels with a regression on the same factors. It looks into the effects of political ideology, population, and racial fish-out-of-water effects on district characteristics. Finally, it revisits Luke Beyer's *Justice by the Grid* to determine whether prior points are used as a code for race or any other identity factor.

Keywords: Priors, Identity, Intersectionality, Justice System, Code

12/4/2019

Predictive Priors

Prior points play a large role in determining the level of punishment a person can expect for committing a crime in North Carolina. They also give strong indication of recidivism. With data from North Carolina courts over the past five years, I will break down different prior points groupings by identity factor to see who has how many priors. I will then predict the number of priors a defendant has based solely on identity factors and their intersects. Finally, I will investigate whether and to what degree these identity factors influence the harshness of punishment at different prior point groupings. This will demonstrate the extent to which prior points are a code for different identities. I hypothesize that:

I. Identity factors are distributed disproportionately among prior poin t groupings, and can be used to predict the number of priors a person might have. Race, sex, district, attorney type, age group, and plea type will all contribute significantly to this prediction.

II. District variations can be explained partially by a racial fish-out-of-water effect as well as political ideology.

III. Each of the above identity factors, especially race, are predictive of harshness at systematically different rates, depending on prior point grouping.

The paper is organized as follows. The next section gives background on the issue based on historical evidence and discusses previous studies of the topic. The following section discusses the source, manipulation, and limitations of the data sets. The following section discusses the identity make-up of the prior point groupings. The next section uses regressive analysis to predict the number of prior points one might have based on identity factors. The following section analyzes the effect of different identity factors at different prior points groupings. In the concluding section, I explain the significance of the findings and posit theories for further research.

Background

North Carolina's judicial sentencing system is different from most. A judge is not free to sentence a defendant to an arbitrary number of years; they must conform to a sentencing schedule. The schedule (graphic 1) consists of rows and columns. The rows correspond to different felony types, A through I. The columns are comprised of different prior point levels. The cell at the intersect of the two contains three ranges. A judge may select a sentence length within the presumptive range, or, should aggravating or mitigating effects be pertinent, from either of those ranges respectively (NCJS, 2018). About 69% of North Carolina's cases end in the presumptive range, 27% in the mitigated, and only about 4% in an aggravated range (Markham, 2011).

This system was created by the North Carolina legislature to fix a systematically broken judicial practice. "Minorities were being sentenced to disproportionately longer sentences, and the system was not successfully rehabilitating people. The state had the largest prison population per capita in the United States," (Beyer, 12). An additional function is that it gives researchers a possible minimum and maximum sentence to compare a judge's sentences. This allows analysis of the effects of non-legal factors (race, sex, etc.) on sentencing outcomes.

Graphic 1 about here

Luke Beyer's *Justice by the Grid* uses this approach and identifies plea type and prior points level as the greatest indicators of harshness. Beyer found other factors, especially race, to be relatively insignificant. This paper will, among other procedures, test the idea that identity factors may only insignificant because they are encoded into prior points. If this were the case, defendants with certain characteristics would be treated more harshly at low or no prior point levels than at higher ones.

The history of the criminal justice system's treatment of black citizens is a driving force in justice research. The general presumption that black people are more blameworthy, threatening, and criminal than white people. They are therefore targeted and punished more harshly by the criminal justice system. This effect is especially pronounced for black men. Hamilton uses upward departures[1] to determine that black people experience worse outcomes than white people. According to Mustard, black people are less likely than white to receive the option of no prison sentence. Baumgartner et al. confirm that black people are more likely to be pulled over in traffic stops, even though they yield more fruitless searches. This effect is especially high for black men. These findings are sufficient reason to take a second look at Beyer's claim that "for high level felonies in North Carolina, black men and black women are not treated statistically harsher than white women" (67).

Studies by Albonetti, 1997; Bickle and Peterson, 1991; Nagel and Johnson, 1994; and Ulmer, 2002, all show that men are punished much more harshly than women are. There is a proven variation between counties regarding sentencing outcomes that are not explained through individual case variation (Ulmer and Johnson, 2004). Champion (1989) showed that public defenders and private attorneys gave different quality representation. Given the importance of all these factors in the criminal justice, each will be included in regressions to predict prior point level as well as in regressions at different prior groupings to revisit Beyer's findings. Many will be investigated graphically for share in prior point groupings.

---

[1] Movement from presumptive range to aggravated range

Data Collection and Measurement

All of the data for this study came from the North Carolina Court System. The courts keep an extensive record of all proceedings from the years 2013-2018 in spreadsheet form. Personal details about the defendant, their alleged crime, the findings of the court, and procedural factors are all included in this treasure-trove of data. The home district of the defendants, characterized by "fips" code allowed me to merge the courts' dataset with one containing basic information about North Carolina's districts. This set contained information about the results of the 2016 presidential election as well as basic demographics on each district. These data were provided by the NC Administrative Office of the Courts, and made available through UNC-CH Political Science department.

The North Carolina Court System only recorded the prior point level of people accused of felony crimes, even though misdemeanors are punished based on a grid similar to that used for felonies. Regardless, this cut the usable data down to about 1.6 million entries. This study focuses mostly on the difference between black and white defendants[2].

From this starting point, I manipulated the data. I first cut out of the dataset anyone who did not have a listing for prior points. I then used Luke Beyer's code to create sex and race variables, as well as general age categories for defendants at the time of their crime. Also of interest to this study were effects of intersectionality. Variables were created to capture the intersect of race and sex (e.g. Black male, White female, etc.) The type of attorney used by a defendant also played a role in this study. Defendants were either appointed a court attorney,

[2] I do this for multiple reasons: Beyer's work focused on the two races, so building on it requires doing the same. The starkest differences appear between black and white defendants. No other group has enough observations to be split among prior point groupings and intersected with sex while maintaining statistical significance.

waived their right to an attorney and represented themselves, attained a private attorney, or used a public defender. A variable for each possibility was created.

The next step was to create a variable to break down the prior points levels. Luke Beyer's model follows the North Carolina felony grid, creating groups I-VI. While it was sensible for Beyer to follow North Carolina's setup, the categorization makes for difficult analysis. For one thing, group VI contains all prior points 17+, which lumps outliers with dozens of points along with those with relatively few. Another point of issue is that group I contains defendants with both 0 and 1 prior point level. It is important for this study to separate out those who have been charged with their first crime from those who are re-entering the criminal justice system. To that end, I created a new set of groups[3]. Tables 2 & 3 show the difference in North Carolina's grouping method and my own (LB_PriorPts).

Tables 1 & 2 about here

I used Beyer's plea breakdown, which recognizes four plea types: Guilty, Not Guilty, Guilty to Lesser, and an Alford Plea[4]. Table 3 shows the breakdown of plea types. [5]

Table 3 Here[6]

---

[3] The prior points levels are broken down into groups 0-10. LB_PriorPts0 contains all those with 0 prior points. All other groups contain the next 5 levels of prior points (LB_PriorPts1 has levels 1, 2, 3 ,4 and 5). LB_PriorPts10 contains all those with 36 or more points.

[4] "An Alford Plea allows the defendant to plead guilty while maintaining that they did not commit the crime. Defendants choose this option because for many reasons such as overwhelming evidence from the prosecution or a desire not to go to trial and risk the penalty," (Beyer, 49)

[5] The overwhelming majority of defendants choose not to plead not guilty. An entire genre of literature attempts to explain why. This statistical fact limits the scope of this research, as there are not enough "not guilty" pleas to analyze the effects of myriad factors at different prior point levels on the outcome of contested cases.

[6] GA- Alford Plea, GL- Guilty to lesser, GU- Guilty, NC- No Contest, NG- Not Guilty, RL- Responsible to Lesser, RS-Responsible

From there the data was ready to be put to use in three distinct ways:

1. Describing the breakdowns of different prior points levels.
2. Predicting the prior point level of an individual based on identity data.
3. Determining whether defendants are treated differently in terms of harshness based on multiple factors at different prior points levels.

Descriptive

To get a picture of who is contained in each prior points section, I dropped all variables except those pertaining to the factor I was interested in (e.g. race). Then, I created percentage for each factor, by dividing the number of instances in a group (e.g. white) by the total number of cases in the dataset. These percentages are displayed graphically, broken down by prior point group[7].

I reiterated this process on race, sex, attorney type, some intersections of sex and race, and age group. [8]

Graphics 2 & 3 here

Graphics 2 and 3 show the percentage of defendants in their 20's and 50's respectively. The trends are almost directly inverted, as one would expect. What is unexpected is that only 10% of defendants charged with their first felony are older than 50.

[7] This process uses the LB_PriorPts groupings for ease of analysis.
[8] All of the graphics are in terms of percentage, not raw numbers. The number of people in the highest prior point levels nears insignificance; the general trends are much more impactful at lower levels.

Two more near-inverse graphs is in the attorney type. Graphic 4 shows attorney type 0, privately retained attorneys. Type 2, displayed in graphic 5, shows court appointed attorneys.[9] Attorney type can be assumed a loose approximation of wealth- anyone who could afford a private attorney would surely take one given his or her superior record (Champion). This approximation makes these findings even more significant.

Graphics 4 & 5 Here

The percentage of black people increases steadily along with prior point level. Considering that North Carolina has a black population of about 21.5% (North Carolina), the proportion of black people in the criminal justice system is disproportionate at every level of prior point. Graphic 6 shows that black people are more likely to re-enter the criminal justice system than the average.

Graphic 6 Here

Another drastic effect appears in the percentage of females in each prior point category. The decrease shown in graphic 7 is near exponential. Like the percentages of black defendants, the appearance of women is disproportionate at every level, becoming more so as prior points increase. Unlike black people, women are vastly underrepresented in the judicial system.

Graphic 7 Here

[9] This set of graphs shows the importance of using prior point groupings other than the NC system's. The difference between 0 and 1 prior point level in both graphs is an important one that may have been lost in the alternative.

Graphics 8, 9, and 10 show the impact of intersectionality on the procurement of prior points. Graphic 8 shows the percentage of each group that is male. There is a slight increase from the 0^{th} through 4^{th} grouping, at which point the trend levels off. Graphic 9 shows the percentage of white defendants in each grouping. The graph peaks at the 1^{st} group, and declines from there. The combination of the two trends creates graphic 10. If one looks at sex or race individually, they might expect the peak percentage for a white man to be at the eighth or first grouping, respectively. By looking at the intersection of the two, it becomes clear that the peak is in the third grouping. This outcome could not be predicted with either trend alone.

Graphics 8, 9, and 10 Here

Predictive

Next, I endeavored to see to what degree a person's prior point level could be predicted by other identity factors. Those include race, sex, attorney type, whether or not they pled guilty, age group, and district. Model 1 shows the full regression.

The regression takes into account the intersects of race and sex. The variables indicate the following: RG_1-white female, RG_2-black female, RG_3-, white male RG_4-black male. LC_plea is 0 if the defendant plead not guilty, 1 if they plead anything else. In the attorney variables, zero is a privately attained attorney, 2 is a court-appointed one, 3 is a case in which the defendant represented themselves. All age groups are in comparison with that below 20 years. Finally, all 44 judicial districts are accounted for. All of the factors are significant at 99% confidence values except for seven districts. Of those, four are significant at the 90% confidence level. This regression predicts that black men, those with a court-appointed attorney, who did not plead guilty, in their 40's, and from District 3 to have the most prior points.

One counter-intuitive outcome is the prediction of prior points by age group. One might expect that defendants in older groups would have accrued, on average, more prior points over the course of their lives. This theory holds true for all but the final age group. Those entering the court system in their 50's or older are predicted to have fewer prior points than those entering in their 40's. This trend has not been explained thoroughly in the criminal justice literature, and requires further investigation. One possible explanation is that 50+ year-olds with lots of priors do not enter the court system because they are currently incarcerated, so those with fewer have more of an effect. The other findings reinforce what is suggested by the literature and my first hypothesis.

I next wanted to peer behind the shroud of district effects. I primarily wanted to see if the percentage white in a district, its population and the political ideology (measured by the percentage of voters that voted for Donald Trump in 2016), could help account for disparities in who was predicted to have prior points. Models 2, 3, 4, and 5 shows the regression with district effects substituted for political ideology. Model 2 excludes all but black defendants, Model 3 excludes all but white, Model 4 only includes males, and Model 5 includes only females. Models 6, 7, 8, and 9 show the effects of the percentage of a district's population that is white on the same groups.

Models 2-5 attempts to explain district differences in prior point acquisition by political ideology. They find that black people have slightly fewer priors in districts that are more conservative, white people have more, males less, and females more. Models 6-9 attempt to show a "fish-out-of-water-effect", whereby minorities are treated more differently the more they are in the numerical minority. While black people do have more prior points the whiter a district, the effect is almost double for white people. Whiter districts also tend to have females with more prior points and males with fewer. Overall, the effect of political ideology and whiteness do not contribute significantly to explaining the variation in predicted prior points by district. All R-squared values were very low. The most dramatic coefficient showed a .01 increase in prior points for each percentage increase in both Trump support and whiteness. This effect was experienced by white people in both cases.

Finally, I ran the full prior point regression again, but with district replaced by district population. Model 10 shows that population has a very small negative correlation with prior points. The difference in R-squared value between model 1 and model 10 show that population does not account for all the variation in district. Hypothesis II is partially fulfilled.

Determinative

Next, I wanted to investigate whether or not prior point level determined how much different identity factors mattered in punishment. To do so, I used Beyer's harshness factor. This was found by taking the verdict of each sentence as a percentage of the maximum verdict (Beyer, 52). I then dropped every case except those where the defendant had the desired prior point group . From there, I ran a regression to try to ascertain what variables could predict harshness. Models 11-17 show the outcomes of this process.

