Proxies for and Predictors of DC Residents' Views on Police

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Abstract

With the grave state of police brutality in the United States, many individuals distrust and feel wary of police. This comes paired with the over-policing of certain groups of individuals and selective enforcement of law in certain neighborhoods. The premise of this research is that residents' opinions on effectiveness of police and on feelings about interactions with police can serve as proxies for satisfaction with police. Prior research has found that accounting for neighborhood crime characteristics diminishes the observed race effect on dissatisfaction with police. Can ward-level crime characteristics predict an individual's negative feelings towards DC metropolitan police? How strong are individual demographic factors in predicting attitudes toward police in DC, with or without accounting for crime? In this research, I employ logistic regression to investigate questions such as these. I find that depending on the proxy used to model satisfaction with police, race could have an observed effect. This significance disappears, however, not with crime characteristics but with inclusion of individuals' opinions on what crimes should be prioritized. People who are concerned over violent crimes, narcotics, and the gun trade, are less likely to view the police force as effective.

Introduction

For the first time, the United States is in a political context in which white liberal citizens are beginning to recognize and admit the existence of police brutality and mass incarceration of black people as a new Jim Crow era. Now more than ever, Americans are willing to be more receptive to research that bolsters the existence of these horrors.

With the beginnings of widespread media coverage of police brutality, more individuals may be critical of police, and thus dissatisfaction with police would grow. Past studies on satisfaction with or trust of police have found that both black and lower-class citizens tend to be less satisfied with police. A past study by Yuning Wu and Ivan Y. Sun found race and class to be particularly important predictors of public satisfaction with police. They found that more marginalized racial and socioeconomic groups, particularly black Americans and lower-class people, tend to be less satisfied with the police. However, once they accounted for neighborhood-level factors including concentrated poverty and violent crime rate, the observed race and class effects disappeared, with those living in mostly-white or mixed neighborhoods reporting higher satisfaction with police.[2] These neighborhood-level factors included concentrated poverty as well as violent crime rate, which is known to be correlated with inequality. Past work by Elaine B. Sharp and Paul E. Johnson studying distrust in police found a substantial race gap as well, which was not diminished by the inclusion of city-level predictors.[3]

These two works are seemingly at odds with one another. Thus, I aim to investigate the strength of both individual-level demographic variables as well as neighborhood-level crime characteristics in predicting negative thoughts or feelings toward police. The dynamics of policing can be very specific to the nature of a particular city, so I focus on a case study of Washington, District of Columbia (DC). DC is a great candidate for this study because it has very good data recordkeeping through OpenDataDC.[1] It also faces many of the problems that a study like this is concerned with: high levels of inequality, concentrated poverty, and extreme racial and socioeconomic segregation. Even more, it is classified into eight numbered wards, which are both socioeconomically and culturally distinct. The city is policed by the Metropolitan Police Department (MPD).

Very different types of crimes happen in different neighborhoods. Opinions on what is best for public safety are shaped by the violence happening within one's specific neighborhood. For example, wealthy residents in neighborhoods with traffic congestion, low incidences of violent crimes, and high incidences of car break-ins will likely be more concerned with police initiatives related to traffic guards or increased police presence to stop petty crimes, neglecting issues that do not hit close to home. Residents from neighborhoods that experience high levels of narcotics use and violent crimes will be more concerned with preventing those, compared with less grave or deadly offenses.

In this work, I investigate whether ward-level crime characteristics can predict an individual's negative feelings towards police. As conflicting conclusions exist in the literature, this work aims to explore the relationship between an individual's demographic characteristics and attitudes towards DC police, once accounting for crime characteristics.

Methods

About the Data

The dataset employed in this work was created using two original datasets, one of crime incidents and the other of survey responses. All data is sourced from OpenDataDC, the DC government's open-access platform to share data with the public.[1]

The crime dataset entitled "Crime Incidents in 2017" contains locations and attributes of incidents reported in the Analytical Services Application crime report database by the District of Columbia Metropolitan Police Department (MPD).