The statistically significant coefficients of each are displayed in bar graphs[10]. The main point of concern is how much identity factors matter at the first appearance in court (prior point group 0), and at any subsequent appearances (group 1 and above). The transition from group 0 to group 1 is that of citizen to convicted felon, and come with all prejudices those words entail. These groups also contain the most individuals, so any effect between the two is multiplied many

[10] Many of the factors proved statistically insignificant, especially at higher prior point levels. Regressions with nothing significant to show are omitted here. This is especially true of district effects.

times. Graphics 13-18 show the more significant changes in identity factors' harshness coefficients. The fact that these distributions are not uniform shows that there is *some* effect of the intersect of prior point group and identity that affects harshness.

RG1 and RG3, being a black female and black male respectively, show similar trends. Both show increases in harshness from prior point groups 0-1 and much greater increases from 1-2. Defendants who pled not guilty or used an Alford plea had similar trends-a slight increase harshness from 0-1 and a large increase from 1-2, whereas those who plead guilty had a slight decrease from 0-1. Defendants that represented themselves had a moderate decrease in harshness from groups 0-1.

Conclusion

Something is wrong in North Carolina. Black people are drastically over-represented in the criminal system, and have re-entered it more than any population. They are punished for felonies at an extreme rate. Males are also more likely to re-enter a court room. Black males are even more likely to have prior points than a combination of the two characteristics would suggest, as are those who do not or cannot retain a private attorney.

The correlations between wealth, race, sex and incarceration are well documented, but have not been shown so completely across such a large population. They have also not been expressed in terms of prior points, where relative effects are directly comparable. For example, the difference in re-entry to the criminal justice system between a white woman and black woman is not large compared to that between a white woman and a black man, or the effect of a privately retained attorney. The common denominator of prior points and the North Carolina Courts system's extensive record make these comparisons possible.

The next logical question is "what is wrong"? Do black people commit more crimes than white people do? The poor more than the rich? Males more than females? The answers to these questions are still up for discussion and research, and are almost certainly not the same. If any of the answers is "no", then there is something fundamentally wrong with our justice system. This study shows that the former of each pair is much more likely to find themselves incarcerated and then arrested and arraigned again. This could point to over-targeting, as in Baumgartner's work (demonstrated by the fruitless search rate), which could lead to cyclical crime and distrust towards the government (Baumgartner et al.).

The type of plea someone gives is also predictive of his or her level of priors. This could indicate that the more interaction a person has with the criminal justice system, the less they try to fight for their freedom. This correlation may be the result of one giving up in the face of the pressure of the state. Alternatively, it could indicate that the oft incarcerated grow savvy in their interactions with the court, since those that plead guilty or guilty to lesser receive less harsh sentences (Beyer, 47).

Some districts have far higher recidivism than others do. A small portion of that discrepancy is due to the racial makeup of those districts, some is due to the political ideology. Even these small discrepancies are subject to intersectionality. Women, men, black, and white people receive different, sometimes even opposite effects based on the characteristics of their homes.

The American ethos promises equal protection under the law to all its citizens. If one's race, sex, wealth, plea, district, *and* all the myriad intersections between them do not cause one to be more criminal than another, it is fair to say that protection is not given equally to all. This study shows that all the factors listed above are relevant in who receives prior points. This is a good indicator of who has been punished for crimes, but also about how harshly they will be punished for any future crimes. North Carolina's grid system ensures that, no matter how one found themselves with prior points, they can be punished for it long after their sentence has been fulfilled. When these prior points appear to result in part from factors irrelevant to any legitimate legal purpose, it is right to study them closely.

The intersect of prior points and identity factors can be a significant one, as graphics 13-18 show. Oftentimes, however, it appears that groups the literature would predict to be treated worse by the justice system (black men, those who have to use public defenders in lieu of private counsel, etc.) seem to receive less harsh punishments than control groups (white women, those who retain private attorneys). Perhaps this decrease in harshness is the courts correcting for some of the prejudice found in the rest of the criminal justice system. Perhaps these disparaged groups are brought into court for less serious offenses than their more privileged counterparts are. If this is the case, the negative harshness coefficients could show that the judicial process, including the sentencing grid, is a corrective one.

However, if all the above is correct, then the courts become less corrective as prior points increase. The people that face increased blameworthiness (Beyer, 3) are treated almost universally worse at the first prior point grouping than at group zero. This could indicate not that priors are used as a code, as originally hypothesized, but that they mitigate the corrective value of the court system.

Tables, Models, and Graphics

Table 1: Frequency of LB_PriorPts Groupings

LB_PriorPts	Freq.	Percent	Cum.
0	946,949	56.06	56.06
1	646,350	38.27	94.33
2	45,844	2.71	97.04
3	24,642	1.46	98.50
4	10,481	0.62	99.12
5	7,755	0.46	99.58
6	3,515	0.21	99.79
7	1,763	0.10	99.89
8	844	0.05	99.94
9	401	0.02	99.97
10	547	0.03	100.00
Total	1,689,091	100.00	

Table 2: Frequency of NC_PriorPts Groupings

NC_PriorPts	Freq.	Percent	Cum.
1	1,154,793	68.78	68.78
2	428,647	25.53	94.31
3	45,743	2.72	97.03
4	24,598	1.47	98.50
5	12,727	0.76	99.25
6	12,533	0.75	100.00
Total	1,679,041	100.00	

Table 3: Frequency of plea types

CRDPLE	Freq.	Percent	Cum.
.	1	0.00	0.00
GA	32,925	1.95	1.95
GL	192,637	11.40	13.35
GU	1,365,374	80.83	94.19
NC	31,346	1.86	96.04
NG	66,751	3.95	100.00
RL	51	0.00	100.00
RS	6	0.00	100.00
Total	1,689,091	100.00	

Model 1: Regression for Prior Point level by race/sex intersect attorney type, age group, and district.

Source	SS	df	MS			
				Number of obs	=	1,378,106
				F(50, 1378055)	=	2311.84
Model	1292715.26	50	25854.3052	Prob > F	=	0.0000
Residual	15411377.5	1,378,055	11.183427	R-squared	=	0.0774
				Adj R-squared	=	0.0774
Total	16704092.7	1,378,105	12.1210595	Root MSE	=	3.3442

crdprpt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LB_RG4						
1	.0996741	.0112881	8.83	0.000	.0775497	.1217984
2	.8128842	.008366	97.17	0.000	.7964872	.8292812
3	1.60614	.0088396	181.70	0.000	1.588815	1.623466
AgeGroup						
20	1.106073	.0101995	108.44	0.000	1.086083	1.126064
30	2.05063	.0107866	190.11	0.000	2.029489	2.071772
40	2.255889	.0116193	194.15	0.000	2.233116	2.278662
50	1.747004	.0124414	140.42	0.000	1.722619	1.771388
LB_District						
2	-.1942046	.0283831	-6.84	0.000	-.2498345	-.1385747
3	.8180326	.0290489	28.16	0.000	.7610977	.8749675
4	-.1957552	.0271232	-7.22	0.000	-.2489158	-.1425946
5	-.3380343	.0252891	-13.37	0.000	-.3876	-.2884686
6	.3500127	.0260211	13.45	0.000	.2990123	.4010131
7	.0280485	.0396944	0.71	0.480	-.0497512	.1058482
8	.1536957	.0402686	3.82	0.000	.0747706	.2326209
9	.4224286	.0261599	16.15	0.000	.3711562	.4737011
10	.5183295	.0271826	19.07	0.000	.4650524	.5716065
11	.1419761	.029222	4.86	0.000	.084702	.1992502
12	.4671545	.0350886	13.31	0.000	.398382	.5359271
13	-.0345504	.0230206	-1.50	0.133	-.0796699	.0105691
14	.3648433	.0323619	11.27	0.000	.3014152	.4282715

15	.0975208	.033781	2.89	0.004	.0313112	.1637304
16	-.4722262	.0274747	-17.19	0.000	-.5260758	-.4183767
17	.0588929	.0284026	2.07	0.038	.0032248	.114561
18	.1302902	.0283143	4.60	0.000	.0747952	.1857852
19	-.1875827	.0292881	-6.40	0.000	-.2449863	-.130179
20	-.7514671	.0299127	-25.12	0.000	-.810095	-.6928392
21	.2099007	.0361545	5.81	0.000	.1390392	.2807623
22	-.8785234	.033396	-26.31	0.000	-.9439785	-.8130683
23	-.2374597	.0335473	-7.08	0.000	-.3032113	-.1717081
24	.5469524	.0313792	17.43	0.000	.4854502	.6084546
25	.4377824	.0245689	17.82	0.000	.3896281	.4859367
26	-.3013253	.026328	-11.45	0.000	-.3529273	-.2497232
27	.1266297	.028426	4.45	0.000	.0709158	.1823436
28	.3718956	.0275703	13.49	0.000	.3178587	.4259324
29	.2958679	.0367065	8.06	0.000	.2239244	.3678115
30	-.3671592	.0308557	-11.90	0.000	-.4276352	-.3066831
31	-.5821545	.0312377	-18.64	0.000	-.6433794	-.5209297
32	.6337403	.0254822	24.87	0.000	.5837961	.6836845
33	.155402	.0268437	5.79	0.000	.1027892	.2080148
34	.2792641	.0286127	9.76	0.000	.2231842	.3353439
35	.3129131	.0283418	11.04	0.000	.2573642	.3684621
36	-.0631519	.0306712	-2.06	0.039	-.1232665	-.0030374
37	.6027283	.0251131	24.00	0.000	.5535074	.6519491
38	-.481649	.024158	-19.94	0.000	-.5289979	-.4343002
39	.514522	.0281187	18.30	0.000	.4594103	.5696337
40	.6747614	.0274371	24.59	0.000	.6209855	.7285372
41	.6804323	.0285364	23.84	0.000	.624502	.7363626
42	.1266298	.0309807	4.09	0.000	.0659088	.1873508
43	-.1529315	.0311716	-4.91	0.000	-.2140268	-.0918363
44	.0430678	.0298221	1.44	0.149	-.0153825	.1015181
_cons	-.386825	.0232845	-16.61	0.000	-.4324619	-.3411882

Model 2: Regression for prior point level by % Trump support for black people

```
. reg crdprpt TrumpDistrictShare
```

Source	SS	df	MS
Model	915.180309	1	915.180309
Residual	9089371.06	622,026	14.6125259
Total	9090286.24	622,027	14.6139737

Number of obs	=	622,028
F(1, 622026)	=	62.63
Prob > F	=	0.0000
R-squared	=	0.0001
Adj R-squared	=	0.0001
Root MSE	=	3.8226

crdprpt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TrumpDistr~e	-.002761	.0003489	-7.91	0.000	-.0034448	-.0020772
_cons	2.51706	.018241	137.99	0.000	2.481308	2.552812

Model 3: Regression for prior point level by % Trump support for white people

```
. reg crdprpt  TrumpDistrictShare
```

Source	SS	df	MS
Model	15134.7313	1	15134.7313
Residual	7493903.04	756,376	9.90764255
Total	7509037.78	756,377	9.92763896

Number of obs	=	756,378
F(1, 756376)	=	1527.58
Prob > F	=	0.0000
R-squared	=	0.0020
Adj R-squared	=	0.0020
Root MSE	=	3.1476

crdprpt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TrumpDistrictShare	.010521	.0002692	39.08	0.000	.0099934	.0110486
_cons	1.200902	.0162406	73.94	0.000	1.169071	1.232733

Model 4: Regression for prior point level by % Trump support for males

Source	SS	df	MS			
				Number of obs	=	1,221,187
				F(1, 1221185)	=	70.35
Model	890.835263	1	890.835263	Prob > F	=	0.0000
Residual	15464680	1,221,185	12.6636668	R-squared	=	0.0001
				Adj R-squared	=	0.0001
Total	15465570.8	1,221,186	12.6643859	Root MSE	=	3.5586

crdprpt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TrumpDistrictShare	-.0018945	.0002259	-8.39	0.000	-.0023372	-.0014518
_cons	2.135458	.0127593	167.36	0.000	2.11045	2.160465

Model 5: Regression for prior point level by % Trump support for females

```
. reg crdprpt TrumpDistrictShare
```

Source	SS	df	MS			
				Number of obs	=	457,250
				F(1, 457248)	=	613.63
Model	3227.30555	1	3227.30555	Prob > F	=	0.0000
Residual	2404830.11	457,248	5.25935621	R-squared	=	0.0013
				Adj R-squared	=	0.0013
Total	2408057.41	457,249	5.2664028	Root MSE	=	2.2933

crdprpt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
TrumpDistrictShare	.0058697	.000237	24.77	0.000	.0054053	.0063341
_cons	.7910154	.0135747	58.27	0.000	.7644094	.8176215

Model 6: Regression for prior point level by % Whiteness support for black people

```
. reg crdprpt PctWhiteDistrict

      Source |       SS           df       MS      Number of obs   =   622,028
-------------+----------------------------------   F(1, 622026)    =     46.28
       Model |  676.284253         1  676.284253   Prob > F        =    0.0000
    Residual |  9089609.95   622,026    14.61291   R-squared       =    0.0001
-------------+----------------------------------   Adj R-squared   =    0.0001
       Total |  9090286.24   622,027  14.6139737   Root MSE        =    3.8227

------------------------------------------------------------------------------
     crdprpt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
PctWhiteDi~t |   .0025073   .0003686     6.80   0.000     .0017849    .0032297
       _cons |   2.223991    .023136    96.13   0.000     2.178645    2.269337
------------------------------------------------------------------------------
```

Model 7: Regression for prior point level by % Whiteness support for white people

```
. reg crdprpt PctWhiteDistrict

      Source |       SS           df       MS      Number of obs   =   756,378
-------------+----------------------------------   F(1, 756376)    =   1416.05
       Model |  14031.7903         1  14031.7903   Prob > F        =    0.0000
    Residual |  7495005.99   756,376  9.90910075   R-squared       =    0.0019
-------------+----------------------------------   Adj R-squared   =    0.0019
       Total |  7509037.78   756,377  9.92763896   Root MSE        =    3.1479

----------------------------------------------------------------------------------
         crdprpt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
PctWhiteDistrict |   .0103324   .0002746    37.63   0.000     .0097942    .0108705
           _cons |   1.083734   .0198896    54.49   0.000     1.044751    1.122717
----------------------------------------------------------------------------------
```

Model 8: Regression for prior point level by % Whiteness support for males

```
. reg crdprpt PctWhiteDistrict

      Source |       SS           df       MS      Number of obs   = 1,221,187
-------------+----------------------------------   F(1, 1221185)   =     15.01
       Model |  190.101066         1  190.101066   Prob > F        =    0.0001
    Residual |  15465380.7 1,221,185  12.6642406   R-squared       =    0.0000
-------------+----------------------------------   Adj R-squared   =    0.0000
       Total |  15465570.8 1,221,186  12.6643859   Root MSE        =    3.5587

------------------------------------------------------------------------------
         crdprpt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
PctWhiteDistrict |  -.0008602    .000222    -3.87   0.000    -.0012953    -.000425
           _cons |   2.088795   .0150321   138.96   0.000     2.059332    2.118257
------------------------------------------------------------------------------
```

Model 9: Regression for prior point level by % Whiteness support for females

```
 reg crdprpt PctWhiteDistrict

      Source |       SS           df       MS      Number of obs   =   457,250
-------------+----------------------------------   F(1, 457248)    =    596.82
       Model |  3138.97964         1  3138.97964   Prob > F        =    0.0000
    Residual |  2404918.43   457,248  5.25954938   R-squared       =    0.0013
-------------+----------------------------------   Adj R-squared   =    0.0013
       Total |  2408057.41   457,249   5.2664028   Root MSE        =    2.2934

------------------------------------------------------------------------------
         crdprpt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
ctWhiteDistrict  |   .0056783   .0002324    24.43   0.000     .0052228    .0061339
           _cons |   .7378354   .0158716    46.49   0.000     .7067276    .7689432
------------------------------------------------------------------------------
```

Model 10: Regression for Prior Point level by race/sex intersect attorney type, age group, and district population.

Source	SS	df	MS		
Model	1088502.28	8	136062.785	Number of obs	= 1,378,106
Residual	15615590.4	1,378,097	11.3312709	F(8, 1378097)	= 12007.73
				Prob > F	= 0.0000
Total	16704092.7	1,378,105	12.1210595	R-squared	= 0.0652
				Adj R-squared	= 0.0652
				Root MSE	= 3.3662

crdprpt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LB_RG4						
1	.0830531	.0111527	7.45	0.000	.0611942	.1049119
2	.8164265	.0084154	97.02	0.000	.7999326	.8329204
3	1.598695	.0086285	185.28	0.000	1.581783	1.615606
AgeGroup						
20	1.106191	.0102618	107.80	0.000	1.086078	1.126304
30	2.055645	.0108511	189.44	0.000	2.034377	2.076913
40	2.262367	.0116891	193.55	0.000	2.239457	2.285277
50	1.745675	.0125128	139.51	0.000	1.72115	1.770199
PopDistrict	-3.41e-07	1.16e-08	-29.45	0.000	-3.64e-07	-3.19e-07
_cons	-.1736786	.0117931	-14.73	0.000	-.1967927	-.1505646

Model 11: Regression for Harshness level by race/sex intersect, attorney type, plea, age group, and District (omitted) at LB_PriorPts=0

```
. reg Harsh i.LB_RG4  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
```

Source	SS	df	MS			
				Number of obs	=	44,587
				F(56, 44530)	=	772.34
Model	1.0637e+09	56	18995157	Prob > F	=	0.0000
Residual	1.0952e+09	44,530	24594.1723	R-squared	=	0.4927
				Adj R-squared	=	0.4921
Total	2.1589e+09	44,586	48421.1924	Root MSE	=	156.83

Harsh	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LB_RG4						
1	4.231728	3.137693	1.35	0.177	-1.918203	10.38166
2	-26.407	2.273379	-11.62	0.000	-30.86287	-21.95114
3	-48.3022	2.431139	-19.87	0.000	-53.06728	-43.53713
LB_plea						
1	-317.7936	1.629867	-194.98	0.000	-320.9882	-314.599
2	-284.4614	5.57836	-50.99	0.000	-295.3951	-273.5277
3	-267.6377	3.02067	-88.60	0.000	-273.5583	-261.7171
AgeGroup						
20	-.4218966	1.780588	-0.24	0.813	-3.91188	3.068086
30	-3.775135	2.513342	-1.50	0.133	-8.701329	1.151058
40	-2.646474	3.229763	-0.82	0.413	-8.976865	3.683917
50	-6.837527	3.688197	-1.85	0.064	-14.06646	.3914026
LB_Atty						
1	.4896987	2.712201	0.18	0.857	-4.826262	5.805659
2	-5.724249	2.193275	-2.61	0.009	-10.0231	-1.425392
3	17.88925	3.381563	5.29	0.000	11.26133	24.51717

Model 12: Regression for Harshness by race/sex intersect, attorney type, plea, age group, and District (omitted) at LB_PriorPts=1

```
reg Harsh i.LB_plea i.LB_RG4 i.AgeGroup i.LB_Atty i.LB_Dist
```

Source	SS	df	MS
Model	2.0638e+09	56	36852717.8
Residual	1.6606e+09	84,463	19660.2511
Total	3.7243e+09	84,519	44064.8373

Number of obs	=	84,520
F(56, 84463)	=	1874.48
Prob > F	=	0.0000
R-squared	=	0.5541
Adj R-squared	=	0.5538
Root MSE	=	140.22

Harsh	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LB_plea						
1	-318.6485	1.058074	-301.16	0.000	-320.7223	-316.5746
2	-244.3239	3.8554	-63.37	0.000	-251.8805	-236.7674
3	-246.3285	1.929338	-127.68	0.000	-250.11	-242.547
LB_RG4						
1	-5.306691	2.320395	-2.29	0.022	-9.854647	-.7587349
2	-23.50349	1.531574	-15.35	0.000	-26.50536	-20.50161
3	-41.18034	1.613497	-25.52	0.000	-44.34278	-38.0179
AgeGroup						
20	-1.852791	1.564829	-1.18	0.236	-4.919843	1.214261
30	.0276609	1.754379	0.02	0.987	-3.410909	3.466231
40	5.585311	2.02555	2.76	0.006	1.615249	9.555372
50	9.262748	2.397718	3.86	0.000	4.563239	13.96226
LB_Atty						
1	-4.142508	1.872292	-2.21	0.027	-7.812186	-.4728303
2	-14.49036	1.572528	-9.21	0.000	-17.5725	-11.40821
3	7.425813	2.250329	3.30	0.001	3.015186	11.83644

Model 13: Regression for Harshness by race/sex intersect, attorney type, plea, age group, and District (omitted) at LB_PriorPts=2

```
reg Harsh i.LB_RG4  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
```

Source	SS	df	MS			
				Number of obs	=	26,708
				F(56, 26651)	=	82.87
Model	20465634.2	56	365457.754	Prob > F	=	0.0000
Residual	117535917	26,651	4410.18786	R-squared	=	0.1483
				Adj R-squared	=	0.1465
Total	138001551	26,707	5167.24271	Root MSE	=	66.409

Harsh	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LB_RG4						
1	11.69809	2.572804	4.55	0.000	6.655253	16.74092
2	-4.024538	1.511006	-2.66	0.008	-6.986189	-1.062887
3	-6.694705	1.553026	-4.31	0.000	-9.738719	-3.650692
LB_plea						
1	-82.5523	1.37049	-60.24	0.000	-85.23854	-79.86607
2	-73.15941	3.038515	-24.08	0.000	-79.11506	-67.20376
3	-72.18858	1.827025	-39.51	0.000	-75.76965	-68.60751
AgeGroup						
20	1.949307	2.317772	0.84	0.400	-2.59365	6.492264
30	7.216478	2.374181	3.04	0.002	2.562957	11.87
40	7.193309	2.494599	2.88	0.004	2.303762	12.08286
50	8.643239	2.742533	3.15	0.002	3.267728	14.01875
LB_Atty						
1	-7.901696	1.769283	-4.47	0.000	-11.36958	-4.433808
2	-9.769144	1.51488	-6.45	0.000	-12.73839	-6.799899
3	.9491424	2.153181	0.44	0.659	-3.271207	5.169492

Model 14: Regression for Harshness by race/sex intersect, attorney type, plea, age group, and District (omitted) at LB_PriorPts=3

```
. reg Harsh i.LB_RG4  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
```

Source	SS	df	MS			
				Number of obs	=	15,133
				F(56, 15076)	=	33.31
Model	3618925.24	56	64623.665	Prob > F	=	0.0000
Residual	29250736.6	15,076	1940.21867	R-squared	=	0.1101
				Adj R-squared	=	0.1068
Total	32869661.8	15,132	2172.19547	Root MSE	=	44.048

Harsh	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LB_RG4						
1	-.6589159	2.495259	-0.26	0.792	-5.549926	4.232094
2	-5.696893	1.498452	-3.80	0.000	-8.634042	-2.759744
3	-7.76035	1.525173	-5.09	0.000	-10.74987	-4.770825
LB_plea						
1	-50.41111	1.320956	-38.16	0.000	-53.00034	-47.82187
2	-41.78249	2.549745	-16.39	0.000	-46.7803	-36.78468
3	-44.53363	1.685106	-26.43	0.000	-47.83664	-41.23062
AgeGroup						
20	1.811362	5.105197	0.35	0.723	-8.195443	11.81817
30	3.277741	5.103312	0.64	0.521	-6.725369	13.28085
40	5.150646	5.137892	1.00	0.316	-4.920245	15.22154
50	8.260346	5.207143	1.59	0.113	-1.946285	18.46698
LB_Atty						
1	-.7913403	1.580105	-0.50	0.617	-3.888538	2.305857
2	-3.414427	1.406277	-2.43	0.015	-6.170901	-.6579539
3	6.650552	1.987888	3.35	0.001	2.754051	10.54705

Model 15: Regression for Harshness by race/sex intersect, attorney type, plea, age group, and District (omitted) at LB_PriorPts=4

```
. reg Harsh i.LB_RG4  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
```

Source	SS	df	MS			
				Number of obs	=	6,506
				F(56, 6449)	=	6.34
Model	377937.025	56	6748.87544	Prob > F	=	0.0000
Residual	6865808.15	6,449	1064.63144	R-squared	=	0.0522
				Adj R-squared	=	0.0439
Total	7243745.17	6,505	1113.56574	Root MSE	=	32.629

Harsh	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LB_RG4						
1	-5.54924	2.987612	-1.86	0.063	-11.40595	.3074715
2	-3.817501	1.876779	-2.03	0.042	-7.49661	-.1383919
3	-4.103056	1.889529	-2.17	0.030	-7.807159	-.3989523
LB_plea						
1	-22.84516	1.49787	-15.25	0.000	-25.78149	-19.90884
2	-14.38986	2.719485	-5.29	0.000	-19.72096	-9.05877
3	-18.95388	1.906621	-9.94	0.000	-22.69149	-15.21627
AgeGroup						
20	-16.96523	9.499639	-1.79	0.074	-35.58767	1.65722
30	-14.75343	9.482454	-1.56	0.120	-33.34219	3.835325
40	-11.37012	9.494595	-1.20	0.231	-29.98268	7.242434
50	-13.96632	9.535512	-1.46	0.143	-32.65908	4.726452
LB_Atty						
1	-4.167221	1.922319	-2.17	0.030	-7.935605	-.3988375
2	-4.681581	1.753033	-2.67	0.008	-8.118107	-1.245056
3	-2.871374	2.46216	-1.17	0.244	-7.698025	1.955277

Model 16: Regression for Harshness by race/sex intersect, attorney type, plea, age group, and District (omitted) at LB_PriorPts=5

```
. reg Harsh i.LB_RG4  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
```

Source	SS	df	MS			
				Number of obs	=	4,778
				F(56, 4721)	=	5.89
Model	283142.097	56	5056.10888	Prob > F	=	0.0000
Residual	4051983.36	4,721	858.289209	R-squared	=	0.0653
				Adj R-squared	=	0.0542
Total	4335125.45	4,777	907.499572	Root MSE	=	29.297

Harsh	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
LB_RG4						
1	-3.18632	3.089078	-1.03	0.302	-9.242355	2.869715
2	-6.829153	2.262786	-3.02	0.003	-11.26527	-2.393036
3	-5.828341	2.269269	-2.57	0.010	-10.27717	-1.379516
LB_plea						
1	-19.00216	1.533538	-12.39	0.000	-22.00861	-15.99571
2	-15.44524	2.897311	-5.33	0.000	-21.12532	-9.765156
3	-17.07883	1.963389	-8.70	0.000	-20.92799	-13.22967
AgeGroup						
20	15.05469	17.04493	0.88	0.377	-18.36133	48.47071
30	15.82234	17.01127	0.93	0.352	-17.52769	49.17237
40	16.00911	17.01088	0.94	0.347	-17.34015	49.35836
50	17.03498	17.0269	1.00	0.317	-16.34568	50.41564
LB_Atty						
1	-2.975423	2.051337	-1.45	0.147	-6.997001	1.046155
2	-3.066339	1.92333	-1.59	0.111	-6.836962	.7042843
3	11.25408	2.893883	3.89	0.000	5.580718	16.92744

Model 17: Regression for Harshness by race/sex intersect, attorney type, plea, age group, and District (omitted) at LB_PriorPts=6

```
. reg Harsh i.LB_RG4  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist

      Source |       SS           df       MS      Number of obs   =     2,256
-------------+----------------------------------   F(56, 2199)     =      3.64
       Model |  181924.904        56  3248.65901   Prob > F        =    0.0000
    Residual |  1960197.94     2,199  891.404247   R-squared       =    0.0849
-------------+----------------------------------   Adj R-squared   =    0.0616
       Total |  2142122.84     2,255  949.943611   Root MSE        =    29.856

------------------------------------------------------------------------------
       Harsh |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      LB_RG4 |
          1  |   3.424352   4.879554     0.70   0.483    -6.144665    12.99337
          2  |   .9541122   3.540686     0.27   0.788    -5.989327    7.897552
          3  |   2.232574   3.490969     0.64   0.523    -4.613368    9.078516
             |
     LB_plea |
          1  |  -24.37022   2.260401   -10.78   0.000    -28.80296   -19.93747
          2  |  -22.57532   4.114001    -5.49   0.000    -30.64305   -14.50758
          3  |  -22.03773   2.870415    -7.68   0.000    -27.66673   -16.40872
             |
    AgeGroup |
         20  |   20.23685   17.71879     1.14   0.254    -14.51046    54.98416
         30  |   18.51618    17.5105     1.06   0.290    -15.82267    52.85502
         40  |   18.60371   17.49458     1.06   0.288    -15.70392    52.91134
         50  |   19.64414   17.51468     1.12   0.262     -14.7029    53.99118
             |
     LB_Atty |
          1  |  -7.942336   3.449967    -2.30   0.021    -14.70787   -1.176801
          2  |  -9.377913   3.299792    -2.84   0.005    -15.84895   -2.906877
          3  |   2.578148   4.618423     0.56   0.577     -6.47878    11.63508
```

Graphic 1: Minimum Sentencing Grid for Felonies Committed on or After October 2013 (NCJS, 2018).