The survey data originates from the "Public Safety Survey from 2017," conducted by the Office of the Deputy Mayor for Public Safety and Justice. The survey was administered so that residents could opt to take it online or complete it in person at community center and libraries. It was publicized through the mayor's weekly newsletter, neighborhood list-servs, and an email to all DC government employees. The survey was conducted in the time period of January 2017 to February 2017, with 3990 valid responses documented. This survey collected respondents' demographic information as well as their opinions on police and highest-priority policy issues.

From the crime data, I generated measures of crime characteristics by ward. These consist of total count of crime in a ward, proportion of overall DC crime that takes place in a ward, as well as proportion of crime within a ward that is a certain offense type. These data were then merged with participants of the public survey dataset by their ward of residence, thus contextualizing their responses given the state of criminal activity and policing in their neighborhoods.

I make the assumption that 2017 crimes are representative of a standard year of crime in DC, so that I can utilize the entirety of the crime data. I also boldly assume that observations which have missing values are "missing at random", and proceed by taking only the complete cases. Further implications of this will be discussed later on. The final dataset contains 1,845 observations of 28 variables.

Statistical Methodologies

In my analysis, I explore how the frequency and nature of crimes in a ward interact with demographic variables to predict attitudes towards police. I use two distinct outcome variables originating from the survey data as proxies for attitudes towards police. The first is an individual's rating of the effectiveness of the MPD, ranging from "Very ineffective" to "Very effective". The second is an individual's rating of personal interactions with police, from "Very negative" to "Very positive". These two variables get at the same nature of like or dislike, trust or distrust, yet they remain distinct entities.

All statistical analyses are conducted in R version 3.4.1. I make particular use of the MASS package's stepwise selection algorithm, the `stepAIC` function, fitting logistic regressions with binary outcomes using the Akaike Information Criterion (AIC). In this, I employ both backwards and forwards model-building techniques. I also use the `polr` function in fitting proportional odds ordered logistic regressions. I examine statistical significance at the $\alpha = 0.05$ level.

I go through three dinstict stages of model-building for both outcome variables, effectiveness and police interactions. These stages differ in which predictors to consider. I first investigate the predictive abilities of exclusively demographic variables, then exclusively crime characteristics, and then the full set of predictors. I bin my dependent outcome variables for logistic regression, otherwise treating them as ordinal.

Results

Before delving into regression analysis, I investigate some exploratory and summary results. To get a sense of the data, I investigate counts of the outcome variables, effectiveness and police interactions, as displayed in Tables 1 and 2. One can see that much of the distributions of both variables lie in the relatively neutral-to-positive zone. This is important to keep in mind when considering limitations of the model later on.

Police interactions	Count
Very negative	38
Negative	104
Neutral	538
Positive	804
Very positive	361

Table 1: Distribution of feelings about interactions with police

Effectiveness	Count
Very Ineffective	80
Ineffective	408
Effective	1153
Very Effective	204

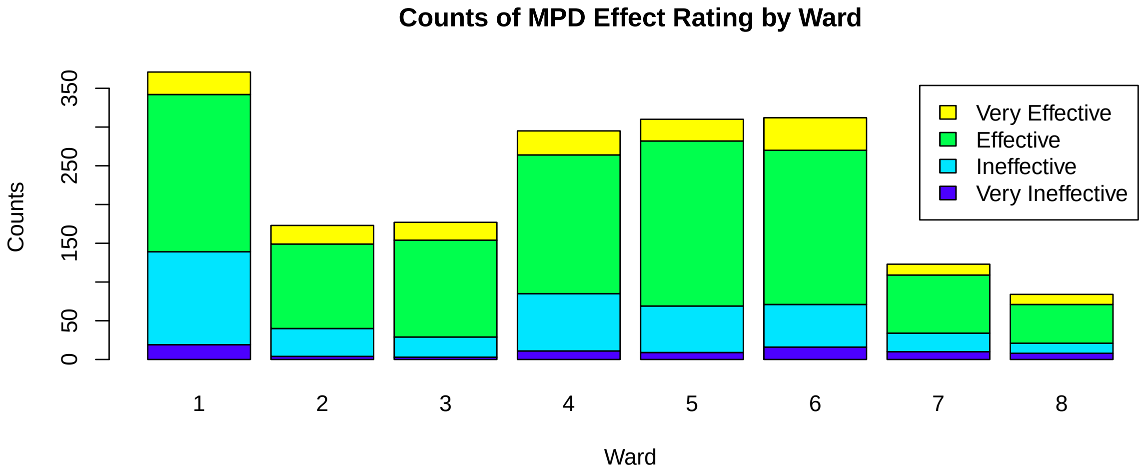
Table 2: Distribution of perceived effectiveness of police