FELONY PUNISHMENT CHART

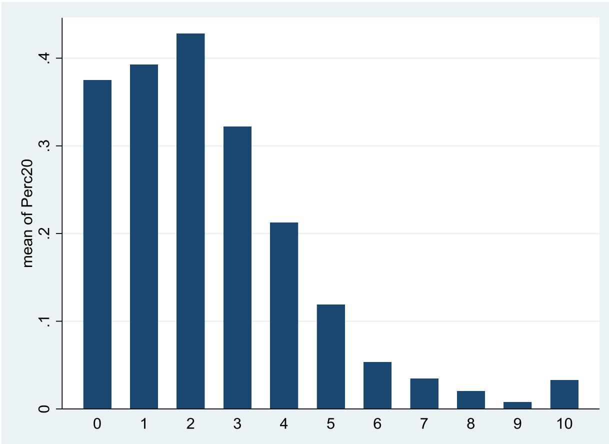
PRIOR RECORD LEVEL

OFFENSE CLASS	I 0-1 Pt	II 2-5 Pts	III 6-9 Pts	IV 10-13 Pts	V 14-17 Pts	VI 18+ Pts	DISPOSITION
A	Death or Life Without Parole Defendant Under 18 at Time of Offense: Life With or Without Parole						
B1	A	A	A	A	A	A	DISPOSITION
	240 - 300	*276 - 345*	*317 -397*	*365 - 456*	*Life Without Parole*	*Life Without Parole*	*Aggravated Range*
	192 - 240	**221 - 276**	**254 - 317**	**292 - 365**	**336 - 420**	**386 - 483**	**PRESUMPTIVE RANGE**
	144 - 192	*166 - 221*	*190 - 254*	*219 - 292*	*252 - 336*	*290 - 386*	*Mitigated Range*
B2	A	A	A	A	A	A	
	157 - 196	*180 - 225*	*207 - 258*	*238 - 297*	*273 - 342*	*314 - 393*	
	125 - 157	**144 - 180**	**165 - 207**	**190 - 238**	**219 - 273**	**251 - 314**	
	94 - 125	*108 - 144*	*124 - 165*	*143 - 190*	*164 - 219*	*189 - 251*	
C	A	A	A	A	A	A	
	73 – 92	*83 - 104*	*96 - 120*	*110 - 138*	*127 - 159*	*146 - 182*	
	58 - 73	**67 - 83**	**77 - 96**	**88 - 110**	**101 - 127**	**117 - 146**	
	44 - 58	*50 - 67*	*58 - 77*	*66 - 88*	*76 - 101*	*87 - 117*	
D	A	A	A	A	A	A	
	64 - 80	*73 - 92*	*84 - 105*	*97 - 121*	*111 - 139*	*128 - 160*	
	51 - 64	**59 - 73**	**67 - 84**	**78 - 97**	**89 - 111**	**103 - 128**	
	38 - 51	*44 - 59*	*51 - 67*	*58 - 78*	*67 - 89*	*77 - 103*	
E	I/A	I/A	A	A	A	A	
	25 - 31	*29 - 36*	*33 - 41*	*38 - 48*	*44 - 55*	*50 - 63*	
	20 - 25	**23 - 29**	**26 - 33**	**30 - 38**	**35 - 44**	**40 - 50**	
	15 - 20	*17 - 23*	*20 - 26*	*23 - 30*	*26 - 35*	*30 - 40*	
F	I/A	I/A	I/A	A	A	A	
	16 - 20	*19 - 23*	*21 - 27*	*25 - 31*	*28 - 36*	*33 - 41*	
	13 - 16	**15 - 19**	**17 - 21**	**20 - 25**	**23 - 28**	**26 - 33**	
	10 - 13	*11 - 15*	*13 - 17*	*15 - 20*	*17 - 23*	*20 - 26*	
G	I/A	I/A	I/A	I/A	A	A	
	13 - 16	*14 - 18*	*17 - 21*	*19 - 24*	*22 - 27*	*25 - 31*	
	10 - 13	**12 - 14**	**13 - 17**	**15 - 19**	**17 - 22**	**20 - 25**	
	8 - 10	*9 - 12*	*10 - 13*	*11 - 15*	*13 - 17*	*15 - 20*	
H	C/I/A	I/A	I/A	I/A	I/A	A	
	6 - 8	*8 - 10*	*10 - 12*	*11 - 14*	*15 - 19*	*20 - 25*	
	5 - 6	**6 - 8**	**8 - 10**	**9 - 11**	**12 - 15**	**16 - 20**	
	4 - 5	*4 - 6*	*6 - 8*	*7 - 9*	*9 - 12*	*12 - 16*	
I	C	C/I	I	I/A	I/A	I/A	
	6 - 8	*6 - 8*	*6 - 8*	*8 - 10*	*9 - 11*	*10 - 12*	
	4 - 6	**4 - 6**	**5 - 6**	**6 - 8**	**7 - 9**	**8 - 10**	
	3 - 4	*3 - 4*	*4 - 5*	*4 - 6*	*5 - 7*	*6 - 8*	

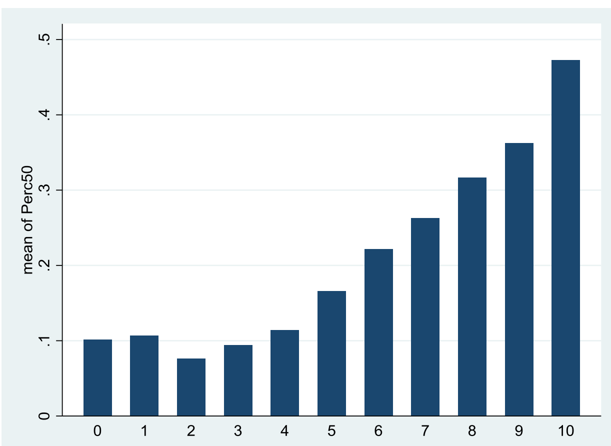
A – Active Punishment I – Intermediate Punishment C – Community Punishment

Numbers shown are in months and represent the range of minimum sentences

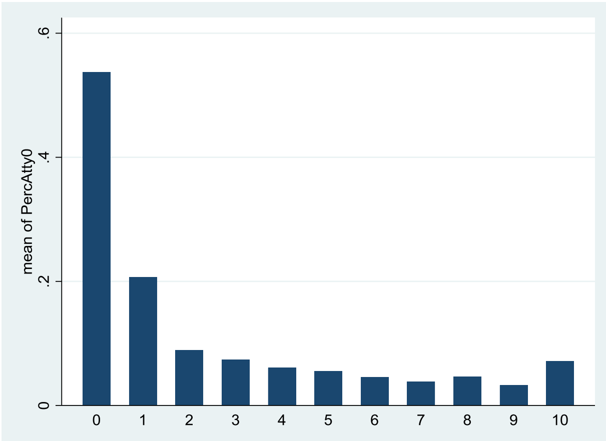
Graphic 2: Percentage of defendants in 20's by prior point group



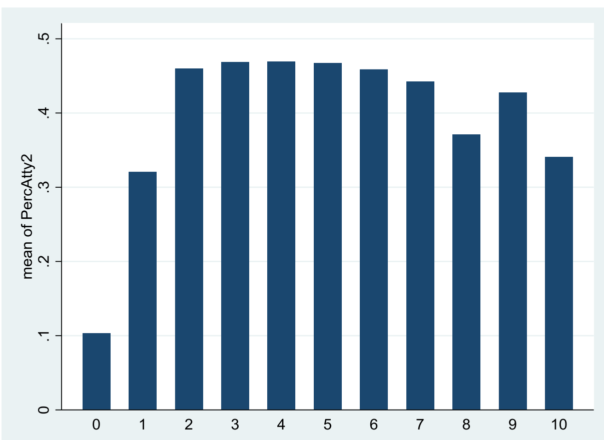
Graphic 3: Percentage of defendants in 50's by prior point group



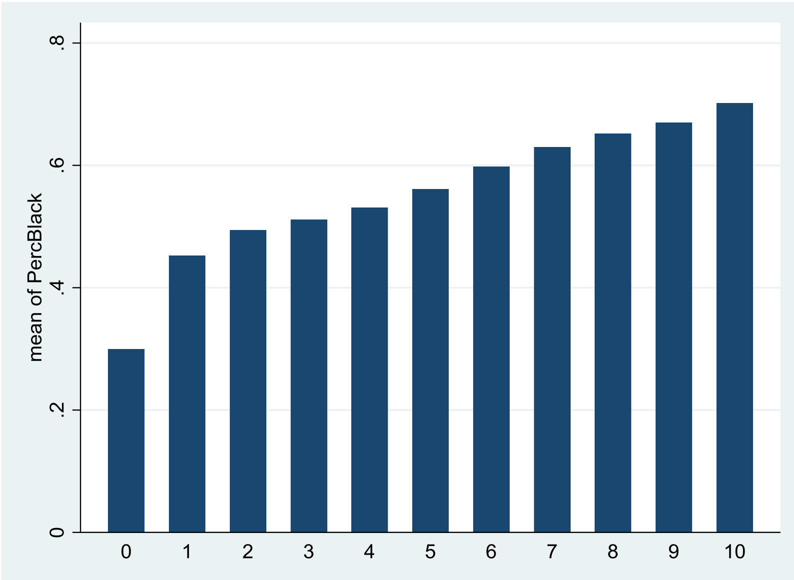
Graphic 4: Percentage of defendants with private attorney by prior point group



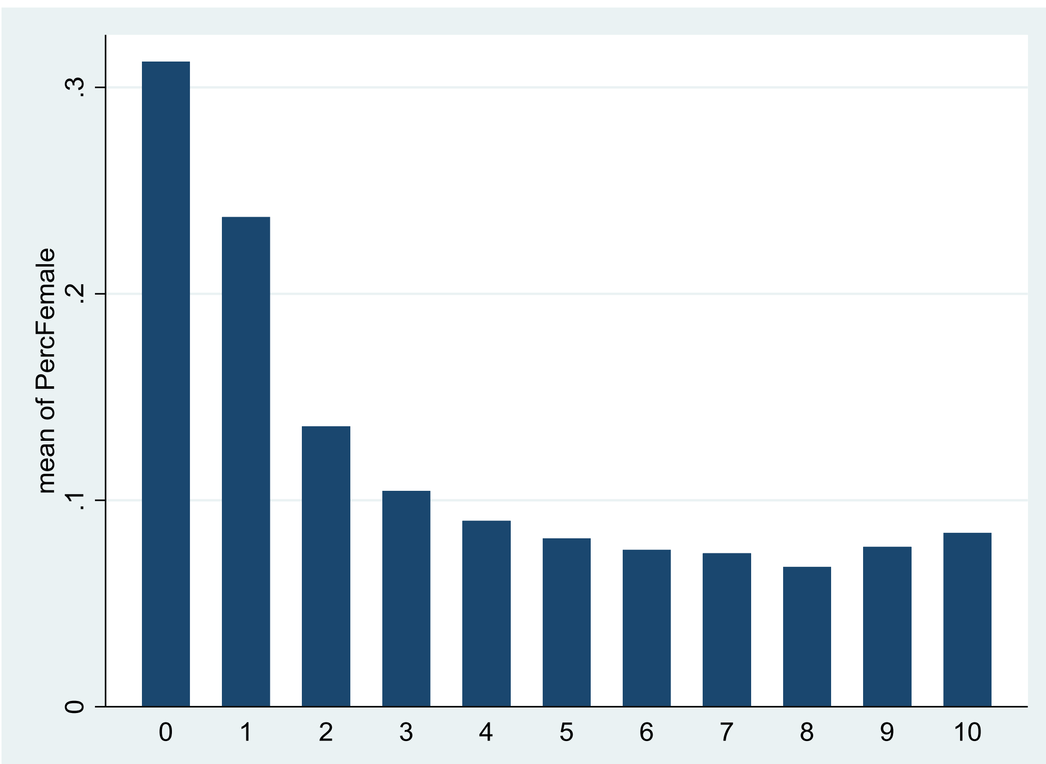
Graphic 5: Percentage of defendants with court-appointed attorney by prior point group



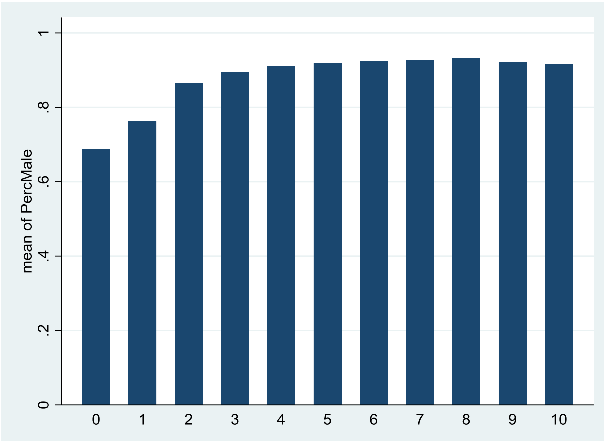
Graphic 6: Percentage of black defendants by prior point group



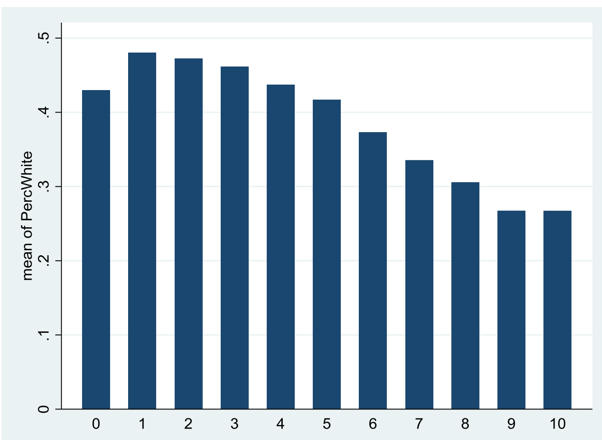
Graphic 7: Percentage of female defendants by prior point group



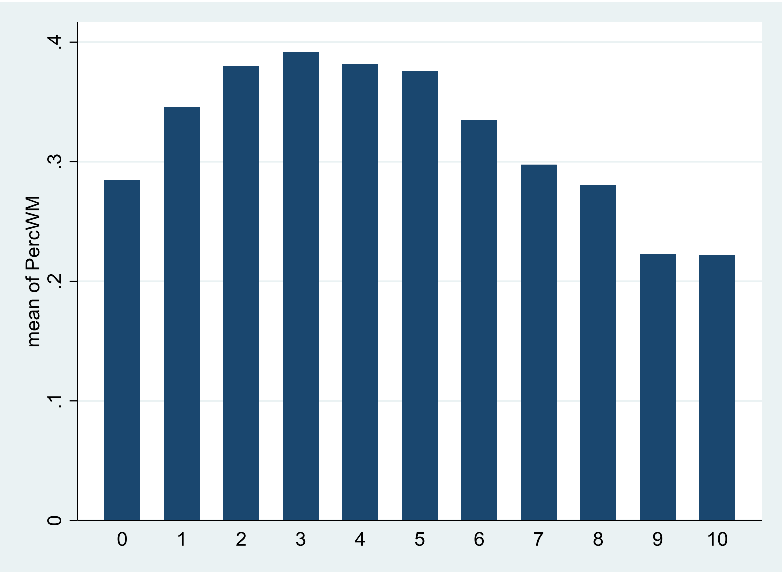
Graphic 8: Percentage of male defendants with by prior point group



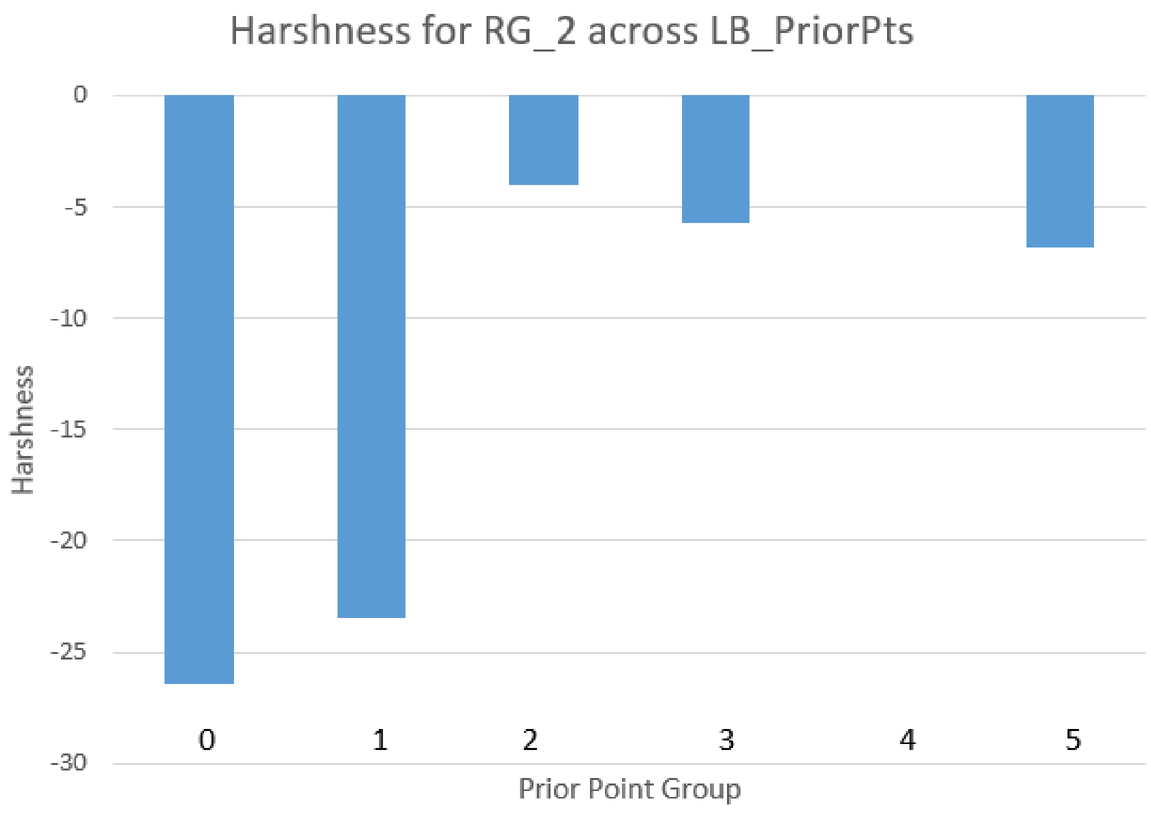
Graphic 9: Percentage of white defendants with by prior point group



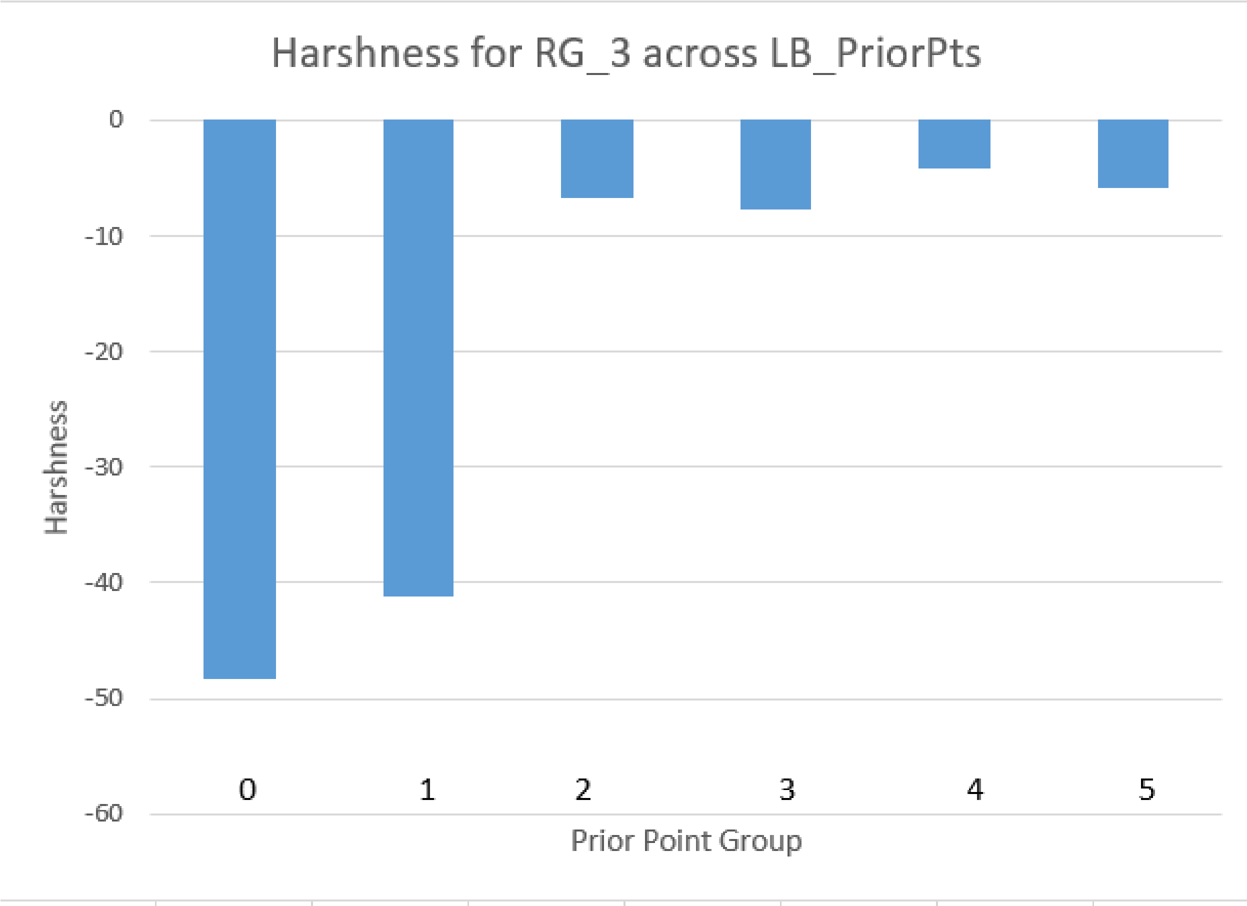
Graphic 10: Percentage of white male defendants with by prior point group



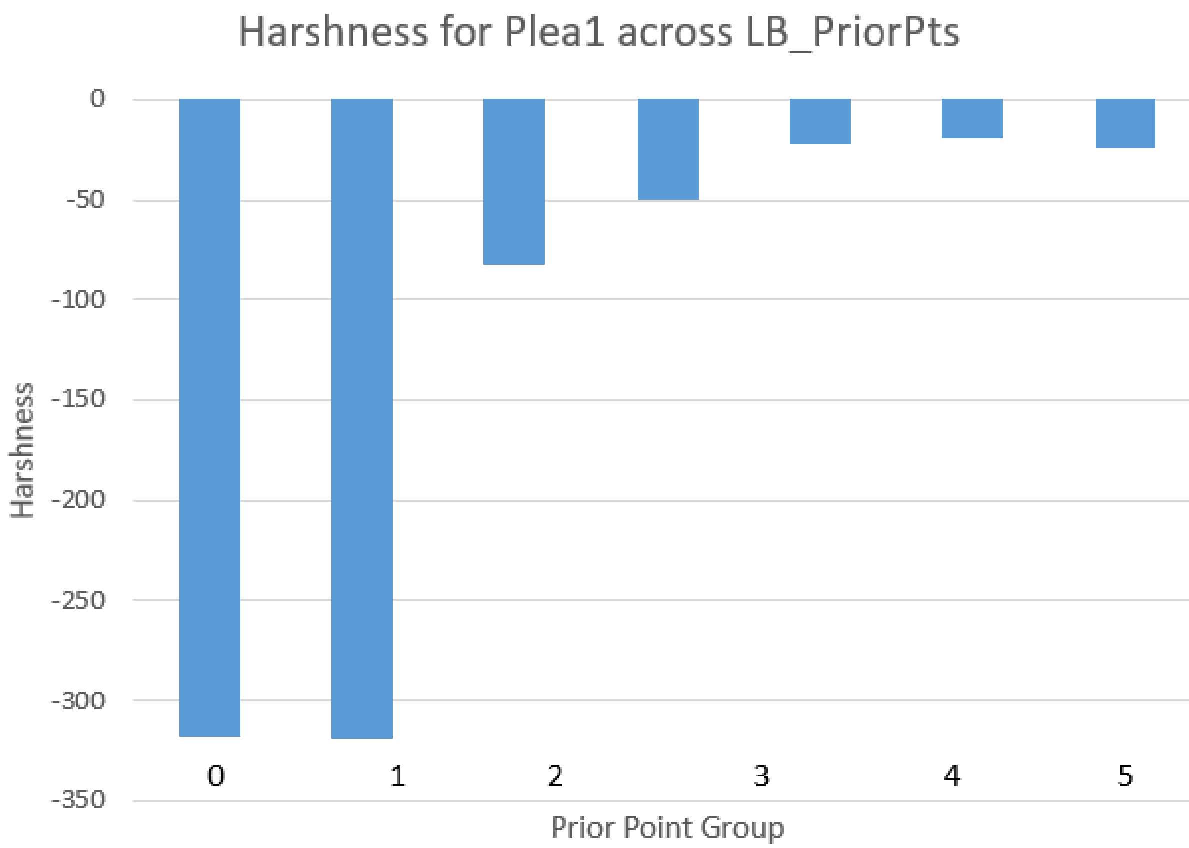
Graphic 11: Harshness coefficient for black females across Prior Point groupings