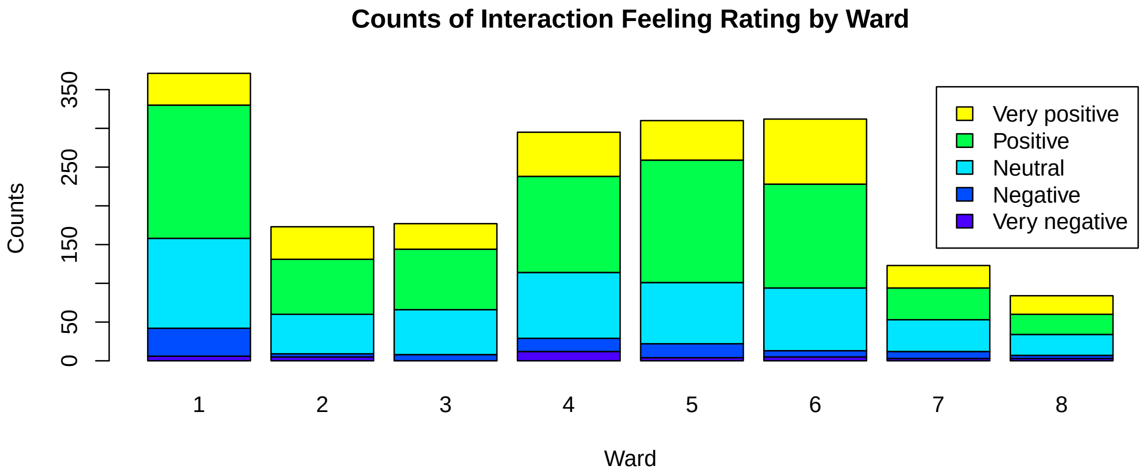
Table 3 is a summary of crimes that happen in each ward. These values are the crime characteristics that appear in the dataset for each individual who is from a specific ward. One can see, in particular, that wards 1, 2, and 3 experience high rates of car break-ins and lower rates of assault with a dangerous weapon, compared with wards 7 or 8 which experience higher proportions of homicides and robberies. At this stage, one can observe that wards are noticeably distinct from one another, even in the absence of demographic data about the specific ward.

Ward	Proportion DC crime	Arson	Assault with weapon	Burglary	Homicide	Car theft	Robbery	Sexual abuse	Car break-in	Other crime
1	0.14	0	0.03	0.03	0.00	0.05	0.06	0.01	0.41	0.41
2	0.18	0	0.02	0.03	0.00	0.04	0.04	0.01	0.30	0.56
3	0.05	0	0.01	0.06	0.00	0.06	0.03	0.00	0.32	0.52
4	0.09	0	0.05	0.05	0.00	0.07	0.07	0.01	0.39	0.35
5	0.14	0	0.06	0.05	0.00	0.09	0.07	0.01	0.31	0.41
6	0.17	0	0.03	0.03	0.00	0.06	0.05	0.01	0.33	0.50
7	0.13	0	0.11	0.05	0.01	0.14	0.10	0.02	0.21	0.37
8	0.10	0	0.13	0.09	0.01	0.10	0.10	0.01	0.20	0.34

Table 3: Crime Characteristics by Ward

In an effort to expose relationships between wards and the outcome variables, it is also helpful to look at stacked barplots by ward that are segmented by response type. One can see that Ward 1 is overrepresented in the dataset, while there are substantially fewer observations from Wards 7 and 8. Ward 1 is a very wealthy, white population, while Wards 7 and 8 consist of the most marginalized communities in DC. It is also helpful to visualize the distributions of positive versus negative feelings. Some relationship is apparent where Ward 1 residents choose very similar proportions of options for our outcome variables, while there is a visible contrast between the barplots for ward 7 and 8 in the respective tables.