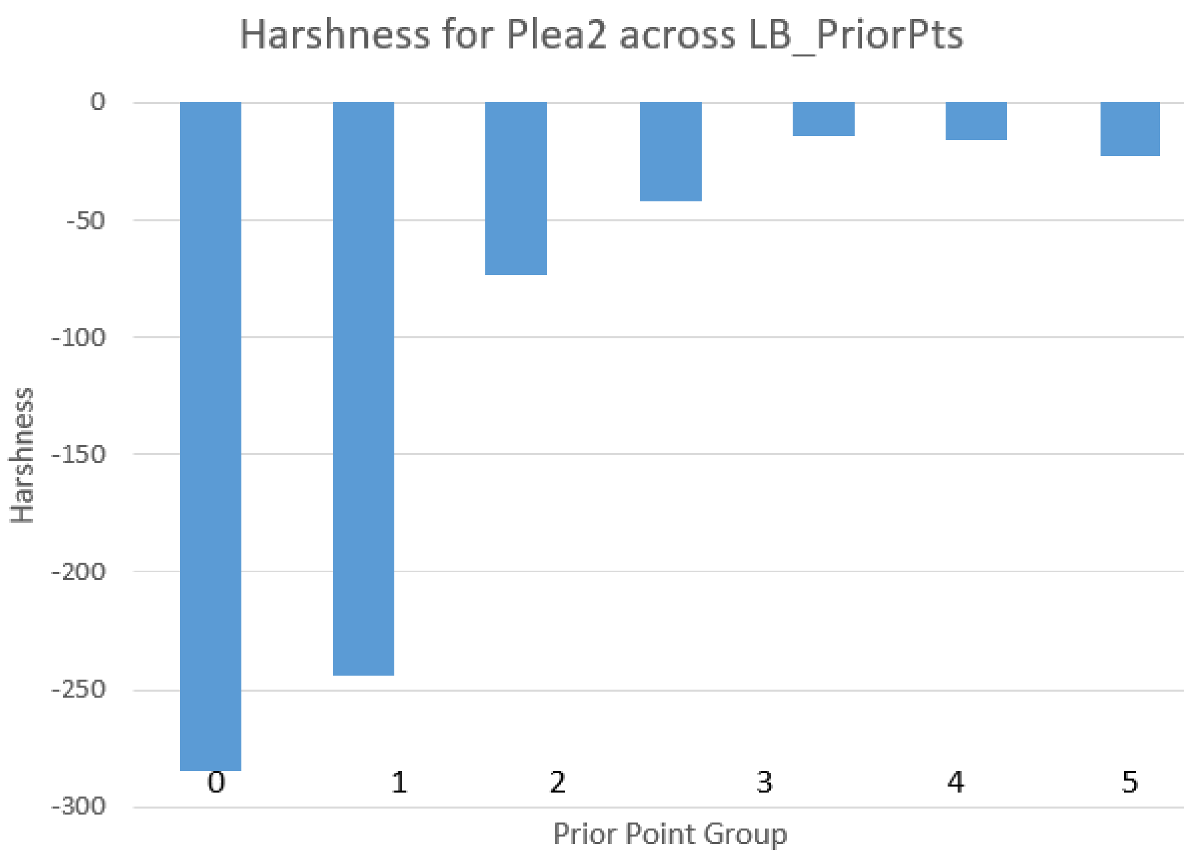
Graphic 12: Harshness coefficient for black males across Prior Point groupings



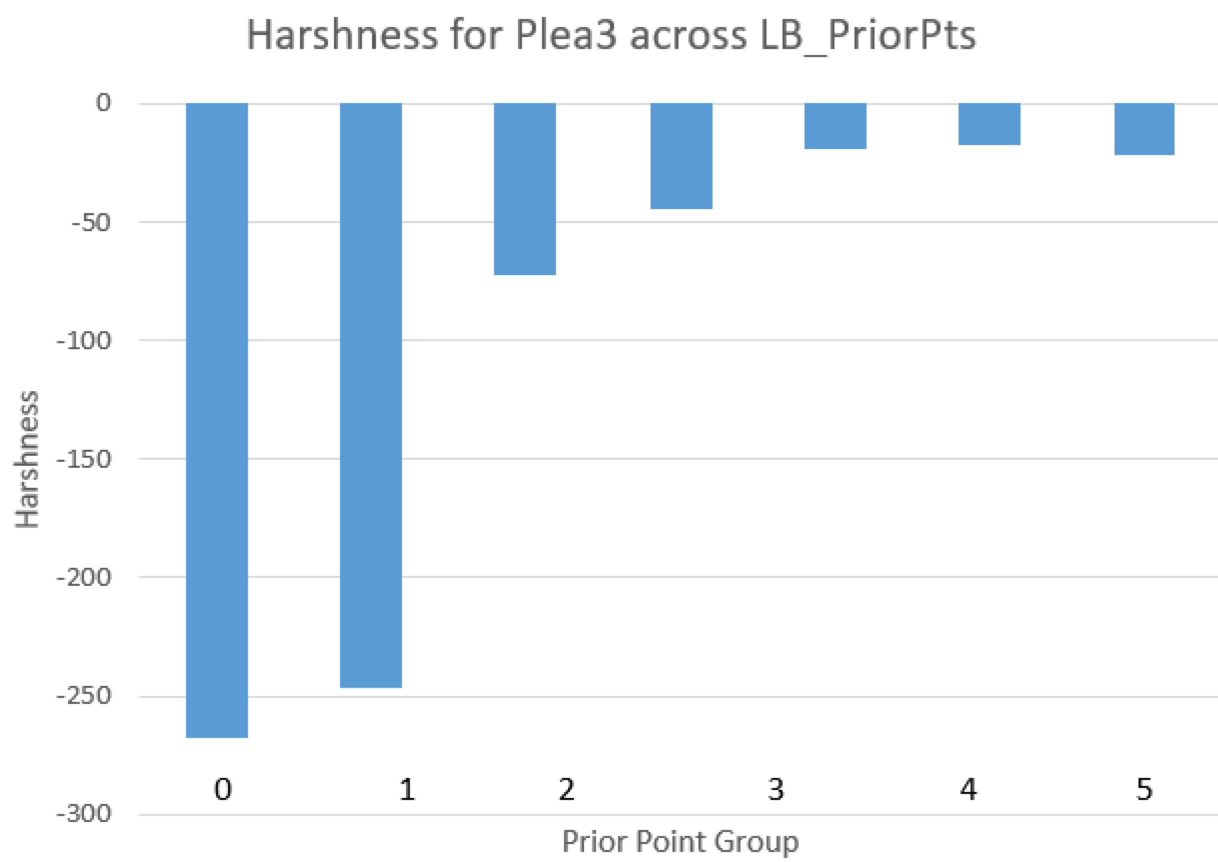
Graphic 13: Harshness coefficient for those who plead guilty across Prior Point groupings



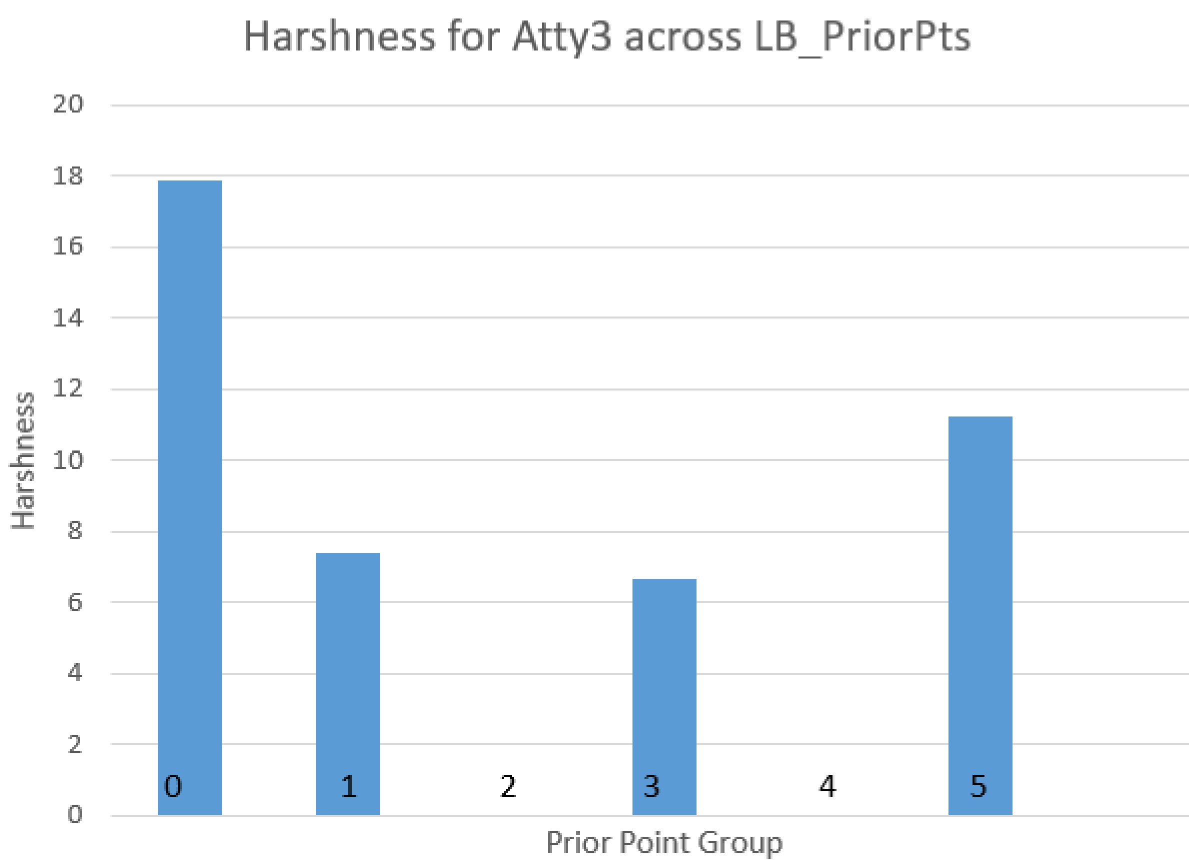
Graphic 14: Harshness coefficient for those who plead not guilty across Prior Point groupings



Graphic 15: Harshness coefficient for those who used the Alford Plea across Prior Point groupings



Graphic 16: Harshness coefficient for those who waived their right to an attorney across Prior Point groupings



References

Albonetti, Celesta A. 1997. “Sentencing under the Federal Sentencing Guidelines: Effects of Defendant Characteristics, Guilty Pleas, and Departures on Sentence Outcomes for Drug Offenses, 1991-1992.” Law & Society Review, 31 (4): 789-822.

Beyer, Luke. “Justice by the Grid.” 8 Mar. 2019, http://fbaum.unc.edu/teaching/Misc/LukeBeyer-2019-JusticeByTheGrid.pdf.

Baumgartner, Frank R., et al. *Suspect Citizens: What 20 Million Traffic Stops Tell Us about Policing and Race*. Cambridge University Press, 2018.Bickle, Gayle S. and Ruth D. Peterson. 1991. “The Impact of Sex-Based Family Roles on Criminal Sentencing.” Social Problems, 38 (3): 372-394. DOI: 10.2307/800605

Brennan, Pauline K. and Cassia Spohn. 2008. “Race/Ethnicity and Sentencing Outcomes Among Drug Offenders in North Carolina.” Journal of Contemporary Criminal Justice, 24 (4): 371-398. DOI: 10.1177/1043986208322712

Champion, Dean J. 1989. “Private counsels and public defenders: A look at weak cases, prior records, and leniency in plea bargaining.” Journal of Criminal Justice, 17 (4): 253-263. DOI: 10.1016/0047-2352(89)90031-7

Horton, Tracey L. 2005. “The effect of North Carolina's Structured Sentencing Act on racial disparity in felony sentencing.” Ph.D. diss Walden University

Abrams, David and Ryan Fackler. 2016. “To plea or not to plea: Evidence from North Carolina.” Presented at Working paper series (Federal Reserve Bank of Atlanta), Atlanta. 1-50. http://in.bgu.ac.il/en/humsos/Econ/Documents/seminars/abstracts/June%202,%202016.pd f

Mustard, David B. 2001. “Racial, Ethnic, and Sex Disparities in Sentencing: Evidence from the U.S. Federal Courts.” The Journal of Law and Economics, 44 (1): 285-314. DOI: 10.1086/320276

Nagel, Ilene H. and Barry L. Johnson. 1994. “The Role of Sex in a Structured Sentencing System: Equal Treatment, Policy Choices, and the Sentencing of Female Offenders under the United States Sentencing Guidelines.” The Journal of Criminal Law and Criminology, 85 (1): 181-221. DOI: 10.2307/1144116

North Carolina Population. (2019-06-05). Retrieved 2019-12-04, from http://worldpopulationreview.com/states/north-carolina/

Ulmer, Jeffrey T. and Brian D. Johnson. 2004. “Sentencing in Context: A Multilevel Analysis.” Criminology, 42 (1): 137-178, DOI: 10.1111/j.1745-9125.2004.tb00516.x

Ulmer, Jeffrey T. and Mindy S. Bradley. 2006. “Variation in trial penalties among serious violent offenses.” Criminology, 44 (3): 631-670. DOI: 10.1111/j.1745- 9125.2006.00059.x