Logistic Regression using Demographic Predictors

I begin by fitting logistic regressions for both outcomes of interest using exclusively demographic predictors. Here, I refer to perceived effectiveness of police as $Mpdeffect$ and to feelings about interactions with police as $Interactfeel$.

Equation 1 is the resulting logistic regression model of $Mpdeffect$ from demographic-only predictors. The results in Table 4 have little to say, boasting an $AIC = 2076.9$, with only three coefficients significant at the $\alpha = 0.05$ level. Its Concordance Index, a measure of predictive ability, is 0.628. It is important to note for interpretation of coefficients that the reference group for $Ethnicity$ is African-American. Thus, the odds ratio of viewing the MPD as effective for white people versus black people (reference group) is $exp(0.30) = 1.35$, significant at $\alpha = 0.05$. This means that white people have a higher odds of viewing the police force as effective when compared with black people. The estimate for American Indian and Unknown are also statistically significant, but they are groups with relatively little data so it may not be reliable. None of the $Agebin$ coefficients are statistically significant.

$$log(\text{odds of } Mpdeffect > \text{Ineffective}) = \beta_0 + \beta_1 Age + \beta_2 Ethnicity \tag{1}$$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	4.08	165.68	0.02	0.98
Age	14.60	762.00	0.02	0.98
Age^2	8.20	775.21	0.01	0.99
Age^3	2.78	651.59	0.00	1.00
Age^4	-2.46	480.17	-0.01	1.00
Age^5	-4.16	315.66	-0.01	0.99
Age^6	-3.73	180.23	-0.02	0.98
Age^7	-1.95	82.98	-0.02	0.98
Age^8	-0.64	26.23	-0.02	0.98
American Indian	-1.25	0.69	-1.80	0.07
Asian/Asian American	-0.27	0.31	-0.88	0.38
Caucasian	0.30	0.15	2.05	0.04
Hispanic/Latino	-0.13	0.26	-0.50	0.61
Middle Eastern/North African	-0.10	0.58	-0.17	0.86
Multiracial	-0.18	0.26	-0.69	0.49
Other	0.22	0.60	0.37	0.71
Pacific Islander/Hawaiian	14.50	1024.48	0.01	0.99
Unknown Ethnicity	-0.93	0.50	-1.87	0.06

Table 4: Logistic regression model of $Mpdeffect$ predicted by demographics only

Equation 2 is the logistic regression model of $Mpdeffect$ from demographic-only predictors. It has an $AIC = 999.6$, which is much lower than for Equation 1, suggesting it is a better model. It has very little predictive ability, however, with $CI = 0.5509$, barely better than a coin flip. Recognizing these limitations, we can still gleam from the model that the odds ratio of viewing police interactions neutrally/positively versus negatively for males versus females is $exp(-0.41) = 0.66$, significant at $\alpha = 0.05$, with 95% confidence interval: (0.47,0.935). This means that males have a higher odds of reporting negative feelings from interactions with police when compared with females.

$$log(\text{odds of } Interactfeel > \text{Negative}) = \beta_0 + \beta_1 Male \tag{2}$$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	2.68	0.13	21.35	0.00
Male	-0.41	0.18	-2.34	0.02

Table 5: Logistic regression model of $Interactfeel$ predicted by demographics only

Both of these models do not do a very good job at prediction, and other than ethnicity, the variables do not tell much of a continuous narrative.

Logistic Regression using Crime Characteristics

In fitting models using exclusively crime characteristics, I found that the choice of which variables were significant in the regression was highly dependent on the order by which they are tested. Thus, both the forward and backward models contain predictors that are statistically significant, while appearing quite different.