Appendix: Code

STATA Code, combination of Beyer's original and Cain's additions.

```
*One, read the database, drop cases before Oct 1, 2013, those not yet resolved, not a-d felonies...
clear
cd E:\Project
use CR-23Feb2019


*drop cases before Oct 1 2013
*------------------------destring crrkcy crocdt crdcst crrddt crrdts, replace
*------------------------sum crrdts
*------------------------drop if crrdts < 20130931
*drop unresolved cases
sum crrddt
drop if crrddt == .
drop if crdofcl=="1"
drop if crdofcl=="2"
drop if crdofcl=="3"
drop if crdofcl=="T"

*Drop cases where the verdicts are measured in days, not months
*-------------------------keep if verdict_unit == 2

*check codes for missing data on derived variables
sum charged_a - verdict_unit
recode charged_a - verdict_unit (-2=.)
recode charged_a - verdict_unit (-1=.)
keep if crdprpt <5000
cd "E:\Project"
save Luke-a.dta, replace

*collapse by disposition - person
clear
use Luke-a.dta
collapse (last) crradd crrcty crrdst crrzip crrdob crrace crrsex crrbondt crrdat crdple (max) crocdt
crdprpt crdcst crrbonda (sum) by(crrddt crrkcy crrnam)
save Luke-b.dta, replace
```

```
tab1 charged_a charged_b* charged_c charged_d charged_e charged_f charged_g charged_h
charged_i charged_a1 charged_1 charged_2 charged_3 charged_if charged_t, miss
tab1 arraigned_a arraigned_b* arraigned_c arraigned_d arraigned_e arraigned_f arraigned_g
arraigned_h arraigned_i arraigned_a1 arraigned_1 arraigned_2 arraigned_3 arraigned_if
arraigned_t, miss
tab1 verdict_a verdict_b* verdict_c verdict_d verdict_e verdict_f verdict_g verdict_h verdict_i
verdict_a1 verdict_1 verdict_2 verdict_3 verdict_if verdict_t, miss

save Luke-b.dta, replace
clear

cd "E:\Project"
use Luke-b.dta

*Creating Race Variable
gen LB_Race = 1 if crrace=="W"
replace LB_Race = 2 if crrace=="B"
replace LB_Race = 3 if crrace=="H"
replace LB_Race = 4 if crrace=="O"
replace LB_Race = 5 if crrace=="I"
replace LB_Race = 6 if crrace=="A"

gen LB_RaceBW = 0 if crrace=="W"
replace LB_RaceBW = 1 if crrace=="B"

*Luke Race Variables
gen Race_white = 0
replace Race_white = 1 if crrace =="W"
gen Race_asian = 0
replace Race_asian = 1 if crrace =="A"
gen Race_black = 0
replace Race_black = 1 if crrace =="B"
gen Race_hispanic = 0
replace Race_hispanic = 1 if crrace =="H"
gen Race_indian = 0
replace Race_indian = 1 if crrace =="I"
gen Race_other = 0
replace Race_other = 1 if crrace =="O"
gen total = 1

tab1 crrace

*Creating Sex Variable
gen LB_Sex = 0 if crrsex=="F"
replace LB_Sex = 1 if crrsex=="M"
tab LB_Sex, miss
```

```
gen LC_Male = 0
gen LC_Female = 0
replace LC_Male = 1 if crrsex=="M"
replace LC_Female = 1 if crrsex=="F"

*Race x gender
gen LB_RG4 = 0 if crrsex=="F" & LB_RaceBW==0
recode LB_RG4 (. = 1) if crrsex=="F" & LB_RaceBW==1
recode LB_RG4 (. = 2) if crrsex=="M" & LB_RaceBW==0
recode LB_RG4 (. = 3) if crrsex=="M" & LB_RaceBW==1

gen RG_WhiteMale = 0
gen RG_WhiteFemale = 0
gen RG_BlackMale = 0
gen RG_BlackFemale = 0
gen RG_HispanicMale = 0
gen RG_HispanicFemale = 0

replace RG_WhiteMale = 1 if crrsex=="M" & crrace== "W"
replace RG_WhiteFemale = 1 if crrsex=="F" & crrace== "W"
replace RG_BlackMale = 1 if crrsex=="M" & crrace== "B"
replace RG_BlackFemale = 1 if crrsex=="F" & crrace== "B"
replace RG_HispanicMale = 1 if crrsex=="M" & crrace== "H"
replace RG_HispanicFemale = 1 if crrsex=="F" & crrace== "H"

*Creating Age Variable
*drop LB_DOB LB_OffDate LB_AgeatCrime
drop if crrdob == "."
destring crrdob, gen(temp_DOB) force
drop if temp_DOB == .
gen temp_YOB = floor(temp_DOB/10000)
gen temp_monthb = temp_DOB - (temp_YOB*10000)
gen temp_MOB = floor(temp_monthb/100)
gen temp_DayOB = temp_monthb - (temp_MOB*100)
gen LB_BirthDate = mdy(temp_MOB , temp_DayOB , temp_YOB)
gen LB_BirthDate2 = LB_BirthDate
format LB_BirthDate2 %td
drop temp_DOB temp_YOB temp_monthb temp_MOB temp_DayOB temp_YOB
LB_BirthDate

*CROCDT
gen double temp_DOC = crocdt
gen temp_YOC = floor(temp_DOC/10000)
gen temp_monthc = temp_DOC - (temp_YOC*10000)
gen temp_MOC = floor(temp_monthc/100)
```

```
gen temp_DayOC = temp_monthc - (temp_MOC*100)
gen LB_ChargeDate = mdy(temp_MOC , temp_DayOC , temp_YOC)
gen LB_ChargeDate2 = LB_ChargeDate
format LB_ChargeDate2 %td
drop temp_DOC temp_YOC temp_monthc temp_MOC temp_DayOC temp_YOC
LB_ChargeDate

gen LB_AgeatCrime = (LB_ChargeDate2 - LB_BirthDate2)/365.25

***To make age categories
*spikeplot on age, or "sum, d"
sum LB_AgeatCrime, d
spikeplot LB_AgeatCrime if LB_AgeatCrime<100, round(1)

egen AgeGroup = cut(LB_AgeatCrime), at(15,20,30,40,50,150)
gen LC_AgeGroup15=0
gen LC_AgeGroup20=0
gen LC_AgeGroup30=0
gen LC_AgeGroup40=0
gen LC_AgeGroup50=0
gen LC_AgeGroup150=0

replace LC_AgeGroup15=1 if AgeGroup==15
replace LC_AgeGroup20=1 if AgeGroup==20
replace LC_AgeGroup30=1 if AgeGroup==30
replace LC_AgeGroup40=1 if AgeGroup==40
replace LC_AgeGroup50=1 if AgeGroup==50
replace LC_AgeGroup150=1 if AgeGroup==150

*Play with that by saying
sort AgeGroup
by AgeGroup: sum LB_AgeatCrime

*This will tell you how it handled cases in the extremens and
*exactly where it drew the lines: 20, or 19.999)

*Creating Socioeconomic Status Variable

*Creating Attorney Variable
gen LB_Atty = 0 if crrdat=="R"
replace LB_Atty = 1 if crrdat=="P"
replace LB_Atty = 2 if crrdat=="A"
replace LB_Atty = 3 if crrdat=="W"

gen LC_Atty1 = 0
gen LC_Atty2 = 0
```

```
gen LC_Atty3 = 0
gen LC_Atty0 = 0

replace LC_Atty1 = 1 if LB_Atty== 1
replace LC_Atty2 = 1 if LB_Atty== 2
replace LC_Atty3 = 1 if LB_Atty== 3
replace LC_Atty0 = 1 if LB_Atty== 0
*LC_Atty0= private, Atty1= public, Atty 2= appointed, Atty= waived

*Creating Population Variable
gen LB_fips = (1) if crrkcy == 000
replace LB_fips = (3) if crrkcy == 010
replace LB_fips = (5) if crrkcy == 020
replace LB_fips = (7) if crrkcy == 030
replace LB_fips = (9) if crrkcy == 040
replace LB_fips = (11) if crrkcy == 050
replace LB_fips = (13) if crrkcy == 060
replace LB_fips = (15) if crrkcy == 070
replace LB_fips = (17) if crrkcy == 080
replace LB_fips = (19) if crrkcy == 090
replace LB_fips = (21) if crrkcy == 100
replace LB_fips = (23) if crrkcy == 110
replace LB_fips = (25) if crrkcy == 120
replace LB_fips = (27) if crrkcy == 130
replace LB_fips = (29) if crrkcy == 140
replace LB_fips = (31) if crrkcy == 150
replace LB_fips = (33) if crrkcy == 160
replace LB_fips = (35) if crrkcy == 170
replace LB_fips = (37) if crrkcy == 180
replace LB_fips = (39) if crrkcy == 190
replace LB_fips = (41) if crrkcy == 200
replace LB_fips = (43) if crrkcy == 210
replace LB_fips = (45) if crrkcy == 220
replace LB_fips = (47) if crrkcy == 230
replace LB_fips = (49) if crrkcy == 240
replace LB_fips = (51) if crrkcy == 250
replace LB_fips = (53) if crrkcy == 260
replace LB_fips = (55) if crrkcy == 270
replace LB_fips = (57) if crrkcy == 280
replace LB_fips = (59) if crrkcy == 290
replace LB_fips = (61) if crrkcy == 300
replace LB_fips = (63) if crrkcy == 310
replace LB_fips = (65) if crrkcy == 320
replace LB_fips = (67) if crrkcy == 330
replace LB_fips = (69) if crrkcy == 340
replace LB_fips = (71) if crrkcy == 350
```

```
replace LB_fips = (73) if crrkcy == 360
replace LB_fips = (75) if crrkcy == 370
replace LB_fips = (77) if crrkcy == 380
replace LB_fips = (79) if crrkcy == 390
replace LB_fips = (81) if crrkcy == 400
replace LB_fips = (83) if crrkcy == 410
replace LB_fips = (85) if crrkcy == 420
replace LB_fips = (87) if crrkcy == 430
replace LB_fips = (89) if crrkcy == 440
replace LB_fips = (91) if crrkcy == 450
replace LB_fips = (93) if crrkcy == 460
replace LB_fips = (95) if crrkcy == 470
replace LB_fips = (97) if crrkcy == 480
replace LB_fips = (99) if crrkcy == 490
replace LB_fips = (101) if crrkcy == 500
replace LB_fips = (103) if crrkcy == 510
replace LB_fips = (105) if crrkcy == 520
replace LB_fips = (107) if crrkcy == 530
replace LB_fips = (109) if crrkcy == 540
replace LB_fips = (111) if crrkcy == 550
replace LB_fips = (113) if crrkcy == 560
replace LB_fips = (115) if crrkcy == 570
replace LB_fips = (117) if crrkcy == 580
replace LB_fips = (119) if crrkcy == 590
replace LB_fips = (121) if crrkcy == 600
replace LB_fips = (123) if crrkcy == 610
replace LB_fips = (125) if crrkcy == 620
replace LB_fips = (127) if crrkcy == 630
replace LB_fips = (129) if crrkcy == 640
replace LB_fips = (131) if crrkcy == 650
replace LB_fips = (133) if crrkcy == 660
replace LB_fips = (135) if crrkcy == 670
replace LB_fips = (137) if crrkcy == 680
replace LB_fips = (139) if crrkcy == 690
replace LB_fips = (141) if crrkcy == 700
replace LB_fips = (143) if crrkcy == 710
replace LB_fips = (145) if crrkcy == 720
replace LB_fips = (147) if crrkcy == 730
replace LB_fips = (149) if crrkcy == 740
replace LB_fips = (151) if crrkcy == 750
replace LB_fips = (153) if crrkcy == 760
replace LB_fips = (155) if crrkcy == 770
replace LB_fips = (157) if crrkcy == 780
replace LB_fips = (159) if crrkcy == 790
replace LB_fips = (161) if crrkcy == 800
replace LB_fips = (163) if crrkcy == 810
```

```
replace LB_fips = (165) if crrkcy == 820
replace LB_fips = (167) if crrkcy == 830
replace LB_fips = (169) if crrkcy == 840
replace LB_fips = (171) if crrkcy == 850
replace LB_fips = (173) if crrkcy == 860
replace LB_fips = (175) if crrkcy == 870
replace LB_fips = (177) if crrkcy == 880
replace LB_fips = (179) if crrkcy == 890
replace LB_fips = (181) if crrkcy == 900
replace LB_fips = (183) if crrkcy == 910
replace LB_fips = (185) if crrkcy == 920
replace LB_fips = (187) if crrkcy == 930
replace LB_fips = (189) if crrkcy == 940
replace LB_fips = (191) if crrkcy == 950
replace LB_fips = (193) if crrkcy == 960
replace LB_fips = (195) if crrkcy == 970
replace LB_fips = (197) if crrkcy == 980
replace LB_fips = (199) if crrkcy == 990


*Import USDA Population database and line up with Fips code
*rename
gen fips = LB_fips+37000
joinby using Luke-additional-county.dta, unm(master)
rename _merge _merge2
joinby LB_District using Luke-additional-District.dta, unm(master)

*Prior  ss  (lose vast majority of set because crdprpt isn't reported for misdemeanors)
destring crdprpt, gen(Points)
drop if crdprpt == .
gen LB_PriorPts = 0
replace LB_PriorPts = 1 if crdprpt == 01 | crdprpt == 02 | crdprpt == 03 | crdprpt == 04 | crdprpt
== 05
replace LB_PriorPts = 2 if crdprpt == 06 | crdprpt == 07 | crdprpt == 08 | crdprpt == 09
replace LB_PriorPts = 3 if crdprpt == 10 | crdprpt == 11 | crdprpt == 12 | crdprpt == 13
replace LB_PriorPts = 4 if crdprpt == 14 | crdprpt == 15 | crdprpt == 16 | crdprpt == 17
replace LB_PriorPts = 5 if crdprpt == 17 | crdprpt == 18 | crdprpt == 19 | crdprpt == 20
replace LB_PriorPts = 6 if crdprpt == 21 | crdprpt == 22 | crdprpt == 23 | crdprpt == 24
replace LB_PriorPts = 7 if crdprpt == 25 | crdprpt == 26 | crdprpt == 27 | crdprpt == 28
replace LB_PriorPts = 8 if crdprpt == 29 | crdprpt == 30 | crdprpt == 31 | crdprpt == 32
replace LB_PriorPts = 9 if crdprpt == 33 | crdprpt == 34 | crdprpt == 35 | crdprpt == 36
replace LB_PriorPts = 10 if crdprpt > 36
tab LB_PriorPts

gen NC_PriorPts = 0
replace NC_PriorPts = 1 if crdprpt == 00 | crdprpt == 01
```

```
replace NC_PriorPts = 2 if crdprpt == 02| crdprpt == 03 | crdprpt == 04 | crdprpt == 05
replace NC_PriorPts = 3 if crdprpt == 06 | crdprpt == 07 | crdprpt == 08 | crdprpt == 09
replace NC_PriorPts = 4 if crdprpt == 10 | crdprpt == 11 | crdprpt == 12 | crdprpt == 13
replace NC_PriorPts = 5 if crdprpt == 14 | crdprpt == 15 | crdprpt == 16 | crdprpt == 17
replace NC_PriorPts = 6 if crdprpt >17
tab NC_PriorPts

tab LB_fips, generate(Dfips)