The results of the backward-selection process are found in Equation 3 and Table 6 below, where $Totalcrime$ refers to count of crimes in a specific ward. This model has a $CI = 0.589$, and $AIC = 2015$. The coefficients tell us that a higher ward-level proportion of robbery results in higher odds of thinking the police are ineffective, while the rest of the predictors result in higher odds of thinking the police are effective.

$$\begin{split} log(\text{odds of } Mpdeffect > \text{Ineffective}) = \beta_0 + \beta_1 Totalcrime \\ + \beta_2 Arson + \beta_3 Burglary + \beta_4 Cartheft + \beta_5 Robbery \end{split} \tag{3}$$

The model built using forward selection does not fare much better. This model is outlined in Equation 4, with coefficients in Table 7. It has a $CI = 0.585$, and an $AIC = 2104$. A higher proportion of car break-ins, robbery or other crime results in lower odds of being satisfied with police.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.38	0.43	0.89	0.37
Total crime	0.00	0.00	2.38	0.02
Arson	646.59	285.36	2.27	0.02
Burglary	18.07	6.11	2.96	0.00
Car theft	13.57	3.58	3.79	0.00
Robbery	-29.30	5.06	-5.79	0.00

Table 6: Logistic regression model of $Mpdeffect$ predicted by crime variables only (backwards)

$$log(\text{odds of } Mpdeffect > \text{Ineffective}) = \beta_0 + \beta_1 Carbreakin + \beta_2 Robbery + \beta_3 OtherCrime + \beta_4 Arson \quad (4)$$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	8.88	2.19	4.05	0.00
Car break-in	-7.97	1.62	-4.93	0.00
Robbery	-37.02	10.05	-3.69	0.00
Other crime	-6.83	2.57	-2.66	0.01
Arson	573.58	280.06	2.05	0.04

Table 7: Logistic regression model of $Mpdeffect$ predicted by crime variables only (forwards)

In an effort to maintain brevity, backwards and forwards models for $Interactfeel$ on crime characteristics will not be discussed in detail. The backwards selection model had $CI = 0.602$, $AIC = 2105$, while the forwards model had $CI = 0.596$, $AIC = 991.7$. The forwards model had a low AIC value because it had significantly fewer terms.

Logistic Regression using Full Set of Predictors

The models built using the entire dataset have much higher predictive ability and hold in importance a mixture of predictors from the various categories. The backwards-built logistic regression of $Mpdeffect$ is one of the strongest models fitted thus far. It has an $AIC = 1572$, but an impressively high $CI = 0.843$. One can conclude from Table 8 that Ward 3, Ward 5, and those who view community-police relations and traffic laws as important, are more likely to view police as more effective. Those who view targeting guns as more important are less likely to view police as effective. On the other side of the spectrum, those who believe the size or presence of the police force should be increased are associated with lower odds of rating the MPD as effective. Gender remains a statistically significant factor, but in this case we find that males have a higher odds of viewing the police as effective versus females.

$$log(\text{odds of } Mpdeffect > \text{Ineffective}) = \beta_0 + \beta_1 Ward + \beta_2 Male + \beta_3 Agebin + \beta_4 Incforce + \beta_5 Incpresence + \beta_6 Communityrelations + \beta_7 Enforcetraffic + \beta_8 Targetguns \quad (5)$$

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.83	165.07	0.01	0.99
Ward 2	0.51	0.25	2.02	0.04
Ward 3	0.93	0.28	3.37	0.00
Ward 4	0.36	0.21	1.70	0.09
Ward 5	0.60	0.21	2.86	0.00
Ward 6	0.34	0.21	1.63	0.10
Ward 7	0.37	0.29	1.28	0.20
Ward 8	0.69	0.36	1.92	0.05
Male	0.25	0.14	1.83	0.07
Age	12.37	760.39	0.02	0.99
Age^2	7.10	775.02	0.01	0.99
Age^3	1.82	650.97	0.00	1.00
Age^4	-2.84	476.41	-0.01	1.00
Age^5	-3.94	308.88	-0.01	0.99
Age^6	-3.87	173.48	-0.02	0.98
Age^7	-1.99	78.74	-0.03	0.98
Age^8	-0.78	24.63	-0.03	0.97
Increased Force	-0.13	0.20	-0.62	0.53
Increased $Force^2$	-0.61	0.15	-3.96	0.00
Increased $Force^3$	-0.02	0.14	-0.15	0.88
Increased Presence	0.37	0.24	1.54	0.12
Increased $Presence^2$	-0.83	0.18	-4.64	0.00
Increased $Presence^3$	0.48	0.15	3.16	0.00
Community Relations	1.19	0.45	2.68	0.01
Community $Relations^2$	-0.39	0.36	-1.11	0.27
Community $Relations^3$	0.33	0.25	1.32	0.19
Traffic Laws	0.03	0.16	0.18	0.86
Traffic $Laws^2$	-0.52	0.14	-3.70	0.00
Traffic $Laws^3$	-0.13	0.12	-1.07	0.28
Target Guns	0.64	0.27	2.35	0.02
Target $Guns^2$	-0.68	0.22	-3.13	0.00
Target $Guns^3$	0.32	0.16	1.97	0.05

Table 8: Logistic regression model of $Mpdeffect$ (backwards)

The forwards-built model of $Mpdeffect$ has many of the same terms as the backwards-built model, only differing in its inclusion of increased force, car break-ins, total crime count, robbery, and targeting narcotics and in its exclusion of ward, a variable which is highly correlated to all of these. This model has an $AIC = 1566$, and $CI = 0.844$. One can come to many of the same conclusions as with the last model.

Now I move on to the full models for outcome $Interactionfeel$. Using the likelihood ratio test, the forward model with additional terms is statistically significant, so I will solely report that one as my final model, as seen in Equation 6.

$$\begin{aligned} log(\text{odds of } Interactionfeel > \text{Negative}) = \beta_0 + \beta_1 Mpdeffect \\ + \beta_2 Incpresence + \beta_3 Male + \beta_4 Nuisance + \beta_5 CrimeEtc \\ + \beta_6 Arson + \beta_7 TargetNarcs \end{aligned} \tag{6}$$

This model has significantly fewer terms than those that predicted $Mpdeffect$, but it maintains a high Concordance Index of 0.874. The Akaike Information Criterion is only 727.4, relatively much smaller than that of the other models, bar the demographic models that did not perform well. Table 10 holds the coefficients for this model. Adjusting for the other variables, males are still more likely to view police interactions as more negative. Those who view nuisance crimes and increased police presence as important are more likely to view police interactions as more positive. Those who think that targeting narcotic drugs is important are more likely to view interactions with police more negatively.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.87	0.77	1.14	0.26
Mpdeffect	3.75	0.70	5.37	0.00
Mpdeffect^2	0.12	0.53	0.23	0.82
Mpdeffect^3	-0.44	0.28	-1.54	0.12
Increased Presence	1.08	0.27	3.99	0.00
Increased Presence^2	-0.36	0.23	-1.58	0.11
Increased Presence^3	-0.48	0.24	-2.00	0.05
Male	-0.60	0.21	-2.93	0.00
Nuisance	-0.16	0.27	-0.60	0.55
Nuisance^2	0.35	0.23	1.50	0.13
Nuisance^3	0.62	0.22	2.82	0.00
Other Crime	4.07	1.65	2.47	0.01
Arson	1041.21	550.29	1.89	0.06
Target Narcotics	0.18	0.26	0.69	0.49
Target Narcotics^2	-0.55	0.22	-2.49	0.01
Target Narcotics^3	0.07	0.23	0.31	0.75

Table 9: Logistic regression model of $Interactionfeel$

Discussion

The differences between perceived effectiveness of police ($Mpdeffect$) and feelings about interactions with police ($Interactfeel$) as proxies for feelings about police were greater than anticipated, as is evident in contrasting regressions. For example, in fitting Model 1 (with outcome $Mpdeffect$) and Model 2 (with outcome $Interactfeel$), using solely demographic predictors, we gained insight into the unadjusted race and gender effects present. When aiming to predict perceived effectiveness of police, there were statistically significant differences between black people and white people, but not by gender. When aiming to predict feelings about interactions with police, there were statistically significant differences by gender, but not race. This is a surprising result, that I can only possibly explain by suggesting that men raised in hypermasculine environments are perhaps more confrontational in their interactions with police. Thus, they could experience poorer outcomes of those interactions, which would be universal across ethnicities. Meanwhile, those white people who are more out of touch with police brutality could be less disillusioned by the police and therefore rate them as effective. Conversely, those who belong to black communities that are more likely to have been negatively impacted by police would view the police as less effective, even if they do not engage in constant confrontations. Perhaps the most powerful result from this stage of the process, however, was demographic characteristics' surprising uselessness in building a powerful model.