tab1 LB_PriorPts, miss
tab1 NC_PriorPts, miss
sum crdprpt
spikeplot LB_PriorPts
spikeplot NC_PriorPts


*Plea type variable
gen LB_plea = 0 if crdple=="GL"
replace LB_plea = 1 if crdple=="GU"
replace LB_plea = 2 if crdple=="NG"
replace LB_plea = 3 if crdple=="GA"

gen LC_plea = 0
replace LC_plea =1 if LB_plea== 1 | LB_plea== 0 | LB_plea== 3

save Luke-c.dta, replace

*Calculate Harshness Variable - use worse possible number. Assume 0 points first. then gen
punishment
*change variable names here from ClassATotal to charged_a etc. through charged_i
clear
use Luke-c.dta

gen LB_Risk0 = 1200*charged_a + 300*charged_b1 + 196*charged_b2 + 92*charged_c +
80*charged_d + 31*charged_e + 20*charged_f + 16*charged_g + 8*charged_h + 8*charged_i if
NC_PriorPts == 1
gen LB_Risk1 = 1200*charged_a + 345*charged_b1 + 225*charged_b2 + 104*charged_c +
92*charged_d + 36*charged_e + 23*charged_f + 18*charged_g + 10*charged_h + 8*charged_i
if NC_PriorPts == 2
gen LB_Risk2 = 1200*charged_a + 397*charged_b1 + 258*charged_b2 + 120*charged_c +
105*charged_d + 41*charged_e + 27*charged_f + 21*charged_g + 12*charged_h + 8*charged_i
if NC_PriorPts == 3
gen LB_Risk3 = 1200*charged_a + 456*charged_b1 + 297*charged_b2 + 138*charged_c +
121*charged_d + 48*charged_e + 31*charged_f + 24*charged_g + 14*charged_h +
10*charged_i if NC_PriorPts == 4
```

```
gen LB_Risk4 = 1200*charged_a + 600*charged_b1 + 342*charged_b2 + 159*charged_c +
139*charged_d + 55*charged_e + 36*charged_f + 27*charged_g + 19*charged_h +
11*charged_i if NC_PriorPts == 5
gen LB_Risk5 = 1200*charged_a + 600*charged_b1 + 393*charged_b2 + 182*charged_c +
160*charged_d + 63*charged_e + 41*charged_f + 31*charged_g + 25*charged_h +
12*charged_i if NC_PriorPts == 6
recode LB_Risk* (.=0)
gen LB_Risk = LB_Risk0+LB_Risk1+LB_Risk2+LB_Risk3+LB_Risk4+LB_Risk5

gen LB_Harsh = verdict_min_b / LB_Risk

gen Harsh = LB_Harsh*100

*Spikeplot of Harshness outcomes
spikeplot Harsh if LB_Atty < 4 & LB_RaceBW < 2 & LB_plea < 4 & LB_PriorPts < 10000 &
Harsh < 100000 & AgeGroup < 100
*LB_Dist < 31, round(5)

*Spikeplot at prior criminal record level
spikeplot NC_PriorPts if LB_Atty < 4 & LB_RaceBW < 2 & LB_plea < 4 & LB_PriorPts <
10000 & Harsh < 100000 & AgeGroup < 100
spikeplot LB_PriorPts if LB_Atty < 4 & LB_RaceBW < 2 & LB_plea < 4 & LB_PriorPts <
10000 & Harsh < 100000 & AgeGroup < 100

*Frequency distribution table of plea types
tab LB_plea if LB_Atty < 4 & LB_RaceBW < 2 & LB_plea < 4 & LB_PriorPts <10000 & Harsh
< 100000 & AgeGroup < 100, miss

*Spikeplot age
spikeplot LB_AgeatCrime if LB_Atty < 4 & LB_RaceBW < 2 & LB_plea < 4 & LB_PriorPts <
10000 & Harsh < 100000 & AgeGroup < 100, round(1)

*Regression (main) - Model 1
reg Harsh NC_PriorPts i.LB_plea i.LB_RG4 i.AgeGroup i.LB_Atty i.LB_Dist

*Regression for 3 levels of risk (low, med, high) - Model 2
drop LB_RiskL
egen LB_RiskL = cut(LB_Risk), at(0,80,120,185,19000)
sum LB_RiskL LB_Risk

sort LB_RiskL by LB_RiskL: reg Harsh LB_PriorPts i.LB_plea i.LB_RG4 i.AgeGroup
i.LB_Atty
i.LB_Dist

*Frequency distribution of age groups with prior points levels
```

```
tab LB_PriorPts AgeGroup if LB_Atty < 4 & LB_RaceBW < 2 & LB_plea < 4 & LB_PriorPts <
10000 & Harsh < 100000 & AgeGroup < 100 & LB_Dist < 31
tab NC_PriorPts AgeGroup if LB_Atty < 4 & LB_RaceBW < 2 & LB_plea < 4 & LB_PriorPts <
10000 & Harsh < 100000 & AgeGroup < 100 & LB_Dist < 31

*Regression to Show that the prior points effect is consistent - Model 3
reg Harsh i.LB_PriorPts i.LB_plea i.LB_RG4 i.LB_Atty i.AgeGroup i.LB_Dist
reg Harsh i.NC_PriorPts i.LB_plea i.LB_RG4 i.LB_Atty i.AgeGroup i.LB_Dist

*Regression combining plea types - Model 4
gen LB_plea2 = 0 if LB_plea==0
replace LB_plea2 = 0 if LB_plea==1
replace LB_plea2 = 0 if LB_plea==3
replace LB_plea2 = 1 if LB_plea==2
reg Harsh LB_PriorPts i.LB_plea2 i.LB_RG4 i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh NC_PriorPts i.LB_plea2 i.LB_RG4 i.AgeGroup i.LB_Atty i.LB_Dist

*Regression to show Race and Sex separated - Model 5
reg Harsh LB_PriorPts i.LB_plea i.LB_RaceBW LB_Sex i.LB_Atty i.AgeGroup i.LB_Dist
reg Harsh NC_PriorPts i.LB_plea i.LB_RaceBW LB_Sex i.LB_Atty i.AgeGroup i.LB_Dist

*Regression if the Defendant had 0 Prior Record Points - Model 6
gen LB_RiskNo = 1200*charged_a + 300*charged_b1 + 196*charged_b2 + 92*charged_c +
80*charged_d + 31*charged_e + 20*charged_f + 16*charged_g + 8*charged_h + 8*charged_i
gen LB_HarshNo = verdict_min_b / LB_RiskNo
gen HarshNo = LB_HarshNo*100
reg HarshNo crdprpt i.LB_plea i.LB_RG4 i.AgeGroup i.LB_Atty i.LB_Dist

*Regression with location factos - Model 7
reg Harsh LB_PriorPts i.LB_plea i.LB_RG4 i.AgeGroup i.LB_Atty pop2010
TrumpDistrictShare PctWhiteDistrict

*Regression without attorney type - Model 8
reg Harsh LB_PriorPts i.LB_plea i.LB_RG4 i.AgeGroup i.LB_Dist

*Running the Regression without Prior Record Points to Look at Effect with Age - Unused
Model
reg Harsh i.LB_plea i.LB_RG4 i.AgeGroup i.LB_Atty i.LB_Dist

drop if Harsh== .
save Luke-d.dta, replace
*LB_RG4=0 WF, 1 BF, 2 WM, 3 BM

clear
use Luke-d.dta
replace TrumpDistrictShare= round(TrumpDistrictShare,1)
```

```
*Run this regression each time
reg Harsh i.LB_RG4  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist

keep if LB_PriorPts==0
save Luke-d-Prior0.dta, replace
reg Harsh i.LB_RG4  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race


clear
use Luke-d.dta
keep if LB_PriorPts==1
save Luke-d-Prior1.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race


clear
use Luke-d.dta
keep if LB_PriorPts==2
save Luke-d-Prior2.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race

clear
use Luke-d.dta
keep if LB_PriorPts==3
save Luke-d-Prior3.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race

clear
use Luke-d.dta
keep if LB_PriorPts==4
save Luke-d-Prior4.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race

clear
use Luke-d.dta
```

```
keep if LB_PriorPts==5
save Luke-d-Prior5.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race

clear
use Luke-d.dta
keep if LB_PriorPts==6
save Luke-d-Prior5.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race

clear
use Luke-d.dta
keep if LB_PriorPts==7
save Luke-c-Prior5.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race

clear
use Luke-d.dta
keep if LB_PriorPts==8
save Luke-d-Prior5.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race

clear
use Luke-d.dta
keep if LB_PriorPts==9
save Luke-d-Prior5.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race

clear
use Luke-d.dta
keep if LB_PriorPts==10
save Luke-c-Prior10.dta, replace
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Atty i.LB_Dist
reg Harsh i.LB_Race##i.LB_Sex  i.LB_plea i.AgeGroup i.LB_Dist
reg Harsh i.LB_Race
```

```
clear
use Luke-c.dta
*Descriptive Race
collapse (sum) Race_asian Race_black Race_hispanic Race_indian Race_other Race_white total,
by (LB_PriorPts)
gen PercWhite = Race_white/total
gen PercAsian = Race_asian/total
gen PercHisp = Race_hispanic/total
gen PercIndian = Race_indian/total
gen PercOther = Race_other/total
gen PercBlack = Race_black/total
graph bar PercBlack, over(LB_PriorPts)
graph bar PercWhite, over (LB_PriorPts)
graph bar PercAsian, over (LB_PriorPts)
graph bar PercIndian, over (LB_PriorPts)
graph bar PercHisp, over (LB_PriorPts)
graph bar PercOther, over (LB_PriorPts)
save DescRace.dta, replace

*Descriptive Attorney
clear
use Luke-c.dta
collapse (sum) LC_Atty0 LC_Atty1 LC_Atty2 LC_Atty3 total, by (LB_PriorPts)
gen PercAtty0 = LC_Atty0/total
gen PercAtty2 = LC_Atty2/total
gen PercAtty3 = LC_Atty3/total
graph bar PercAtty0, over(LB_PriorPts)
graph bar PercAtty2, over (LB_PriorPts)
graph bar PercAtty3, over (LB_PriorPts)
save DescAtty.dta, replace
*LC_Atty0= private, Atty1= public, Atty 2= appointed, Atty3= waived

*Descriptive Sex
clear
use Luke-c.dta
collapse (sum) LC_Male LC_Female total, by (LB_PriorPts)
gen PercMale = LC_Male/total
gen PercFemale = LC_Female/total
graph bar PercMale, over(LB_PriorPts)
graph bar PercFemale, over (LB_PriorPts)
save DescSex.dta, replace

*Descriptive SexRace
clear
use Luke-c.dta
```

```
collapse (sum) RG_BlackFemale RG_BlackMale RG_HispanicFemale RG_HispanicMale
RG_WhiteFemale RG_WhiteMale total, by (LB_PriorPts)
gen PercBF= RG_BlackFemale/total
gen PercBM= RG_BlackMale/total
gen PercHF= RG_HispanicFemale/total
gen PercHM= RG_HispanicMale/total
gen PercWF= RG_WhiteFemale/total
gen PercWM= RG_WhiteMale/total
graph bar PercBF, over(LB_PriorPts)
graph bar PercBM, over(LB_PriorPts)
graph bar PercWF, over(LB_PriorPts)
graph bar PercWM, over(LB_PriorPts)
graph bar PercHF, over(LB_PriorPts)
graph bar PercHM, over(LB_PriorPts)

*Descriptive Age Group
clear
use Luke-c.dta
collapse (sum) LC_AgeGroup15 LC_AgeGroup20 LC_AgeGroup30 LC_AgeGroup40
LC_AgeGroup50 total, by (LB_PriorPts)
gen Perc15 = LC_AgeGroup15/total
gen Perc20 = LC_AgeGroup20/total
gen Perc30 = LC_AgeGroup30/total
gen Perc40 = LC_AgeGroup40/total
gen Perc50 = LC_AgeGroup50/total
graph bar Perc15, over (LB_PriorPts)
graph bar Perc20, over (LB_PriorPts)
graph bar Perc30, over (LB_PriorPts)
graph bar Perc40, over (LB_PriorPts)
graph bar Perc50, over (LB_PriorPts)
save DescAge.dta, replace


*Descriptive Location
clear
use Luke-c.dta


clear
use Luke-c.dta
keep if crrace== "B"
reg crdprpt TrumpDistrictShare
reg crdprpt PctWhiteDistrict

clear
use Luke-c.dta
```

```
keep if crrace== "W"
reg crdprpt  TrumpDistrictShare
reg crdprpt PctWhiteDistrict

clear
use Luke-c.dta
keep if crrsex== "M"
reg crdprpt  TrumpDistrictShare
reg crdprpt PctWhiteDistrict

clear
use Luke-c.dta
keep if crrsex== "F"
reg crdprpt TrumpDistrictShare
reg crdprpt PctWhiteDistrict

*reg crrptpy c.(dfips1- dfips199) c.(male)#c.(race)

clear
use Luke-c.dta
reg crdprpt i.LB_RG4 LC_Atty0 LC_Atty2 LC_Atty3  LC_plea i.AgeGroup i.LB_Dist
reg crdprpt i.LB_RG4 LC_Atty0 LC_Atty2 LC_Atty3  LC_plea i.AgeGroup TrumpShare
reg crdprpt i.LB_RG4 LC_Atty0 LC_Atty2 LC_Atty3  LC_plea i.AgeGroup PopDistrict
reg crdprpt i.LB_RG4 LC_Atty0 LC_Atty2 LC_Atty3  LC_plea i.AgeGroup PctWhiteDistrict
```

Poli490H Class Reflection

Luke Cain

I was in my own group, investigating if it was possible to predict prior points and the intersects priors have with other identity factors in terms of determining punishment harshness.

I did all of the work. I replicated Luke Beyer's study, conducted a literature review, described the breakdown of prior points, predicted their causes with many regressions, ran regressions to see if courts used prior points as a code for any identity factors, and wrote about it all.

I had never opened STATA before this class. I now feel confident parsing and manipulating large data sets, creating graphical representations of data, and running and interpreting linear regressions. I know more about the capabilities and process of mapping and using GIS and feel that, with a little practice, I could master that skill too.

I knew relatively little about criminal justice before this class. I now know about the North Carolina sentencing grid, the fruitlessness of traffic stops and stop-and-frisk, broken windows policing, and the severity of racial discrepancy at all levels of the criminal justice system. On top of that, I learned more about the academic world. This project is the first serious one I have completed in college. I have read academic papers and presented on topics before but it was always a synthesis of other people's work. In this course, I have learned some about what it means to be a researcher.