However, when continuing into the sphere of models exclusively based on crime characteristics, we faced similar issues. Predictive power of the regressions only strengthened when considering both demographic variables and crime characteristics together, along with opinions on other police-related policy issues. The latter of the three seemed to hone in on the possible relationships between neighborhood crime and opinions of police, from a slightly different lens than the crime characteristics did. We saw in the regressions for perceived effectiveness that people who value the strengthening of community-police relations and traffic laws as important are more likely to view the MPD as effective. This gets at what was hypothesized earlier, that people who are more concerned with non-violent and misdemeanor-type offenses are going to think the police are doing a good job. In contrast, those concerned with the illegal gun trade have a higher odds of viewing the MPD as ineffective.

Potential Limitations

In considering these analyses, there is a lot of concern over whether the dataset is representative, or whether it is inherently skewed in the way it was collected and/or cleaned. In cleaning the data, I boldly assumed that missing values were "missing at random", and dropped every observation that had any missing. It is not likely that this is the case, however. Especially because these data stem from surveys that could have been handwritten, it is likely that participants opted not to answer certain questions. In fact, the three variables with the highest counts of missing observations were answers to questions concerning effectiveness of the MPD, whether the MPD should increase their use of force, and community policing, all of which have to do with feelings about police.

This suspicion is bolstered somewhat by the distributions of the outcomes of interest being weighted towards positive or neutral answers, particularly for those who rated the effectiveness of MPD as "Effective" and those who viewed their interactions with police as "Neutral." There will also be response bias depending on what options participants are given: participants are allowed a neutral option in deciding how police-interactions feel but are forced to decide between extremes of effective versus ineffective in rating the MPD's effectiveness. Those who are on the fence and would have gone for a more middle-ground option might be more tempted to choose the slightly more positive "Effective" over the critical "Ineffective."

In fitting models using exclusively crime characteristics, I found that the choice of which variables were significant in the regression was highly dependent on the order by which they are tested. These variables are not linearly dependent in the classical sense, but they are highly correlated with one another. Thus, choosing one over another should not generate significantly different results from a model. However, in order to ensure choice of the most proper crime characteristics, these models would have significantly benefitted from best subset analysis.

The estimates for nearly all the crime characteristics are also tricky to interpret, by nature of the values of the variables. The estimates are significantly larger than the estimates seen using demographic predictors, which is because these inputs are proportions ranging from 0 to 1. A coefficient, however, suggests what effect a 1-unit change would have on the log odds, which is not interpretable.

Conclusion

We cannot conclude that ward-level crime characteristics or demographic factors alone can predict attitudes toward police in DC. What is more revealing is being able to combine information on these predictors with individuals' thoughts on various issues related to crime. It is also striking to see such disparate results by gender.

These results are not consistent with the past findings referenced earlier. However, they are not necessarily inconsistent. The data utilized in this research did not account for the same type of socioeconomic individual-level information as did the past work. As well, it is likely that opinions on prioritizing certain crime issues are shaped by life experiences including crime characteristics of a neighborhood. My creation of crime characteristics could be overgeneralized or misunderstood in another way, taking away importance from these crucial variables. Yet, to conclude from the findings of my study, I have found that race effects are diminished with the addition of the crime policy issue variables, but that crime characteristics as standalone are no more effective than demographics. The observed race effects only initially exist, however, depending on which proxy is used.

Future researchers should be cautious of and take careful time to assess proxies representing vagueties such as "satisfaction." My findings show that one's understanding of which predictors matter can shift greatly along with a shift in understanding of the proxy variable. Inconsistencies in the literature might arise from this issue, so that from an outside perspective they appear to be seemingly contradictory.

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